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ABSTRACT

We measure the individual and collective viewpoints of US Congress members on various economic policies by scraping their Twitter accounts. Tweets that criticize (support) a particular company are associated with a significant negative (positive) stock price reaction in a narrow time window around the tweet. A sharp partisan divide emerges, with Republicans and Democrats coordinated in both their support and opposition for different industries emanating from disparate legislative agendas. Members of congress coordinate within parties to push legislation through their social media accounts. As an illustrative and relevant example, we analyze the Tax Cuts and Jobs Act of 2017 and document significant aggregate stock market responses to the real-time evolution of partisan viewpoints about the bill.

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1 Introduction

Social media platforms have become an increasingly important tool for politicians to engage with the public and to coordinate among each other in real time. Both federal and state elected government officials actively maintain social media accounts by posting a large volume of content in a constant flow. For example, the members of congress collectively average around 30,000 tweets per month, where 20% of those posts communicate important stances on key economic agendas. 91% of these politicians tweet about a trending economic issue each month, with such tweets often eliciting the greatest amount of engagement and discord between Democrats and Republicans. Partisanship is strongly exhibited by the coordination within parties to push key agendas collectively through their social media accounts, with a particularly high volume of tweets relating to proposed legislation occurring on the corresponding roll call day. In this paper, we examine the informational content of tweets related to future economic policies, such as tax reforms or antitrust interventions. Using high-frequency asset price data, we find evidence that these tweets generate statistically significant movements in asset valuations, suggesting revisions in market expectations about future policies.

We measure individual and collective viewpoints about policy from the Twitter accounts of a comprehensive panel of US politicians at high frequencies over the past two election cycles to help address the following questions. How has partisanship among individual politicians evolved over the past decade? How do politicians interact within party and across party lines to achieve their policy objectives? To what extent can politicians influence expectations about future policies and consequently the state of the economy or the fortune of individual companies and industries? The answers to these questions highlight how social media is an important way for politicians to communicate their stance on policy in real time that can sway public opinion on key economic agendas.

Strong patterns of partisanship emerge when the tweets by members of congress are examined collectively. We find that Democrats and Republicans tend to direct support and criticism at different industries and policies. When common topics are discussed by both parties, there is substantial disagreement across parties but increasing solidarity within. We find an increasing low-frequency trend in measures of partisanship, consistent with the evidence from congressional speeches documented in Gentzkow, Shapiro, and Taddy (2019b). Over the presidential cycle, there is an increasing divergence in opinions on economic agendas across party lines in the first two years of the presidential cycle, leading to the mid-term elections, followed by a progressive decline in the last two years. Politicians with a different (same) political affiliation as the incumbent president tend to have a more negative (positive) outlook towards economic policies. Interestingly, a reversal in general outlook occurs for the same politician when the political affiliation of the president changes after an election. In sum, we find that there are rising differences in viewpoints across parties, but increasing similarity within parties for a wide range of economic agendas.

We use a high-frequency identification approach to understand whether these partisan viewpoints impact asset prices and market expectations about policies. Specifically, we use tick-by-tick asset price data to check whether tweets by politicians can move asset prices for individual companies and for the overall stock market. Given the strong degree of partisanship among members of congress, individual politician tweets about a policy or a company should encode valuable information about the overall stance of the party affiliated with the politician.

Our analysis begins by analyzing a large sample of tweets by members of congress that explicitly target individual companies. We find that posts criticizing (supporting) specific firms are associated with a statistically significant decrease (increase) in the stock price of the targeted firm in a one-minute window around the tweet, and the results are robust to various window lengths. Similar coefficient estimates are obtained if the sample is restricted to only Democrat or only Republican politicians. More influential politicians (committee chairs, party leaders of the house and senate) also have a larger average impact. Overall, the significant stock price responses suggest that these tweets induce revisions in market expectations about broader policy objectives, such as tax reforms, regulation, and antitrust policies.

The politician tweets about individual firms are then linked to broad economic agendas by sorting them into groups based on industry. A clear partisan divide emerges as Democrats tend to target different industries than Republicans and the politicians in each party are highly unified in either their support or opposition for particular industries.

For industries targeted by both parties, there is significant discord between parties, indicative of a polarizing issue. For example, Republicans strongly support the banking industry, while Democrats strongly oppose it. The tweets are also linked to specific policy reforms by extracting the most common hashtags from the collection of social media posts categorized at the industry-party level. The use of hashtags provides a direct and clean way to identify the post's topic without requiring any estimation. We find clear evidence that politician tweets that are critical (supportive) of firms within a particular industry have negative (positive) effect on their stock prices.

Members of congress also coordinate within parties to push or oppose specific legislation through their social media accounts. As an illustrative and relevant example, we analyze the *Tax Cuts and Jobs Act* of 2017. Focusing on tweets related to a particular policy reform allows us to study how partisan agendas affect market expectations about the policy reform in real time as the legislative process unfolds. We focus on tweets by members of congress relating to taxes as that is the policy instrument that is mentioned the most in our sample. The intensity of the tweets surges in the months leading up to the 2017 tax reform but with strongly opposing views across parties, identified through hashtags. The tweets by Republicans (Democrats) are overwhelmingly supportive (critical) of tax cuts and we find that they have a positive (negative) impact on the stock market. If the tweets relating the tax reform are from the accounts of politicians that co-sponsored the bill, belonged to the Committee on Ways and Means, or on the Senate Finance Committee, we find that the magnitude and statistical significance of the effects to be enhanced.

Our paper relates to the literature measuring partisanship on congressional and media platforms. Gentzkow and Shapiro (2010) and Martin and Yurukoglu (2017) analyze partisanship and political polarization from media sources such as newspapers and cable news. Greenstein and Zhu (2012) document Wikipedia entries lean Democrat on average. Gentzkow et al. (2019b) and Jensen, Naidu, Kaplan, Wilse-Samson, Gergen, Zuckerman, and Spirling (2012) measure partisanship in congressional speeches. Birney, Graetz, and Shapiro (2006) examine the role of public opinion on political legislation. We complement this literature by measuring congressional partisanship about economic agendas at high frequencies from the social media accounts of members of congress and by studying the impact of the social media posts on stock prices. Our results provide support for the view that social media can swing expectations about future policies and are therefore a powerful communication tool to convey political views.

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), Bianchi, Kind, and Kung (2019), Hoberg and Moon (2019), Kelly, Manela, and Moreira (2019), and Gentzkow, Kelly, and Taddy (2019a)) and high-frequency identification in macroeconomics (e.g., Gürkaynak, Sack, and Swanson (2005), Bernanke and Kuttner (2005) Nakamura and Steinsson (2018), and Bianchi et al. (2019)).[1] We build on this literature by highlighting that congressional tweets about policy contain important information about stock prices and risk.

More broadly, our work relates to papers examining the impact of partisanship on stock returns (e.g., Santa-Clara and Valkanov (2003), Belo, Gala, and Li (2013), Kelly, Pástor, and Veronesi (2016), and Pástor and Veronesi (2020)). These papers focus on linkages between the party of the incumbent president and aggregate stock returns. We complement this literature but differ by focusing on how partisan agendas of members of congress affect firm-level returns.

2 Data description

In this section, we provide an overview of the Twitter data used in our analysis. We first explain how we select tweets and then document patterns in the data that reveal a clear divide across party lines and fluctuations in the level of disagreement.

2.1 Congressional social media posts

Our primary data source is the complete set of tweets created by members of the U.S. Senate and House of Representatives from the 113th Congress to the 116th Congress. The prevalence of social media posts as a congressional communication tool offers several advantages in our empirical analysis relative to traditional mediums of communication.

[1] See Gürkaynak and Wright (2013) for a survey on high-frequency event studies in macroeconomics.

In particular, tweets are in a standardized format and they have a time stamp that is accurate to the second. Both of these features allow us to directly measure the individual congressional viewpoints at high frequencies.

Every official, campaign, and personal account for each congressional member are obtained from their congressional websites. We then append data on the state, party, chamber, congressional committee, rank therein, and record their entire history of legislative roll call votes. Moreover, to determine the political ideology of each member, we use the DW-NOMINATE estimates of Carroll, Lewis, Lo, McCarty, Poole, and Rosenthal (2015). DW-NOMINATE scores provide a measure of legislators' ideological locations over time by estimating how similar their voting records are. Congress members who did not list a Twitter account on their website or do not have a verified account are dropped. On average, around 85 percent of the congressional accounts are captured. Furthermore, information on institutional accounts that change hands between consecutive congressional terms are not collected such that we can link each account to a single legislator.

To extract common messages from these posts, the text is passed through a series of standard pre-processing steps. First, a list of common English words and common phrases used in social media such as "Watch LIVE on" are removed.[2] Second, URLs, links to websites, image captions, and emojis are dropped. Third, posts that contain photos or videos are eliminated, unless the posts have some useful text, such as a title or a brief description. Finally, the text is converted to lowercase font, common contractions expanded, and punctuation, hyphens, and apostrophes are deleted.

Viewed collectively, politicians generate a large amount of social media content. Overall, our dataset contains 2.5 million tweets from 740 different Twitter accounts. In a median month, the median member of congress produces 42 tweets per month with a total of 1,200 likes and retweets per tweet. Overall, these social media posts contain 77,000 unique words, written a total of 30 million times.

[2]The list of common English words that we used is from the Python Natural Language Toolkit

2.1.1 Partisan viewpoints: Categorizing the posts

We aim to capture the subset of social media posts by members of congress that contain their views about policy-related economic topics. To this end, we begin by selecting posts that contain at least one keyword associated with the following six categories: (1) government budget; (2) homeland security; (3) energy, commerce, and labor; (4) regulation; (5) corporations; and (6) healthcare. Appendix A reports the complete set of keywords included in each topic. Broadly, these posts capture directly the viewpoints of politicians and cover a wide range of topics, including opinions about tax policy (e.g., Rep Paul Ryan (SpeakerRyan) "An army of lobbyists will come to protect special interest provisions & derail #TaxReform. But conservatives cannot shrink from this moment." 12 Oct 2017, 14:05:44 EST, Tweet.) to stances about specific companies (e.g., Dem Elizabeth Warren (@ewarren) "Amazon has too much power. Under my plan to #BreakUpBigTech , entrepreneurs would have a fighting chance to compete against tech giants." 25 June 2019, 15:43:43, Tweet.)

