Political Polarization in Financial News*

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Abstract

Standard explanations for political polarization of news don't apply to financial news. Nevertheless, we find strong evidence of political polarization in corporate financial news on both intensive and extensive margins of coverage. To control for firm and newspaper heterogeneity, we compare coverage of the same firm-level events by newspapers with opposing ideologies. We find that politics-driven disagreement in news increases trading, and investors respond to news about a stock in the newspaper they read by trading more and in the same direction as other investors who read the same news. The results are consistent with polarization leading to information segregation.

Keywords: Media bias, Financial news, Finance and politics, Textual analysis, Trading volume, Individual investors.

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1. Introduction

Reporting on Tesla's massive stock rally in early 2020, a *Wall Street Journal* article led with "Those outsized gains don't match Tesla's more modest fundamentals, which include annual losses," while on the same day an article in the *New York Times* began "There's a new rocket ship from Elon Musk: Tesla's stock."[1] Between 2018 and 2020, over 90% of Tesla's campaign contributions supported political candidates from the Democratic Party. Is the difference in the tone of financial news coverage between the (conservative) *Wall Street Journal* and (liberal) *New York Times* explained by the company's political alignment with the news source?

Readers seeking confirmation of their political views can lead to polarization in the coverage of political news (Mullainathan and Shleifer (2005); Groseclose and Milyo (2005); Gentzkow and Shapiro (2006))[2,3] However, news that is *ex post* verifiable, such as the weather, sports, and financial news, is not expected to be politically biased (Gentzkow and Shapiro (2006)). Moreover, a large literature in finance has shown that financial news is read not to confirm political beliefs but to inform financial decisions (Huberman and Regev (2001); Tetlock (2007); Barber and Odean (2008); Fang and Peress (2009); Tetlock (2011); Engelberg and Parsons (2011); Dougal et al. (2012); Garcia (2013); Hillert, Jacobs, and Muller (2014); Ben-Rephael, Da, and Israelsen (2017)). And in fact most major newspapers have separate business and editorial page editors.

Our main contribution is to show that politics can influence firms' signals to investors through the media, and thereby affect investor trading behavior. First, we find that an article about a firm is more likely to appear in the newspaper the firm is politically aligned with, and use more favorable language, suggesting that newspapers cater to the views of their

[1] "Tesla Rally Stirs Memories of Past Market Bubbles," *The Wall Street Journal*, February 5, 2020 and "Backed by Bulls and Helped by Bears, Tesla's Stock Soars," *The New York Times*, February 5, 2020.

[2] Mullainathan and Shleifer (2005) argue that if readers hold beliefs that they want to see confirmed, then even competitive media would report news with a slant, and Gentzkow and Shapiro (2006) show that even if consumers demand news without bias, a media firm concerned with its reputation for accuracy will report news that confirms the readers' prior beliefs.

[3] Evidence suggests that political polarization has increased dramatically in the United States in recent decades (Bishop (2008); Abramowitz and Saunders (2008); Gentzkow, Shapiro, and Taddy (2019)), which is backed by survey results from Pew indicating that "when it comes to getting news about politics and government, liberals and conservatives inhabit different worlds" (Mitchell et al. (2014)).

readership even when reporting corporate financial news. Second, consistent with political polarization leading to segregation in the information sets of investors, we find that there is more trading on days where there is more politics-induced disagreement in the reporting of financial news. Third, we provide direct evidence of information segregation by showing that when news about a stock appears in the newspaper an individual investor is likely to read, the investor trades more and in the same direction as other investors who read the same paper. Our results suggest that political polarization in the reporting of financial news affects investor trading decisions.

Identifying the impact of political polarization on the reporting of financial news poses a number of challenges. First, it requires comparison of the same news reported by newspapers with differing political ideologies. Second, we need to measure political alignment between newspapers and firms. Third, we need to distinguish political alignment from other characteristics of newspapers and firms that may affect coverage.

To address these challenges, we compare three decades of articles published in the conservative *Wall Street Journal (WSJ)* and the liberal *New York Times (NYT)* covering financial news on the 100 largest listed firms in the United States. These are the two most widely circulated national newspapers with business news sections, and their editorial pages occupy opposite ends of the political spectrum (Gentzkow and Shapiro (2010)).[4] To identify firm-level political affiliation we use campaign contributions by employees and corporate political action committees to Democratic and Republican Party candidates.[5] By examining differences in reporting between the two newspapers about the same firm at the same point in time, we ensure that our results are not driven by differences in firm and newspaper characteristics that affect coverage.

On the extensive margin, we show that a newspaper is more likely to cover, to write longer articles about, and publish good rather than bad financial news on politically aligned

[4]We define newspaper ideology based on Gentzkow and Shapiro (2010)'s language-based measure of political slant, which identifies the *New York Times* as left of center and the *Wall Street Journal* as right of center (Figure 1 in their paper).

[5]Campaign contributions have been widely used in the literature as a measure of corporate political affiliation, see for example, Claessens, Feijen, and Laeven (2008); Cooper, Gulen, and Ovtchinnikov (2009); Aggarwal, Meschke, and Wang (2012); Ovtchinnikov and Pantaleoni (2012); Akey (2015), among others.

firms.[6] For example, a one standard deviation increase in campaign contributions to the Republican Party increases article length by about 4% in the *WSJ* relative to the *NYT*. We observe stronger results for firms at the political extremes, indicating that our political alignment measure captures political activity. These results control for firm, quarter, topic fixed effects, *Firm* $\times$ *Quarter* fixed effects, and firm-level advertising and profitability.

On the intensive margin, we show that the tone of an article about a firm varies based on the political alignment between the firm and the news source.[7] For example, an article in the *WSJ* about a firm that donated only to Republican Party candidates in the previous election cycle uses 20% more positive words than an article in the *NYT*. In contrast, an article in the *WSJ* about a firm that donated only to Democratic Party candidates uses 10% fewer positive words compared to the *NYT*. We observe the opposite pattern for negative words where, compared to the *NYT*, the *WSJ* uses fewer negative words in articles about firms that are top donors to the Republican Party. We also find tone differences are stronger in the lead paragraph, which is read by more readers, than the rest of the article, suggesting that politics-driven differences in coverage are a key part of financial news articles.

To control for non-random coverage, we follow Fracassi, Petry, and Tate (2016) and Kempf and Tsoutsoura (2020) and include *Firm* $\times$ *Quarter* and *Paper* $\times$ *Quarter* fixed effects in the tone regressions, which absorb time-varying firm and newspaper characteristics that can affect coverage, and allow us to compare coverage across newspapers for the same firm-specific events. Additionally, using the sale of the *WSJ* to the News Corporation as a shock that may have shifted the political ideology of the newspaper further to the right, we find that the *WSJ* is more likely to publish an article about a politically aligned firm and use more positive language in these articles following the ownership change. Providing further support for our hypothesis that political alignment between the firm and newspaper affects financial news coverage, we show that journalists who worked for both newspapers switch their tone when they switch jobs to reflect alignment between the newspaper they work for

[6] To ensure that we capture news about a specific firm we restrict the analysis throughout to articles that mention just one firm or at most two firms.

[7] An anecdote from our sample: On July 20, 2004, 3M Co. announced earnings. The *WSJ* led its story with: "Quarterly Net for 3M Rose 25% on Units' Strength," while a *NYT* article on the same event began: "3M Shares Fall in Disappointing Earnings Outlook." In 2004, 80% of political contributions from 3M were to Republicans.

and the firm they are writing about. We also show that the results are stronger for the most politically active firms, indicating that we capture political activity rather than other firm characteristics. We show that our results are not driven by coverage of different firm events by newspapers because the results are robust to restricting the sample to articles published about the same firm on the same day in both papers. Finally, we include two-digit topic fixed effects and also obtain similar results when we restrict the sample to specific topics such as earnings announcements, indicating that the results are not driven by differences in the coverage of topics between the newspapers.

Financial news is a major source of information for investors. Our results show that the political alignment between a firm and news source can affect financial news coverage. Since political polarization causes individuals to seek out news sources that match their views (Iyengar and Hahn (2009); Gentzkow and Shapiro (2011)), disagreement in the coverage of financial news can segregate the information sets of investors. Although the effect of disagreement in financial news coverage on stock market returns is ambiguous if one source reports it as good news while the other as bad news, theory suggests that disagreement among investors about the value of a stock can lead to trade (Milgrom and Stokey (1982); Karpoff (1986); Harris and Raviv (1993)). Thus, we study the effect of disagreement in financial news coverage on firm-level abnormal trading volume.

To establish that the stock market response is driven by investor response to the news rather than to major events, we conduct the analysis on a sub-sample of firms with exactly two articles on a given day, which eliminates "big" event days that may generate volume, and test whether differences in reporting between the newspapers affect trading behavior. Specifically, we compare firms with two articles in one paper (no disagreement) to firms with one article in each paper (high disagreement), and control for *Firm* $\times$ *Year* fixed effects, which absorb unobservable firm characteristics correlated with political alignment and volume. Since major events get more coverage, to control for such events we include the total number of articles written about a firm on a given day in all news sources on Factiva (about 30,000 sources). Finally, we directly show that individual investors respond to financial news.

We find that abnormal trading volume for a firm is higher on days when both newspapers cover the firm (high disagreement), compared to days on which just one newspaper covers the firm (no disagreement). Consistent with the hypothesis that politically induced disagreement in financial news coverage affects trading behavior, we find that more politically active firms experience the greatest increase in abnormal trading volume on days when there is likely to be more disagreement. We also show that the greater the difference in the tone of coverage about a firm between the two newspapers, the greater the increase in trading volume, especially for more politically active firms. Our results are consistent with the hypothesis that political polarization in financial news coverage can increase segregation in the information sets of investors, and thereby affect investor behavior.

Lastly, we provide direct evidence that individual investors respond to the news. We match data on individual investor trades from a retail brokerage data set to newspaper circulation data based on the zipcode location of the investors. The advantage of the brokerage data is that it is from 1991 to 1996 when most online financial news sources did not exist, which allows for a clean test of whether newspapers affect investor behavior. We find that individual investors trade more in a stock if the newspaper they are more likely to read publishes a story about that stock, but do not respond to news published in the paper they are less likely to read. We also find that investors respond to news about a stock published in the newspaper they read by trading in the same direction as other investors who read the same newspaper. These results support our hypothesis that investors read different news sources and that disagreement in financial news coverage affects investor behavior.

1.1. Related literature

Our paper contributes to the politics and finance literature that finds positive effects of political connections, campaign contributions, and lobbying on firm value (Fisman (2001); Faccio (2006); Borisov, Goldman, and Gupta (2016)), and documents the effect of political bias on economic expectations (Mian, Sufi, and Khoshkhou (2017); Meeuwis et al. (2019); Kempf and Tsoutsoura (2020); Cookson, Engleberg, and Mullins (2020)). For example, Mian, Sufi, and Khoshkhou (2017) find that Republican party aligned households had more optimistic economic expectations following the 2016 election than Democratic party aligned households, Meeuwis et al. (2019) show that political party affiliation affected household investment behavior following the 2016 presidential election, Kempf and Tsoutsoura (2020) show that credit rating analysts behave in a partisan fashion based on the party of the president, which affects their broad economic outlook, and Cookson, Engleberg, and Mullins (2020) find that during the COVID-19 crisis Republican investors were more optimistic about stocks that had suffered the most. While these papers study how political biases affect the broad economic outlook of individuals, we study how political biases affect the production of information about a cross-section of firms. We find political bias in the reporting of firm-specific financial news based on the political alignment between firms and newspapers, and show that this biased information may influence individual investors' trading decisions.

Second, our paper is related to recent studies that examine the responses of firms and investors to political bias in the media. In a working paper, Luo, Manconi, and Massa (2020) find that following the acquisition of Dow Jones by News Corporation, stock prices of Republican firms respond less to Dow Jones Newswires sentiment although they do not find an increase in bias, which they interpret as a 'fake news' effect. In two related papers, Baloria and Heese (2018) assume that Fox News is politically biased against Democratic firms, and show that firms affiliated with the Democratic Party that are located in markets with Fox News channels suppress bad news; and Knill, Liu, and McConnell (2019) show that firms led by Republican-leaning CEOs headquartered in regions where Fox News was introduced increase their investment expenditures during the Bush presidency. While these studies assume there is political slant in a single media outlet and focus on firm or investor responses following an event, we examine how differences in political alignment between firms and two major newspapers with opposing political ideologies affect the reporting of firm-specific events over three decades, find strong evidence of political polarization in the coverage of corporate financial news, and show that this can lead to segregration in the information sets of investors.

Third, our paper is broadly related to studies that examine whether connections between firms and the media affect coverage. For example, Reuter and Zitzewitz (2006) and Gurun and Butler (2012) show that coverage may be correlated with advertising, and Dyck, Volchkova, and Zingales (2008) show that public relations by an investment fund increased coverage of corporate governance violations by Russian firms. We focus on the role of political alignment between the firm and newspaper, and control for journalist fixed effects and firm-level advertising expenditures in our regressions.

Fourth, our paper is related to the literature on the impact of financial news on markets and firms. For example, Huberman and Regev (2001) and Tetlock (2011) observe that stock market returns respond to stale news; Barber and Odean (2008) find that individual investors buy stocks reported in the news; Fang and Peress (2009) show that media coverage reduces information frictions; Engelberg and Parsons (2011) find that local media coverage predicts local trading; Dougal et al. (2012) show that short-term returns on the Dow Jones Industrial Average can be predicted using fixed-effects for columnists at the *Wall Street Journal*; Garcia (2013) finds that the predictability of stock returns using news content is concentrated in recessions; Hillert, Jacobs, and Muller (2014) show that the media can exacerbate investor biases; and Ben-Rephael, Da, and Israelsen (2017) develop a measure of abnormal institutional investor attention using searching and reading activity for specific stocks on Bloomberg terminals, and show that the impact of news on financial markets depends on the nature of the readership. These studies do not consider political bias in the reporting of the news. We contribute to this literature by showing that financial news coverage varies based on the political alignment between the firm and news source, that segregation in the information sets of investors due to political polarization generates abnormal trading volume, and that investors respond to news about a stock in the newspaper they are more likely to read, and trade in the same direction as other investors who read the same paper.

2. Data

Our sample consists of the 100 largest publicly traded firms (based on market capitalization in 2016) in the United States, for which we collect over a quarter century of news articles published in the *New York Times* and the *Wall Street Journal* that mention these firms between 1990 and 2016. We focus on larger firms because they are likely to get more news coverage. We choose the *New York Times* and *Wall Street Journal* for three reasons: First, these are the two most widely circulated national newspapers in the United States that are also important sources of business news; Second, their editorial positions occupy opposite ends of the political spectrum (Gentzkow and Shapiro (2010)), which allows us to study the effects of political polarization on news coverage; third, the finance literature has used both newspapers to study the effect of financial news on markets (e.g. Huberman and Regev (2001); Tetlock (2007); Dougal et al. (2012); Garcia (2013)).

