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ABSTRACT

We use a high-frequency identification approach to document that individual politicians affect asset prices. We exploit the regular flow of viewpoints contained in Congress members' tweets. Supportive (critical) tweets increase (decrease) the stock prices of the targeted firm and the corresponding industry in minutes around the tweet. The bulk of the stock price effects is concentrated in the tweets revealing news about future legislative action. The effects are amplified around committee meeting days, especially when the tweet originates from committee members and influential politicians. Overall, we show that Congress members' social media accounts are an important source of political news.

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1 Introduction

Social medias have become an increasingly important tool for politicians to communicate with the public. Both federal and state elected government officials actively maintain Twitter accounts by posting a large volume of content regularly. For example, Congress members collectively average around 30,000 tweets per month, where 20 percent of those posts communicate important viewpoints on key economic agendas. Around 90 percent of these politicians tweet about a trending economic issue each month, with large surges in social media activity occurring around roll call votes. The tweets offer direct and accurate to the second snapshots of politicians' opinions that are widely available to the public. This paper examines the informational content of tweets by U.S. Congress members by studying their effect on asset prices. We find that these tweets contain a large set of new and unique information about future legislative or economic action.

We scrape the official Twitter accounts of all members of the U.S. Senate and House of Representatives. We then select tweets that explicitly convey an opinion about a specific company to facilitate identification, yielding around 11K tweets and 500 unique firm mentions. Textual analysis is used to classify if the tone is critical or supportive in a continuous measure. Our benchmark analysis estimates the effect of the politicians' opinions on the stock prices of the targeted firm in the minutes around each tweet. The identifying assumption is that no additional information affecting the stock price is systematically released over such a short time window. We find that supportive (critical) tweets increase (decrease) the stock prices of the targeted firms in a statistically significant way. We further demonstrate the robustness of this result by controlling for a comprehensive time-stamped event database, which encompasses both scheduled firm-level and macro news, as well as unscheduled events. We, therefore, provide direct evidence that Congress members affect asset prices through social media.

The high-frequency approach we adopt in our benchmark analysis allows us to accurately determine the immediate impact of a tweet on stock prices. However, these estimates may not capture the full extent of the effect, as market participants may require time to fully process and respond to the new information conveyed in the tweet. Therefore, we progressively expand the event window from minutes to several days after posting the tweet. By extending the post-event window, we observe a significant increase in the effects compared to our high-frequency estimates. For instance, when we extend the event window to a full day, the estimated effects magnify by a factor of 4. Moreover, stock returns continue to exhibit a gradual drift according to the tone over the two following days but then flatten out with no subsequent reversals. There are also no perceptible price trends in the days or minutes preceding the tweets.

We further examine the economic relevance and persistence of the effects by implementing a long-short portfolio strategy based on the information contained in the congressional tweets. Specifically, the long portfolio buys the affected stocks when the tweets are particularly supportive, while the short portfolio sells the affected stocks when the tweets are particularly critical. We construct these value-weighted portfolios at the end of each day following the tweets and rebalance them daily. The long-short portfolio strategy generates mean returns of 100 basis points per month. Importantly, we demonstrate that these returns remain largely unaffected even after controlling for standard risk factors. Overall, the strong stock price responses suggest that the tweets by U.S. Congress members contain new and relevant information that gets priced in over the next few days.

We next examine in detail if a systematic news source is contained in these Congress members' tweets targeting firms. We find that a significant fraction of these congressional tweets reveals news about future legislative and economic actions, and the bulk of the stock price effects is concentrated in these tweets relating to policy. Our primary method of identifying tweets relating to future legislation is to isolate the congressional tweets targeting firms on days of House and Senate committee meetings and hearings (henceforth, meetings, for short). We focus on the information flow around committee meetings for two primary reasons. First, congressional committees are integral to the legislative process, allowing lawmakers to acquire specialized knowledge in specific areas within their jurisdiction. This knowledge empowers committee members to draft, evaluate, and propose legislation that undergoes discussion and voting by the entire House or the Senate. Second, committee meetings and hearings often correspond to important junctures in the legislative process shaped by the committees (e.g., debating proposed amendments to legislation, suggesting new policy actions to address critical issues, expert witnesses giving opinions about a legislative proposal, etc.).

We posit that significant information about future legislation or economic action is unveiled on committee meeting days. We evaluate to what extent this new information is transmitted through the congressional Twitter accounts. To this end, we exploit meeting details (date, topics, and if the meeting is related to a specific legislative proposal) and committee member characteristics to identify a subset of the congressional tweets providing viewpoints about firms that explicitly relate to news about future legislative actions. We find that stock price effects are significantly amplified on meeting days when the tweet originates from committee members of the meeting or influential politicians (e.g., Cohen, Coval, and Malloy (2011) and Cohen and Malloy (2014)) and contains text that closely relates to meeting topics or references a specific legislative proposal associated with the meeting. Tweets explicitly linked to a particular bill or joint resolution also affect the stock prices of other firms in the same industry as the targeted firm. The industry effect appeals to the observation that legislation rarely affects a single firm (Cohen, Diether, and Malloy (2013)). We also find that news about future legislation is revealed on days around the meetings, especially by committee members.

We use an alternative method for identifying tweets related to policy and to entertain the possibility that news about legislative action can be revealed on any day, including around meetings. The alternative method is also used as external validation for our primary method of identifying tweets about legislation on meeting days and exploiting meeting details. We start with the full set of congressional tweets targeting firms on all days and then use two search criteria. The first criterion selects tweets based on text similarity with the policy-related word dictionary of Hassan, Hollander, Van Lent, and Tahoun (2019) that uses information from sources such as political newspaper articles, press releases by members of Congress, and bill sponsorships. The second criterion selects tweets that contain hashtags related to legislative and economic actions. We take the union of these two sets of tweets selected according to each criterion to form the set of policy-relevant tweets.

Around 43% of the 11K congressional tweets are classified as policy-relevant tweets. The stock price effects are significantly larger for the policy-relevant tweets, while the effects are smaller and only marginally significant for the non-policy-relevant tweets.

Approximately 58% of the policy-relevant tweets occur on meeting days, reinforcing the notion that a substantial portion of legislative news via Twitter is generated on meeting days. Nevertheless, we still find that valuable news is produced outside of meeting days. As external validation of our baseline method for identifying legislative tweets on meeting days, the majority of the committee member tweets on meeting days are captured using this alternative method.

Overall, our paper illustrates how Congress members utilize Twitter as an important platform for communicating news about policy to the public. We find strong evidence that congressional viewpoints about firms affect their stock prices primarily because they reveal news about future legislative and economic action.

Our findings that stock prices respond significantly to political news extracted from politician tweets provide direct support for the economic mechanisms featured in the models of Pástor and Veronesi (2012) and Pástor and Veronesi (2013). These papers show that political news shapes investor beliefs about which government policy is likely to be adopted in the future. Asset prices therefore respond to the continual flow of political signals before a policy is implemented. Our paper extracts political signals directly from the social media accounts of a large panel of U.S. Congress members. The effect of the signals on asset prices is then identified using a high-frequency approach.

An emerging literature examines the impact of politics on stock returns (Santa-Clara and Valkanov (2003), Belo, Gala, and Li (2013), Kelly, Pástor, and Veronesi (2016), Addoum and Kumar (2016), and Pástor and Veronesi (2020)). These papers focus on linkages between the incumbent president's party and aggregate stock returns. Our paper complements this literature by providing granular evidence tying individual politicians' viewpoints to stock price responses. Cohen et al. (2013) find that legislators' voting decisions contain important information about stock returns. Cohen et al. (2013) show that legislation affects asset prices after it gets passed (i.e., news about *realized* legislation). We instead obtain political signals that start months before voting (i.e., news about *expected* legislation). A novel aspect of our analysis is that we can observe regular snapshots of the political climate and legislative intent of Congress members even before the official proposal of the legislation. These signals forecast roll call votes and move the stock price of the targeted firm and the corresponding industry portfolio.

Our methodological approach connects to a literature using textual analysis to extract information that affects stock returns (e.g., Boudoukh, Feldman, Kogan, and Richardson (2013), Buehlmaier and Whited (2018), Chen, De, Hu, and Hwang (2014), Engle, Giglio, Kelly, Lee, and Stroebel (2020), Giglio, Maggiori, Rao, Stroebel, and Weber (2021), Hoberg and Moon (2019), Kelly, Manela, and Moreira (2019), Gentzkow, Kelly, and Taddy (2019a), Cookson, Engelberg, and Mullins (2021), Cookson, Lu, Mullins, and Niessner (2022), and Arteaga-Garavito, Croce, Farroni, and Wolfskeil (2021)) and high-frequency identification in macroeconomics (e.g., Gürkaynak, Sack, and Swanson (2005), Bernanke and Kuttner (2005), Nakamura and Steinsson (2018), and Bianchi, Gómez-Cram, Kind, and Kung (2023)). Kuchler and Stroebel (2021) document linkages between social media engagement and stock market investments. We build on these strands of literature by highlighting that congressional social media accounts are an important source of political news to market participants.

Our paper relates to the literature measuring political opinions from media platforms. Mullainathan and Shleifer (2005), Gentzkow and Shapiro (2010), and Martin and Yurukoglu (2017) analyze political polarization from media sources such as newspapers and cable news. Gentzkow, Shapiro, and Taddy (2019b) and Jensen, Naidu, Kaplan, Wilse-Samson, Gergen, Zuckerman, and Spirling (2012) measure partisanship in congressional speeches. Cookson, Engelberg, and Mullins (2020) show that partisanship shapes investor beliefs. Birney, Graetz, and Shapiro (2006) examine the role of public opinion on political legislation. We complement this literature by measuring congressional viewpoints about economic agendas at high frequencies directly from the social media accounts of individual Congress members and by studying the impact of social media posts on stock prices.

2 Data

Our primary data source is the complete set of posts on Twitter (i.e., tweets) by members of the U.S. Senate and House of Representatives from January 2013 to December 2020. The prevalence of the Twitter platform as a congressional communication tool offers several advantages in our empirical analysis relative to traditional communication mediums. In particular, tweets are in a standardized format and include a time-stamp that is accurate to the second. Both of these features allow us to directly measure the viewpoints of individual politicians at high frequencies.

We obtain every official, campaign, and personal account for each Congress member from their congressional websites. Congress members who did not list a Twitter account on their website or do not have a verified account are dropped. Information on institutional accounts that change hands between consecutive congressional terms is not collected, so each account can be linked to a single legislator. We capture around 85 percent of the congressional accounts.

Politicians generate a large amount of social media content. Our dataset contains 2.5 million tweets from 740 different Twitter accounts. There are 30 million total words contained in these posts, with 77,000 unique words. In a median month, the median member of Congress produces 42 tweets per month, totaling 1,200 likes and retweets per tweet.

A central part of our benchmark analysis is to exploit tweets by members of Congress that explicitly convey an opinion about individual companies. Identifying firm mentions in a congressional social media post faces several challenges. First, politicians may mention the same company using different versions or variations of its name. For example, *Apple Inc* appears as *Apple Computer Inc* in Compustat. However, politicians most likely will write either *Apple* or the Twitter account of the company *@Apple* in their tweets. Alternatively, they could even target the company by mentioning the name of the CEO *Tim Cook* or the Twitter account of the CEO *@tim_cook* instead of the company name itself. Second, a politician may mention a company name (or several variations of its name) in a tweet without expressing a view about the company being mentioned. For example, H.R. Keith Ellison (@keithellison) writes, "'Good morning! We are on *Apple* Podcasts!" 8 August 2019, 16:50:31 EST, Tweet. This problem is exacerbated if the company name has multiple meanings. For instance, Sen. Chris Coons (@ChrisCoons) "Heading to Bridgeville for *Apple* Scrapple! #netde" 11 October 2014, 16:19:04 EST, Tweet. In both cases, Congress members mentioned the word *Apple*, although neither expressed an opinion about the company. Identifying politicians' tweets that target specific companies would be greatly simplified if we just searched for a stock using its

Fig. 1. **Tweets by members of Congress targeting companies**

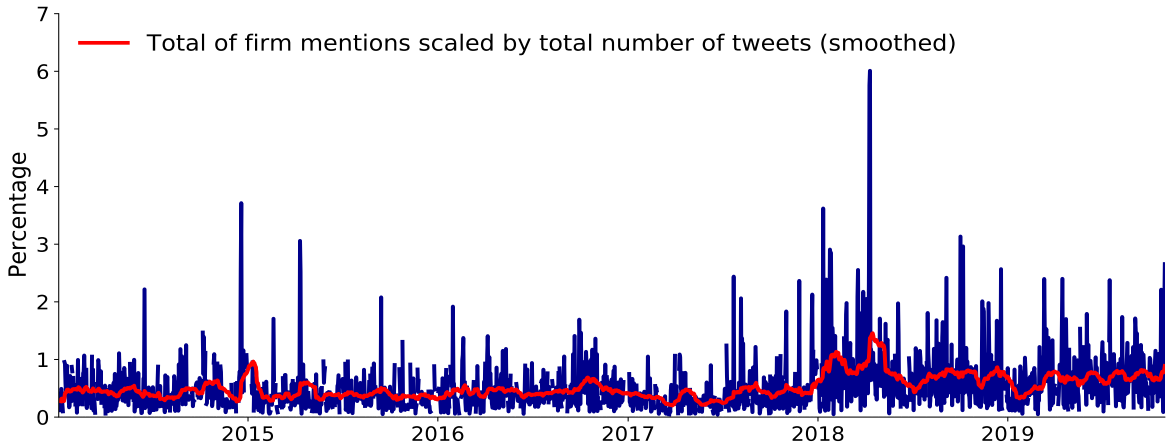


Fig. 2. *Notes*: This figure shows the daily number of tweets targeting an individual company. The count is scaled by the total number of tweets posted each day. The red line depicts the smoothed series obtained by taking a 15-day moving average. The raw series is in blue. We use the complete set of tweets created by any member of the U.S. Senate and House of Representatives from the 113th Congress to the 116th Congress.

ticker. However, in our setting, politicians seldom refer to a company using its ticker.

The challenges above are addressed as follows. To make the sample construction manageable, our search is restricted to stocks in the Russell 3000 index. This index contains the 3,000 largest U.S. traded stocks, comprising roughly 98% of the U.S. equity market index in terms of market capitalization. We then select tweets that contain either: (1) the full company legal name or parts thereof, after removing common words such as 'Inc' or 'Corp' (for the company's legal name, we use both CONML and CONM in Compustat), (2) the official Twitter account for each company, or (3) the Company CEO name or corresponding Twitter account. This search generates a total of 24,032 matches. To avoid the problem that a company name might have multiple meanings, we also manually checked all 24,032 matches to distinguish those that were erroneously classified and did not explicitly mention a company. We will use this subset of false-positive tweets for placebo tests in the Internet Appendix.

Our selection criteria yield 11,602 tweets by members of Congress that explicitly convey their opinions about 454 unique firms. Figure 2 plots the total number of congressional tweets that express an opinion about a company each day, scaled by the total number of congressional tweets posted during that day. The average value equals

0.5%, which amounts to six daily tweets, since Congress as whole posts on average 1,100 tweets per day. The figure also exhibits a substantial amount of variation over time, with a standard deviation of 0.46%.

After selecting the tweets that express opinions about specific companies, we proxy for politician viewpoints about companies using a relative tone measure that classifies the tweet as being supportive or critical. The lexicon developed by Loughran and McDonald (2011) is used to compute the tone systematically. Loughran and McDonald (2011) create word dictionaries of negative and positive words that account for the nuances of finance jargon. Using these dictionaries, we then count the number of positive and negative words for each tweet. We define the relative $Tone$ measure as the difference between the positive and the negative word count scaled by the total number of words contained in the tweet.[1,2] To improve the interpretability of the estimated coefficients in the next sections, we standardize the tone measure by subtracting its mean and dividing it by its standard deviation.

Our benchmark analysis estimates the impact of politician viewpoints on firm valuations with a high-frequency identification approach. For this analysis, we use tick-by-tick data on stock prices from the NYSE Trade and Quote (TAQ) database. We keep all tweets posted during regular trading days from 9:30 to 16:00 Eastern Time (ET) and collect the firm's ticker for all companies mentioned in our sample, which is then used to merge with the TAQ database. The raw series is cleaned following the procedures described in Brownlees and Gallo (2006).

While the high-frequency approach facilitates a clean identification of immediate

[1] Intuitively, the tweet will support the company if the tone measure is positive (e.g., Sen. James Lankford (@SenatorLankford) *"The positive news just keeps on coming. Wal-Mart now joining the growing list of companies w/ plans to increase wages for workers because of the #TaxCutsandJobsAct" 01 November 2018, 15:58:06 EST, Tweet.*, $Tone = 3.57\%$), and it will criticize the company if the tone measure is negative (e.g., Sen. Ron Wyden (@RonWyden) *"@SenWarren and I are demanding the FTC investigate whether Amazon's reckless treatment of Americans' personal data broke the law"* 24 October 2019, 12:01:53 EST, Tweet., $Tone = -11.76\%$). The average $Tone$ measure is -0.61% with a standard deviation of 5.7%. Figure B.1 in the Internet Appendix shows the time series variation of this series.

[2] In our benchmark analysis, we rely on the Loughran and McDonald dictionaries to interpret the sentiment of tweets and news headlines. These dictionaries are chosen for their tractability, scalability, and established effectiveness in numerous related textual contexts (e.g., Tetlock (2007), Tetlock, Saar-Tsechansky, and Macskassy (2008), Das and Chen (2007), Chen et al. (2014)). In Section C of the Internet Appendix, we further reinforce our findings with robustness checks using five alternative tone measures: FinBERT, Vader, TextBlob, ChatGPT, and manual classification. We find very similar results when using these alternative tone measures.

impacts, this approach might not fully capture the total scale of the impact, as it might take time for market participants to completely assimilate and respond to the new information from the tweet. To establish the economic significance of our findings, we incrementally expand the event window from minutes to days after the tweets. In these daily tests, we employ daily return data from the Center for Research in Security Prices (CRSP). These returns are calculated using closing prices from one day to the next, and we aggregate the tone measure to the daily level in a similar vein, ensuring a precise alignment between the daily tone measure for a company and its daily returns. More specifically, we compute the average tone measure of all tweets about each company, posted between one market closing time at 16:00 ET to the next available closing time of the subsequent business day at 16:00 ET. Lastly, an added advantage of focusing on daily event windows is that it allows us to consider the full set of tweets, not just those posted during regular trading hours for which we have high-frequency stock prices.

2.1 Controlling for other news

Our empirical tests focus on stock price fluctuations within either intraday or daily event windows surrounding the tweets. The rationale is that the tweets introduce a substantial amount of news within the event window, facilitating a high-frequency identification approach. However, it is feasible that other news affecting a company may systematically arise near or within these narrow event windows. Such news could potentially influence asset prices, prompt responses from politicians on social media, and be correlated with the tone of the politicians' tweets. To alleviate concerns regarding these potential confounding effects, we incorporate a comprehensive set of controls in our tests.

We search for news articles concerning our target companies on Factiva, RavenPack, and Benzinga. These platforms collate and process articles from premium newswires, regulatory news providers, and press releases. We obtained 193,683 firm-specific news headlines in total, and each was timestamped to the exact minute.

We scrape all tweets from 103 major news media outlets (e.g., WSJ, Reuters, and FT) and then identify those that relate to the firms targeted in the congressional tweets. Out of 18 million tweets from media outlets, we identified 201,542 tweets related to our companies. Table A.2 in the Internet Appendix lists the names and usernames of the news media outlets used. As with the previous tone measure, we calculate the tone of both news headlines and social media posts from these outlets by determining the difference between the percentage of positive and negative words.

We obtain news related to earnings and revenue announcements by compiling analyst forecasts of earnings per share and sales from the Thomson Reuters I/B/E/S Detail History File and the actual figures from the I/B/E/S Actuals File database. We obtain each analyst's expectations using their most recent estimates for the same firm and fiscal quarter, all collected within the 45 days leading up to the earnings and revenue announcement dates. The consensus among analysts is derived by taking the median of all these forecasts across analysts within this 45-day window. We define the news on earnings and revenue announcement dates as the deviation between the actual realizations and the consensus forecasts, normalized by the standard deviation of this difference. Furthermore, in addition to analysts' expectations, we consider news in earnings and revenue announcements stemming from management guidance. For each firm issuing such guidance, we leverage the firm's forecasts for the upcoming quarter to calculate the news component. In total, we have 42,533 earnings and revenue news announcements, each pinpointed to the precise minute.

We also account for revisions in individual analysts' expectations concerning earnings and revenue. For each analyst issuing a forecast, we compute the news component by taking the difference between the newly-issued forecast and the consensus of analysts, which is calculated by taking the median of all forecasts issued within the preceding 45 days. We then normalize this difference by dividing it by its standard deviation. In total, we have 2,791,778 timestamped revisions in individual analyst expectations.

We include macroeconomic news releases obtained from the Bloomberg Professional Service, including the precise announcement time for each macroeconomic indicator (e.g., Change in Nonfarm Payrolls, Initial Jobless Claims, and FOMC announcements). We compute the difference between the realized and expected values for each indicator, normalizing this difference by the standard deviation. For the analysts' forecasts, we employ the median forecast from the most recent weekly survey of economists conducted by Bloomberg prior to the announcement. In line with Bianchi et al. (2023), we focus on the top 50 macroeconomic indicators, as determined by the Bloomberg Relevance score. Overall, we have 11,189 timestamped macro news announcements.

We incorporate the firm-level Bloomberg news sentiment measure that Bloomberg constructs using a supervised machine learning algorithm to ascertain the sentiment measure of a news story (sourced from Bloomberg News, web content, and selected premium news wires) towards a specific company. A firm's sentiment scores are calculated as a confidence-weighted average of story-level sentiments from the preceding 24 hours. These scores are released each morning roughly 10 minutes before the market opening.[3]

All public information available at the start of the event window should already be factored into asset prices. However, to address concerns about price drifts occurring just prior to a politician's tweet—potentially reflecting the market's assimilation and processing of other news—we control for the intraday cumulative return in all regressions. This cumulative return is calculated from market opening to 15 minutes before the politician's tweet. In our daily test, the cumulative return refers to the daily return of the preceding day.