After assigning the economic topic for each tweet, the tone of the tweet is measured (e.g., supportive, neutral, or critical stance on a particular policy), which is used to compute the extent of partisanship across key economic topics. To systematically compute the tone, lexicon developed by Loughran and McDonald (2011) is used to categorize tweets that are supportive or critical for a specific policy-related economic topic. Loughran and McDonald (2011) create word dictionaries of negative and positive words that account for the nuances of finance jargon.[3] Using these dictionaries, we then search for tweets that contain positive and negative words. A social media post by a member of congress is classified as 'critical' (or has a negative outlook towards) the associated economic topic if it includes at least one negative word. Similarly, a tweet is classified as 'supportive' (or has a favorable outlook) towards the topic if the tweet contains at least one positive word. Finally, if a post includes negative and positive words or neither, the tweet is flagged with a neutral tone. In each month, the average (median) number of tweets produced by congress that supports an economic-related topic is 707 (610), criticizes is 1539 (1255),

[3] Loughran and McDonald (2011) generate a list of 2,337 words (353 words) that typically have negative (positive) implications in a financial sense. See `https://sraf.nd.edu/textual-analysis/` for details.

and are neutral is 2382 (2316).

2.2 Variation in partisan viewpoints

We next document that our topic and tone measures fluctuate significantly at high frequencies, often varying based on current debates of policy-related issues or important events of the day. We document that within these key topics, there is substantial disagreement across parties, but increasing solidarity within. Overall, these results highlight a strong degree of partisanship, as measured directly from congressional social media accounts. We later show that updates regarding partisan viewpoints about economic policies generate significant movements in asset prices, indicating revisions in market expectations about the policies themselves. These policy interventions cover regulation, tax reforms, and the threat of antitrust intervention.

2.2.1 Trends in partisanship

Collective viewpoints. To measure the collective viewpoints, we proceed in three steps. First, only tweets by members of congress that are related to an economic topic as defined in the section above are selected. Second, for every month, the number of tweets that are either supportive or critical are separately counted, and then scaled by the total number of tweets posted during that month. Third, partisan confidence is defined as the difference between the fraction of supportive and critical tweets within a party that month. We do these three steps for Democrats and Republicans separately and we further standardize these measure.

Figure 1 plots the resulting standardized partisan confidence measure. The dashed vertical lines depict election days in the United States. Democrats exhibit a supportive attitude towards economic policies during the Obama presidency, but shifted to a critical attitude immediately after the 2016 election when Trump was elected president. We find the opposite pattern for Republicans. Appendix B shows similar partisanship patterns when we focus on each of the 6 categories of policy-related economic topics separately. The collective viewpoints from the members of congress about policy vary substantially over time and track the electoral calendar in timing. Next, we show the same pattern

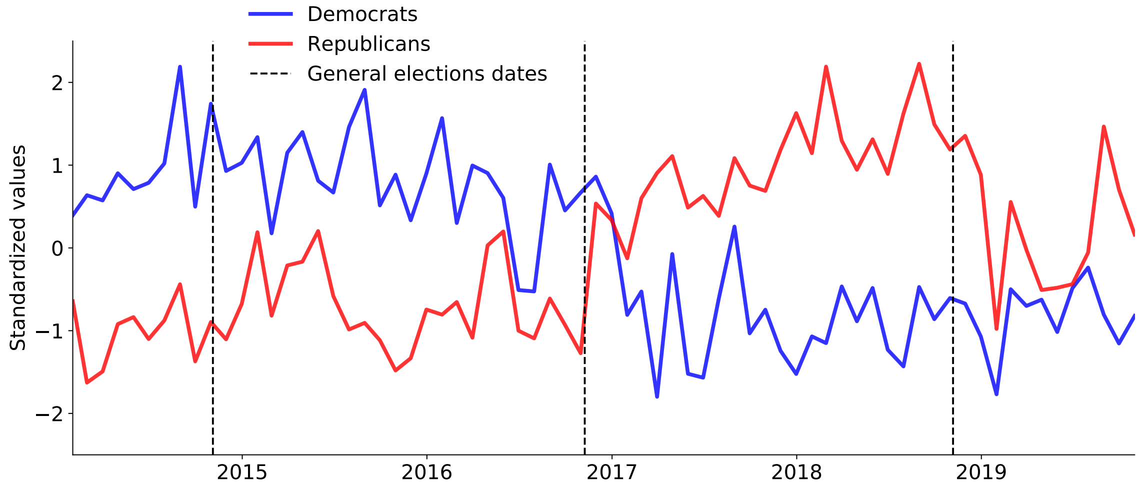

Fig. 1. **Collective viewpoints**. This figure shows the standardized partisan confidence measure. We compute this measure by taking the difference between the number of tweets that support and criticise a policy-related economic topic. We scale these difference in counts by the total number of tweets posted during that month. We further standardize the series to have a zero mean and unit variance. We report results for Democrats (blue line) and Republicans (red line) separately. 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.

holds true when we measure the individual viewpoints.

Individual viewpoints. To measure individual viewpoints, for every member of congress the number of tweets that are supportive and critical for an economic topic are counted. These counts are then aggregated at the monthly level and scaled by the total number of tweets posted by the same politician over the same month. Both Republicans and Democrats express critical and supportive views about various economic policies. On average, 17.7% of the tweets posted by a politician contained a positive word. Thus, given a typical member of congress that posts 11 tweets per month about a policy-related economic topics, 2 of those tweets have on average a positive outlook towards economic policies. The standard deviation of the tweets per month that contained a positive word is 8.9%. Similarly, the average number of tweets per politician that contained a negative word was 25.8% over the entire sample with a standard deviation of 13.1%. It follows that at the politician level, the confidence in the economic outlook (defined as the difference between the supportive and critical tweet measures) has a negative mean; that is, a typical member of congress post tweets that have about 8.1% more negative than positive words.[4]

[4]This result could be by construction, since the word dictionaries that we are using contain more

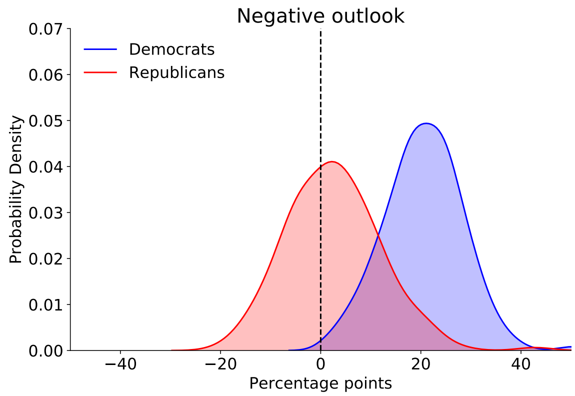

Fig. 2. **Individual viewpoints** This figure shows the probability density estimates of the difference between the percentage of tweets with negative (left panel) and positive (right panel) outlook towards economic policies after and before the 2016 presidential election. We compute this difference in percentages for each member of congress and then aggregate them out for Democrats (blue shaded area) and Republicans (red shaded area) separately. 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.

These averages hide a substantial amount of variation, both across party affiliation and over time. Figure 2 shows the probability density estimates of the difference between the percentage of tweets with negative (left panel) and positive (right panel) outlook towards economic policies after and before the 2016 presidential election. The average member of congress affiliated to the Democratic Party increased tweets with a critical outlook by 20 percentage points since 2016 – where virtually all members of the Democratic Party had more critical viewpoints about policy. In contrast, for Republicans the average negative outlook did not change after the election. Interestingly, however, the Republicans exhibit an increase in tweets that contain a positive outlook, where the average increase is 17 percentage points. Finally, Appendix B shows that the results above are robust if we focus within each of the 6 categories of policy-related economic topics independently.

Appendix B presents additional results. Salient cross-sectional patterns emerge between characteristics of the politicians and the direction of the tweets over the past two election cycles. First, politicians are more likely to tweet positively about policy-related economic topics when they are affiliated with the same party as the incumbent president. Second, individual DW-NOMINATE scores based on roll call voting data is predictive of both the direction and intensity of the tweets relative to their party. Third, we also

negative words than positive words. For our purposes, we care about the time series properties rather than the level per se.

construct a party loyalty measure based on past roll call voting patterns. Politicians that have a stronger record of voting with their party also tend to tweet more positively about policies associated with their party. Fourth, leaders of the house, senate, and standing committees tweet more positively and with greater frequency in support of agendas originating from their affiliated party. Fifth, at business cycle frequencies, we find a cyclical component in disagreement across parties that coincides with the presidential cycle where there is rising disagreement for economic policies in the first two years of the presidential cycle before declining in the last two years as shown in Figure B.3 in Appendix B.

Next, we relate tweets to congressional votes. We show that the majority of these policy-related tweets occur precisely on days of key procedural congressional votes related to substantive issues that divide parties such as taxation and budget resolutions.

2.2.2 Policy-related economic roll call votes and social media post.

To link tweets to congressional votes, we proceed in two stages. In the first stage, the roll call votes taken during the 113th-116th Congresses are linked to the policy-related economic topics. To do this, for each roll call we use their corresponding title or brief descriptions as compiled through the electronic voting machines[5] and identify roll calls that include at least one of the topic keywords described in Section 2.1.1. Broadly, these roll calls capture key bills and motions related to tax policy, budget resolutions, the national debt limit, and social welfare policy. Interestingly, these roll calls address core issues that divide parties as manifested in the ex-post vote outcomes.