From Factiva we gather all articles from the print editions of the *New York Times* and the *Wall Street Journal* that mention any of the firms in our sample between 1990 and 2016. We collect the text of each article, section and page numbers, topic codes that classify articles, and the name of the journalist when identified. To clearly identify the content of the article with a specific firm, we focus on articles that mention either a single firm or at most two firms.

We use the standard Loughran and McDonald (2011) financial dictionary to classify the tone of a financial news article. We count the number of positive and negative words in each article to create our measures of tone, and control for the length of articles by dividing by the total number of words in an article. Specifically we measure the tone of an article using the following three variables: *Positive Words/Total Words*, which is the ratio of positive words to the total number of words in the article (in thousands); *Negative Words/Total Words*, which is the ratio of negative words to the total number of words in the article (in thousands); and *Tone*, equal to *(Positive-Negative)/(Positive + Negative Words).* These variables are described in Table 2.

We collect data on campaign contributions made by employees and Political Action Committees (PACs) of firms from the Center for Responsive Politics, which obtains the data from the Federal Election Commission. Donations are available for every two-year election cycle between 1990 and 2016. We aggregate donations to the firm level and construct the fraction of total campaign contributions by employees and firm-level PACs to Republican Party candidates in an election cycle (% *Contributions to Republican Party*), and the fraction of campaign contributions to Democratic Party candidates (% *Contributions to Democratic Party*). We match campaign contributions data from the previous two-year election cycle for each firm to each year of the financial news data. Lastly, we obtain firm-level market data from CRSP and financial characteristics from Compustat.

To study the information sets of investors and whether their trading behavior is affected by the news, we collect data on newspaper readership and trading activity by geographic location. We use newspaper circulation data from the Alliance for Audited Media, which tracks the number of paid newspaper subscriptions across the United States. The data provide annual subscription information for each newspaper in 210 Designated Market Areas (DMAs). We match the circulation data to a large discount brokerage dataset on individual investors from Barber and Odean (2000). The brokerage data are from 1991 to 1996, which makes it well suited to examine the impact of printed news since it predates most online news. Using zip codes, we identify the DMA from the newspaper circulation data associated with each investor in the brokerage data. For each year, we classify each investor into one of two groups, DMA_{WSJ} and DMA_{NYT}, based on which newspaper has the largest circulation in the DMA where the investor is located. DMAs with more subscriptions to the NYT are mostly concentrated in the Northeast region during this period, while those with more subscriptions to the WSJ are more geographically dispersed.

Tables 1, 2 and 3 report summary statistics that describe the data. From Table 1 Panel A, we observe that firms in our data donated about \$1.2 million on average per election cycle, of which 51% was to Republican Party candidates and 47% to Democratic Party candidates. The remaining contributions are to third party and independent candidates. Firm-level PAC contributions are \$774,000 on average, nearly twice as high as total employee contributions, which are \$430,000 on average. Table 1, Panel B describes the size, profitability, and total advertising expenditures of the firms in our sample.

Table 2 describes the tone of financial news coverage for both the newspapers. Both the WSJ and the NYT use more negative than positive words, and the number of positive and negative words used is similar across both newspapers, which shows that both papers use similar tone in their coverage. In the regressions we control for differences in coverage across the two papers with newspaper fixed effects, *Paper* $\times$ *Quarter* fixed effects, article length, and financial topic fixed effects.

In Table 3, we provide univariate analyses comparing the coverage of firms based on their political alignment with the news source. Based on quintiles of campaign contributions to either party, we classify firms as being Republican (Top quintile of the fraction of campaign contributions to the Republican Party) or Democratic (Bottom quintile of the fraction of campaign contributions to the Republican Party). We then compare the tone of coverage in the article (Panel A) and the lead paragraph (Panel B), across firms. The results show that the *WSJ* uses more positive words in articles about firms that are in the top quintile of donations to the Republican Party, whereas the *NYT* does the opposite (column (1)). Both the *WSJ* and the *NYT* use more negative words in their coverage of financial news for Republican firms, but the *WSJ* uses more negative words in articles about Democratic firms than the *NYT* (column (2)). Comparing tone in column (3), we observe that the *WSJ* uses a less negative tone in articles about firms that donate more to Republican Party candidates than to Democratic Party candidates, whereas the *NYT* uses a less negative tone in articles about firms that donate more to Democratic Party candidates than to Republican Party candidates.

3. Likelihood of financial news coverage and political alignment

The media "may not be successful much of the time in telling people what to think, but it is stunningly successful in telling its readers what to think about" (Cohen (1963)). In this section, we study coverage along the extensive margin. That is, we test how political alignment between the newspaper and the firm affects the likelihood of coverage and article length. Below, we describe our empirical strategy, baseline results, and robustness checks.

3.1. Likelihood of coverage

We start by studying the relative likelihood that an article about a firm on a given day is published in the politically aligned newspaper. To ensure that an article is about a specific firm we conduct the analysis on two sub-samples, articles that mention only 1 firm and articles that mention at most 2 firms, and estimate the following linear probability specification:

$$Pr(Coverage_{i,j,t} = 1) = \beta_1 \; Political \; Alignment_{i,t} + \beta_2 X_{i,t} + \alpha_{Firm} + \alpha_{Quarter} + \alpha_{Topic} + \epsilon_{i,j,t} \tag{1}$$

where *Coverage* is equal to 1 if an article about firm i is in the *Wall Street Journal* and zero if it is in the *New York Times* on date t. We use three measures of political alignment: % *Contributions to Republican Party*, which is the share of firm level campaign contributions to Republican Party candidates in a political cycle, (equivalent to 1-% *Contributions to Democratic Party*); and *Top Republican Donor* and *Top Democratic Donor*, which are indicator variables that take the value of one if the firm is in the top 20$^{\text{th}}$ percentile of campaign contributions in the sample to the respective political party in the previous election cycle. These last two variables capture highly politically active firms. The results from estimating model (1) are reported in Table 4.

The key parameter of interest is β_1, which captures the differential likelihood that on a given day an article about a firm will appear in the politically aligned paper. Our empirical strategy removes potential confounding factors by comparing coverage between the two newspapers based on political alignment controlling for firm, quarter, and topic fixed effects (two-digit topic codes from Factiva) and firm-level characteristics such as total advertising and profitability. To focus on politics, we study coverage of highly politically active firms, those in the top 20$^{\text{th}}$ percentile of campaign contributions in the sample in an election cycle. Lastly, we study whether political alignment affects the length of articles and the likelihood of coverage based on whether the news is good or bad.

Figure 1A describes the results reported in column (1) of Table 4 with predicted likelihood of coverage as a function of political alignment measured by % *Contributions to Republican Party*. Comparing the slopes of the relative likelihood of coverage in the two newspapers as a function of political alignment, we observe that on a given day, an article about a firm that donates more to the Republican Party is more likely to appear in the *Wall Street Journal* (dashed line) than in the *New York Times* (solid line).

The results reported in Table 4 show that the differences in the likelihood of coverage are statistically significant. The positive coefficient of *Contributions to Republican Party*

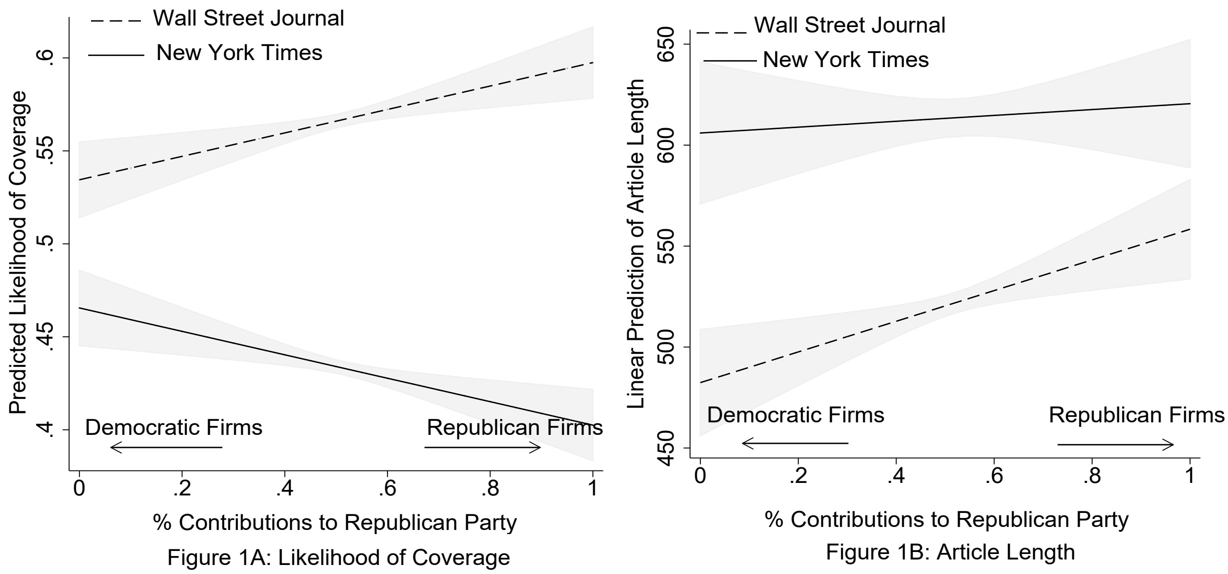

Figure 1: Results from Table 4 of likelihood of coverage and Table 5 of article length as a function of % *Contributions to Republican Party*. Figure 1A (left) describes the likelihood that an article about a firm appears in the *WSJ* (dashed line) or the *NYT* (solid line). Figure 1B (right) describes article length (total words) in the *WSJ* (dashed line) and *NYT* (solid line). Shaded area represents 95% confidence intervals for the coefficient estimates.

shows that on average articles about firms that donate more to the Republican Party are significantly more likely to appear in the *WSJ* than in the *NYT* (columns (1) and (2)). For example, in column (1) for the sample of articles that mention just 1 firm, we find that a one standard deviation increase in the share of donations to the Republican Party by a firm increases the relative likelihood that an article about the firm will be printed in the *WSJ* rather than the *NYT* by nearly 3% relative to the mean likelihood that an article is printed in the *WSJ* of 51%. Controlling for firm-level advertising expenses and profits, we obtain similar results for the sample of articles that mention at most 2 firms (column (4)). Lastly, comparing firms that are in the top 20$^{\text{th}}$ percentile of contributions to either political party, from column (4) we note that an article about a top Republican Party donor is significantly less likely to appear in the *NYT* than in the *WSJ* (columns (6) and (8)).

3.2. Length of article

The positive relationship between the likelihood of coverage in the *WSJ* and contributions to Republican Party candidates could arise if the *WSJ* prints more articles than the *NYT* and more firms are aligned with the Republican Party in our sample. To address this we study whether the article's length varies based on political alignment since the number of words is unlikely to be driven by a mechanical correlation between the number of articles and firms.

Using the sample of articles that mention exactly 1 firm, we estimate model (2) below with the dependent variable equal to the total number of words in the article:

$$Words_{i,j,t} = \beta_1\, WSJ \times\ Political\ Alignment_{i,t} + \beta_2 X_{i,t} + \alpha_{Firm} \times \alpha_{Quarter} + \alpha_{Topic} + \epsilon_{i,j,t} \quad (2)$$

where *Words* is equal to the total number of words in an article, and the remaining variables are described under model (1) above. The results are reported in Table 5.

In Figure 1B, we compare predicted article length in the two newspapers as a function of political alignment from the regression results in column (1) of Table 5. The upward sloping line for the *Wall Street Journal* (dashed line) shows that the paper writes longer articles about firms that donate more to Republican Party candidates. In contrast, the slope for the *NYT* (solid line) suggests that article length does not vary significantly based on political alignment in this paper.

The results from estimating model (2) are reported in Table 5. We start by estimating the baseline specification in columns (1) and (3) with firm, quarter, paper, and topic fixed effects, and firm-level advertising expenses and profits, and add *Firm* × *Quarter* fixed effects in columns (2) and (4). Table 5, column (1) shows that compared to the *New York Times*, the *Wall Street Journal* writes longer financial news articles about firms that donate more to Republican Party candidates. The results are robust to adding interacted *Firm* × *Quarter* fixed effects in column (2). From column (2) we observe that a one standard deviation increase in donations to the Republican Party increases article length by over 18 words in the *WSJ* compared to the *NYT*, a 4% increase relative to the mean article length of 500 words. Lastly, we note from the negative and statistically significant coefficient of *WSJ* × *Top Democratic Donor* in columns (3) and (4) that compared to the *WSJ* the *NYT* publishes longer articles about top Democratic Party donors.

3.3. Likelihood of covering good versus bad news

We also test whether the likelihood of coverage depends on the type of news. Using the tone of coverage in one newspaper to measure whether it is good or bad news, we study whether the other paper has an article about the same firm on the same day based on the type of news and the political alignment with the firm. Using the sample of articles that only mention 1 firm, we estimate the following linear probability model:

$$\begin{aligned} Pr(Article\ in\ j \geq 1)_{i,j,t} = \beta_1\ Political\ Alignment_{i,t} \times\ Good/Bad\ News_{i,k,t} \\ + \beta_2\ Political\ Alignment_{i,t} + \beta_3\ Good/Bad\ News_{i,k,t} \\ + + \beta_4\ X_{i,t} + \alpha_{Firm} \times \alpha_{Quarter} + \epsilon_{i,j,t} \end{aligned} \tag{3}$$

where the dependent variable is equal to 1 if newspaper j publishes at least one article on firm i on the same day as newspaper k, and zero otherwise. We use the tone of coverage in the other newspaper to capture if it is good or bad news. Specifically, *Good News* and *Bad News* are the number of positive and negative words respectively in articles published in the newspaper k about a given firm on a given day. We use the measures of *Political Alignment* described under model (1), and also control for firm-level advertising expenses and profits. We start with firm and quarter fixed effects and then include *Firm* $\times$ *Quarter* fixed effects to absorb variation in coverage stemming from firm-specific idiosyncratic shocks.

The results are reported in Table 6. In columns (1)-(6) of Table 6, we use all articles that are printed in the *New York Times* on a given firm, and estimate whether the likelihood of coverage in the *Wall Street Journal* of the same firm on the same day varies based on whether it is a good or bad news day for politically aligned firms. In columns (7)-(12), we use all articles that are printed in the *WSJ* on a given firm on a given day, and estimate whether the likelihood of coverage in the *NYT* of the same firm on the same day varies based on the type of news and the politics of the firm.

