# Political Speeches and Stock Market Outcomes*

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**Abstract**

Using data on political speeches, I demonstrate that U.S. presidential candidates influence stock market outcomes. Political speeches that contain economic information increase aggregate market returns and trading volume but decrease market volatility. Speeches with a net negative linguistic tone have the opposite effect. The magnitude of the effect becomes stronger during the first months of campaigns and varies based on the prevailing market conditions. In the cross-section of stock returns, I show that industries with high government exposure are more sensitive to government-spending information and that politically sensitive industries do not react more strongly to candidate speeches. Overall, my findings suggest that political speeches affect investor expectations and, in turn, stock market outcomes.

*JEL Classification:* G12, G14, G18.

*Keywords*: Presidential candidate, political speech, political campaign, elections, policy uncertainty, finance and politics.

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## Abstract

Using data on political speeches, I demonstrate that U.S. presidential candidates influence stock market outcomes. Political speeches that contain economic information increase aggregate market returns and trading volume but decrease market volatility. Speeches with a net negative linguistic tone have the opposite effect. The magnitude of the effect becomes stronger during the first months of campaigns and varies based on the prevailing market conditions. In the cross-section of stock returns, I show that industries with high government exposure are more sensitive to government-spending information and that politically sensitive industries do not react more strongly to candidate speeches. Overall, my findings suggest that political speeches affect investor expectations and, in turn, stock market outcomes.



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# 1. Introduction

On July 7, 2008, Barack Obama promised, if elected, to eliminate all capital gains taxes on start-ups and small businesses to encourage more innovation and job creation. Consistent with the view that investors use all available information to identify *ex ante* what firms could benefit from the policies of the winning party, the S&P 500 index increased the following day by 1.71%, and the Dow Jones micro-cap index increased by 3.63%. Although a growing number of studies document systematic changes in stock returns, volatility and option trading before elections,[1] the role of presidential candidates during these periods of political uncertainty remains unclear.

Presidential candidates are in the media spotlight for several months during their campaigns.[2] To shape public opinion in their favor and ultimately win the election, candidates constantly travel around the country to interact with local voters and give political speeches (Brady and Johnston, 2006). Although presidential candidates give a large number of political speeches, the speech content can be very different depending on their campaign strategy.

Political speeches often provide information about the position of presidential candidates on public issues and future policy changes (Marcus, 1982; Conover and Feldman, 1989; Franklin, 1991; Holbrook, 1999).[3] Instead of presenting their own platform, candidates may also choose to conduct a "negative campaign" by criticize the platform and attributes of their opponent (Lau and Pomper, 2002). This strategy aims to not only obfuscate their opponent's positions but also create negative affective judgments in voters who will act in their favor (Kelley, 1960; Conover and Feldman, 1986).[4] Since presidential candidates are able to influence the public opinion about the economy, they are also likely to affect investor expectations, and in turn asset prices.

[1] For example, see Boutchkova, Doshi, Durnev and Molchanov (2012), Kelly, Pástor and Veronesi (2016), and Addoum and Kumar (2016).
[2] For example, see Shaw (1999) and Freedman and Goldstein (1999).
[3] For instance, on August 18, 2016, Donald Trump promised to "repeal and replace Obamacare", and on October 10, 2016, Hillary Clinton stated that "she is never going to let anyone privatize social security".
[4] Candidates use this strategy because sentiment is a major determinant of voters' perceptions (Kinder, 1978; Marcus and MacKuen, 1993).

Motivated by this evidence, I investigate whether the political speeches of U.S. presidential candidates have a *direct* effect on stock market outcomes. To test my conjecture, I hand-collect the transcripts of presidential candidate speeches from the archives of the American Presidency Project (APP) and the U.S. Government Publishing Office (GPO). These transcripts contain information about the date and speech content of all major Democratic and Republican nominees for the 2004-2016 period.

Using this novel dataset and a regression specification that accounts for several stock market and political factors, I demonstrate that following political speeches, there is an increase in excess market returns of 26 basis points. This result is significant at the 1% level and robust to different specifications. The magnitude of the effect is larger than the mean excess market return (i.e. -44 basis points) and economically significant. However, the direction and the magnitude of this effect are not similar among presidential candidates and vary based on the prevailing market conditions. Since my dataset contains full speech transcripts, I utilize this information to investigate whether presidential candidates exert a different impact because of the heterogeneous content in their speeches.

First, I examine whether political speeches convey economic information to investors that is likely to affect investor expectations concerning firms' cash flows and discount rates. For instance, such information may include the candidate's intentions regarding policy changes after winning the election. If political speeches are informative, then stock prices should incorporate and reflect this new information (Campbell and Shiller, 1987).

Using the Baker, Bloom and Davis (2016) policy-specific dictionaries (BBD), which allow me to quantify economic information, I find that informative speeches affect stock market returns. Specifically, my findings show that a 1% increase in the number of sentences that contain

information about monetary policy, national security and entitlement programs increase excess market returns by 19, 6 and 7 basis points, respectively.[5] I do not find a significant effect on *aggregate* excess market returns when candidate speeches contain more information about fiscal policy, healthcare, regulation, trade policy, and sovereign debt.[6]

Second, I investigate whether candidate speeches affect investor sentiment and, in turn, stock market returns. To persuade the broad mass of voters, candidates often attempt to influence voter sentiment by using a very negative tone when criticizing their opponent (Lau and Pomper, 2002). Similarly, recent studies in the finance literature show that the linguistic tone in several domains such as the media, corporate fillings, and conference calls affects investor sentiment and, consequently, market returns (Tetlock, 2007; Feldman, Govindaraj, Livnat and Segal, 2010; Druz, Wagner and Zeckhauser, 2016; Chen, Demers and Lev, 2016). Motivated by this evidence, I examine whether the tone of candidate speeches influences stock market returns.

My results show that the negative linguistic tone of candidate speeches predicts negative excess market returns. In particular, I demonstrate that a 1% increase in the *net negative tone* of a speech decreases excess market returns by 1 basis point.[7] This result is significant at the 1% level and robust to different specifications. The effect is comparable in magnitude, albeit somewhat smaller, to the pessimism effect that the media induce in investors (Tetlock, 2007).

Since candidates often choose to discuss some topics at the beginning and other topics at the end of their campaign, I also examine whether the content of their political speeches varies

[5] These effects are not comparable because the variables are not standardized. Standardizing them, I find that a one standard deviation increase in the length of the discussion regarding national security, monetary policy and entitlement programs increases excess market returns by 9, 7, and 4 basis points, respectively.

[6] A potential reason is that some policy changes may have a positive effect on a subset of stocks but a neutral or negative effect on another subset of stocks. For example, an increase in government spending is more likely to affect firms with high government exposure rather than firms with low government exposure. In this case, we will not be able to observe an effect on aggregate stock market outcomes but, instead, will observe an effect on the stock returns of firms with high government exposure. I discuss this case in more detail and provide empirical evidence in Section 4.1.

[7] To compare its magnitude with the coefficient estimates of the policy-specific variables, I standardize this variable and find that a one standard deviation increase in the net negative tone decreases excess market returns by 5 basis points.

during the pre-election period. Indeed, I find that candidates discuss monetary policy and national security more extensively during the first half of their campaigns. Further, presidential candidates use a more negative tone at the end of their campaign, most likely because as the election day approaches, they prefer to criticize their opponent's positions (Lau and Pomper, 2002). As a result, in comparison to the early-campaign period, the effect of political speeches decreases by 38 basis points during the late-campaign period.

Next, I examine the effect of political speeches on stock market volatility. Recent studies document an increase in stock market volatility around major political events that entail high levels of uncertainty, such as general elections (Bialkowski, Gottschalk and Wisniewski, 2008; Boutchkova et al., 2012; Pástor and Veronesi, 2013; Addoum and Kumar, 2016). Since political speeches influence stock market returns by either providing information to market participants or affecting investor sentiment around this period, they may also influence the prevailing level of risk and, consequently, stock market volatility.

Following the methodology of García (2013), I find that candidate speeches may have a positive or negative impact on volatility depending on their content. Specifically, I demonstrate that informative speeches decrease market volatility whereas speeches with a stronger net negative tone increase market volatility. These findings are consistent with the view that informative speeches decrease the prevailing level of risk and, consequently, increase stock market prices[8] whereas a negative effect on investor sentiment has the opposite effect (Tetlock, 2007).

Although my previous findings suggest that only some types of economic information influence excess market returns, it is still possible that other types of information affect only a particular subset of stocks, thus making it difficult to detect an effect on the aggregate level. To

[8] According to the net present value (NPV) formula, a decrease in the discount rate (i.e., a decrease in the denominator of the formula) would increase the price of the financial asset.

explore this possibility, I focus on the government-spending information that candidates convey through their speeches. According to my conjecture, political speeches that contain government-spending information are more likely to influence firms with high government exposure.

To test my conjecture, I use the industry-level government exposure measure of Belo, Gala, and Li (2013), which allows me to identify whether an industry has high or low government exposure. Consistent with my conjecture, I find that industries with high (low) government exposure are more (less) sensitive to speeches that contain government-spending information. Specifically, I demonstrate that a 1% increase in the government-spending information of speeches decreases the excess stock returns of industries with high government exposure by 12.89%. These findings suggest that although some information does not influence aggregate market returns, it may have a statistically and economically significant impact on the stock returns of specific industries.

Since it is possible that investors change the composition of their portfolio holdings depending on their political preferences (Hong and Kostovetsky, 2012), I also examine whether politically sensitive industries react more strongly to the speeches of presidential candidates.[9] In line with my main empirical findings, which show that investors react based on the content of political speeches, I do not find any supportive evidence that politically sensitive industries react more strongly to the speeches of candidates who belong to a specific political party.

Divergence of opinion among investors could be another reason why some types of policy-specific information do not affect stock returns. In this case, due to the existence of heterogeneous beliefs and likelihood functions among investors (Harris and Raviv, 1993), stock prices would

[9] In this case, investors who support the Republican party may become more optimistic about the market when a Republican candidate gives a speech and consequently decide to buy Republican stocks (i.e., tobacco stocks). Similarly, investors who support the Democratic party may react more strongly to the speeches of Democratic candidates but have a neutral or negative reaction to the speeches of Republican candidates.

remain unchanged, but the trading volume would increase because some investors would sell their stocks whereas others would buy them (Kandel and Pearson, 1995; Garfinkel, 2009).