A common measure of the partisan divide based on roll call voting is the *party difference measure* (e.g., Rohde, 1991; Snyder Jr and Groseclose, 2000). The party difference for a given roll call j is

$$\text{RollCall}_j = \left| \frac{1}{\#D} \sum_{i \in D} v_{ij} - \frac{1}{\#R} \sum_{i \in R} v_{ij} \right| \times 100\% \quad \text{with} \quad v_{ij} = \begin{cases} 1, & \text{if legislator } i \text{ votes yea} \\ 0, & \text{if legislator } i \text{ votes nay} \end{cases}$$

where D and R denote the set of Democratic and Republican legislators, respectively.

[5]This data can be download in a suitable format for analysis from Lewis, Poole, Rosenthal, Boche, Rudkin, and Sonnet (2018).

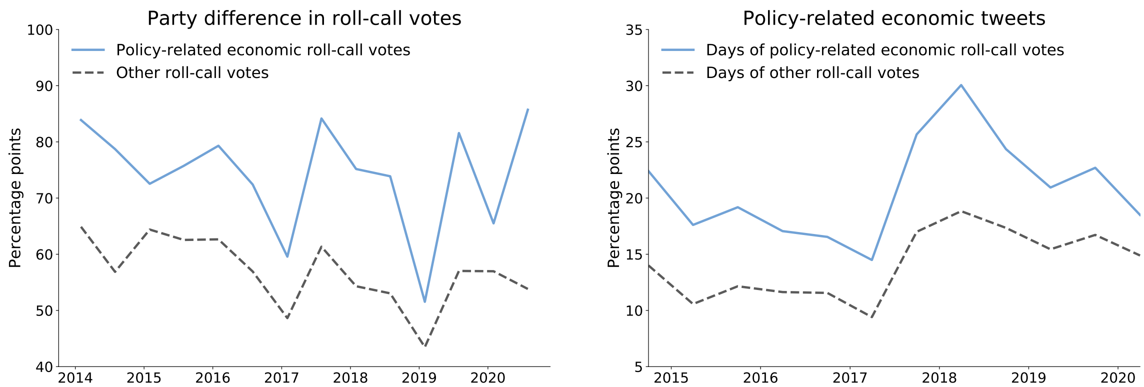

Fig. 3. **Social media posts and roll-call votes.** The left panel shows the party difference measure based on roll calls. This measure is defined as the absolute value of the difference between the percentage of Republicans who voted yea and the percentage of Democrats who voted yea. We depict this measure for roll calls related to policy-economic topics (blue line) and other type of roll calls (gray dashed line). We smooth the series by taking the average of the party difference measures in a given quarter. The right panel shows the total number of policy-related tweets as percentage of the total number of congressional tweets. We further distinguish between tweets posted during days in which a policy-related economic roll call was voted (blue line) or not (gray dashed line). Finally, we smooth both series by aggregating the daily time series to quarterly series. 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.

A value close to one implies that the vote on roll call j was lopsided across party lines. Whereas a value close to zero implies that the vote was by-partisan, with a similar fraction of yea votes in the two parties. The left panel of Figure 3 plots the party difference measures for roll calls linked to the policy-related economic topics (blue line) and any other roll call (gray dashed line). The series is smoothed by taking the average of the party difference measures in a given quarter. The basic finding is that policy-related economic roll-call votes are more contested, where the average difference is 20 percentage points.

Next, we select tweets by members of congress that contain the relevant economic keywords and were posted on the same day as the roll calls recorded in the first stage. The right panel of Figure 3 plots the total number of policy-related tweets as percentage of the total number of congressional tweets. We further distinguish between tweets posted during days in which a policy-related economic roll call was voted (blue line) or not (gray dashed line). Finally, both series are smoothed by aggregating the daily time series to quarterly series. The figure shows that there is a high volume of tweets related to proposed legislation occurring on the corresponding roll call days. This increase in tweets is also large in magnitude. For instance, over the entire sample, members of congress as a whole increase their policy-related social media content by about 10 percentage points.

Overall, these findings suggest rising differences in viewpoints across parties but increasing similarity within parties for a wide range of economic agendas. Our cross-sectional evidence illustrates how the Twitter posts by members of congress are strongly consistent with their political ideology and therefore provides representative snapshots of their viewpoints at high frequencies.

3 Partisan viewpoints and stock price responses

We next show that these partisan viewpoints have a significant effect on asset prices. Our analysis begins by analyzing a large sample of tweets by members of congress that explicitly target individual companies. We then trace out movements in asset prices at the tweet-company-level in a narrow window around the tweet.

3.1 Identifying firm mentions in congressional social media posts.

Identifying firm mentions in a congressional social media post is challenging for two reasons. First, different 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, Dem. 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, Dem. Chris Coons (@ChrisCoons) "Heading to Bridgeville for *Apple* Scrapple! #netde" 11 October 2014, 16:19:04 EST, Tweet.[6] In both of these cases, members of

[6]The Apple Scrapple Festival is held annually during the second weekend in October in Bridgeville, Delaware.

congress mentioned the word *Apple*, though neither was targeting the company. This task of identifying tweets of politicians that target specific companies would be greatly simplified, if we just search for a stock using its ticker. However, in our setting politicians seldom refer to a company by means of its ticker.

The aforementioned challenges 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 identify tweets that contained either: (1) the full company legal name or parts thereof, after removing common words such as 'Inc' or 'Corp.'[7], (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 manually went through all twenty-four thousand matches and drop those that were erroneously classified and had nothing to do with companies. In total, we drop 4,936 of observations.

The content of each tweet is further classified as follows. First, all tweets that do not directly express a view about the company are dropped. Second, the remaining tweets are sorted into three mutually exclusive categories: Supporting the firm (e.g., Rep. 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 2014, 15:58:06 EST, Tweet.), criticising the firm (e.g., Dem. Elizabeth Warren (@SenWarren) " @Walmart rakes in billions from the #GOPTaxScam and sends the profits straight to Wall Street, while many employees struggle to put food on the dinner table. These share buybacks are a perfect example of how our economy is rigged against working families." 30 May 2018 2014, 15:02:40 EST, Tweet.), or neutral (i.e., tweets that do no clearly support or criticise a company). In the Appendix, robustness checks are reported where the tweets are classified using the positive and negative word dictionaries of Loughran and McDonald (2011).

Since we are interested in studying the impact of partisan viewpoints on firm valuations, these tweets are then hand-matched with tick-by-tick data on stock prices from the

[7]For company legal name we use both CONML and CONM in Compustat.

NYSE Trade and Quote (TAQ) database. To do this, we keep all tweets posted during regular trading days from 9:30 to 16:00 Eastern Standard Time (EST) and collect the firm's ticker for all companies mentioned in our sample which we then use to merge with the TAQ data. The raw TAQ data is well known for having wrong observations, this is especially the case when working with TAQ data at the firm level. To address this issue the raw series is cleaned following procedures described in Brownlees and Gallo (2006), and then we manually go through all observations to further detect and remove wrong observations. This generates a total of 5,694 firm-tweet observations. Table B.2 in Appendix present sample statistics broken down by industries.

3.2 Response of asset prices to partisan viewpoints

A high-frequency identification strategy is used to estimate the effect of partisan viewpoints contained in the social media accounts of members of congress on asset prices. Specifically, the following equation is estimated:

$$\Delta p_{i,t} = a + b^s \cdot t^s_{i,t} + b^c \cdot t^c_{i,t} + \epsilon_t, \tag{1}$$

where $\Delta p_{i,t}$ is the change in log prices of stock i at time t. The regressors are dummy variables indicating if the politician tweet relating to firm i is supportive, $t^s_{i,t}$, or critical, $t^c_{i,t}$, and ϵ_t is the error term. The intercept a captures the average effect of a tweet that is not either supportive or critical. The parameters of interest are b^s and b^c, which measure the average marginal response of asset prices around each politician tweet depending on whether the tweet is supportive or critical. Thus, the overall effects of a supportive and critical tweet are $a + b^s$ and $a + b^c$, respectively.

We focus on movements in asset prices in a narrow window around the tweet. The identifying assumption is that there is no other relevant information being released within this short time window affecting asset prices. Log price changes are computed using a 90-second window going from 30 seconds before the tweet to 60 seconds after it. If there is not a trade at those exact seconds, we select the price associated with the last trade 30 seconds before the tweet and the first trade 60 seconds after the tweet. To ensure that the information is up-to-date, prices for which the last and first trades happened either

Table 1. **Response of asset prices to partisan viewpoints**

	Regression						
	Returns				Volatility		
Coef.	Tot (1)	Dem (2)	Rep (3)		Tot (4)	Dem (5)	Rep (6)
a	0.23	0.60	-0.33	a	2.96	3.11	2.93
	[1.44]	[2.90]	[-1.22]		[33.96]	[28.86]	[15.48]
b^s – Support	4.48	4.55	4.58	b^{s-c}	5.01	4.76	5.21
	[11.23]	[7.98]	[7.46]		[20.26]	[15.14]	[9.98]
b^c – Criticize	-8.01	-8.16	-9.04		–	–	–
	[-13.29]	[-15.60]	[-5.73]		–	–	–
nObs	5,694	2,434	1,998		5694	2434	1998

This table reports the effect of tweets by members of congress that explicitly target individual companies on the stock price of the targeted firm. For the first three regressions, the dependent variable is the 90-second stock price change of the targeted firm, while the regressors are dummy variables indicating if the politician tweet is in support or criticises the targeted firm. The constant in this regression measures the average effect of the tweets by members of congress that do no clearly support or criticise a company. For the last three regressions, the dependent variable is the absolute value of the 90-second stock price change of the targeted firm, while the regressor is a dummy variables indicating if the politician tweet is either in support or against the targeted firm. We double cluster the standard errors at the day-politician level. We report t-statistics in brackets and all numbers are in basis points.

60 minutes or more before and after the tweet are disregarded, respectively. After all of these considerations, the average window goes from 37 seconds before the tweet to 67 seconds after it.