We address concerns of illiquidity by using the Amihud (2002) illiquidity measure (ILLIQ). We calculate ILLIQ by taking the minute-level ratio of absolute stock return to its dollar volume, averaging from market open to 15 minutes before the tweet. We control for intraday market volatility by calculating the volatility (mean of absolute returns) from the market open to 15 minutes before the tweet. In our daily test, ILLIQ (volatility) refers to the ILLIQ (volatility) value of the preceding day. We also account for standard risk factors, including the market, size, value, and momentum factors.

Section A.2 in the Internet Appendix provides a detailed description of these controls. Table A.1 in the Internet Appendix lists these variables, offer their definitions, and provides their data sources.

[3]Even though having the Bloomberg news sentiment measure at the minute level would be beneficial for our analysis, the high-frequency sentiment/news feeds are only available in real-time. Unfortunately, historical data for these feeds are not available; the most recent data is accessible up to six months prior to the current date.

3 Congressional tweets and stock prices

This section documents how politicians' viewpoints about a company conveyed in a tweet have a material impact on stock prices. In Section 3.1, we investigate the immediate impact by analyzing stock price reactions within a minute-level window around the tweet. By focusing on this narrow timeframe, we effectively mitigate the possibility of systematic releases of other relevant information that could potentially influence stock prices. Section 3.2 progressively expands the event window from minutes to a day to show that the effects not only persist over time but also grow significantly in magnitude. Finally, Section 3.3 explores the economic relevance of our findings through long-short portfolios and monthly portfolio alphas.

3.1 High-frequency identification

The aim of this subsection is to determine the impact of congressional tweets on the stock prices of companies explicitly mentioned in the tweets. We structure our results around the following equation:

$$\Delta p_{i,t} = a + b \cdot Tone_{i,t} + \epsilon_{i,t}, \tag{1}$$

where $\Delta p_{i,t}$ represents the log change in company i's stock price in basis points (bps) within a narrow window surrounding the tweet posted at the timestamp t. The standardized tone of the tweet referencing company i, denoted by $Tone_{i,t}$, captures whether the tweet supports or criticizes the company. The error term is given by $\epsilon_{i,t}$, and the regression coefficients are denoted by a and b. The parameter of interest is b, which quantifies the average marginal response of stock prices in bps around each tweet when the tone measure is one standard deviation higher.

The identifying assumption of our high-frequency approach is that no other relevant information affecting the stock prices is systematically released within a specific time window around the tweet at time t. Within this brief time frame, changes in $\Delta p_{i,t}$ are driven by the news component present in the tweet. We utilize a $[-1 \text{ min}, +5 \text{ min}]$

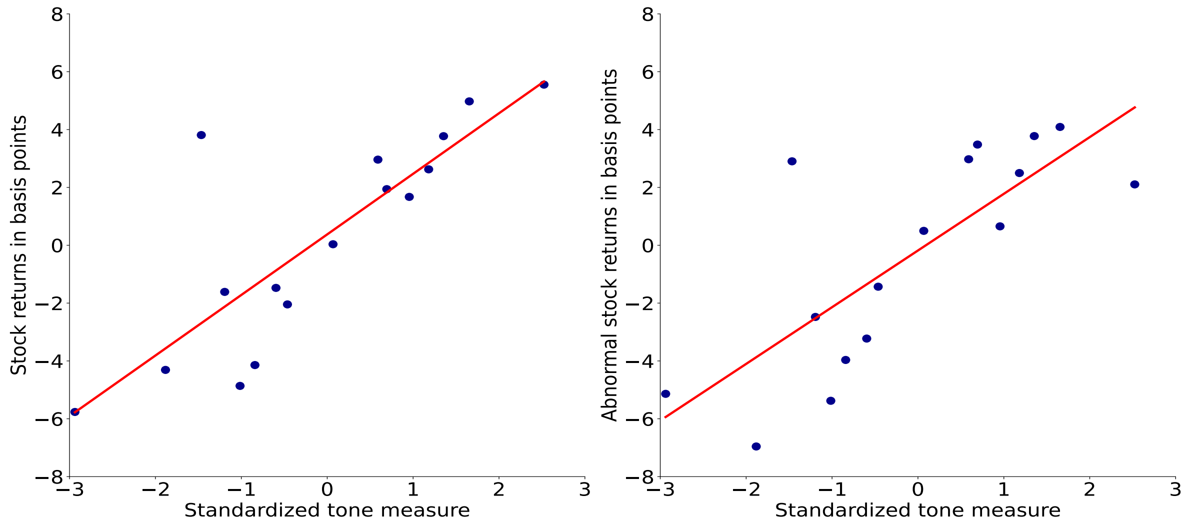
window surrounding the tweet in our benchmark estimation.[4] This means that we calculate the difference between the log price of the first trade occurring 5 min after the tweet and the log price of the last transaction 1 min prior to the tweet. If no trades occur before and after 10 minutes, we conclude that the tweet did not influence the stock price. On average, the time gap between stock prices before and after the tweet is 7 minutes and 25 seconds. Figure A.1 in the Internet Appendix offers a visual representation of the selection process for the two trade observations.

We offer a graphical representation of the results in Figure 3. The left panel of the figure displays the average stock price reactions for various tone measure levels. We initially sort tweets into equal-sized bins based on their tone measure and subsequently calculate both the average tone measure and the average high-frequency returns for each sorted bin. The red line characterizes the regression fit. The figure reveals a strong positive relationship between stock price changes and our tone measure. For instance, companies in the first decile experience an average stock price reduction of around -5.66 basis points (t-statistic = -3.78), whereas the average stock price change for companies in the last decile is 5.41 basis points (t-statistic = 3.03). The right panel repeats the analysis using abnormal returns, calculated as the difference between a company's stock return and the aggregate market return, to account for overall market movements. We observe similar results: The excess stock return of companies criticized (supported) by a tweet tends to decrease (increase) within minutes following the tweet.

We proceed to estimate equation (1) utilizing a pooled ordinary least squares (OLS) regression. In all subsequent regressions, we apply stock fixed effects and cluster the standard errors at the firm and day levels. Table 1 contains the results. In column 1, the coefficient estimate for $Tone_{i,t}$ is 2.13 (t-statistic = 2.94), indicating that stock returns tend to rise by approximately 2 bps on average 5 minutes after the tweet when the tone measure increases by one standard deviation. This estimate implies that supportive (critical) opinions about companies lead to an increase (decrease) in stock valuations,

[4] The rationale behind the asymmetric time window is as follows. We select a 1 min window before the tweet because it represents the shortest time frame we can choose, given that we are working with minute-level stock prices. Conversely, we allocate a 5 min window after the tweet to allow market participants sufficient time to react to the tweet, but not so long that the event window becomes contaminated by other events occurring after the tweet. A brief window minimizes the likelihood of additional tweets falling within this period.

Fig. 3. **Binned scatter plot of the tone measure and stock returns**



Notes: This figure charts stock returns for portfolios sorted by their tone measure. We first sort tweets into bins based on their tone measure. We then compute both the average tone measure and the average high-frequency returns for each of the sorted bins. The left panel presents stock returns, while the right panel displays abnormal returns, calculated as the difference between a company's stock return and the aggregate market return. The tone measure is standardized, and returns are in basis points. The red lines represent the regression fit lines.

consistent with the scatter plot presented above.

The remaining three columns in Table 1 progressively incorporate tighter controls for news. Column 2 includes firm-level controls, column 3 adds macro-level controls with the firm-level ones, and column 4 incorporates firm and macro-level controls alongside abnormal returns, calculated as the difference between a company's stock return and the aggregate market return.[5] The key takeaway is that the point estimate of 2.13 remains largely unaffected by the introduction of more refined controls. We provide a detailed description of these controls in Section 2.1 and in Section A.2 of the Internet Appendix.

[5]To account for the timestamped firm-level and macro-level controls detailed in Section 2.1, we determine if they occur within a 20-minute interval surrounding the $[-1 \text{ min}, +5 \text{ min}]$ window of the tweet. If the news is within this time frame, we incorporate it as a control; otherwise, we assign this value to zero. Notably, we observe that in approximately 10% of instances, a news item falls within the $[-1 \text{ min}, +5 \text{ min}]$ event window. For additional robustness, Table B.1 in the Internet Appendix presents results using a similar specification, but replacing the 20-minute interval with different window sizes for the controls, namely: 10 min, 30 min, 60 min, and 120 min.

Table 1. **High-frequency stock prices responses to congressional viewpoints**

Coefficient	Variable	*Raw returns* (1)	(2)	(3)	*Abnormal returns* (4)
a	1	-0.07	-0.46	-0.46	-0.25
		[-0.19]	[-1.36]	[-1.37]	[-0.40]
b	$Tone_{i,t}$	2.13	2.52	2.53	2.20
		[2.94]	[2.87]	[2.89]	[2.81]
R-squared (%)		0.59	0.93	1.02	0.90
Observations		4,876	4,716	4,716	4,716
Firm-level controls		No	Yes	Yes	Yes
Macro-level controls		No	No	Yes	Yes

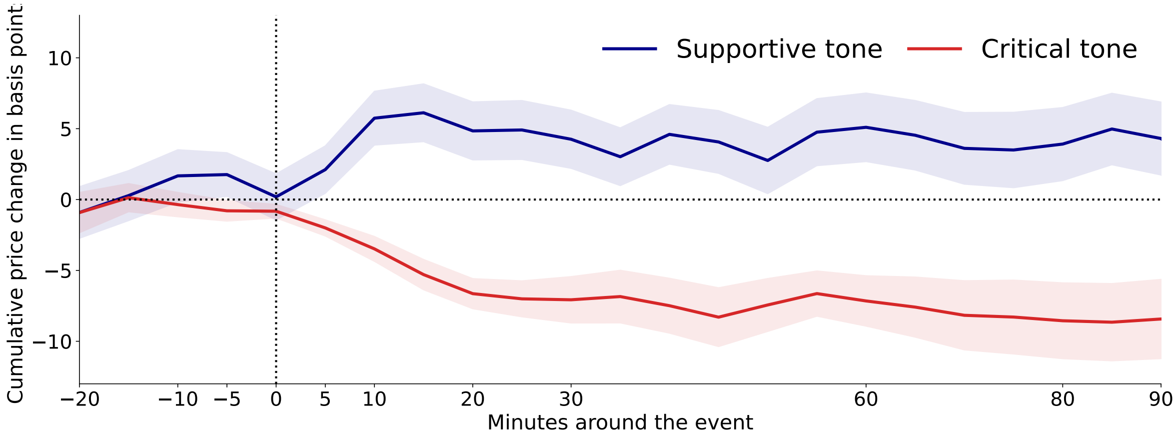
The table presents regression estimates for the equation: $\Delta p_{i,t} = a + b \cdot Tone_{i,t} + \epsilon_{i,t}$, where $\Delta p_{i,t}$ denotes the change in log stock prices for stock i around tweet t. A 6-minute window (1 minute before and 5 minutes after the event t) is used to calculate price changes. $Tone_{i,t}$ represents the tone measure. Stock fixed effects are used in all regressions. Column 2 includes firm-level controls, column 3 adds macro-level controls to firm-level controls, and column 4 includes firm-level controls, macro-level controls, and abnormal returns, calculated as the difference between a company's stock return and the aggregate market return. Firm-level controls consist of intraday illiquidity measures, cumulative stock returns up to 10 minutes before the tweet, timestamped stock news article headlines, stock-related tweets from news media accounts, analysts' cash-flow revisions, and forecast errors. Macro-level controls consist of news announcements of the top 50 macroeconomic indicators. Event-based controls use a 20-minute window around the tweet (10 minutes before and 10 minutes after the stock prices used to compute $\Delta p_{i,t}$). Standard errors are clustered at the firm and day levels, with t-statistics in brackets. $Tone_{i,t}$ is standardized, while $\Delta p_{i,t}$ is in basis points. R-squared statistics are reported as percentages.

3.2 Persistence of effects

The previous subsection showed that the opinion of politicians about a company conveyed in a tweet has a statistically significant impact on its stock price in a short window around the tweet. In this subsection, we explore longer event windows to reveal that these effects not only persist over time but also grow in magnitude. By expanding the event window, we can more accurately gauge the economic significance of these effects, as it may take time for market participants to fully assimilate and respond to the new information presented in the tweet.

Figure 4 displays the effect of tweets on stock prices as the event window progressively expands. First, firms are sorted into 10 deciles based on their tone measure. Second, for each stock in a decile, the cumulative stock price response is calculated from 20 minutes before the tweet to 90 minutes after. The red line represents the average cumulative

Fig. 4. **Event-study plot: Minutes around the event**



This figure shows the effect of congressional tweets on stock prices across various event windows. Tweets are initially sorted into 10 deciles based on their tone measure. For each stock in a decile, cumulative returns are calculated from 20 minutes before the tweet to 90 minutes after. The red line represents the average cumulative return for the first decile, corresponding to politicians' tweets criticizing the targeted firm, while the blue line depicts the average cumulative return for the last decile, where politicians' tweets support the targeted firm. Blue and red shadings indicate the 95% error bands.

return for the first decile, which corresponds to politicians' tweets criticizing the targeted firm, while the blue line illustrates the average cumulative return for the last decile, where politicians' tweets are in support of the targeted firm. Blue and red shadings indicate the 95% error bands.

Figure 4 illustrates several important points. First, in the minutes leading up to the tweets, stock prices for companies with the most supportive tone measure did not exhibit a different trend compared to those of the companies with the most critical tone measure. Second, the tweets had an immediate impact on stock prices, with the direction of the impact depending on whether the opinion is supportive or critical. Third, as the post-event window extends to 90 minutes, the estimated effects increase substantially compared to the high-frequency benchmark estimates using a 6-minute event window. For example, the estimated effect decreases from -2.00 bps (t-statistics = -3.25) to approximately -8.42 bps (t-statistics = -4.21) for the bottom decile.

We subsequently expand the event window to one day. Using data from all trading days in our sample period (i.e., days with and without politician tweets targeting company i), we estimate the following panel OLS regression:

$$r_{i,t} = a_0 + a_1 I_{i,t} + b \cdot (Tone_{i,t} \times I_{i,t}) + \epsilon_{i,t}, \tag{2}$$

Table 2. **Daily asset prices responses to congressional viewpoints**

Coefficient	Variable	Raw returns (1)	Residualized returns using CAPM (2)	FF3 (3)	FF4 (4)
a_0	1	-0.70	-3.46	-4.82	-3.81
		[-0.07]	[-0.95]	[-1.47]	[-1.35]
a_1	$I_{i,t}$	-9.56	-7.73	-6.73	-5.96
		[-2.98]	[-3.09]	[-2.93]	[-2.58]
b	$Tone_{i,t} \times I_{i,t}$	8.31	7.25	7.01	7.23
		[2.94]	[3.01]	[2.89]	[2.91]
R-squared (%)		0.73	0.76	0.80	0.78
Observations		719,388	716,351	716,351	716,351
Firm-level controls		Yes	Yes	Yes	Yes
Macro-level controls		Yes	Yes	Yes	Yes

The table presents regression estimates for the equation: $r_{i,t} = a_0 + a_1 I_{i,t} + b\,(Tone_{i,t} \times Ii, t) + \epsilon_{i,t}$, where $r_{i,t}$ denotes the daily stock return for company i, $I_{i,t}$ is a dummy variable equal to one if a tweet about company i occurs on day t, and zero otherwise. $Tone_{i,t}$ represents the daily tone measure. All regressions use stock fixed effects and incorporate firm-level and macro-level controls. Firm-level controls include daily illiquidity and volatility measures, weekly cumulative stock returns up to day $t-1$ before the tweet, Bloomberg news sentiment measure for company i on day t and $t-1$, daily tone measures for stock news article headlines and stock-related tweets from news media accounts, analysts' cash-flow revisions, and forecast errors. Macro-level controls consist of news announcements for the top 50 macroeconomic indicators. Column 1 reports results with using raw returns; column 2 with CAPM-adjusted returns; column 3 with Fama-French three-factor model-adjusted returns; and column 4 with Fama–French/Carhart four-factor model-adjusted returns. Stock returns are in basis points, and $Tone_{i,t}$ is standardized. The full panel of stock returns is used. Standard errors are clustered at the firm and day levels, with t-statistics in brackets. R-squared statistics are reported as percentages.

where $r_{i,t}$ represents the daily stock return for company i (in bps), $I_{i,t}$ is a dummy variable equal to one if a tweet about company i is posted on day t, and zero otherwise. $Tone_{i,t}$ denotes the standardized daily tone measure. All regressions employ stock fixed effects and include both firm-level and macro-level controls. Standard errors are double clustered at the stock and day level. We provide a detailed description of the controls in Section 2.1 and in Section A.2 of the Internet Appendix. When aggregating the timestamp controls to a daily frequency, we consolidate all news occurring before 4 pm. Any news occurring after 4 pm is merged with the subsequent day's news. This approach aligns with the methodology we employ for aggregating the tone measure to the daily frequency.

Column 1 of Table 2 presents the regression results using daily returns. The estimated effects are approximately four times larger when employing a 1-day post-event window.

For instance, the estimated coefficient on $\text{Tone}_{i,t}$ is around 8.31 (t-statistic = 2.94), indicating that daily returns are 8.31 bps higher when the tone is one-standard-deviation higher using a daily event window, compared to 2.53 bps using a six-minute event window from our benchmark analysis (see column 3 in Table 1). The remaining columns of Table 2 apply various daily return adjustments: CAPM-adjusted returns in column 2, Fama-French three-factor model-adjusted returns in column 3, and Fama-French/Carhart four-factor model-adjusted returns in column 4. Columns 2 through 4 demonstrate that the coefficient for the tone measure remains largely unchanged when accounting for standard risk factors. Hence, the results are robust when transitioning to daily data, and the effects increase in magnitude.

3.3 Portfolio results

We further examine the persistence of the effects by creating long and short portfolios based on the information contained in the congressional tweets. The performance of this approach offers an alternative means of assessing the economic relevance of our findings and simplifies the comparison of economic magnitudes with the existing literature, as we can transform the intraday and daily parameter estimates for the tone measure into monthly alphas.

To form the portfolios, we first compare the tone measure of a tweet, $Tone_{i,t}$, for stock i on day t with the tone measures of all tweets for all companies in the previous 12 months. If $Tone_{i,t}$ is above the 90th percentile, the tweet is considered supportive of firm i, and we purchase the stock. If $Tone_{i,t}$ is below the 90th percentile, the tweet is deemed critical of firm i, and we sell the stock. To execute the buy or sell order, we allow for a one-business-day gap between day t of the ranking period and day $t+1$ of the holding period. Next, we form long and short portfolios by value-weighting all stocks that received a buy or sell signal during the day, respectively. The portfolios are rebalanced daily. Lastly, after obtaining the daily portfolio returns for the long and short sides, we accumulate the daily returns at the monthly frequency and create the long-short portfolio that buys the long portfolio and sells the short portfolio.[6]

[6]We aggregate the long and short portfolios from daily to monthly frequency before forming the long-short portfolio to avoid losing observations on days with only supportive or critical tweets about a

Table 3. **Performance Evaluation: Mean returns and factor alphas**

	Portfolio returns relative to the day of the tweet				
	Day $t+1$			Day $t-1$	Day t
	Short	Long	Long - Short	Long - Short	Long - Short
	(1)	(2)	(3)	(4)	(5)
Average return	-0.20	0.99	1.19	-0.02	1.30
Standard deviation	4.64	4.85	6.02	5.23	7.72
CAPM alpha	-0.84	0.40	1.13	0.10	1.83
	[-2.40]	[1.87]	[3.68]	[0.12]	[4.22]
FF3 alpha	-0.99	0.23	1.12	0.16	1.91
	[-1.98]	[1.48]	[3.32]	[0.20]	[4.95]
FF4 alpha	-1.04	0.10	1.03	0.18	2.11
	[-2.13]	[1.32]	[3.14]	[0.24]	[4.91]

This table presents monthly mean returns and monthly factor alphas for three distinct portfolios. The long (short) portfolio buys stock i if the corresponding tone measure is above (below) the 90th (10th) percentile of the tone distribution computed over the previous 12 months. We value-weight the stocks to create portfolios when multiple firms are assigned to the same leg on the same day. In columns 1 through 3, to execute the buy or sell order, we allow for a one-business-day gap between day t of the ranking period and day $t+1$ of the holding period. In columns 4 and 5, we execute the buy or sell order on day $t-1$ and on day t, respectively. The portfolios are rebalanced daily. Once we obtain the daily portfolio returns for the long and short sides, we accumulate the daily returns at the monthly frequency. The "Long-Short" portfolio buys the long portfolio and sells the short portfolio. The alphas represent the intercepts from time series regressions of the portfolio excess returns on factor alphas. The four factors include the aggregate market excess return, the size factor, the value factor, and the momentum factor. Standard errors adjust for heteroskedasticity and autocorrelation. Returns are in percent. We report the t-statistics in brackets.

Table 3 presents the average monthly long-short portfolio returns in percentage points. Column 3 reveals that based on this strategy, the long-short portfolio generates substantial abnormal returns. The long-short portfolio consistently earns significant abnormal returns, whether using CAPM alphas, three-factor alphas, or four-factor alphas, with abnormal returns ranging from 1.03% per month (t-statistic = 3.14) to 1.13% per month (t-statistic = 3.68). It is worth noting that the majority of this spread is attributable to the short side, where the abnormal returns for the short portfolio range from -0.84% to -1.04% per month (t-statistic = -2.40 and t-statistic = -2.13, respectively).

Columns 4 and 5 of Table 3 explore abnormal portfolio returns one day before the politician's tweet and on the day of the tweet itself. While these portfolio returns are unattainable since we use the forward-looking information of $Tone_{i,t}$ for portfolio sorting,

firm. Aggregating to the monthly frequency ensures that we have complete observations for each month in our sample.

they provide valuable insights. They enable us to determine if there is any significant run-up before the tweet (column 4) and measure the economic impact of the tweet on the day it is posted (column 5). Column 4 shows no noticeable run-up in pre-tweet returns, suggesting that politician tweets are not echoing other news related to company i. This is consistent with the high-frequency evidence shown in Figure 4, where the returns of low- and high-tone tweets did not display different trends in the minutes leading up to the tweets. Column 5 reveals that the effects are significantly higher on the day of the tweet. However, as demonstrated in column 3, it takes some time for the information to be fully incorporated into asset prices. In Figure B.3 of the Internet Appendix, we extend the event-time cumulative abnormal returns to the long-short portfolio returns from day $t-6$ to day $t+15$. We find consistent results of no pre-event returns; however, returns significantly drift upward for the next four days and then flatten out.

