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CLIENTELE POLITICAL IDEOLOGY AND ASSET PRICES

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ABSTRACT

I propose a novel measure of clientele political ideology at the firm level using data from social media. Under Democratic presidencies, firms with the most liberal clientele exhibit excess stock returns that are 19.2 percentage points per year higher than under Republican presidencies. This partisan gap decreases monotonically with clientele conservatism, reaching 3.6 percentage points per year for firms with the most conservative clientele. These differences in returns around the presidential-partisan cycle do not seem to be attributable to differences in risk exposure or in volatility. The analysis around close presidential elections shows the portfolio of firms with clienteles whose beliefs are aligned more closely with those of the winning party begins to exhibit relatively higher abnormal returns in the days after the election.

CHAPTER 1

INTRODUCTION

Political polarization has been increasing in the US over the last two decades. Ideological differences seem to have expanded beyond divergences in political opinions and are now influencing decisions related to everyday life. Political ideology appears to influence the decisions that individuals make about where they live, whom they marry, and from which media outlets they receive news, among others.[1] Differences in ideology also influence how individuals perceive future economic conditions (Duch et al., 2000; Bartels, 2002; Ladner and Wlezien, 2007; Mian et al., 2017), and some evidence suggests ideology could also explain changes in consumption behavior throughout the political cycle (Gerber and Huber, 2009).

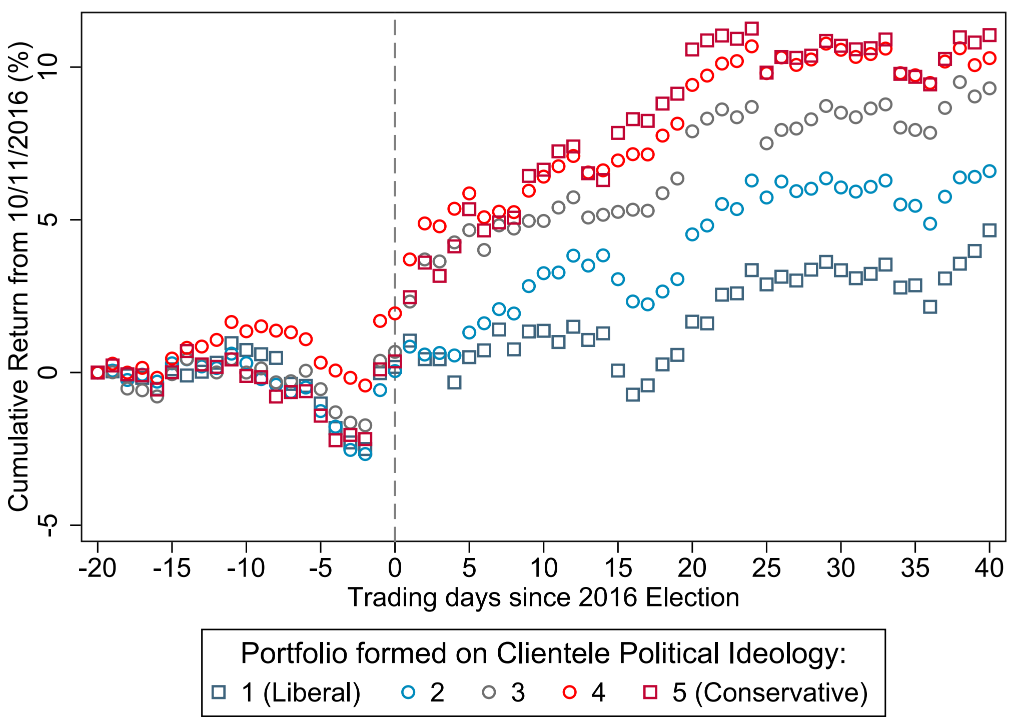
Moreover, recent literature suggests polarization across the political spectrum is influencing consumers' preferences, with liberal and conservative consumers differing in the goods they favor. For example, Ordabayeva and Fernandes (2018) study how political ideology determines the strategies that consumers adopt to differentiate themselves in the marketplace, finding that more conservative consumers prefer products that vertically differentiate them as better than others (high-status luxury brands), whereas more liberal consumers prefer products that show they are unique (e.g., products with unconventional designs and colors). Kim et al. (2018) suggest the differences between the preferences of liberal consumers and those of conservative ones could be explained by their desire to maintain or advance their social status. Conservatives like to maintain their social status, which induces them to exhibit a greater desire for luxury goods.

Given the large increase in political polarization, the role of political ideology in shaping consumer tastes, and the effect of partisan preferences on beliefs about future economic

1. Many of these facts have been carefully documented by various reports on political polarization by Pew Research Center (2014a,b). Several other studies have also documented the large increase in political polarization (e.g. Mason 2013, 2015; Gentzkow 2016).

conditions and spending, we can reasonably expect the impact of political news on a firm's stock returns to be associated with the political ideology of the firm's clientele. Figure 1.1 presents the cumulative stock returns beginning 20 trading days before the 2016 presidential election for five different portfolios formed on the basis of the political ideology of firms' clienteles. Immediately following election day, firms with relatively more conservative clienteles start exhibiting higher returns than firms with more liberal clienteles. Almost one month after the election, the difference in cumulative stock returns between the two extreme portfolios is approximately nine percentage points.

Figure 1.1: Cumulative Returns around 2016 Presidential Election



Note: The portfolios are formed on the basis of the measure of clientele political ideology presented in section 3. The y-axis corresponds to the cumulative returns on value-weighted portfolios from 20 trading days before the election day.

In this paper, I study the degree of heterogeneity across firms in the political ideology of their clienteles, and examine whether this heterogeneity is associated with firms' stock returns throughout the political cycle. To answer this question, I construct a measure of clientele political ideology based on the inferred political ideology of a firm's Twitter followers. This measure allows me to understand how much political polarization exists across firms' clienteles, and to study how heterogeneity in this dimension is associated with differences in stock returns under Democratic and Republican presidencies.

The main finding of the paper is that no statistically significant differences in average returns exist across portfolios formed on the basis of clientele political ideology. However, large and significant differences exist in stock returns between Democratic and Republican presidencies; these differences do depend on the political ideology of a firm's clientele. For the portfolio of firms with the most liberal clienteles, the difference in average excess returns between Democratic and Republican presidencies is 19.2 percentage points per year. On the other hand, the portfolio of firms with the most conservative clientele exhibits a difference of only 3.6 percentage points. These results are consistent with the well-documented fact that stock returns are higher under Democratic presidents than under Republican ones (Santa-Clara and Valkanov, 2003; Pástor and Veronesi, 2017). Moreover, the partisan gap in returns does not seem to be attributable to differences in risk exposure or in volatility. When analyzing the trend of returns around recent close presidential elections (2000, 2004, and 2016), I find the portfolio of firms with clienteles whose beliefs are aligned more closely with those of the winning party begin to exhibit relatively higher abnormal returns.

My measure of clientele political ideology is constructed using data from Twitter. I assume a firm's Twitter followers are a good proxy for its clientele.[2] To construct my measure, I first use the Survey of American Trends Panel Wave 1, produced by the Pew Research Center, to determine the association between individuals' political ideology and their choice of media outlets. Then, I infer users' political ideology based on the set of media

2. Many companies offer services to analyze consumers' preferences and consumption trends, using social media data. For example, LikeFolio use data from Twitter to track consumer behavior dynamics. Statsocial.com also uses Twitter data to analyze the demographics and preferences of firms' clientele.

outlets they follow on Twitter. Next, I define a firm's clientele political ideology as the average ideology score among the firm's Twitter followers. I present three robustness checks to verify the validity of my measure. First, I compute the political ideology of members of Congress's Twitter audiences in the same way I do for firms, and compare it with a measure of political ideology based on politicians' roll-call voting records. Second, I construct an alternative measure based on the number of influential Republican and Democratic accounts followed by individual users on Twitter, and compare this alternative measure with my preferred measure. Third, I compute the political ideology of media outlets' audiences based on their Twitter followers and compare it with the measure obtained from the Survey of American Trends. All these robustness checks indicate my measure of political ideology is effective at capturing differences in clientele political ideology across firms. Moreover, the exercise with members of Congress allows me to compare how much political polarization exists across firms' clientele. As expected, clienteles are less polarized than the Twitter audiences of members of Congress; the most liberal (conservative) clienteles are comparable to the audience of a moderate Democrat (Republican) politician.

I focus on the last seven presidential elections for two reasons. First, my data are inherently limited because I only observe the Twitter network as of 2018. In addition to the impossibility of reconstructing the network for previous years, Twitter was only launched in 2006 and was not widely used by firms until 2009. I provide some evidence suggesting the network is persistent over time. However, given this limitation in my data, I have restricted the analysis to relatively recent elections. The second reason for this limited chronological scope is that political polarization seems to have increased sharply in the last two decades; differences in political ideology across firms' clientele are therefore more likely to be of importance today than many decades ago.[3]

3. Table A2 extends the period of analysis from 1984 to 2018. It shows the main result of the paper does not change. The partisan gap is larger for firms with more liberal clienteles and a long-short strategy as the one described in section 4 produces a positive alpha after controlling for common risk factors.

My paper is related to the literature on asset pricing that studies the differences in asset returns around the presidential cycle and the market response to political outcomes. Santa-Clara and Valkanov (2003) and Pástor and Veronesi (2017) show that market excess returns are higher under Democratic presidencies than under Republican ones; the difference is around nine percentage points per year for the 1927-1998 period and 17.4 percentage points per year between 1999 and 2015. Unlike this existing research, I document that this partisan gap in excess returns varies with the political ideology of the firm's clientele. Although my results do not provide an explanation of why excess returns are higher under Democratic presidencies, any explanation of the partisan gap in returns should address the heterogeneity across clientele political ideology that I document here.

My paper is also related to Belo et al. (2013), who study the impact of political cycles on the cross-section of US stock returns through the government spending channel. Their findings suggest that under Democratic presidencies, the returns of firms with high government exposure are approximately 6.1 percentage points higher than those with low government exposure, but that under Republican presidencies, firms with low government exposure outperform firms with high government exposure by 4.8 percentage points. My paper exploits cross-sectional differences in firms' exposure to liberal and conservative clientele and not exposure to government spending.

Recent work by Meeuwis et al. (2018) analyzes how individuals' portfolio choices changed after the unexpected result of the 2016 election according to their political affiliation, inferred based on the zip code where they live. Their findings suggest that relative to Democrats, Republican investors increased the risk in their portfolios following the election. My analysis does not consider differences in portfolio choices across individuals; rather, it examines how the market perceives future expected cash flows and volatility across firms with clientele of different political ideologies. Studying not only whether Republican investors increased the share of equity in their portfolio, but also if they have a stronger preference for firms with relatively more conservative clientele would be interesting.

My analysis around close elections is similar to the one in Snowberg et al. (2007), who use high-frequency data to understand how the market responded to exit polls during the 2000 and 2004 elections. I focus on the 2000, 2004, and 2016 elections, and my analysis is on the cross section of firms using daily data.

My paper is also related to the literature that uses social media to measure political ideology (Conover et al. 2011; Pennacchiotti and Popescu 2011; Zamal et al. 2012; Cohen and Ruths 2013; Colleoni et al. 2014; Barberá 2015; Garimella and Weber 2017). I used a network-based measure, which the literature has found to be more accurate than content-based measures (Conover et al., 2011). My contribution to this literature is to use the Survey of American Trends Panel to construct estimates for individuals who are not necessarily engaged in political conversations over Twitter.

Finally, my work is indirectly related to studies that use social media data to study asset prices. Most of the literature in this area has focused on text analysis to capture market sentiment about specific stocks (Oliveira et al., 2013; Sun et al., 2016; Bartov et al., 2017) or sentiment regarding political news or events (Nisar and Yeung, 2018; Ge et al., 2018). Unlike studies that focus on tweets' contents and use text analysis, I exploit the use of social media linkages between users and firms to understand how clienteles' preferences could explain asset prices.

CHAPTER 2

DATA

In this section, I describe the data I use and provide descriptive statistics of the main variables. The data come from four different sources: (1) Information about a firm's interactions with individuals is from Twitter; (2) the 2014 survey of American Trends Panel Wave 1 by Pew Research Center is used to determined the association between individuals' political ideology and their media choice set; (3) stocks returns and market value were obtained from the Center for Research in Security Prices (CRSP), and financial fundamentals are from Compustat; and (4) the market return, the risk-free rate, the Fama-French factors size (SMB), value (HML), profitability (RMW) and investment (CMA), and the Carhart momentum factor (UMD) were obtained from French's website data library.[1]

2.1 Twitter Data

The main source of data for this project is Twitter. Twitter is a social media platform in which users can interact by posting, liking, and reposting short messages. Launched in 2006, today it counts 335 million monthly active users.[2] Each user has the option to follow the contents posted by other politicians, firms, government organizations, as well as other users. Many firms use Twitter to advertise their products, provide customer service by replying to users' messages, disseminate news announcements, and so on. Through an API application, Twitter allows users to download data about accounts' followers, tweets, friends, and so on. The API application imposes limits on the rate at which the information can be downloaded. For this reason, a careful selection of the data must be made.

1. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

2. Source: Twitter Second Quarter 2018 Earnings Press Release https://investor.twitterinc.com/static-files/1b7e0fca-06c4-4dab-bf7a-456deb954daa

For each of the S&P 500 firms, I manually search for their main Twitter accounts. Often companies use multiple Twitter handles to tailor the information to different audiences (by country, language, product line, or to customers, employees, and prospective employees). In such instances, I select the main corporate Twitter handle, which in most cases corresponds to the handle linked from the company's official website. Among the S&P 500 firms, 37 have an active corporate Twitter account.[3] Using the list of handles, I connect to the Twitter API to download the list of followers for each account. Thus, for each firm, I have a list of Twitter accounts that have chosen to follow the firm on this social media platform.[4]

Each list of followers consists of an array of unique identifiers representing the company's followers. These unique identifiers allow me to later link to additional information about the followers. For each follower, I can obtain basic information such as the number of followers, number of tweets, number of accounts followed, date when the account was created, handle name, a short basic text description of the follower's profile, their geographical location for users who opt in to make it publicly available, as well as the content of tweets posted by the user. Perhaps the most useful information about a follower is what other accounts she follows. Using the unique identifier, it is possible to verify if an account is also a follower of certain politicians, media outlets, other firms, and so on. In the next section, I explain how I use the array of media outlets followed by an individual to determine her political ideology.

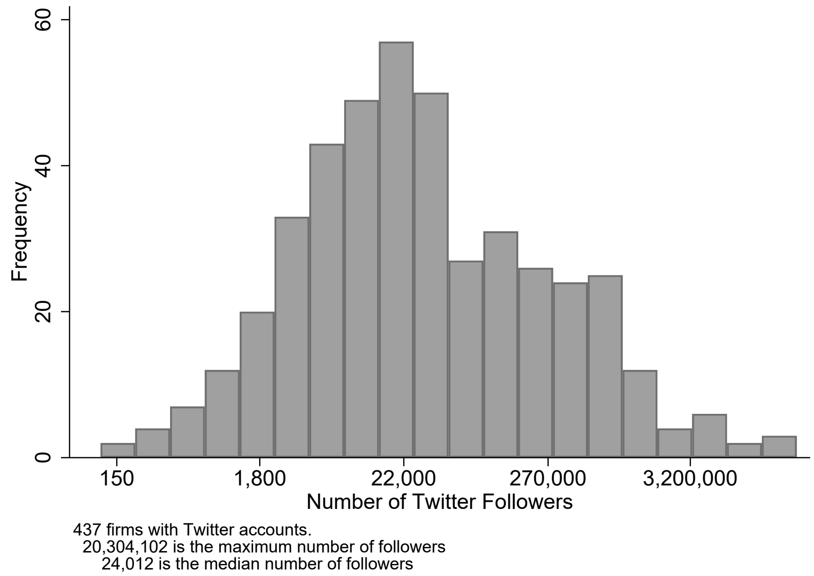
Firms differ greatly in their presence on social media. Figure 2.1 shows a histogram of the number of followers for the S&P 500 firms with Twitter accounts. The top five firms with the most followers are Google (20.3 million), Facebook (14 million), Starbucks (11.9 million), Microsoft (8.4 million), and Nike (7.4 million). Among the 437 firms with Twitter accounts, there are 90.6 million unique followers; 70% of these individuals follow only one of

3. Appendix A.4 presents the list of Twitter handles used for all S&P 500 firms.

4. All the data were downloaded between March 27, 2018, and April 11, 2018.

the S&P 500 firms, 15% follow two firms, and the remaining 15% follow three or more firms.