Table 1 presents the estimates. We estimate equation (1) by running a pooled panel regression, where we double cluster the standard errors at the day-politician level. We report t-statistics in brackets and all numbers are in basis points (bps).

The first column of Table 1 shows that there is a statistically significant relation between the tweets targeting a specific firm and the corresponding stock price. We find that, on average, posts that criticize particular firms are associated with a statistically significant decrease in the stock price of the targeted firm. The coefficient estimate for b^c of -8 bps (t-statistic = -13) shows that stock prices fall by an average of -7.78 bps ($= a + b^c$). Conversely, when members of congress support a specific firm we find that stock prices tend to increase by 4.71 bps ($= a+b^s$). The point estimate for the constant, a, is just above 0, but not statistically significant. The constant in this regression measures the average effect of the tweets by members of congress that do not clearly support or criticise a company. As shown in regressions (2) and (3), the point estimates are remarkably similar if we restrict the sample to only Democrat or Republican politicians. This suggest that our results are not driven by one specific party in particular.

The average absolute price variation around the politician tweets is estimated next. Specifically, the following regression is run:

$$|\Delta p_{i,t}| = a + b^{s-c} \cdot t_{i,t}^{s-c} + \epsilon_t, \tag{2}$$

where $t_{i,t}^{s-c}$ is the dummy variable that equals one if the politician tweet is support or criticises firm i. Column (4) presents the estimates, where again we double cluster the standard errors at the day-politician level are clustered and t-statistics are reported in brackets. The average effect is positive and statistically significant. The magnitude of the effect is large – a congressional social media posts that targets specific company generates an increase of about 62% in the absolute average price variation. Columns (5) and (6) show similar results when the focus is on the tweets made by politicians from each party separately.

Results in Section 2 illustrate that social media posts by members of congress contain a strong degree of partisanship. Moreover, as shown above, posts that target a specific company have a substantial effect on the stock price of the targeted company. Next, the politician tweets targeting specific companies are linked to broader partisan agendas.

3.3 Partisan viewpoints and agendas across industries

How do partisan agendas impact market expectations about future economic policy? To tackle this question, we condition on policy agendas systematically targeting particular industries. To this end, we sort the tweets targeting companies into different industries. An analysis of the text contained in the tweets grouped in industries allows us to relate to broader policy objectives. We find large differences in attitudes towards industries across parties but strong unanimity within. Movements in asset prices are then analyzed in a narrow window around these viewpoints. Finally, these viewpoints across sectors are linked to specific partisan agendas.

Social media post are categorized as follows. Each company in our dataset is assigned to an industry based on their four-digit SIC code. The industry definitions are provided on Kenneth French's website. The average partisan viewpoint about industry j is computed by taking the difference between the sum of the tweets that are supportive and the sum of the tweets that are critical about firms in the industry. This measure is then scaled by the total number of tweets assigned to industry j. A positive value means that on average politicians tweet more in support of industry j. In contrast, negative values imply that members of congress tend to criticise that specific industry.

To measure the effect of partisan viewpoints on asset prices, for each industry, the following panel regression is estimated:

$$\Delta p_{i,t}^{ind-j} = a^{ind-j} + b^{ind-j} \cdot t_{i,t}^{ind-j} + \epsilon_{ind-j,t}, \tag{3}$$

where the time unit t is the exact time of the tweet. The dummy variable, $t_{i,t}^{ind-j}$, equals one if the politician either supports or criticises firm i in industry j. $\Delta p_{i,t}^{ind-j}$ denotes the corresponding change in log stock prices in a small time window around the tweet. A negative (positive) coefficient $b^{ind-j} < 0$ ($b^{ind-j} > 0$) implies that tweets by members of congress decrease (increase) on average stock prices assigned to industry j. The intercept a^{ind-j} captures the average effect of a the tweets that are neutral about firms in industry j.

In Figure 4, the average tick-by-tick stock price change is displayed (i.e., $a^{ind-j}+b^{ind-j}$) as a function of the average partisan viewpoints. Each circle corresponds to one industry and binned scatter plots broken down by political parties are presented.

A striking pattern in partisan viewpoints emerge once the tweets targeting individual firms are aggregated at the industry level. Republicans tweet more negatively about the Printing and Publishing industry (hereafter referred to simply as Books) and the Business Services sector (BusSv), whereas they tweet more positively about Banking (Banks), Communication (Telcm), Restaurants and Hotels (Meals), Retail (Rtail), and Automobiles (Autos). Conversely, Democrats most frequently attack firms in the Banks, Telcm, BusSv, and Pharmaceutical Products (Drugs) sectors, while they typically support firms in the Autos, Rtail, Electronic Equipment (Chips), and Consumer Goods (Hshld) industries.

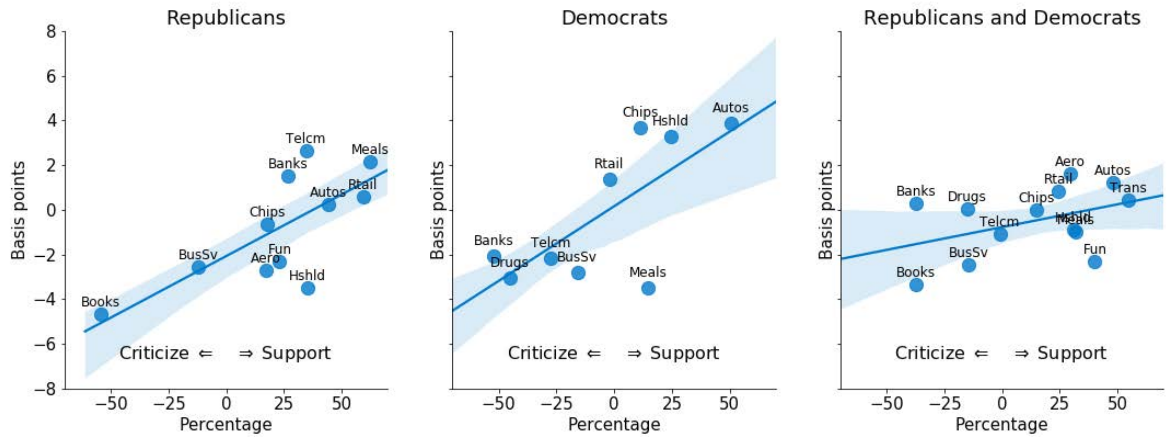

Fig. 4. **Partisan viewpoints toward industry sectors and industry returns.** This figure shows the average tick-by-tick stock price change as a function of the average partisan viewpoints. Each dot corresponds to one industry and we present binned scatter plots broken down by political parties. For each industry, we compute the average partisan viewpoint by taking the difference between the sum of tweets that are in support and the sum of tweets that criticise specific firms. We then scale this measure by the total number of tweets assigned to that specific industry. The x-axis reports this measure and it's in percentage points. To compute the average tick-by-tick stock price change, we run the following regression:

$$\Delta p_{i,t}^{ind-j} = a^{ind-j} + b^{ind-j} \cdot t_{i,t}^{ind-j} + \epsilon_{ind-j,t},$$

where $\Delta p_{i,t}$ denotes the 90-second log stock price change of the targeted firm and $t_{i,t}^{ind-j}$ is a dummy variable that equals one if the politician tweet mentions firm i in industry j. The y-axis reports the average stock price change (i.e., $a^{ind-j} + b^{ind-j}$) in basis points.

For firms in a few industries that are targeted by both parties, there is significant discord between parties, indicative of a polarizing issue. For example, Republicans strongly support Banks and Telcm, while Democrats strongly oppose both.

As shown in the figure, for both parties the range in partisan viewpoints is quite wide and goes from around -54 percentage points to 62 percentage points. This wide spread in partisan viewpoints serves our empirical approach well as, if any, the wider the spread, the wider the differential impact on industry returns from changes in partisan viewpoints, all else being equal. Indeed, the variation in industry returns ranges from -5 basis points to 3 basis points for Republicans and goes from -4 basis points to +4 basis points for Democrats.

Once the regression is conditioned on political party, a strong positive relation between the industry returns and the partisan viewpoints measure emerges as shown in the first two panels of Figure 4 and highlighted by the positive slope of the regression line. Table 2 shows the regression estimates of industry returns on partisan viewpoints by party. For both Republicans and Democrats, a one standard deviation increase in the measure of

Table 2. **Partisan viewpoints toward industry sectors and industry returns**

	Regression		
Coef.	Republicans (1)	Democrats (2)	Republicans and Democrats (3)
Constant	-2.05	0.50	-0.76
	[-2.68]	[0.58]	[-1.65]
Partisan viewpoints	0.06	0.07	0.02
	[3.16]	[2.71]	[1.48]
R-squared	0.58	0.51	0.18

This table reports estimates from OLS regressions. The dependent variable is the average industry return computed as in equation (3) in the main text. The independent variable is the average partisan viewpoints toward industry sectors. We report t-statistics in brackets using robust standard errors.

partisan viewpoints increases industry returns by around 2 basis points. Moreover, this factor explains above 50 percent of the differential impact on industry returns, as shown in the bottom row of the table.

A clear partisan divide emerges as Democrats tend to target different industries than Republicans and the politicians in each party are highly unified in either their support or opposition for particular industries. To show this, we present results where we do not condition on the political party. The third scatter-plot of Figure 4 shows that the strong monotonic relationship between the partisan viewpoints and industry returns previously documented disappears when we do not condition on the political party. Regression estimates in the third column of Table 1 confirm this message: the slope is 0.02 with a t-stat of 1.48. In other words, partisan viewpoints are strongly related to industry returns, but only when we condition on the political party. This is one of our most striking findings.