4 News about future congressional actions

This section provides an economic interpretation of why congressional tweets referencing individual companies affect their stock prices according to the tone. We show that the bulk of the stock price effects is concentrated in tweets relating to legislative and economic actions. Our results suggest Twitter is an important public communication tool for politicians to reveal news about policy agendas.

Section 4.1 identifies tweets relating to legislation on committee meeting days by exploiting meeting details (date, topics, specific bills) and committee member characteristics. Committee meetings often correspond to important junctures in the legislative life cycle, where we posit that a significant amount of news about future legislative action is unveiled. We evaluate to what extent this news is transmitted through congressional tweets. Section 4.3 considers an alternative method for classifying tweets relating to policy agendas and entertains the possibility that news about legislative action can also be revealed through congressional tweets beyond the meeting days. This alternative method also provides external validation for our primary tweet classification method focusing on committee meetings. Section 4.4 examines the economic relevance of our findings and Section 4.5 presents additional results.

4.1 *News around committee meetings*

Our analysis in this section centers on tweets posted on days surrounding scheduled House and Senate committee meetings. Committees play a vital role in the legislative process of Congress, providing lawmakers with the opportunity to acquire specialized knowledge in specific areas within their jurisdiction. This knowledge empowers committee members to draft, evaluate, and propose legislation that will undergo discussion and voting by the entire membership of the House or the Senate (for details, see Johnson III, Sullivan, and Wickham (2017)).

By analyzing tweets around committee meetings, we capitalize on the fact that a significant amount of news related to legislative actions is unveiled on these days. We aim to determine whether some of this information is transmitted through politicians' social media accounts. Our tests exploit politicians' characteristics (e.g., committee membership and legislative effectiveness scores) and meeting details (e.g., if a session involved debates, amendments, or rewrites of specific legislation).

We scrape the House and Senate committee meetings and hearings schedule from the website `www.congress.gov`. We extract the date and details of each meeting and identify the committee responsible for holding the meeting. This data is collected from the 113th Congress to the 115th Congress. To complement this information, we utilize the congressional committee assignment dataset from Stewart III and Woon (2017). This dataset provides comprehensive records of membership on all congressional committees, including the date of appointment and termination, allowing us to track committee assignment changes throughout our sample period.[7]

Table B.4 in the Internet Appendix presents summary statistics on committee meetings. During our sample period, each committee in the House held an average of 224 meetings, while each committee in the Senate held an average of 159 meetings. These meetings collectively accounted for approximately 41% of the total days in our sample.[8]

[7]The dataset is updated periodically from the Congressional Record and can be found at `http://web.mit.edu/17.251/www/data_page.html`.

[8]Table B.3 of the Internet Appendix provides an overview of the number of unique committees per Congress, the average number of members per committee per Congress, and the average number of committees each member belongs to. In the House, there are around 26 unique committees, on average, with each committee having around 34 members. On average, House members belong to 2 committees. In the Senate, there are approximately 24 on average, with each committee having around 17 members.

Table 4 presents the results by conditioning on various meeting details and politicians' characteristics, with each column progressively tightening the link to news about future legislative action. The first four columns examine stock price changes within a 6-minute window around the tweets, using the methodology described in Section 3.1. All regressions incorporate firm fixed effects and include firm and macro-level controls. These tests isolate the price reactions attributed to the information conveyed in the tweets. The narrow time frame and the inclusion of a comprehensive set of firm and macroeconomic controls make it unlikely that other news significantly impacting stock prices and systematically correlated to the tone would occur during this event window. We further conduct a validity check for meetings with a known time-stamp. We ensure that the tweets do not coincide within a two-hour window following the start of the meeting. This check allows us to verify that this subset of tweets does not drive our results.

Column 1 repeats the analysis conducted in Section 3.1 (refer to column 4 of Table 1) by regressing abnormal returns on the tone measure. The estimated coefficient on $Tone_{i,t}$ is 2.20 (with a t-statistic of 2.81), indicating that abnormal returns, on average, increase by 2.20 basis points when the tone measure is one standard deviation higher. Moving through columns 2 to 4, we progressively introduce more refined regressors, allowing us to flesh out the underlying mechanism further. In column 2, we include a dummy variable, $Meeting_t$, which takes the value of one if the day of the tweet coincides with a committee meeting and zero otherwise. The coefficient on $Tone_{i,t} \times Meeting_t$ in column 2 is 0.76 (with a t-statistic of 2.65). This implies that the estimated coefficient on the tone measure is around 45% higher on days with committee meetings compared to days without committee meetings.

Column 3 delves deeper into the impact of tweets during committee meetings by distinguishing between tweets posted by Congress members who are part of the committee holding the meeting and those who are not. The rationale behind this test is that if the tweets disclose legislative news relevant to these committee meetings, the tweets from insiders on these committees will likely be more informative on average. Consequently, the estimated effects are expected to be concentrated among this subset of tweets. We introduce the dummy variable $Meeting\ and\ Member_{i,t}$ to capture this distinction. It

Senate members, on average, belong to 4 committees.

Table 4. **Stock price responses around committee meetings**

Frequency Dependent variable	High-frequency Abnormal returns				Daily FF4 abnormal returns
Regressors	(1)	(2)	(3)	(4)	(5)
$Tone_{i,t}$	2.20	1.70	1.70	1.70	6.05
	[2.81]	[2.56]	[2.56]	[2.56]	[2.54]
$Tone_{i,t} \times Meeting_t$		0.76	0.13	0.13	0.48
		[2.65]	[0.50]	[0.50]	[1.01]
$Tone_{i,t} \times Meeting\ and\ Member_{i,t}$			1.38	1.33	4.74
			[2.49]	[2.21]	[1.87]
$Tone_{i,t} \times Meeting,\ Member$				1.01	4.50
$and\ TextSimilar_{i,t}$				[2.67]	[2.31]
1	-0.25	-1.04	-1.04	-1.04	-6.76
	[-0.40]	[-1.31]	[-1.30]	[-1.30]	[-1.52]
$Meeting_t$		1.28	0.90	0.90	3.08
		[1.37]	[0.97]	[0.97]	[0.50]
$Meeting\ and\ Member_{i,t}$			0.98	1.62	-5.24
			[0.85]	[1.12]	[-1.01]
$Meeting,\ Member$				-1.37	-7.33
$and\ TextSimilar_{i,t}$				[-1.56]	[-0.97]
R-squared (%)	0.90	0.92	0.91	0.92	0.83
Observations	4,708	4,708	4,708	4,708	11,355
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes

Moving through columns 1 to 4, we progressively introduce more refined regressors. In column 2, $Meeting_t$ is a dummy variable that equals one if a tweet coincides with a committee meeting and zero otherwise. In column 3, $Meeting\ and\ Member_{i,t}$ is a dummy variable that equals one if a politician's tweet occurs on a day when their corresponding committee is holding a meeting and zero otherwise. In column 4, $Meeting,\ Member\ and\ TextSimilar_{i,t}$ is a dummy variable that equals one if the text similarity measure is above its median value and the politician belongs to the committee holding the meeting and zero otherwise. The dependent variable in columns 1 to 4 is is abnormal returns, calculated as the difference between a company's stock return and the aggregate market return using a 6-minute window around the tweet. In column 5, the dependent variable is the Fama-French/Carhart four-factor model-adjusted returns. $Tone_{i,t}$ represents the tone measure. All regressions use stock fixed effects and incorporate firm-level and macro-level controls. Firm-level controls include illiquidity and volatility measures, weekly cumulative stock returns up to day $t-1$ before the tweet, Bloomberg news sentiment measure for company i on day t and $t-1$, tone measures for stock news article headlines, and stock-related tweets from news media accounts, analysts' cash-flow revisions, and forecast errors. Macro-level controls consist of news announcements for the top 50 macroeconomic indicators. Stock returns are in basis points, and $Tone_{i,t}$ is standardized. Standard errors are clustered at the firm and day levels, with t-statistics in brackets. R-squared statistics are reported as percentages.

equals one if a politician tweets about a company on a day when their corresponding committee is holding a meeting and zero otherwise. The regression results indicate a substantial effect of tweets posted by committee members on the same day of their meetings, with a large and significant coefficient on $Tone_{i,t} \times Meeting,\ and\ Member_{i,t}$ (1.38; t= 2.49).

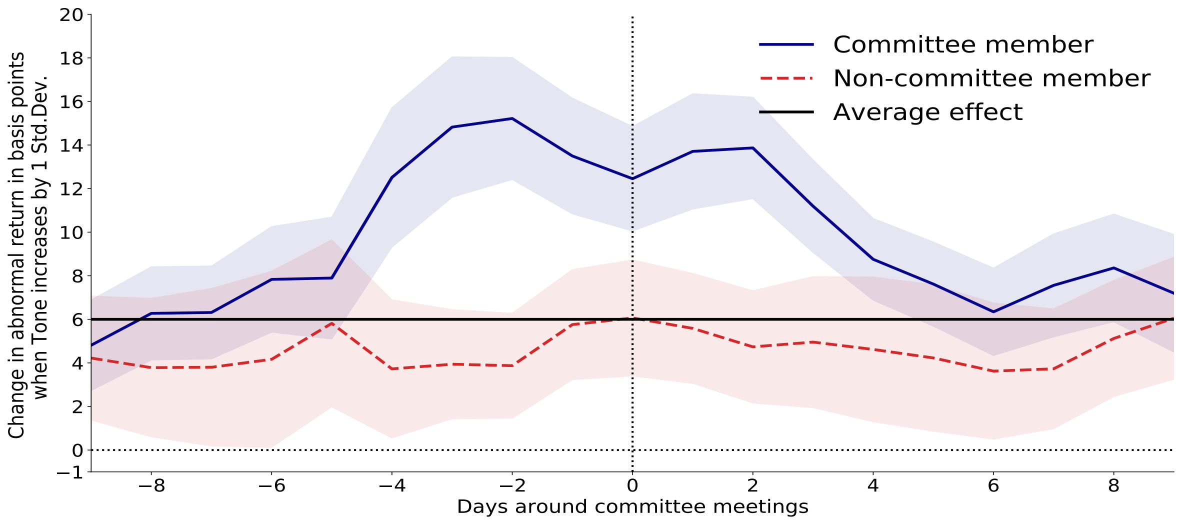
In contrast, the coefficient on $Tone_{i,t} \times Meeting_t$, capturing the effect of non-committee members' tweets during committee meetings, is small and insignificant (0.13; t= 0.50). Overall, the estimated impact of tweets by members of Congress during their committee meetings is 3.21 basis points per one-standard-deviation higher tone measure. This effect is approximately 89% larger than on non-meeting days.

Column 4 further refines the test by conditioning on the committee meeting details. This test captures the idea that tweets from committee members participating in the meeting (as in column 3) and also discussing closely related topics in the tweet are likely to be even more informative. We compute the TF-IDF (Term Frequency-Inverse Document Frequency) cosine similarity measure to identify closely associated tweets and the meeting details. A dummy variable, $Meeting,\ Member,\ and\ TextSimilar_{i,t}$, is created, taking the value of one if the tweet occurs on a meeting day, the text similarity measure is above its median value, and the politician belongs to the committee holding the meeting, but zero otherwise. In column 4, the interaction term $Tone_{i,t} \times Meeting,\ Member,\ and\ TextSimilar_{i,t}$ is observed to be large and significant (1.01; t= 2.67). This coefficient indicates that tweets by members of Congress on meeting days with text that closely aligns with the meeting topics have a 145% larger effect than tweets on non-meeting days.

In column 5, we expand the event window to a day. If a member of Congress posts about the same firm multiple times on the same day, we aggregate all the tweets into a single observation. Similar to our previous approach, we aggregate the tweets daily by considering all tweets posted between two consecutive market closing times. This ensures alignment with daily returns. The dependent variable we focus on is the Fama-French/Carhart four-factor model-adjusted returns. Column 5 shows that our daily specification consistently yields similar findings as our high-frequency estimates. For instance, we observe that tweets by members of Congress closely related to the topic of their committee meetings have an effect of approximately 160% larger than other tweets.

To further examine the persistence of the effects, we conduct a portfolio test similar to Table 3. However, in this case, we restrict the analysis to tweets posted by politicians

Fig. 5. **Daily asset prices responses around committee meeting days**



This figure shows the daily estimated effect of politicians' tweets about a company during the period spanning 9 days before and 9 days after the committee meeting day. Day 0 denotes the actual committee meeting day. The blue line represents the estimated effect of politicians' tweets specifically from the corresponding committee, while the red line represents the estimated effect of politicians' tweets not affiliated with the committee, covering the same time frame. We use a daily event window to compute the stock price responses. The blue and red shadings indicate the 95% error bands.

during committee meetings on the same day as their meetings. The results show that the alphas remain substantial and statistically significant, ranging from 1.20% to 1.49%. These alpha values are approximately 30 bps higher than those reported in Table 3. Table B.5 in the Internet Appendix reports the results.

We next expand our analysis to include the days surrounding committee meetings. By examining a broader time range, we can better understand when pertinent information regarding the meeting begins circulating. Figure 5 depicts the estimated effect of politicians' tweets on a specific company within nine days preceding and following the committee meeting day. Here, day 0 represents the day of the scheduled committee meeting. We measure the estimated effects using a daily event window around the tweet and distinguish between the effects of politicians' tweets affiliated with the committee under examination and those originating from politicians not associated with the committee. If the tweets reveal important information about the meeting, it follows that the tweets by politicians directly participating in the committee are expected to be, on average, more informative. Consequently, these tweets should elicit a more pronounced price reaction.

Figure 5 depicts the daily estimated effects of politicians' tweets affiliated with the committee under examination (represented by the blue line labeled "Committee member") and those not originating from politicians associated with the committee (illustrated by the red dotted line labeled "Non-committee member"). These effects are statistically indistinguishable and remain around the unconditional estimated value, highlighted by the black straight line, of approximately 6 basis points per one-standard-deviation higher tone measure during the five days preceding the committee meeting. However, a distinct pattern emerges approximately four days before the meeting day. The effect of tweets from members of Congress directly involved in the meeting experiences a substantial increase, reaching a peak value of approximately 16 basis points per one-standard-deviation higher tone measure just two days before the meeting. Notably, this effect is approximately 2.5 times higher than the unconditional estimate.

The impact on subsequent days after the meeting remains consistently high, gradually dissipating in a monotonic manner and returning to the unconditional estimate after approximately six days. In contrast, the effects of tweets from politicians not directly involved with the committee meeting (represented by the red dotted line) do not exhibit this distinct pattern. Instead, their estimated effects hover around 6 basis points per one-standard-deviation tone measure throughout the entire 19-day event window.

4.2 Meetings about Legislative Proposals

A subset of committee meetings evaluates specific legislative proposals (e.g., bills or joint resolutions). These meetings can potentially reveal more precise information about future legislative actions than meetings not connected to particular proposals. To this end, this subsection refines the analysis conducted in Table 4 by focusing on congressional tweets referencing firms related to the subset of meetings evaluating specific legislative proposals. These tweets link closely to future legislative actions and effective legislators within the life cycle of particular bills or joint resolutions.

The legislative process begins with a member of Congress introducing a bill. Upon introduction, the bill is assigned a designation based on the chamber of origin, such as H.R. or H.J.Res. for House-originated bills or joint resolutions and S. or S.J.Res. for Senate-originated measures. The bill also receives a number, typically ordered sequentially within the particular two-year Congress. In most cases, the bill is referred to the committee of jurisdiction, responsible for reviewing measures related to the relevant policy area, as determined by the House Speaker or the Senate presiding officer.

Our approach consists of two steps to identify the days on which each bill is considered in each committee. First, we examine every step documented in the "All Actions" section of the bill summary, which provides a detailed record of the legislative process. We then select the relevant days during which a bill undergoes committee deliberations. For bills that involve multiple committees or are divided into segments assigned to different committees, we include all pertinent committees of our analysis, accounting for any potential overlap or division. Additionally, if the committee of referral delegates the bill to subcommittees for further study, hearings, revisions, or approval, we aggregate the outcomes of these subcommittees at the committee level. Overall, for bills that successfully transitioned into public law, there exists an average time gap of 187 days (with a median of 145 days) between the period when a bill is in a committee and its ultimate enactment.

Table 5 presents the results of our analysis using a daily event window. In column 1, we examine the impact of the tone measure on both committee meeting days and non-committee meeting days, similar to the approach employed in column 2 of Table 4 with our high-frequency regression. In column 2 of Table 5, we differentiate committee meeting days based on their association with proposed bills using the dummy variable $Meeting\ and\ Bill_t$. This variable takes a value of 1 when a committee meeting discusses a specific bill and 0 otherwise. We find a positive and statistically significant coefficient (2.43, $t = 2.01$) for the interaction term $Tone_{i,t} \times Meeting\ and\ Bill_t$, indicating that tweets with a one-standard-deviation higher tone measure during committee meeting days related to bills have a 59% greater impact on abnormal returns compared to tweets with a one-standard-deviation tone measure posted outside committee meetings.

Suppose politicians' tweets offer insights into their potential future legislative actions. In that case, we expect more precise information about the future course of policy among the politicians of the committee of jurisdiction, as previously demonstrated, and among legislators with a proven track record of navigating the legislative process effectively. To assess the effectiveness of Members of Congress in lawmaking, we utilize the Legislative

Effectiveness Score (LES) data for the House and the Senate, sourced from Volden and Wiseman (2014) and Volden and Wiseman (2018), respectively. The LES is calculated for each member of Congress by considering a weighted average of fifteen indicators that collectively capture their ability to advance their sponsored bills throughout the legislative life cycle. These stages include bill sponsorship, actions in committee, actions beyond committee, passage in the House/Senate, and eventual enactment into law. The weights assigned to each indicator depend on the bill's significance, categorized as commemorative, substantive, or substantive and significant.

In Column 3 of Table 5, we present the test results by introducing a dummy variable $Meeting,\ Bill\ and\ Les_{i,t}$. This variable takes on the value of 1 if there is a committee meeting on that day, the meeting discusses a particular bill or joint resolution, and the LES value for politician i is above the median LES score (calculated using the scores of all members of Congress in the Congress chamber and corresponding Congress). The estimated coefficient on the interaction of the tone of politician i's tweet, meeting discussing a bill, and high LES score ($Tone_{i,t} \times Meeting,\ Bill\ and\ Les_{i,t}$) is positive and statistically significant (1.75, t = 1.91). This interaction term suggests that the estimated effects for a one-standard-deviation higher tone measure are almost double the impact observed for less effective legislators, and it is 86% larger than tweets posted outside committee meetings.

Our previous analysis has primarily focused on examining the stock price responses of the referenced firm. However, proposed legislation often has implications for an entire industry rather than just an individual company (e.g., Cohen et al. (2013)). Therefore, if the subset of tweets we have studied influences investors' expectations regarding future legislative actions, we expect similar stock price responses among other companies operating in the same industry as the firm mentioned in the tweets.

To investigate whether tweets referencing a specific firm also impact other firms within the same industry, we assign each company to an industry based on its four-digit SIC code, utilizing the 49 industry definitions provided on Kenneth French's website. We then construct industry portfolios and conduct a similar test to Column 3 of Table 5, replacing the individual stock returns with industry returns. Additionally, to account for overall market movements, we compute abnormal industry returns by subtracting the

Table 5. **News about bills around committee meeting days**

Frequency / Dependent variable	Daily FF4 abnormal returns			Daily industry abnormal returns
Regressors	(1)	(2)	(3)	(4)
$Tone_{i,t}$	6.05	6.05	6.05	1.58
	[2.54]	[2.54]	[2.54]	[1.67]
$Tone_{i,t} \times Meeting_t$	2.72	1.12	1.12	1.77
	[2.64]	[1.86]	[1.86]	[1.73]
$Tone_{i,t} \times Meeting\ and\ Bill_t$		2.43	2.33	1.89
		[2.01]	[1.87]	[2.27]
$Tone_{i,t} \times Meeting,\ Bill\ and\ Les_{i,t}$			1.75	0.96
			[1.91]	[1.97]
1	-6.76	-6.76	-6.76	-7.10
	[-1.52]	[-1.52]	[-1.52]	[-1.79]
$Meeting_t$	0.71	0.77	0.77	0.87
	[0.13]	[0.13]	[0.13]	[0.18]
$Meeting\ and\ Bill_t$		5.41	4.21	6.97
		[0.37]	[0.13]	[1.89]
$Meeting,\ Bill\ and\ Les_{i,t}$			5.89	-1.14
			[0.97]	[-0.07]
R-squared (%)	0.78	0.79	0.82	0.54
Observations	11,355	11,355	11,355	11,321
Firm-level controls	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes

Moving through columns 1 to 3, we progressively introduce more refined regressors. In column 1, $Meeting_t$ is a dummy variable that equals one if a tweet coincides with a committee meeting and zero otherwise. In column 2, $Meeting\ and\ Bill_t$ is a dummy variable that takes the value of 1 when a committee meeting discusses a specific bill and 0 otherwise. In column 3, $Meeting,\ Bill\ and\ Les_{i,t}$ take the value of 1 on committee meeting days discussing a bill, and if the LES value for politician i is above the median LES score (calculated using the scores of all members of Congress in the same chamber and corresponding Congress). The dependent variable in columns 1 to 3 is the Fama-French/Carhart four-factor model-adjusted returns. In column 4, the dependent is the industry-adjusted returns obtained by subtracting the industry return from the aggregate market return. $Tone_{i,t}$ represents the tone measure. All regressions use stock fixed effects and incorporate firm-level and macro-level controls. Stock returns are in basis points, and $Tone_{i,t}$ is standardized. Standard errors are clustered at the firm and day levels, with t-statistics in brackets. R-squared statistics are reported as percentages.

market return from the industry returns.

Column 4 of Table 5 presents the results. The key finding from this column is that politicians' tweets posted on committee meeting days evaluating proposed legislation significantly affect the industry stock prices overall. These industry effects become notably stronger when an effective legislator posts the tweet. For instance, the estimated coefficient associated with the interaction term ($Tone_{i,t} \times Meeting,\ Bill\ and\ Les_{i,t}$) is substantial and statistically significant (0.96, $t = 1.97$). The magnitude of these effects suggests that the influence of these politicians' tweets during committee meeting days is approximately four times larger than all other tweets. Moreover, it is worth mentioning that the estimated coefficient on $Tone_{i,t}$ (i.e., politicians' tweets outside committee meeting days) is marginally significant ($t = 1.67$), although considerably smaller in magnitude. This result suggests the presence of other politicians' tweets that may contain news about future policy or economic actions, thereby affecting industry returns outside of committee meeting days. We investigate this possibility in the subsequent section.