In line with this conjecture, I find that trade policy information positively predicts market trading volume but does not have a significant effect on market returns. To exclude the possibility that trade policy information affects only a subset of stocks, I also examine how the stocks of export-oriented firms respond to such information since these firms are more likely to be sensitive to trade policy information. Once again, I find that trade policy information predicts a higher trading volume for these firms but does not have a significant effect on their stock returns.

In the last part of my empirical investigation, I perform a number of additional checks to ensure that my results are robust. First, I use a falsification test in which I find an insignificant relationship between the lead values of political speeches and past market returns. Second, I show that political speeches are likely to draw the attention of investors since television networks mention the presidential candidates significantly more on the days of their political speeches. Third, I show that my results are robust when I winsorize my dependent variable and when I use alternative measures of excess returns. Finally, my results are robust when I consider speeches from an alternative campaign period such as the period when both candidates are the presumptive nominees of their political parties.

The primary and, to the best of my knowledge, novel contribution is that this study shows that presidential candidates have a *direct* effect on stock market outcomes. A number of recent studies show that before national elections, investors change their portfolio compositions (Addoum and Kumar, 2016), firms reduce their corporate investments (Julio and Yook, 2012), stock market volatility is higher (Boutchkova et al., 2012), and stock options are more expensive (Kelly, Pástor and Veronesi, 2016). This paper extends this literature by showing that during this period of high

uncertainty, presidential candidates influence investor trading and, in turn, stock market outcomes.

My empirical findings also provide support to prior theoretical research on how political news affect stock prices. Specifically, Pástor and Veronesi (2013) develop a theoretical model to explain how political news, such as a prime minister announcement, can revise investor expectations regarding the likelihood that the government will implement certain policies in the future. Consistent with their prediction, my findings suggest that the stock market is very sensitive to political news since even politicians who may not be in power yet influence asset prices and trading volume.

This paper also shows that the negative linguistic tone of political speeches predicts negative stock returns. This finding contributes to the finance literature that examines whether the tone of financial documents (e.g., corporate fillings and conference calls) and non-financial document (e.g., newspaper articles) affects stock market returns (Tetlock, 2007; Tetlock, Saar-Tsechansky and Macskassy, 2008; Feldman et al., 2010; Druz et al., 2016; Chen et al., 2016).

More broadly, the findings of this paper contribute to the growing literature at the intersection of politics and finance. In particular, recent studies in this literature demonstrate that the election outcome influences individual behavior and stock price reactions (Huang and Low, 2017; Wagner, Ziegler and Zeckhauser, 2017). Further, Gulen and Ion (2016) show that political uncertainty has a strong, long-lasting impact on corporate investments spanning up to two years, and Julio and Yook (2012) demonstrate that the level of corporate investment declines before national elections.[10] Other studies focus on stock return implications when there is proximity to political power (Cooper, Gulen and Ovtchinnikov, 2010; Kim, Pantzalis and Park, 2012). My paper contributes to this literature by showing that politicians such as presidential candidates

[10] Jens (2017) finds similar results around U.S. gubernatorial elections.

influence stock market outcomes.

The rest of the paper is organized as follows. In Section 2, I describe the data and the main variables of my analysis. Sections 3, 4 and 5 present the empirical results. In Section 6, I conduct several tests to examine the robustness of my findings. Section 7 concludes with a brief summary.

## 2. Presidential Candidate Speeches

### *2.1 Sample*

I use two main sources to obtain the transcripts of presidential candidate speeches: the American Presidency Project (APP) and the U.S. Government Publishing Office (GPO). The APP is a non-profit and non-partisan project, hosted at the University of California, Santa Barbara, that contains more than 123,720 documents related to major political events. The GPO is the federal government's official office; it preserves any information products of the U.S. government. Using the APP archive allows me to obtain the speech transcripts for all major Democratic and Republican nominees except George W. Bush during the 2004-2016 period. Since the APP contains only the speeches of John Kerry for the 2004 elections, I enrich my dataset by obtaining the speech transcripts of George W. Bush from the GPO archive.[11] To be consistent across datasets, I consider GPO transcripts that are associated with the campaign and not the presidential activity of George W. Bush (i.e., statements, memorandums and letters to Congress).[12]

### *2.2 Preprocessing the transcripts of candidate speeches*

To minimize any potential measurement error, I preprocess the transcripts before I quantify the

[11] In Section 3.1, I discuss the implications of using both datasets and show that my results are robust when the speeches of the 2004 pre-election period are excluded from the sample.

[12] For instance, on July 2, 2004, George W. Bush released a statement after signing a law that allows the Department of Homeland Security (DHS) to consolidate headquarters staff at the Complex for the foreseeable future. On July 8, 2004, George W. Bush released another statement to offer his condolences to the people of Austria and to the Klestil family for the death of President Thomas Klestil. Such transcripts are not related to the election campaign, and therefore, I do not consider them in my sample.

information and linguistic tone of political speeches. Specifically, following Loughran and McDonald (2011), I filter out common words that represent first names, last names, geographic locations and currencies.[13] Further, I do not consider words that reflect the reaction of the audience during the speeches.[14] To avoid the common problem of overstemming, I maintain the initial form of words, which allows me to minimize any potential word misclassification.[15] To be consistent, I replace any word abbreviations in the text with their full form.[16] Finally, I separate each speech transcript into sentences, and I consider only those sentences that include at least three words to minimize any potential measurement error related to incorrect punctuation, the syntax of sentences and the effect of common phrases.[17]

*2.3 Quantifying economic information*

To quantify the economic information of speeches, I use the policy-specific dictionaries of Baker et al. (2016). Specifically, Baker et al. (2016) construct several dictionaries related to "government spending", "taxes", "fiscal policy", "monetary policy", "national security", "entitlement programs", "healthcare", "regulation", "trade policy" and "sovereign debt and current crises", and they measure the daily frequency of newspaper articles that contain these terms.

To examine whether political speeches affect investor expectations, I focus on the content of their text. Specifically, in each speech, I count the average number of sentences containing policy-specific terms. The advantage of this methodology is that it allows me to measure the extent

[13] For more information, see http://www3.nd.edu/~mcdonald/Word_Lists.html.
[14] The majority of speech transcripts contain information regarding the reaction of the audience. For instance, the transcript may refer to the audience in the following manner: [Applause]. Other words that are commonly used to present the audience's reaction are: "applause", "boo", "booing", "boos", "chanting", "cheers", "cheers and applause", "chuckles", "crosstalk", "extended cheers, applause", "inaudible, "inaudible, cheers, applause", "laughs", "laughter", "sic", and "sustained cheers, applause".
[15] For example, if I stem the words "general" and "generate", both of them will have the same root (i.e., gener).
[16] For example, I replace "n't" with "not", "'ll" with "will", "I'm" with "I am", "won't" with "will not", etc.
[17] Some transcripts include punctuation mistakes. Imposing this filter allows me to minimize such mistakes. Additionally, presidential candidates often use phrases such as "Thank you" when they respond to the audience. This filter minimizes the noise that these common phrases impose on the measures.

of the discussion for each policy and, therefore, to identify whether the speeches are informative.[18]

*2.4 Identifying the linguistic tone of political speeches*

To measure the linguistic tone of texts, recent studies use the Harvard-IV-4 and the Loughran and McDonald (2011) dictionary (LM).[19] Whereas the Harvard-IV-4 list can identify the text tone in several contexts, such as sociology and psychology, the LM dictionary can better reflect the linguistic tone of economic texts since it minimizes the misclassification of words with economic meaning.[20] Since the vast majority of candidate speeches contain economic information, I use the LM dictionary to identify their linguistic tone.

To measure the net negative linguistic tone in each speech (*Negative tone*), I subtract the number of sentences that contain positive words from the number of sentences that contain negative words, and I divide this number by the total number of sentences.

*2.5 Descriptive statistics*

Table I reports information about the speech content among different presidential candidates. In total, my sample contains 1058 speeches occurring during the 2004-2016 pre-election periods. During my sample period, George W. Bush has the most speeches compared to any other candidate; in contrast, Donald Trump has the least speeches. Table I also shows that George W. Bush gives the longest speeches (i.e., 300 sentences). On the other hand, the candidate with the shortest speeches is John McCain (i.e., 122 sentences).

When we focus on the content of speeches, we observe that it varies among presidential candidates. For instance, during the 2008 campaign period, Barack Obama discussed healthcare

[18] For instance, a speech that uses 1% of sentences is likely to convey less information than a speech that uses 20% of sentences to discuss fiscal policy.
[19] For example, see Tetlock (2007), Tetlock et al. (2008), Loughran and McDonald (2011), Da, Engelberg and Gao (2011), Engelberg, Reed and Ringgenberg (2012), García (2013), Ahern and Sosyura (2014), and Agarwal, Chen and Zhang (2016).
[20] For instance, the word "tax" is classified as negative in the Harvard list; however. if a candidate suggests a decrease in "taxes", then it has a positive rather than a negative meaning.

issues more extensively than John McCain, whereas John McCain focused more on issues related to fiscal policy. Further, I find that the discussion agenda changes across years. For example, compared to other election years, the candidates discussed about national security more in 2004, most likely due to the 2003 invasion of Iraq and the rise of terrorism. Although candidates have different agendas, the results presented in Table I suggest that fiscal policy is always at the forefront of the public discussion.

The last column of Table I presents information about the linguistic tone of the speeches. Once again, the results show that there is a significant variation in the tone of speeches among candidates. For example, during the 2004 election campaign, John Kerry gave more negative speeches than George W. Bush. On the other hand, during the campaign in 2016, the political speeches of Donald Trump were more negative than the speeches of Hillary Clinton. These results show that the tone of speeches is specific for each candidate and not necessarily similar among the presidential nominees of the same political party.

Overall, these findings suggest that presidential candidates follow different campaign strategies, which depend on their personal style and the issues of public interest.