3.3.1 Inferring partisan agendas from partisan viewpoints

Partisan viewpoints are linked to specific agendas and policy reforms. To show this, we leverage the specific structure of our dataset and extract the most common hashtags from the collection of social media posts, organizing by industry and by party. These hashtags are then linked to partisan agendas and policy reforms. The use of hashtags is

Table 3. **Most common hashtags by Industry and Party**

Republicans			Democrats		
Industry	hashtag	Percentage	Industry	hashtag	Percentage
		Disagreement between parties			
Banks	#TaxReform	25.93	Banks	#GOPTaxScam	15.38
	#TaxCutsandJobsAct	14.81		#BankLobbyistAct	7.69
	#TaxRelief	7.41		#ConsumersFirst	7.69
	#ProGrowth	3.70		#DoddFrankRollback	4.62
	#SmallBusiness	3.70		#WithABuckFiftyAWeek	4.62
		Solidarity between parties			
BusSv	#StopTheBias	4.68	BusSv	#Facebook	4.74
	#Facebook	4.42		#BreakUpBigTech	4.28
	#ZuckerbergHearing	3.90		#Zuckerberg	3.36
	#China	2.60		#CambridgeAnalytica	2.14
	#Google	2.34		#HonestAds	1.83
		To each party its own			
Books	#FakeNews	18.75	Drugs	#GOPTaxScam	19.51
	#Republican	12.50		#BigPharma	9.76
	#Kentucky	6.25		#SOTU	4.88
	#SchumerShutdown	6.25		#ABetterDeal	4.88
	#Israel	6.25		#EndRxMonopolyPrices	2.44

The table shows for each industry the most common hashtags used by Republicans and Democrats. We also report the hashtag count scale by the sum of all hashtags used in each sector.

useful for our purposes because it provides a direct and clean way to identify the topic of the post without requiring any estimation.

Table 3 lists the five most common topics discussed by each political party and for four different industries. The appendix presents the list of topics discussed for the remaining industries. It turns out that the most popular topics in each industry align closely with specific partisan agendas and policy reforms. These results together with the significant stock price responses documented above, suggest that these tweets by members of congress are tightly linked to revisions in market expectations about broader policy objectives. In the appendix, each hashtag is described in detail, while below we highlight few examples.

There is significant discord in partisan viewpoints about firms in the Banking sector. The difference in opinion arises mostly on common issues that tend to divide parties the most, like taxation. Republican legislators used hashtags such as #TaxReform,

#TaxCutsandJobsAct, and #TaxRelief to support the Tax Cuts and Jobs Act of 2017. Democrats strongly opposed this legislation through the use of the opposing hashtag #GOPTaxScam. High-tax firms in the Banking industry had a particularly big exposure to these proposed tax cuts and, therefore, to the related partisan viewpoints. In the next section, this tax reform is analyzed in detail and we link aggregate market price movements at high frequencies to the legislative history of the bill and to the substantial uncertainties therein.

Bipartisanship is exhibited for some industries, such as, the business services sector. Certain topics (#Facebook, #Google,#ZuckerbergHearing, #Zuckerberg, #BreakUp-BigTech) reflect bipartisan consensus on antitrust lawsuits. Collectively, the social media posts by members of congress reflect their concerns about the increasingly dominant role that online platforms exert and imply significant regulatory challenges for the targeted firms such as Amazon, Apple, Facebook, Google, or Microsoft. Republican lawmakers also used the hashtag #StopTheBias to target big tech companies of biases against their viewpoints. Democrats in the U.S. Senate and some Republican senators used the hashtag #HonestAds in support of a bill called the "Honest Ads Act" that regulates political ads and help prevent foreign interference in U.S. elections.

Firms in other industries tend to be targeted only by a single party. For instance, Republicans use #FakeNews to attack firms in the printing and publishing industry. By contrast, Democrats used #BigPharma and #EndRxMonopolyPrices to criticise firms in Pharmaceutical sector and to push legislative proposals aiming to reduce the industry's prices and profits.

4 Partisan viewpoints within policy reforms

The results in Section 3 demonstrate how members of congress coordinate support and opposition within and across party lines for different industries, originating from disparate legislative agendas. Moreover, these partisan viewpoints have a significant effect on industry returns once we conditioned on the political party. In this section, we condition on each legislative agenda and identify –within a specific policy reform– the effect of partisan viewpoints on stock prices.

Our analysis focuses on the Public Law 115–97, commonly referred to as the Tax Cuts and Jobs Act (henceforth TCJA) or the 2017 tax reform.[8] This tax reform is used as an illustrative case of how members of congress can influence expectations about policy by communicating their stance in real time through their social media accounts. The 2017 tax reform is one of the most important bills in our sample since it made the largest changes to the US 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 US corporate tax system, including a reduction in the federal corporate tax rate from 35 percent to 21 percent.[9] 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).[10] 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.

[8]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."

[9]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`.

[10]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/`.

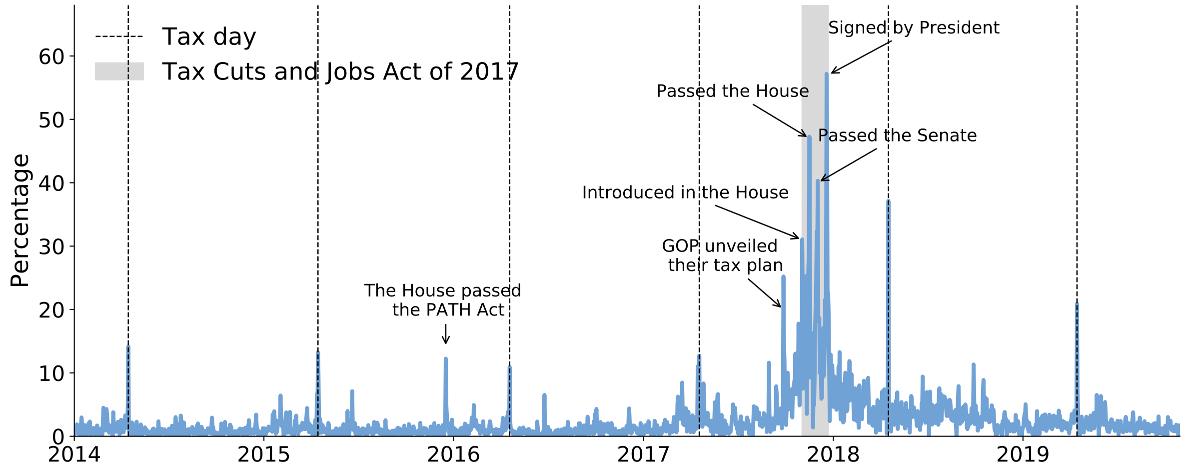

Fig. 5. **Tax-related posts.** This figure shows the percentage of congressional post containing tax related word or hashtag, such as "tax", "taxation", and "#TrumpCuts" in a given day. The gray shaded area in the figure highlights the time the bill spent in Congress till it became Public Law. We use 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.

4.1 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. The main advantage of this approach is that congressional social media posts provide representative snapshots of their viewpoints at high frequencies. Importantly, we show that these partisan viewpoints about policy generate significant revisions in market expectations.

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 5 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. Noteworthy, this spike in tweet intensity confirms the message of Section 2.2.2 that documented a high volume of tweets related to proposed legislation occurring on the corresponding roll call days. 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.

4.2 Corporate taxes and the aggregate market: A high-frequency identification approach

To what extent can politicians influence market expectations about policy? To answer this question 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.

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.[11]

[11] We did not use directly the party of the politician to classify the tweets because it was not entirely

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 3.1 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 4 presents the results. All estimated coefficients are in basis points. In regression 1 we estimate the following model of aggregate stock prices:

$$\Delta p_t = a + b^{s/c} \cdot t_{i,t}^{s/c} + \epsilon_t, \tag{4}$$

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 4 conditions on the direction of the tweet:

$$\Delta p_t = a + b^s \cdot t_{i,t}^s + b^c \cdot t_{i,t}^c + \epsilon_t. \tag{5}$$

$t_{i,t}^s$ 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 basis points higher, with a t-statistic of 2.11 on the difference. Conversely, tweets critical of the reform decrease valuations. The effect is

a party-line vote. Although, no Democrat supported the bill, there were 13 Republicans who voted against it.

Table 4. **Effect of politicians on returns: Tax related tweets**

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

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:

$$\Delta p_t = a + \left(b^s + b^{s-imp} \cdot I_{imp,t}\right) \cdot t_{i,t}^s + \left(b^c + b^{c-imp} \cdot I_{imp,t}\right) \cdot t_{i,t}^c + \epsilon_t, \tag{6}$$

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) passed/agreed to in House (11/16/2017); (4) Passed/agreed to in Senate (12/02/2017); (4) Resolving differences between the House and Senate (12/20/2017); and (5) Signed into law by the President (12/22/2017).

Column (3) of Table 4 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 basis points ($= a + b^s + b^{s-imp}$), 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:

$$\Delta p_t = a + \left(b^s + b^{s-inf} \cdot I_{inf,t}\right) \cdot t^s_{i,t} + \left(b^c + b^{c-inf} \cdot I_{inf,t}\right) \cdot t^c_{i,t} + \epsilon_t, \tag{7}$$

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 basis points. In contrast, the point estimate effect of negative viewpoints is - 0.46 basis points, but not statistically significant.

Overall, these results suggest that members of congress coordinate within parties to push legislation through their social media accounts. Given the strong degree of partisanship among policymakers, individual politician tweets about policy encodes valuable information about the overall stance of the party affiliated with the politician.

5 Conclusion

Strong patterns of partisanship emerge when the tweets by members of congress are examined collectively. This measure of partisanship fluctuates significantly at high-frequencies on current debates of policy-related issues and important events of the day such as roll call votes. Republicans and Democrats are highly coordinated in both their support and opposition for different economic agendas and generate a significant revision in market expectations about future policy. Using tick-by-tick asset price data and a high-frequency identification approach, we document that these partisan viewpoints impact asset prices at the firm, industry, and the aggregate level. Our results provide support for the view that social media can swing expectations about future policies and are therefore a powerful communication tool to convey political views. We provide direct evidence that members of congress affect asset prices.

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Appendix A Words used in the policy-related economic topics

Next we present the keywords that we used for each category. To assign the hashtags to each category we proceeded in two steps. First, we search for the most common hashtags used by all members of congress. Second, we manually classify each one of these common hashtags into one category.