4.3 Including policy news outside of committee meeting days

Our analysis thus far has primarily focused on news about legislative actions on committee meeting days. We now entertain the possibility that news about future legislative action can be revealed on non-meeting days. In this subsection, we use an alternative method to identify congressional tweets referencing firms relating to policy agendas on all days. This alternative method combines selected tweets from two search criteria.

The first criterion selects tweets based on text similarity with the politics-related word dictionary developed by Hassan et al. (2019). This dictionary is created by comparing a training library of political text, which includes political newspaper articles, speeches, press releases by Congress members, and bill sponsorships sourced from `OnTheIssues.org`, with a training library of nonpolitical text.[9] The politics-related word dictionary consists of two-word combinations (bigrams) present in the political texts but absent in the nonpolitical texts. The resulting dictionary covers various political topics, including economic policy, budget and regulation, trade, technology and infrastructure, security and defense, health, environment, tax policy, and institutions and political process. After selecting bigrams related to political matters, we calculate the frequency of their occurrence in each tweet by dividing the count of instances by the total number of words. Based on this frequency measure, we then select tweets that fall within the top quartile, indicating a higher proportion of policy conversation captured by the identified bigrams.

[9]The nonpolitical library consists of bigrams extracted from a textbook on financial accounting (Libby, Libby, and Short, 2011) and is supplemented with newspaper articles from Factiva. The newspaper articles were published in the New York Times, USA Today, the Wall Street Journal, and the Washington Post, specifically focusing on corporate performance, ownership changes, and corporate actions.

The second criterion identifies tweets that contain relevant hashtags related to legislative and economic actions by Congress. The use of hashtags provides a direct method for determining the topic of a post without the need for any estimation. These hashtags closely align with specific congressional actions and reflect the viewpoints of lawmakers. For example, Republican legislators used hashtags such as #TaxReform, #TaxCutsandJobsAct, and #TaxRelief to support the Tax Cuts and Jobs Act of 2017, while Democrats used opposing hashtags such as #GOPTaxScam and #TrumpCuts to express their opposition. These hashtags were related to the significant changes made to the U.S. tax code through the 2017 tax reform, which was the most extensive in over thirty years.[10] Another example is the use of hashtags like #S2155, #DoddFrankRollback, #BankLobbyistAct, and #Relief4MainStreet, which lawmakers employed to express their views on the Crapo Bill, which aimed to reverse specific reforms of the Dodd-Frank Act.

Democrats used notable hashtags such as #BigPharma and #EndRxMonopolyPrice to criticize pharmaceutical companies and advocate for legislative proposals targeting industry prices and profits. Additionally, the hashtag #HonestAds was used by Democrats in the U.S. Senate and some Republican senators to support the "Honest Ads Act," a bill that aims to regulate political ads and prevent foreign interference in U.S. elections. Furthermore, the bipartisan consensus on antitrust lawsuits was reflected in the hashtag #BreakUpBigTech. You can refer to Figure B.4 in the Internet Appendix for a visual representation of the distribution of policy-relevant hashtags obtained from tweets targeting a specific firm.

We take the union of these two sets of tweets based on the two criteria and create a dummy variable denoted as $Policy_t$, which takes the value of 1 if the tweet is in the union of the two sets and 0 otherwise. This alternative method selects congressional tweets relating to potential future legislative action on all days (including meeting days). According to this alternative method, approximately 43 percent of the 11K+ congressional tweets referencing firms are classified as containing policy-relevant content. Among these tweets, around 58 percent are posted during committee meetings, while 42 percent are

[10]The short title "Tax Cuts and Jobs Act" was not approved by Senate, and to comply with Senate rules, the official title of the bill was changed to "An Act to provide for reconciliation pursuant to titles II and V of the concurrent resolution on the budget for fiscal year 2018."

posted during non-committee meetings. This difference is statistically significant, with a t-statistic of 4.5, indicating that a substantial portion of political news is generated on committee meeting days. We also find that 63% of the tweets on meeting days by committee members are captured in this alternative method, providing external validation for the approach of selecting congressional tweets linked to legislative action on meeting days, featured in Section 4.1.

Nevertheless, Table 6 demonstrates that valuable news is also generated outside of meeting days, echoing the results in Figure 5. Column 1 shows that policy-relevant tweets exhibit significantly stronger effects. The interaction term ($Tone_{i,t} \times Policy_t$) in column 1 is large and statistically significant (7.63, $t = 2.86$). The magnitude of this coefficient indicates that a one-standard-deviation higher tone in tweets with high policy relevance leads to an 11.63 basis point higher increase in stock prices. Notably, the coefficient on $Tone_{i,t}$ alone is positive but only marginally statistically significant. This suggests that the stock price effects documented in Section 3 are primarily concentrated in the policy-relevant tweets. Notably, in an untabulated result, we find that the difference in the estimated coefficient of the tone interacted with the policy relevance measure on committee meeting days ($Tone_{i,t} \times Policy_t \times Meeting_t$) and outside of committee meeting days ($Tone_{i,t} \times Policy_t$) is positive but small and statistically insignificant (1.1, $t = 0.65$). This suggests that significant news about future legislation is also revealed outside of committee meeting days.

In column 2 of Table 6, we observe that the effects become even more pronounced when focusing on tweets from effective politicians, as measured by their high legislative effectiveness scores. Tweets with a high political tone from politicians who have demonstrated their adeptness in navigating the legislative process generate significantly more prominent effects. The coefficient on the interaction term $Tone_{i,t} \times Policy\ and\ Les_{i,t}$ equals 2.34 (t-statistics = 1.71), indicating that the impact of high political tone tweets from effective legislators is 34% greater compared to less effective legislators.

We introduce an additional test to examine whether the effects on stock prices are intensified when the tweets are related to news about future congressional actions. One implication is that tweets from more powerful legislators may carry greater informational value, as these politicians are likely to have the ability to garner additional support

Table 6. **Stock return responses to policy-relevant congressional viewpoints**

Dependent variable	Daily FF4 abnormal returns			Daily industry abnormal returns		
Regressors	(1)	(2)	(3)	(4)	(5)	(6)
$Tone_{i,t}$	4.00	4.00	4.00	1.14	1.14	1.14
	[1.66]	[1.66]	[1.66]	[1.44]	[1.44]	[1.44]
$Tone_{i,t} \times Policy_t$	7.63	6.86	6.20	2.15	1.95	1.72
	[2.86]	[2.12]	[2.06]	[2.23]	[1.91]	[1.96]
$Tone_{i,t} \times Policy\ and\ Les_{i,t}$		2.34			0.65	
		[1.71]			[1.71]	
$Tone_{i,t} \times Policy\ and\ Powerful_{i,t}$			2.95			0.82
			[1.84]			[1.89]
1	-4.67	-4.67	-4.67	7.50	7.50	7.50
	[-1.48]	[-1.48]	[-1.48]	[1.37]	[1.37]	[1.37]
$Policy_t$	-4.33	-6.06	-5.70	-4.00	-4.58	-5.05
	[-0.94]	[-1.14]	[-0.89]	[-0.97]	[-1.00]	[-1.00]
$Policy\ and\ Les_{i,t}$		5.98			3.65	
		[1.25]			[0.62]	
$Policy\ and\ Powerful_{i,t}$			2.38			2.42
			[0.39]			[0.34]
R-squared (%)	0.77	0.78	0.78	0.54	0.55	0.54
Observations	11,355	11,355	11,355	11,321	11,321	11,321
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes	Yes

In columns 1 to 3, the dependent variable is the daily FF4 abnormal returns for company i. In columns 4 and 6, industry-adjusted returns are used, obtained by subtracting the industry return from the aggregate market return. The dummy variable $Policy_t$ takes the value of 1 if either of the two conditions is satisfied. The first condition is if the scaled frequency of bigrams related to political matters falls within the top quartile. The second condition is if the tweet contains hashtags associated with political matters. The variable $Policy\ and\ Les_{i,t}$ is a dummy variable indicating whether the politician's LES score is above the median LES score and if the tweet satisfies the two conditions. $Policy\ and\ Powerful_{i,t}$ is a dummy variable indicating whether the politician belongs to a powerful committee at the time of the tweet and if the tweet satisfies the two conditions. The variable $Tone_{i,t}$ represents the daily tone measure. All regressions include stock fixed effects and control for firm-level and macro-level controls. Standard errors are clustered at the firm and day levels, and t-statistics are reported in brackets. The R-squared statistics are reported as percentages. Returns are expressed in basis points, and $Tone_{i,t}$ is standardized.

for a bill. To test this hypothesis, we adopt the approach used by Cohen et al. (2011) and Cohen and Malloy (2014), where a politician's power level is determined based on the committees they are a part of at each point in time. We create a dummy variable, $Policy\ and\ Powerful_{i,t}$, which takes the value of 1 if politician i serves in a powerful committee at the time of the tweet, and if the tweet contains political text (i.e., satisfies the two conditions mentioned above).

As in Cohen et al. (2011) and Cohen and Malloy (2014), we refer to the list of the ten most influential committees provided by Edwards and Stewart III (2006). In the Senate, these committees include Finance, Veterans Affairs, Appropriations, Rules, Armed Services, Foreign Relations, Intelligence, Judiciary, Budget, and Commerce. In the House, the influential committees are Ways and Means, Appropriations, Energy and Commerce, Rules, International Relations, Armed Services, Intelligence, Judiciary, Homeland Security, and Transportation and Infrastructure.

Column 3 of Table 6 presents the results, demonstrating that when we focus on policy-relevant tweets, the effects on stock returns are significantly amplified if the tweet comes from a powerful politician (i.e., the triple interaction term $Tone_{i,t} \times Policy\ and\ Powerful_{i,t}$). The estimated effect is 2.95 (t-statistics = 1.84), indicating a substantial 28% increase relative to the impact observed for policy-relevant tweets posted by less powerful politicians. Finally, in columns 4 to 6, we replicate the analysis using industry-adjusted returns instead of individual abnormal stock returns. The main takeaway is that policy-relevant tweets also exhibit a significant industry effect (2.15, t = 2.23), indicating that their influence extends beyond the targeted firm. Conversely, non-policy-relevant tweets have a minimal and statistically insignificant impact on industry returns (1.14, t = 1.44). Moreover, we find that the influence of policy-relevant tweets on industry returns is further amplified when they originate from effective politicians (column 5) or powerful politicians (column 6).

Next, we conduct a portfolio test, similar to Section 3.3, to examine the return predictability of policy-relevant tweets and assess their economic significance. The results are presented in Table 7. Column 3 of the table shows that the long-short portfolio spread using policy-relevant tweets generates significant monthly returns, ranging from 1.28% in four-factor alpha (t-statistic = 2.55) to 1.56% in CAPM alpha (t-statistic = 2.24). In contrast, column 6 indicates that non-policy-relevant tweets exhibit alphas close to zero and lack statistical significance.

Table 7. **Performance Evaluation: Factor alphas**

	Sorting variable					
	Policy-relevant tweets			Other tweets		
	Short	Long	Long - Short	Short	Long	Long - Short
	(1)	(2)	(3)	(4)	(5)	(6)
CAPM alpha	-1.19	0.43	1.56	-0.58	-0.19	0.32
	[-1.94]	[1.61]	[2.24]	[-0.94]	[-0.35]	[0.76]
FF3 alpha	-1.22	0.29	1.45	-0.69	-0.35	0.28
	[-2.42]	[1.61]	[2.87]	[-0.90]	[-0.50]	[0.54]
FF4 alpha	-1.16	0.18	1.28	-0.84	-0.41	0.36
	[-2.29]	[1.30]	[2.55]	[-1.16]	[-0.57]	[0.68]

This table presents monthly factor alphas for the long-short returns using two different subsets of tweets. The policy-relevant tweets are those that satisfy two conditions. The first condition is if the scaled frequency of bigrams related to political matters falls within the top quartile. The second condition is if the tweet contains hashtags associated with political matters. The for each subset of tweets, we form long and short portfolios. The long (short) portfolio buys stock i if the corresponding tone measure is above (below) the 90th (10th) percentile of the tone distribution computed over the previous 12 months. We value-weight the stocks to create portfolios when multiple firms are assigned to the same leg on the same day. The portfolios are rebalanced daily. Once we obtain the daily portfolio returns for the long and short sides, we accumulate the daily returns at the monthly frequency. The "Long-Short" portfolio buys the long portfolio and sells the short portfolio. The alphas represent the intercepts from time series regressions of the portfolio excess returns on factor alphas. The four factors include the aggregate market excess return, the size factor, the value factor, and the momentum factor. Standard errors adjust for heteroskedasticity and autocorrelation. Returns are in percent. We report the t-statistics in brackets.

4.4 Economic relevance

To assess the economic relevance of our findings, we compare the magnitudes of the effects documented in the previous sections to those reported in the existing literature. In our benchmark analysis in Section 3, we find monthly factor alphas ranging from 1.03% to 1.13%. These alphas increase further when focusing on tweets more likely to contain news about future congressional actions. For instance, in Section 4.1, when examining tweets closely linked to committee meetings and posted by relevant committee members, the alphas increase by approximately 30 basis points, ranging from 1.20% to 1.49%. Furthermore, in Section 4.3, when focusing on tweets containing a relatively large share of words related to political matters or relevant hashtags related to legislative and economic actions, the alphas increase even further, ranging from 1.28% to 1.56%.

To provide context for these alphas, we compare them to the effects of realized legislation on affected industries reported in prior studies. For example, Cohen et al. (2013)

find that a long-short portfolio based on congressional viewpoints inferred from legislators' voting records generates monthly alphas ranging from 0.76% to 2.01%, depending on the stringency of data cuts. In the most informative data cut, where only industries mentioned prominently and firms located in the interested senator's home state are considered, the alphas range between 1.84% to 2.01%. Thus, overall, our estimated effects are in line with theirs.

Alternatively, we can compare our results to the findings of studies that utilize social media sentiment to predict stock returns. For instance, Sul, Dennis, and Yuan (2017) extract sentiment measures related to firms from Twitter and construct a trading strategy based on these tweets, resulting in economic gains of an 11%-15% annual return. If we annualize our alphas, we find that the magnitude of our effects is of similar magnitude.

4.5 Additional analysis

We provide additional analysis in the Internet Appendix. To gain further insights into the economic factors underlying the observed stock price responses, in Section D of the Internet Appendix, we examine the impact of congressional tweets on stock analysts' forecasts for future cash flows. Specifically, we investigate whether stock analysts revise their expectations about future firm cash flows in the days immediately following congressional tweets, particularly during the one-week period in which we observe a price drift after the tweet. Our findings reveal that the tone of the politicians' viewpoints predicts subsequent sales and earnings revisions, although we do not find statistical significance in forecast revisions for earnings (t-statistic $= 1.3$). Furthermore, we show that these forecast revisions lead to improved forecast accuracy and lower subsequent revenue and earnings forecast error predictability. This evidence further highlights that the tweets with politicians' viewpoints potentially contain new information about future firm fundamentals.

Section E of the Internet Appendix provides detailed case studies further highlighting the influence of Congress members in shaping expectations regarding future policy through their real-time communication via social media. These case studies specifically focus on the timeline of politicians' viewpoints within two specific bills, providing insights into the dynamics surrounding these legislative proposals. The timeline around these bills illustrates how surges in relevant news from politician accounts occurred months before the bills became public law. Notably, we find surges in relevant news and discussions from these accounts, particularly during key legislative milestones such as committee meetings in the Senate and House.

In line with our benchmark analysis, we observe that the subset of tweets specifically related to the bills examined in our case studies resulted in substantial price reactions for firms operating in the affected industries, further supporting the notion that the content of the tweets carries valuable information for market participants. Moreover, the tone of the tweets closely aligns with the actual voting behavior of the politicians, lending credibility to the viewpoints expressed by politicians on social media platforms. Overall, these case studies provide further support for the idea that these tweets contain important new information about the likelihood or specific details of the proposed legislation.

5 Alternative explanations

Our findings in Section 4 provide strong evidence that the bulk of stock price effects resulting from congressional tweets are concentrated in tweets related to future legislative actions. Furthermore, these effects are significantly magnified when the tweets originate from influential, powerful, and effective politicians. The impact extends beyond the targeted firms in the tweets and influences the stock prices of other companies within the same industry, consistent with the notion that legislative news is revealed. However, it is important to acknowledge that alternative explanations may exist that could potentially contribute to explaining our results. This section examines some of these potential alternative explanations.

One plausible alternative explanation revolves around the idea that the tweets, rather than conveying new-news content, serve as a means to attract additional attention to existing company news, thereby mitigating investor underreaction (Huberman and Regev, 2001). This notion aligns with the findings of Blankespoor, Miller, and White (2014), who argue that tweets can effectively enhance the visibility of company news and help reduce investors' tendency to underreact to such information. In this context, the active involvement of politicians on social media platforms facilitates the dissemination of previously released information. As a result, news about companies is more rapidly incorporated into stock prices, even without genuinely new information being presented in the tweets.[11]

If politicians' tweets attracted additional attention and facilitated the dissemination of information, we would expect to see more substantial effects in response to tweets about less visible companies that receive limited media or analyst coverage. These companies often encounter challenges in promptly disseminating news due to the media's tendency to prioritize coverage of high-visibility firms (Miller, 2006). Moreover, popular politicians with a substantial following and significant engagement on social media, as indicated by metrics such as likes, retweets, or replies, often referred to as political "show horses," should have the most significant impact. These politicians can draw more attention to company news, which is particularly beneficial for less visible firms.

We employ four distinct indicators gauging firm visibility to test these predictions. The first indicator is firm size, measured by market capitalization, as smaller companies tend to have lower visibility. The second indicator of firm visibility is the number of analysts covering a company within 30 days before the politician's social media post. Additionally, we incorporate measures of media attention, including the number of articles and social media posts explicitly discussing a particular company within 30 days preceding the politician's social media post. Subsequently, we construct a dummy variable, denoted as $Attention_{i,t}$, which takes a value of 1 if the firm i falls within the bottom quartile based on each of these four visibility indicators and 0 otherwise. This variable allows us to identify firms with relatively lower visibility across multiple dimensions.

Columns 1 through 4 in Table 8 display the results based on a daily event window. The coefficient estimates for the interaction term $Tone_{i,t} \times Attention_{i,t}$ are statistically insignificant across all four measures of firm visibility, ranging between -0.46 and 0.75, with t-statistics below 1. These findings indicate that politicians' tweets do not have a differential impact on the stock returns of low-visibility and high-visibility firms.

Finally, we investigate whether popular politicians who generate significant engage-

[11] For related evidence on the relation between Twitter content and stock returns and earnings, see Bartov, Faurel, and Mohanram (2018), and Sul et al. (2017).

Table 8. **Stock price responses and firm visibility**

Dependent variable: Daily FF4 abnormal returns	Visibility measure				
Regressors	Size mkt. cap. (1)	N of analysts (2)	N news articles (3)	N tweets from news media (4)	Politicians' popularity (5)
$Tone_{i,t}$	8.09	7.44	7.98	7.82	8.17
	[2.40]	[2.38]	[3.00]	[2.73]	[2.70]
$Tone_{i,t} \times Attention_{i,t}$	0.02	0.75	-0.46	-0.12	0.15
	[0.00]	[0.17]	[-0.23]	[-0.02]	[0.24]
1	-8.32	-6.97	-5.85	-5.36	-7.82
	[-2.17]	[-1.61]	[-2.54]	[-2.10]	[-2.58]
$Attention_{i,t}$	4.13	1.39	-4.61	-2.04	2.24
	[0.81]	[0.22]	[-0.46]	[-0.37]	[0.55]
R-squared (%)	0.77	0.79	0.78	0.78	0.79
Observations	11,355	11,355	11,355	11,355	11,355
Firm-level controls	Yes	Yes	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes	Yes	Yes

The table presents regression estimates for the equation: $r_{i,t} = a_0 + a_1 Attention_{i,t} + b\,(Tone_{i,t} \times Attention_{i,t}) + \epsilon_{i,t}$. The dependent variable, $r_{i,t}$, represents the daily FF4 abnormal returns for company i. The variable $Tone_{i,t}$ denotes the daily tone measure. The first four columns introduce a dummy variable $Attention_{i,t}$ to identify firms with relatively lower visibility across different dimensions. Column 1 utilizes firm size, while column 2 employs analyst coverage. Columns 3 and 4 use the number of articles and social media posts specifically discussing a particular company. The variable $Attention_{i,t}$ takes a value of 1 if the firm i falls within the bottom quartile based on each of these four visibility indicators and 0 otherwise. In column 5, the variable $Attention_{i,t}$ takes the value of 1 if the cumulative sum of likes, retweets, and replies of all tweets posted by each politician in the preceding 30 days falls within the top quartile, and 0 otherwise. In all regressions, we incorporate firm-level and macro-level controls. Stock returns are in basis points, and $Tone_{i,t}$ is standardized. Standard errors are clustered at the firm and day levels, with t-statistics in brackets. R-squared statistics are reported as percentages.

ment on social media elicit stronger price reactions. The rationale behind this test is that if politicians attract additional attention to existing company news, we would expect more pronounced effects for those with a broader reach. These politicians can effectively communicate the news to a larger audience and potentially help mitigate investor underreaction. To identify popular politicians, we create a dummy variable that takes the value of 1 if the cumulative sum of likes, retweets, and replies of all tweets posted by each politician in the preceding 30 days falls within the top quartile, and 0 otherwise. Column 5 in Table 8 displays the results of this analysis. The findings reveal that the interaction term between tone and the popularity dummy is small and statistically insignificant (0.15, t = 0.24). This implies that there is no evidence to suggest that the tweets of popular politicians have a stronger impact on stock prices.

Overall, we do not find stronger stock price effects on less visible firms and tweets from more popular politicians, which help to rule out the notion that politicians' tweets primarily influence stock markets by attracting attention to existing news and mitigating investor underreaction.

6 Discussion

Lastly, we delve into the broader question of the role played by Twitter, and social media platforms in general, in disseminating information related to congressional actions. Our perspective is that Twitter serves as a new channel for conveying the same information about congressional actions conveyed through alternate technology but now at a "lower cost" and "higher effectiveness" for politicians. The ease with which politicians can now post new information to the public through Twitter compared to press releases in the past facilitates communication with increased regularity, evidenced by the high frequency of tweets per day by each politician, potentially smoothing out the information flow from politicians. Our empirical analysis using high-frequency stock price reactions shows that the politicians' tweets' content is an important source of political news.