## 3. Political Speeches and Stock Market Outcomes

### *3.1 Candidate speeches and stock market returns*

To examine the impact of candidate speeches on the stock market, I adopt a linear regression specification in which the dependent variable is the daily excess market return at time *t+1*, measured as the value-weighted return of all CRSP firms listed on the NYSE[21] minus the risk-free rate.[22] In my regression specification, I include five lag values of excess returns (i.e., from time *t*

[21]In Section 6.3, I show that my results are robust when using the returns of firms listed on Nasdaq or AMEX. Using NYSE returns in my main specification allows me to be consistent with the variable of the NYSE volume that I use to capture potential liquidity effects.

[22] To proxy for the risk-free rate, I use the daily one-month Treasury Bill. I obtain these data from Kenneth French's data library. For more information, see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

to *t-4*) to capture any potential return autocorrelation that may arise due to market microstructure phenomena.[23] To capture potential liquidity effects, the regressions include five lag values of the detrended log of the daily NYSE volume (*Volume*), which I obtain from the NYSE database.[24] To capture the prevailing market uncertainty, I control for five lags of detrended squared NYSE residuals (*Volatility*), which proxy for market volatility.[25] To address potential calendar effects, I include in my specification calendar month and day-of-the-week dummy variables.

In the regressions, I also control for political factors that are likely to influence stock market returns. Specifically, to capture the well-known return premium that exists under Democratic presidencies (Santa-Clara and Valkanov, 2003), I include the dummy variable $Pres_{Dem}$, which is equal to one when the president is a member of the Democratic party, otherwise zero.[26] Another factor that is likely to influence market outcomes is the change in expectations regarding the potential winner of the election (Snowberg, Wolfers, and Zitzewitz, 2007). To proxy for this factor, I obtain presidential poll data from the RealClearPolitics (RCP) media company and use the average poll index that RCP provides for each candidate.[27] To construct the proxy, I subtract the daily Republican average poll index from the daily Democratic average poll index.[28] Because election companies conduct interviews for several days and, therefore, the poll index may not fully incorporate repeating daily swings in political uncertainty, I also use data from the Iowa Electronic Market (IEM) to construct an alternative proxy. The IEM is an online platform that allows

[23] Some of these phenomena are related to the bid-ask bounce, nonsynchronous trading, and transactions costs (Tetlock, 2007).
[24] I use the detrended log volume because the log volume is not a stationary measure. To detrend the log volume, I follow a method based on Campbell, Grossman, and Wang (1993), Tetlock (2007) and Dougal et al. (2012). Specifically, I calculate the moving average of the past 60 days of log volume, which I subtract from the daily log volume.
[25] Following the method of Tetlock (2007) and Dougal et al. (2012), I calculate the detrended squared NYSE residuals in the following manner. First, I demean the market return to obtain a residual. Second, I square this residual, and then, I subtract its past 60-day moving average. My results are robust to using alternative measures of volatility, such as conditional market volatility and volatility index (VIX).
[26] Specifically, this dummy variable is equal to one from January 20, 2009 (i.e., this is the date when Barack Obama was inaugurated as President of the United States), to the end of my sample (since Donald Trump was inaugurated on January 20, 2017). My results remain similar when defining $Pres_{Dem}$ as being equal to one from January 1, 2009.
[27] To construct this index, RCP collects data on all available polls provided by large media networks (such as Bloomberg, Reuters, Economist, LA Times, FOX and NBC news) and calculates the daily equal-weighted poll estimate for each presidential candidate. For more information, see http://www.realclearpolitics.com.
[28] To have a stationary measure, I use the daily change of this measure (i.e., $\Delta Poll_{Dem\text{-}Rep}$) as a control variable in my specification.

individuals to trade "shares" of political candidates from the 2004 presidential elections and onwards. To construct my alternative proxy, I use the daily "prices" of candidates that reflect the likelihood of winning the election, and I calculate the difference between the daily prices of Democrats and Republicans (i.e., $ElectionMkt_{Dem\text{-}Rep}$). Because IEM data are available for a shorter sample period (i.e., from June 1, 2004), I use the election poll data in my main specification.[29]

In my regression specification, I also control for time-invariant unobservable characteristics that are present during every pre-election period by including a dummy variable that is equal to one from January 1 until the election day for each election year. To minimize the effect of outliers, I include dummy variables to capture the effect of the Lehman Brothers collapse and the Brexit referendum on the U.S. stock market.

More formally, I estimate the following linear regression:

$$R_{t+1} = c + \beta_1 \cdot Speech_t + \gamma_1 \cdot Pres_{Dem_t} + \gamma_2 \cdot \Delta Poll_{Dem-Rep_t} + \varphi \cdot Controls_t + \varepsilon_{t+1} \qquad (1)$$

where the main variable of interest is $Speech_t$, which corresponds to a dummy variable that is equal to one when a presidential candidate gives a speech at time *t*, otherwise zero. In this specification, $\beta_1$ captures the average effect of candidate speeches on excess market returns. $Controls_t$ is a vector that includes several control variables such as the five lags of daily excess NYSE returns, the five lags of the detrended daily log NYSE volume, the five lags of detrended squared NYSE residuals, the day-of-the-week dummies, a dummy variable for each month of the year, the pre-election period dummy variable, a dummy to capture the effect of the Lehman Brothers collapse and a dummy to capture the effect of the Brexit referendum on June 23, 2016.[30] To obtain robust standard

[29] My results remain unchanged when using IEM data to proxy for political uncertainty.
[30] The dummy variable for the Lehman Brother collapse is equal to one for one month after the date when the company filed for bankruptcy (i.e., September 16, 2008). My results are robust to the exclusion of Lehman Brothers and Brexit dummy variables and to alternative definitions (e.g., being equal to one for a longer or shorter period).

errors, I use the Newey and West (1987) method, which accounts for heteroskedasticity and autocorrelation up to five lags.

Columns (1) to (6) of Table II present the coefficient estimates and their corresponding t-statistics. My results show that the political speeches of presidential candidates have a positive effect on the excess market returns of the following day. Specifically, columns (1) and (2) show that political speeches increase excess market returns by 44 basis points. Including in my specification the pre-election dummy variable, I find that within this period, political speeches increase excess market returns by 26 basis points (i.e., columns (3) and (4)). Overall, my results are robust to different specifications, and the magnitude of the effect is economically significant (the average excess market return is equal to -44 basis points).

Examining the estimates of the control variables, I demonstrate that under Democratic presidencies, there is a positive return premium in the stock market, which is in line with the findings of Santa-Clara and Valkanov (2003). Interestingly, I find that election polls do not predict future market returns; however, I obtain a significant correlation between the "prices" of the presidential candidate "shares" and the market returns of the following day.

Since the previous specification captures the average effect of political speeches, I estimate the following regression specification to capture the individual effects of presidential candidates:

$$R_{t+1} = c + \sum_{i=1}^{12} \beta_{i,1} \cdot Candidate_{i,t} + \gamma_1 \cdot Pres_{Dem_t} + \gamma_2 \cdot \Delta Poll_{Dem-Rep_t} + \varphi \cdot Controls_t + \varepsilon_{t+1} \quad (2)$$

where $Candidate_{i,t}$ is a set of twelve dummy variables that correspond to either the name of each presidential candidate or their combinations. For example, when George W. Bush gives a speech, *Bush* is equal to one, otherwise zero. Similarly, when John Kerry gives a speech, *Kerry* is equal to

one, otherwise zero. When both George W. Bush and John Kerry give a speech on the same date, then *Bush-Kerry* is equal to one, otherwise zero.[31]

Columns (7) to (12) present my results. I find that the speeches of different presidential candidates do not have the same effect on stock market returns. Specifically, I show that the political speeches of George W. Bush have the strongest positive effect on the stock market since they increase excess market returns by 77 basis points. The political speeches of John Kerry increase excess market returns by 71 basis points. Following the dates when both George W. Bush and John Kerry or both John McCain and Barack Obama give a speech, there is an increase of 66 or 72 basis points, respectively. In contrast, following the days when Donald Trump or both Donald Trump and Hillary Clinton give a speech, there is a decrease in excess market returns of 30 or 48 basis points, respectively.

Because some presidential candidates have a significant impact on market returns but others do not, I use several *F*-tests to examine whether: (i) $\beta = 0$ for all presidential candidates, (ii) $\beta = 0$ when the political speeches of U.S. presidents are excluded, (iii) $\beta = 0$ when the political speeches of George W. Bush are not considered since I obtained the data on his political speeches from a different dataset, and (iv) $\beta = 0$ when only the coefficient estimates of the political speeches for the 2008-2016 period are considered. In all tests, I find that the *p*-values range between 0.00 and 0.02, which suggests that my results do not reflect only the effect of political speeches that are given by specific candidates or that occur in certain periods.

Overall, the results in Table II show that presidential candidates influence market returns through their political speeches. However, the magnitude of the effect is not the same among

[31] Because presidential candidates often give political speeches on the same day, particularly as the election day approaches, considering these dates as separate cases allows me to minimize the multicollinearity among the candidate dummy variables. Further, this specification allows me to estimate the average effect of such cases on excess market returns.

presidential candidates.

*3.2 Speech content and stock market returns*

In this section, I examine whether the magnitude of the effect among candidates is different because the content of their political speeches is different. In particular, I exploit the variation in the content of speeches to examine two potential channels through which speech content is likely to affect stock market returns.

First, I examine whether speeches that convey economic information to investors influence the excess market returns of the following date. Motivated by the notion that stock market valuations reflect all available information about firms' cash flows and discount rates, I conjecture that an increase in the economic information of speeches that is likely to affect investor expectations would affect excess market returns.

Second, I investigate whether the linguistic tone of speeches predicts stock market returns. Motivated by prior work that shows that the tone of newspaper articles and financial documents affects investor sentiment and, consequently, stock market returns,[32] I test whether the linguistic tone of speeches influences excess market returns.

To test my conjecture, I estimate the following linear regression:

$$R_{t+1} = c + \sum_{i=1}^{7} \beta_{i,1} \cdot Policy_{i,t} + \theta_1 \cdot Negative\ tone_t + \gamma_1 \cdot Pres_{Dem_t} + \gamma_2 \cdot \Delta Poll_{Dem-Rep_t} + \varphi \cdot Controls_t + \varepsilon_{t+1} \quad (3)$$

where $Policy_{i,t}$ corresponds to the following set of variables: *Fiscal policy* (or *Government*

[32] For example, see Tetlock (2007), Feldman et al. (2010), Druz et al. (2016), and Chen et al. (2016).