Figure 2.1: Histogram of Number of Twitter Followers



The number of followers on Twitter is positively correlated with market capitalization and total revenue (see Figures A1 and A2). The logarithm of the number of followers has a correlation of 0.43 with the logarithm of market capitalization and of 0.44 with the logarithm of total revenue. These positive correlations are not surprising; if a firm's Twitter network of followers is a good proxy for its network of customers or clientele, firms with a wider geographical presence and larger market share will tend to have a stronger presence on social media.[5]

One limitation of my data is that they only capture clientele networks as of 2018, when the data were downloaded. Using the Twitter API, going back in time and obtaining the network of customers for previous years is not possible. Even if the data were available,

5. Firms' use of Twitter suggests that they view their followers as clientele. In particular, many firms use Social Media Management Tool (SMMT) or Social Media Management System (SMMS) to analyze their interactions with customers on social media. SMMT or SMMS allow firms to not only manage the contents shared on their social media accounts, but also to receive information about the individuals interested in their content. Some of the companies offering SMMT and SMMS services include sprout social, zoho.com, brandwatch, hootsuite, among others.

reconstructing the Twitter networks prior to 2010 would not be very informative for a few reasons. First, Twitter was launched in 2006, and by the end of 2010, it had around 50 million active users, which is less than one-fifth of what it has today.[6] Second, more than 80% of the firms analyzed created their accounts after 2009; in particular, 172 out of the 437 firms created their account in 2009, 62 in 2010, 57 in 2011, and by 2012, 400 firms had created Twitter accounts. In sum, access to historical Twitter networks would allow me to construct a measure of clientele political ideology for the last eight years at best.[7]

Not observing the Twitter network for previous years is definitely a limitation. However, one has to assume the network is very persistent over time, with little variation in the composition of followers happening during this time. Evidently, over time, new users sign up to Twitter, and thus the total number of followers for a firm will tend to grow, but one can expect that the composition of the 2018 Twitter network to be representative of what it was a few years ago. Thus, an important assumption I make is that the current follower composition for a firm is informative about a its clientele composition and that such clientele composition does not change much over time. In 2016, when I first started to gather data for this paper, I downloaded the list of followers for the firms with Twitter accounts at that time.[8] Out of the 437 firms with Twitter data as of 2018, I have the list of followers for 418 firms. When comparing the list of followers between 2016 and 2018, I find the median firm has preserved 91% of the followers it had in 2016. Also, most firms increased their base of followers; only 5 out of 418 firms reduced their follower count and in no case for more than 3%. The median firm increased its followers by 23%.

6. Source: https://www.statista.com/chart/2883/twitters-user-growth/

7. Some studies try to infer the timing of the creation of social links on Twitter using the fact that the list of followers obtained from the Twitter API are in chronological order from when one account started following the other account (Meeder et al., 2011; Garimella and Weber, 2017). These methods will only capture users chronologically from the existing list of followers, whereas those individuals who decided to stop following a firm prior to when the data were downloaded will not be observed.

8. The list of followers for these firms was downloaded from the Twitter API between October 2016 and November 2016.

Despite its limitations, Twitter data are probably a unique source to know more about a firm's clientele. No other data will allow us to not only identify a firm's linkages to individuals, but also to obtain a measure of political ideology. For example, using detailed credit card data could help us identify a firm's clientele, but saying more about the political ideology or preferences for those individuals for whom the credit card data provide information would potentially be difficult. Another alternative is the Nielsen panel. These data have even bigger limitation. First, they are limited to goods that can be purchased in a store or a supermarket. Second, they provide detailed information at the product level but without a product-to-firm correspondence it would be impossible to identify which products are sold by a firm; one would have to create such a correspondence. Finally, inferring the political ideology of individuals sampled by the Nielsen panel is also impossible. Therefore, using the Twitter data is a good alternative that allows us if not to precisely measure the political ideology of a firm's clientele, to at least provide a sorting of firms based on political ideology.

Also from Twitter, I obtain the list of followers for 31 of the major media outlets in the United States. The list of media outlets is defined based on those included in the 2014 Survey of American Trends Panel Wave 1 by Pew Research center. Among these media outlets are 116.2 million unique followers on Twitter; 49% of these individuals follow only one media outlet, 18.5% follow two media outlets, 10.5% follow three media outlets, and the remaining 20% follow four or more media outlets. The media outlets with the largest audience on Twitter are The New York Times (42 million followers) and CNN (40 million).[9]

One-third of the 90.6 million Twitter accounts that follow at least one S&P 500 firm also follow at least one of those 31 major media outlets listed. The percentage of followers

9. Table A8 lists all 31 media outlets, their Twitter handles, followers count, number of tweets, and date when their accounts were created.

following at least one media outlet varies by firm. This percentage is the largest for NASDAQ, Goldman Sachs, BlackRock, and Charles Schwab, with over 80% of users following media outlets. On the other hand, Activison, Facebook, and Nike have the smallest percentage of users also following media outlets, with a proportion between 15% and 25%.

To check the quality of my measure, I also obtained Twitter followers for all members of the US Congress (429 House Representatives and 99 Senators), as well as 38 Twitter accounts identified as being influential for Republicans and Democrats.[10]

2.2 Pew Research Center's American Trends Panel

To understand the media preferences across the spectrum of political ideology, I used the 2014 Survey of American Trends Panel Wave 1 by the Pew Research Center. The survey is a nationally representative panel of adults in the US. This first wave of the American Trends Panel inquires in particular about media consumption, for example, whether or not you have heard of a list of media outlets, from which media outlets you get news from, and whether you trust them. The survey also inquires about a series of questions regarding individuals' political and social views. Based on the answers to the questions, a political ideology score is assigned to each individual.

The political ideology of an individual is defined utilizing a scale composed of 10 questions of individuals' attitudes about the size and scope of government, the social safety net, immigration, homosexuality, business, the environment, foreign policy, and racial discrimination.

10. The influential Republican and Democrat Twitter accounts were identified by Brandwatch. The list of influential Democrats' Twitter accounts was obtained from https://www.brandwatch.com/blog/react-the-most-influential-democrats-on-twitter/ and the list of influential Republicans' Twitter accounts were obtained from https://www.brandwatch.com/blog/react-ranked-influential-republicans-twitter/. From the list of influential Republican Twitter accounts, two were no longer active at the time when the data were downloaded: @A_M_Perez and @ChuckNellis.
From the 435 House of Representative seats, 6 seats were vacant in September 2018, when the data were downloaded. Also, Senator Jon Llewellyn Kyl did not have an active Twitter account at the time.

Table 2.1 lists the 10 questions used in the construction of the individual political ideology score. Each conservative position will add one point to the political ideology score and each liberal position subtracts one point. Thus, an individual who agrees with all 10 conservative statements will receive a political ideology score of 10, the most conservative, and if she agrees with all 10 liberal statements, the political ideology score will be -10, the most liberal. The resulting political ideology score ranges from -10 (most liberal) to 10 (most conservative). Based on the political ideology score, 5 ideological categories are defined: very liberal (-10 to -7), lean liberal (-6 to -3), neutral (-2 to +2), lean conservative (+3 to +6), and very conservative (+7 to +10).

Table 2.1: Questionnaire for Policy Ideology Index

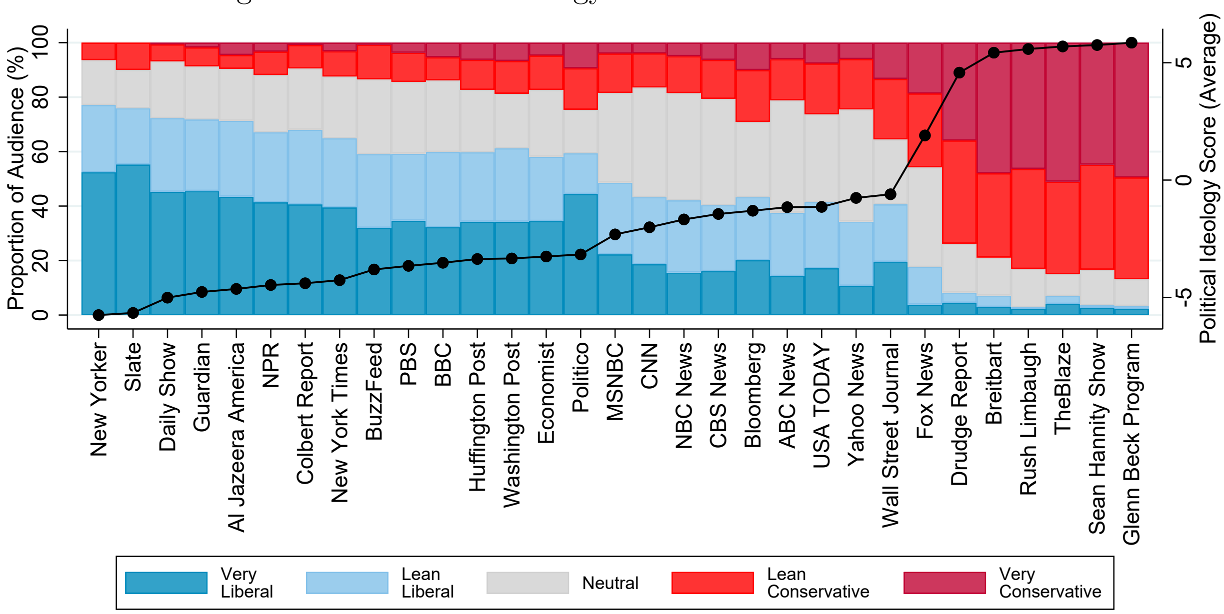
	Liberal Position	Conservative Position
1	Government often does a better job than people give it credit for	Government is almost always wasteful and inefficient
2	Government regulation of business is necessary to protect the public interest	Government regulation of business usually does more harm than good
3	Poor people have hard lives because government benefits don't go far enough to help them live decently	Poor people today have it easy because they can get government benefits without doing anything in return
4	The government should do more to help needy Americans, even if it means going deeper into debt	The government today can't afford to do much more to help the needy
5	Racial discrimination is the main reason why many black people can't get ahead these days	Blacks who can't get ahead in this country are mostly responsible for their own condition
6	Immigrants today strengthen our country because of their hard work and talents	Immigrants today are a burden on our country because they take our jobs, housing and health care
7	Good diplomacy is the best way to ensure peace	The best way to ensure peace is through military strength
8	Business corporations make too much profit	Most corporations make a fair and reasonable amount of profit
9	Stricter environmental laws and regulation are worth the cost	Stricter environmental laws and regulations cost too many jobs and hurt the economy
10	Homosexuality should be accepted by society	Homosexuality should be discouraged by society

Source: Appendix A from Pew Research Center (2014b)

One important finding of the report on political polarization and media habits by the Pew Research Center (2014a) is the minimal overlap in the news sources liberals and conservatives turn to and trust. This finding allows me to better predict an individual's political ideology score based on the array of media outlets she follows. For example, one of the findings in the October 2014 Pew report is that very conservative individuals are clustered around a single news source, with 47% citing Fox News as their main source for news about government and politics. Very liberal individuals, on the other hand, have a wider variety of media outlets. The main sources of news among liberals are MSNBC, NPR, and CNN, with around 12% each. The average number of media outlets from which a very conservative individual gets her news from is 4.7, and for very liberal individuals, it is 5.8. Likewise, the average number of media outlets distrusted by very conservative individuals is larger than the number distrusted by very liberal individuals: 8.2 and 4.7, respectively.

Figure 2.2 shows the average political ideology score of a media outlet's audience, as well as the composition of its audience based on the five political categories previously defined. The New Yorker, Slate, The Daily Show, and The Guardian are among the media outlets with the most liberal audience. On the other extreme of the political ideology spectrum, the Glenn Beck program, the Sean Hannity Show, The Blazze, and The Rush Limbaugh Show are the media outlets with the most conservative audience. Among the most popular media outlets, CNN and NBC have a more liberal audience than Fox News. Given the large heterogeneity in audiences' political ideology across media outlets, predicting reasonably well the political ideology of an individual by simply knowing the array of media outlets she uses should be possible. For example, using a logit model to predict if an individual is conservative (very or leaning conservative) accurately predicts the political position for 84% of the individuals.

Figure 2.2: Political Ideology of Media Outlets' Audiences



Note: The primary axis corresponds to the percentage of the audience of a media outlets classified as Very Liberal, Lean Liberal, Neutral, Lean Conservative, or Very Conservative. The secondary axis corresponds to the average political ideology score of a media outlet's audience. A media outlet's audience is defined as the individuals who reported to obtained their news from that media outlet in the 2014 Survey of American Trends Panel Wave 1.

CHAPTER 3

POLITICAL IDEOLOGY INDEX

This section explains the construction of the measure of clientele political ideology. First, I explain in detail the methodological steps to construct the measure, and later I present three different robustness exercises to test the effectiveness of the measure in ranking firms based on their clientele political ideology.

The construction of the measure at the firm level is based on the inferred political ideology score of its followers. I first infer the political ideology score of each firm's follower and later aggregate to obtain the average political ideology score of the firm's clientele. To predict an individual's political ideology, I analyze the set of media outlets she follows on Twitter. The basic idea is that liberals and conservatives have very different media-outlet preferences. Then, by observing an individual's choice of media outlets, inferring her political ideology is possible.

Previous studies have measured individuals' political ideology using Twitter data (see e.g. Golbeck and Hansen, 2011; Pennacchiotti and Popescu, 2011; Conover et al., 2011; Zamal et al., 2012; Colleoni et al., 2014; Barberá, 2015). Two different approaches to estimate political ideology have been proposed: a content-based method in which the political preferences of an individual are inferred based on the content she posts and shares on social media, and a second approach based on the structure of the network of friends, followers, or people with whom a user interacts on social media. This network-based approach seems to achieve higher accuracy than the content-based approach in predicting political ideology (Conover et al., 2011).

As a robustness check, I compare my measure of political ideology applied to three different samples. First, I construct the political ideology of US members of Congress audiences based on their Twitter social links. I compare the Twitter-based measure of political ideology across US members of Congress with an index of political ideology based on their roll-call voting records. Second, I construct an alternative measure of political ideology based not on which media outlets an individual follows, but on her social links with the Twitter accounts of influential Republicans and Democrats. Finally, I compute the measure of political ideology for media outlets' audiences, and I compare it with the measure obtained using the 2014 Survey of American Trends Panel.

3.1 Methodology to Estimate Clientele Political Ideology

To infer the political ideology of a firm's followers, I take as observable the set of media outlets that an individual follows. Given the large heterogeneity in political ideology across media outlets' audiences shown in Figure 2.2, predicting an individual's political ideology reasonably well by simply knowing the array of media outlets she uses should be possible. But observing the set of media outlets an individual follows is only one part of the process in predicting her political ideology; one also needs to impose a criterion to decide which combinations of media outlets predict an individual is more likely to be a liberal or conservative. Here is where I take advantage of the 2014 Survey of American Trends. In these data, we have a nationally representative sample of individuals who jointly report their preferred array of media outlets and their opinion about political and social issues, from which we construct a political ideology score. Thus, one could use that sample of individuals to map an array of media outlets to a political ideology score.

From the Pew survey data, I compute the average political ideology score among individuals with a specific choice of media outlets observed in the Twitter data. That is, for each possible combination of the 31 media outlets in the data, I compute the average political score. However, over 2 billion media-outlet sets (more exactly 2^{31}) are possible. Thus, the Twitter data may have media-outlet sets that are not in the Pew survey data. To overcome this limitation, I estimate an ordered logit model in which the political ideology score is regressed on a set of binary variables, one for each media outlet, corresponding to the array of media outlets chosen by the individual.[1] Based on the results of these models, we can infer that those who get their news from CBS News, NBC News, NPR, The Washington Post, The New York Times, The Huffington Post, BBC, MSNBC, CNN, PBS, The Daily Show, BuzzFeed, and Al Jazeera America are more likely to be liberals. On the other hand, individuals who get their news from the Rush Limbaugh Show, the Sean Hannity Show, Drudge Report, The Blaze, Fox News, the Glenn Beck Program, the Walls Street Journal, USA Today, Yahoo News, and The Economist are more likely to be conservatives.[2]

Using the average political score for each possible media-outlet set and the estimated coefficients and cutoffs from the ordered logit model estimated on the data from the 2014 Survey of American Trends Panel Wave 1, I infer the political ideology of each individual in the Twitter sample. First, if the media-outlet set of an individual exists in the Pew survey data, I assign that individual the average political score among those individuals who use the same media-outlet set. If her media-outlet set is not in the Pew survey data, her political ideology score is predicted using the estimated model from the Pew survey and the array of media outlets she follows. That is, I use the ordered logit model estimates to predict the individual political ideology score.

Finally, to compute the political ideology score of a firm's clientele, I take the average of the individual political scores across the firm's Twitter followers. Note that not every firm follower is also a media-outlet follower. As I mentioned above, one-third of the 90.6 million firms' followers also follow at least one of the media outlets considered. Thus, the measure of clientele political ideology is computed only for those individuals who follow at least one

1. Table A1 shows the estimation of the ordered logit model and a linear regression as a reference.

2. The correlation between the predicted individual political score using the ordered logit model and the observed ideology in the Pew survey is 0.74.

media outlet and from which we can infer a measure of political ideology.