In Figure 2A we describe the results from columns (1) and (7) of Table 6 of the likelihood of same day coverage based on the type of news and political alignment. In Figure 2A (left) we observe that for firms that donate more to the Republican Party the *WSJ* is more likely to publish an article if it is good news (solid line), and less likely to publish an article if it

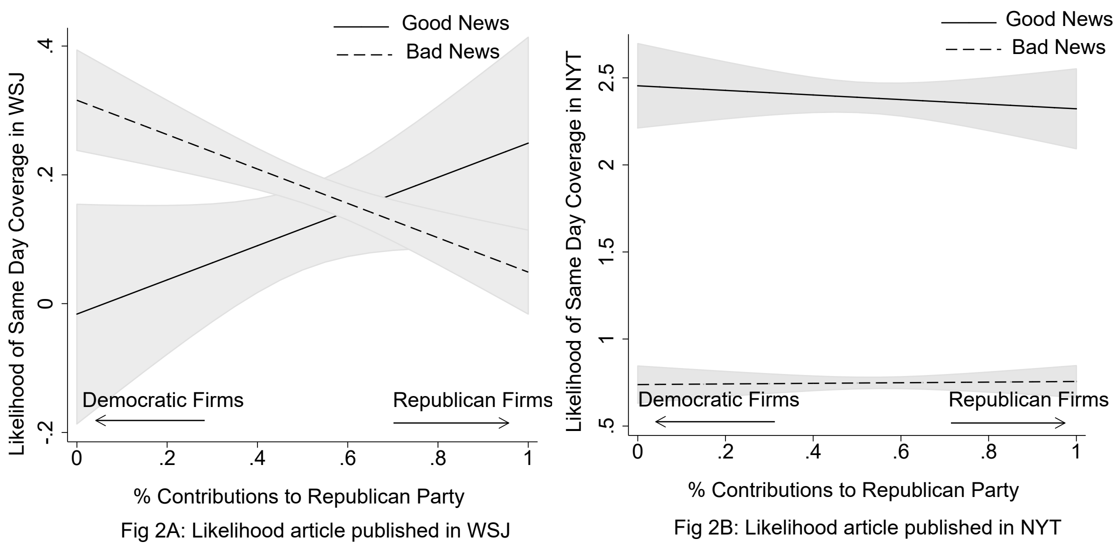

Figure 2: Results from Table 6 describing likelihood of coverage based on type of news as a function of % *Contributions to Republican Party*. Figure 2A (left) describes the likelihood that the *WSJ* publishes an article on the same day as the *NYT* if it is good news (solid line) and bad news (dashed line). Figure 2B (right) describes the likelihood that the *NYT* publishes an article on the same day as the *WSJ* if it is good news (solid line) and bad news (dashed line). The shaded area represents 95% confidence intervals.

is bad news (dashed line). In contrast, in Figure 2B (right), we observe that the *NYT* does not report good or bad news significantly differently based on political alignment with the firm.

From the results reported in Table 6 columns (1)-(3), the coefficients of the interaction between contributions to the Republican Party and the type of news show that if it is good news (more positive tone in the *NYT*), then the *WSJ* is more likely to publish an article on the same day if the firm contributes more to the Republican Party. In contrast, if it is bad news (more negative tone in the *NYT*), the *WSJ* is less likely to publish an article on the same day if the firm contributes more to the Republican Party. The positive coefficient of *Bad News* suggests that firms that donate only to the Democratic Party are more likely to be covered by the *WSJ* on bad news days. In column (3), we control for *Firm* × *Quarter* fixed effects and obtain similar results.

In columns (4)-(6) of Table 6, we study whether coverage varies for more politically extreme firms. From the coefficients of the interaction terms we observe that the *WSJ* is more likely to publish an article about a top Republican Party donor if it is good news (columns (4)-(6)), and less likely if it is bad news (columns (4) and (6)). The opposite is true for top donors to the Democratic Party (columns (4)-(6)). The coefficients remain stable when we control for *Firm* × *Quarter* fixed effects, indicating that firm-specific idiosyncratic shocks do not bias our estimates (Altonji, Elder, and Taber (2005); Oster (2019)). Lastly, in columns (7)-(12), we use all articles that are printed in the *Wall Street Journal* on a given firm on a given day, and study the likelihood of same day coverage in the *New York Times*. The results suggest that the *NYT* does not report differently about politically aligned firms based on the type of news.

4. Tone of financial news coverage

4.1. Political affiliation and tone of coverage

To capture differences in tone, we estimate the following specification on the two subsamples of articles that mention only 1 firm or at most 2 firms:

$$\begin{aligned} Tone_{i,j,t} = \beta_1 \times \ WSJ_{j,t} \times \ Political\ Alignment_{i,t} \ + \beta_2 \times \ Political\ Alignment_{i,t} \\ + \beta_3 \times \ X_{i,t} + \alpha_{Firm} \times \alpha_{Quarter} + \alpha_{Paper} \times \alpha_{Quarter} + \alpha_{Topic} + \epsilon_{i,j,t} \end{aligned} \tag{4}$$

The main parameter of interest is β_1, which captures how the *Wall Street Journal* covers politically aligned firms (firms that donate more to Republican Party candidates), compared to the *New York Times*. Studying whether tone of coverage varies based on the political alignment between the firm and the newspaper is empirically challenging because political alignment may capture other firm and newspaper characteristics that vary over time and affect coverage. Our empirical strategy removes potential confounding factors by comparing coverage between the two newspapers, and controlling for *Firm* × *Quarter* fixed effects and *Paper* × *Quarter* fixed effects, which shuts down variation in coverage stemming from firm-specific and newspaper-specific idiosyncratic shocks. To focus on politics, we study coverage of firms at the political extremes (top 20$^{\text{th}}$ percentile of contributions in the sample). We also control for advertising expenses and profitability, and cluster the standard errors at the *Firm* × *Quarter* level. Additionally, we look at differences in coverage following the acquisition of

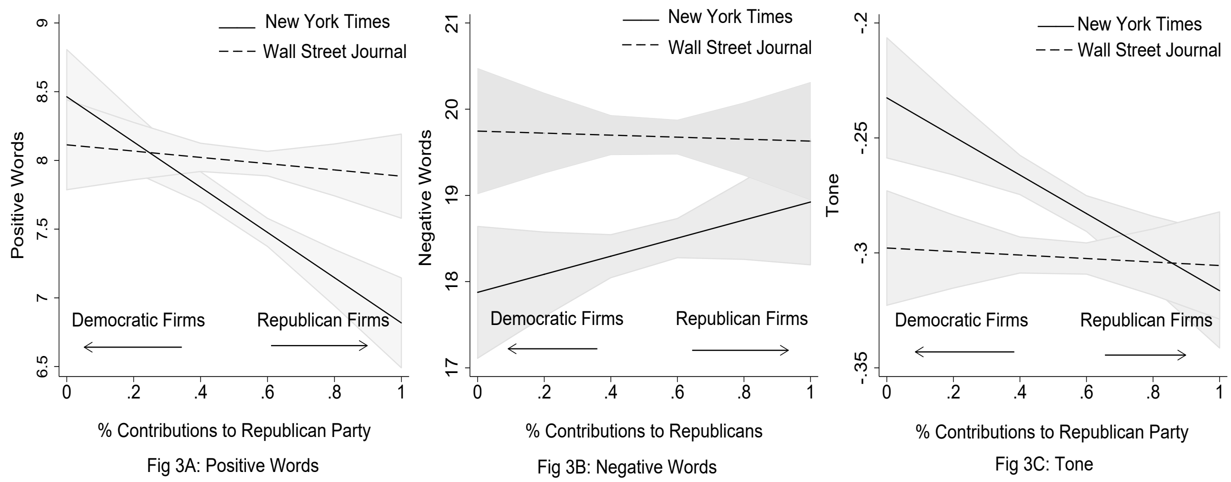

Figure 3: Results from Table 7 of number of positive words, negative words, and tone in an article as a function of % *Contributions to Republicans*. Figure 3A (left) describes results from Table 7A for *Positive Words per Total Words* in the *WSJ* (dashed line) and the *NYT* (solid line). Figure 3B (center) describes results from Table 7B for *Negative Words per Total Words* in the *WSJ* (dashed line) and the *NYT* (solid line). Figure 3C (right) describes results from Table 7C for *Tone* in the *WSJ* (dashed line) and the *NYT* (solid line). Shaded area represents 95% confidence intervals.

the *WSJ* by a more politically conservative owner; consider a sub-sample of articles written by journalists who switch jobs between the two papers to control for journalist fixed effects; and to compare coverage of the same firm-specific events we focus on a sub-sample of articles covering the same firm on the same day in both papers.

We use the following measures of tone described in Section 2: *Positive Words/Total Words*; *Negative Words/Total Words*; and *Tone = (Positive Words – Negative Words)/(Positive Words + Negative Words)*. *WSJ* is an indicator variable, which is equal to one if the article is published in the *Wall Street Journal*, and 0 if it is published in the *New York Times*. The political alignment measures are the same as discussed under specification (1).

In Figure 3A, we describe the predicted values of the number of positive words to total words in an article as a function of political alignment, from the regression results reported in column (1) of Table 7A. The relative slopes of the two newspapers suggest that the difference in tone based on political alignment is greater for the *NYT*. The downward slope for the *New York Times* (solid line) shows that it uses fewer positive words in articles about firms that donate more to the Republican Party. In contrast, the *Wall Street Journal* (dashed line) does not appear to write more positively about politically aligned firms.

In Table 7 Panel A we report the results from estimating model (4) with *Positive Words/Total Words* as the dependent variable. The coefficient of the interaction between *% Contributions to Republican Party* and *WSJ* in columns (1)-(6) is positive and statistically significant at the 1 percent level, which suggests that compared to the *WSJ* financial news coverage in the *NYT* is less positive for firms that are aligned with the Republican Party, and more positive for firms that are aligned with the Democratic Party. The coefficient of our variable of interest, the interaction between *WSJ* and different measures of political alignment, remains stable as we saturate the model with more restrictive fixed effects suggesting that firm and newspaper-specific idiosyncratic shocks do not bias our estimates.

The results are also economically significant. From the coefficient of the interaction term in column (5) of Table 7, Panel A, we find that for a firm at the mean level of contributions to Republicans (about 51%), an article published in the *WSJ* includes 10% more positive words than an article in the *NYT*, relative to the mean number of positive words (about 8 words). Extending the sample to articles that mention at most two firms (columns (2), (4), and (6)) we obtain similar results. The estimated coefficient of the direct effect of *% Contributions to Republican Party* has a negative sign in columns (1)-(4), which suggests that the *NYT* uses fewer positive words in articles about firms that donate more to Republican Party candidates, and more positive words about firms that donate more to Democratic Party candidates.

Considering firms at the political extremes, the results reported in columns (7)-(12) of Table 7, Panel A show that firms that are top political donors are likely to be covered more positively by the politically aligned newspaper. For example, compared to the *New York Times*, the *Wall Street Journal* uses fewer positive words in articles about top Democratic Party donors (columns (7)-(12)) and covers top Republican donors slightly more positively (columns (9)-(12)). Correspondingly, the positive and statistically significant coefficient of *Top Democratic Donor* and negative and significant coefficient of *Top Republican Donor* in columns (7)-(10) suggest that the *NYT* uses more positive language in articles about top Democratic Party donors and less positive language about top Republican Party donors.

In Figure 3B we describe the predicted value of the number of negative words to total words in an article as a function of political alignment, from the results reported in column (1) of Table 7B. From the slope of the predicted tone, we observe that coverage in the *New York Times* (solid line) is slightly more negative for firms that are more closely aligned with the Republican Party. In contrast, it does not appear that the *WSJ* reports more or less negatively about firms based on their politics.

In Table 7, Panel B, we report the results from estimating model (4) with *Negative Words/Total Words* in the article as the dependent variable. The results show that compared to the *NYT*, the *WSJ* uses fewer negative words in articles about firms that donate more to the Republican Party, although the difference in negative words used is statistically significant only for top political donors. In columns (7) and (12) we find that compared to the *NYT*, articles published by the *WSJ* use fewer negative words for top Republican Party donors.

In Figure 3C we describe the results reported in column (1) of Table 7C comparing the predicted tone of coverage across the two newspapers as a function of political alignment. The downward sloping predicted tone for the *NYT* (solid line) suggests that firms that donate more to the Republican party receive less positive coverage in that newspaper. In contrast, the tone of coverage in the *WSJ* does not appear to vary significantly based on political alignment with the firm (dashed line).

In Table 7, Panel C, we report the results from estimating model (4) with *Tone (Positive Words – Negative Words)/(Positive Words + Negative Words)* as the dependent variable, and the interaction between *WSJ* and political alignment as the main explanatory variable of interest. Controlling for firm, newspaper, quarter, topic fixed effects, firm characteristics (columns (1)-(4)), and *Firm* $\times$ *Quarter* and *Paper* $\times$ *Quarter* fixed effects (columns (5) and (6)), we show that the tone of coverage in the *NYT* is less positive compared to the *WSJ* for Republican-leaning firms. We also find that the tone of coverage is more positive for top Republican Party donors (columns (7)-(12)) and more negative for top Democratic Party donors (column (11)), in the *WSJ* relative to the *NYT*.

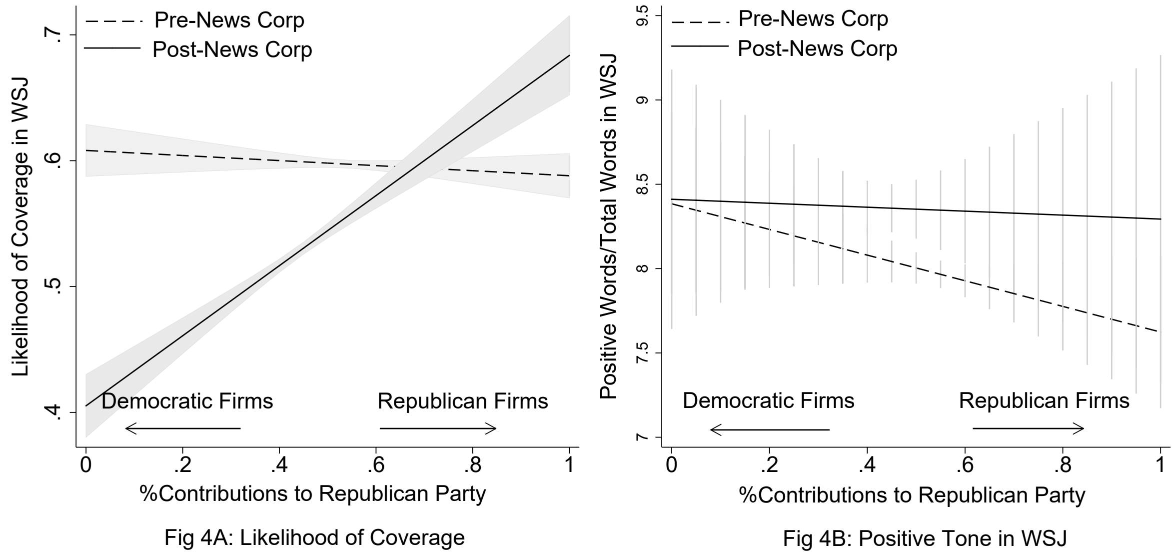

Figure 4: Results from Internet Appendix Table 1 comparing the likelihood and tone of coverage as a function of % *Contributions to Republican Party* before and after the *WSJ* was acquired by News Corporation. Fig 4A (left) shows the likelihood that an article about a firm on a given day appears in the *WSJ* versus the *NYT* in the Pre-News Corp (dashed line) and Post-News Corp (solid line) years. Shaded area represents 95% confidence intervals. Figure 4B (right) shows the ratio of positive words to total words in the *WSJ* in the Pre-News Corp (dashed line), and Post-News Corp (solid line) years. Spikes represent 95% confidence intervals.