*spending* and *Taxes*), *Monetary policy*, *National security*, *Entitlement programs* (or *Healthcare*),[33] *Regulation, Trade policy* and *Sovereign debt*. Each of these explanatory variables is equal to the average number of sentences that contain policy-specific terms.[34] Therefore, these measures reflect the policy-specific information of each speech. To measure the negative tone of the speech (*Negative tone*), I subtract the number of sentences that contain positive words from the number of sentences that contain negative words and divide this number by the total number of sentences.

Table III display my findings. The results show that a 1% increase in the number of sentences that discuss issues related to monetary policy, national security and entitlement programs increases excess market returns by 19, 6 and 7 basis points, respectively. In contrast, I demonstrate that a 1% increase in the negative linguistic tone of speeches decreases excess market returns by 1 basis point.[35] At the bottom of the table, I conduct *F*-tests with the null hypothesis that $\beta = 0$ for the set of policy-specific variables, and I find the null hypothesis to be rejected at the 1% level.

Although I find the length of the discussion regarding fiscal policy, healthcare, trade policy, regulation and sovereign debt to have an insignificant effect on market returns, it is still possible that such information affects only a subset of stocks, thus making it difficult to detect an effect on the aggregate level. In Section 4.1, I discuss an example and provide evidence that confirms this conjecture.

### *3.3 Does speech content change during the campaign?*

The campaigns of presidential candidates last for several months before the elections. During this period, candidates often choose to adjust their campaign strategy and broadly discuss several issues

[33] I use either the *Entitlement programs* variable or the *Healthcare* variable in my specification since they share common search-terms (e.g., Medicaid, Medicare).
[34] When a candidate gives more than one speech on the same day, I use the average value.
[35] Standardizing these variables to compare the magnitude of their effect, I find that the discussion regarding national security has the strongest effect (i.e., 9 basis points for a one standard deviation increase), followed by monetary policy, entitlement programs and negative tone, which influence excess market returns by 7, 4 and -5 basis points, respectively.

of public interest. In this section, I examine whether the content of speeches varies significantly between the beginning and the end of campaigns, and I provide evidence concerning the corresponding market reaction.

Figure 1 shows that the content of speeches is different between the first half and the second half of political campaigns (i.e., the last 150 days). In particular, during the second half of the campaign periods, presidential candidates discuss taxes, entitlement programs, and sovereign debt significantly more. In contrast, there is significantly less discussion concerning monetary policy and national security. Further, during the last period of their campaign, presidential candidates use a more negative tone in their speeches, most likely because they prefer to criticize their opponent's positions as the election day approaches. If investors react to the set of information that political speeches convey, then the market reaction would be different between the early and late stage of the campaigns.

Panel A of Table IV presents the results. Consistent with my conjecture, I find that early-campaign political speeches increase excess market returns by 45 basis points; however, this effect decreases by 38 basis points when political speeches occur at the late stage of the campaign. Although these results show that early-campaign political speeches have a stronger positive effect, it is still possible that this effect partially exists not only because the amount of information and the topics of discussion are different but also because candidates change their previous stands on public issues.

For instance, consider a naïve example in which the presidential candidate does not promise any change in corporate tax rates at the early stage of his campaign. However, while trying to persuade more voters as the election day approaches, he promises to cut corporate taxes by 10%. In this example, the amount of discussion is not necessarily different between the two periods, but

we would still observe a stock market reaction because the investor expectations concerning firms' cash flows would change (assuming that the candidate's promise was credible).

To explore this possibility, I estimate a regression specification in which I include the interaction of content-specific variables with a dummy variable (i.e., *Late campaign*) that is equal to one during the second half of the pre-election period, otherwise zero. My conjecture is that if candidates convey positive (negative) content-specific information at the early stage of their campaign but at the late stage of their campaign, change their stand on this issue, then we would observe a market reaction.

Panel B of Table IV displays my results, which demonstrate that the effect of content-specific information about fiscal policy, monetary policy, national security, entitlement programs, trade policy, regulation and linguistic tone is not different between the two periods. However, I find that the market reaction is different for healthcare and sovereign debt information, which suggests that during the late stage of their campaigns, presidential candidates provide different information about these two issues.

Overall, the results in Table IV show that presidential candidates discuss different topics and, in some cases, change their stand on certain topics during their campaigns. As a result, the market reaction is different between these two periods. These findings are consistent with my conjecture that the market reaction depends on the amount and the quality of information that presidential candidates convey to investors.

### *3.4 Speech content and stock market volatility*

Because the winner of the election is not yet known, policy uncertainty is higher before presidential elections (e.g., Baker et al., 2016). Recent studies document that the increase in policy uncertainty leads to not only changes in asset prices but also higher stock return volatility (Bialkowski et al.,

2008; Boutchkova et al., 2012; Pástor and Veronesi, 2013; Addoum and Kumar, 2016). Motivated by this evidence, I conjecture that informative political speeches would decrease stock market volatility whereas market volatility would increase if the linguistic tone of speeches influences investor sentiment (Tetlock, 2007).

To capture the time-varying market volatility, I follow the methodology of García (2013). Specifically, I estimate a GARCH(1,1) model in which the return equation has a constant, $R_t = \mu + \varepsilon_t$, and conditional volatility takes the following form: $\sigma_{t+1}^2 = \omega + \alpha_1 \varepsilon_t^2 + \tau_1 \sigma_t^2$, where $\sigma_t^2 \equiv var(\varepsilon_t^2)$.[36] To capture the effect of speech content on market volatility, I use conditional market volatility as the dependent variable and control for the content-specific variables as in equation (3).

Table V presents the results. Consistent with my conjecture, I find that the discussion related to monetary policy and national security decreases market volatility. Similarly, the coefficient estimates of all other policy-specific variables, except *Fiscal policy*, have a negative sign, though these estimates are insignificant. In line with the findings of Tetlock (2007), I also find that the negative tone of speeches has a positive effect on market volatility. Taken together, these findings suggest that informative speeches decrease the prevailing market risk whereas political speeches with a more negative tone have the opposite effect.

*3.5 Interaction with the prevailing market conditions*

Recent studies show that the reaction of investors to financial news depends on the prevailing market conditions (Dougal et al., 2012; García, 2013). Motivated by this evidence, I examine whether current stock market conditions amplify or attenuate the effect of candidate speeches.

To test whether the speeches of presidential candidates interact with the prevailing stock

[36] I draw similar conclusions when using other models to capture conditional volatility.

market conditions, I follow the methodology of Dougal et al. (2012). Specifically, I estimate a regression specification that includes the interactions of the current and lag values of market returns with the dummy variables of candidate speeches. More formally, the regression specification takes the following form:

$$\begin{aligned} R_{t+1} = c &+ \sum_{i=1}^{12} \beta_{i,1} \cdot Candidate_{i,t} + \sum_{i=1}^{12} \eta_{i,1} \cdot Candidate_{i,t} \times Excess\ Return_t \\ &+ \sum_{i=1}^{12} \theta_{i,1} \cdot Candidate_{i,t} \times Excess\ Return_{t-1} \\ &+ \sum_{i=1}^{12} \xi_{i,1} \cdot Candidate_{i,t} \times Excess\ Return_{t-2} \\ &+ \gamma_1 \cdot Pres_{Dem\ t} + \gamma_2 \cdot \Delta Poll_{Dem-Rep\ t} + \varphi \cdot Controls_t + \varepsilon_{t+1} \end{aligned} \quad (4)$$

where $\beta_{i,1}$ captures the unconditional effect of presidential candidate speeches on the excess market returns at time *t+1* and $\eta_{i,1}$, $\theta_{i,1}$ and $\xi_{i,1}$ show the conditional effect of presidential candidate speeches that depends on the excess market returns at time *t*, *t-1* and *t-2*, respectively.

Table VI presents the results, which show that the prevailing market conditions influence how investors respond to the political speeches of presidential candidates. Specifically, I find that the excess market returns at time *t* and *t-1* interact with the political speeches at time *t* and, in turn, influence the excess market returns at time *t+1*. For instance, following an excess market return of 100 basis points and the political speeches of Barack Obama and Donald Trump, the excess market return would be expected to decrease by 22.89 and 45.51 basis points, respectively. Further, I conduct *F*-tests that show that the variable set of interactions between political speeches and excess returns at time *t* and *t-1* are significant.

Overall, these findings demonstrate that the prevailing market conditions influence the response of investors to the political speeches of presidential candidates.

## 4. Political Speeches and Industry Returns

Hitherto, my findings indicate that the political speeches of presidential candidates influence aggregate stock market outcomes. In this section, I use industry returns to examine whether the effect of speeches varies among industries.

My first aim is to explore the possibility that a particular set of information has a significant impact on a subset of stocks, even though its effect on aggregate market returns is smaller or insignificant. Although, candidate speeches are likely to convey various industry-related information, it is not always easy to establish a clear relationship between a particular set of information and different types of industries. Given this limitation, I focus on the government-spending information that political speeches convey to investors. According to my conjecture, industries that have high government exposure would be more sensitive to government-spending information than industries with low government exposure.

Further, I examine whether politically sensitive industries react more strongly to political speeches. Recent evidence suggests that the political preferences of investors can influence their portfolio holdings (Hong and Kostovetsky, 2012). Therefore, it is possible that investors with political preferences pay more attention to political speeches and react more strongly when the candidate of their favored political party gives a speech. In this case, the stock returns of Republican (Democratic) industries would be more sensitive to the political speeches of Republicans (Democrats). To explore this possibility, I use two industry-level political sensitivity measures: (i) the time-varying measure of Addoum and Kumar (2016) and (ii) the sin stocks defined in Hong and Kacperczyk (2009).

### *4.1 Government-spending information and the government exposure of industries*

To identify industries with high (low) government exposure, I use the measure of Belo et al.

(2013), which allows me to estimate the government exposure of each industry in the Fama and French (1997) portfolio.[37] The sample of my data is for the 2004-2011 period.