Among the most liberal clienteles are five firms whose main business model is predominantly in retail sales of clothing, accessories, and jewelry (Gap Inc., Coach New York, Urban Outfitters, Tiffany & Co., and Nordstrom). On the other hand, the most conservative clienteles seem to be predominantly in the oil sector (Range Resources, Pioneer Natural Resources, Newfield Exploration, and Helmerich & Payne).[3]

3.2 Robustness of the Measure of Political Ideology

3.2.1 Political Ideology for US Members of Congress Audiences

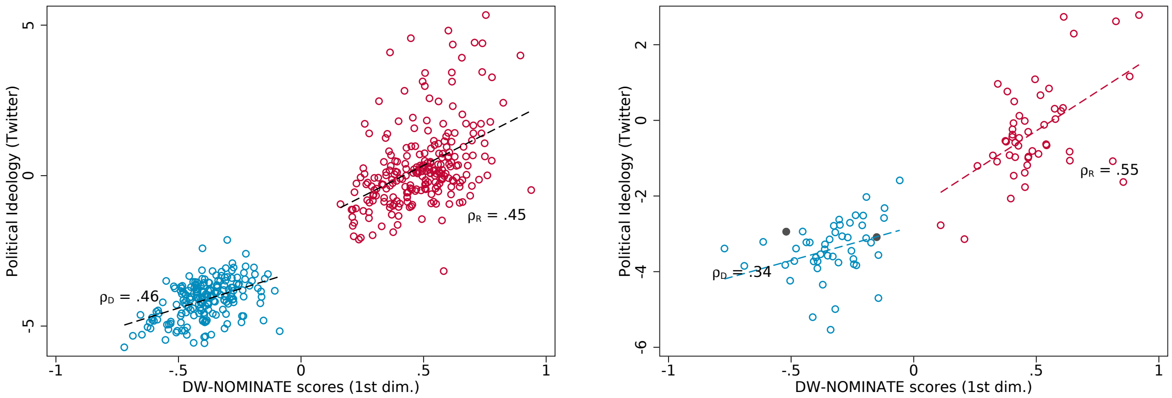
To validate my measure of political ideology, I compute the average political ideology of members of US Congress's Twitter followers. I apply the same procedure I used to compute the political ideology of S&P 500 firms' clienteles to members of US Congress. My measure should be able to properly differentiate between Republican and Democrats politicians, as well as produce an informative within-party ranking based on their audience's political ideology. Following Barberá (2015), I compare my measure of political ideology with the DW-NOMINATE score,[4] a measure of political ideology based on politicians roll-call voting records (Poole and Rosenthal, 1997). Figure 3.1 compares the two measures for each US member of Congress. Each data point represents a different member of Congress: red dots corresponds to Republicans, blue dots to Democrats, and black dots to independents.

We can see that the Twitter-based measure of political ideology correlates relative closely with the measure based on roll-call voting records. The correlation between the two is 0.91 among US House Representatives and 0.87 among US Senators. The Twitter-based

3. Table A3 reports the top-10 most liberal and most conservatives clienteles.

4. Source: https://voteview.com/

Figure 3.1: Political Ideology Estimates for Members of US Congress



(a) House of Representatives

(b) Senate

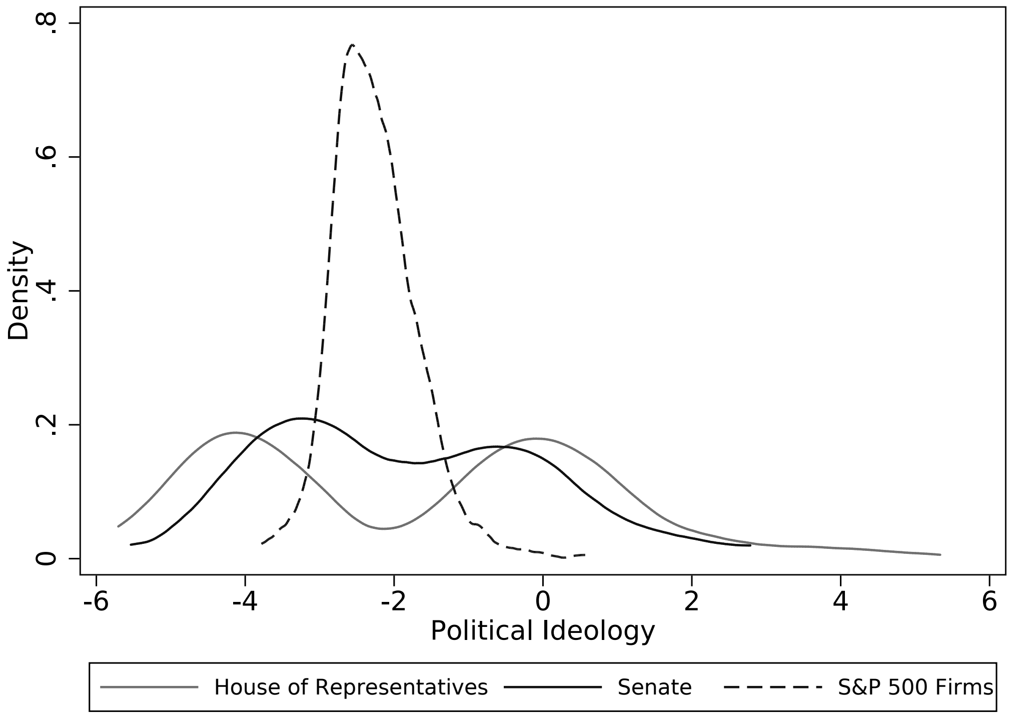
Note: The DW-NOMINATE score (1st dim.) is obtained from https://voteview.com. My data contain 428 US House Representatives and 99 US Senators. At the time of the Twitter data collection six seats were empty in the US House of Representatives, for Representative William Troy Balderson (Ohio), DW-NOMINATE score was not available, and Senator Jon Llewellyn Kyl (Arizona) did not have an active Twitter account.

measure provides not only a clear separation between political parties, but also a relatively good within-party sorting. A similar robustness exercise is presented in Barberá (2015), who develops a Bayesian spatial following model to infer political ideology using Twitter. The within-party correlations of my measure are slightly smaller than those obtained by Barberá. However, the correlation computed for all members of the House and the correlation for all members of the Senate are of comparable magnitude. Barberá's estimates are a useful reference point to understand how well my measure of political ideology performs. Nevertheless, the correlations reported in his study and those presented here are not exactly comparable, because the sample of members of Congress is different. Barberá's data correspond to the US members of Congress prior to 2015, and my measure is for all members of Congress as of 2018. Also, Barberá limits his analysis to only those Twitter accounts of US members of Congress with more than 5,000 followers, resulting in a limited sample of 231 members. Here, I include all 527 US members with Twitter accounts.

Computing the political ideology of US members of Congress's audiences also has the advantage of allowing me to compare where in the political spectrum (liberal to conservative) are the clienteles of the S&P 500 firms. Figure 3.2 plots the distribution of political ideology for S&P 500 firms' clienteles, US House of Representatives' audiences, and US Senators' audiences. As expected, we can see a bimodal distribution of political ideology for US members of Congress, both in the House of Representatives and in the Senate. For S&P 500 firms' clienteles, we see that the distribution is unimodal and with less dispersion than the distribution for members of Congress's audiences. This result is not surprising. An individual's decision to buy or follow a firm depends on her preferences, which could be shaped by her political ideology but also by many other personal circumstances. On the other hand, political ideology should be the key dimension when deciding to vote for or to follow a politician. So we should expect larger ideological polarization across politicians' audiences than across firms' clienteles. However, we see a considerable dispersion in political ideology across firms' clienteles.

Comparing the distribution of political ideology for US members of Congress's audiences and S&P 500 firms' audiences also allows us to better understand how polarized a firm's political clientele can become. For example, the firms on the left tail of the distribution have a clientele whose political ideology is comparable to that of the audiences of moderate members of Congress. For example, the political ideology score for two of the most liberal firms' clientele, Gap Inc. and Urban Outfitters, are comparable to the political ideology score for moderate democratic senators such as Kirsten Gillibrand, a junior US Senator from New York and former member of the Blue Dog Coalition, a group of moderate Democrats. Similarly, on the right tail of the distribution, we can see the most conservative clientele are comparable to the audience of moderate to average Republicans. Two of the firms with the most conservatives clienteles, Range Resources and Archer Daniels Midland, are comparable in political ideology to the audience of Republican Senator Marco Rubio, former

Figure 3.2: Distribution of Political Ideology Score for S&P 500 Firms' Clientele and Audience of Members of US Congress



Note: The graph shows the empirical distribution of political ideology computed using Twitter for S&P 500 firms (437 firms with Twitter accounts), US House of Representatives (428 members), and the US Senate (99 member).

presidential candidate who was perceived as being the most moderate relative to his two stronger contenders, Ted Cruz and Donald Trump.

The comparison between the Twitter-based measure and the one based on roll-call voting records should make us confident that the estimates of clientele ideology are informative about the political differences across firms. Even if prediction error is present in the estimation of individual political ideology scores, I expect the individuals' prediction errors to be independent of the firm. Thus, when aggregating at the firm level, the prediction error should have mean zero, and our estimates of clientele political ideology should be more precise than the predicted individual political ideology scores. However, to further test the accuracy of the measure of political ideology, I compare the predicted political ideology of an individual with her preferences for following influential Republicans and Democrats on Twitter. If Twitter networks exhibit high levels of political homophily, as documented by Colleoni et al. (2014), we should expect that individuals with a higher political ideology score (more conservatives) will tend to follow more influential Republicans than Democrats, and the opposite should hold for more liberal individuals.

3.2.2 An Alternative Measure of Political Ideology

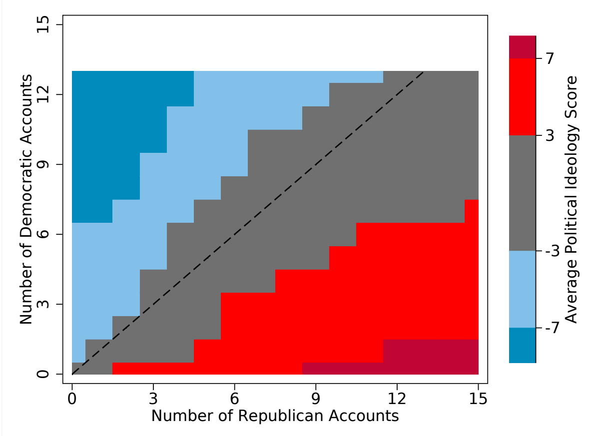
I take 38 Twitter accounts identified by Brandwatch as being influential for Democrats and Republicans, and I compute my measure of political ideology for all of their followers. Later, I compare the average political ideology score with the number of influential Democrats and Republicans an individual follows. The 38 influential political Twitter accounts have a combined total of 12.3 million followers, of which 68% follow at least one media outlet, that is, approximately 8.3 million. Figure 3.3 (a) shows the relation between number of influential Republican and Democratic accounts followed and the predicted political score computed using the set of media outlets. We can see that individuals who follow more Republicans than Democrats have on average higher political ideology scores, and the opposite holds when more Democrats than Republicans are followed.

Using the list of influential political accounts one can also construct an alternative measure of political ideology base solely on the number of Republican ($\#republican_i$) and Democratic ($\#democrats_i$) accounts followed. I will call this measure the political homophily measure, which will be defined to take values between -1 (most liberal) and +1 (most conservative) as

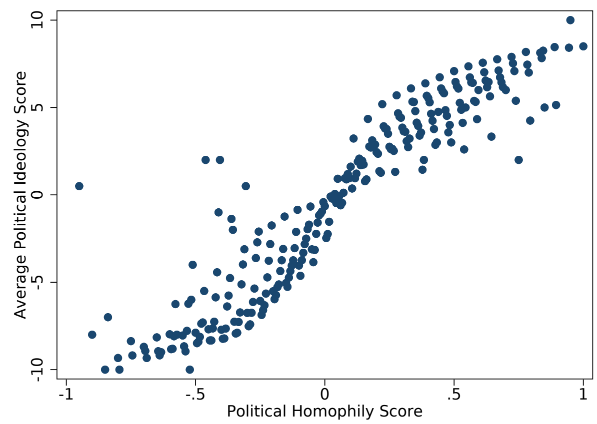
$$polhom_i = \frac{\#republicans_i}{18} - \frac{\#democrats_i}{20} \tag{3.1}$$

The correlation between my measure of political ideology $polideo_i$ and this alternative measure $polhom_i$ is 0.57. Moreover, Figure 3.3 (b) shows the average measure of political

Figure 3.3: Political Ideology Score and the Number of Influential Republicans and Democrats



(a) Average Political Score and Number of Influential Republicans and Democrats Followed



(b) Alternative Measure of Political Ideology

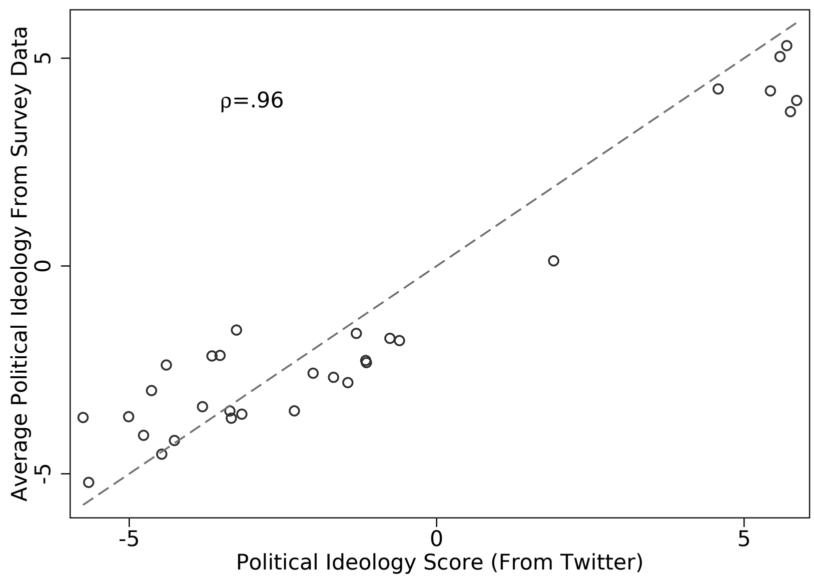
Note: For panel (a), the X-axis represents the number of Republican accounts an individual follows from a list of 18 possible accounts. The Y-axis represents the number of Democratic accounts an individual follow from a list of 20 possible accounts. For each cell (number of Republicans - number of Democrats) the average political ideology score is reported. Cells with less than 300 individuals were excluded. For panel (b), the Y-Axis corresponds to the average political ideology score $polideo_i$ by bins of the measure of political homophily measure $polhom_i$.

ideology ($polideo_i$) by bins of the measure of political homophily where a clear positive relation between the two can be seen.

3.2.3 Political Ideology of Media Outlets' Audiences

An additional robustness check is use the Twiter data to compute the measure for each of the media outlets. That is, I can treat each media outlet like a firm and compute the political ideology ($polideo_i$) for all of its followers, to later take the average across followers and obtain a measure of the audience's political ideology, which will be comparable to the measure obtained from the 2014 Survey of American Trends Panel, and is reported for all media outlets in Figure 2.2. Figure 3.4 shows the relation between the two measures of audience political ideology. The correlation between the two measures is 0.96, and as we can see, the measure obtained after inferring followers' political ideology and later aggregating across followers predicts the observed data well.

Figure 3.4: Robustness of the Measure of Political Ideology for Media Outlets



Note: Each dot represents a media outlet from the list of Table A8. The dashed line is the 45° line. The X-axis corresponds to the measure of political ideology computed using data from Twitter. The Y-axis corresponds to the average political ideology among the media-outlet users from the Survey of American Trends.

In these three robustness checks, we can see the measure of political ideology based on Twitter followers and their media-outlet preferences tracks relatively well the political ideology of members of US Congress and of the audiences of media outlets. It also seems to be consistent with an alternative measure of political ideology based on the homophilic properties of the social network.

CHAPTER 4

RESULTS AND DISCUSSION

In this section, I present the main findings of the paper. First, I present evidence suggesting the association between returns and the presidential-partisan cycle, as documented by Santa-Clara and Valkanov (2003), is heterogeneous across firms and depends on the political ideology of the firm's clientele. Second, I analyze the differences in returns of portfolios formed on clientele political ideology around close elections.

4.1 Portfolios Formed on Clientele Political Ideology

I rank firms based on the measure of clientele political ideology presented in section 3. Then each firm is sorted into one of five portfolios formed on clientele political ideology. The first portfolio corresponds to firms with the most liberal clientele, and the fifth portfolio groups firms with the most conservative clientele. Table 4.1 report the average excess returns, volatility, and Sharpe ratio for each of the five portfolios. We can see no large differences in returns and volatility across portfolios. A statistical test cannot reject the hypothesis that expected excess returns are equal across portfolios. These results could suggest the political ideology of a firm's clientele is not relevant to understanding the cross-sectional differences in stock returns. However, I will show in the next section that the clientele political ideology is key to understanding the differences in returns around the political cycle.

4.2 Differences in Returns around Presidential-Partisan Cycle

4.2.1 Differences across Portfolios Formed on Clientele Political Ideology

Taking the portfolios formed on the basis of the political ideology of firms' clienteles, I compare the differences in average excess returns between Democratic and Republican presidencies.