We also believe that the Twitter platform provides several novel aspects of political communication beyond making information revelation more efficient. First, Twitter allows politicians to communicate directly with the public, avoiding intervention by the media, who were previously the gatekeepers of political news (e.g., Jungherr, Rivero, and Gayo-Avello (2020)). Therefore, Twitter gives politicians control of the content delivered to the public without potential distortions from media bias, or timing lags in reporting. From the econometrician's standpoint, a benefit of direct communication is the precise timestamps of the news without the potential timing lags associated with the media coverage. Second, Twitter allows immediate feedback from the public on proposed policy actions absent in traditional media communications. The dialogue between the politician and the public can, in turn, influence policymaking (e.g., Grossman (2022)).

7 Conclusion

We document that politicians' social media are an important public communication tool to disseminate news about future policy. We extract political viewpoints from individual U.S. Congressional Twitter accounts. Politicians' tweets that support (criticize) a specific firm increase (decrease) the stock price within minutes of the tweet. The price response persists for several days, and then flattens out with no subsequent reversals. A trading strategy that exploits the slow diffusion of political news earns sizable abnormal returns, highlighting the economic significance of the new information contained in the tweets.

We find that the bulk of the stock price effects is concentrated in the subset of congressional tweets targeting firms revealing news about future legislative action. The stock price effects are significantly magnified on meeting days when the tweet originates from committee members or influential politicians and contains text that closely relates to meeting topics or references a specific legislative proposal associated with the meeting. Congressional tweets explicitly relating to a bill or joint resolution have strong industry effects, reflecting the notion that legislation rarely affects a single firm.

References

Addoum, J. M., Kumar, A., 2016. Political sentiment and predictable returns. Review of Financial Studies 29, 3471–3518.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of financial markets 5, 31–56.

Andersen, T. G., Bollerslev, T., Diebold, F. X., Vega, C., 2003. Micro effects of macro announcements: Real-time price discovery in foreign exchange. American economic review 93, 38–62.

Arteaga-Garavito, M. J., Croce, M., Farroni, P., Wolfskeil, I., 2021. When the markets get co.v.i.d: Contagion, viruses, and information diffusion. Working paper, Bocconi University.

Auerbach, A. J., 2018. Measuring the effects of corporate tax cuts. Journal of Economic Perspectives 32, 97–120.

Balduzzi, P., Elton, E. J., Green, T. C., 2001. Economic news and bond prices: Evidence from the us treasury market. Journal of financial and Quantitative analysis 36, 523–543.

Bartov, E., Faurel, L., Mohanram, P. S., 2018. Can twitter help predict firm-level earnings and stock returns? The Accounting Review 93, 25–57.

Belo, F., Gala, V. D., Li, J., 2013. Government spending, political cycles, and the cross section of stock returns. Journal of Financial Economics 107, 305–324.

Bernanke, B. S., Kuttner, K. N., 2005. What explains the stock market's reaction to federal reserve policy? Journal of Finance 60, 1221–1257.

Bianchi, F., Gómez-Cram, R., Kind, T., Kung, H., 2023. Threats to central bank independence: High-frequency identification with twitter. Journal of Monetary Economics 135, 37–54.

Birney, M., Graetz, M. J., Shapiro, I., 2006. Public opinion and the push to repeal the estate tax. National Tax Journal pp. 439–461.

Blankespoor, E., Miller, G. S., White, H. D., 2014. The role of dissemination in market liquidity: Evidence from firms' use of twitter™. The accounting review 89, 79–112.

Boudoukh, J., Feldman, R., Kogan, S., Richardson, M., 2013. Which news moves stock prices? a textual analysis. Tech. rep., National Bureau of Economic Research.

Brownlees, C. T., Gallo, G. M., 2006. Financial econometric analysis at ultra-high frequency: Data handling concerns. Computational Statistics & Data Analysis 51, 2232–2245.

Buehlmaier, M. M., Whited, T. M., 2018. Are financial constraints priced? evidence from textual analysis. Review of Financial Studies 31, 2693–2728.

Chen, H., De, P., Hu, Y. J., Hwang, B.-H., 2014. Wisdom of crowds: The value of stock opinions transmitted through social media. Review of Financial Studies 27, 1367–1403.

Cohen, L., Coval, J., Malloy, C., 2011. Do powerful politicians cause corporate downsizing? Journal of political Economy 119, 1015–1060.

Cohen, L., Diether, K., Malloy, C., 2013. Legislating stock prices. Journal of Financial Economics 110, 574–595.

Cohen, L., Malloy, C. J., 2014. Friends in high places. American Economic Journal: Economic Policy 6, 63–91.

Cookson, J. A., Engelberg, J., Mullins, W., 2021. Echo chambers. Available at SSRN 3603107 .

Cookson, J. A., Engelberg, J. E., Mullins, W., 2020. Does partisanship shape investor beliefs? evidence from the covid-19 pandemic. The Review of Asset Pricing Studies 10, 863–893.

Cookson, J. A., Lu, R., Mullins, W., Niessner, M., 2022. The social signal. Available at SSRN .

Das, S. R., Chen, M. Y., 2007. Yahoo! for amazon: Sentiment extraction from small talk on the web. Management science 53, 1375–1388.

Edwards, K., Stewart III, C., 2006. The value of committee assignments in congress since 1994. In: *Annual Meeting of the Southern Political Science Association, Atlanta, GA*.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., Stroebel, J., 2020. Hedging climate change news. Review of Financial Studies 33, 1184–1216.

Gentzkow, M., Kelly, B., Taddy, M., 2019a. Text as data. Journal of Economic Literature 57, 535–74.

Gentzkow, M., Shapiro, J. M., 2010. What drives media slant? evidence from us daily newspapers. Econometrica 78, 35–71.

Gentzkow, M., Shapiro, J. M., Taddy, M., 2019b. Measuring group differences in high-dimensional choices: method and application to congressional speech. Econometrica 87, 1307–1340.

Giglio, S., Maggiori, M., Rao, K., Stroebel, J., Weber, A., 2021. Climate change and long-run discount rates: Evidence from real estate. Review of Financial Studies 34, 3527–3571.

Grossman, E., 2022. Media and policy making in the digital age. Annual Review of Political Science 25, 443–461.

Gürkaynak, R. S., Sack, B., Swanson, E., 2005. Do actions speak louder than words? the response of asset prices to monetary policy actions and statements-ijcb-may 2005. International Journal of Central Banking .

Hassan, T. A., Hollander, S., Van Lent, L., Tahoun, A., 2019. Firm-level political risk: Measurement and effects. The Quarterly Journal of Economics 134, 2135–2202.

Hoberg, G., Moon, S. K., 2019. The offshoring return premium. Management Science 65, 2876–2899.

Huberman, G., Regev, T., 2001. Contagious speculation and a cure for cancer: A nonevent that made stock prices soar. The Journal of Finance 56, 387–396.

Jensen, J., Naidu, S., Kaplan, E., Wilse-Samson, L., Gergen, D., Zuckerman, M., Spirling, A., 2012. Political polarization and the dynamics of political language: Evidence from 130 years of partisan speech [with comments and discussion]. Brookings Papers on Economic Activity pp. 1–81.

Johnson III, C. W., Sullivan, J. V., Wickham, T. J., 2017. House practice: A guide to the rules, precedents, and procedures of the house. Government Printing Office.

Jungherr, A., Rivero, G., Gayo-Avello, D., 2020. Retooling politics: How digital media are shaping democracy. Cambridge University Press.

Kelly, B., Pástor, L., Veronesi, P., 2016. The price of political uncertainty: Theory and evidence from the option market. Journal of Finance 71, 2417–2480.

Kelly, B. T., Manela, A., Moreira, A., 2019. Text selection. Tech. rep., National Bureau of Economic Research.

Kuchler, T., Stroebel, J., 2021. Social finance. Annual Review of Financial Economics 13.

Libby, R., Libby, P., Short, D., 2011. Financial Accounting. McGraw Hill.

Loughran, T., McDonald, B., 2011. When is a liability not a liability? textual analysis, dictionaries, and 10-ks. Journal of Finance 66, 35–65.

Martin, G. J., Yurukoglu, A., 2017. Bias in cable news: Persuasion and polarization. American Economic Review 107, 2565–99.

Miller, G. S., 2006. The press as a watchdog for accounting fraud. Journal of Accounting Research 44, 1001–1033.

Mullainathan, S., Shleifer, A., 2005. The market for news. American economic review 95, 1031–1053.

Nakamura, E., Steinsson, J., 2018. High-frequency identification of monetary non-neutrality: the information effect. The Quarterly Journal of Economics 133, 1283–1330.

Pástor, L., Veronesi, P., 2012. Uncertainty about government policy and stock prices. Journal of Finance 67, 1219–1264.

Pástor, L., Veronesi, P., 2013. Political uncertainty and risk premia. Journal of financial Economics 110, 520–545.

Pástor, L., Veronesi, P., 2020. Political cycles and stock returns. Journal of Political Economy 128, 4011–4045.

Santa-Clara, P., Valkanov, R., 2003. The presidential puzzle: Political cycles and the stock market. Journal of Finance 58, 1841–1872.

Stewart III, C., Woon, J., 2017. Congressional committee assignments, 103rd to 114th congresses, 1993–2017: the house and the senate, november 17, 2017 version. Accessed on May 2023 .

Sul, H. K., Dennis, A. R., Yuan, L., 2017. Trading on twitter: Using social media sentiment to predict stock returns. Decision Sciences 48, 454–488.

Tetlock, P. C., 2007. Giving content to investor sentiment: The role of media in the stock market. Journal of Finance 62, 1139–1168.

Tetlock, P. C., Saar-Tsechansky, M., Macskassy, S., 2008. More than words: Quantifying language to measure firms' fundamentals. Journal of Finance 63, 1437–1467.

Volden, C., Wiseman, A. E., 2014. Legislative effectiveness in the United States congress: The lawmakers. Cambridge university press.

Volden, C., Wiseman, A. E., 2018. Legislative effectiveness in the united states senate. The Journal of Politics 80, 731–735.

Wagner, A. F., Zeckhauser, R. J., Ziegler, A., 2018. Unequal rewards to firms: Stock market responses to the trump election and the 2017 corporate tax reform. In: *AEA Papers and Proceedings*, vol. 108, pp. 590–96.

For Online Publication

Using Social Media to Identify the Effects of Congressional Viewpoints on Asset Prices

Francesco Bianchi Roberto Gómez-Cram Howard Kung

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Appendix Table of Contents

Appendix A - Data

A.1 Variable definitions and data sources

In Table A.1, we have listed the variables used along with their corresponding sources. For more information on how the main variables were computed, please refer to Appendix A.2.

Table A.1. **Variable definitions and data sources**

Variable	Definition	Source
$\Delta p_{i,t}$	Change in log stock prices for stock i around the tweet at time t. The change is computed in a 6-minute window around the tweet (the last trade at least 1 minute before and the first trade at least 5 minutes after). See Section A.2 for details.	TAQ
$\Delta p_{SPY,t}$	Change in log stock prices for the market around the tweet at time t. The change is computed in a 6-minute window around the tweet. See Section A.2 for details.	TAQ
$\Delta p^{ab}_{i,t}$	The abnormal stock price change is computed as $\Delta p^{ab}_{i,t} = \Delta p_{i,t} - \Delta p_{SPY,t}$. See Section A.2 for details.	TAQ
$r_{i,t}$	Daily stock price return for stock i on day t.	CRSP
Controls		
$r^{ab}_{i,t}$	Daily abnormal returns for stock i on day t. We compute excess returns using three different models: the CAPM, Fama French 3 factors, and Fama French/Carhart 4 factors. See Section A.2 for details.	CRSP
$r_{SMB,t}$, $r_{HML,t}$, $r_{MOM,t}$	Daily size (SMB), value (HML), and momentum (MOM) factors.	CRSP, & K. French's website
$BloombergSentiment_{i,t}$	Bloomberg company-level news sentiment measure. This variable is available at the daily frequency. See Section A.2 for details.	Bloomberg
ILLIQ	Amihud (2002) illiquidity measure. In the high-frequency test, we compute ILLIQ by taking the minute-level ratio of absolute stock return to its dollar volume averaged from market open to 15 minutes before the tweet.	CRSP, & TAQ
LNATQ	Log of assets as of the fiscal quarter-end date.	Compustat
$S^{rev-a}_{i,t}$ and $S^{eps-a}_{i,t}$	Revenue and earnings surprises are derived from *analysts'* forecasts for stock i. The actual revenue and earnings values are disclosed at the exact second timestamp t. See Section A.2 for details.	I/B/E/S

Continued on next page

Table A.1 – continued from previous page

Variable	**Definition**	**Source**
$S_{i,t}^{rev-f}$ and $S_{i,t}^{eps-f}$	Revenue and earnings surprises are derived from *firms'* forecasts for stock i. The actual revenue and earnings values are disclosed at the exact second timestamp t. See Section A.2 for details.	I/B/E/S
$SR_{i,t}^{rev-a}$ and $SR_{i,t}^{eps-a}$	Revisions in analysts' forecasts for revenue and earnings per share. See Section A.2 for details.	I/B/E/S
$S_{k,t}^{macro}$	News about macroeconomic indicator k at time t. This macro news is given by the difference between the realized value and the expected value of the indicator. To standardize this difference, we divide it by the sample standard deviation. See Section A.2 for details.	Bloomberg

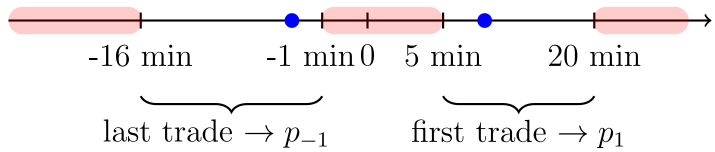


Fig. A.1. *Notes*: Time zero denotes the time of the tweet. We are interested in the difference between the log-price of the stock after the tweet and the log-price of the stock before the tweet. We allow for a [-1 minutes,+5 minutes] window around the tweet to give time to markets to react to the new information. If there is traded price before and after 15 minutes around the [-1 minutes,+5 minutes] window, we assume that the tweet did not have an impact on the price of the stock.

A.2 Details on the data construction

High-frequency stock returns. Figure A.1 provides a visual depiction of the event window used to compute the stock returns, $\Delta p_{i,t}$, in a tight window around the tweet. Time zero denotes the time of the tweet. We are interested in the difference between the log price of the stock after the tweet and the log price of the stock before the tweet. We allow for a [-1 minutes,+5 minutes] window around the tweet to give time to markets to react to the new information. If there is no trade before and after 15 minutes, we conclude that the tweet did not have an impact on the price of the stock.

High-frequency abnormal stock returns. The abnormal return for stock i is given by:

$$\Delta p_{i,t}^{ab} = \Delta p_{i,t} - \Delta p_{SPY,t},$$

where $\Delta p_{SPY,t}$ denotes the change in log stock prices for the aggregate market in the same event window as the one used to compute $\Delta p_{i,t}$. For the aggregate market we take as a proxy the SPY ETF, which is designed to track the S&P 500 stock market index.

A.2.1 Firm-level controls

Intraday cumulative returns. The intraday cumulative return is computed as the minute-level cumulative return from the market open up until 15 minutes before the last trading price used to compute $\Delta p_{i,t}$.

Intraday cumulative abnormal return. The intraday cumulative abnormal return is computed as the difference in cumulative returns between stock i and the aggregate market cumulative return from the market open up until 15 minutes before the last trading price used to compute $\Delta p_{i,t}$.

Daily abnormal return. To calculate abnormal returns, we compute excess returns using three different models: the CAPM, Fama French 3 factors, and Fama French/Carhart 4 factors. We use a rolling 252-day estimation window for each model and require a minimum data availability of 126 days.

A.2.2 Controls in innovations

Bloomberg company-level news sentiment measure. We employ the Bloomberg company-level news sentiment measure as a control variable. This metric is derived from a supervised machine-learning algorithm that assesses the sentiment of news articles (sourced from Bloomberg News, web content, and select premium news wires) concerning a specific company. The intraday sentiment score is updated every two minutes using an eight-hour rolling window for Bloomberg news and every minute using a 30-minute rolling window for Twitter. Company-level daily sentiment scores are computed as a confidence-weighted average of story-level sentiments from the preceding 24 hours for both News and Twitter sources, and are released each morning approximately 10 minutes prior to the market opening.

News-media articles. We conducted a comprehensive search for news articles related to our target companies using Factiva, RavenPack, and Benzinga. These platforms aggregate and analyze articles from premium newswires, regulatory news providers, and press releases. In total, we collected 193,683 firm-specific news headlines, with each headline timestamped to the exact minute.

Tweets from news media outlets. To capture the tweets from major news media outlets that are relevant to the firms mentioned in the congressional tweets, we conducted a comprehensive scraping of tweets from 103 prominent news media outlets, including WSJ, Reuters, and FT. From a dataset of 18 million tweets from these media outlets, we identified a total of 201,542 tweets that were related to our target companies. The names and usernames of the news media outlets used in our analysis can be found in Table A.2.

A.2.3 Controlling for firm-specific cash-flow news

Revenue and earnings news releases. We also control for revenue and earnings surprises in our regressions. To create these controls, we collect individual analyst sales and earnings per share forecasts from the Thomson Reuters I/B/E/S Detail History File and obtain actual figures from the I/B/E/S actuals file database. We focus solely on forecasts made within 45 days preceding the announcement of total fiscal quarter revenues and earnings. To ensure the utilization of the most recent estimates for each analyst, we retain only the last forecast submitted for the same firm and fiscal quarter within the 45-day window. Subsequently, we calculate the consensus forecast by computing the median of all analysts' forecasts.

The revenue forecast news is then represented as:

$$S_{i,t}^{rev-a} = \frac{A_{i,t}^{rev} - E_{i,t}^{rev-a}}{\hat{\sigma}_i^{rev}},$$

where $A_{i,t}^{rev}$ signifies the actual revenue for stock i disclosed at the precise second timestamp t. The analysts' consensus is denoted by $E^{rev-a}i,t$. We standardize this difference by dividing it by the sample standard deviation of $A^{rev}i,t - E^{rev-a}i,t$, represented as $\hat{\sigma}_i^{rev-a}$. This standardization enables us to compare firm surprises with varying sales magnitudes but does not impact the statistical significance of our estimates since $\hat{\sigma}_i^{rev-a}$ remains constant for any given firm. We adopt a similar approach to compute the earnings news: $S_{i,t}^{eps-a} = \frac{A_{i,t}^{eps} - E_{i,t}^{eps-a}}{\hat{\sigma}_i^{eps-a}}$.

The majority of firms also provide revenue and earnings per share guidance. We utilize these management-issued forecasts to construct firm-based (as opposed to analyst-based) revenue

Table A.2. **Twitter accounts from news media outlets**

Name	Username	Name	Username
ABC News	abc	Quartz	qz
Al Jazeera English	ajenglish	Radar Online	radar_online
AlterNet	alternet	RealClearPolitics	realclearnews
American Thinker	americanthinker	RedState	redstate
Axios	axios	Reuters UK	reutersuk
BBC Breaking News	bbcbreaking	Salon	salon
Bipartisan Report	bipartisanism	Slate	slate
Bloomberg Quicktake	quicktake	TIME	time
Breitbart News	breitbartnews	TMZ	tmz
Business Insider	businessinsider	Talking Points Memo	tpm
BuzzFeed News	buzzfeednews	The Advocate	theadvocatemag
CBS News	cbsnews	The American Conservative	amconmag
CNBC	cnbc	The American Independent	amerindependent
CNN	cnn	The Associated Press	ap
CNN International	cnni	The Atlantic	theatlantic
Chicago Tribune	chicagotribune	The Christian Science Monitor	csmonitor
Common Dreams	commondreams	The Daily Beast	thedailybeast
Conservative Tribune	conserv_tribune	The Daily Signal	dailysignal
Daily Caller	dailycaller	The Daily Wire	realdailywire
Daily Kos	dailykos	The Denver Post	denverpost
Daily Mail US	dailymail	The Economist	theeconomist
Democracy Now!	democracynow	The Federalist	fdrlst
FORTUNE	fortunemagazine	The Fiscal Times	thefiscaltimes
Financial Times	ft	The Forward	jdforward
Forbes	forbes	The Guardian	guardian
Foreign Policy	foreignpolicy	The Hill	thehill
Fox News	foxnews	The Independent	independent
Free Beacon	freebeacon	The Intercept	theintercept
Free Speech TV	freespeechtv	The Nation	thenation
Houston Chronicle	houstonchron	The New Republic	newrepublic
HuffPost	huffpost	The New York Times	nytimes
Jacobin	jacobinmag	The New Yorker	newyorker
Judicial Watch	judicialwatch	The Real News	therealnews
LifeNews.com	lifenewshq	The Root	theroot
Los Angeles Times	latimes	The Wall Street Journal	wsj
MSNBC	msnbc	The Washington Post	washingtonpost
MarketWatch	marketwatch	The Washington Times	washtimes
Mother Jones	motherjones	The Week	theweek
NBC News	nbcnews	TheBlaze	theblaze
NPR	npr	ThinkProgress	thinkprogress
National Review	nro	Townhall.com	townhallcom
New York Daily News	nydailynews	Truthout	truthout
New York Post	nypost	Twitchy Team	twitchyteam
Newsweek	newsweek	USA TODAY	usatoday
Newsy	newsy	VANITY FAIR	vanityfair
OZY	ozy	VICE UK	viceuk
PBS NewsHour	newshour	Vox	voxdotcom
PJ Media	pjmedia_com	WND News	worldnetdaily
POLITICO	politico	Washington Monthly	monthly
Palmer Report	palmerreport	Wonkette	wonkette
ProPublica	propublica	Your News Wire	yournewswire
Quartz	qz		

This table provides the names and Twitter usernames of the news media accounts whose posts serve as controls in our analysis.

and earnings surprises, represented as:

$$S_{i,t}^{rev-f} = \frac{A_{i,t}^{rev} - E_{i,t}^{rev-f}}{\hat{\sigma}_i^{rev-f}}, \qquad \text{and} \qquad S_{i,t}^{eps-f} = \frac{A_{i,t}^{eps} - E_{i,t}^{eps-f}}{\hat{\sigma}_i^{eps-f}},$$

where the firm forecasts are given by $E_{i,t}^{rev-f}$ and E^{eps-f}. In this context, the subscript f designates the firm-based forecast. For these forecasts, we select the most recent prediction available for each firm within a given fiscal quarter.