Panel A of Table VII shows the five industries with the highest and lowest government exposure. Unsurprisingly, the industries with the highest government exposure are related to defense, shipbuilding and aircraft construction. On the other hand, the tobacco and alcohol industries are those with the lowest government exposure.

To test whether industries with high (low) government exposure are more (less) sensitive to government-spending information, I calculate the rolling average government exposure of the last six months for each industry and then sort these values each month. *Gov. exposure*$_{High}$ (*Gov. exposure*$_{Low}$) corresponds to a dummy variable that is equal to one for the top (bottom) five industries in terms of government exposure, otherwise zero.

The results in Panel B of Table VII demonstrate that industries with high government exposure are more sensitive to the government-spending information of political speeches. In particular, columns (1) and (2) show that, on average, industries with high government exposure have positive excess industry returns. However, an increase in the government-spending information of political speeches decreases the excess industry returns of the following day by 12.89%. Consistent with my conjecture, I also find that the government-spending information of political speeches does not affect the stock returns of industries with low government exposure. These results are robust when controlling for Carhart's (1997) four factors and including date fixed effects to exploit the within-date variation and capture the daily average return across industries.

*4.2 Politically sensitive industries*

Next, I examine whether Republican (Democratic) industries are more sensitive to the speeches of

[37]I would like to thank Jawad Addoum for sharing the government exposure data with me.

Republicans (Democrats). To identify politically sensitive industries, I use two different measures.

First, I use the Addoum and Kumar (2016) measure of political sensitivity (*PolSens*) to classify whether an industry is Republican or Democratic. This measure allows me to identify which of the 48 Fama and French (1997) industry portfolios have higher stock returns under Democratic or Republican presidencies. A positive (negative) *PolSens* indicates that the industry earns higher stock returns under Republican (Democratic) presidencies.

Panel A of Table VIII presents the top five performing industries during Democratic and Republican presidencies. In line with the findings of Addoum and Kumar (2016), I find that industries related to computers, pharmaceuticals and communications earn high stock returns under Democratic presidencies. On the other hand, the coal, mining and shipping industries perform better under Republican presidencies.

According to my conjecture, the political speeches of Republicans (Democrats) are more likely to influence industries that have higher stock returns under Republican (Democratic). To test this conjecture, I cluster the speeches according to the political party of the candidate. Specifically, $Speech_{Rep}$ ($Speech_{Dem}$) is a dummy variable that is equal to one when Republicans (Democrats) give political speeches, otherwise zero. When both Republicans and Democrats give a speech on the same date, $Speech_{Both}$ is equal to one, otherwise zero.[38] I present my results in Panel B of Table VIII, in which I find no evidence that the political speeches of Republicans (Democrats) have a stronger effect on Republican (Democratic) industries. This finding is robust under different specifications.

To further explore the possibility that some industries react more (less) strongly to the political speeches given by the candidates of a specific political party, I test whether the political

[38] Similar to previous tests, I considerate the days on which both candidates have speeches separately to reduce the multicollinearity between the political speech dummy variables. My results remain unchanged when these speeches are not treated separately.

speeches of Republicans (Democrats) increase (decrease) the stock returns of sin stocks (Hong and Kacperczyk, 2009). Panel C of Table VIII presents my findings, which demonstrate that the stock returns of sin stocks are not influenced by the political speeches of Republicans or Democrats. Once again, this result is robust to different regression specifications.

Overall, the results in Table VIII suggest that politically sensitive industries do not react more strongly to the political speeches of certain presidential candidates. These results are in line with my main conjecture that stock prices are influenced by the content of political speeches.

## 5. Political Speeches, Trading Volume and Investor Disagreement

The results in Table III suggest that policy-specific information related to government spending, taxes, fiscal policy, healthcare, trade policy, regulation and sovereign debt do not affect excess market returns. However, as shown in Table VII, some types of information (i.e., government-spending information) may be relevant only to certain industries and, in turn, influence only their stock returns, thus making it difficult to detect any effect on the aggregate level. Another reason why some types of information do not affect excess market returns is the potential divergence of opinion among investors (also known as investor disagreement).

Divergence of opinion among investors results from the different interpretations of public information that arise due to the existence of heterogeneous beliefs and likelihood functions (Harris and Raviv, 1993). In the presence of new information but no price fluctuations, an increased trading volume is considered a proxy for investor disagreement (Kandel and Pearson, 1995; Garfinkel, 2009). Motivated by this evidence, in this section, I examine whether policy-specific information that does not influence stock returns increases trading volume.

### *5.1 Speech content and market trading volume*

To explore this notion, I first examine the effect of political speeches on market trading volume.

Table IX presents the results, which show that among different types of policy-specific information that do not affect market returns, only trade policy information has a significant effect on trading volume. Although this finding cannot rule out the possibility that political speeches that convey trade policy information more strongly affect only a subset of stocks, it may also suggest that this type of information creates a divergence of opinion among investors. In the following section, I examine this conjecture in more detail.

Focusing on the other policy-specific information contained in political speeches, the results presented in Table IX show that information about monetary policy and entitlement programs increases not only stock market returns but also trading volume. Consistent with the findings of Tetlock (2007), I also find that a negative tone predicts lower trading volume but that the absolute measure of negative tone has a positive effect on trading volume.

*5.2 Trade policy information, stock turnover and investor disagreement*

Although trade policy information can have an indirect effect on a variety of firms, it is more likely that export-oriented firms would be more sensitive to this information. Therefore, my conjecture is that if political speeches that contain trade policy information do not influence the stock returns of export-oriented firms but have a positive impact on their stock turnover (measured as the daily volume scaled by the number of common shares outstanding), then a divergence of opinion among investors is likely to exist.

To identify export-oriented firms, I obtain firm-specific export data from Compustat segment files for the 2008-2016 period. Since firms with a higher (lower) volume of exports could be more (less) sensitive to potential changes in trade policies, I construct the *Exports* variable, which is equal to the export sales of the company during the previous year, scaled by the value of total assets at the beginning of that year. To control for the heterogeneity among firms and potential

economic shocks, I include firm and date fixed effects in my regression specification.

Table X presents my findings. Columns (1) and (2) of Table X demonstrate that trade policy information does not have a stronger effect on the stock returns of export-oriented firms. However, the results presented in columns (3) and (4) show that there is a significant increase in their stock turnover when political speeches convey more trade policy information. Overall, these findings suggest that during my sample period, there is a divergence of opinion among investors when presidential candidates convey trade policy information through their political speeches.

## 6. Robustness Tests

In this section, I perform a set of tests to examine alternative explanations for my findings and test whether my results are robust to different measures of market returns and sample specifications. In particular, I use: (i) a falsification test to ensure that my results are not driven by other unobservable factors, (ii) television coverage to validate the salience of political speeches, (iii) different measures of market returns to examine whether my results are robust, and (iv) an alternative campaign period during which all of the uncertainty that may be associated with primaries and caucuses has been resolved.

### *6.1 Falsification test*

To establish that my results do not arise due to the presence of unobservable factors, I use a falsification test. Specifically, in this test, I measure the effect of future speeches on the stock market returns of the previous days. If my conjecture that political speeches influence market returns is accurate, then we should not observe any significant effect between future speeches and stock market returns.

Panel A of Table XI presents my results. As expected, I find that political speeches that

occur at time *t+2* do not affect the stock returns at time *t+1*.

*6.2 Television coverage*

In this section, I examine whether presidential candidates draw the attention of TV networks on the dates of their speeches. If political speeches are salient events, then presidential candidates are more likely to draw media attention on the days of their speeches.

To test this conjecture, I obtain data from the Global Database of Events, Language, and Tone (GDELT). The GDELT is an open database that monitors a selection of national networks. Among other activities, the GDELT also records, on a daily basis, how many times the major television networks mentioned each presidential candidate during their campaigns in 2016.[39] Although, the sample period of this dataset is limited, the daily frequency of data should allow us to capture a potential association between political speeches and media attention, which is also likely to hold during previous campaigns.

Panel B of Table XI shows my results. I find that on the day of political speeches, the major television networks mention the names of presidential candidates 25.45% more often. This finding suggests that political speeches draw media attention and that, therefore, it is likely that they will also draw investor attention.

*6.3 Alternative measures of market returns*

To examine whether my results are robust, I use alternative measures of market returns. Specifically, instead of using value-weighted NYSE returns, I use as dependent variables: (i) the NYSE excess returns winsorized at the 1% level, (ii) the equally-weighted NYSE excess returns,

[39] Specifically, the GDELT monitors only the following networks because these networks have mentioned the political candidates a meaningful number of times: Aljazeera America, Bloomberg, CNBC, CNN, Comedy Central, FOX Business, FOX News, LinkTV and MSNBC. Further, the GDELT notes that all news shows are monitored on each station, with the sole exception of Comedy Central, in which only the "At Midnight with Chris Hardwick", "The Nightly Show with Larry Wilmore", and "The Daily Show with Jon Stewart" are monitored due to their focus on current events.

and (iii) the value-weighted excess return of all CRSP firms listed on the NYSE, Nasdaq or AMEX.

I present these results in Panels C, D, and E of Table XI. In all specifications, I find that political speeches increase excess market returns. These results are highly significant at the 1% or 5% level.

*6.4 Alternative campaign period*

I also use a robustness test that considers the political speeches occurring in an alternative campaign period. In particular, in previous tests, I consider all political speeches that presidential candidates give from January 1 of each election year until the election day. In this section, I use a shorter campaign period to minimize the possibility that my main findings reflect only the effect of political speeches occurring before a candidate is recognized as the final presidential nominee of his political party.

To examine this possibility, I use only the political speeches that presidential candidates give after they have been recognized as the presumptive nominees of their political parties. Presumptive nominees are the presidential candidates: (i) who have already won the majority of delegates through primaries and caucuses prior to the convention and (ii) who remain as the only candidates since all other challengers have dropped out of the race. Therefore, using only the political speeches of presumptive nominees allows me to demonstrate that my results are robust to the exclusion of speeches occurring when there is additional uncertainty related to the choice of the final presidential nominee for each political party.

Panel F of Table XI presents my results. Although, the number of political speeches is significantly smaller during this sample period, my results are similar to those in Table II and show that political speeches increase the excess market returns of the following day.