4.2. News Corporation acquisition of *The Wall Street Journal*

In December 2007 Dow Jones, the parent company of the *Wall Street Journal*, was acquired by the News Corporation. We study the effect of this change in ownership of the *WSJ* to a more politically conservative owner as a potential shock to the political ideology of the newspaper that may have shifted it further to the right.

First, we compare the likelihood that an article about a firm appears in the newspaper based on political alignment, before and after the News Corporation acquisition of the *WSJ*. We estimate model (1) for two sub-samples of data: articles published from 1990 to 2008 (Pre-News Corporation) and articles published from 2008 to 2016 (Post-News Corporation). The results are reported in Internet Appendix Table 1, columns (1)-(4). Figure 4 graphically describes the results from columns (2) and (4) of the table.

Following the acquisition, the upward sloping solid line in Figure 4A shows that compared to the *NYT*, the likelihood that an article appears in the *WSJ* is significantly higher for more Republican firms in the post-News Corporation years. In contrast, the slope of the dashed line in Figure 4A suggests that the relative likelihood of coverage was not significantly different between the *WSJ* and the *NYT* for more Republican firms in the pre-News Corporation years.

We also examine if the tone of coverage changes in the *Wall Street Journal* following its acquisition by News Corporation, by estimating model (4) for the pre- and post-News Corporation years. The results are reported in Internet Appendix Table 1, columns (5)-(8). In Figure 4B we graphically describe the results from columns (6) and (8) of the table with *Positive Words/Total Words* as the dependent variable. Prior to its acquisition by News Corporation, the *WSJ* used fewer positive words in articles about firms that contributed more to Republican Party campaigns (dashed line), whereas after its acquisition it uses about the same number of positive words (solid line), suggesting that the tone of coverage of politically aligned firms changed following the ownership change. This evidence is consistent with our hypothesis that political alignment between the firm and newspaper affects financial news coverage.

4.3. Journalist versus newspaper ideology

To further establish that our results are explained by the political alignment between the firm and the newspaper, we identify journalists who write for both newspapers and study the sub-sample of articles written by journalists who switch between the *New York Times* and the *Wall Street Journal*. This tests whether the journalist's ideology, rather than political alignment between the firm and the paper, drives the results. We restrict the sample to journalists who have written at least one article in the financial news sections of both newspapers.[8]

In Table 8 we compare the tone of articles written by the same journalist across both newspapers by including journalist fixed effects and firm, topic, and election cycle fixed effects. Thus, we control for firm characteristics in addition to electoral cycle shocks, while addressing the fact that journalists may focus on different topics and be influenced by their personal politics. We do not include quarterly interacted fixed effects in this model because

[8]During this period 165 journalists wrote at least one article for both newspapers.

of a sharp reduction in the number of observations when considering the small sub-sample of journalists who write articles for both newspapers.

The results reported in Table 8 are similar to the baseline results in Table 7, indicating that when journalists switch newspapers, they adopt the ideology of their new employer in their reporting. For example, compared to articles written by a journalist in the *NYT*, articles written in the *WSJ* by the same journalist use more positive words (columns (1) and (2)) and a more positive tone (column (10)) about firms that donate more to the Republican Party), and are top donors to Republican Party candidates (column (4)). In contrast, a journalist switching from the *NYT* to the *WSJ* uses more negative words (column (8)) and a more negative tone (columns (11) and (12)), in articles about top donors to Democratic Party candidates. These results support our hypothesis that political alignment captures the ideological affinity between the firm and the newspaper, which is also consistent with the previous results showing that coverage in the *WSJ* changes following its acquisition by News Corporation.

4.4. Newsday at both newspapers

If newspapers cover different firms or topics, this may generate differences in tone irrespective of the political affiliation of the firm. Below, we compare coverage of the same firm-specific events between the two newspapers by comparing the sub-sample of articles written about the same firm on the same day by both newspapers.

The results reported in Table 9 from estimating specification (4) are similar to those reported for the full sample in Table 7. For example, from the coefficients of the interaction term reported in columns (1)-(4) of Table 9, we find that on average, compared to the *NYT*, the *WSJ* uses more positive words about firms that donate more to the Republican Party. The results for negative words are not statistically significant because of the smaller sample size. We also find that articles in the *WSJ* use a more positive tone for firms that donate more to the Republican Party (columns (10) and (12)). We also estimate but to save space do not report the results using top donors, which are similar to those obtained in the main analysis in Table 7. Our results show that the same firm-specific events are covered differently based on the political alignment between the firm and the newspaper.

4.5. Financial news and earnings announcements

To ensure that we capture financial news coverage and not political news, we conduct some additional analysis. First, we restrict the sample to articles that begin in the financial sections of either newspaper, and second, we focus on articles that cover a specific financial topic: earnings announcements.

In Table 10, Panel A, we focus on articles that are in the financial/business news sections of the *WSJ* and *NYT*. The results are similar to those obtained for the baseline results in Table 7. From the coefficient of the interaction terms, we find that compared to the *NYT*, articles in the *WSJ* about Republican leaning firms use more positive words (columns (1) and (2)) and more positive tone (columns (9) and (10)), while articles about top Democratic Party donors use fewer positive words (columns (3) and (4)), and more negative tone (columns (11) and (12)). In contrast, articles in the *WSJ* about top donors to the Republican Party use more positive words compared to the *NYT* (column (5)).

We also study the sub-sample of articles reporting on corporate earnings announcements. The results in Table 10, Panel B, are similar to the baseline results in Table 7 and show that even in the case of quarterly announcements of firm earnings statistics, newspaper coverage varies based on the political alignment between the firm and the news source.

4.6. Tone of coverage and placement

We show that political polarization in financial news coverage is a key aspect of these articles by studying whether the tone varies based on the placement within the article. Specifically, we estimate model (4) for two sub-samples: the lead paragraph of an article and the remaining paragraphs of the article. We then compare *Positive Words/Total Words* in the lead paragraph, which is more likely to be read, to the rest of the article. The results are reported in Table 11.

Comparing the coefficients of the interaction between *WSJ* and political alignment in the lead paragraph (columns (1)and (2)) to the rest of the article (columns (3) and (4)) reported in Table 11, we observe from the coefficient magnitudes that the effects are larger in the lead paragraph than the rest of the article. Relative to the *NYT*, Republican leaning firms obtain more positive coverage in the *WSJ* in the lead paragraph compared to the rest of the article. In contrast, top Democratic Party donors are covered more positively in the lead paragraph (column (2)) of the *NYT* relative to the rest of the article (column (4)). The results are similar but less statistically significant for the remaining measures of tone and to save space we do not report them. Our results suggest that politically induced differences in the tone of coverage are an important part of financial news articles.

5. Political bias in financial news coverage and investor behavior

5.1. Abnormal daily trading volume and disagreement

We show that political polarization can generate disagreement in the reporting of corporate financial news. Since polarization causes individuals to seek out news sources that match their views (Iyengar and Hahn (2009); Gentzkow and Shapiro (2011); Mitchell et al. (2014)),[9] this may segregate the information sets of investors. Theory suggests that disagreement among investors about the value of a stock can lead to trade (Milgrom and Stokey (1982); Karpoff (1986); Harris and Raviv (1993)).[10] Therefore, we study whether disagreement in financial news due to political polarization is correlated with trading volume.

Empirically, it is challenging to show that financial news affects markets since news is more likely to be reported when there are newsworthy events. We start with a sub-sample of news days with exactly two articles on a given firm, which eliminates "big" news days when there is likely to be more articles about a firm, and ensures similar levels of coverage across newspapers. We then compare days on which both articles are printed in one newspaper to days on which one article is printed in each newspaper. If there is disagreement in coverage due to political polarization, then we would expect abnormal trading volume to be higher

[9] Iyengar and Hahn (2009) show that Republicans and Democrats read news from sources that share their political affinity; Gentzkow and Shapiro (2011) find that ideological segregation is common in the consumption of traditional news media; and a Pew survey of media habits suggest that there is little overlap in the news sources of liberals and conservatives (Mitchell et al. (2014)).

[10] Disagreement among investors about returns is central to trading in financial markets (Milgrom and Stokey (1982); Karpoff (1986); Harris and Raviv (1993)). Empirically, investor disagreement has been linked to portfolio choices (Meeuwis et al. (2019)) and trading volume (Xiong (2013); Carlin, Longstaff, and Matoba (2014)), generated by differences in information sets (Cookson and Niessner (2020)).

on days when the news is reported in both newspapers, rather than days on which the same amount of coverage is concentrated in one newspaper. We also control for *Firm* $\times$ *Quarter* fixed effects, and firm-specific variables that are known to affect trading volume.

We use different horizons for *Abnormal Volume* to ensure that the recent past does not measure an unusual period for volume. Specifically, abnormal trading volume is measured as the dollar trading volume on day t divided by the average daily dollar trading volume for the same stock over the previous 30 days, 90 days, 180 days, and 1 year.

Results from non-parametric tests are reported in Table 12. In Panel A, restricting the sample to exactly 2 articles on a given day for a firm, we compare abnormal trading volume on days in which both articles about a firm are in one paper ("no disagreement") to days on which one article is printed in each paper ("high disagreement"). The results show that abnormal trading volume is significantly higher on days on which both newspapers report on the firm compared to days on which only one newspaper reports on the firm. For example, in Table 12, Panel A, the differential impact on trading volume of having two articles in one paper versus one article in each paper is $454,000, where the 6 month mean trading volume is $2.91 million. In Panel B, we expand the sample to two or more articles that mention just 1 firm on a given day and find similar results.

5.2. Abnormal trading volume, disagreement, and political alignment

We study whether the effect of disagreement in financial news coverage on abnormal volume varies based on the political characteristics of firms. Since news coverage and volume may both be correlated with firm-specific events, we estimate the following specification on a sample restricted to days on which there are exactly two articles that mention a firm in one or either newspaper:

$$Abnormal\ Volume_{i,t} = \beta_1\ High\ Disagreement_{i,t} \times\ Top\ Donor_{i,t} + \beta_2\ Top\ Donor_{i,t} + \beta_3 X_{i,t} + \alpha_{Firm} \times \alpha_{Year} + \epsilon_{i,j,t} \quad (5)$$

where *Abnormal Volume* is the dollar trading volume on day t divided by the average daily dollar trading volume for the same stock over the previous 30 days, 90 days, 180 days and 1 year; *High Disagreement* is equal to one if there is one article in each newspaper that mentions the firm, and equal to zero if both articles are reported only in one paper; *Top Donor* is an indicator variable that is equal to one if the firm is in the top 20$^{\text{th}}$ percentile of campaign contributions in the sample to either Republican or Democratic Party candidates; and $X_{i,t}$ includes stock characteristics that affect abnormal volume including *Absolute Returns, Lagged Absolute Returns*, and *Lagged Abnormal Volume*, and news characteristics including *Total Number of Articles* and *Total Words.* Lastly, we include *Firm* $\times$ *Year* fixed effects to absorb time-varying firm characteristics and cluster the standard errors at the *Firm* $\times$ *Year* level. The results are reported in Table 13.

Coverage in one versus both papers is not randomly assigned across firms. For example, both papers may cover a firm when a newsworthy event occurs. Our main parameter of interest is β_1, the coefficient of the interaction between disagreement and *Top Donor*, hence the identification assumption is that any systematic differences between stocks that are covered in one versus both papers do not interact differentially between top and non-top political donors. We believe this is a reasonable assumption because if newsworthy events rather than disagreement in the news drive volume, such events are unlikely to occur exclusively for more politically active firms. We also include the total number of articles about a firm on a given day across all 30,000 news sources in Factiva (*Total Number of Articles*) and article length (*Total Words*) since there is likely to be more coverage and longer articles about major events.

In Figure 5A we describe the results from column (2) of Table 13. Specifically, we compare the predicted abnormal trading volume (relative to previous 31 days) for firms that are top political party donors on "no disagreement" days with both articles in one paper to "high disagreement" days with one article in each paper. The negative slope of "no disagreement" days (dashed line) and the positive slope of "high disagreement" days (solid line) suggest that abnormal trading volume is higher for more politically active firms compared to less politically active firms on days on which there is disagreement in the reporting of firm-specific financial news.

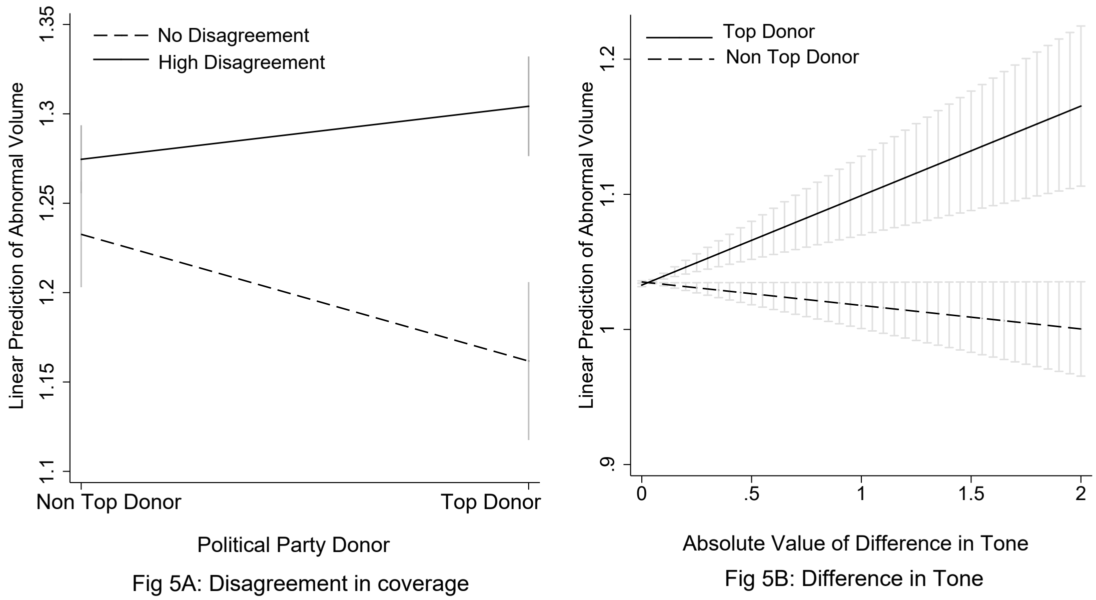

Figure 5: Describes the linear prediction of *Abnormal Trading Volume* relative to previous 31 days from Table 13 and Table 14. Figure 5A (left) compares abnormal volume on *No Disagreement* days (dashed line) to *High Disagreement* days (solid line) based on whether the firm is a top political party donor. Figure 5B (right) compares abnormal trading volume for firms that are top donors (solid line) to those that are not top donors (dashed line) as a function of the absolute value of the difference in the tone of coverage between the two newspapers. The shaded spikes represent 95% confidence intervals.