Revisions in analysts' forecasts. We also account for revisions in analysts' forecasts for revenue and earnings per share. For each firm and fiscal quarter-end, we acquire the newly issued forecast from every analyst. The surprise in the forecast is determined by the difference between the newly issued forecast and the average of all previously issued forecasts for the same fiscal quarter-end. This difference is then scaled by its standard deviation. The forecast revisions for revenue and earnings are represented by $SR_{i,t}^{rev-a}$ and $SR_{i,t}^{eps-a}$, respectively.

A.2.4 Controlling for macroeconomic announcements

We use real-time data from the Bloomberg Professional Service to account for macroeconomic news. Specifically, we control for macroeconomic news releases by computing the difference between the realized value and the expected value of macroeconomic indicator k at time t, denoted A_{kt} and E_{kt} respectively. We standardize this difference by dividing it by the sample standard deviation of $A_{kt} - E_{kt}$, denoted $\hat{\sigma}_k$, following the approach in Balduzzi, Elton, and Green (2001), Andersen, Bollerslev, Diebold, and Vega (2003) and Bianchi et al. (2023):

$$S_{kt}^{macro} = \frac{A_{kt} - E_{kt}}{\hat{\sigma}_k}.$$

This standardization allows us to compare indicators with different units of measurement but does not affect the statistical significance of our estimates, as $\hat{\sigma}_k$ is constant for any given indicator.

To obtain the expected value E_{kt} for each indicator, we use the median forecast from the most recent weekly survey of economists conducted by Bloomberg prior to the announcement. Bloomberg collects forecasts from major consulting firms and investment banks and reports the median forecast shortly before each release. We provide a list of the 50 macroeconomic indicators used as controls in Table B.4.

Table A.3. **Macroeconomic announcements**

Event	Ticker	Relevance	Count	Time
Change in Nonfarm Payrolls	NFP TCH Index	99.213	95	08:30:00
Initial Jobless Claims	INJCJC Index	98.425	413	08:30:00
FOMC Rate Decision (Upper Bound)	FDTR Index	97.638	126	14:00:00
GDP Annualized QoQ	GDP CQOQ Index	96.850	94	08:30:00
CPI MoM	CPI CHNG Index	96.063	95	08:30:00
ISM Manufacturing	NAPMPMI Index	95.276	190	10:00:00
U. of Mich. Sentiment	CONSSENT Index	94.488	190	10:00:00
Conf. Board Consumer Confidence	CONCCONF Index	93.701	95	10:00:00
Durable Goods Orders	DGNOCHNG Index	92.913	139	08:30:00
Retail Sales Advance MoM	RSTAMOM Index	92.126	95	08:30:00
New Home Sales	NHSLTOT Index	91.339	95	10:00:00
Industrial Production MoM	IP CHNG Index	90.551	95	09:15:00
Markit US Manufacturing PMI	MPMIUSMA Index	90.000	111	09:45:00
Unemployment Rate	USURTOT Index	89.291	95	08:30:00
Housing Starts	NHSPSTOT Index	88.976	95	08:30:00
Existing Home Sales	ETSLTOTL Index	88.189	95	10:00:00
ADP Employment Change	ADP CHNG Index	87.402	95	08:15:00
PPI Final Demand MoM	FDIDFDMO Index	86.614	82	08:30:00
Personal Spending	PCE CRCH Index	85.827	95	08:30:00
Personal Income	PITLCHNG Index	85.827	95	08:30:00
Factory Orders	TMNOCHNG Index	85.039	95	10:00:00
Trade Balance	USTBTOT Index	84.252	95	08:30:00
Leading Index	LEI CHNG Index	83.465	95	10:00:00
Empire Manufacturing	EMPRGBCI Index	82.677	95	08:30:00
MNI Chicago PMI	CHPMINDX Index	81.890	188	09:45:00
Wholesale Inventories MoM	MWINCHNG Index	81.102	144	10:00:00
ISM Services Index	NAPMNMI Index	79.528	190	10:00:00
Philadelphia Fed Business Outlook	OUTFGAF Index	78.740	95	08:30:00
GDP Price Index	GDP PIQQ Index	77.480	94	08:30:00
Import Price Index MoM	IMP1CHNG Index	77.165	95	08:30:00
CPI Ex Food and Energy MoM	CPUPXCHG Index	76.850	95	08:30:00
Pending Home Sales MoM	USPHTMOM Index	76.378	94	10:00:00
Monthly Budget Statement	FDDSSD Index	75.591	95	14:00:00
ISM Prices Paid	NAPMPRIC Index	74.016	285	10:00:00
Current Account Balance	USCABAL Index	71.653	31	08:30:00
Richmond Fed Manufact. Index	RCHSINDX Index	70.866	95	10:00:00
CPI YoY	CPI YOY Index	70.079	95	08:30:00
Markit US Services PMI	MPMIUSSA Index	70.000	74	09:45:00
Change in Manufact. Payrolls	USMMMNCH Index	69.449	95	08:30:00
Continuing Claims	INJCSP Index	68.898	413	08:30:00
FHFA House Price Index MoM	HPIMMOM Index	68.504	95	09:00:00
Personal Consumption	GDPCTOT Index	67.795	94	08:30:00
PPI Final Demand YoY	FDIUFDYO Index	67.716	82	08:30:00
PPI Ex Food and Energy MoM	FDIDSGMO Index	66.142	82	08:30:00
PPI Ex Food and Energy YoY	FDIUSGYO Index	65.354	82	08:30:00
Retail Sales Ex Auto MoM	RSTAXMOM Index	64.488	95	08:30:00
Dallas Fed Manf. Activity	DFEDGBA Index	63.779	94	10:30:00
Capacity Utilization	CPTICHNG Index	63.386	95	09:15:00
Building Permits	NHSPATOT Index	62.283	95	08:30:00
NFIB Small Business Optimism	SBOITOTL Index	61.417	94	06:00:00

The table lists the macroeconomic announcements we use as controls in our analysis. We identified the top 50 macroeconomic announcements based on their relevance score, which is a metric calculated by Bloomberg. The relevance score is determined by the number of "alerts" set by all users for a particular event relative to all alerts set for other U.S. economic events. We also include the count and time of each announcement. Count represents the number of announcements within our sample period, spanning from January 2013 to December 2020. Time denotes the Eastern Time (ET) at which the announcement was most commonly released during our sample period, but we always use the actual release time in our analysis.

Appendix B - Additional figures and tables

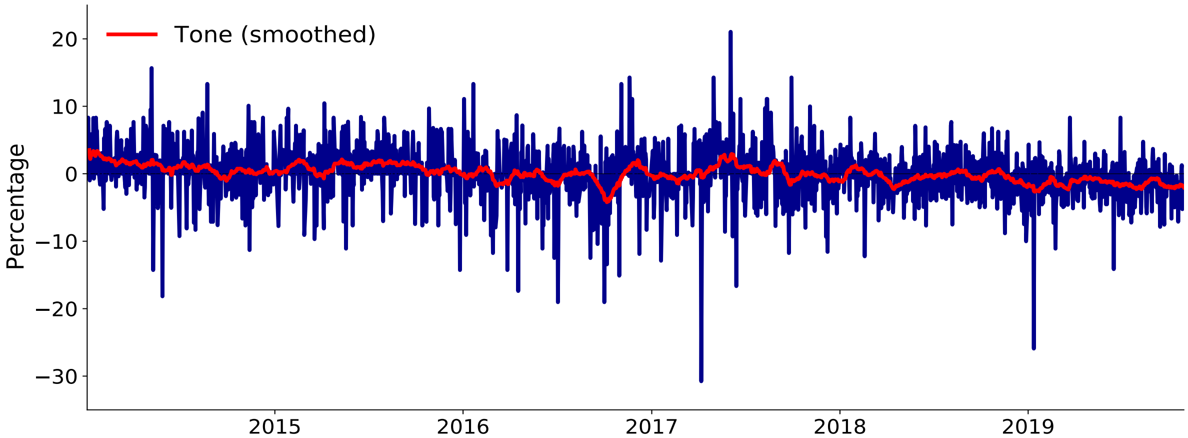


Fig. B.1. *Notes*: This figure shows the daily tone measure. To systematically compute the tone, lexicon developed by Loughran and McDonald (2011) is used. Using these dictionaries, we then count the number of positive and negative words that each tweet has. We define the *Tone* measure as the difference between the positive and the negative word count scaled by the total number of words contained in the tweet.

Table B.1. **High-frequency stock prices responses to congressional viewpoints**

		Event windows for event-based controls			
		10 min	30 min	60 min	120 min
Coef	Variable	(1)	(2)	(3)	(4)
a	1	-0.22	-0.20	-0.20	-0.19
		[-0.36]	[-0.32]	[-0.32]	[-0.30]
b	$Tone_{i,t}$	2.18	2.19	2.16	2.16
		[2.29]	[2.30]	[2.27]	[2.27]
R-squared (%)		0.83	0.84	0.87	0.80
Observations		4,716	4,716	4,716	4,716
Firm-level controls		Yes	Yes	Yes	Yes
Macro-level controls		Yes	Yes	Yes	Yes

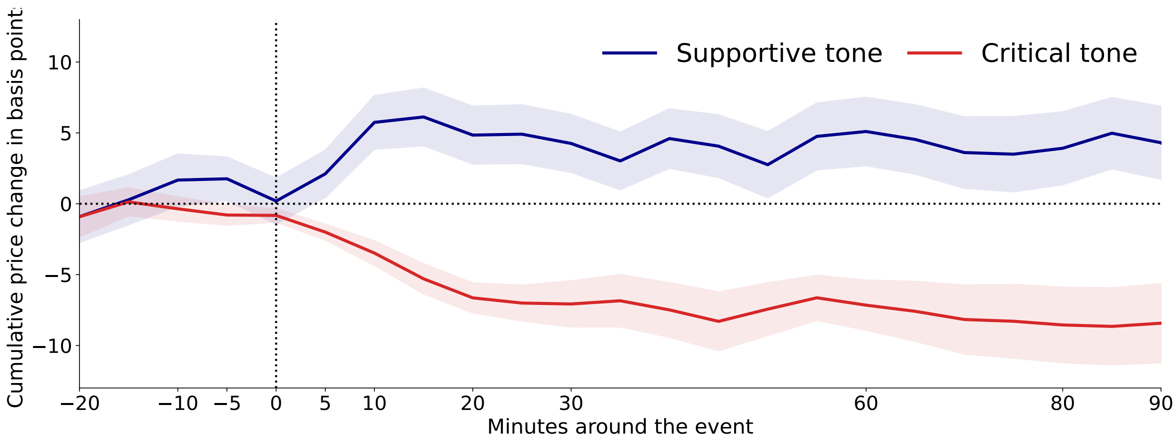
The table presents regression estimates for the equation: $\Delta p_{i,t} = a + b \cdot Tone_{i,t} + \epsilon_{i,t}$, where $\Delta p_{i,t}$ denotes the change in log stock prices for stock i around tweet t. A 6-minute window (1 minute before and 5 minutes after the event t) is used to calculate price changes. $Tone_{i,t}$ represents the tone measure. All regressions use stock fixed effects and incorporate firm-level controls, macro-level controls, and abnormal returns. Firm-level controls include intraday illiquidity measures, cumulative stock returns up to 10 minutes before the tweet, timestamped stock news article headlines, stock-related tweets from news accounts, analysts' cash-flow revisions, and forecast errors. Macro-level controls consist of news announcements of the top 50 macroeconomic indicators. Event-based controls use varying time windows around the tweet. Column 1 applies a 10-minute window (5 minutes before and 5 minutes after), column 2 uses a 30-minute window (15 minutes before and 15 minutes after), column 3 employs a 60-minute window (30 minutes before and 30 minutes after), and column 4 utilizes a 120-minute window (60 minutes before and 60 minutes after). The abnormal returns are calculated as the difference between a company's stock return and the aggregate market return. Standard errors are clustered at the firm and date levels, with t-statistics in brackets. $Tone_{i,t}$ is standardized, while $\Delta p_{i,t}$ is in basis points. R-squared statistics are reported as percentages.

Table B.2. **High-frequency stock prices responses to congressional viewpoints: Placebo tweets**

Coef	Variable	*Raw returns* (1)	(2)	(3)	*Abnormal returns* (4)
a	1	-0.30	-0.35	-0.35	-0.01
		[-1.48]	[-1.65]	[-1.65]	[-0.03]
b	$Tone_{i,t}$	-0.06	-0.17	-0.17	-0.06
		[-0.96]	[-0.45]	[-0.53]	[-0.87]
R-squared (%)		0.21	0.34	0.34	1.04
Observations		7,517	7,269	7,269	7,269
Firm-level controls		No	Yes	Yes	Yes
Macro-level controls		No	No	Yes	Yes

In this table, we use the false-positive tweets for placebo tests. The table presents regression estimates for the equation: $\Delta p_{i,t} = a + b \cdot Tone_{i,t} + \epsilon_{i,t}$, where $\Delta p_{i,t}$ denotes the change in log stock prices for stock i around tweet t. A 6-minute window (1 minute before and 5 minutes after the event t) is used to calculate price changes. $Tone_{i,t}$ represents the tone measure. Stock fixed effects are used in all regressions. Column 2 includes firm-level controls, column 3 adds macro-level controls to firm-level controls, and column 4 includes firm-level controls, macro-level controls, and abnormal returns, calculated as the difference between a company's stock return and the aggregate market return. Firm-level controls consist of intraday illiquidity measures, cumulative stock returns up to 10 minutes before the tweet, timestamped stock news article headlines, stock-related tweets from news media accounts, analysts' cash-flow revisions, and forecast errors. Macro-level controls consist of news announcements of the top 50 macroeconomic indicators. Event-based controls use a 20-minute window around the tweet (10 minutes before and 10 minutes after the stock prices used to compute $\Delta p_{i,t}$). Standard errors are clustered at the firm and date levels, with t-statistics in brackets. $Tone_{i,t}$ is standardized, while $\Delta p_{i,t}$ is in basis points. R-squared statistics are reported as percentages.

Fig. B.2. **Event-study plot: Minutes around the event**



This figure shows the effect of Congress tweets on stock prices across various event windows. Tweets are initially sorted into 4 quartiles based on their tone measure. For each stock in each quartile, cumulative returns are calculated from 20 minutes before the tweet to 90 minutes after. The red line represents the average cumulative return for the first quartile, corresponding to politicians' tweets criticizing the targeted firm, while the blue line depicts the average cumulative return for the last quartile, where politicians' tweets support the targeted firm. Blue and red shadings indicate the 95% error bands. For color interpretation in this figure legend, please refer to the web version of this article.

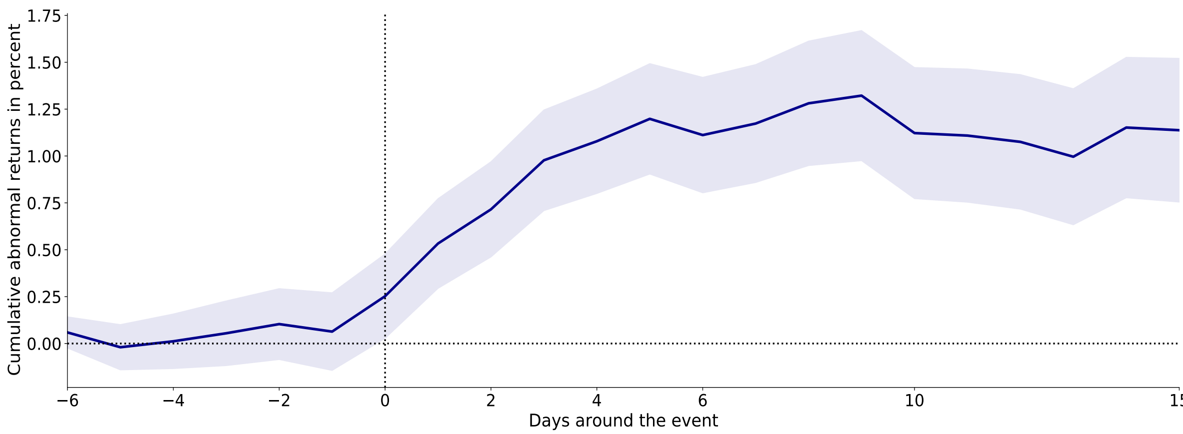


Fig. B.3. *Notes*: The figure shows the average event-time cumulative abnormal returns (CARs) to the Long-Short portfolio returns from day $t-6$ to day $t+15$. The long (short) portfolio purchases stock i if the corresponding tone measure on day t is above (below) the 90th (10th) percentile of the tone distribution computed over the previous 12 months. We value-weight the stocks to create portfolios whenever multiple firms are assigned to the same leg on the same day. The cumulative returns are computed individually for the long and short portfolios using CAPM-adjusted returns. This figure then presents the average return spread from 6 days before the tweet to 15 days following the tweet. Blue shadings indicate the 95% error bands. For color interpretation in this figure legend, please refer to the web version of this article.

Table B.3. **Summary Statistics of Congressional Committees**

	House			Senate		
	Unique # committee	Avg. # of members per committee	Avg. # of committees member belongs	Unique # committee	Avg. # members per committee	Avg. # committees member belongs
Congress	(1)	(2)	(3)	(4)	(5)	(6)
113	27	32.85	1.98	25	17.64	4.08
114	27	31.89	1.93	25	17.12	4.12
115	23	35.96	1.86	23	18.65	4.09

This table provides an overview of the number of unique committees per Congress (columns 1 and 4), the average number of members per committee per Congress (columns 2 and 5), and the average number of committees each member belongs to (columns 3 and 6).

Table B.4. **Summary Statistics of Congressional Committees Meetings**

House			Senate		
Committee	# Meetings	% of days with meetings	Committee	# Meetings	% of days with meetings
AGRICULTURE	153	5.0	AGING (SPECIAL COMMITTEE)	102.0	3.2
APPROPRIATIONS	239	7.8	AGRICULTURE, NUTRITION, AND FORESTRY	74.0	2.4
ARMED SERVICES	326	10.7	APPROPRIATIONS	204.0	8.0
BUDGET	66	2.2	ARMED SERVICES	179.0	6.2
EDUCATION AND LABOR	76	2.4	BANKING, HOUSING, AND URBAN AFFAIRS	259.0	8.2
EDUCATION AND THE WORKFORCE	122	3.9	BUDGET	29.0	0.9
EDUCATION AND THE WORKPLACE	187	6.1	COMMERCE, SCIENCE, AND TRANSPORTATION	305.0	9.7
ENERGY AND COMMERCE	485	15.4	ENERGY AND NATURAL RESOURCES	276.0	8.8
ENERGY INDEPENDENCE AND GLOBAL WARMING	1	0.0	ENVIRONMENT AND PUBLIC WORKS	250.0	8.0
ETHICS	1	0.0	FINANCE	198.0	6.3
EVENTS SURROUNDING THE 2012 TERRORIST ...	15	0.5	FOREIGN RELATIONS	306.0	9.8
FINANCIAL SERVICES	362	12.2	GOVERNMENTAL AFFAIRS	46.0	1.5
FOREIGN AFFAIRS	456	14.5	HEALTH, EDUCATION, LABOR, AND PENSIONS	216.0	6.9
GOVERNMENT REFORM	323	10.3	HOMELAND SECURITY AND GOVERNMENTAL AFFAIRS	328.0	10.4
HOMELAND SECURITY	176	5.6	INDIAN AFFAIRS (SELECT COMMITTEE)	135.0	4.3
HOUSE ADMINISTRATION	91	2.9	INTELLIGENCE (SELECT COMMITTEE)	54.0	2.9
INTELLIGENCE (SELECT)	83	3.0	JUDICIARY	168.0	5.7
INTERNATIONAL RELATIONS	154	5.2	RULES AND ADMINISTRATION	24.0	0.8
JUDICIARY	374	12.0	SMALL BUSINESS	12.0	0.4
NATIONAL SECURITY	83	2.7	SMALL BUSINESS AND ENTREPRENEURSHIP	97.0	3.1
NATURAL RESOURCES	336	10.7	VETERANS' AFFAIRS	91.0	2.9
OVERSIGHT AND GOVERNMENT REFORM	492	15.8			
RULES	236	7.6			
SCIENCE AND TECHNOLOGY	110	3.5			
SCIENCE, SPACE, AND TECHNOLOGY	343	11.1			
SMALL BUSINESS	342	10.9			
TRANSPORTATION AND INFRASTRUCTURE	267	8.5			
VETERANS AFFAIRS	349	11.1			
WAYS AND MEANS	262	8.4			

The table presents information on committee meetings in the House and the Senate. For each chamber, the names of the committees are listed. The table also includes the total number of committee meetings observed in our sample from the 113th to the 116th Congress. Additionally, the column labeled "% of days with meetings" represents the percentage of days with a committee meeting held by each specific committee, indicating the proportion of days in which a meeting took place out of the total days observed.

Table B.5. **Performance Evaluation: Mean returns and factor alphas**

	Long - Short returns		
	All	Meetings	Meeting & member
	(1)	(2)	(3)
CAPM alpha	1.13	1.26	1.47
	[3.68]	[3.27]	[2.45]
FF3 alpha	1.12	1.24	1.49
	[3.32]	[3.20]	[2.57]
FF4 alpha	1.03	1.20	1.40
	[3.14]	[3.21]	[2.33]

This table presents monthly factor alphas for the long-short returns of three distinct strategies. In column 1, the long (short) portfolio buys stock i if the corresponding tone measure is above (below) the 90th (10th) percentile of the tone distribution computed over the previous 12 months. In column 2, we require that the tweet also occurs on a day of a committee meeting, while in column 3, we require that the politician's tweet occurs on a day when their corresponding committee is holding a meeting. We value-weight the stocks to create portfolios when multiple firms are assigned to the same leg on the same day. To execute the buy or sell order, we allow for a one-business-day gap between day t of the ranking period and day $t+1$ of the holding period. The portfolios are rebalanced daily. Once we obtain the daily portfolio returns for the long and short sides, we accumulate the daily returns at the monthly frequency. The "Long-Short" portfolio buys the long portfolio and sells the short portfolio. The alphas represent the intercepts from time series regressions of the portfolio excess returns on factor alphas. The four factors include the aggregate market excess return, the size factor, the value factor, and the momentum factor. Standard errors adjust for heteroskedasticity and autocorrelation. Returns are in percent. We report the t-statistics in brackets.