## 7. Conclusion

This paper examines whether presidential candidates influence stock market outcomes during their campaigns. Specifically, I conjecture that the political speeches of presidential candidates, which either convey economic information to investors or influence investor sentiment, would affect the expectations of investors regarding firms' cash flows and discount rates and, consequently, influence stock market outcomes.

Consistent with my conjecture, I demonstrate that the political speeches of presidential candidates affect stock returns, volatility and trading volume. The magnitude of this effect depends on the content of the speeches. Specifically, I show that informative political speeches increase stock returns and trading volume and decrease volatility. Political speeches with a more negative linguistic tone have the opposite effect. The impact of speeches becomes stronger during the first months of candidates' campaigns and varies based on the prevailing market conditions.

In the cross-section of stock returns, I demonstrate that industries with high government exposure are more sensitive to government-spending information, even though such information does not have a significant impact on aggregate market returns. Further, I show that there is a divergence of opinion among investors when presidential candidates convey trade policy information. Exploring the alternative explanation that stock price reactions arise because Republican (Democratic) industries are more sensitive to the political speeches of Republicans (Democrats), I do not find any supportive evidence.

Collectively, these findings suggest that through their political speeches, presidential candidates influence investor expectations and, in turn, stock market outcomes. In future research, it would be interesting to examine how politicians affect the decisions of other market participants such as corporate managers and equity analysts.

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**Table I**
**Speeches of Presidential Candidates**

This table presents information for each presidential candidate during the pre-election period. The pre-election period starts from January 1 of each election year and ends on the election day. Due to the limited availability, the 2004 election poll data are available from March 9 until November 2, 2004. To calculate the policy information, I count the number of sentences that included policy-specific words, as defined by Baker et al. (2016), and I divide the number by the total number of sentences for each speech. To measure the net linguistic tone of each speech, I use the Loughran and McDonald (2011) dictionary, subtracting the number of sentences that contain positive words from the number of sentences that contain negative words and then dividing the number by the total number of sentences for each speech.

| Candidate | Year | Polls | No. Speeches | Speech length | Government spending | Taxes | Fiscal policy | Monetary policy | National security | Entitlement programs | Healthcare | Regulation | Trade policy | Sovereign debt | Negative tone |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Bush | 2004 | 45.76% | 334 | 299.77 | 0.04% | 2.99% | 3.03% | 0.67% | 2.78% | 1.33% | 2.75% | 0.17% | 0.08% | 0.00% | 16.36% |
| Kerry | 2004 | 44.65% | 87 | 123.60 | 0.19% | 3.43% | 3.60% | 0.21% | 3.26% | 1.14% | 4.73% | 0.48% | 0.32% | 0.01% | 23.56% |
| McCain | 2008 | 43.83% | 140 | 121.80 | 0.43% | 5.06% | 5.33% | 0.60% | 2.05% | 0.44% | 1.68% | 0.68% | 0.20% | 0.00% | 30.85% |
| Obama | 2008 | 46.67% | 181 | 135.16 | 0.14% | 4.60% | 4.72% | 0.50% | 2.63% | 0.61% | 2.76% | 0.44% | 0.16% | 0.00% | 28.37% |
| Romney | 2012 | 44.84% | 93 | 161.43 | 0.73% | 3.03% | 3.68% | 0.44% | 0.86% | 0.80% | 2.57% | 0.23% | 0.07% | 0.00% | 18.97% |
| Obama | 2012 | 47.38% | 105 | 222.58 | 0.11% | 5.51% | 5.56% | 0.09% | 1.80% | 0.98% | 3.24% | 0.10% | 0.11% | 0.00% | 15.36% |
| Trump | 2016 | 41.60% | 57 | 165.25 | 0.25% | 2.75% | 3.00% | 0.29% | 2.41% | 0.32% | 1.62% | 0.39% | 0.69% | 0.11% | 30.64% |
| Clinton | 2016 | 46.44% | 61 | 186.44 | 0.03% | 1.01% | 1.04% | 0.19% | 0.81% | 0.22% | 1.50% | 0.41% | 0.04% | 0.00% | 16.93% |

## Table II
## Presidential Candidate Speeches and Stock Market Returns

This table presents the coefficient estimates and their corresponding t-statistics for equations (1) and (2). The regression is based on a sample period from January 1, 2004, to December 31, 2016. Each coefficient estimate measures the impact on excess returns at time *t+1*. *Speech* is equal to one when a presidential candidate gives a speech, otherwise zero. The name of each presidential candidate represents a dummy variable, which is equal to one when the candidate gives a speech on that day but his opponent does not. If both candidates give a speech on the same day, then I create another dummy variable with the combination of their names (i.e., when George W. Bush and John Kerry give a speech on the same day, *Bush-Kerry* is equal to one, otherwise zero). $Pres_{Dem}$ is a dummy variable equal to one when the president is a member of the Democratic party, otherwise zero. $Poll_{Dem\text{-}Rep}$ is equal to the daily difference in the national polls that are given for the Democratic and the Republican candidate, measured in percentage points. $Poll_{Dem\text{-}Rep}$ is equal to zero for the post-election period. $\Delta Poll_{Dem\text{-}Rep}$ is equal to the difference between time *t* and *t-1*. $ElectionMkt_{Dem\text{-}Rep}$ is equal to the daily difference in the Iowa Electronic Market (IEM) prices that are given for the Democratic and the Republican candidate. In the regression specifications, I also include five lags of daily excess NYSE returns (i.e., from time *t* to *t-4*), five lags of the detrended daily log NYSE volume, five lags of detrended squared NYSE residuals, day-of-the-week dummies, a dummy variable for each month of the year, a pre-election dummy variable that is equal to one from January 1 until the election day for each election year, a dummy to capture the effect of the Lehman Brothers collapse, a dummy to capture the Brexit effect and a constant term. I also present the *p*-values and *F*-statistics from *F*-tests with the following null hypotheses: $\beta_{i,1} = 0, \forall\, i$; $\beta_{i,2}=0, \forall\, i$, where *Bush*, *Bush-Kerry*, $Obama_{2012}$, *Romney-Obama* $\notin i$; $\beta_{i,3}=0, \forall\, i$, where *Bush*, *Bush-Kerry* $\notin i$; and $\beta_{i,4}=0, \forall\, i$, where *Bush*, *Kerry* and *Bush-Kerry* $\notin i$. To obtain robust standard errors, I use a Newey and West (1987) variance/covariance matrix, which accounts for heteroskedasticity and autocorrelation up to five lags. *, ** and *** measure significance at the 10%, 5%, and 1% level, respectively.

| | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Speech | 0.0044*** | (5.60) | 0.0026*** | (2.96) | 0.0026*** | (2.94) | | | | | | |
| Bush | | | | | | | 0.0096*** | (8.70) | 0.0077*** | (6.72) | 0.0076*** | (6.63) |
| Kerry | | | | | | | 0.0089*** | (4.69) | 0.0071*** | (3.67) | 0.0072*** | (3.74) |
| Bush-Kerry | | | | | | | 0.0085*** | (6.63) | 0.0066*** | (4.84) | 0.0065*** | (4.82) |
| McCain | | | | | | | 0.0029 | (0.88) | 0.0011 | (0.32) | 0.0011 | (0.32) |
| $Obama_{2008}$ | | | | | | | 0.0036 | (1.54) | 0.0017 | (0.70) | 0.0018 | (0.74) |
| McCain-Obama | | | | | | | 0.0091** | (2.54) | 0.0072** | (2.03) | 0.0072** | (2.01) |
| Romney | | | | | | | 0.0013 | (1.10) | -0.0007 | (-0.52) | -0.0006 | (-0.47) |
| $Obama_{2012}$ | | | | | | | 0.0002 | (0.15) | -0.0018 | (-1.14) | -0.0016 | (-1.03) |
| Romney-Obama | | | | | | | -0.0007 | (-0.38) | -0.0029 | (-1.45) | -0.0029 | (-1.41) |
| Trump | | | | | | | -0.0008 | (-0.48) | -0.0030* | (-1.67) | -0.0030* | (-1.71) |
| Clinton | | | | | | | -0.0010 | (-0.51) | -0.0031 | (-1.49) | -0.0031 | (-1.45) |
| Trump-Clinton | | | | | | | -0.0026** | (-2.31) | -0.0048*** | (-3.82) | -0.0053*** | (-3.75) |
| $Pres_{Dem}$ | 0.0107*** | (10.58) | 0.0109*** | (10.73) | 0.0109*** | (10.77) | 0.0126*** | (10.55) | 0.0128*** | (10.73) | 0.0128*** | (10.75) |
| $\Delta Polls_{Dem\text{-}Rep}$ | -0.0005 | (-0.49) | -0.0006 | (-0.52) | | | -0.0006 | (-0.60) | -0.0007 | (-0.64) | | |
| $\Delta ElectionMkt_{Dem\text{-}Rep}$ | | | | | -0.0117* | (-1.85) | | | | | -0.0111* | (-1.80) |

**Table II**—*Continued*

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Pre-election dummy | No | Yes | Yes | No | | Yes | | Yes | |
| Additional controls | Yes | Yes | Yes | Yes | | Yes | | Yes | |
| $H_0$: | | | | $\beta_1 = 0$ | | | | | |
| *p*-value/F-stat | | | | 0.00 | 7.76 | 0.00 | 6.14 | 0.00 | 5.97 |
| $H_0$: | | | | $\beta_2 = 0$ | | | | | |
| *p*-value/F-stat | | | | 0.00 | 3.76 | 0.00 | 3.69 | 0.00 | 3.70 |
| $H_0$: | | | | $\beta_3 = 0$ | | | | | |
| *p*-value/F-stat | | | | 0.00 | 3.01 | 0.00 | 3.05 | 0.00 | 3.05 |
| $H_0$: | | | | $\beta_4 = 0$ | | | | | |
| *p*-value/F-stat | | | | 0.09 | 1.66 | 0.02 | 2.21 | 0.02 | 2.16 |
| N | 3,266 | 3,266 | 3,266 | 3,266 | | 3,266 | | 3,266 | |
| $R^2$ | 0.2177 | 0.2202 | 0.2207 | 0.2283 | | 0.2312 | | 0.2316 | |