Table 4.1: Average Excess Returns for Portfolios Formed on Clientele Political Ideology

Portfolios	Annualized Average Excess Returns (%)	Annualized Volatility (%)	Sharpe Ratio
Most Liberal	15.49	14.99	1.03
2	17.19	15.42	1.11
3	16.48	15.82	1.04
4	13.50	13.79	0.98
Most Conservative	15.93	15.43	1.03

Note: The portfolios are value-weighted. The F-Test for comparison of multiple means cannot reject the null hypothesis that all expected excess returns are equal across the five portfolios (P-value = 0.93). The period is from 1992:11 to 2018:02.

Table 4.2 summarizes the differences in average excess returns around the presidential-partisan cycle across portfolios. First, we can see that average returns for all portfolios are larger under Democratic than Republican presidencies. This observation is consistent with the findings of Santa-Clara and Valkanov (2003) and Pástor and Veronesi (2017). The first study finds that in the 1927-1998 period, the difference in excess returns between Democratic and Republican presidencies is nine percentage points per year for the value-weighted portfolio and 16 percentage points per year for the equal-weighted portfolio. Similarly, Pástor and Veronesi document that in the 1999-2015 period, the gap is even larger: 17.4 percentage points per year. Here, the gap is between 3.96 and 19.57 percentage points per year for value-weighted portfolios and between 4.62 and 15.39 for equal-weighted portfolios. Thus, my results are consistent with those previously documented in the literature.

The most interesting result to highlight from this exercise is that the difference in excess returns between Democratic and Republican presidencies seems to decrease monotonically from the most liberal to the most conservative portfolio. For example, notice that for the value-weighted portfolio of firms with the most conservative clientele, the difference in average excess returns between Democratic and Republican presidencies is not statistically significant. However, the portfolio of firms with the most liberal clientele exhibits excess returns that are 19.6 percentage points higher when a Democrat is in the White House. Clientele political ideology could be important in understanding how the presidential-partisan cycle is associated with stock returns.

Table 4.2: Average Returns of Portfolios Formed on Clientele Political Ideology under Republican and Democratic Presidencies

Portfolios	Value-Weighted			Equal-Weighted		
	Democratic	Republican	Difference	Democratic	Republican	Difference
Most Liberal	22.57***	3.36	19.21***	21.33***	6.54	14.79**
	(3.22)	(4.52)	(5.23)	(3.41)	(6.02)	(6.62)
2	23.20***	6.89	16.32***	21.89***	11.52**	10.36*
	(3.23)	(4.97)	(5.62)	(3.11)	(5.03)	(5.52)
3	21.63***	7.64	13.99**	20.66***	7.50	13.16**
	(3.78)	(4.67)	(5.72)	(3.55)	(5.69)	(6.36)
4	16.98***	7.55*	9.43*	17.18***	8.63	8.55
	(2.75)	(4.56)	(5.13)	(3.37)	(5.73)	(6.28)
Most Conservative	17.24***	13.68***	3.56	16.26***	11.67*	4.59
	(3.77)	(5.22)	(5.97)	(4.09)	(6.06)	(6.76)
Observations		304			304	
R-squared		0.001 to 0.033			0.001 to 0.016	

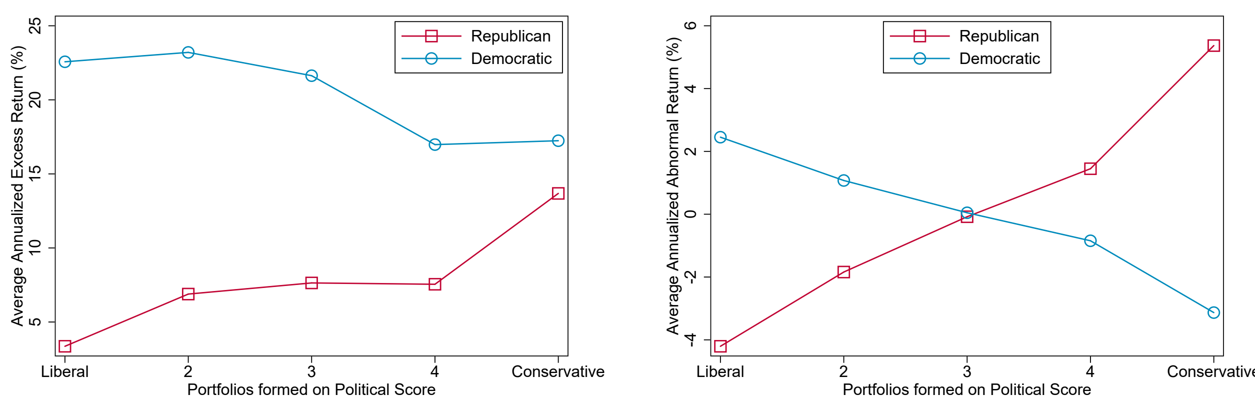
Note: All coefficients are in annual percentage points. Newey-West standard errors are reported in parentheses. Standard errors are computed with a maximum of 6 lags. The period is from 1992:11 to 2018:02. *** p<0.01, ** p<0.05, * p<0.1

One possibility is that these differences across portfolios formed on clientele political ideology are explained by differences in market betas.[1] The political cycle affects the overall

1. Table A4 shows the factor loadings of each portfolio under Democratic and Republican presidencies

performance of the market, but the larger difference for firms with more liberal clientele could be explained by those firms having relatively larger market betas than most conservative firms.[2] To account for this possibility, I compute average abnormal returns from the CAPM model under Democratic and Republican presidencies. Figure 4.1 (b) shows the average abnormal return across portfolios.[3] We can see the difference in returns between Democratic and Republican presidencies persists; moreover, the difference is even larger among firms with more liberal clientele.[4]

Figure 4.1: Portfolio Returns and the Presidential-Partisan Cycle



(a) Excess Returns

(b) Abnormal Returns (Market Model)

Note: Figure (a) shows average excess returns for the value-weighted portfolios formed on clientele political ideology. Figure (b) shows average abnormal returns of a the market model for the value-weighted portfolios formed on clientele political ideology. All rates are represented in annualized percentage points. The blue line corresponds to Democratic presidencies and the red line corresponds to Republican presidencies. The period is from 1992:01 to 2018:02.

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for the 3-factor model.

2. The correlation between the market beta and the clientele political ideology score is -0.012. So the difference in the presidential-partisan premium across portfolios is unlikely to be explained by differences in market betas.

3. Figure A3 shows abnormal returns computed using the 3-factor and 4-factor model. A similar pattern between clientele political ideology and average abnormal returns is observed.

4. The difference in average abnormal returns between Democratic and Republican presidencies is positive and statistically significant for the portfolio with the most liberal clientele and negative and statistically significant for the portfolio with the most conservative clientele

4.2.2 Expected or Unexpected Returns?

Following Santa-Clara and Valkanov (2003), I decompose the differences in excess returns between Democratic and Republican presidencies into two parts: the differences in expected returns and the differences in unexpected returns. As they argue in their study, if the differences in excess returns of a portfolio are mostly explained by differences in expected returns, such a portfolio must carry a higher risk premium for Democratic presidencies. Contrarily, if the difference in realized excess returns is due to differences in unexpected returns, the market beliefs about the returns of a portfolio must be consistently outperformed under Democratic presidencies. Because the portfolio with the largest differences in realized returns between Democratic and Republican presidencies is the one with the most liberal clientele, the differences in returns are unlikely to be due to the fact that firms with liberal clientele will carry a larger risk premium for Democratic presidencies.

To decompose realized excess returns in unexpected and expected components, I use the same business-cycle variables used in Santa-Clara and Valkanov (2003). That is, I use the dividend-price ratio (DP_t), the default spread (DSP_t), the term spread (TSP), and the relative interest rate (RR_t). The dividend-price ratio is defined as the value-weighted dividend of the portfolio relative to the value-weighted price. The default spread is defined as the difference between yields of BBA corporate bonds and yields of AAA bonds.[5] The term spread is constructed as the difference between the 10-year and 3-month Treasury.[6] The relative interest rate is the difference between the three-month Treasury-bill rate and its one-year moving average. First, I run a regression of realized excess returns of a portfolio on the lagged values of the business-cycle controls, and then the expected and unexpected returns are defined as the fitted values and the residuals of that regression, respectively.

5. The yields for BAA and AAA corporate bonds were retrieved from FRED, Federal Reserve Bank of St. Louis. They correspond to the Moody's Seasoned Corporate Bond Yields.

6. The term spread was also retrieved from FRED, Federal Reserve Bank of St. Louis. It corresponds to the series "T10Y3MM".

Table 4.3: Expected and Unexpected Returns under Republican and Democratic Presidencies

Portfolios	Expected Returns			Unexpected Returns		
	Democratic	Republican	Difference	Democratic	Republican	Difference
Most Liberal	16.46***	14.86***	1.60	6.11*	-11.49**	17.61***
	(1.04)	(2.05)	(2.27)	(3.18)	(4.45)	(5.25)
2	18.62***	16.12***	2.50	4.58	-9.24**	13.82***
	(0.68)	(1.49)	(1.60)	(3.16)	(4.51)	(5.25)
3	17.81***	14.00***	3.81*	3.82	-6.36	10.18*
	(0.91)	(1.91)	(2.11)	(3.94)	(4.55)	(5.77)
4	14.96***	12.45***	2.51	2.02	-4.90	6.92
	(0.54)	(1.80)	(1.87)	(2.76)	(4.54)	(5.16)
Most Conservative	17.42***	12.44***	4.98**	-0.18	1.24	-1.42
	(1.34)	(1.51)	(2.02)	(4.00)	(4.95)	(5.90)
Observations		3104			304	
R-squared		0.02 to 0.10			0.0001 to 0.03	

Note: All coefficients are in annual percentage points. Newey-West standard errors are reported in parentheses. The standard errors are computed with a maximum of 6 lags. The expected returns are computed as the fitted values of a regression of excess returns on the lagged value of the set of business-cycle controls: dividend-price ratio (DP_t), the default spread (DSP_t), the term spread (TSP_t), and the relative interest rate (RR_t). The period is from 1992:11 to 2018:02. *** p<0.01, ** p<0.05, * p<0.1

Table 4.3 shows the differences in expected and unexpected returns around the presidential-partisan cycle. These results suggest the differences in excess returns between Democratic and Republican presidencies are mostly explained by differences in unexpected returns. The differences in expected returns are only statistically significant for some portfolios, and they are significantly smaller in magnitude relative to the differences seen in unexpected returns. Moreover, the differences in expected returns around the presidential-partisan cycle and the clientele political ideology of a firm do not seem to be related. By contrast, the differences in unexpected returns seem to be associated with the clientele political ideology. Firms with the most liberal clientele exhibit larger differences in unexpected returns between Democratic and Republican presidencies. Remember this exercise is subject to the criticism that we do not observe the true expected returns; thus, any test about the risk premium is jointly a test of the model of expected returns. However, this exercise is useful to understand what could explain the differences in excess returns around the presidential-partisan cycle. In section 4.3, where we study how the market responds around close election, remembering these results will be useful. If Democratic presidencies carry a higher risk premium, we would expect a drop on impact in asset prices when a Democratic president gets elected, because the market will demand a higher expected return. Based on the analysis of expected and unexpected returns presented here, it does seem to be the case that prices respond on impact after the outcome of an election. By contrast, we should expect gradual price changes.

4.2.3 Long-Short Portfolio

An alternative way to test if clientele political ideology is associated with differences in returns around the presidential-partisan cycle is to estimate the alpha (α) of a long-short portfolio in which we hold the winning portfolio every time the political party controlling the White House changes. In other words, when a Democratic president gets elected, the zero-cost strategy will take a long position in the portfolio of the most liberal clientele firms and short in the portfolio of most conservative clientele firms, and when a Republican president gets elected, the long and short positions will get reversed. From Table 4.2, we can see that under Republican presidencies, the portfolio of firms with most conservative clientele exhibit a return that is 10.32 percentage points per year higher than the return of the portfolio of firms with the most liberal clientele. By contrast, when a Democratic president is in office the return of the portfolio of most liberal clienteles is 5.33 percentage points per year higher than the return of the portfolio of most conservative clienteles.

Table 4.4: Long-Short Portfolio

	(1)	(2)	(3)	(5)
Model	CAPM	3-factor	4-factor	5-factor
$MKT_t - r_{f,t}$	0.003	-0.02	0.10	0.04
	(0.07)	(0.07)	(0.07)	(0.08)
SMB_t		0.03	-0.01	0.13
		(0.11)	(0.09)	(0.12)
HML_t		-0.16	-0.06	-0.22
		(0.15)	(0.12)	(0.15)
UMD_t			0.31***	
			(0.06)	
RMW_t				0.26**
				(0.13)
CMA_t				-0.02
				(0.21)
α	7.14***	7.70***	4.72**	6.32**
	(2.57)	(2.65)	(2.35)	(2.85)
Observations	304	304	304	304

Note: All coefficients are in annual percentage points. Newey-West standard errors are reported in parentheses. The standard errors are computed with a maximum of 6 lags. Column (1) corresponds to the regression $r_t^{L-S} = \alpha + \beta_{MKT}\left(MKT_t - r_{f,t}\right) + \varepsilon_t$, where r_t^{L-S} denotes the returns of the long-short portfolio described above. Column (2) corresponds to the estimation of the 3-factor model proposed by Fama and French (1993). Column (3) estimates the 4-factor model proposed by Carhart (1997). Column (4) estimates the 5-factor model proposed by Fama and French (2015). The period is from 1992:11 to 2018:02. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.4 shows the estimation of α for this long-short strategy for four different models of expected returns (CAPM, 3-factor, 4-factor, and 5-factor). We can see that in all three models, the estimated α is positive and statistically significant. From all five factors considered, the return of our long-short portfolio is the most correlated with the momentum portfolio ($\rho = 0.39$). This relatively high correlation with the momentum portfolio is not surprising, because the long-short strategy is set such that we exploit the fact that firms with the most liberal clientele outperformed the market under Democratic presidencies, and firms with the most conservative clientele outperformed the market under Republican presidencies. In other words, the long-short portfolio I propose here is a political momentum portfolio that only gets rebalanced every four years if the party that controls the White House changes. Note that the long-short portfolio proposed in this section is rebalanced once the outcome of the election is known. Thus, by knowing the political ideology of firms' clientele, we could exploit the presidential-partisan cycle and obtain abnormal returns that are between 4.9 and 7.8 percentage points per year higher than what traditional models of expected returns predict.[7]

4.2.4 Firm-Level Analysis

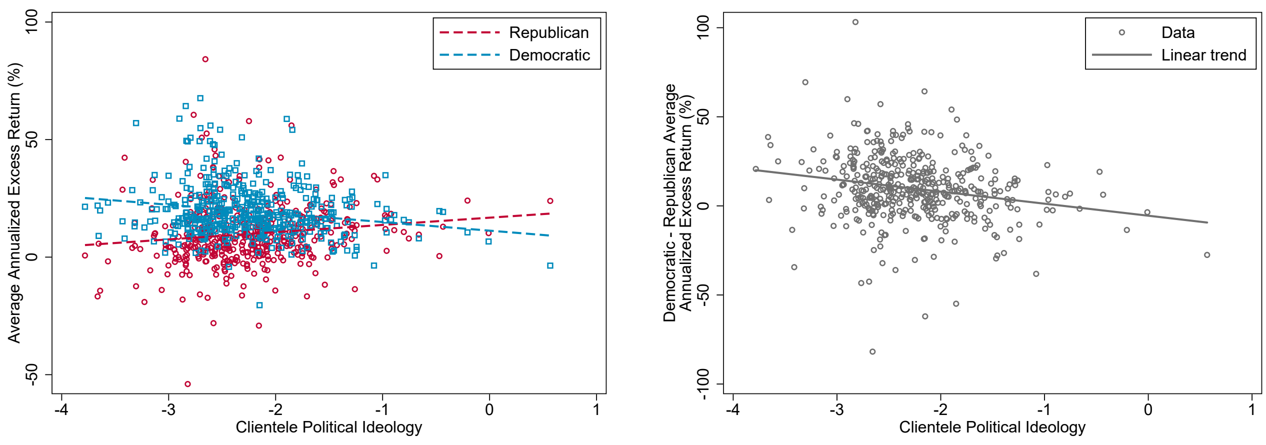
In the previous section, I used portfolios formed on clientele political ideology. Forming portfolios to test asset-pricing models is a common practice in the empirical asset-pricing literature. The argument in favor of this approach is that factor-loading and risk-premia estimates using portfolios are more precise than those estimates obtained using individual securities. However, Ang et al. (2018) argue that using portfolios could reduce the cross-sectional variation in factor loadings, which will increase the standard error of the risk-premia estimates. For this reason, in this section, I exploit the cross-section variation in clientele political ideology to better understand how this dimension could be associated with differences in returns between Democratic and Republican presidencies.