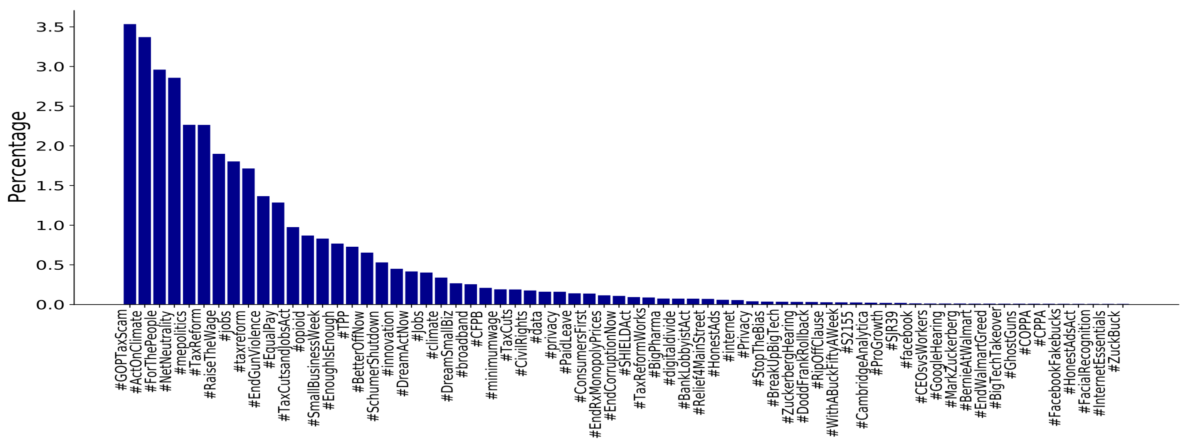


Fig. B.4. *Notes*: This figure shows the policy relevant hashtags obtained from all tweets that target a firm. The vertical bars indicate the percentage of times each specific hashtags is mentioned scaled by all tweets that contain a hashtag.

Appendix C - Alternative tone measures

In the main text, we use the lexicon developed by Loughran and McDonald (2011) to systematically compute the tone measure of the relevant tweets. This appendix supplements our findings with robustness results derived from five alternative tone measures. These include FinBERT, Vader, TextBlob, ChatGPT, and manual classification.

FinBERT is a language model grounded in Google's bidirectional encoder representations from transformers (BERT) model. Pre-trained on a comprehensive financial corpus, FinBERT is designed to comprehend nuanced financial language. Vader, standing for Valence Aware Dictionary and sEntiment Reasoner, is a sentiment analysis tool that employs a lexicon and rule-based approach, specifically engineered to discern social media sentiment. TextBlob, on the other hand, is a straightforward lexicon-based sentiment analyzer reliant on a pre-established dictionary of words and weights.

ChatGPT is a large-scale language model developed by OpenAI, which we utilize to assign a positive, negative, or neutral tone to each tweet. We also employ manual classification for tone assignment. The ChatGPT and human sentiment labeling follows the prompt: *'As an investor, analyze the sentiment expressed in the following tweet and determine whether it suggests a bullish, bearish, or neutral stance on the security mentioned: Tweet: "{text}" The sentiment expressed in this tweet is:"*.

Table C.6 displays regression results for high-frequency log price changes against these tone measures as per the specification:

$$\Delta p_{i,t} = a + b \cdot Tone_{i,t} + \epsilon_{i,t}. \tag{C.1}$$

This regression is further detailed in the main text via equation (1). In columns 1-3, $\Delta p_{i,t}$ represents the change in log stock prices for stock i at tweet t. In columns 4-6, $\Delta p_{i,t}$ signifies abnormal returns, calculated as the difference between a company's stock return and the market return. Price changes are calculated using a 6-minute window (1 minute pre-tweet and 5 minutes post-tweet). Across these different tone measures, we document very similar results. A positive tone has a positive and statistically significant effect on the stock price as implied by the positive slope coefficient $\hat{b}$, regardless of whether we employ raw or abnormal returns. The estimated coefficients range from 2.13 to 2.88, where all t-statistics are above 2.

Table C.7 exhibits regression results utilizing a daily event window. Specifically, we estimate the following OLS regression:

$$r_{i,t} = a_0 + a_1 I_{i,t} + b\,(Tone_{i,t} \times I_{i,t}) + \epsilon_{i,t}, \tag{C.2}$$

This regression is further explained in the main text via equation (2). In line with the findings reported in the main text, the estimated coefficients $\hat{b}$ are positive and statistically significant across all tone measures, demonstrating the robustness of our results.

Finally, Table C.8 monthly mean returns and factor alphas for a "Long-Short" portfolio, derived using various sentiment measures. In columns 1 to 3, the portfolio longs (shorts) stock i if its tone measure is above (below) the 90th (10th) percentile of the preceding 12-month tone distribution. Columns 4 and 5 use ChatGPT and research assistants' classifications of tweets as positive, negative, or neutral. Here, the portfolio longs (shorts) stock i if its tone is positive (negative). When multiple firms share the same tone on the same day, we form value-weighted portfolios. Buy or sell orders are executed with a one-business-day gap between the ranking period's end (day t) and the holding period's start (day $t+1$). Daily portfolio

Table C.6. **High-frequency stock prices responses: Alternative tone measures**

		Raw returns			*Abnormal returns*		
		FinBert	Vader	TextBlob	FinBert	Vader	TextBlob
Coef	Variable	(1)	(2)	(3)	(4)	(5)	(6)
a	1	-0.61	-0.47	-0.37	-0.32	-0.26	-0.25
		[-1.75]	[-1.34]	[-1.37]	[-0.80]	[-0.68]	[-0.46]
b	$Tone_{i,t}$	2.67	2.88	2.31	2.34	2.39	2.13
		[2.64]	[2.27]	[2.16]	[2.62]	[2.72]	[2.54]
R-squared (%)		0.49	0.67	0.54	0.50	0.48	0.53
Observations		4716	4716	4716	4716	4716	4716
Firm-level controls		Yes	Yes	Yes	Yes	Yes	Yes
Macro-level controls		Yes	Yes	Yes	Yes	Yes	Yes

The table presents regression estimates for the equation: $\Delta p_{i,t} = a + b \cdot Tone_{i,t} + \epsilon_{i,t}$. In columns 1-3, $\Delta p_{i,t}$ represents the change in log stock prices for stock i at tweet t. In columns 4-6, $\Delta p_{i,t}$ signifies abnormal returns, calculated as the difference between a company's stock return and the market return. Price changes are calculated using a 6-minute window (1 minute pre-tweet and 5 minutes post-tweet). $Tone_{i,t}$ denotes the standardized tone measure using different sentiment measures specified at each column's top. In all regressions, we include stock fixed effects, firm-level controls, and macro-level controls. Firm-level controls consist of intraday illiquidity measures, cumulative stock returns up to 10 minutes before the tweet, timestamped stock news article headlines, stock-related tweets from news media accounts, analysts' cash-flow revisions, and forecast errors. Macro-level controls consist of news announcements of the top 50 macroeconomic indicators. Event-based controls use a 20-minute window around the tweet (10 minutes before and 10 minutes after the stock prices used to compute $\Delta p_{i,t}$). Standard errors are clustered at the firm and date levels, with t-statistics in brackets. $Tone_{i,t}$ is standardized, while $\Delta p_{i,t}$ is in basis points. R-squared statistics are reported as percentages.

returns, rebalanced daily, are accumulated monthly to form the "Long-Short" portfolio. The alphas represent the intercepts from time series regressions of the portfolio excess returns on factor alphas. The main takeaway from the table is that the alphas are positive and statistically significant across all alternative tone measures.

Table C.7. **Daily asset prices responses to congressional viewpoints: Alternative tone measures**

		Raw returns			*Residualized returns using FF4*		
		FinBert	Vader	TextBlob	FinBert	Vader	TextBlob
Coef	Variable	(1)	(2)	(3)	(4)	(5)	(6)
a_0	1	-0.44	-0.13	-0.33	-3.65	-3.50	-3.57
		[-0.05]	[-0.01]	[-0.03]	[-1.57]	[-1.51]	[-1.54]
a_1	$I_{i,t}$	-11.61	-9.12	-10.21	-8.51	-6.24	-7.27
		[-2.78]	[-2.44]	[-2.73]	[-2.86]	[-2.31]	[-2.56]
b	$Tone_{i,t} \times I_{i,t}$	9.83	7.31	4.30	8.47	6.48	4.89
		[2.78]	[2.50]	[2.49]	[2.94]	[2.90]	[2.37]
R-squared (%)		0.84	0.99	0.57	0.75	0.77	0.69
Observations		719,388	716,351	716,351	719,388	716,351	716,351
Firm controls		Yes	Yes	Yes	Yes	Yes	Yes
Macro controls		Yes	Yes	Yes	Yes	Yes	Yes

The table presents regression estimates for the equation: $r_{i,t} = a_0 + a_1 I_{i,t} + b\,(Tone_{i,t} \times Ii,t) + \epsilon_{i,t}$. In columns 1-3, $r_{i,t}$ denotes the daily stock return for company i. In columns 4-6, $r_{i,t}$ denotes daily Fama–French/Carhart four-factor model-adjusted returns. $Tone_{i,t}$ denotes the standardized tone measure using different sentiment measures specified at each column's top. All regressions use stock fixed effects and incorporate firm-level and macro-level controls. Firm-level controls include daily illiquidity and volatility measures, weekly cumulative stock returns up to day $t-1$ before the tweet, Bloomberg news sentiment measure for company i on day t and $t-1$, daily tone measures for stock news article headlines and stock-related tweets from news media accounts, analysts' cash-flow revisions, and forecast errors. Macro-level controls consist of news announcements for the top 50 macroeconomic indicators. Stock returns are in basis points, and $Tone_{i,t}$ is standardized. The full panel of a firm's stock returns (i.e., days with and without politician tweets targeting company i) is used. Standard errors are clustered at the firm and date levels, with t-statistics in brackets. R-squared statistics are reported as percentages.

Table C.8. **Mean returns and factor alphas: Alternative tone measures**

	Long-Short portfolio returns using different sentiment measures				
	FinBert (1)	Vader (2)	TextBlob (3)	ChatGPT (4)	Manual (5)
Average return	1.66	1.05	1.36	1.95	1.20
Standard deviation	3.71	4.27	4.94	7.93	7.21
CAPM alpha	1.34	1.33	1.25	1.55	1.45
	[3.64]	[4.68]	[3.73]	[2.71]	[2.94]
FF3 alpha	1.39	1.31	1.35	1.48	1.41
	[3.40]	[3.17]	[3.91]	[2.52]	[2.59]
FF4 alpha	1.38	1.32	1.33	1.44	1.40
	[3.24]	[4.34]	[3.36]	[2.18]	[2.15]

This table presents monthly mean returns and factor alphas for a "Long-Short" portfolio, derived using various sentiment measures. In columns 1 to 3, the portfolio longs (shorts) stock i if its tone measure is above (below) the 90th (10th) percentile of the preceding 12-month tone distribution. Columns 4 and 5 use ChatGPT and research assistants' classifications of tweets as positive, negative, or neutral. Here, the portfolio longs (shorts) stock i if its tone is positive (negative). When multiple firms share the same tone on the same day, we form value-weighted portfolios. Buy or sell orders are executed with a one-business-day gap between the ranking period's end (day t) and the holding period's start (day $t+1$). Daily portfolio returns, rebalanced daily, are accumulated monthly to form the "Long-Short" portfolio. The alphas represent the intercepts from time series regressions of the portfolio excess returns on factor alphas. The four factors include the aggregate market excess return, the size factor, the value factor, and the momentum factor. Standard errors adjust for heteroskedasticity and autocorrelation. Returns are in percent. We report the t-statistics in brackets.

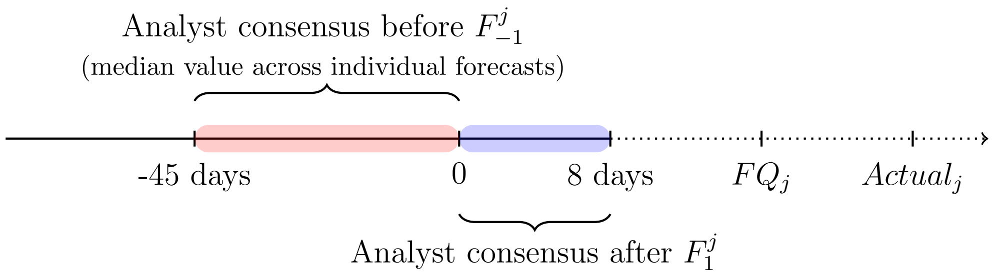


Fig. D.5. *Notes*: This figure illustrates how the forecast revisions and surprises for firm i are computed. Time zero denotes the day of the tweet. The analyst consensus for fiscal quarter j before the tweet (i.e., F_{-1}^{j}) is equal to the median of all forecasts submitted 45 days to one day prior to the tweet. The analyst consensus after the tweet (i.e., F_1^j), equals the median value for all forecasts submitted between day zero and day eight. Forecast revisions are defined as the difference between the analyst consensus (i.e., $FR_j = F_1^j - F_{-1}^{j}$).Forecast errors are given by the difference between the firm's actual sales and the analyst consensus before (i.e., $FE_j = Actual_j - F_{-1}^{j}$).

Appendix D - Real effects

In order to gain further insights into the economic factors underlying the observed stock price responses, we examine the impact of congressional tweets on stock analysts' forecasts for future cash flows. Specifically, our analysis focuses on two aspects: firstly, whether analysts revise their forecasts following these tweets, and secondly, whether the tweets predict analysts' forecast errors. The first exercise allows us to assess whether professionals believe that the tweets contain valuable information about the performance of a company. The second exercise allows to assess whether this is in fact the case. Assuming that the analysts produce a forecast that already incorporates the available information, a positive surprise in revenue or earnings following a tweet with a positive (negative) tone indicates that the tweet anticipated positive (negative) developments for the targeted company.

Figure D.5 illustrates how the forecast revisions and surprises for sales of firm i are computed. To construct our sample of forecast errors and revisions, we collect analyst-by-analyst sale forecasts from the Thomson Reuters I/B/E/S Detail History File and the actual figures from the I/B/E/S actuals file database. Let FQ_j denote the fiscal quarter j, $Actual_j$ is the corresponding sales realization, and time zero depicts the day of the tweet. We keep all analyst forecasts for the current (i.e., $j = 0$) and next fiscal quarter (i.e., $j = 1$). To compute the analyst consensus for fiscal quarter j before the day of the tweet (i.e., F_{-1}^{j}), we calculate the median of all forecasts submitted 45 days to one day prior to the tweet. To compute the analyst consensus after the day of the tweet (i.e., F_1^j), we compute the median value for all forecasts submitted between day zero and day eight.

Suppose an analyst makes several estimates for the same firm and event window over the same fiscal quarter. In that case, we take the forecast closest to the day of the tweet to ensure that we consider the most recent estimate. We define forecast revisions as the change in the analyst consensus (i.e., $FR^j = F_1^j - F_{-1}^{j}$) before and after the day of the tweet. Forecast errors are computed as the difference between the firm's actual sales and the analyst consensus before the day of the tweet (i.e., $FE^j = Actual_j - F_{-1}^{j}$). Finally, we scale forecast revisions and surprises by the stock price before the previous fiscal quarter announcement and multiply by 100.

The reason for using a relatively short window of eight days after the tweet is that it

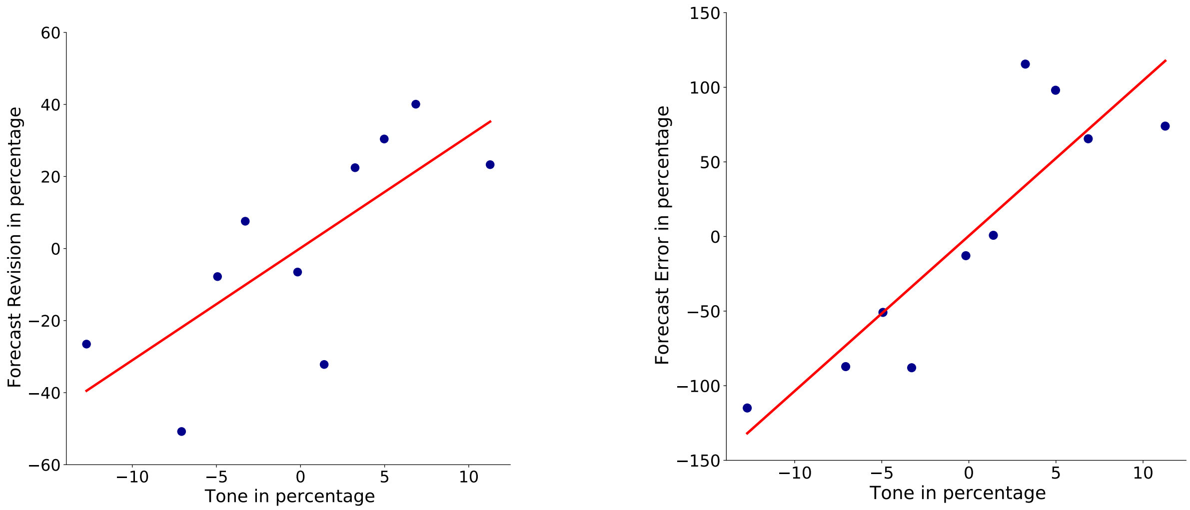


Fig. D.6. *Notes*: We sort the tone measure into 10 bins. The left panel reports the average tone measure and the average price-scaled sales forecast revision for each of the 10 sorted bins. The right panel reports the average tone measure and the average price-scaled sales forecast error for each of the 10 sorted bins. Forecast revision is the difference between the consensus sales forecast after and before the tweet. Sales forecast error is the difference between reported quarterly sales and the consensus sales forecast before the tweet. All variables are in percentage. The red lines denote the regression fit lines.

takes about a week for the information to be fully reflected in asset prices (see, for instance, Figure B.3). Hence, this short window attempts to capture analysts forecasts issued precisely during this learning period. The idea behind the relatively long window of 45 days before the tweet is that we want to use as many forecasts as possible when computing the analyst consensus before the tweet. However, taking a longer window raises the concern that some material information for the fiscal quarter j could have been released during this more extended sample period. Therefore, we add meaningful firm and macro-level controls in our regression tests.

Figure D.6 illustrates the strong positive relation between the tone of the tweets and the analysts' forecast revisions (left panel) and between the tone of the tweets and the analysts' forecast errors (right panel). On the horizontal axis, we report the tone for the tweets after sorting them in 10 different bins. The vertical axis of the left panel is the average price-scaled sales forecast revision. The vertical axis of the right panel is the average price-scaled sales forecast error. All variables are in percentages and the red lines denote the regression fit lines. Thus, a positive tone leads to a positive revision in expectations and positive forecast errors.

We formalize this finding by presenting regression results in Panel A of Table D.9. All regressions include stock fixed effects and add firm-level and macro-level controls. In column 1, we regress forecast revisions $FR^j_{i,t}$ on the variables $Tonei,t$ and $Tone_{i,t} \times political_{i,t}$, where $political_{i,t}$ represents the legislative tweets that satisfy two conditions. The first condition is if the scaled frequency of bigrams related to political matters falls within the top quartile, and the second condition is if the tweet contains hashtags associated with political matters. Column 1 shows that a one-standard-deviation increase in the tone measure of legislative tweets is associated with a 14.14 higher analyst sales forecast (relative to prices) in the days immediately following a tweet. To provide context, the scaled analyst revisions in our sample have a standard deviation of 475 (with a mean of -18.5). Importantly, the estimated effect on non-legislative tweets is considerably smaller and not statistically significant (4.6, $t = 1.5$).

In column 2, we further investigate whether the tone of the tweets can predict forecast

Table D.9. **Real effects of congressional viewpoints**

A. Revenue

		Surprises	
	Revisions $(F_1^j - F_{-1}^j)$	Before $(Actual_j - F_{-1}^j)$	After $(Actual_j - F_1^j)$
Regressors	(1)	(2)	(3)
$Tone_{i,t}$	4.636	12.480	11.597
	[1.507]	[1.411]	[1.105]
$Tone_{i,t} \times political$	8.512	19.748	15.985
	[2.354]	[2.483]	[1.679]
Observations	5,284	11,355	5,284
Firm-level controls	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes

B. Earnings

		Surprises	
	Revisions $(F_1^j - F_{-1}^j)$	Before $(Actual_j - F_{-1}^j)$	After $(Actual_j - F_1^j)$
Regressors	(1)	(2)	(3)
$Tone_{i,t}$	0.004	0.009	0.005
	[1.143]	[1.669]	[1.117]
$Tone_{i,t} \times political$	0.006	0.023	0.013
	[1.319]	[3.730]	[1.533]
Observations	5,284	11,355	5,284
Firm-level controls	Yes	Yes	Yes
Macro-level controls	Yes	Yes	Yes

Panel A reports results for revenue, while panel B report results for earnings per share. In column 1, the dependent variable is the price-scaled sales/earnings forecast revision $FR_{i,t}^j$. In column 2, the dependent variable is the price-scaled sales/earnings forecast error $FE_{i,t}^j$. In column 3, the dependent variable is the price-scaled sales/earnings forecast errors computed with respect to the consensus analysts' forecasts produced over the 8 days after the tweet. Figure D.5 provides the details on how we compute these measures. The dummy variable *politcal* takes the value of 1 if either of the two conditions is satisfied. The first condition is if the scaled frequency of bigrams related to political matters falls within the top quartile. The second condition is if the tweet contains hashtags associated with political matters. The variable $Tone_{i,t}$ represents the daily tone measure. All regressions include stock fixed effects and control for firm-level and macro-level controls. Standard errors are clustered at the firm and day levels, and t-statistics are reported in brackets. $Tone_{i,t}$ is standardized.

errors. We measure forecast errors using $FE_{i,t}^j(before)$, which represents the price-scaled sales forecast errors relative to the consensus analysts' forecasts generated in the 45 days prior to the tweet. Column 2 shows that the tone of legislative tweets has a significant and positive effect on forecast errors. The coefficient estimate for legislative tweets is large, with a value of 19 (t-statistic = 2.5). This indicates that the tone of legislative tweets contains valuable information that helps predict forecast errors. In contrast, the estimated effect on non-legislative tweets is positive but considerably smaller and not statistically significant (12.48, t = 1.4).