## Table III
## Content of Candidate Speeches and Stock Market Returns

This table presents the coefficient estimates and their corresponding t-statistics for equation (3). Each coefficient estimate measures the impact of a one-percent increase in the speech content variable on excess market returns at time *t+1*. In all estimations, I include similar control variables as in Table II. I also present the *p*-values and *F*-statistics from *F*-tests with the following null hypotheses: $\beta_{i,1}=0, \forall\, i$, where *Government spending*, *Taxes*, *Monetary policy*, *National security*, *Entitlement programs*, *Trade policy*, *Regulation* and *Sovereign debt* $\in i$; $\beta_{i,2}=0, \forall\, i$, where *Government spending*, *Taxes*, *Monetary policy*, *National Security*, *Healthcare*, *Trade policy*, *Regulation* and *Sovereign debt* $\in i$; $\beta_{i,3}=0, \forall\, i$, where *Fiscal policy*, *Monetary policy*, *National security*, *Entitlement programs*, *Trade policy*, *Regulation* and *Sovereign debt* $\in i$; and $\beta_{i,4}=0, \forall\, i$, where *Fiscal policy*, *Monetary policy*, *National security*, *Healthcare*, *Trade policy*, *Regulation* and *Sovereign debt* $\in i$. All content-specific variables are measured in percentage points. To obtain robust standard errors, I use a Newey and West (1987) variance/covariance matrix, which accounts for heteroskedasticity and autocorrelation up to five lags. *, ** and *** measure significance at the 10%, 5%, and 1% level, respectively.

| | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Government spending | 0.0005 | (0.27) | 0.0004 | (0.22) | | | | |
| Taxes | -0.0001 | (-0.49) | -0.0001 | (-0.41) | | | | |
| Fiscal policy | | | | | -0.0001 | (-0.48) | -0.0001 | (-0.41) |
| Monetary policy | 0.0018* | (1.84) | 0.0019* | (1.88) | 0.0019** | (2.11) | 0.0019** | (2.12) |
| National security | 0.0006*** | (4.28) | 0.0006*** | (4.17) | 0.0006*** | (4.30) | 0.0006*** | (4.19) |
| Entitlement programs | 0.0007** | (2.04) | | | 0.0007** | (2.17) | | |
| Healthcare | | | 0.0002 | (1.05) | | | 0.0002 | (1.10) |
| Trade policy | 0.0006 | (0.51) | 0.0005 | (0.45) | 0.0007 | (0.59) | 0.0006 | (0.52) |
| Regulation | -0.0003 | (-0.34) | -0.0004 | (-0.54) | -0.0003 | (-0.36) | -0.0005 | (-0.57) |
| Sovereign debt | -0.0128 | (-1.29) | -0.0136 | (-1.38) | -0.0129 | (-1.28) | -0.0137 | (-1.38) |
| Negative tone | -0.0001* | (-1.86) | -0.0001* | (-1.70) | -0.0001* | (-1.83) | -0.0001* | (-1.68) |
| Controls | Yes | | Yes | | Yes | | Yes | |
| $H_0$: | $\beta_1 = 0$ | | $\beta_2 = 0$ | | $\beta_3 = 0$ | | $\beta_4 = 0$ | |
| *p*-value/F-stat | 0.00 | 3.88 | 0.00 | 3.46 | 0.00 | 4.38 | 0.00 | 3.88 |
| N | 3,266 | | 3,266 | | 3,266 | | 3,266 | |
| $R^2$ | 0.2243 | | 0.2239 | | 0.2242 | | 0.2239 | |

## Table IV
## Variation in the Content of Political Speeches During Campaigns

This table focuses on the effect of political speeches during the last 5 months of campaigns. In Panel A, I examine whether late-campaign speeches have a different effect on the excess market returns of the following day compared to early-campaign speeches. *Late campaign* is a dummy variable equal to one for the last 150 days before the elections, otherwise zero. In Panel B, I examine whether the content of political speeches has a different impact between the first and second half of the campaign. In all regression specifications, I include similar control variables as in Table II. To obtain robust standard errors, I use a Newey and West (1987) variance/covariance matrix, which accounts for heteroskedasticity and autocorrelation up to five lags. *, ** and *** measure significance at the 10%, 5%, and 1% level, respectively.

Panel A: Early-campaign vs late-campaign political speeches

| | Coef. | t-stat |
|---|---|---|
| | (1) | (2) |
| Speech*Late campaign | -0.0038** | (-2.36) |
| Speech | 0.0045*** | (4.36) |
| Late campaign | 0.0016 | (1.33) |
| Controls | Yes | |
| N | 3,266 | |
| $R^2$ | 0.2213 | |

Panel B: Speech content and the effect of late-campaign political speeches

| | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Government spending*Late campaign | 0.0032 | (0.83) | 0.0021 | (0.54) | | | | |
| Taxes*Late campaign | -0.0004 | (-0.95) | -0.0004 | (-0.95) | | | | |
| Fiscal policy*Late campaign | | | | | -0.0003 | (-0.84) | -0.0004 | (-0.90) |
| Monetary policy*Late campaign | 0.0006 | (0.28) | 0.0001 | (0.03) | 0.0009 | (0.43) | 0.0002 | (0.10) |
| National security*Late campaign | -0.0002 | (-0.50) | -0.0002 | (-0.62) | -0.0002 | (-0.50) | -0.0002 | (-0.66) |
| Entitlement programs*Late campaign | 0.0007 | (0.92) | | | 0.0008 | (1.06) | | |
| Healthcare*Late campaign | | | 0.0006** | (2.00) | | | 0.0007** | (2.35) |
| Trade policy*Late campaign | 0.0009 | (0.33) | 0.0007 | (0.27) | 0.0013 | (0.53) | 0.0010 | (0.41) |
| Regulation*Late campaign | 0.0005 | (0.32) | 0.0006 | (0.35) | 0.0004 | (0.23) | 0.0005 | (0.31) |
| Sovereign debt*Late campaign | -0.0397*** | (-2.69) | -0.0421*** | (-2.82) | -0.0407*** | (-2.73) | -0.0431*** | (-2.89) |
| Negative tone*Late campaign | -0.0001 | (-0.58) | -0.0001 | (-0.52) | -0.0001 | (-0.45) | -0.0001 | (-0.43) |

**Table IV**—*Continued*

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Late campaign | 0.0007 | (0.65) | 0.0006 | (0.49) | 0.0009 | (0.77) | 0.0006 | (0.53) |
| Government spending | -0.0008 | (-0.73) | -0.0006 | (-0.62) | | | | |
| Taxes | 0.0001 | (0.60) | 0.0001 | (0.66) | | | | |
| Fiscal policy | | | | | 0.0001 | (0.55) | 0.0001 | (0.64) |
| Monetary policy | 0.0018* | (1.93) | 0.0019** | (2.07) | 0.0016* | (1.87) | 0.0018** | (2.05) |
| National security | 0.0006*** | (4.30) | 0.0006*** | (4.38) | 0.0006*** | (4.35) | 0.0006*** | (4.45) |
| Entitlement programs | 0.0003 | (0.59) | | | 0.0002 | (0.49) | | |
| Healthcare | | | -0.0001 | (-0.41) | | | -0.0001 | (-0.46) |
| Trade policy | 0.0001 | (0.08) | 0.0000 | (0.01) | 0.0000 | (0.02) | -0.0000 | (-0.04) |
| Regulation | -0.0005 | (-0.50) | -0.0003 | (-0.31) | -0.0005 | (-0.49) | -0.0003 | (-0.28) |
| Sovereign debt | 0.0229** | (2.41) | 0.0239** | (2.51) | 0.0240** | (2.57) | 0.0248*** | (2.65) |
| Negative tone | -0.0001 | (-1.10) | -0.0001 | (-1.03) | -0.0001 | (-1.20) | -0.0001 | (-1.14) |
| Controls | Yes | | Yes | | Yes | | Yes | |
| N | 3,266 | | 3,266 | | 3,266 | | 3,266 | |
| $R^2$ | 0.2259 | | 0.2262 | | 0.2254 | | 0.2260 | |

## Table V
## Candidate Speeches and Market Volatility

This table presents coefficient estimates that show how the content of candidate speeches affects conditional market volatility. To obtain conditional volatility, I estimate a GARCH(1,1) model in which the return equation has a constant mean, $R_t = \mu + \varepsilon_t$, and conditional volatility takes the following form: $\sigma_{t+1}^2 = \omega + \alpha_1 \varepsilon_t^2 + \tau_1 \sigma_t^2$, where $\sigma_t^2 \equiv var(\varepsilon_t^2)$. Panel A reports the coefficient estimates that measure the impact of each speech content on conditional volatility at time *t+1*. To capture conditional heteroskedasticity, I also include similar control variables as in Table II. To improve readability, all regression coefficients are multiplied by 100. *, ** and *** measure significance at the 10%, 5%, and 1% level, respectively.

| | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Government spending | 0.0034 | (1.25) | 0.0036 | (1.28) | | | | |
| Taxes | 0.0004 | (1.29) | 0.0004 | (1.34) | | | | |
| Fiscal policy | | | | | 0.0004 | (1.42) | 0.0004 | (1.46) |
| Monetary policy | -0.0045*** | (-2.83) | -0.0045*** | (-2.87) | -0.0041*** | (-2.63) | -0.0041*** | (-2.65) |
| National security | -0.0005** | (-2.32) | -0.0005** | (-2.29) | -0.0005** | (-2.33) | -0.0005** | (-2.32) |
| Entitlement programs | -0.0008 | (-1.36) | | | -0.0007 | (-1.24) | | |
| Healthcare | | | -0.0003 | (-1.40) | | | -0.0002 | (-1.09) |
| Trade policy | -0.0010 | (-0.81) | -0.0009 | (-0.74) | -0.0006 | (-0.52) | -0.0005 | (-0.43) |
| Regulation | -0.0016 | (-1.47) | -0.0014 | (-1.32) | -0.0017 | (-1.58) | -0.0016 | (-1.50) |
| Sovereign debt | -0.0063 | (-0.98) | -0.0052 | (-0.82) | -0.0066 | (-1.07) | -0.0059 | (-0.96) |
| Negative tone | 0.0002* | (1.71) | 0.0002* | (1.66) | 0.0002* | (1.83) | 0.0002* | (1.82) |
| Controls | Yes | | Yes | | Yes | | Yes | |
| N | 3,266 | | 3,266 | | 3,266 | | 3,266 | |
| $R^2$ | 0.5440 | | 0.5440 | | 0.5435 | | 0.5433 | |