In Panel A of Table 13, we restrict the sample to articles that mention only 1 firm on a given day and in Panel B we include articles that mention up to 2 firms. We start with firm and year fixed effects and progressively saturate the model with more restrictive *Firm* $\times$ *Year* fixed effects. We find that trading volume is higher on days when there is more disagreement in coverage, with one article in each newspaper, compared to days with no disagreement, with both articles in the same paper. This effect is also economically significant. In column (8), where the dependent variable is abnormal trading volume relative to the 6 month sample mean trading volume, we find that coverage in both newspapers versus coverage in just one paper increases abnormal trading volume on average by \$261,000, where average abnormal trading volume (relative to the past 6 months) is \$2.91 million. These results are robust to *Firm* $\times$ *Year* fixed effects, absolute returns, lagged absolute returns, lagged abnormal trading volume, total number of articles in all news sources, and article length.

Our results also show that the effect of disagreement on abnormal trading volume is greater for firms that are more politically extreme. The estimated coefficient of the interaction between *High Disagreement* and *Top Donor* is positive and statistically significant for all specifications, indicating that the increase in abnormal trading volume is driven by coverage of the most politically active firms. From column (9) of Table 13 we observe that coverage in both newspapers increases daily abnormal trading volume for firms at the political extremes by \$407,400 relative to the sample mean abnormal trading volume, compared to an increase of \$174,600 on average for firms not at the political extremes.

The results show that politically induced disagreement in the coverage of corporate financial news leads to greater trading among investors, suggesting that political polarization leads to segregation in the information sets of investors.

5.3. Disagreement in tone and abnormal trading volume

Next we study whether abnormal trading volume is directly related to differences in the tone of coverage that arise due to political polarization. To capture sentiment we look at the full sample of trading days between 1990 and 2016, and restrict the news articles to those which mention only one firm to capture tone measures about the specific firm. We estimate the following specification:

$$\begin{aligned} Abnormal\ Volume_{i,t} = \beta_1\ Tone\ Differences_{i,t} \times\ Top\ Donor_{i,t} \\ + \beta_2 X_{i,t} +\ Firm \times\ Year\ FE + \epsilon_{i,j,t} \quad (6) \end{aligned}$$

The *Abnormal Volume* variables and firm specific control variables are described under model (5). We use three measures of *Tone Differences*: *Difference in Positive Words*$_{i,t}$ = $|(\frac{Positive\ Words}{Total\ Words})^{WSJ}_{i,t} - (\frac{Positive\ Words}{Total\ Words})^{NYT}_{i,t}|$; *Difference in Negative Words*$_{i,t}$; and *Difference in Tone*$_{i,t}$, which are constructed similarly. We use the full sample to accurately capture sentiment and control for major events that are likely to have more news coverage by including *Number of Articles*, which is the total number of articles published in both newspapers on a given day about a firm. We also control for *Firm* $\times$ *Year* fixed effects, which absorb time-varying firm-specific factors that may affect volume, and cluster the standard errors at the *Firm* $\times$ *Year* level.

In Figure 5B we describe the results from column (2) of Table 14, which reports the predicted one-month abnormal trading volume for firms that are top political party donors as a function of the absolute value of the difference in the tone of coverage between the two newspapers. The positive slope of "Top Donor" (solid line) compared to the negatively sloped line for non top donors (dashed line) suggests that abnormal trading volume is higher for more politically active firms compared to less politically active firms on days on which there is greater disagreement in the tone of financial news coverage about a firm between the two newspapers.

The results reported in Table 14 show that disagreement in tone is associated with higher abnormal trading volume for firms at the political extremes. For example, the coefficients of the two interaction terms, *Top Donor* $\times$ *Difference in Positive Words* and *Top Donor* $\times$ *Difference in Negative Words* in column (1) of Table 14 are positive and statistically significant, which suggests that greater the difference in both positive and negative words used between the two papers about a firm, the higher the trading volume, especially for firms that are highly politically active. The coefficient of *Difference in Positive Words* is also positive, but the coefficient of the direct effect is smaller in magnitude than that of its interaction with *Top Donor*, which suggests that disagreement is associated with higher trading volume in more politically extreme firms. Lastly, the coefficient of *Top Donor* in column (1) suggests that abnormal trading volume is lower for highly politically active firms when there isn't disagreement in financial news coverage.

Using absolute differences in *Tone* in column (2) we observe a similar pattern. Abnormal trading volume is higher when there is more disagreement in news coverage, and this difference is greater for firms at the political extremes. The remaining columns of Table 14 use different windows of *Abnormal Volume* to show that the recent past does not measure an unusual period for volume. The results are similar across all the measures of abnormal trading volume. The coefficient of the interaction term has a positive sign but is less statistically significant for *Top Donor* $\times$ *Difference in Negative Words* for the longer time horizons of abnormal volume.

We control for firm specific variables that affect abnormal trading volume such as lagged abnormal volume, absolute returns, and lagged absolute returns, and *Firm* $\times$ *Year* fixed effects, which absorb unobservable firm characteristics that vary over time. To control for newsworthy days where there may be more coverage and higher trading volume, we include the total number of articles published about a firm in both newspapers on a given day. Our results also show that the difference in abnormal volume is driven by more politically extreme firms.

Our results are consistent with the theoretical prediction that disagreement between investors is key to trading in stock markets. We show that politically generated disagreement in financial news coverage is correlated with abnormal trading volume.

5.4. Readership and herding behavior

In this section, we establish the direct link between individual investor trading and the news they read. Using individual investor trades and newspaper circulation data we study two questions. First, do investors respond to news published in the paper they are more likely to read, and second, do investors herd with others who read the same paper.

To identify the newspaper an individual investor is more likely to read we use annual newspaper circulation data, which measures the number of annual paid subscriptions for each newspaper in 210 designated market areas (DMAs) across the United States. To identify the trades of individual investors we use the large discount brokerage data from Barber and Odean (2000). These data are for the years 1991 to 1996, which pre-dates online news, making it particularly well suited to examine the impact of print articles in newspapers on investor trading behavior. We match investors by zipcode to the DMAs in the newspaper circulation data.

We start by examining whether investors react to the news. Each year, we classify each investor into one of two information groups, DMA_{WSJ} and DMA_{NYT}, based on which newspaper has the largest number of paid subscriptions in the investor's DMA. We assume that an individual investor is more likely to read the newspaper with the highest circulation in the zipcode where they live. DMAs with the highest relative *New York Times* circulation are concentrated in the Northeast region, while those with the highest relative *Wall Street Journal* circulation tend to be located in more rural areas across the country.[11]

For each of the two groups of investors, we aggregate for each day all buys and sells separately for a given stock. Using the aggregated buys and sells, we create an abnormal dollar trading volume measure defined the same way as in the previous section. Specifically, we aggregate daily dollar trading volume in a given stock for each group and divide that number by the trailing average over the previous year in the same group. This normalization allows us to compare investment behavior across the two groups even if the total number of investors and trades aren't always balanced.[12]

For each day, and for each stock, we have two observations, one for the set of investors living in the DMAs that are more likely to read the *WSJ*, and one for those in the DMAs that are more likely to read the *NYT*. To study the reaction of investors to the news they are more likely to read, we estimate the following model:

$$\begin{aligned} Abnormal\ Volume_{i,j,t} &= \beta_1\ News\ Read_{i,j,t} + \beta_2\ News\ Other_{i,j,t} \\ &\quad + \beta_3 X_{i,t} +\ DMA_j +\ Firm \times\ Year\ FE + \epsilon_{i,j,t} \qquad (7) \end{aligned}$$

where i refers to the stock, and $j \in (NYT,\ WSJ)$ is the DMA group where the investor lives based on which newspaper has higher circulation. Each day, for each stock, and for each of the two DMA groups, we regress abnormal dollar trading volume on *News Read* and *News Other*, which are binary variables indicating whether there was at least one article that mentions the firm published in the newspaper with more subscriptions and fewer subscriptions respectively, on a given day, in the zipcode where the investor lives. We include DMA_j, which is an indicator variable for the DMA where the investor lives, to control for differences in regional characteristics between the two groups of investors. The control variables in $X_{i,t}$ include

[11]The five DMAs with the highest *New York Times* subscriptions during this period are: New York, CT-NJ-NY-PA; Albany-Schenectady-Troy, MA-NY-VT; Binghamton, NY-PA; Hartford-New Haven, CT; and Elmira, NY. The top five for the *Wall Street Journal* are: Bakersfield, CA; Beaumont-Port Arthur, TX; Monroe-El Dorado, AR-LA; Cheyenne-Scottsbluff-Sterling, NE-WY; and Casper-Riverton, WY.

[12]Average daily dollar trading volume is \$1.3 million in the sample stocks from the DMA_{WSJ} investors. The investors in DMA_{NYT} have an average daily dollar trading volume of about \$0.1 million in sample stocks.

absolute returns and lagged absolute returns. Additionally, we progressively saturate the regression with *Firm*, *Year*, and *Firm* × *Year* fixed effects.

In Table 15, Panel A we report the results from estimating model (7) using 175,268 day-stock-DMA group observations. From the results in columns (1)-(3), we note that trading volume is positively related both to news printed in the newspaper that an investor is more likely to read (*News Read*) and to news in the other newspaper (*News Other*), but the coefficient of the former variable is larger and more statistically significant. However, controlling for firm fixed effects and interacted firm and year fixed effects, we find that individual investors react to news published in the paper they are more likely to have read but not to news in the other paper, since the coefficient of news printed in the other newspaper does not remain statistically significant (columns (4) and (5)). These results are robust to controlling for absolute returns, absolute lagged returns, *Firm, Year*, and *Firm* × *Year* fixed effects.

To further establish that investors respond to the news, we study whether investors trade in the same direction as other investors who are likely to read the same paper. Therefore, we examine whether investors herd with other investors when they trade, based on the news. Using the aggregated dollar values of all buys and sells in each of the two information groups, DMA_{WSJ} and DMA_{NYT}, for a given stock on a given day, we measure the signed dollar volume as the total sells minus the total buys. Using the absolute value of this measure, we divide by its 365-day trailing average. This variable *Herding* captures herding or agreement between traders. It is greater than one in value when investors behave more similarly - mostly buying or mostly selling - than they have over the previous year, on average. We hypothesize that if investors respond to the news they read, then herding will be stronger when news is published in the newspaper that the investors are more likely to read, than when news is published in the paper they are less likely to read.

Panel B of Table 15 provides the results with *Herding* as the dependent variable, and the main explanatory variables *News Read* and *News Other*. Without controlling for firm fixed effects, we find that investors herd more in response to news about a firm published in the paper they are likely to read than to news published in the other paper (columns (1)-(3)). However, once we control for *Firm*, and *Firm* × *Year* fixed effects, we observe that investors herd with other investors who read the same newspaper in response to news about a firm published in that paper, but not when the news is published in the newspaper that they are less likely to read (columns (4) and (5)).

These results suggest that differences in exposure to the news printed in the *WSJ* versus the *NYT* directly affects investors' trading behavior. Investors trade more if news about a stock is published in the newspaper they are more likely to read, than if it is published in a newspaper they are less likely to read. To further support the hypothesis that trading behavior is affected by the news, we show that investors trade in the same direction as other investors who read the same paper when news about a stock appears in that paper.

6. Conclusion

We show that newspapers may cater to their readership even when covering corporate financial news, such as quarterly earnings announcements, which does not lend itself to partisan interpretation. Comparing over a quarter century of financial news articles in the liberal *New York Times* to the conservative *Wall Street Journal*, we find that the likelihood of coverage of firm-specific financial news varies based on the political alignment of firms with newspapers. Top donors to the Republican Party are more likely to be covered by the *Wall Street Journal* and less likely to be covered by the *New York Times*. We also show that bad news is less likely to be covered and good news is more likely to be covered if the firm is politically aligned with the news source. Finally, our results suggest that newspapers write more positively about the financial news of politically aligned companies, and less positively about the financial news of companies that are aligned with the opposing political party.

To support our hypothesis that the likelihood and tone of coverage are affected by the political alignment between the newspaper and the firm, we show that the *Wall Street Journal* becomes more partisan in its coverage following its acquisition by the more conservative News Corporation. We also find that journalists who work for both newspapers switch their tone to reflect the ideology of the paper they work for and that newspapers are more likely to cover good news and less likely to cover bad news about politically aligned firms. The results are similar when the sample is restricted to articles about the same firm on the same day in both papers, suggesting that our results are not driven by differences in topics and firms covered by newspapers. Lastly, we show that tone differences are stronger in the lead paragraph of an article, which is more likely to be read, suggesting that politically driven coverage differences are a key part of financial news articles.

Political polarization implies that market participants may be exposed to different news about the same firm on the same day. Consistent with this argument, we find that disagreement between news sources increases trading volume, and these effects are larger for firms at the political extremes. Studying the direct link between investors and the news they read, we show that investors respond to news about a stock printed in the newspaper they are more likely to read by trading more in that stock, whereas they do not respond to news printed about a stock in a newspaper they are less likely to read. We also find that investors tend to trade in the same direction on the news as other investors who are likely to read the same newspaper. Our results show that political polarization can segregate the information sets of investors, which in turn can affect investor behavior.

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Table 1: Political and Financial Characteristics of Firms

This table describes the political and financial characteristics of firms for the years 1990 to 2016. In Panel A, *Total Contributions* is the dollar value of campaign contributions made by political action committees and employees of firms in every two year election cycle between 1990 and 2016. *Contributions to Democratic (Republican) Party* is the dollar value of contributions made by firms to Democratic (Republican) Party candidates between 1990 and 2016, *% Contributions to Democratic (Republican) Party* is the fraction of total campaign contributions made to Democratic (Republican) Party candidates. In Panel B, we describe the financial characteristics of firms from 1990-2016. *Advertising Expenses* is the log value of firm-level advertising expenditures and *Profitability* is the log value of firm-level EBIT.

Table 1A: Political Characteristics

Variable	**Number of observations**	**Mean**	**Median**	**Minimum**	**Maximum**	**Standard Deviation**
Total Contributions ($)	61,083	1,175,953	817,305	0	9,931,070	1,249,369
Contributions to Democratic Party ($)	61,083	554,899	311,115	0	4,945,273	662,534
Contributions to Republican Party ($)	61,083	621,054	404,635	0	7,588,805	691,108
% Contributions to Democratic Party	61,083	47%	45%	0	1	20%
% Contributions to Republican Party	61,083	51%	54%	0	1	21%

Table 1B: Financial Characteristics

Variable	**Number of observations**	**Mean**	**25th Pctl**	**Median**	**75th Pctl**
(Log) Assets	2171	9.744	8.977	9.941	10.716
Profitability	2171	0.111	0.073	0.114	0.161
Advertising Expenses	2171	0.018	0.000	0.000	0.022

Table 2: Tone of Financial News Coverage

This table describes the variables we used to capture tone. We use the Loughran and McDonald (2011) financial dictionary to classify the tone of a financial news article. *Positive Words per 1000 words*, is the ratio of positive words to the total number of words in the article (in thousands); *Negative Words per 1000 words*, is the ratio of negative words to the total number of words in the article (in thousands); and *Tone* is defined as *(Positive-Negative Words)/(Positive +Negative Words)*.