Figure 4.2 shows the relation between the average excess return and the political ideology

7. This is an ex-post analysis because my measure of political ideology was constructed using data as of 2018. The political ideology of a firm's clientele is unlikely to have changed drastically in the period of analysis. However, to confirm this trading strategy will deliver positive abnormal returns, an out-of-sample test will be needed.

of a firm's clientele under Democratic and Republican presidencies. Panel (a) shows that excess returns seem to be decreasing in our measure of clientele political ideology ($polideo_i$) under Democratic presidencies. That is, firms with more conservative clienteles show lower returns than firms with more liberal clienteles when the White House is controlled by a Democrat. On the other hand, under Republican presidencies, the relation between average excess returns and clientele political ideology is reversed. Panel (b) shows the difference between excess returns under Democratic and Republican presidencies for each firm.

Figure 4.2: Excess Returns and Presidential-Partisan Cycles by Firm



(a) Average Excess Returns (b) Difference in Average Excess Returns

Note: Panel (a) shows average excess returns for each firm under Democratic and Republican presidencies plotted against their clientele political ideology score. Panel (b) shows the difference in a firm's average excess returns between a Democratic and a Republican presidency, plotted against their clientele political ideology score. Each point in the graph represents a firm. All rates are represented in annualized percentage points. The lines correspond to a linear regression line fitted to the data. The period is from 1992:01 to 2018:02.

More formally, I regress the excess return of a firm against its clientele political ideology under Democratic and Republican presidencies, separately. Table 4.5 Panel (a) shows the estimation of a specification of the form $r_{it} - r_{ft} = \beta_0 + \beta_1 polideo_i + u_{it}$, where r_{it} is the returns of a firm, r_{ft} is the risk-free rate, and $polideo_i$ is the political ideology of a firm's clientele. We can see the coefficient on clientele political ideology is negative under Democratic presidencies, and positive under Republican presidencies. Moreover, the difference in these coefficients is statistically significant, suggesting the clientele political ideology affects returns differently depending on what party is in control of the presidency. One possibility is that the difference in excess returns by clientele ideology is due to differences in market betas. To rule out this possibility, I run the same specification but use abnormal returns instead of excess returns. The last three columns in Panel (a) show that the relation between clientele political ideology and stock returns changes with the presidential cycle. Under Democratic presidencies, firms with more liberal clienteles tend to have relatively higher abnormal returns, and the opposite holds under Republican presidencies.

Table 4.5: Firm-Level Regressions

(a) Regressions without Industry Controls

Dependent Variable:	Excess Return			Abnormal Returns (Market Model)		
	Democratic	Republican	Difference	Democratic	Republican	Difference
Clientele Political Ideology Score	-3.67***	3.08***	-6.75***	-2.17***	3.71***	-5.88***
	(0.92)	(1.10)	(1.44)	(0.52)	(0.87)	(1.02)
Observations	437	437	874	437	437	874
R-Squared	0.04	0.02	0.16	0.04	0.04	0.05

(b) Regressions with Industry Controls

Dependent Variable:	Excess Return			Abnormal Returns (Market Model)		
	Democratic	Republican	Difference	Democratic	Republican	Difference
Clientele Political Ideology Score	-2.52**	2.24*	-4.76***	-1.70***	2.83***	-4.52***
	(0.98)	(1.20)	(1.55)	(0.55)	(0.96)	(1.11)
Observations	424	424	848	424	424	848
R-Squared	0.28	0.12	0.29	0.15	0.18	0.18

Note: Standard errors in parentheses. All coefficients are in annual percentage points. Abnormal returns are computed from a regression $r_{it} = \alpha_i + \beta_i r_{Mt} + \varepsilon_{it}$ for each firm, where r_{it} is the return of a firms, and r_{Mt} is the market return. The period is from 1992:11 to 2018:02. *** p<0.01, ** p<0.05, * p<0.1.

Another concern is that most of the cross-sectional variation in clientele political ideology is explained by industry. Thus, the differences in returns around the political cycle could be not necessarily associated with clientele political ideology, but instead with how the market perceives the policies implemented by Republicans and Democrats to affect different industries. To rule out this possibility, I regress excess and abnormal returns against clientele political ideology and industry fixed effects. By including industry fixed effects, I am able to analyze how within-industry differences in clientele political ideology are associated with within-industry differences in returns. Table 4.5 Panel (b) shows the estimation of these regressions including industry fixed effects. We can see the magnitude and statistical significance of all the coefficients remains relatively unchanged. Thus, even within-industry variation in clientele political ideology is associated with differences in returns around the presidential-partisan cycle.

4.3 Event Study around Close Elections

I analyze the returns of the portfolios formed on clientele political ideology around close elections to understand how the market responds when political uncertainty is resolved. The analysis around close elections could help us understand if the differences in the partisan-gap across clientele political ideology are explained by differences in expected returns, or by the market being systematically surprised by the policies of Democratic presidents. If investors demand smaller expected returns for Republican presidencies, either because they perceive Republican presidencies as a period of relatively lower volatility, or because risk aversion is low when Republicans win the presidency (Pástor and Veronesi, 2017), we could expect to see an immediate increase in asset prices once a Republican wins the presidency, or in the days leading up to the election if the election outcome was anticipated. However, the results from the previous section suggest the portfolio of firms with relatively more liberal clienteles exhibits a higher difference in excess returns between Democratic and

Republican presidencies. Thus, if the partisan gap is explained by differences in expected returns, investors under Democratic presidencies must demand even higher expected return for firms with relatively more liberal clientele. This possibility seems unlikely because it would imply that under Democratic presidencies, firms with more liberal clienteles are perceived as relatively more risky.

I focus the analysis around close elections because doing so allows me to better identify the effect of political shocks on stock returns. As Shelton (2005) and Snowberg et al. (2007) emphasize, identifying elections that transmit essentially no news is important. If the market anticipates the outcome of the election, comparing returns around the election day will not allow us to identify how the market responds to political shocks. By contrast, close elections will provide a public signal, which we expect the market will quickly incorporate into asset prices. The identification assumption is that around the election day, no other factors differentially affect returns of firms with liberal and conservative clientele. Snowberg et al. (2007) adopted a similar identification strategy to analyze equity returns, interest rates, oil prices, and exchange rates around the 2000 and 2004 election, and Meeuwis et al. (2018) focus on the unexpected 2016 election to analyze changes in portfolio choice by investors' political party affiliation.

The 2000, 2004, and 2016 elections, in that order, have the smaller electoral votes margin between the winner and the runner-up.[8] The 2016 election not only had a relatively small electoral vote margin in favor of Donald Trump, but also, until the day of the election, the polls and political betting markets had Hillary Clinton as the favorite to win the election. Thus, not only was the 2016 election a close election, but its outcome was also relatively unexpected. The two elections George W. Bush won were also close elections. The 2000

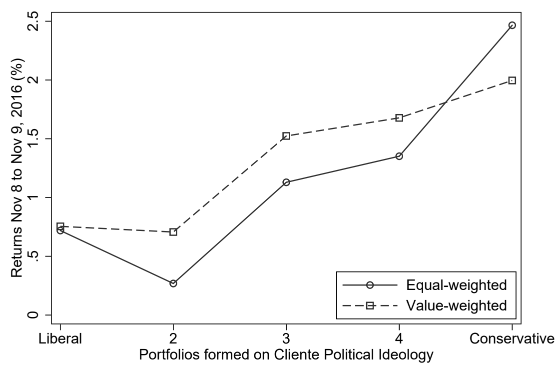
8. Table A5 summarizes the results and probabilities of the Republican candidate winning for the last seven presidential elections.

election against Al Gore had no clear favorite heading into election day. Moreover, the outcome of the election remained uncertain from November 7, 2000 until December 12, 2000, when the Supreme Court ruled regarding the Florida vote recount, giving George W. Bush the sufficient electoral votes to become the president. The next day, Al Gore gave a concession speech, putting an end to 25 trading days of uncertainty about the outcome of the election. For the 2004 election, once again, there was not a clear favorite between Bush and John Kerry. The probability of Bush winning the election was only 55% according to Snowberg et al. (2007). On the other hand, the elections won by Bill Clinton and Barack Obama were relatively anticipated. In both the 1992 and 1996 elections, Bill Clinton confidently lead the polls months ahead of the election. In the 2008 election, Barack Obama had had a comfortable lead in the polls since early October. The 2012 election between Obama and Mitt Romney seemed to have been closer because Obama did not have a wide advantage in the polls just weeks before the election. However, the election polls seem to be a good proxy for the popular vote and not for how the electoral college is going to be split between the two candidates. The expert in electoral forecast, Nate Silver, from FiveThirtyEight, predicted the probability of Obama winning the election was close to 85%, and at the end, a wide margin in electoral votes was in favor of Obama.

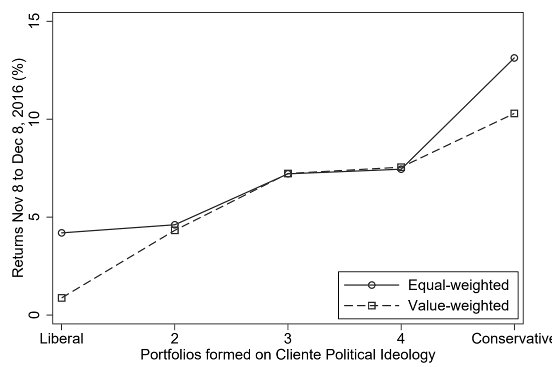
4.3.1 2016 Presidential Election

In addition to the results of the 2016 presidential election being unexpected, fundamental differences in the economic and policy plans between Donald Trump an Hillary Clinton also existed (Meeuwis et al., 2018). If clientele political ideology helps explain differences in returns around the political cycle, we could expect to see a heterogeneous market response following the election results. Figure 4.3 shows the returns one day and one month after the 2016 election for the five portfolios formed on clientele political ideology. From Panel (a), we can see that one day after the election, all portfolios exhibit positive returns, with the portfolio of firms with more conservative clientele having the highest returns at around 2%. When we consider the one-month returns, the relation between clientele political ideology and stock returns is even clearer. The more conservative the clientele of firms in a portfolio, the higher the returns of the portfolio once Donald Trump got elected.[9]

Figure 4.3: Returns after the 2016 Presidential Election for Portfolios Formed on Clientele Political Ideology



(a) One-day returns



(b) One-month returns

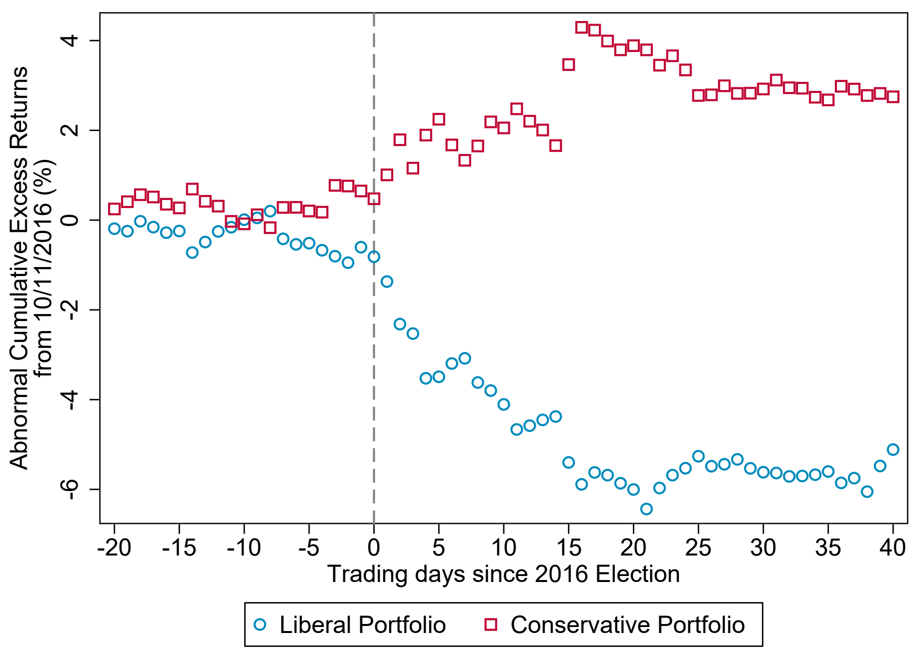
Comparing portfolio returns one day and one month after the election provides suggestive evidence that the market response is more favorable for firms with relatively more conservative clientele when a Republican gets to the White House. However, these differences could be explained by market betas or even by returns across portfolios drifting apart days before the election. To better analyze the effect that the election had on stock returns, the most appropriate approach is an event study around the day of the election.

For the event study around the election date, I define the event window to be from 20 trading days before to 40 trading days after the election. The event window before the election corresponds roughly to one calendar month, a time in which the presidential campaigns are capturing most of the media attention and in which the differences in the

9. Figure A4 plots the one-day and one-month returns against the measure of clientele political ideology by firm. The slope of the regression line in both graphs is positive and statistically significant.

political platforms of the two candidates has become evident. The event window after the election corresponds to almost two calendar months after the election, a time in which the new government has had the opportunity to send public signals about which policies it will prioritize, but the government has not yet changed, so no actual policies have been implemented. I compute abnormal returns based on the market model for each day in the event window. To avoid potential biases in the estimation of abnormal returns that coincide with the presidential race, I define the estimation window to be the one-year window before the presidential race between the Republican and Democratic candidate starts. That is, I estimate the market model $r_{jt} = \beta_0 + \beta_1 r_{Mt} + \varepsilon_{jt}$ using daily returns for a portfolio between July 2015 and June of 2016.[10]

Figure 4.4: Event Study around 2016 Presidential Election



Note: Abnormal returns are computed using the market model. The estimation window is between July 2015 and June 2016. Liberal portfolio refers to the portfolio of firms with clientele political ideology below the 20th percentile. Conservative portfolio refers to the portfolio of firms with clientele political ideology above the 80th percentile.

10. Primary elections usually take place in the first semester of election year. The presidential race between the Democratic and Republican candidate does not start until early July.

Figure 4.4 show the event study around the 2016 presidential election. We can see how the cumulative abnormal returns (CAR) of the two portfolios (liberal and conservative clientele) are almost parallel until the day of the election. After the election, the portfolio of firms with the more conservative clienteles exhibits positive abnormal returns, and the portfolio of firms with the more liberal clientele exhibits negative abnormal returns, which almost mirror each other. Almost one month after the election (20 trading days), the difference in CAR between the two portfolios is around 9.5 percentage points.

Table 4.6: Event Study around 2016 Presidential Election

	CAR [-20 to 0]	CAR [1 to 5]	CAR [1 to 10]	CAR [1 to 15]	CAR [1 to 20]	CAR [21 to 40]
Liberal Portfolio	-0.815	-2.675***	-3.291***	-4.585***	-5.187***	0.889
	(0.577)	(0.0001)	(0.001)	(0.0002)	(0.0003)	(0.533)
Conservative Portfolio	0.476	1.772*	1.579	2.990*	3.411*	-1.140
	(0.803)	(0.05)	(0.222)	(0.061)	(0.067)	(0.539)
Difference	1.291	4.447***	4.87**	7.574***	8.599***	-2.029
	(0.673)	(0.002)	(0.019)	(0.003)	(0.004)	(0.496)

Note: Abnormal returns are computed using the market model. The estimation window is between July 2015 and June 2016. Liberal portfolio refers to the portfolio of firms with clientele political ideology below the 20th percentile. Conservative portfolio refers to the portfolio of firms with clientele political ideology above the 80th percentile. P-Values are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

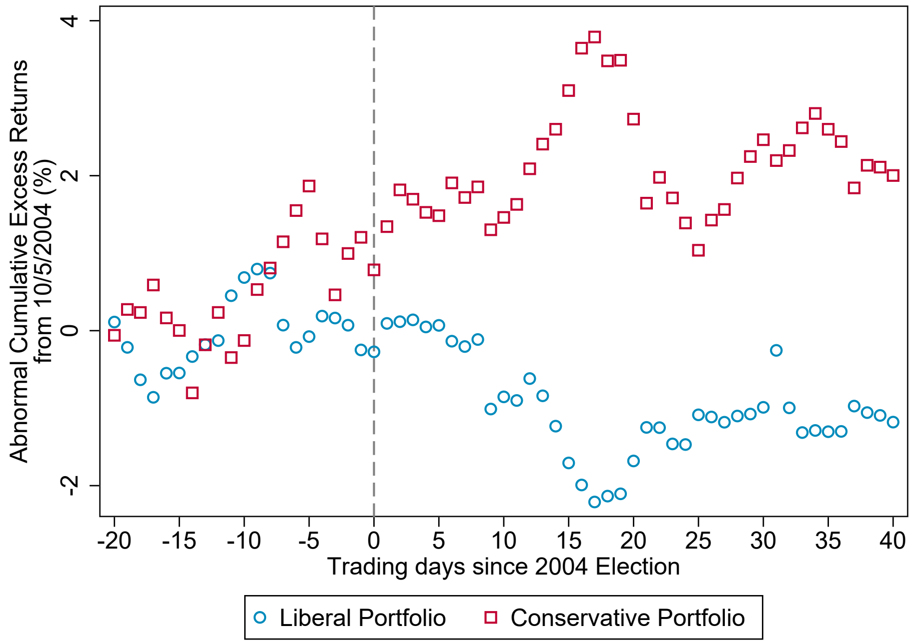
Table 4.6 summarizes the formal statistical tests for cumulative abnormal returns around the 2016 presidential election. We can see that no statistically significant differences exist in cumulative abnormal returns from 20 days before until election day. This finding suggests the market did not anticipate the outcome of the election. Just five days after the election the difference in cumulative abnormal returns between the two portfolios is 4.4 percentage points, and the difference continues to increase, reaching 8.6 percentage points at 20 days. In the 21- to 40-day window, no statistically significant difference exists in CAR. The 8.6-percentage-point difference in cumulative abnormal returns between portfolios formed on political ideology 20 trading days after the election is economically and statistically significant. Moreover, given how unexpected the outcome of the 2016 election was, a firm's clientele political ideology seems to have been a relevant dimension to understand the market response to changes in the governing party.