Next, we test whether these forecast revisions end up improving forecast accuracy and leading to lower subsequent forecast error predictability. We update the measure of forecast error by using the newly issued forecasts generated over the 8 days after the tweet (i.e., $FE(after)^j_{i,t} = Actual_j - F^j_1$). Column 3 of Table D.9 reports the results. Interestingly, we still find that the estimated coefficient is positive but smaller and with reduced statistical significance. This result suggests that although analyst forecasts move in the right direction following the tweets, the revisions are not large enough to eliminate the forecast error predictability fully.

In Panel B of Table D.9, we extend our analysis to examine the effects on earnings per share (EPS) and find consistent patterns with the results observed for sales. However, the statistical significance is somewhat reduced for forecast revisions, while forecast errors exhibit stronger significance.

Column 1 shows that a positive tone is associated with positive revisions in EPS forecasts, but the evidence is weaker than revenues. The point estimate for forecast revisions is positive but not statistically significant (0.006, $t = 1.3$), suggesting that the impact of tone on forecast revisions for EPS is less pronounced than for revenues. Moving to column 2, we find that the tone measure strongly predicts forecast errors, particularly for legislative tweets. The coefficient estimate for legislative tweets is 0.023 (t-statistic = 3.7), indicating that a higher tone in legislative tweets is associated with higher forecast errors (i.e., analysts' forecast were too low relative to actual values). Finally, in column 3, we examine the post-tweet revision of forecast errors by analysts. The results show that after revising their forecasts following the tweet, the predictability of forecast errors becomes significantly smaller (with t-statistics of 1.1 and 1.5). This implies that the incorporation of information from the tweets leads to improved forecast accuracy and reduces the predictability of forecast errors.

Appendix E - Case Studies

In this section of the Internet Appendix, we provide detailed case studies that highlight the influence of members of Congress in shaping expectations about policy through their real-time communication via social media. These case studies focus on specific bills and serve as valuable illustrations of how congressional representatives can impact public perception and expectations by effectively conveying their stance through social media platforms.

E.1 Crapo bill

An important legislative initiative that generated a large volume of congressional social media activity and intense media scrutiny is the Crapo Bill, officially called Economic Growth, Regulatory Relief, and Consumer Protection Act (S.2115), which was signed into law in 2018. The bill takes the name from Mike Crapo (R-ID), the United States Senator who sponsored it and the chair of the Senate Banking Committee at the time the bill was passed. The bill passed the Senate vote by a margin of 67 to 31 in March 2018, passed the House by a Yea-Nay vote of 258 - 159, and was signed by former President Donald Trump in May 2018.

The bill was perceived as favorable for the banking sector because it was relaxing several restrictions introduced after the 2008/9 financial crisis. The bill raised the asset threshold for banks to be considered too big to fail from $50 billion to $250 billion. The bill also eliminated the Volcker Rule for small banks with less than $10 billion in assets. The Volcker rule takes the name from the ex-Fed Chairman Paul Volcker who proposed it in the aftermath of the 2008/9 financial crisis to restrict commercial banks from engaging in proprietary trading backed by deposits.

Figure E.7 shows the percentage of congressional tweets that explicitly reference the Crapo Bill given by the following hashtags: #S2155, #DoddFrankRollback, #BankLobbyistAct, and #Relief4MainStreet. We distinguish between the tweets made by members of congress who voted Yea (blue bars) or Nay (white bars). The number of tweets related to the bill clearly increases on the main legislative events, suggesting that the Congress members use the tweets to communicate their views on the bill.

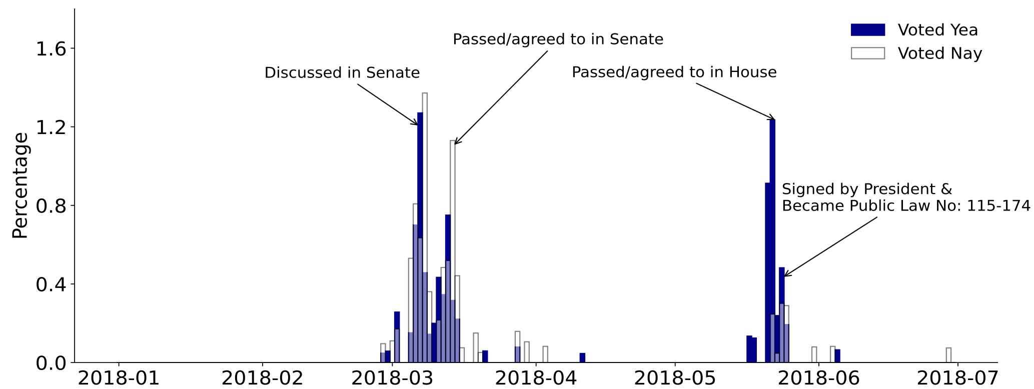


Fig. E.7. *Notes*: This figure shows the percentage of congressional posts that explicitly reference the Crapo Bill (officially called Economic Growth, Regulatory Relief, and Consumer Protection Act (S.2115)) as identified by the following hashtags #S2155, #DoddFrankRollback, #BankLobbyistAct, and #Relief4MainStreet. We further divide the tweets made by members of congress who voted Yea (blue bars) or Nay (white bars). The bill passed the Senate with an amendment by Yea-Nay vote of 67 - 31. The bill passed the House by Yea-Nay vote of 258 - 159.

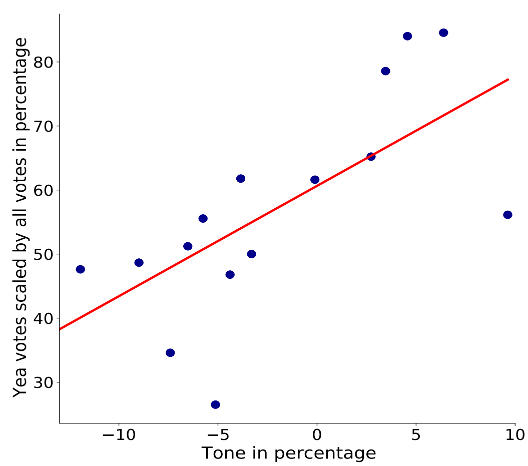


Fig. E.8. *Notes*: This figure shows the percentage of yea votes as function of the tone measure. For each Congress member, we compute the average tone in the tweets referring to the Crapo Bill. We then sort the resulting averages based on their tone measure into bins and compute the average tone measure over the corresponding bin. We then track how the Congress members in each bin voted and compute the percentage of yea votes for the corresponding bin. The tone measure is computed over all tweets that explicitly reference the Crapo Bill (officially called Economic Growth, Regulatory Relief, and Consumer Protection Act (S.2115)) as identified by the following hashtags #S2155, #DoddFrankRollback, #BankLobbyistAct, and #Relief4MainStreet. The bill passed the Senate with an amendment by Yea-Nay vote of 67 - 31. The bill passed the House by Yea-Nay vote of 258 - 159. All variables are in percentage. The red line denotes the regression fit line.

As a next step, we analyze the relation between the tone used in the tweets and subsequent votes. For each Congress member, we compute the average tone in the tweets referring to the Crapo Bill. We then sort the Congress members based on the tone measure into bins and compute the average tone measured over the corresponding bin. We then track how the Congress members in each bin voted and compute the percentage of yea votes for the

Table E.10. **Daily banking price responses to congressional viewpoints**

Coef	Variable	Daily FF4 banking abnormal returns
β_1	1	6.59
		[1.17]
β_2	*political*	-5.90
		[-1.46]
β_3	$Tone_{i,t}$	0.82
		[0.19]
β_4	$Tone_{i,t} \times political$	25.3
		[2.62]
Industry-level controls		Yes
Macro-level controls		Yes
Observations		1,006

The dependent variable are abnormal returns for the banking sector. The dummy variable *political* equals one when the tweet contains one of the hashtags that refer to the Crapo bill: #S2155, #DoddFrankRollback, #BankLobbyistAct, and #Relief4MainStreet. The variable $Tone_{i,t}$ represents the daily tone measure. All regressions control for firm-level and macro-level controls. The R-squared statistics are reported as percentages. Returns are expressed in basis points, and $Tone_{i,t}$ is standardized.

corresponding bin. We then plot the percentage of yea votes as a function of the average tone in Figure E.8. We find that the tone is a strong predictor of how the Congress members vote, underscoring the credibility of the viewpoints contained in the politician tweets. These results provides support for the idea that markets and analysts use the tweets to extract information about the likelihood or specific details of the proposed legislation.

Table E.10 presents the results. The dummy variable *political* equals one when the tweet contains one of the hashtags that refer to the Crapo bill: #S2155, #DoddFrankRollback, #BankLobbyistAct, and #Relief4MainStreet. The parameter of interest is β_4, which measures the effect of the politician viewpoint about the Crapo bill on the banking industry abnormal return. Table E.10 shows that the effect of the politician viewpoints on stock prices is concentrated on the tweets that explicitly mention the Crapo bill. A one-standard-deviation higher tone measure implies an additional 25 bps (t-statistic = 2.62) in abnormal daily returns. Notably, the effect of all other tweets is just above zero, but not statistically significant.

E.2 Tax Cuts and Jobs Act

In this section, we focus on the Public Law 115–97, commonly referred to as the Tax Cuts and Jobs Act (henceforth TCJA) or the 2017 tax reform.[12] The 2017 tax reform is an important bill in our sample since it made the largest changes to the U.S. tax code in over thirty years. For example, the tax reform had an important impact on firms given that the major changes were to the U.S. corporate tax system, including a reduction in the federal corporate tax rate

[12] The short title "Tax Cuts and Jobs Act" was not approved by Senate and to comply with Senate rules, the official title of the bill was changed to "An Act to provide for reconciliation pursuant to titles II and V of the concurrent resolution on the budget for fiscal year 2018."

from 35 percent to 21 percent.[13] This reform moved swiftly through the legislative process taking less than three months from the release of a nine-page "Unified Framework for Tax Reform" on September 27, 2017 to a nearly 200 page final bill signed into law by President Trump on December 22, 2017. The bill was extensively revised as it was rushed by Republicans through the House and Senate generating substantial uncertainty both in the actual content of the bill and on whether it would pass (Wagner, Zeckhauser, and Ziegler, 2018).[14] The uncertainty remained until the passing of the bill. Importantly, members of congress actively used their social media accounts to communicate their stance about these changes in real time. For instance, Democrat Senator Dick Durbin (@SenatorDurbin) posted "Trying to review the #GOPTaxScam but they are making hand-written changes to brand new text as we speak – can anyone else read this?" [attached a screenshot of a page of the bill with the changes], 1 Dec, 2017, 23:25:27 EST, Tweet.

E.2.1 The legislative process of the Tax Cuts and Jobs Act

The legislative process of the Tax Cuts and Jobs Act directly is captured from the Twitter accounts of the members of Congress. To identify the legislative process of the Tax Cuts and Jobs Act, we start by building an index of tax related terms based on our panel of congressional social media posts. All posts that contain a tax related word or hashtag are counted, such as "tax", "taxation", and "#TrumpCuts" in a given day. This raw count is then scaled by the total number of congressional tweets posted in the same day. Figure E.9 depicts the resulting index. The gray shaded area in the figure highlights the time the bill spent in Congress until it became Public Law.

The figure shows significant spikes on the main legislative events of the tax reform. Republicans unveiled their tax plan on September 27. On November 2, the House Ways and Means Committee introduced the bill, which was then passed on November 16. On the same day, the Senate Finance Committee passed a draft of the bill, which was subsequently passed by the Senate in the early hours of December 2. After reconciling the difference between the House and Senate bills, the final version of the bill passed each chamber in a mostly party line vote. Finally, the President signed the bill into law on December 22. The figure also displays other events such as the Tax day (dotted vertical lines) which usually falls on the 15 of April of each year. In the U.S., the Tax Day denotes the due date on which individual income tax returns should be submitted to the federal government.

E.2.2 Corporate taxes and the aggregate market

Next, we use a high-identification approach and focus on movements in asset prices in a short time window around the tweets that communicate the congressional viewpoints about the 2017 tax reform. The key finding is that these viewpoints provide real-time updates to market participants about the stance of each party to the continually changing provisions made to the bill.

[13] Auerbach (2018) provides a detail explanation of the main changes of the the Tax Cuts and Jobs Act. The full set of changes are in `https://www.congress.gov/bill/115th-congress/house-bill/1`.

[14] It is important to note that the Republican party did not have 60 or more votes in the Senate to pass the bill over a Democratic filibuster. However, the Republicans passed the tax cuts via a procedural maneuver known as budget reconciliation. This fast-track process allows the bill to be passed by majority vote as long as the bill does not increase the deficit in the next decade. For details on this see Alex Tausanovitch & Sam Berger, Center for American Progress, TheImpact of the Filibuster on Federal Policymaking (Dec. 5, 2019), available at `https://www.americanprogress.org/issues/democracy/reports/2019/12/05/478199/impact-filibuster-federalpolicymaking/`.

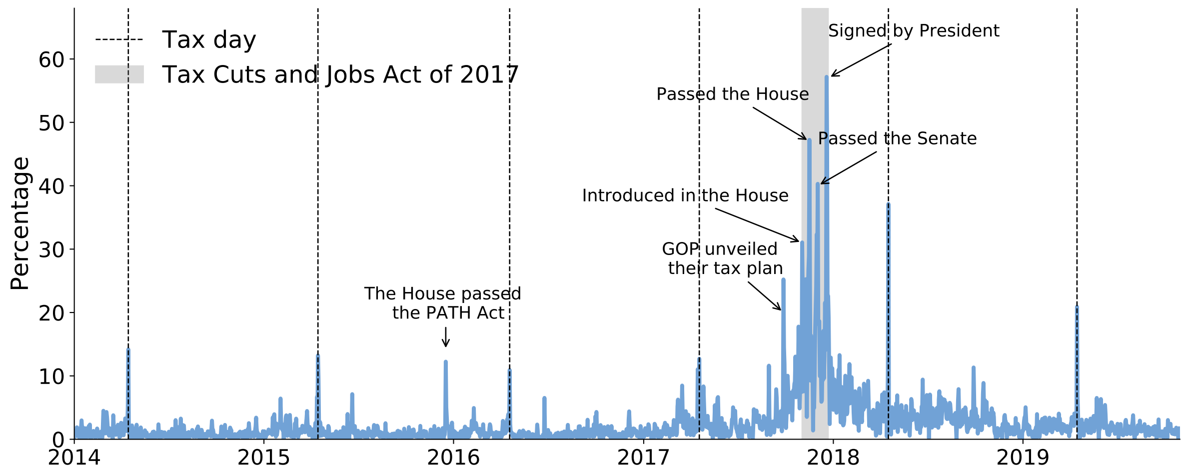


Fig. E.9. *Notes*: This figure shows the percentage of congressional post containing tax related word or hashtag, such as "tax", "taxation", and "#TrumpCuts" in a given day. The gray shaded area in the figure highlights the time the bill spent in Congress till it became Public Law. We use the complete set of tweets created by any member of the U.S. Senate and House of Representatives from the 113th Congress to the 116th Congress.

We proceed in two steps. In the first step, we select posts that explicitly express a view about the tax reform, and classify them as being supportive or critical of the tax framework. Members of congress primarily used four hashtags (#TaxReform, #TaxCutsandJobsAct, #TrumpCuts, #GOPTaxScam) to engage with the public and express their viewpoints about the GOP's tax bill. Therefore, to select the tax reform tweets posts are selected that contain any of these four hashtags. All of these tweets that do not directly express a view about the reform are dropped. We then classify the remaining tweets. To do so, for each politician we cross-referenced the use of hashtags with the *ex*-post voting behavior. It turns out that 92% and 98% of the tweets containing the hashtags #TaxReform and #TaxCutsandJobsAct, respectively, were posted by a legislator who voted in support of the bill. Conversely, 100% of the tweets that contained #TrumpCuts and #GOPTaxScam came from a member of congress who voted against the bill.[15] Therefore, to avoid subjectivity in the classification procedure, we classify a tweet being in support of the bill if it contains #TaxReform or #TaxCutsandJobsAct, and opposing the bill if it contains either #TrumpCuts or #GOPTaxScam.

In the second step, we measure the average effect of the politician tweet that is either in support or opposes the tax reform on the aggregate stock market. Specifically, for the aggregate stock market we take the intraday prices of the exchange-traded fund that tracks the S&P 500 stock market index (henceforth, SPY) which is obtained from the TAQ database. To clean the raw tick-by-tick series, the same procedure as in Section 2 is followed and a 90-second window around the tweet is used. Similarly, only the tweets posted during normal NYSE trading hours are used, which begin at 9:30 a.m. EST and end at 4 p.m EST.

Table E.11 presents the results. All estimated coefficients are in basis points. In regression 1 we estimate the following model of aggregate stock prices:

$$\Delta p_t = a + b^{s/c} \cdot t_{i,t}^{s/c} + \epsilon_t, \tag{E.1}$$

[15] We did not use directly the party of the politician to classify the tweets because it was not entirely a party-line vote. Although, no Democrat supported the bill, there were 13 Republicans who voted against it.

Table E.11. **Effect of politicians on returns: Tax related tweets**

Coefficient	Variable	Estimated coefficients [t-statistics]				
		(1)	(2)	(3)	(4)	(5)
a	1	0.0164 [14.448]	0.0164 [14.541]	0.0164 [14.522]	0.0164 [14.587]	0.0164 [14.573]
$b^{s/c}$	$t_{i,t}^{s/c}$	0.0746 [0.5922]				
b^{s}	$t_{i,t}^{s}$		0.3729 [2.1108]	0.3387 [1.8069]	0.2120 [1.0051]	0.1585 [0.7080]
b^{c}	$t_{i,t}^{c}$		-0.2237 [-1.4157]	-0.1567 [-0.8312]	-0.1889 [-1.0589]	-0.1234 [-0.5916]
b^{s-imp}	$I_{imp,t} \cdot t_{i,t}^{s}$			0.6251 [1.6560]		0.7613 [1.9182]
b^{c-imp}	$I_{imp,t} \cdot t_{i,t}^{c}$			-0.4745 [-2.0457]		-0.4703 [-2.0313]
b^{s-inf}	$I_{inf,t} \cdot t_{i,t}^{s}$				0.5866 [1.9035]	0.6297 [2.0241]
b^{c-inf}	$I_{inf,t} \cdot t_{i,t}^{s}$				-0.2876 [-1.0641]	-0.2795 [-0.9904]
Observations		357,815	357,815	357,815	357,815	357,815

This table reports the effect of tweets that explicitly express a view about the 2017 tax reform on the aggregate stock market. In all regressions, the dependent variable variable is the 90-second log stock price of the SPY ETF. The independent variables are a constant, $t_{i,t}^{s}$ and $t_{i,t}^{c}$ are dummy variables indicating if the politician tweet is in support or opposes the bill, an indicator for important days $I_{imp,t}$, which equals one if the tweet was posted on an important day in the legislative process, and an indicator, $I_{inf,t}$, that equals one if the tweet was posted by a politician that co-sponsored the bill or if she/he belonged either to the Committee on Ways and Means or to the Senate Finance Committee. We report t-statistics in brackets and all estimated coefficients are in basis points.

where Δp_t denotes the 90-second log aggregate stock price change and $t_{i,t}^{s/c}$ is a dummy variable that equals one if politician i tweeted at time t that was supportive or critical of the tax reform. The intercept a captures the average effect of the policy-related economic topics. When we do not condition on the direction of the tweet, the estimated coefficient $b^{s/c}$ is economically small and statistically insignificant (t-statistic = 0.59).

Regression 2 in Table E.11 conditions on the direction of the tweet:

$$\Delta p_t = a + b^s \cdot t_{i,t}^{s} + b^c \cdot t_{i,t}^{c} + \epsilon_t. \tag{E.2}$$

$t_{i,t}^{s}$ and $t_{i,t}^{c}$ are dummy variables indicating if the politician tweet is supportive or critical of the bill. A striking change is evident in the estimated coefficients. Social media post that are supportive of the tax reform increase on average valuations on the aggregate stock market index. It is 0.37 bps higher, with a t-statistic of 2.11 on the difference. Conversely, tweets critical of the reform decrease valuations. The effect is somewhat smaller of around -0.22, but not statistically significant (t-statistic = -1.4).

Next, we add one additional element to the regression to assess the extent to which the informational content of the congressional tweets differ on crucial days of the legislative process:

$$\Delta p_t = a + \left(b^s + b^{s-imp} \cdot I_{imp,t}\right) \cdot t^s_{i,t} + \left(b^c + b^{c-imp} \cdot I_{imp,t}\right) \cdot t^c_{i,t} + \epsilon_t, \tag{E.3}$$

where $I_{imp,t}$ is an indicator that equals one if the tweet was posted on an important day in the legislative process. The important days in the legislative process of the 2017 tax reform are: (1) Republicans unveil their tax plan on the 27 of September of 2017; (2) The bill was introduced in the house (11/02/2017); (3) Committee Consideration and Mark-up Session Held (Action By: Committee on Ways and Means, 11/06/2017 and 11/07/2017); (4) passed/agreed to in House (11/16/2017); (5) Passed/agreed to in Senate (12/02/2017); (6) Resolving differences between the House and Senate (12/20/2017); and (7) Signed into law by the President (12/22/2017).

Column 3 of Table E.11 presents the results. The estimates b^{s-imp} of 0.62 (t-statistic= 1.65) and b^{c-imp} of -0.47 (t-statistic= -2.04) show that a disproportionate amount of news about the provisions of the tax reform are revealed during these important days. During these days, the effect of supporting viewpoints is 0.98 bps ($= a + b^s + b^{s-imp}$), while the effect of opposing viewpoints is -0.61 ($= a + b^c + b^{c-imp}$).

Regression 4 modifies the previous specification to evaluate whether more influential politicians also have a larger market impact:

$$\Delta p_t = a + \left(b^s + b^{s-inf} \cdot I_{inf,t}\right) \cdot t^s_{i,t} + \left(b^c + b^{c-inf} \cdot I_{inf,t}\right) \cdot t^c_{i,t} + \epsilon_t, \tag{E.4}$$

where $I_{inf,t}$ is an indicator that equals one if the tweet was posted by a politician that co-sponsored the bill or if they belonged either to the Committee on Ways and Means or to the Senate Finance Committee, which are the government bodies in the House and Senate, respectively, in charge of making provisions to the tax reform. Column 4 highlights that positive viewpoints of more influential politicians have an average effect of 0.81 bps. In contrast, the point estimate effect of negative viewpoints is - 0.46 bps, but not statistically significant.