	The Wall Street Journal				
Variable	**Observations**	**Mean**	**Median**	**25th Percentile**	**75th Percentile**
Positive words per 1000 words	33,948	8.1	7.0	2.9	11.6
Negative words per 1000 words	33,948	19.6	15.9	7.8	27.2
Tone	32,010	-0.314	-0.385	-0.750	0.000
Lead Paragraph Positive per 1000 Words	33,948	7.7	0.0	0.0	13.0
Lead Paragraph Negative per 1000 Words	33,948	21.0	13.9	0.0	32.1
	The New York Times				
Variable	**Observations**	**Mean**	**Median**	**25th Percentile**	**75th Percentile**
Positive words per 1000 words	25,741	7.5	6.9	2.4	10.9
Negative words per 1000 words	25,741	18.7	15.0	7.2	26.1
Tone	23,944	-0.309	-0.379	-0.742	0.000
Lead Paragraph Positive per 1000 Words	25,741	7.1	0.0	0.0	12.5
Lead Paragraph Negative per 1000 Words	25,741	19.7	12.8	0.0	30.6

Table 3: Coverage by Political Affiliation of Firms

This table describes the tone of articles based on the political affiliation between the firm and the newspaper. Political contribution quintiles sort firms into quintiles based on the fraction of firm-level campaign contributions to the Republican and Democratic parties. In Panel A, we use the text in the entire article, and in Panel B we compare tone in the lead paragraph across campaign contribution quintiles.

Panel A: Article

Newspaper	Political Contribution Quintile	(1) Positive words/Total Words	(2) Negative Words/Total Words	(3) Tone
WSJ	Republican	8.31	20.00	-0.36
WSJ	2	8.91	19.62	-0.35
WSJ	3	8.11	19.65	-0.39
WSJ	4	7.57	19.12	-0.41
WSJ	Democratic	8.01	15.84	-0.30
NYT	Republican	6.57	19.72	-0.47
NYT	2	7.39	18.56	-0.39
NYT	3	7.23	18.52	-0.39
NYT	4	7.25	18.73	-0.38
NYT	Democratic	7.97	13.99	-0.22

Panel B: Lead Paragraph

Newspaper	Political Contribution Quintile	(1) Positive words/Total Words	(2) Negative Words/Total Words	(3) Tone
WSJ	Republican	8.23	21.95	-0.43
WSJ	2	9.41	20.32	-0.34
WSJ	3	7.63	20.88	-0.42
WSJ	4	7.46	20.19	-0.43
WSJ	Democratic	7.24	17.53	-0.34
NYT	Republican	6.72	21.24	-0.49
NYT	2	7.13	18.93	-0.41
NYT	3	6.97	19.12	-0.42
NYT	4	6.98	19.89	-0.43
NYT	Democratic	7.46	14.36	-0.22

Table 4: Likelihood of financial news coverage and political alignment

This table describes the results from a linear probability model of the likelihood of coverage based on political alignment between firms and newspapers. The sample includes articles that only mention 1 firm (columns 1 and 3) or at most 2 firms (columns 2 and 4). The dependent variable is an indicator variable equal to one if the article is published in the *Wall Street Journal*, and equal to 0 if the article is published in the *New York Times*. *% Contributions to Republican Party* is the percentage of campaign contributions donated to Republican Party candidates by the firm in a given election cycle; *Top Republican Donor* is an indicator variable equal to 1 if the firm's contribution to the Republican Party is in the top 20th percentile of all contributions to the Republican party in the sample in a given cycle; *Top Democratic Donor* is an indicator variable equal to 1 if the firm's contributions to the Democratic Party is in the top 20th percentile of all contributions to the Democratic Party in the sample in a given cycle; *Advertising Expenses* is the log value of firm-level advertising expenditures and *Profitability* is the log value of firm-level EBIT. Standard errors are reported in parentheses. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Contributions to Republican Party	0.063***	0.074*	0.012	0.045***				
	(0.020)	(0.041)	(0.023)	(0.017)				
Top Republican Donor					0.010	0.017***	0.014	0.024***
					(0.009)	(0.007)	(0.010)	(0.008)
Top Democratic Donor					0.006	0.009	0.016*	0.017***
					(0.008)	(0.006)	(0.009)	(0.006)
Advertising Expenses			0.477***	0.461***			(0.001)	(0.000)
			(0.145)	(0.112)			(0.145)	(0.112)
Profitability			0.010***	0.012***			(0.000)	(0.000)
			(0.003)	(0.002)			(0.003)	(0.002)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,021	107,792	52,913	91,260	61,027	107,801	52,917	91,266
R-squared	0.196	0.209	0.187	0.191	0.196	0.209	0.187	0.191

Table 5: Length of article and political alignment

The dependent variable *Total Words* is equal to the total number of words in an article for the sample of articles that mention just 1 firm. *WSJ* is an indicator variable equal to one if the article is published in the *Wall Street Journal* and equal to 0 if it is published in the *New York Times*. *% Contributions to Republican Party* is the percentage of campaign contributions donated to Republican Party candidates by the firm in a given election cycle; *Top Republican Donor* is an indicator variable equal to 1 if the firm's contribution to the Republican Party is in the top 20th percentile of all contributions to the Republican party in the sample in a given cycle; *Top Democratic Donor i* s an indicator variable equal to 1 if the firm's contributions to the Democratic Party is in the top 20th percentile of all contributions to the Democratic Party in the sample in a given cycle; *Advertising Expenses* is the log value of firm-level advertising expenditures and Profitability is the log value of firm-level EBIT. Standard errors are reported in parentheses. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.%

	(1)	(2)	(3)	(4)
WSJ × % Contributions to Republican Party	61.671**	87.610***		
	(24.326)	(24.443)		
% Contributions to Republican Party	14.067			
	(32.761)			
WSJ × Top Republican Donor			-23.277	-27.764
			(18.735)	(20.450)
WSJ × Top Democratic Donor			-40.326***	-44.539***
			(11.805)	(11.822)
Top Republican Donor			7.461	
			(16.521)	
Top Democratic Donor			-4.843	
			(12.752)	
Advertising Expenses	-27.389		-17.502	
	(154.165)		(154.018)	
Profitability	-7.062*		-7.183*	
	(3.640)		(3.671)	
Firm FE	Yes		Yes	
Paper FE	Yes	Yes	Yes	Yes
Quarter FE	Yes		Yes	
Firm FE × Quarter FE		Yes		Yes
Topic FE	Yes	Yes	Yes	Yes
Observations	52,913	59,601	52,917	59,603
R-squared	0.111	0.187	0.111	0.187

Table 6: Likelihood of Covering Good and Bad news

This table describes likelihood of coverage based on whether it is a good or bad news day. The sample includes articles that mention only 1 firm. In columns (1)-(6) the dependent variable is an indicator variable that is equal to one if the *WSJ* publishes a financial news article about a firm the same day that the *NYT* publishes an article about the same firm; In columns (1)-(6), *Good News* is the total number of positive words in the NYT article and *Bad News* is the total number of negative words in the NYT article. In columns (5)-(8) the dependent variable is equal to one if the *NYT* publishes a financial news article on a firm the same day as the *WSJ* publishes an article about the same firm; *Good News* is the total number of positive words in the *WSJ* article and *Bad News* is the total number of negative words in the *WSJ* article. *% Contributions to Republican Party* is the percentage of campaign contributions given by the firm to Republican Party candidates in a given election cycle; *Top Republican Donor* is an indicator variable equal to 1 if the firm's contr*ibution to the Republican Party is in the top 20th percentile of all donations to the Republican party in the sample in a given cycle;* Top Democratic Donor is an indicator variable equal to 1 if the firm's contributions to the Democratic Party is in the top 20th percentile of all donations to the Democratic Party in the sample in a given cycle; *Advertising Expenses* is the log value of firm-level advertising expenditures and *Profitability* is the log value of firm-level EBIT. Standard errors are reported in parentheses. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

	Wall Street Journal Coverage						**New York Times Coverage**					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
% Contributions to Republican Party × Good News	0.283*	0.403**	0.466**				-0.133	-0.272	-0.330			
	(0.160)	(0.179)	(0.184)				(0.315)	(0.357)	(0.327)			
% Contributions to Republican Party × Bad News	-0.280***	-0.281***	-0.240***				0.033	-0.078	0.154			
	(0.066)	(0.075)	(0.080)				(0.131)	(0.140)	(0.146)			
Top Republican Donor × Good News				0.227*	0.369***	0.290**				1.033**	0.720*	0.996**
				(0.118)	(0.136)	(0.136)				(0.405)	(0.405)	(0.405)
Top Republican Donor × Bad News				-0.171***	-0.034	-0.126***				0.703***	0.672***	0.739***
				(0.040)	(0.056)	(0.049)				(0.124)	(0.129)	(0.127)
Top Democratic Donor × Good News				-0.102	-0.173**	-0.174**				0.505***	0.217	0.528***
				(0.077)	(0.087)	(0.084)				(0.189)	(0.176)	(0.190)
Top Democratic Donor × Bad News				0.074**	0.088**	0.074*				0.317***	0.256***	0.300***
				(0.033)	(0.037)	(0.039)				(0.068)	(0.073)	(0.071)
Good News	-0.037	-0.064	-0.155	0.109***	0.159***	0.109**	2.452***	2.742***	2.485***	2.193***	2.496***	2.122***
	(0.089)	(0.102)	(0.100)	(0.042)	(0.046)	(0.047)	(0.187)	(0.195)	(0.193)	(0.115)	(0.091)	(0.117)
Bad News	0.326***	0.318***	0.262***	0.174***	0.151***	0.129***	0.735***	0.813***	0.624***	0.681***	0.699***	0.637***
	(0.039)	(0.044)	(0.046)	(0.014)	(0.015)	(0.017)	(0.077)	(0.079)	(0.082)	(0.043)	(0.049)	(0.043)
% Contributions to Republican Party	0.134***	0.012					0.008	-0.022				
	(0.034)	(0.041)					(0.021)	(0.024)				
Top Republican Donor				-0.007	-0.022					-0.063***	-0.065***	
				(0.018)	(0.023)					(0.010)	(0.011)	
Top Democratic Donor				-0.038**	-0.031*					-0.040***	-0.024**	
				(0.015)	(0.017)					(0.010)	(0.011)	
Advertising Expenses		-0.313			-0.308			-0.598***			-0.615***	
		(0.230)			(0.231)			(0.155)			(0.155)	
Profitability		0.040***			0.039***			0.018***			0.017***	
		(0.005)			(0.005)			(0.003)			(0.003)	
Firm FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Quarter FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Firm × Quarter FE			Yes			Yes			Yes			Yes
Observations	26,481	22,227	24,888	26,481	22,227	24,888	34,601	30,740	33,041	34,607	30,744	33,043
R-squared	0.108	0.094	0.264	0.109	0.094	0.264	0.349	0.364	0.438	0.357	0.369	0.445

Table 7: Tone of financial news coverage and political alignment

The table presents regression results describing the tone of coverage based on the political alignment between the firm and the newspaper. Odd-numbered columns include articles that mention at most 1 firm; even numbered columns include articles that mention at most 2 firms. The dependent variable in Panel A is the number of *Positive Words/Total Words* in the article, in Panel B the number of *Negative Words/Total Words* in the article, and Panel C is *Tone* measured as the ratio of (Positive-Negative Words) to (Positive +Negative Words) in an article. *WSJ* is an indicator variable that is equal to 1 if the article is published in the *Wall Street Journa* l and 0 if it is published in the *New York Times* ; *% Contributions to Republican Party* is the percentage of campaign contributions given by the firm to Republican Party candidates in a given election cycle; *Top Republican Donor* is an indicator variable equal to 1 if the firm's contribution to the Republican Party is in the top 20th percentile of all donations to the Republican party in the sample in a given cycle; *Top Democratic Donor* is an indicator variable equal to 1 if the firm's contributions to the Democratic Party is in the top 20th percentile of all donations to the Democratic Party in the sample in a given cycle; *Advertising Expenses* is the log value of firm-level advertising expenditures and *Profitability* is the log value of firm-level EBIT. Standard errors are reported in parentheses. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

Panel 7A: Positive Words per 1000 Words

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms
WSJ × % Contributions to Republican Party	1.422***	1.618***	1.696***	1.891***	1.498***	1.387***						
	(0.419)	(0.432)	(0.432)	(0.383)	(0.322)	(0.250)						
% Contributions to Republican Party	-1.643***	-1.984***	-1.215**	-1.726***								
	(0.539)	(0.434)	(0.555)	(0.454)								
WSJ × Top Republican Donor							0.378	0.458	0.502*	0.610**	0.483**	0.450**
							(0.294)	(0.328)	(0.256)	(0.271)	(0.246)	(0.187)
WSJ × Top Democratic Donor							-0.567***	-0.445**	-0.569***	-0.441*	-0.432***	-0.332***
							(0.169)	(0.215)	(0.177)	(0.224)	(0.143)	(0.114)
Top Republican Donor							-0.548	-0.516*	-0.449	-0.455*		
							(0.334)	(0.305)	(0.326)	(0.273)		
Top Democratic Donor							0.698***	0.601***	0.820***	0.622***		
							(0.212)	(0.197)	(0.161)	(0.177)		
Advertising Expenses			5.285	5.650*					4.959	5.447*		
			(3.516)	(2.885)					(3.539)	(2.963)		
Profitability			-0.148**	-0.149***					-0.136**	-0.150***		
			(0.061)	(0.053)					(0.062)	(0.052)		
Firm FE	Yes	Yes	Yes	Yes			Yes	Yes	Yes	Yes		
Paper FE	Yes	Yes	Yes	Yes			Yes	Yes	Yes	Yes		
Quarter FE	Yes	Yes	Yes	Yes			Yes	Yes	Yes	Yes		
Firm × Quarter FE					Yes	Yes					Yes	Yes
Paper × Quarter FE					Yes	Yes					Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,021	107,792	52,913	91,260	59,601	106,608	61,027	107,801	52,917	91,266	59,603	106,613
R-squared	0.064	0.059	0.067	0.063	0.174	0.136	0.064	0.059	0.067	0.062	0.173	0.136