4.3.2 2004 Presidential Election

Figure 4.7 plots the event study for the 2004 election. A pattern similar to that of the 2016 election can be observed. Cumulative abnormal returns of the two portfolios seem to drift apart a few days after the election, reaching the maximum difference (5.9 percentage points) 17 days after the election. The difference between the two portfolios does not seem as large as for the 2016 election. One possible explanation for this result is that the 2004 election did not result in a change in the political party in control of the presidency. The results observed for 2016 could be the result of how the market interprets the policy announcement by the new government. After the 2004 election, investors could expect a continuation of the policies of President Bush, and even the announcement of new policies could have been filtered much better by investors, because, during the previous four years, they could have learned how to read the signals sent by the government.

Table 4.6 summarizes the formal statistical tests for cumulative abnormal returns around the 2004 presidential election. We can see no differences in CAR in the 20-day period ahead of the election. The differences in CAR are only slightly statistically significant for the 15-day period after the election.

Figure 4.5: Event Study around 2004 Presidential Election



Note: Abnormal returns are computed using the market model. The estimation window is between July 2003 and June 2004. Liberal portfolio refers to the portfolio of firms with clientele political ideology below the 20th percentile. Conservative portfolio refers to the portfolio of firms with clientele political ideology above the 80th percentile.

Table 4.7: Event Study around 2004 Presidential Election

	CAR [-20 to 0]	CAR [1 to 5]	CAR [1 to 10]	CAR [1 to 15]	CAR [1 to 20]	CAR [21 to 40]
Liberal Portfolio	-0.273	0.341	-0.581	-1.434	-1.408	0.501
	(0.851)	(0.622)	(0.556)	(0.24)	(0.322)	(0.724)
Conservative Portfolio	0.785	0.699	0.677	2.314*	1.945	-0.728
	(0.579)	(0.299)	(0.481)	(0.051)	(0.16)	(0.598)
Difference	1.058	0.358	1.258	3.748*	3.354	-1.229
	(0.649)	(0.746)	(0.425)	(0.054)	(0.139)	(0.587)

Note: Abnormal returns are computed using the market model. The estimation window is between July 2003 and June 2004. Liberal portfolio refers to the portfolio of firms with clientele political ideology below the 20th percentile. Conservative portfolio refers to the portfolio of firms with clientele political ideology above the 80th percentile. P-Values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.3.3 2000 Presidential Election

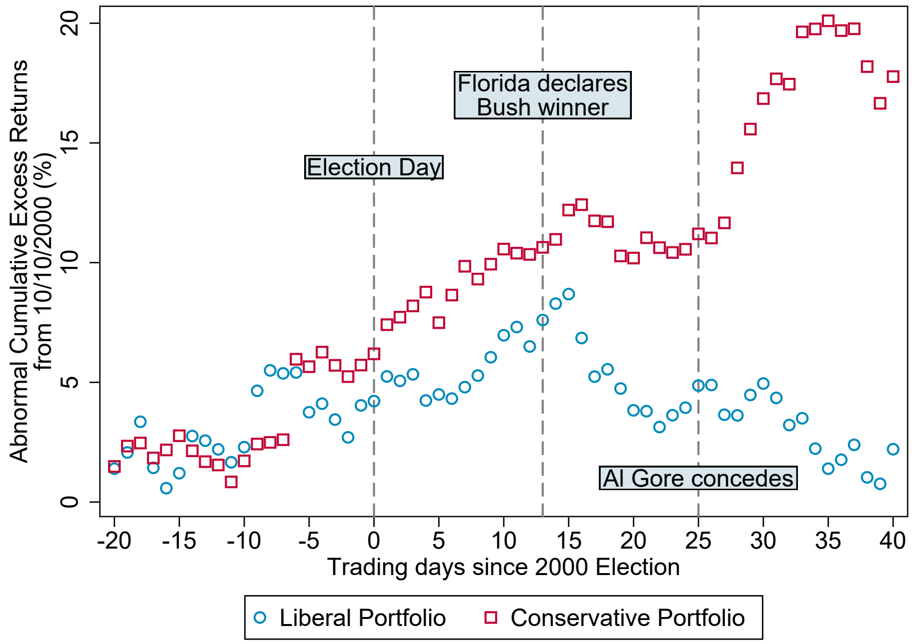
Analyzing the November 7, 2000, presidential election requires us to consider some historical background about events that took place in the weeks following the election. By the end of election day, Mr. Bush had 246 electoral votes and Mr. Gore had 266. The final results for Florida were still pending, and whoever win that state was going to also win the presidency because Florida carries 25 electoral votes. By November 8, Florida put Mr. Bush ahead of Mr. Gore by only 1,725 votes. A full machine recount was completed by November 10, reducing the margin in favor of Mr. Bush to 327 votes. On November 26 (7:30 pm EST), Florida's Secretary of State declared Mr. Bush the winner of the 25 electoral votes, and therefore the winner of the presidential election. However, Mr. Gore did not concede the victory to Mr. Bush, and legal proceedings continued at the US Supreme Court. On December 12, the US Supreme Court ruled in favor of Mr. Bush, thereby stopping the Florida recount. Finally, on December 13 (9:00 pm EST), Mr. Gore conceded the victory to Mr. Bush.[11]

Figure 4.6 shows the event study for the 2000 election. We can see that CAR for the two portfolios were moving in parallel the days before the election. Immediately after election day, the CAR of the portfolio of firms with the most conservative clientele seems to be slightly higher than the CAR of the portfolio of firms with the most liberal clientele. The difference in CAR seems to remain constant at around 3.7 percentage points until more or less the day Florida's Secretary of State declared Mr. Bush as the winner of the 25 electoral votes. CAR increased by around 2.8 percentage points in the 10 days following the Florida announcement. Finally, after Mr. Gore's concession speech, the CAR of the two portfolios drifted apart, reaching a maximum of 18.7 percentage points 35 trading days after the election. Clearly, the timeline of events suggests the uncertainty about the election

11. A good summary of the timeline of events following the 2000 election day can be found at: https://www.theguardian.com/world/2000/dec/14/uselections2000.usa

outcome was not resolved until the US Supreme Court ruled in favor of Mr. Bush and Mr. Gore gave a concession speech the next day.

Figure 4.6: Event Study around 2000 Presidential Election



Note: Abnormal returns are computed using the market model. The estimation window is between July 1999 and June 2000. Liberal portfolio refers to the portfolio of firms with clientele political ideology below the 20th percentile. Conservative portfolio refers to the portfolio of firms with clientele political ideology above the 80th percentile.

To formally test the differences in CAR between the two portfolios, I focus not on the election date as with the other two elections. Instead, I analyze the difference in returns when the uncertainty about the election was resolved, namely, when Al Gore gave his concession speech. Table 4.8 shows the formal statistical test around this date. We can see that just five days after, the gap in CAR increased by 5.5 percentage points and continued to increase for the next five days. The CAR of the portfolio of firms with liberal clienteles remained relatively constant after the outcome of the election was resolved. The difference comes from a sharp increase in CAR of the portfolio of firms with more conservative clienteles. Given that the resolution of the election outcome was completely exogenous, and given the large difference in CAR between the two portfolios once the uncertainty was resolved (11.9 percentage points in 10 days), a firm's clientele political ideology again seems to have been a relevant dimension for understanding the market response to changes in the governing party.

Table 4.8: Event Study around Al Gore's Concession Speech

	CAR [-20 to 0]	CAR [1 to 5]	CAR [1 to 10]	CAR [1 to 15]	CAR [1 to 20]	CAR [21 to 40]
Liberal Portfolio	0.870	-0.101	-3.413	-2.650	-4.804	3.636
	(0.808)	(0.953)	(0.160)	(0.378)	(0.169)	(0.298)
Conservative Portfolio	1.640	5.421**	8.514***	5.977	3.859	3.632
	(0.722)	(0.014)	(0.006)	(0.122)	(0.391)	(0.419)
Difference	0.770	5.522**	11.927***	8.626*	8.663	-0.004
	(0.895)	(0.049)	(0.003)	(0.078)	(0.129)	(0.999)

Note: Abnormal returns are computed using the market model. The estimation window is between July 1999 and June 2000. Liberal portfolio refers to the portfolio of firms with clientele political ideology below the 20th percentile. Conservative portfolio refers to the portfolio of firms with clientele political ideology above the 80th percentile. P-Values are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.4 Differences in Volatility

Differences in average excess returns between Republican and Democratic presidencies could be the result of differences in volatility. Santa-Clara and Valkanov (2003) does not find evidence of differences in volatility that could explained the partisan gap in returns for the stock market as a whole. However, it could be that are significant differences when we consider differences across clientele political ideology. Table 4.9 reports average volatility across portfolios. We can see no portfolio shows statistically significant differences in volatility between Democratic and Republican periods. Thus, it does not seem plausible that the partisan gap in excess returns is explained by differences in volatility.

Table 4.9: Average Volatility of Portfolios Formed on Clientele Political Ideology

Portfolios	Average Volatility		
	Democratic	Republican	Difference
Most Liberal	0.995***	1.013***	-0.018
	(0.070)	(0.114)	(0.124)
2	1.039***	1.084***	-0.046
	(0.077)	(0.130)	(0.137)
3	1.058***	1.031***	0.026
	(0.100)	(0.115)	(0.132)
4	0.998***	1.054***	-0.056
	(0.082)	(0.119)	(0.128)
Most Conservative	1.047***	1.044***	0.003
	(0.096)	(0.104)	(0.119)

Note: Volatility of value-weighted portfolio returns is computed monthly using daily data. Months with less than 15 observations are excluded. Newey-West standard errors are reported in parentheses.The period is from 1992:11 to 2018:02. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4.5 Differences in Sales Surprises

The results presented above suggest a relation between clientele political ideology and stock returns throughout the political cycle. Firms with more liberal clienteles tend to outperform firms with more conservative clienteles during Democratic presidencies, and the opposite holds for Republican presidencies. Moreover, no differences in volatility or risk exposure to common factors exist across portfolios formed on clientele political ideology that could explain the differences in the partisan gap. In this section, I investigate the relation between clientele political ideology and firms' fundamentals throughout the partisan cycle. More specifically, I study whether the relation between a firm's clientele political ideology and the firm's stock returns is related to the expectation of different cash flows in the future. That is, if during Democratic periods, liberal consumers are more optimistic about the future economic conditions and these consumers change their consumption spending, we would expect higher future cash flow for firms with more liberal clienteles during Democratic presidencies.

I take quarterly sales from COMPUSTAT and compare how abnormal sales are associated with clientele political ideology under Democratic and Republican periods.[12] To calculate abnormal sales, I decompose quarterly sales for each firm in expected and unexpected sales using the regression specification

$$sales_{it} = \theta_{0i} + \sum_{\tau=1}^{4} \theta_{\tau i} sale_{i,t-\tau} + \varepsilon_{it} \tag{4.1}$$

Expected sales are defined as the fitted values $\left(\hat{sales}_{it}\right)$ from the previous specification, whereas unexpected sales are the residuals ($\hat{\varepsilon}_{it}$). I define abnormal sales ($abnsale_{it}$) as the percentage deviation from expected sales

$$abnsales_{it} = 100 \times \frac{\hat{\varepsilon}_{it}}{\hat{sales}_{it}} \tag{4.2}$$

Under the hypothesis that consumers' political ideology influences their consumption spending behavior, we expect abnormal sales to have a positive relation with a firm's clientele conservatism during Republican presidencies, and a negative relation during Democratic presidencies. To corroborate this hypothesis, I estimate the specification

$$abnsales_{it} = \beta_0 + \beta_1 REP_t \times polideo_i + \beta_2 DEM_t \times polideo_i + \lambda_t + \xi_j + u_{it} \tag{4.3}$$

where REP_t and DEM_t are binary variables denoting if the period corresponds to a Democratic or Republican presidency, λ_t is a quarter-specific component, and ξ_j is an

12. I use the variable *saleq* from COMPUSTAT. Before estimating the specification in Equation 4.1, I adjust the series of quarterly sales to be expressed in real terms and remove the seasonality specific to each firm.

industry-specific component. The specification in Equation 4.3 allows us to study how abnormal sales vary across firms with different clientele political ideology under Democratic and Republican presidencies, separately. Table 4.10 shows the estimation of the specification in Equation 4.3. We can see that during Republican periods, clientele conservatism is associated with larger abnormal sales, and during Democratic periods the relation between clientele conservatism and abnormal sales is reversed. These results suggest the expected future cash flow mechanism could explain the relation between clientele political ideology and the partisan gap in returns.

Table 4.10: Abnormal Sales and Clientele Political Ideology

	(1)	(2)	(3)	(4)
	1992-2018	1992-2018	After 2016 Election	After 2016 Election
$DEM \times polideo_i$	-0.789***	-0.512**		
	(0.270)	(0.217)		
$REP \times polideo_i$	0.173	0.460**	0.538**	0.483*
	(0.214)	(0.205)	(0.269)	(0.249)
Industry Effects	No	Yes	No	Yes
Observations	35,783	35,783	1,746	1,746
R-Squared	0.095	0.098	0.126	0.133

Note: Standard errors are clustered at the firm level and are reported in parentheses The period is from 1992:11 to 2018:02. *** p<0.01, ** p<0.05, * p<0.1.

CHAPTER 5

CONCLUSION

Motivated by the increase in political polarization in the last two decades and evidence suggesting that individuals on opposite sides of the political spectrum have different preferences for goods, this paper studies how differences in stock returns under Democratic and Republican presidencies compare across firms with different clientele political ideologies. The results of this paper suggest the political ideology of a firm's clientele is associated with the differences in returns throughout the presidential-partisan cycle. Moreover, the differences in the presidential-partisan gap do not seem to be attributable to differences in risk exposure or in volatility.

The results of the paper suggest that differences in the composition and preferences of a firm's clientele could affect the firm's stock price. Using social media data seems to be useful at capturing the differences in firms' clienteles and to study how differences in dimensions other than political ideology could have an effect on asset returns. Further research could use data from social media to capture firms' exposure to regional shocks due to the location of their customers, or to understand differences in competition faced by firms by comparing the overlap of a firm's networks with those of its closest competitor, among other questions.