- **Government budget:** taxes, tax, taxation, taxed, tariff, tariffs, government spending, federal budget, budget battle, balanced budget, defense spending, military spending, entitlement spending, fiscal stimulus, budget deficit, federal debt, national debt, debt ceiling, fiscal footing, government deficits, balance the budget, fiscal stimulus, debt ceiling, debt limit, welfare, food stamps, AFDC, tanf, oasdi, earned income tax credit, EITC, public assistance, head start program, entitlement program, wic program, government subsidies, deficit, budget, national debt, federal debt, sovereign debt, government policy, public policy, government spending, government expenditures, entitlement spending, entitlement expenditures, unemployment insurance, unemployment benefits, disability insurance, disability benefits, welfare reform, fiscal stimulus, Fiscal stimulus, fiscal policies, fiscal policy, fiscal reform
  - **Related hashtags:** #TaxDay, #taxreform, #TaxReform, #TaxCutsandJobsAct, #TrumpCuts, #GOPTaxScam, #IRS,#TrumpShutdown, #TrumpBudget, #SchumerShutdown, #EndTheShutdown, #budget, #DontShutDownOurSecurity, #StandWithPP.
- **Homeland security:** national security, war, military conflict, terrorism, terror, defense spending, military spending, police action, armed forces, base closure, military procurement, saber rattling, naval blockade, military embargo, no-fly zone, military invasion, national security, military invasion, military conflict, military embargo, military procurement, war, armed forces, police action, base closure, saber rattling, naval blockade, no-fly zone, defense spending, defense expenditures, military spending, military expenditures
  - **Related hashtags:** #NDAA, #SecDef, #ISIL, #ISIS, #Benghazi, #Ukraine, #NorthKorea, #Syria, #Iran, #IranDeal.
- **Energy, commerce, and labor:** carbon tax cap, pollution controls, environmental restrictions, clean air act, clean water act, energy policy, drill restrict, import tariffs, import duty, import barrier, government subsidies, government subsidy, wto, world trade organization, trade treaty, trade agreement, trade policy, trade act, doha round, uruguay round, gatt, dumping, trade policy, trade act, trade agreement, trade treaty, duty, duties, import tariff, import barrier, minimum wage, minimum wage, union rights, card check, national labor rel. board, nlrb, collective bargaining, right to work, closed shop, worker compensation, maximum hours,

wages and hours, advanced notice requirement, affirmative action, overtime requirements, at-will employment, equal employment opportunity, eeo, osha, immigration, unemployment insurance, unemployment benefits,

  - **Related hashtags:** #JobsReport, #jobs, #RaiseTheWage, #climatechange, #ClimateChange, #energy, #GreenNewDeal, #ParisAgreement, #ActOnClimate, #EPA, #KeystoneXL, #China, #Russia, #USMCA, #TPP.

- **Regulation:** banking supervision, bank supervision, glass-steagall, tarp, thrift supervision, dodd-frank, financial reform, commodity futures trading commission, cftc, house financial services committee, basel, capital requirement, Volcker rule, bank stress test, securities and exchange commission, sec, deposit insurance, fdic, fslic, ots, occ, firrea, truth in lending, union rights, card check, collective bargaining law, national labor relations board, nlrb, minimum wage, living wage, right to work, closed shop, wages and hours, workers compensation, prescription drugs, drug policy, food and drug admin, FDA, Gramm- Rudman, Bank supervision, thrift supervision, malpractice reform, constitutional re- form, financial reform, medical insurance reform, welfare reform, tort reform, constitutional amendment, Glass-Steagall, Dodd-Frank, housing financial services committee, capital requirement, security exchange commission, sec, deposit insurance, fdic, fslic, ots, occ, firrea, truth in lending, monometallist, bimetallist, silver coinage, gold coinage, alcohol prohibition, liquor prohibition, bill

  - **Related hashtags:** #EqualityAct, #RenewUI, #VAWA, #FarmBill, #NetNeutrality, #EqualPay, #SCOTUS, #EnoughIsEnough, #EndGunViolence, #gunviolence, #DisarmHate, #NoBillNoBreak, #SOTU.

- **Healthcare:** health care, Medicaid, Medicare, health insurance, malpractice tort reform, malpractice reform, prescription drugs, drug policy, food and drug administration, FDA, medical malpractice, prescription drug act, medical insurance reform, medical liability, affordable care act, Obamacare, health care, social security, Medicare, Medicaid, affordable care act, nutritional assistant program, health insurance, health benefits, medical insurance reform, constitutional reform

  - **Related hashtags:** #Trumpcare, #TrumpCare, #MedicareForAll, #ProtectOurCare, #AHCA, #GetCovered, #ACA, #healthcare, #Medicaid, #Obamacare, #SocialSecurity, #ObamaCare, #GrahamCassidy, #PayMoreForLess, #CHIP

- **Corporations:** For each company listed in the CRSP dataset, we searched the legal company name, as well as common variations of the name. This search produced a total of 24,032 matches. A team of research assistants read these 24,032 tweets and found 4,936 matches that were erroneously classified, which we drop from the sample. These false positive mainly arise because we search for common variations of the company names. For example, when looking for tweets that mention the company *Apple Inc.*, we search for *apple* too, which gave rise to the following false positive: Senator Chuck Grassley (@ChuckGrassley) "Every so often senators have the chance to host Thursday Lunch Group w our caucus 2day was my turn so I served a typical Iowa meal: pork chop green beans potatoes *apple* crisp + ICE CREAM" 2 July 2018, 18:52:26 EST, Tweet.

Appendix B Additional results

B.1 Disagreement across parties and solidarity within parties

We present robustness to the set of categories used in the policy-related economic topics. Specifically, we replicate Figure 1 and Figure 2 of the main text, but considering only tweets that contain at least one keyword associated with our 6 categories. By and large, we find similar patterns when we restrict the post by each category separately.

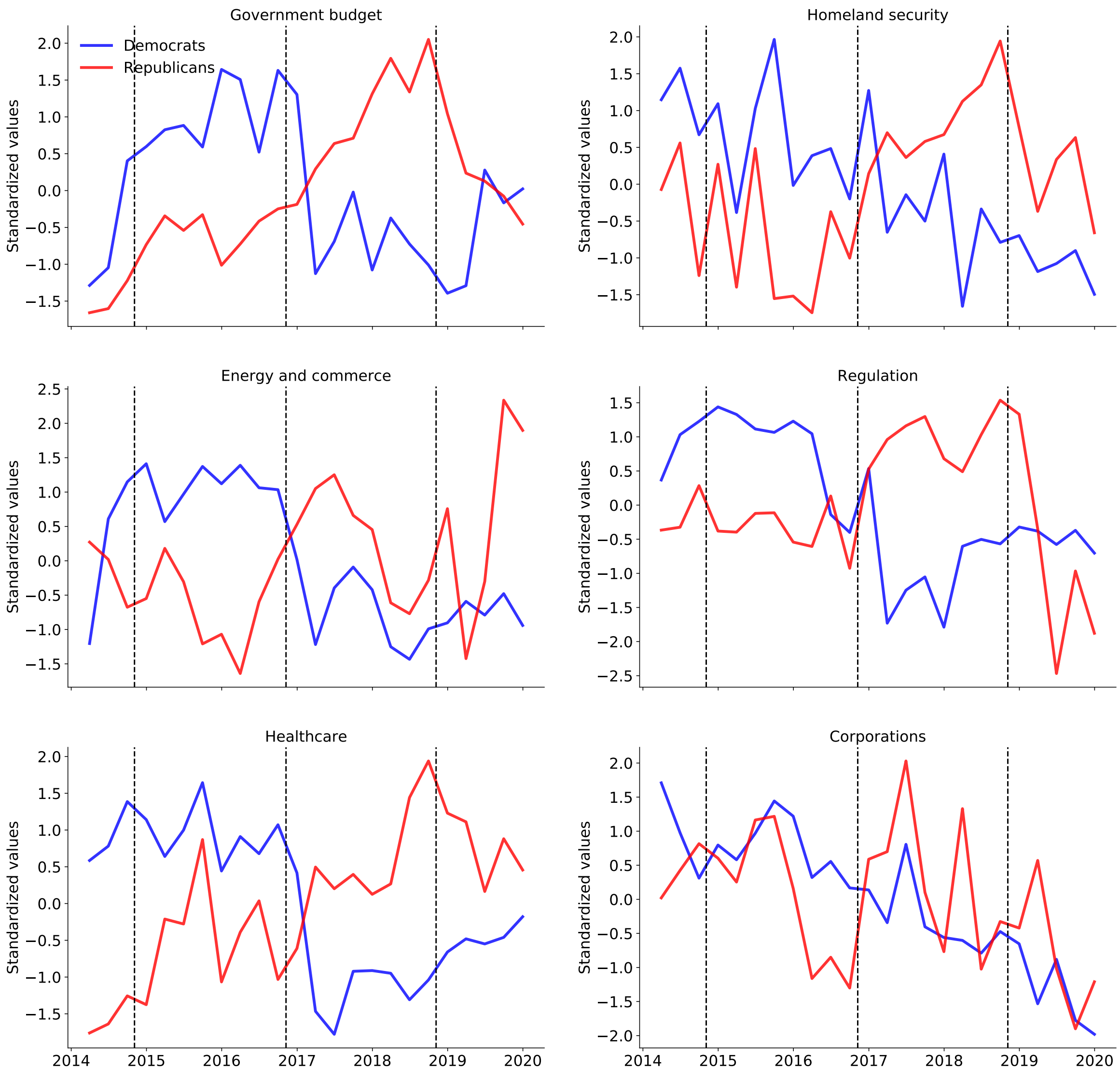

Fig. B.1. **Collective viewpoints by category** This figure shows the standardized partisan confidence measure. We compute this measure by taking the difference between the number of tweets that support and criticise a policy-related economic topic. We scale these difference in counts by the total number of tweets posted during that month. We further standardize the series to have a zero mean and unit variance. We report results for Democrats (blue line) and Republicans (red line) separately. 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.