Table 7 Panel B: Negative Words per 1000 Words

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms
WSJ × % Contributions to Republican Party	-1.165	-1.341	-0.559	-1.268	0.018	-0.068						
	(1.051)	(0.836)	(1.133)	(0.933)	(0.654)	(0.502)						
% Contributions to Republican Party	1.048	2.003	-1.133	0.159								
	(1.597)	(1.218)	(1.858)	(1.445)								
WSJ × Top Republican Donor							-1.256*	-1.021	-0.800	-1.013	-0.559	-0.829**
							(0.725)	(0.672)	(0.634)	(0.629)	(0.491)	(0.396)
WSJ × Top Democratic Donor							-0.151	-0.080	-0.214	-0.148	-0.068	-0.112
							(0.387)	(0.302)	(0.447)	(0.328)	(0.294)	(0.219)
Top Republican Donor							1.080	1.152	0.594	0.951		
							(0.803)	(0.721)	(0.631)	(0.611)		
Top Democratic Donor							-0.163	-0.296	0.049	-0.101		
							(0.602)	(0.515)	(0.667)	(0.559)		
Advertising Expenses			-16.252	-13.178					-16.056	-12.973		
			(11.593)	(9.467)					(11.543)	(9.373)		
Profitability			0.275	0.221					0.249	0.210		
			(0.198)	(0.148)					(0.190)	(0.142)		
Firm FE	Yes	Yes	Yes	Yes			Yes	Yes	Yes	Yes		
Paper FE	Yes	Yes	Yes	Yes			Yes	Yes	Yes	Yes		
Quarter FE	Yes	Yes	Yes	Yes			Yes	Yes	Yes	Yes		
Firm × Quarter FE					Yes	Yes					Yes	Yes
Paper × Quarter FE					Yes	Yes					Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,021	107,792	52,913	91,260	59,601	106,608	61,027	107,801	52,917	91,266	59,603	106,613
R-squared	0.220	0.216	0.227	0.223	0.330	0.297	0.220	0.216	0.227	0.223	0.330	0.297

Table 7 Panel C: Tone

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms
WSJ × % Contributions to Republican Party	0.076**	0.089**	0.064	0.089**	0.054**	0.062***						
	(0.037)	(0.034)	(0.042)	(0.037)	(0.025)	(0.019)						
% Contributions to Republican Party	-0.084	-0.107***	-0.019	-0.057								
	(0.056)	(0.040)	(0.062)	(0.047)								
WSJ × Top Republican Donor							0.036*	0.038*	0.029*	0.042**	0.019	0.034**
							(0.019)	(0.022)	(0.016)	(0.020)	(0.017)	(0.014)
WSJ × Top Democratic Donor							-0.021	-0.014	-0.014	-0.007	-0.018*	-0.011
							(0.014)	(0.016)	(0.015)	(0.014)	(0.011)	(0.009)
Top Republican Donor							-0.032	-0.040*	-0.013	-0.030*		
							(0.022)	(0.021)	(0.018)	(0.018)		
Top Democratic Donor							0.034	0.026	0.032	0.020		
							(0.023)	(0.020)	(0.023)	(0.019)		
Advertising Expenses			0.469	0.330					0.456	0.323		
			(0.330)	(0.272)					(0.322)	(0.264)		
Profitability			-0.014**	-0.014**					-0.013**	-0.013**		
			(0.006)	(0.006)					(0.006)	(0.005)		
Firm FE	Yes	Yes	Yes	Yes			Yes	Yes	Yes	Yes		
Paper FE	Yes	Yes	Yes	Yes			Yes	Yes	Yes	Yes		
Quarter FE	Yes	Yes	Yes	Yes			Yes	Yes	Yes	Yes		
Firm × Quarter FE					Yes	Yes					Yes	Yes
Paper × Quarter FE					Yes	Yes					Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,021	107,792	52,913	91,260	59,601	106,608	61,027	107,801	52,917	91,266	59,603	106,613
R-squared	0.119	0.116	0.124	0.121	0.233	0.197	0.119	0.116	0.124	0.121	0.233	0.197

Table 8: Is it the journalist or the newspaper's ideology?

The table presents regression results for the subsample of articles written by journalists who switch between the two newspapers and have written at least 1 article in the financial news section at both papers. The sample is restricted to articles that only mention 1 firm. The dependent variable in columns (1)-(4) is *Positive Words/Total Words* in the article, in columns (5)-(8) it is *Negative Words/Total Words*, and in columns (9-12) it is *Tone* (Positive-Negative Words)/(Positive +Negative Words). *WSJ* is an indicator variable that is equal to 1 if the article is published in the Wall Street Journal and 0 if it is published in the New York Times; *% Contributions to Republican Party* is the percentage of campaign contributions given by the firm to Republican Party candidates in a given election cycle; *Top Republican Donor* is an indicator variable equal to 1 if the firm's contribution to the Republican Party is in the top 20th percentile of all donations to the Republican party in the sample in a given cycle; *Top Democratic Donor* is an indicator variable equal to 1 if the firm's contributions to the Democratic Party is in the top 20th percentile of all donations to the Democratic Party in the sample in a given cycle. Standard errors are reported in parentheses. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Positive Words				**Negative Words**				**Tone**			
	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms
WSJ × % Contributions to Republican Party	3.000*	2.310*			-3.68	-3.98			0.13	0.21**		
	(1.700)	(1.270)			(3.750)	(2.740)			(.130)	(.100)		
% Contributions to Republican Party	-5.240**	-2.6*			1.24	6.05*			-0.22	-0.3**		
	(1.960)	(1.490)			(4.270)	(3.410)			(.160)	(.130)		
WSJ × Top Republican Donor			1.26	1.45*			4.13	1.2			-0.03	0.02
			(1.420)	(.780)			(3.120)	(1.840)			(.100)	(.060)
WSJ × Top Democratic Donor			-1.06	-0.56			2.39	2.28**			-0.13**	-0.09**
			(.680)	(.500)			(1.590)	(1.140)			(.050)	(.040)
Top Republican Donor			-0.94	-1.46*			-1.6	1.1			-0.05	-0.08
			(1.040)	(.790)			(2.340)	(1.660)			(.090)	(.060)
Top Democratic Donor			1.29***	0.52			-1.53	-1.61*			0.08*	0.04
			(.490)	(.410)			(1.250)	(.980)			(.040)	(.030)
WSJ	-2.31***	-1.33*	-0.52	-0.18	3.09*	2.01	0.2	-0.78	-0.1	-0.09	0.01	0.04
	(.890)	(.710)	(.530)	(.380)	(1.780)	(1.370)	(1.410)	(1.010)	(.060)	(.050)	(.050)	(.030)
Journalist FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cycle FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,507	2,948	1,507	2,948	1,507	2,948	1,507	2,948	1,507	2,948	1,507	2,948
R-squared	0.19	0.12	0.19	0.12	0.33	0.3	0.33	0.3	0.27	0.21	0.28	0.21

Table 9: Newsday at Both Newspapers

This table reports results for the sample of articles where both newspapers have published articles on the same firm on the same day. The sample is restricted to articles that mention just 1 firm. The dependent variable in columns (1)-(4) is *Positive Words/Total Words* in an article, in columns (5)-(8) is the number of *Negative Words/Total Words*, and in columns (9)-(12) it is *Tone* defined as (Positive-Negative Words)/(Positive +Negative Words). *WSJ* is a dummy variable that is equal to 1 if the article is published in the *Wall Street Journal* and 0 if it is published in the *New York Times*; *% Contributions to Republican Party* is the percentage of campaign contributions given by the firm to Republican Party candidates in a given election cycle;. Standard errors are reported in parentheses. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Positive Words				**Negative Words**				**Tone**			
	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms
WSJ × % Contributions to Republican Party	2.015***	2.075***	2.114***	2.052***	0.698	0.018	1.529	0.310	0.040	0.066**	0.028	0.064**
	(0.452)	(0.338)	(0.469)	(0.342)	(0.918)	(0.697)	(0.943)	(0.693)	(0.034)	(0.026)	(0.036)	(0.026)
% Contributions to Republican Party	-1.949***	-2.252***			0.963	1.515			-0.089	-0.123***		
	(0.642)	(0.499)			(1.674)	(1.303)			(0.056)	(0.044)		
Firm FE	Yes	Yes			Yes	Yes			Yes	Yes		
Paper FE	Yes	Yes			Yes	Yes			Yes	Yes		
Quarter FE	Yes	Yes			Yes	Yes			Yes	Yes		
Firm × Quarter FE			Yes	Yes			Yes	Yes			Yes	Yes
Paper × Quarter FE			Yes	Yes			Yes	Yes			Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,522	38,437	21,974	38,191	22,522	38,437	21,974	38,191	22,522	38,437	21,974	38,191
R-squared	0.084	0.071	0.235	0.186	0.241	0.237	0.390	0.355	0.139	0.130	0.301	0.254

Table 10: Financial Section and Earnings Announcements

The table presents regression results describing the tone of coverage based on the political affiliation of the firm and the ideology of the newspaper where the sample is restricted to financial news. The sample is restricted to articles that mention just 1 firm. In Panel A, the sample is restricted to articles that begin in the financial sections of the *Wall Street Journal* and the *New York Times*. In Panel B the articles are restricted to earnings announcements topics. The dependent variable in columns (1)-(4) is the number of *Positive Words/Total Words* in the article, in columns (5)-(8) is the number of *Negative Words/Total Words* in the article, and the dependent variable *Tone* in columns (9-12) is defined as (Positive-Negative Words)/(Positive +Negative Words). *WSJ* is a dummy variable that is equal to 1 if the article is published in the *Wall Street Journal* and 0 if it is published in the *New York Times*; *% Contributions to Republican Party* is the percentage of campaign contributions given by the firm to Republican Party candidates in a given election cycle; *Top Republican Donor* is an indicator variable equal to 1 if the firm's contribution to the Republican Party is in the top 20th percentile of all donations to the Republican party in the sample in a given cycle; *Top Democratic Donor* is an indicator variable equal to 1 if the firm's contributions to the Democratic Party is in the top 20th percentile of all donations to the Democratic Party in the sample in a given cycle. Standard errors are reported in parentheses. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

Table 10 Panel A: Financial Section

	Positive Words				Negative Words				Tone			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
WSJ × % Contributions to	1.668***	1.610***			-0.827	0.737			0.088**	0.066**		
Republican Party	(0.443)	(0.433)			(1.222)	(0.874)			(0.041)	(0.032)		
% Contributions to Republican Party	-1.796***				-0.092				-0.079			
	(0.624)				(1.826)				(0.065)			
WSJ × Top Democratic Donor			-0.645***	-0.448**			0.017	-0.278			-0.044*	-0.034**
			(0.213)	(0.199)			(0.704)	(0.412)			(0.024)	(0.015)
WSJ × Top Republican Donor			0.448	0.570*			-1.326	-0.814			0.019	0.015
			(0.333)	(0.320)			(0.812)	(0.627)			(0.023)	(0.022)
Top Democratic Donor			0.860***				-0.467				0.060	
			(0.252)				(0.977)				(0.037)	
Top Republican Donor			-0.706*				1.329				-0.028	
			(0.407)				(0.912)				(0.025)	
Firm FE	Yes		Yes		Yes		Yes		Yes		Yes	
Paper FE	Yes		Yes		Yes		Yes		Yes		Yes	
Quarter FE	Yes		Yes		Yes		Yes		Yes		Yes	
Firm × Quarter FE		Yes		Yes		Yes		Yes		Yes		Yes
Paper × Quarter FE		Yes		Yes		Yes		Yes		Yes		Yes
Financial Section	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,412	41,848	43,418	41,850	43,412	41,848	43,418	41,850	43,412	41,848	43,418	41,850
R-squared	0.070	0.207	0.070	0.207	0.230	0.356	0.230	0.356	0.125	0.266	0.125	0.266

Table 10 Panel B: Earnings Announcement Topic

	Positive Words				Negative Words				Tone			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
WSJ × % Contributions to Republican Party	3.551***	2.856**			-0.860	2.531			0.088**	0.066**		
	(1.055)	(1.177)			(1.880)	(1.634)			(0.041)	(0.032)		
% Contributions to Republican Party	-2.162*				-2.078				-0.079			
	(1.250)				(2.561)				(0.065)			
WSJ × Top Democratic Donor			-1.370**	-0.420			-0.895	-0.820			-0.044*	-0.034**
			(0.568)	(0.511)			(0.992)	(0.791)			(0.024)	(0.015)
WSJ × Top Republican Donor			0.955	0.940			-2.236	0.077			0.019	0.015
			(0.785)	(0.846)			(1.347)	(1.181)			(0.023)	(0.022)
Top Democratic Donor			1.297*				0.011				0.060	
			(0.654)				(1.713)				(0.037)	
Top Republican Donor			-1.115*				1.401				-0.028	
			(0.637)				(1.452)				(0.025)	
Firm FE	Yes		Yes		Yes		Yes		Yes		Yes	
Paper FE	Yes		Yes		Yes		Yes		Yes		Yes	
Quarter FE	Yes		Yes		Yes		Yes		Yes		Yes	
Firm × Quarter FE		Yes		Yes		Yes		Yes		Yes	YES	Yes
Paper × Quarter FE		Yes		Yes		Yes		Yes		Yes		Yes
Earnings Topic	Yes	Yes		Yes		Yes		Yes		Yes		Yes
Observations	8,750	6,353	8,752	6,353	8,750	6,353	8,752	6,353	43,412	41,848	43,418	41,850
R-squared	0.131	0.466	0.131	0.466	0.157	0.516	0.157	0.516	0.125	0.266	0.125	0.266

Table 11: Contrasting Coverage in Lead Paragraph versus Remaining Article

The table presents regression results contrasting coverage in the lead paragraph versus the rest of the article. The dependent variable is *Positive Words/Total Words* in the article. *WSJ* is a dummy variable that is equal to 1 if the article is published in the *Wall Street Journal* and 0 if it is published in the *New York Times*; *% Contributions to Republican Party* is the percentage of campaign contributions given by the firm to Republican Party candidates in a given election cycle; *Top Republican Donor* is an indicator variable equal to 1 if the firm's contribution to the Republican Party is in the top 20th percentile of all donations to the Republican party in the sample in a given cycle; *Top Democratic Donor* is an indicator variable equal to 1 if the firm's contributions to the Democratic Party is in the top 20th percentile of all donations to the Democratic Party in the sample in a given cycle. Standard errors are reported in parentheses. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

	Lead Para		Remaining Para	
	(1)	(2)	(3)	(4)
WSJ × % Contributions to	1.917***		1.176***	
Republican Party	(0.543)		(0.340)	
WSJ × Top Democratic Donor		-0.654***		-0.389***
		(0.249)		(0.149)
WSJ × Top Republican Donor		0.092		0.320
		(0.406)		(0.251)
Firm × Quarter FE	Yes	Yes	Yes	Yes
Paper × Quarter FE	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes
Observations	59,601	59,603	59,601	59,603
R-squared	0.135	0.135	0.165	0.165

Table 12: Non-parametric tests of trading volume

Panel A describes mean, standard errors and t tests comparing abnormal volume for firms with exactly two articles that mention a firm on a given day in the same newspaper, compared to abnormal volume on days where one article that mentions the firm in each paper are published. *Abnormal Volume_T =Ratio of Abnormal Volume* on day t to *Average Abnormal Volume* over previous T period, where T= 1 month, 3 months, 6 months and 1 year. Panel B describes the same variables for firms with two or more articles in one or both newspapers.