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CHAPTER A

APPENDICES

A.1 Additional Figures

Figure A1: Number of Twitter Followers and Market Capitalization

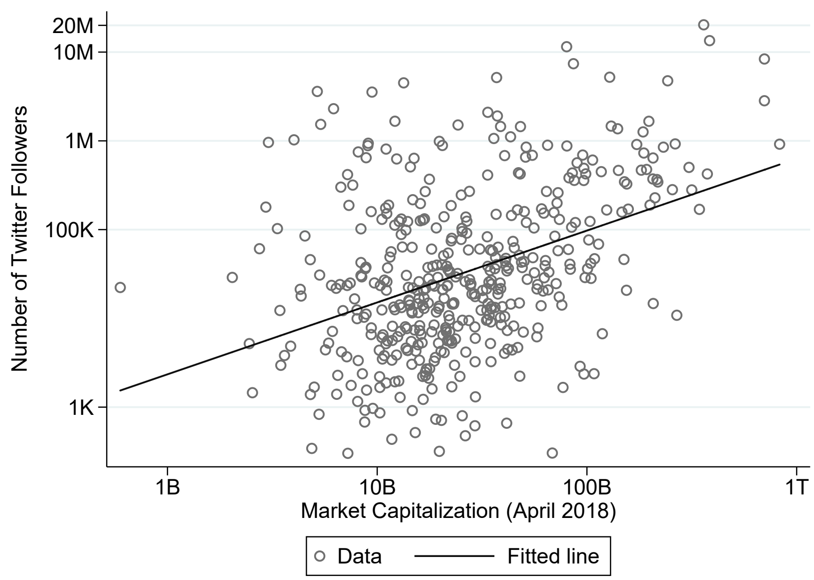


Figure A2: Number of Twitter Followers and Total Revenue

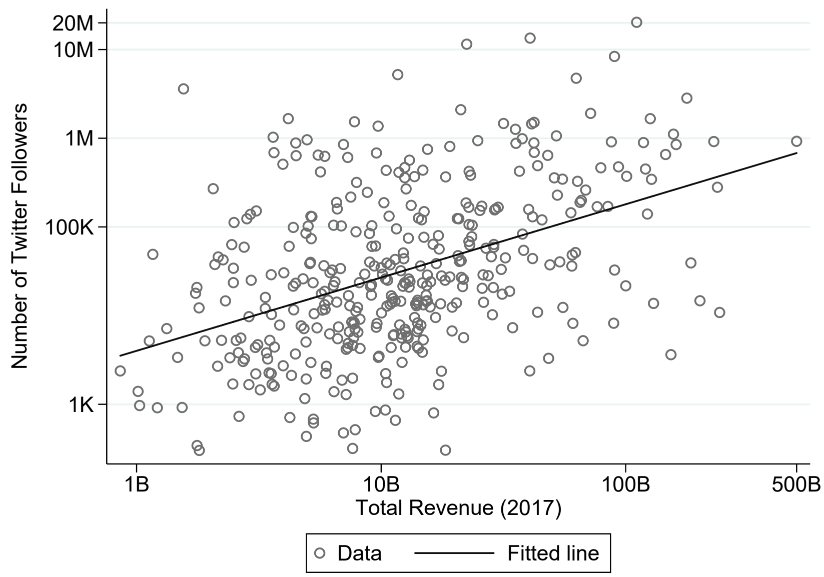
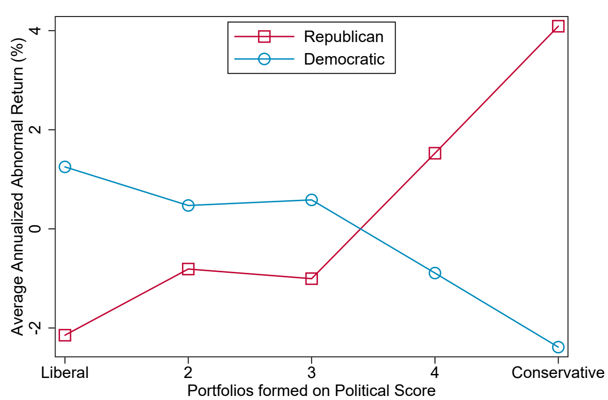
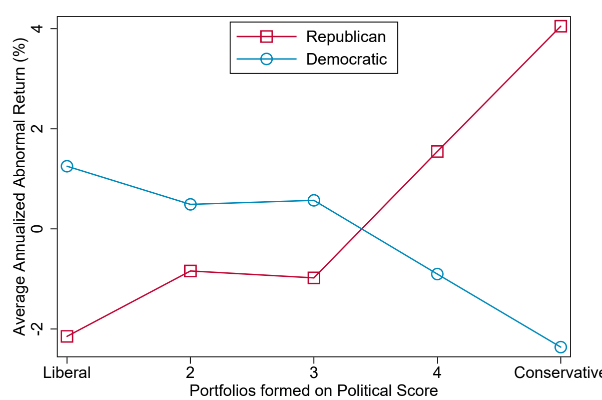


Figure A3: 3-Factor and 4-Factor Abnormal Returns and the Presidential-Partisan Cycle



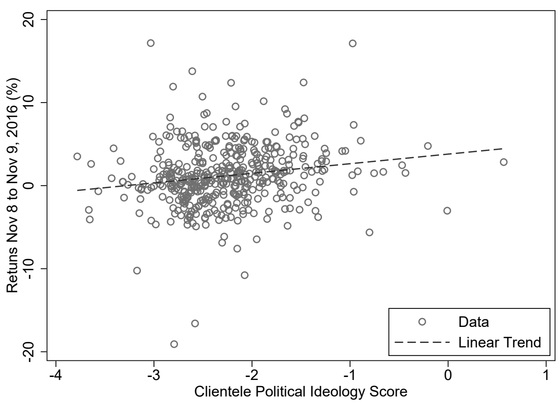
(b) Abnormal Returns (3-Factor Model)



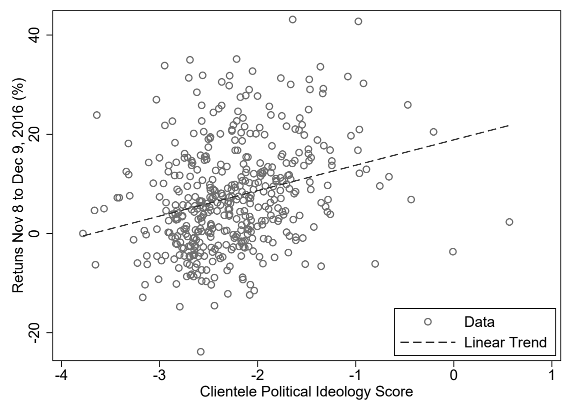
(b) Abnormal Returns (4-Factor Model)

Note: Figure (a) shows average abnormal returns for 3-factor model for the value-weighted portfolios. Figure (b) shows average abnormal returns for 4-factor model for the value-weighted portfolios. All rates are represented in annualized percentage points. The blue lines correspond to Democratic presidencies and the red lines correspond to Republican presidencies. The period is from 1992:01 to 2018:02.

Figure A4: Returns After Trump Election and Clientele Political Ideology



(a) One-day returns



(b) One-month returns

A.2 Additional Tables

Table A1: Predicting Political Ideology

VARIABLES	Order Logit	Linear Regression
ABC News	0.100	0.270
	(1.264)	(1.471)
CBS News	-0.155*	-0.358*
	(-1.774)	(-1.779)
NBC News	-0.149*	-0.393**
	(-1.817)	(-2.084)
NPR	-0.946***	-1.936***
	(-9.091)	(-8.496)
Rush Limbaugh Show	0.877***	1.877***
	(5.246)	(5.119)
Sean Hannity Show	1.252***	2.711***
	(8.060)	(7.852)
Washington Post	-0.475***	-0.915***
	(-3.156)	(-2.676)
New York Times	-0.750***	-1.613***
	(-6.557)	(-6.213)
Drudge Report	1.022***	2.442***
	(5.475)	(5.805)
Huffington Post	-0.274**	-0.612**
	(-2.534)	(-2.543)
Breitbart	0.394	0.311
	(1.560)	(0.559)

Table A1 (continued)

VARIABLES	Order Logit	Linear Regression
TheBlaze	0.797***	1.711***
	(3.966)	(3.750)
Guardian	-0.184	-0.381
	(-0.827)	(-0.801)
BBC	-0.264***	-0.618***
	(-2.602)	(-2.692)
New Yorker	-0.359	-0.702
	(-1.563)	(-1.435)
Fox News	1.025***	2.519***
	(13.200)	(14.687)
MSNBC	-0.292***	-0.604***
	(-3.565)	(-3.237)
CNN	-0.246***	-0.611***
	(-3.504)	(-3.798)
PBS	-0.240**	-0.619***
	(-2.304)	(-2.673)
Colbert Report	-0.185	-0.348
	(-1.277)	(-1.038)
Daily Show	-0.830***	-1.867***
	(-5.918)	(-5.855)
Glenn Beck Program	0.623***	1.177***
	(3.234)	(2.657)

Table A1 (continued)

VARIABLES	Order Logit	Linear Regression
Wall Street Journal	0.599***	1.321***
	(4.576)	(4.480)
USA TODAY	0.214**	0.416*
	(1.971)	(1.707)
Slate	-0.136	-0.217
	(-0.565)	(-0.417)
Politico	-0.238	-0.318
	(-1.237)	(-0.739)
Yahoo News	0.160**	0.397**
	(2.085)	(2.233)
Bloomberg	0.253	0.575
	(1.412)	(1.430)
BuzzFeed	-0.511***	-1.209***
	(-2.918)	(-3.062)
Al Jazeera America	-0.361**	-0.827**
	(-1.997)	(-2.085)
Economist	0.375*	0.441
	(1.820)	(0.976)
Observations	2,901	2,901
Pseudo R2 / R2	0.105	0.435

z-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A2: Main Results for the Extended Period 1984-2018

(a) Partisan Gap across Portfolios Formed on Clientele Political Ideology

Portfolio	Democratic	Republican	Difference
Most Liberal	22.57***	10.36***	12.21**
	(3.22)	(3.81)	(4.77)
2	23.20***	8.85**	14.36***
	(3.22)	(3.46)	(4.51)
3	21.63***	11.55***	10.08**
	(3.78)	(3.53)	(4.98)
4	16.98***	11.70***	5.28
	(2.75)	(3.34)	(4.19)
Most Conservative	17.24***	14.04***	3.20
	(3.77)	(3.48)	(4.81)

(b) Long-Short Portfolio

	(1)	(2)
Model	CAPM	3-Factor
$MKT_t - r_{f,t}$	-0.02	-0.04
	(0.05)	(0.05)
SMB_t		0.08
		(0.09)
HML_t		-0.07
		(0.13)
α	4.66**	4.97**
	(2.14)	(2.20)
Observations	400	400

Note: All coefficients are in annual percentage points. Newey-West standard errors are reported in parentheses. The standard errors are computed with a maximum of 6 lags. Column (1) corresponds to the regression $r_t^{L-S} = \alpha + \beta_{MKT}\left(MKT_t - r_{f,t}\right) + \varepsilon_t$, where r_t^{L-S} denotes the returns of the long-short portfolio described above. Column (2) corresponds to the estimation of the 3-factor model proposed by Fama and French (1993). The period is from 1984:11 to 2018:02. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Top Firms by Clientele Political Ideology

Top 10 Firms with the Most Liberal Clientele

Name	Industry	Political Score
Gap Inc.	Retail-Family Clothing Stores	-3.78
Interpublic Group	Services-Advertising Agencies	-3.66
Consolidated Edison	Electric & Other Services Combined	-3.65
TEGNA Inc.	Television Broadcasting Stations	-3.64
Omnicom Group	Services-Advertising Agencies	-3.57
Coach New York	Leather & Leather Products	-3.45
Urban Outfitters	Retail-Family Clothing Stores	-3.41
Tiffany & Co.	Retail-Jewelry Stores	-3.34
Nordstrom	Retail-Family Clothing Stores	-3.32
Scripps Networks	Cable & Other Pay Television Services	-3.32

Top 10 Firms with the Most Conservative Clientele

Name	Industry	Political Score
News Corporation	Newspapers: Publishing & Printing	0.57
Range Resources	Crude Petroleum & Natural Gas	-0.21
Archer Daniels Midland	Fats & Oils	-0.01
Pioneer Natural Resources	Crude Petroleum & Natural Gas	-0.44
Newfield Exploration	Crude Petroleum & Natural Gas	-0.47
Genuine Parts Co.	Wholesale-Motor Vehicle Supplies	-0.66
Snap-On Inc.	Cutlery, Handtools & General Hardware	-0.75
Realty Income Corporation	Real Estate Investment Trusts	-0.80
General Dynamics Mission Systems	Aircraft	-0.89
Helmerich & Payne	Drilling Oil & Gas Wells	-0.92

Table A4: Factor Loading for Portfolios Formed on Clientele Political Ideology

Portfolios	Republican			Democratic			Differences Between Dem. and Rep.		
	$MKT_t - r_{f,t}$	SMB_t	HML_t	$MKT_t - r_{f,t}$	SMB_t	HML_t	$MKT_t - r_{f,t}$	SMB_t	HML_t
Liberal	1.007***	-0.374***	-0.199***	0.857***	-0.273***	-0.082	0.157***	-0.093	-0.109
	(0.031)	(0.040)	(0.041)	(0.040)	(0.062)	(0.057)	(0.050)	(0.074)	(0.070)
2	0.993***	-0.129***	-0.164***	0.964***	-0.143**	-0.077	0.032	0.016	-0.084
	(0.031)	(0.040)	(0.042)	(0.038)	(0.058)	(0.054)	(0.049)	(0.072)	(0.069)
3	1.093***	0.012	0.176***	0.916***	0.060	0.226***	0.180***	-0.046	-0.047
	(0.031)	(0.041)	(0.042)	(0.026)	(0.041)	(0.038)	(0.046)	(0.067)	(0.064)
4	0.928***	-0.239***	0.164***	0.897***	-0.120**	0.327***	0.027	-0.124*	-0.168***
	(0.026)	(0.034)	(0.036)	(0.034)	(0.053)	(0.048)	(0.043)	(0.063)	(0.060)
Conservative	0.953***	-0.079	0.418***	0.888***	0.110	0.345***	0.051	-0.205**	0.055
	(0.038)	(0.049)	(0.051)	(0.053)	(0.083)	(0.076)	(0.064)	(0.094)	(0.090)
	Difference Across Portfolios								
F-Stat	5.44	13.51	36.33	1.03	7.25	14.99			
P-Value	0.0002	00.000	0.000	0.390	0.000	0.000			
Observations	112			192					
R-Squared	0.745 - 0.925			0.793 - 0.874					

Table A5: List of Recent Presidential Elections Results

Election Year	Democratic Candidate	Republican Candidate	Electoral Votes			Probability of Republican Winning
			Winner	Runner-up	Margin	
1992	Bill Clinton	George H. W. Bush	370	168	202	7.8%
1996	Bill Clinton	Bob Dole	379	159	220	7.0%
2000	Al Gore	George W. Bush	271	266	5	61.5%
2004	John Kerry	George W. Bush	286	251	35	55.0%
2008	Barack Obama	John McCain	365	173	192	5.9%
2012	Barack Obama	Mitt Romney	332	206	126	14.9%
2016	Hillary Clinton	Donald Trump	304	227	77	28.6%

Note: The probability of Republican wining the presidency for 1992, 1996, 2000, and 2004 are from Snowberg et al. (2007). The probabilities for 2008, 2012, and 2016 are from Fivethirtyeight.

Table A6: Average Returns of Portfolios Formed on Clientele Political Ideology for Limited Sample of Firms

Portfolio	Democratic	Republican	Difference
Most Liberal	21.22***	1.77	19.45***
	(3.28)	(4.21)	(5.03)
2	22.28***	5.83	16.45***
	(3.23)	(4.89)	(5.57)
3	19.62***	8.05*	11.57**
	(3.55)	(4.52)	(5.47)
4	16.37***	6.80	9.57*
	(2.76)	(4.42)	(5.04)
Most Conservative	16.71***	12.60**	4.10
	(3.62)	(4.89)	(5.66)

Note: This table is produced excluding firms that were created after 1992 (172 firms were excluded based on this criteria). All coefficients are in annual percentage points. Newey-West standard errors are reported in parentheses. Standard errors are computed with a maximum of 6 lags. The period is from 1992:11 to 2018:02. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

A.3 Literature on Measuring Political Ideology

In this appendix, I summarize very briefly the main studies that use social media to measure political ideology. Other studies not discussed here include Pennacchiotti and Popescu (2011), Colleoni et al. (2014), and Garimella and Weber (2017).

Perhaps one of the most relevant works in this literature is Conover et al. (2011). They compare the accuracy of various approaches for estimating political ideology using social media. The results suggest that network-based methods have higher accuracy than content-based estimates. They use network analysis to study a dataset of retweets, allowing them to identify clusters of users defined by their political ideology, left or right. When comparing these methods in their training data corresponding to nearly 1,000 Twitter users who self-report their ideology, they find that the network-based methods have an accuracy close to 95%.

A more contemporaneous work with an innovative methodology is Barberá (2015). He develops a Bayesian spatial following model in which ideology is a latent variable. He recognizes that network-based methods rely on the assumption that networks exhibit homophilic properties. However, the homophilic feature of social networks can be explained not only by individuals connecting with those with similar political preferences to their own, but also by connections based on other similarities between individuals. Therefore, the use of methods where the clusters emerge naturally, such as those employed by Conover et al. (2011), should be limited to samples in which users are actively engaged in political discussions on social media. In fact, Cohen and Ruths (2013) find the high accuracy in capturing political ideology reported by previous network-based studies (Zamal et al. (2012) and Conover et al. (2011)) dropped from around 90% to 65% when applied to politically modest users. According to their work, the reason for the difference in accuracy is that the previous studies based their accuracy measures on users who self-reported their political affiliation. To overcome this problem, Barberá (2015) models the probability that an individual follows an elite Twitter account (those with discriminatory predictive power in the political dimension, such as news outlets, politicians, etc.) as a function of the Euclidean distance in their latent political ideology. Using simulation-based estimation methods, he is able to jointly estimate the latent ideology for elite and regular Twitter users.

Golbeck and Hansen (2011) estimate the political preferences of news-outlet audiences. Their measure is based on overlap between the network of members of Congress and the network of a media outlet. For each member of Congress, the authors use a political ideology score based on voting records produced by Americans for Democratic Action (ADA). This score ranks members of Congress from most conservative to most liberal based on their vote on a key set of issues. Thus, an individual's political ideology is inferred based on the ADA score of the members of Congress she follows. Later, the authors estimate the political ideology of a news outlet's audience by aggregating the inferred score among those Twitter accounts who are in the list of followers of the target media outlet and on the sample of followers of members of Congress. Not surprisingly, they find the news outlet with the most conservative audience is Fox News, and the most liberal audience belongs to Morning Edition by NPR. These findings are consistent with the findings of the report on political polarization and media consumption by Pew Research Center (2014a).