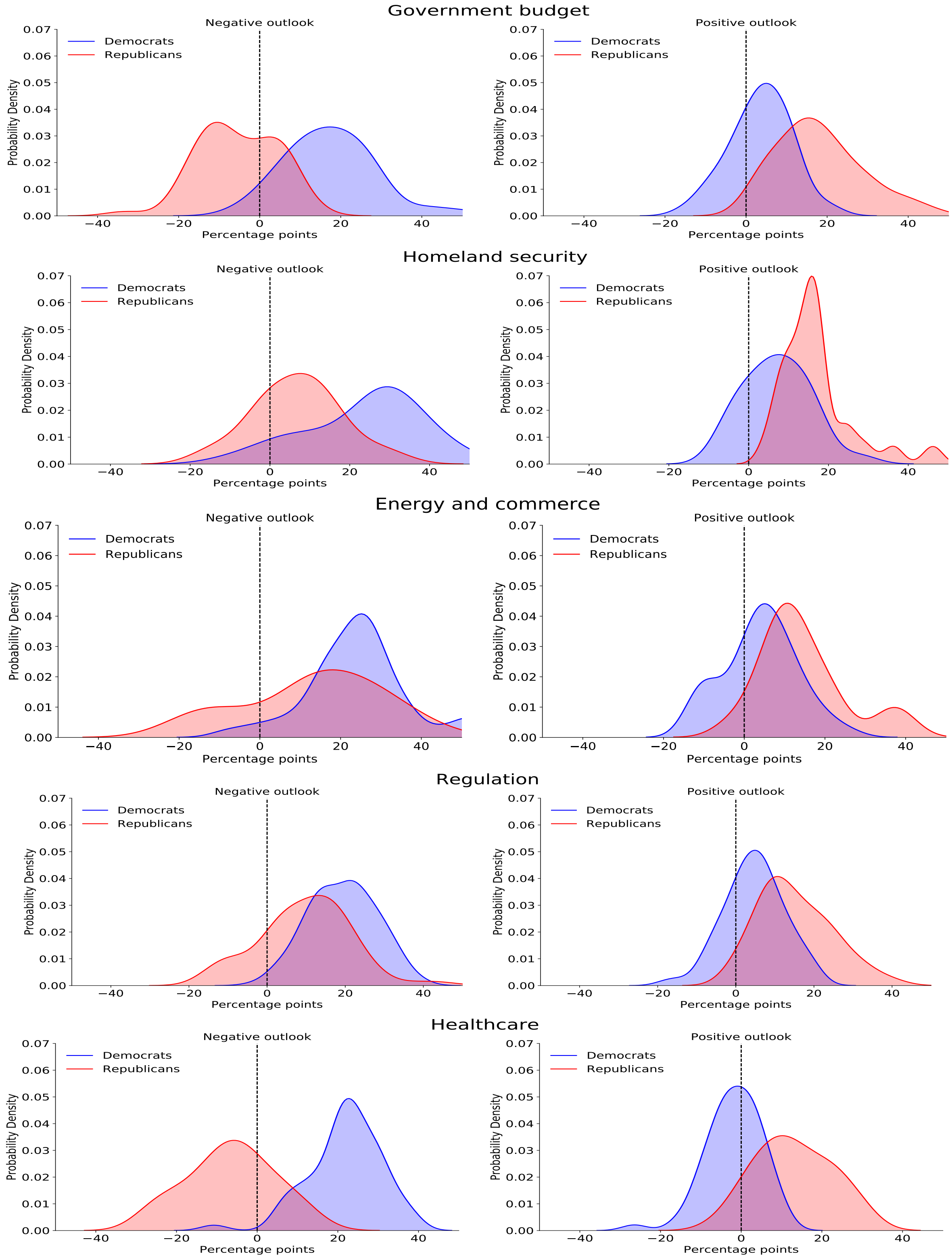

Fig. B.2. **Individual viewpoints by category** This figure shows the probability density estimates of the difference between the percentage of tweets with negative (left panel) and positive (right panel) outlook towards economic policies after and before the 2016 presidential election. We compute this difference in percentages for each member of congress and then aggregate them out for Democrats (blue shaded area) and Republicans (red shaded area) separately. 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.

B.2 Measuring Partisanship: Cross-sectional evidence.

In this section, we focus on the relation between characteristics of the members of congress and the tone of the tweet. More specifically, we consider how the tone of the tweet of legislator i is related to: (1) party affiliation, (2) political ideology, (3) political rank, and (4) party loyalty.

The benchmark regression model is:

$$t_{i,t} = a + bD_{i,t} + \epsilon_{i,t}, \tag{B.1}$$

where $t_{i,t}$ takes a value of 1 (-1) if the tweet if legislator i at time t contains a topic keyword and a positive (negative) word, and takes a value of 0 otherwise. $D_{i,t}$ denotes a dummy variable specific to each regression specification. In all regressions we double cluster the standard errors at the date-legislator level. Table B.1 presents model estimates, and we discuss below the results.

Party affiliation. To test whether party affiliation is related to the tone of the tweet, we consider two different model specifications for equation B.1. In the first one, the dummy variable $D_{i,t}$ takes a value of 1 if politician i belongs to the party that has majority in her/his chamber and a value of 0 otherwise. In the second one, the dummy variable $D_{i,t}$ takes a value of 1 if politician i is affiliated with the same party as the incumbent president and 0 otherwise. Columns (1) and (2) of Table B.1 present the estimated coefficients. The estimated coefficient for the second specification is positive and statistically significant, indicating that members of congress are more likely to tweet positively about policy-related economic topics when they are affiliated with the same party as the incumbent president. Interestingly, if politician i belongs to the party that has

Political ideology. We extent the previous model specification, where we interact the dummy variable "Party president" that takes a value of 1 if politician i is affiliated with the same party as the incumbent president and 0 otherwise with the absolute value of her/his DW-NOMINATE score from the roll call voting data. We add an extra dummy variable, "Not party president" that takes a value of 1 if politician i does not belong to the party of the president and, similarly, we interact the dummy with the absolute value of her/his DW-NOMINATE score. The estimated coefficients suggest that DW-NOMINATE scores based on roll call voting data is predictive of both the direction and intensity of the tweets relative to their party.

Political rank. The model estimated is identical to the one in Specification (4), but instead of interacting the dummy variables with the DW-NOMINATE scores, we flag if politician i are leaders of the house, senate, and standing committees. The estimated coefficients suggest tweet with greater frequency in support of the agendas originating from their affiliated party;

Party loyalty. We also construct a party loyalty measure based on past roll call voting patterns. Specifically, for each legislator we compute the percentage of times she/he vote in line with her/his party over the her/his entire career.[12] Note, a member voted with her/his party if she/he cast a similar vote to the majority of their party. We then

[12] We find similar results if instead we compute the percentage of times she/he vote in line with her/his party for each congress.

Table B.1. **Measuring Partisanship: Cross-sectional evidence**

	(1)	(2)	(3)	(4)	(5)
Chamber majority	-4.5287				
	[-0.9312]				
Party president		10.463			
		[2.9129]			
Party president $\times$|DW-score|$_i$			2.0354		
			[0.2471]		
Not party president $\times$|DW-score|$_i$			-25.598		
			[-4.9192]		
Party president and leader				6.0983	
				[1.3835]	
Not party president and leader				-10.678	
				[-3.3034]	
Party president and party loyalty					15.752
					[2.8673]
Const	-18.580	-24.549	-16.996	-20.254	-29.033
	(-7.2726)	(-7.3878)	(-5.1374)	(-8.5310)	(-6.9734)
Observations	3,480	3,480	3,480	3,220	3,480

The dependent variable is our measure of disagreement. The independent variables are (1) $I_{i_p,chamber_p}$ dummy variable that takes a value of 1 if politician i belongs to party p and is in chamber j (either senate or house) and the party majority of chamber j is party p. (2) $I_{i_p,president_p}$ dummy variable that takes a value of 1 if politician i has the same party affiliation as the president. (2) and (3) We interact the dummy $I_{i_p,president_p}$ with the absolute value of the politician i DW-nominate score. $I_{i_p,president_{not-p}}$ dummy variable that takes a value of 1 if politician i has a different party affiliation as the president. (4) and (5) we consider only politicans that were leaders of the house, senate or a committee. (6) and (7) we consider the politicans that wanted to impeach Trump. (6) we only consider the cabinet accounts. These accounts are managed by the party associated to the presidency.

interact this party loyalty measure with the "Party president" dummy variable. The coefficient is positive and statistically significant, suggesting that members of congress that have a stronger record of voting with their party also tend to tweet more positively about policies associated with their party.

Table B.2. **Summary Statistics: Firms mentioned in politician tweets**

	Number of tweets			Number of firm mentions		Average size	Sentiment	
Industry	Tot	Dem	Rep	Average	Unique	(millions)	Dem	Rep
BusSv	2881.00	1778.00	1103.00	92.94	31	372110.27	-0.16	-0.12
Rtail	1044.00	592.00	452.00	47.45	22	485573.96	-0.02	0.59
Autos	445.00	273.00	172.00	44.50	10	50140.00	0.51	0.44
Banks	434.00	352.00	82.00	15.50	28	226142.20	-0.52	0.27
Telcm	393.00	225.00	168.00	43.67	9	166406.10	-0.28	0.35
Chips	359.00	161.00	198.00	25.64	14	661321.86	0.11	0.18
Aero	357.00	126.00	231.00	89.25	4	107454.53	0.52	0.17
Meals	326.00	209.00	117.00	40.75	8	70201.74	0.15	0.62
Books	230.00	85.00	145.00	115.00	2	4014.04	-0.08	-0.54
Trans	186.00	66.00	120.00	15.50	12	47721.02	0.12	0.78
Hshld	148.00	57.00	91.00	24.67	6	16973.12	0.25	0.35
Drugs	138.00	102.00	36.00	9.86	14	201840.02	-0.45	0.69
Fun	137.00	85.00	52.00	45.67	3	68596.28	0.51	0.23

Each company in our dataset is assigned to an industry based on their four-digit SIC code. The industry definitions are provided on Kenneth French's website. The average partisan viewpoint about industry i is computed by taking the difference between the sum of the tweets that are supportive and the sum of the tweets that are critical about firms in the industry. This measure is then scaled by the total number of tweets assigned to industry i. To search for the firm mentions, 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.