Panel A: Two articles

	Number of Newspapers		
	One	Both	Diff (Both-One)
	(1)	(2)	(3)
Abnormal Volume_31	1.129	1.344	0.215***
	(0.010)	(0.013)	(0.016)
Abnormal Volume_91	1.156	1.365	0.160***
	(0.011)	(0.014)	(0.017)
Abnormal Volume_181	1.187	1.394	0.156***
	(0.012)	(0.014)	(0.018)
Abnormal Volume_365	1.245	1.446	0.149***
	(0.013)	(0.015)	(0.020)
Observations	4,612	6,943	

Panel B: Two or more articles

	Number of Newspapers		
Variable	One	Both	Diff (Both-One)
	(1)	(2)	(3)
Abnormal Volume_31	1.083	1.259	0.176***
	(0.007)	(0.008)	(0.011)
Abnormal Volume_91	1.104	1.279	0.175***
	(0.007)	(0.009)	(0.011)
Abnormal Volume_181	1.133	1.306	0.172***
	(0.008)	(0.009)	(0.012)
Abnormal Volume_365	1.188	1.354	0.166***
	(0.009)	(0.010)	(0.013)
Observations	9,685	12,409	

Table 13: Disagreement and trading volume

This table describes regression results with abnormal volume for firms as the dependent variable as a function of coverage in one or both newspapers. The sample is restricted to days on which there are exactly two articles about a firm in either or one each in both newspapers. In Panel A the sample is restricted to days on which there are exactly two articles that only mention 1 firm, on a given day in the same or both newspapers. In Panel B we consider articles that mention up to 2 firms. *Abnormal Volume_T=Ratio of Dollar Trading Volume* on day t to *Average Daily Trading Volume* over previous T period, where T= 1 month, 3 months, 6 months and 1 year; *Both Papers* is an indicator variable that is equal to one if there is one article that mentions only this firm in each newspaper, and equal to zero if the articles are in one paper only; *Top Donor* is an indicator variable that is equal to one if the firm is in the top 20th percentile of donations to either the Republican or the Democratic parties in the sample in a given election cycle; *Total Number of Articles* is the total number of articles in all news sources on Factiva on that day that mention the firm and *Total Words* is the total number of words in the article. Standard errors clustered at the firm-year level are reported in parentheses. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

Panel A: 1 ticker per article

	Abnormal Volume_31			**Abnormal Volume_91**			**Abnormal Volume_182**			**Abnormal Volume_One Year**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Top Donor × High Disagreement		0.091***	0.103***		0.085**	0.093***		0.081**	0.096***		0.074*	0.091**
		(0.034)	(0.034)		(0.034)	(0.034)		(0.037)	(0.036)		(0.041)	(0.041)
High Disagreement	0.093***	0.065***	0.037	0.093***	0.060**	0.035	0.093***	0.062**	0.037	0.094***	0.054**	0.035
	(0.024)	(0.025)	(0.024)	(0.024)	(0.025)	(0.025)	(0.025)	(0.026)	(0.026)	(0.025)	(0.026)	(0.027)
Top Donor		-0.026	-0.069***		-0.007	-0.055**		-0.006	-0.059**		0.005	-0.060**
		(0.032)	(0.025)		(0.034)	(0.025)		(0.036)	(0.026)		(0.040)	(0.029)
Total Words	1.250***	1.246***	1.704***	1.228***	1.438**	1.939***	1.211***	1.508**	2.055**	1.211***	1.479**	1.992**
	(0.465)	(0.464)	(0.530)	(0.456)	(0.590)	(0.684)	(0.454)	(0.675)	(0.798)	(0.458)	(0.663)	(0.776)
Total Number of Articles	0.003	0.002	0.019	0.005	-0.003	0.015	0.006	-0.008	0.013	0.006	-0.006	0.015
	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.019)
Absolute Returns	20.765***	20.717***	21.460***	20.763***	21.664***	23.008***	20.788***	22.953***	24.465***	20.771***	24.255***	25.835***
	(1.855)	(1.853)	(1.960)	(1.856)	(2.287)	(2.503)	(1.859)	(2.661)	(2.944)	(1.865)	(2.747)	(3.060)
Lagged Absolute Returns	1.169	1.179	2.974*	1.470	2.017	3.737*	2.008	2.872	4.677**	2.043	2.569	4.555*
	(1.790)	(1.792)	(1.770)	(1.567)	(2.188)	(2.091)	(1.446)	(2.436)	(2.324)	(1.273)	(2.600)	(2.365)
Lagged Abnormal Volume	0.156**	0.156**	0.135*	0.139**	0.213**	0.189**	0.111**	0.217**	0.187**	0.102**	0.256***	0.210**
	(0.076)	(0.076)	(0.073)	(0.064)	(0.091)	(0.085)	(0.055)	(0.096)	(0.089)	(0.044)	(0.095)	(0.086)
Firm FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Year FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Firm × Year FE			Yes			Yes			Yes			Yes
Observations	11,549	11,549	11,441	11,549	11,549	11,441	11,549	11,549	11,441	11,549	11,549	11,441
R-squared	0.470	0.471	0.590	0.462	0.489	0.602	0.454	0.499	0.609	0.452	0.510	0.621

Table 13 Panel B: Upto 2 tickers per article

	Abnormal Volume_31			Abnormal Volume_91			Abnormal Volume_182			Abnormal Volume_One Year		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Both Papers	0.060***	0.046***	0.039**	0.049***	0.035*	0.026	0.045**	0.031*	0.021	0.032	0.018	0.012
	(0.000)	(0.008)	(0.027)	(0.006)	(0.054)	(0.151)	(0.017)	(0.097)	(0.261)	(0.104)	(0.344)	(0.532)
Top Donor		0.045**	0.036		0.049**	0.046**		0.047*	0.050**		0.046*	0.054**
x Both Papers		(0.046)	(0.107)		(0.035)	(0.041)		(0.061)	(0.034)		(0.089)	(0.036)
Top Donor		0.009	-0.022		0.011	-0.028**		0.014	-0.030**		0.014	-0.032**
		(0.647)	(0.109)		(0.609)	(0.043)		(0.521)	(0.036)		(0.567)	(0.038)
Total Words	0.015	0.014	0.022*	0.020	0.019	0.027**	0.022	0.021	0.029**	0.024	0.023	0.032**
	(0.258)	(0.291)	(0.080)	(0.149)	(0.173)	(0.047)	(0.145)	(0.167)	(0.047)	(0.125)	(0.144)	(0.032)
Total Number of Articles	0.228	0.228	0.248	0.246	0.247	0.266	0.257	0.258	0.282	0.261	0.262	0.287
	(0.136)	(0.135)	(0.158)	(0.134)	(0.134)	(0.149)	(0.155)	(0.154)	(0.164)	(0.186)	(0.186)	(0.188)
Absolute Returns	18.913***	18.891***	19.143***	19.524***	19.500***	19.838***	20.215***	20.191***	20.566***	21.373***	21.349***	21.671***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Absolute Returns	-0.245	-0.240	0.931	0.251	0.256	1.423	0.953	0.958	2.081	0.566	0.570	1.892
	(0.887)	(0.889)	(0.578)	(0.902)	(0.900)	(0.469)	(0.679)	(0.678)	(0.357)	(0.810)	(0.809)	(0.395)
Lagged Abnormal Volume	0.199***	0.199***	0.190**	0.261***	0.261***	0.255***	0.268***	0.268***	0.260***	0.310***	0.310***	0.286***
	(0.008)	(0.008)	(0.012)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.006)	(0.000)	(0.000)	(0.001)
Firm FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Year FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Firm × Year FE			Yes			Yes			Yes			Yes
Observations	22,090	22,090	21,940	22,090	22,090	21,940	22,090	22,090	21,940	22,090	22,090	21,940
R-squared	0.400	0.400	0.456	0.432	0.432	0.491	0.447	0.447	0.505	0.467	0.467	0.527

Table 14: Disagreement in Tone and Trading Volume

This table describes regression results with abnormal volume for firms as the dependent variable as a function of disagreement in the tone of coverage between the two papers. The sample includes all days for which there is trading volume data on the stocks in our sample between 1990 and 2016 and articles in the *NYT* and *WSJ* that mention only 1 firm. *Abnormal Volume_T=Ratio of Dollar Trading Volume* on day t to *Average Daily Trading Volume* over previous T period, where T= 1 month, 3 months, 6 months and 1 year. *Top Donor* is a indicator variable that is equal to one if the firm is in the top 20th percentile of donations to either the Republican or the Democratic parties in the sample in a given cycle. *Difference in Positive Words* is equal to the absolute value of the difference between *Positive Words in WSJ/Total Words in WSJ* and *Positive Words in NYT/Total Words in NYT*. *Difference in Negative Words* is equal to the absolute value of the difference between *Negative Words in WSJ/Total Words in WSJ* and *Negative Words in NYT/Total Words in NYT*. *Difference in Tone* is the absolute value of the difference in *Tone* between the two newspapers. To control for newsworthy days, *Number of articles* is the total number of articles in a given day in either the *NYT* or the *WSJ* that mention only this firm. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

	Abnormal Volume_31		Abnormal Volume_91		Abnormal Volume_181		Abnormal Volume_One Year	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top Donor × Difference in Positive Words	2.676***		2.939***		2.698***		2.829***	
	(0.006)		(0.002)		(0.005)		(0.004)	
Top Donor × Difference in Negative Words	0.874**		0.744*		0.657		0.506	
	(0.027)		(0.054)		(0.116)		(0.248)	
Top Donor × Difference in Tone		0.075***		0.075***		0.071***		0.069***
		(0.000)		(0.000)		(0.000)		(0.000)
Difference in Positive Words	1.931***		1.394**		1.178**		0.962*	
	(0.001)		(0.011)		(0.035)		(0.093)	
Difference in Negative Words	-0.222		-0.136		-0.050		0.111	
	(0.288)		(0.523)		(0.819)		(0.633)	
Difference in Tone		-0.014		-0.016*		-0.014		-0.011
		(0.115)		(0.074)		(0.125)		(0.257)
Top Donor	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Number of Articles	0.036***	0.049***	0.037***	0.049***	0.036***	0.047***	0.037***	0.047***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Words	0.014	0.002	0.016	0.004	0.017	0.007	0.019	0.009
	(0.208)	(0.841)	(0.202)	(0.702)	(0.169)	(0.559)	(0.143)	(0.480)
Absolute Returns	15.807***	15.810***	16.153***	16.155***	16.774***	16.776***	17.763***	17.765***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Absolute Returns	1.082***	1.086***	1.450***	1.454***	1.717***	1.720***	2.111***	2.114***
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Abnormal Volume	0.222***	0.222***	0.294***	0.294***	0.315***	0.316***	0.323***	0.323***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	824,349	824,349	824,349	824,349	824,349	824,349	824,349	824,349
R-squared	0.185	0.185	0.246	0.246	0.276	0.276	0.311	0.311

Table 15: Newspaper Readership and Herding

The table presents regression results with abnormal dollar trading volume as the dependent variable in Panel A and abnormal absolute signed dollar trading volume as the dependent variable in Panel B in a given firm's stock. *News Read* and *News Other* are indicator variables equal to one if at least one article mentioning the firm is published in the newspaper with more subscriptions and fewer subscriptions respectively on a given day in the zipcode where the investor lives. Investors are classified into two groups, *DMA_WSJ*, and *DMA_NYT*, based on whether the *WSJ* or the *NYT* has more subscriptions in the Designated Market Area (DMA) where the investor lives. *Abnormal Dollar Trading Volume* is defined as the aggregate dollar trading volume on a given day within the DMA groups divided by the trailing 365 day average. *Herding* is defined as the absolute value of the signed dollar trading volume scaled by the trailing 365 day average of the same variable. Signed dollar trading volume is the net of the dollar volume of buys minus sells. Additional control variables are the *DMA_NYT* indicator, the absolute value of the lagged stock returns, and the absolute value of the contemporaneous stock returns. Standard errors are clustered at the firm level. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

Table 15 Panel A: Abnormal Dollar Trading Volume

	(1)	(2)	(3)	(4)	(5)
News Read	0.220***	0.216***	0.217***	0.086***	0.079***
	(0.028)	(0.028)	(0.028)	(0.016)	(0.016)
News Other	0.149***	0.144***	0.144***	0.019	0.014
	(0.025)	(0.024)	(0.024)	(0.013)	(0.013)
DMA_NYT	-0.320***	-0.319***	-0.318***	-0.349***	-0.358***
	(0.025)	(0.025)	(0.025)	(0.023)	(0.022)
Abs Lag Ret		3.389***	3.332***	4.009***	4.023***
		(0.849)	(0.855)	(0.776)	(0.742)
Abs Ret		5.240***	5.178***	5.833***	5.870***
		(1.120)	(1.125)	(1.092)	(1.067)
Firm FE	No	No	No	Yes	No
Year FE	No	No	Yes	Yes	No
Firm × Year FE	No	No	No	No	Yes
Observations	175,636	175,636	175,636	175,636	175,636
R-squared	0.02	0.02	0.02	0.05	0.05

Table 15 Panel B: Herding (Abnormal Absolute Signed Dollar Trading Volume)

	(1)	(2)	(3)	(4)	(5)
News Read	0.182***	0.180***	0.180***	0.058***	0.051***
	(0.021)	(0.022)	(0.022)	(0.010)	(0.010)
News Other	0.125***	0.122***	0.123***	0.005	0.000
	(0.019)	(0.019)	(0.019)	(0.009)	(0.009)
DMA_NYT	-0.306***	-0.306***	-0.305***	-0.333***	-0.343***
	(0.025)	(0.025)	(0.025)	(0.023)	(0.022)
Abs Lag Ret		2.202***	2.147***	2.636***	2.601***
		(0.572)	(0.577)	(0.485)	(0.457)
Abs Ret		3.058***	3.000***	3.464***	3.451***
		(0.665)	(0.667)	(0.591)	(0.566)
Firm FE	No	No	No	Yes	No
Year FE	No	No	Yes	Yes	No
Firm × Year FE	No	No	No	No	Yes
Observations	175,636	175,636	175,636	175,636	175,636
R-squared	0.02	0.02	0.02	0.05	0.05

INTERNET APPENDIX

Appendix Table 1 : News Corporation Acquisition

In columns (1)-(4), the dependent variable is *WSJ*, which is equal to one if there is an article that mentions the firm in the *Wall Street Journal*, and equal to 0 if the article is published in the *New York Times*. In columns (5)-(8), the dependent variable is equal to the ratio of *Positive Words/Total Words* in the *Wall Street Journal.* Pre News Corporation includes the years 1990-2007 and Post News Corporation includes the years 2008-2016. *% Contributions to Republican Party* is the percentage of campaign contributions donated to Republican candidates by the firm in that election cycle; The sample includes articles that only mention 1 firm (odd numbered columns) or at most 2 firms (even numbered columns). Standard errors are reported in parentheses. *significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

	WSJ				Positive Words/Total Words in WSJ			
	Pre News Corporation		Post News Corporation		Pre News Corporation		Post News Corporation	
	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms	1 firm	2 firms
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Contributions to Republican Party	-0.042*	-0.020	0.255***	0.278***	-0.761	-1.176***	-0.117	-0.770
	(0.025)	(0.019)	(0.041)	(0.028)	(0.499)	(0.375)	(0.877)	(0.567)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Topic FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,550	76,817	15,470	30,973	26,779	45,883	7,808	16,344
R-squared	0.195	0.205	0.260	0.274	0.084	0.077	0.122	0.107