A.4 List of Twitter Accounts Handles

S&P 500 Companies' Twitter Handles

Table A7: List of S&P 500 Companies' Twitter Handles

Company Name	Twitter Handle	Company Name	Twitter Handle	Company Name	Twitter Handle
3M	3M	SCE	SCE	Nike	Nike
Abbott	AbbottGlobal	Edwards Lifesciences	EdwardsLifesci	NiSource	NiSourceInc
AbbVie	abbvie	Electronic Arts	EA	Nordstrom	Nordstrom
Accenture	Accenture	Emerson	Emerson_News	Norfolk Southern	nscorp
Activision	Activision	Entergy	Entergy	Northern Trust	NorthernTrust
Acuity Brands	AcuityBrands	Equifax Inc.	Equifax	Northrop Grumman	northropgrumman
Adobe	Adobe	Equinix, Inc.	Equinix	NRG Energy, Inc.	nrgenergy
Advance Auto Parts	AdvanceAuto	Equity Residential	EquityRes	NVIDIA	nvidia
The AES Corporation	TheAESCorp	Essex Property Trust	EssexProperties	O'Reilly Auto Parts	oreillyauto
Aetna	Aetna	Estee Lauder	EsteeLauder	Occidental Petroleum	OXY_Petroleum
Aflac	Aflac	Eversource Energy	EversourceCorp	Omnicom Group	Omnicom
Agilent Technologies	Agilent	Exelon Corporation	Exelon	ONEOK	ONEOK
Air Products	airproducts	Expeditors	EXPD_Official	Oracle	Oracle
Akamai Technologies	Akamai	Express Scripts	ExpressScripts	Parker Hannifin	ParkerHannifin
Alaska Airlines	AlaskaAir	Extra Space Storage	extraspace	Paychex	Paychex
Albemarle Corp.	AlbemarleCorp	ExxonMobil	exxonmobil	PayPal	PayPal
Alcoa	Alcoa	F5 Networks	F5Networks	Pentair	Pentair
Allergan plc	Allergan	Facebook	facebook	People's United Bank	peoplesunited
Alexion	AlexionPharma	Fastenal	FastenalCompany	PepsiCo	PepsiCo
Allegion US	AllegionUS	Federal Realty	FederalRealty	PerkinElmer	PerkinElmer
Alliance Data	AllianceData	FedEx	FedEx	Perrigo Company plc	PerrigoCompany
Allstate	Allstate	FIS	FISGlobal	Pfizer Inc.	pfizer
Google	google	Fifth Third Bank	FifthThird	PG&E	PGE4Me
Altria	AltriaNews	First Solar	FirstSolar	Philip Morris Intl	InsidePMI
Amazon.com	amazon	FirstEnergy Corp.	FirstEnergyCorp	Phillips 66	Phillips66Co
Ameren Corporation	AmerenCorp	Fiserv	Fiserv	Pioneer	PXDtweets
American Airlines	AmericanAir	FLIR	flir	Pitney Bowes	PitneyBowes
AEP	AEPnews	Flowserve	Flowserve	PNC Bank	PNCBank
American Express	AmericanExpress	Fluor Corporation	FluorCorp	Ralph Lauren	RalphLauren
AIG	AIGinsurance	FMC Corporation	FMCCorp	PPG	ppg
American Water	amwater	FMC Technologies	FMC_Tech	PPL Electric	PPLElectric
Ameriprise Financial	ameriprise	Foot Locker	footlocker	PPL Corporation	PPLCorp
AmerisourceBergen	Healthcare_ABC	Ford Motor Company	Ford	Citizens Bank	CitizensBank
AMETEK Inc.	AMETEKInc	Fortune Brands H&S	FBHS_News	Principal	principal
Amgen	Amgen	Franklin Templeton	FTI_Global	P&G	ProcterGamble
Amphenol Corp	amphenol	Freeport-McMoRan	FM_FCX	Progressive	Progressive
Analog Devices, Inc.	ADI_News	Frontier Comm	FrontierCorp	Prologis	Prologis
Anthem, Inc.	AnthemInc	Gap Inc.	GapInc	Prudential	Prudential

Table A7 (continued)

Company Name	Twitter Handle	Company Name	Twitter Handle	Company Name	Twitter Handle
Aon	Aon_plc	Garmin	Garmin	PSE&G	PSEGdelivers
Apache Corporation	ApacheCorp	General Dynamics	GDMS	Public Storage	PublicStorage
Aimco	AimcoApts	General Electric	generalelectric	Pulte Homes	PulteHomes
Apple Support	AppleSupport	GGP	GGP_Inc	Qorvo, Inc.	QorvoInc
Applied Materials	Applied_Blog	General Mills	GeneralMills	Quanta Services	Quanta_Services
ADM	TradeADMIS	General Motors	GM	Qualcomm	Qualcomm
Gallagher	GallagherGlobal	NAPA AUTO PARTS	NAPAKnowHow	Quest Diagnostics	QuestDX
AssurantNews	AssurantNews	Gilead Sciences	GileadSciences	Range Resources	Range_Resources
AT&T	ATT	Global Payments Inc.	GlobalPayInc	Raytheon	Raytheon
Autodesk	autodesk	Goldman Sachs	GoldmanSachs	Realty Income	RealtyIncome
ADP	ADP	Goodyear	goodyear	Red Hat, Inc.	RedHat
AutoNation	AutoNation	Grainger	grainger	Regeneron	regeneron
AutoZone	autozone	Halliburton	Halliburton	Regions News	RegionsNews
Avago Technologies	Avagotech	Hanes	Hanes	Republic Services	RepublicService
AvalonBay	AvalonBay	Harley-Davidson	harleydavidson	Reynolds American	RAI_News
Avery Dennison	AveryDennison	HARMAN	Harman	Robert Half	roberthalf
BHGE	BHGECO	Harris Corporation	HarrisCorp	Rockwell Automation	ROKAutomation
Ball Corporation	BallCorpHQ	The Hartford	TheHartford	Rockwell Collins	rockwellcollins
Bank of America	BankofAmerica	Hasbro	HasbroNews	Royal Caribbean	RoyalCaribbean
BNY Mellon	BNYMellon	HCA	HCAhealthcare	Ryder	RyderSystemInc
Baxter International	baxter_intl	Helmerich & Payne	HelmerichPayne	Salesforce	salesforce
BB&T	askBBT	Hess Corporation	HessCorporation	Scripps Networks	ScrippsNet
BD	BDandCo	HPE	HPE	Seagate	Seagate
Bed Bath & Beyond	BedBathBeyond	Hologic	Hologic	Sealed Air	Sealed_Air
Berkshire Hathaway	BHHSRealEstate	The Home Depot	HomeDepot	Sempra Energy	SempraEnergy
Best Buy	BestBuy	Honeywell Now	HoneywellNow	Sherwin-Williams	SherwinWilliams
Biogen	biogen	Hormel Foods	HormelFoods	SIMON	ShopSimon
BlackRock	blackrock	HP	HP	Skyworks Solutions	skyworksinc
H&R Block	HRBlock	Humana	Humana	SL Green	SLGreen
The Boeing Company	Boeing	Huntington Bank	Huntington_Bank	Smucker's	smuckers
BorgWarner	BorgWarner	Illumina	illumina	Snap-on Tools	Snapon_Tools
Boston Properties	BXP_NYC	IngersollRand	IngersollRand	Southern Company	SouthernCompany
Boston Scientific	bostonsci	Intel	intel	Southwest Airlines	SouthwestAir
Bristol-Myers Squibb	bmsnews	ICE	ICE_Markets	Southwestern Energy	SWN_R2
Brown-Forman	BrownFormanJobs	IBM	IBM	Spectra Energy	spectraenergy
C.H. Robinson	CHRobinsonInc	International Paper	IntlPaperCo	S&P Global	SPGlobal
CA Technologies	Cainc	Interpublic Group	InterpublicIPG	StanleyBlack&Decker	StanleyBlkDeckr
Cabot Oil & Gas	CabotOG	IFF Inc.	IFF	Staples US	Staples
Campbell Soup Co	CampbellSoupCo	Intuit	Intuit	Starbucks Coffee	Starbucks
Capital One	CapitalOne	Intuitive	IntuitiveSurg	State Street	StateStreet
Cardinal Health	cardinalhealth	Invesco US	InvescoUS	Stericycle Inc	Stericycle_Inc
Henry Schein	HenrySchein	Iron Mountain	IronMountain	SunTrust	SunTrust
CarMax	CarMax	J.B. Hunt 360	jbhunt360	Symantec	symantec

Table A7 (continued)

Company Name	Twitter Handle	Company Name	Twitter Handle	Company Name	Twitter Handle
Carnival Corporation	CarnivalPLC	Johnson & Johnson	JNJNews	Synchrony	synchrony
Caterpillar Inc.	CaterpillarInc	Johnson Controls	johnsoncontrols	Sysco Corporation	Sysco
CBRE	CBRE	J.P. Morgan	jpmorgan	T. Rowe Price	TRowePrice
CBS Tweet	CBSTweet	Juniper Networks	JuniperNetworks	Target	Target
Celgene Corporation	Celgene	Kellogg Company	KelloggCompany	TE Connectivity	TEConnectivity
Centene	Centene	KeyBank	keybank	TEGNA	TEGNA
CenterPoint Energy	energyinsights	Kimberly-Clark Corp.	KCCorp	Teradata	Teradata
CenturyLink	CenturyLink	Kimco	kimcorealty	Texas Instruments	TXInstruments
Cerner	Cerner	Kinder Morgan	Kinder_Morgan	Textron Systems	TXTSystems
Charles Schwab Corp	CharlesSchwab	KLA-Tencor	KLATencor_Info	HERSHEY'S	Hersheys
Spectrum	GetSpectrum	Kohl's	Kohls	Travelers	Travelers
Chesapeake Energy	Chesapeake	Kraft Heinz Company	KraftHeinzCo	Thermo Fisher	thermofisher
Chevron	Chevron	Kroger	kroger	Tiffany & Co.	TiffanyAndCo
Chipotle	ChipotleTweets	L Brands	L_Brands	WarnerMedia	WarnerMediaGrp
Chubb NA	ChubbNA	LabCorp	LABCORP	TSYS	TSYS_TSS
Cigna	Cigna	Lam Research	LamResearch	TripAdvisor	TripAdvisor
Cintas Corporation	CintasCorp	Legg Mason	leggmason	21st Century Fox	21CF
Cisco	Cisco	Lennar	Lennar	Tyson Foods	TysonFoods
Citi	Citi	Level 3	Level3	UDR Apartments	UDRMarketing
Citrix	citrix	Eli Lilly	LillyPad	Ulta Beauty	ultabeauty
The Clorox Company	CloroxCo	Lincoln Financial	lincolnfingroup	U.S. Bank	usbank
CMEGroup	CMEGroup	Linear Technology	LinearTech	Under Armour	UnderArmour
Consumers Energy	ConsumersEnergy	LKQ Corporation	LKQCorp	Union Pacific	UnionPacific
Coach	Coach	Lockheed Martin	LockheedMartin	United Airlines	united
The Coca-Cola Co.	CocaColaCo	Lowe's	Lowes	UnitedHealth Group	UnitedHealthGrp
Cognizant	Cognizant	LyondellBasell	LyondellBasell	UPS	UPS
Colgate-Palmolive Co	CP_News	M&T Bank	MandT_Bank	United Rentals	United_Rentals
Comcast	comcast	Macy's	Macys	United Technologies	UTC
Comerica Cares	comericacares	Marathon Oil	MarathonOil	UHS, Inc.	UHS_Inc
Conagra Brands	ConagraBrands	Marathon Petroleum	MarathonPetroCo	Unum	unumnews
ConocoPhillips	conocophillips	Marriott Internat'l	MarriottIntl	Urban Outfitters	UrbanOutfitters
Con Edison	ConEdison	Marsh & McLennan	MMC_Global	VF Corporation	VFCorp
Constellation Brands	cbrands	Masco Corporation	MascoCorp	Varian	VarianMedSys
Corning Incorporated	Corning	Mastercard	Mastercard	VERISIGN	VERISIGN
Coty Inc.	COTYInc	Mattel	Mattel	Verisk	Verisk
CSRA Inc.	CSRA_inc	McCormick Spices	mccormickspices	Verizon	verizon
CSX	CSX	McDonald's	McDonaldsCorp	Vertex	VertexPharma
Cummins Inc.	Cummins	McKesson Corp	McKesson	Viacom	Viacom
CVS Health	CVSHealth	Medtronic News	Medtronic	Visa	Visa
D.R. Horton	DRHorton	Merck	Merck	Walmart	Walmart
Danaher U	Danaher_U	MetLife	MetLife	Walgreens	Walgreens
Darden Restaurants	darden	METTLER TOLEDO	mettlertoledo	Walt Disney Co	WaltDisneyCo
DaVita Kidney Care	DaVita	Michael Kors	MichaelKors	Waste Management	WasteManagement

Table A7 (continued)

Company Name	Twitter Handle	Company Name	Twitter Handle	Company Name	Twitter Handle
John Deere	JohnDeere	MicrochipTech	MicrochipTech	Waters Corporation	WatersCorp
Delphi Technologies	delphitech	MicronTech	MicronTech	Wells Fargo	WellsFargo
Delta	Delta	Microsoft	Microsoft	Welltower	Welltower
Devon Energy	DevonEnergy	Molson Coors	MolsonCoors	Western Digital	WesternDigital
Digital Realty	digitalrealty	Mondelez Intl	MDLZ	Western Union	WesternUnion
Discover	Discover	Monsanto Company	MonsantoCo	WestRock	WestRock
Discovery Inc	DiscoveryIncTV	Moody's Investors	MoodysInvSvc	Weyerhaeuser	Weyerhaeuser
Dollar General	DollarGeneral	Morgan Stanley	MorganStanley	Whirlpool Corp	WhirlpoolCorp
Dollar Tree	DollarTree	The Mosaic Company	MosaicCompany	Whole Foods Market	WholeFoods
Dominion Energy	DominionEnergy	Motorola Solutions	MotoSolutions	Williams	WilliamsUpdates
Dover	DoverCorp	Mylan	MylanNews	Willis Towers Watson	WTWcorporate
Dow	DowChemical	Nasdaq	NASDAQ	WEC Energy Group	WECEnergyGroup
Dr Pepper Snapple	DrPepperSnapple	NOV	NOVGlobal	Xcel Energy MN	XcelEnergyMN
DTE Energy	DTE_Energy	Navient	Navient	Xerox	Xerox
DuPont News	DuPont_News	NetApp	NetApp	Xilinx	XilinxInc
Duke Energy	DukeEnergy	Netflix US	netflix	XL Catlin	XLCatlin
Dun & Bradstreet	DnBUS	Newell Brands	newell_brands	Xylem Inc.	XylemInc
E*TRADE	etrade	Newfield Exploration	Newfield3	Yahoo	Yahoo
Eastman Chemical	EastmanChemCo	Newmont Mining	Newmont	Yum! Brands	yumbrands
Eaton	eatoncorp	News Corp	newscorp	Zimmer Biomet	zimmerbiomet
eBay	eBay	NextEra Energy, Inc.	nexteraenergy	Zoetis	Zoetis
Ecolab	Ecolab	Nielsen	Nielsen		

Media Outlets' Twitter Account Handles

Table A8: List of Media Outlets

Media Outlet	Twitter Handle	Number of Twitter Followers	Number of Tweets	Year when the Twitter Account was created
ABC News	ABC	13,839,248	219,287	2009
CBS News	CBSNews	6,398,822	186,054	2008
NBC News	NBCNews	6,119,447	163,333	2008
NPR	NPR	7,527,509	157,787	2007
Rush Limbaugh	rushlimbaugh	592,984	1,178	2011
Sean Hannity	seanhannity	3,703,249	38,752	2009
Washington Post	washingtonpost	12,703,210	281,444	2007
New York Times	nytimes	41,792,447	330,660	2007
Drudge Report	DRUDGE_REPORT	1,383,376	227,373	2008
Huffington Post	HuffPost	11,386,691	510,624	2008
Breitbart News	BreitbartNews	970,527	95,483	2012
TheBlaze	theblaze	667,917	89,205	2007
Guardian	guardian	7,252,973	462,355	2009
BBC	BBCWorld	23,576,970	282,802	2007
New Yorker	NewYorker	8,488,360	80,180	2008
Fox News	FoxNews	17,895,228	403,710	2007
MSNBC	MSNBC	2,153,448	140,123	2007
CNN	CNN	40,206,027	198,913	2007
PBS	PBS	2,241,288	72,591	2008
Stephen Colbert	StephenAtHome	18,210,980	5,836	2008
Daily Show	TheDailyShow	7,619,396	15,796	2010
Glenn Beck	glennbeck	1,183,420	15,185	2008
Wall Street Journal	WSJ	15,865,239	251,708	2007
USA TODAY	USATODAY	3,633,822	260,113	2008
Slate	Slate	1,768,878	349,186	2008
Politico	politico	3,614,487	283,718	2007
Yahoo News	YahooNews	1,105,876	181,719	2007
Bloomberg	business	4,836,770	372,973	2009
BuzzFeed	BuzzFeed	6,504,533	197,883	2007
Al Jazeera America	AJEnglish	4,845,547	210,538	2007
Economist	TheEconomist	23,315,381	149,603	2007