Table B.3. **Appendix: Most common hashtags by Industry and Party**

Republicans			
Industry	hashtag	Percentage	Description
Telcm	#TaxReform	17.24	The tax reform plan announced by President Trump in 2017
	#LetsKeepWorking	6.90	The slogan for governor election in Florida in 2014
	#Florida	3.45	State of Florida
	#Trump4Prez	3.45	Trump for president
	#TaxCuts	3.45	Republicans' 2017 tax cuts
Rtail	#TaxReform	11.94	The tax reform plan announced by President Trump in 2017
	#TaxCutsandJobsAct	11.44	Republicans 2017 Tax Cuts and Jobs Act
	#Walmart	2.99	Walmart
	#TaxReformWorks	2.99	In support of the 2017 Tax reform
	#veterans	1.99	U.S. veterans
Meals	#TaxCutsandJobsAct	27.12	Republicans 2017 Tax Cuts and Jobs Act
	#TaxReform	20.34	The tax reform plan announced by President Trump in 2017
	#China	5.08	Republicans are turning to attacks on China
	#SOTU	5.08	The State of the Union Addres
	#TaxCutsAndJobsAct	3.39	Republicans 2017 Tax Cuts and Jobs Act
Hshld	#Ohio	14.29	State of Ohio
	#TaxReform	10.71	The tax reform plan announced by President Trump in 2017
	#Walker16	7.14	Scott Walker ran for President of the US in 2016
	#HarleyDavidson	7.14	Trump's policy pushed Harley-Davidson's production abroad
	#small	3.57	Small government
Chips	#TaxReform	27.14	The tax reform plan announced by President Trump in 2017
	#China	11.43	Republicans are turning to attacks on China
	#TaxCutsandJobsAct	7.14	Republicans 2017 Tax Cuts and Jobs Act
	#TaxReformWorks	2.86	In support of the 2017 Tax reform
	#InnovationInitiative	2.86	Array of Innovation Initiative Bills
Autos	#jobs	10.20	Job creation
	#KYMakes	4.08	Kentucky had a record-braking year of export in 2017
	#GMRecall	4.08	GM recall scandal in 2014
	#Kentucky	4.08	State of Kentucky
	#Tesla	4.08	Company Tesla
Aero	#Iran	25.36	Trump's targeted killing of Iranian top military commander
	#Boeing	13.77	Boeing's 737 Max 8 aircraft was grounded because of
	#TaxReform	7.97	The tax reform plan announced by President Trump in 2017
	#jobs	3.62	Job creation
	#AZ05	2.17	Arizona' 5th congressional district

The table shows for each industry the most common hashtags used by Republicans. We also report the hashtag count scale by the sum of all hashtags used in each sector.

Table B.4. **Appendix: Most common hashtags by Industry and Party**

Democrats			
Industry	hashtag	Percentage	Description
Telcm	#NetNeutrality	28.04	Proposal to restore the 2015 net neutrality rules
	#ATTUnfair	4.67	AT&T workers strike for unfair labor practice
	#GOPTaxScam	3.74	The Republicans tax reform is meant to benefit the rich
	#OneMoreVote	2.80	Democrats seek for one more vote for Net Neutrality
	#TX33	2.80	Texas's 33rd congressional district
Rtail	#BreakUpBigTech	6.75	Break up big tech companies
	#FightFor15	3.80	Democrats introduce $15 minimum wage bill
	#RaiseTheWage	3.38	House passed Raise the Wage Act
	#GOPTaxScam	2.95	The Republicans tax reform is meant to benefit the rich
	#jobs	2.53	Create more jobs
Meals	#tobeincollege	7.87	College Achievement plan
	#EqualPay	3.37	Democrats champion equal pay for equal work
	#CAPtheTuitionGap	2.25	College Achievement plan helps cap the tuition gap
	#tcot	2.25	Top Conservatives on Twitter
	#RaiseTheWage	2.25	House passed Raise the Wage Act
Hshld	#GOPTaxScam	17.86	The Republicans tax reform is meant to benefit the rich
	#MadeInWI	10.71	Made in Wisconsin
	#CNYRising	7.14	Central New York rising
	#ABetterDeal	7.14	Democrats unveiled A Better Deal for the American people
	#TradeWar	7.14	US-China trade war
Chips	#Apple	18.03	Apple' employee heavily lean Democrats
	#LGBT	3.28	Democrats focus on LGBT issues
	#climate	3.28	Democrats' new climate plan
	#TodaysClimateFact	3.28	Today's climate fact, need to fight for the climate
	#StopCISA	3.28	Stop Cybersecurity Information Sharing Act
Autos	#KCMO	6.72	Kansas City, Missouri
	#NAIAS	5.22	North American International Auto Show
	#MO	5.22	Missouri
	#F150	5.22	Ford F-150 pickup truck
	#KC	2.99	Kansas City

The table shows for each industry the most common hashtags used by Democrats. We also report the hashtag count scale by the sum of all hashtags used in each sector.

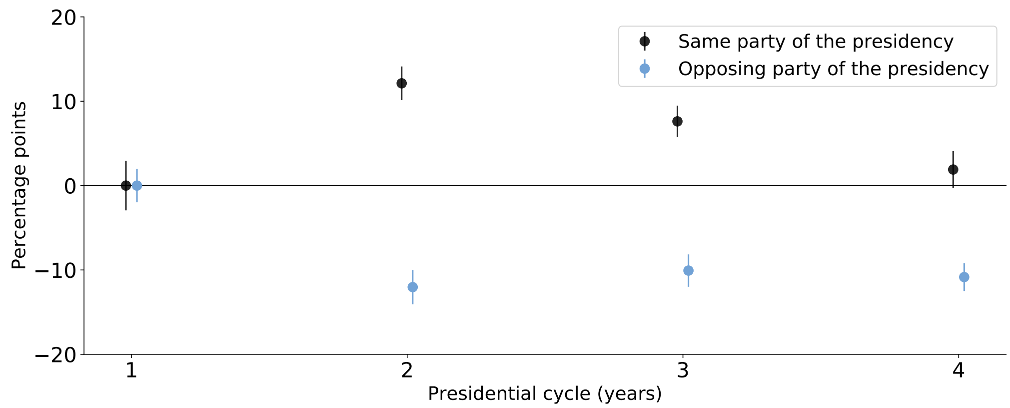

Fig. B.3. **Presidential cycle** This figure reports the partisan confidence measure across different years in the presidential cycle. We report values for members of congress that are in the same party or the opposing party of the presidency. We compute this measure by taking the difference between the number of tweets that support and criticize a policy-related economic topic. We scale these differences in counts by the total number of tweets posted during that month. We further center the series such that in the first year of the presidency, both measures equal zero. 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

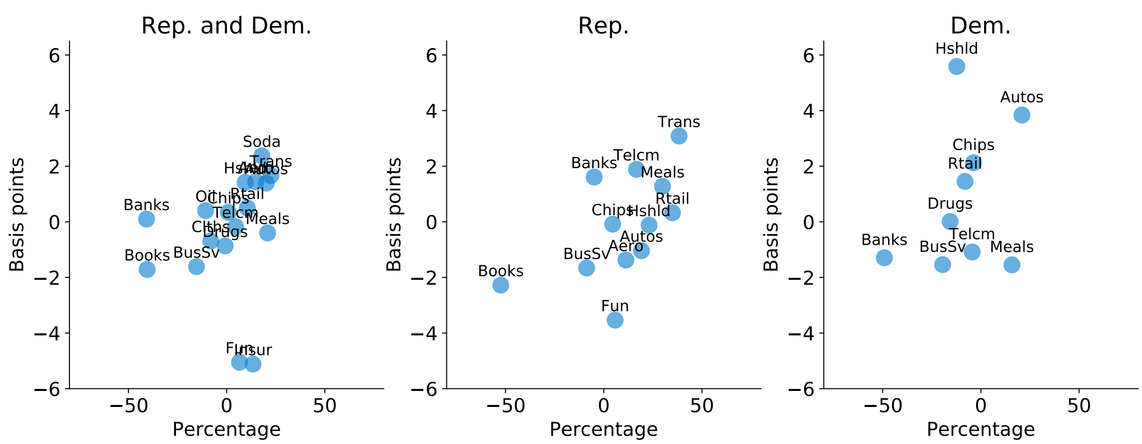

Fig. B.4. **Sentiment and Industry effect: bag of words** This figure shows the average tick-by-tick stock price change as a function of the average partisan viewpoints. Each dot corresponds to one industry and we present binned scatter plots broken down by political parties. For each industry, we compute the average partisan viewpoint by taking the difference between the sum of tweets that are in support and the sum of tweets that criticise specific firms. We use the word dictionaries of negative and positive words from Loughran and McDonald (2011) to categorize the tweets. We then scale this measure by the total number of tweets assigned to that specific industry. The x-axis reports this measure and it's in percentage points. To compute the average tick-by-tick stock price change, we run the following regression:

$$\Delta p_{i,t}^{ind-j} = a^{ind-j} + b^{ind-j} \cdot t_{i,t}^{ind-j} + \epsilon_{ind-j,t},$$

where $\Delta p_{i,t}$ denotes the 90-second log stock price change of the targeted firm and $t_{i,t}^{ind-j}$ is a dummy variable that equals one if the politician tweet mentions firm i in industry j. The y-axis reports the average stock price change (i.e., $a^{ind-j} + b^{ind-j}$) in basis points.