## Table VI
## The Interaction of Stock Market Returns and Presidential Candidate Speeches

This table presents the coefficient estimates and their corresponding t-statistics for equation (4). In all regression specifications, I include similar control variables as in Table II. I also present the *p*-values and *F*-statistics from *F*-tests with the following null hypotheses: $\beta_{i,1} = 0, \forall\, i$; $\eta_{i,1} = 0, \forall\, i$; $\theta_{i,1} = 0, \forall\, i$; and $\xi_{i,1} = 0, \forall\, i$. To obtain robust standard errors, I use a Newey and West (1987) variance/covariance matrix, which accounts for heteroskedasticity and autocorrelation up to five lags. *, ** and *** measure significance at the 10%, 5%, and 1% level, respectively.

| | $\beta_1$ | t-stat | $\eta_1$ | t-stat | $\theta_1$ | t-stat | $\xi_1$ | t-stat |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Bush | 0.0057*** | (4.52) | -0.1351 | (-1.33) | -0.1375 | (-1.15) | -0.1274 | (-1.26) |
| Kerry | 0.0072*** | (3.11) | -0.2169 | (-1.23) | 0.3216* | (1.76) | 0.0773 | (0.45) |
| Bush-Kerry | 0.0070*** | (4.82) | 0.2288* | (1.69) | -0.0277 | (-0.19) | -0.0644 | (-0.54) |
| McCain | 0.0029 | (0.92) | 0.2235 | (1.19) | -0.6454*** | (-3.50) | 0.1521 | (0.65) |
| $Obama_{2008}$ | -0.0019 | (-0.47) | -0.2289* | (-1.70) | -0.1395 | (-0.82) | 0.1024 | (0.82) |
| McCain-Obama | 0.0024 | (0.51) | -0.2632*** | (-2.70) | -0.2124 | (-1.31) | -0.0800 | (-0.59) |
| Romney | -0.0003 | (-0.26) | 0.0104 | (0.10) | -0.1446 | (-0.93) | -0.0681 | (-0.64) |
| $Obama_{2012}$ | -0.0015 | (-0.95) | -0.0745 | (-0.26) | -0.3142 | (-1.28) | -0.2691 | (-1.16) |
| Romney-Obama | -0.0022 | (-1.24) | 0.1582 | (1.12) | -0.2388 | (-1.53) | -0.2926 | (-1.56) |
| Trump | -0.0027 | (-1.19) | -0.4551*** | (-4.31) | 0.2516** | (1.97) | 0.4105 | (1.60) |
| Clinton | -0.0043* | (-1.87) | -0.3447 | (-1.46) | -0.2462 | (-0.93) | -0.2675* | (-1.79) |
| Trump-Clinton | -0.0046*** | (-3.72) | -0.0257 | (-0.11) | 0.2927 | (1.23) | 0.1869 | (1.07) |
| Controls | Yes | | | | | | | |
| $H_0$: | $\beta_1 = 0$ | | $\eta_1 = 0$ | | $\theta_1 = 0$ | | $\xi_1 = 0$ | |
| *p*-value/F-stat | 0.00 | 5.21 | 0.00 | 3.57 | 0.01 | 2.35 | 0.27 | 1.21 |
| N | 3,266 | | | | | | | |
| $R^2$ | 0.2518 | | | | | | | |

## Table VII
## Government-Spending Information and the Government Exposure of Industries

This table focuses on the government exposure of industries and examines whether industries with high exposure are more sensitive to government-spending information. Panel A presents information about the five industries with the highest and lowest government exposure. Panel B shows the coefficient estimates and their corresponding t-statistics when the dependent variable is the excess industry returns at time *t+1*. *Gov. exposure*$_{High}$ is a dummy variable equal to one for the five industries with the highest government exposure over the last six months, otherwise zero. *Gov. exposure*$_{Low}$ is a dummy variable equal to one for the five industries with the lowest government exposure during the last six months, otherwise zero. *Mktrf*, *Smb*, *Hml* and *Mom* correspond to Carhart's (1997) four factors. In all regression specifications, I include as control variables similar industry characteristics (i.e., five lags of excess industry returns, five lags of the detrended log of the daily industry volume and five lags of detrended squared return residuals) and political factors as in equation (1). My sample is for the 2004-2011 period. To account for heteroscedasticity and autocorrelation, I cluster standard errors at the level of the trading day. *, ** and *** measure significance at the 10%, 5%, and 1% level, respectively.

Panel A: Industries and exposure to the government sector

| High government exposure | Government exposure | Low government exposure | Government exposure |
|---|---|---|---|
| Defense | 85.30% | Insurance | 5.38% |
| Shipbuilding, railroad equipment | 61.60% | Healthcare | 2.89% |
| Aircraft | 41.58% | Retail | 1.89% |
| Petroleum and natural gas | 36.96% | Beer & liquor | 1.52% |
| Entertainment | 33.10% | Tobacco products | 0.73% |

Panel B: Government-spending information and industry government exposure

| | Coef. (1) | t-stat (2) | Coef. (3) | t-stat (4) | Coef. (5) | t-stat (6) |
|---|---|---|---|---|---|---|
| Government spending*Gov. exposure$_{High}$ | -0.1289* | (-1.86) | -0.1253* | (-1.85) | -0.1110* | (-1.71) |
| Government spending*Gov. exposure$_{Low}$ | 0.0243 | (0.29) | 0.0275 | (0.33) | 0.0163 | (0.20) |
| Gov. exposure$_{High}$ | 0.0226* | (1.86) | 0.0218* | (1.79) | 0.0198 | (1.62) |
| Gov. exposure$_{Low}$ | -0.0012 | (-0.08) | -0.0013 | (-0.08) | -0.0012 | (-0.08) |
| Government spending | 0.2004 | (0.65) | 0.1735 | (0.57) | | |

**Table VII**—*Continued*

| | | | |
|---|---|---|---|
| Mktrf | | -0.1309*** | (-2.93) |
| Smb | | 0.2075** | (2.05) |
| Hml | | 0.0611 | (0.60) |
| Mom | | 0.0073 | (0.16) |
| Other policies and tone | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes |
| Date F.E. | No | No | Yes |
| N | 96,432 | 96,432 | 96,432 |
| $R^2$ | 0.0240 | 0.0312 | 0.6408 |

## Table VIII
## Candidate Speeches and the Political Sensitivity of Industries

This table examines whether the political speeches of presidential candidates have a stronger effect on politically sensitive industries. To measure the time-varying political sensitivity of industries (*PolSens*), I follow the methodology of Addoum and Kumar (2016), which allows me to identify industries that have higher stock returns under Democratic and Republican presidencies. Specifically, a positive (negative) *PolSens* indicates that the industry earns higher stock returns under Republican (Democratic) presidencies. Panel A presents the top five performing industries under Democratic and Republican presidencies. Panel B shows the coefficient estimates and their corresponding t-statistics when examining whether politically sensitive industries react more strongly to the political speeches of Republicans and Democrats. In Panel C, I examine whether sin stocks react more strongly to the political speeches of Republicans or Democrats. *Sin stocks* are defined as stocks in the tobacco, guns, and alcohol industries. *Mktrf*, *Smb*, *Hml* and *Mom* correspond to Carhart's (1997) four factors. In all regression specifications, I include as control variables similar industry characteristics (i.e., five lags of excess industry returns, five lags of the detrended log of the daily industry volume and five lags of detrended squared return residuals) and political factors as in equation (1). To account for heteroscedasticity and autocorrelation, I cluster standard errors at the level of the trading day. *, ** and *** measure significance at the 10%, 5%, and 1% level, respectively.

Panel A: Industries and political sensitivity

| Ranking | Higher returns during Democratic presidencies | Higher returns during Republican presidencies |
|---|---|---|
| 1. | Computers | Coal |
| 2. | Pharmaceutical products | Non-metallic and industrial metal mining |
| 3. | Communication | Shipping containers |
| 4. | Printing and publishing | Personal services |
| 5. | Electronic equipment | Agriculture |

Panel B: Industry returns and political sensitivity

| | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Speech_{Dem}$*PolSens | -0.0148 | (-0.28) | -0.0157 | (-0.30) | -0.0137 | (-0.27) |
| $Speech_{Rep}$*PolSens | 0.0155 | (0.55) | 0.0152 | (0.54) | 0.0134 | (0.50) |
| $Speech_{Both}$*PolSens | 0.0202 | (0.43) | 0.0186 | (0.40) | 0.0163 | (0.38) |
| $Speech_{Dem}$ | -0.1518 | (-1.13) | -0.1665 | (-1.26) | | |
| $Speech_{Rep}$ | -0.0381 | (-0.42) | -0.0448 | (-0.50) | | |
| $Speech_{Both}$ | -0.0018 | (-0.01) | -0.0055 | (-0.04) | | |
| PolSens | -0.0051 | (-0.62) | -0.0048 | (-0.57) | -0.0068 | (-0.93) |
| Mktrf | | | -0.0963*** | (-2.76) | | |
| Smb | | | 0.1553** | (1.99) | | |
| Hml | | | 0.0180 | (0.22) | | |
| Mom | | | 0.0018 | (0.05) | | |
| Controls | Yes | | Yes | | Yes | |
| Date F.E. | No | | No | | Yes | |
| N | 156,768 | | 156,768 | | 156,768 | |
| $R^2$ | 0.0160 | | 0.0203 | | 0.6073 | |

**Table VIII**—*Continued*

| Panel C: Industry returns and sin-stocks | | | | | | |
|---|---|---|---|---|---|---|
| | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $Speech_{Dem}$*Sin-stocks | 0.1159 | (1.12) | 0.1123 | (1.09) | 0.1004 | (0.96) |
| $Speech_{Rep}$*Sin-stocks | -0.0562 | (-0.93) | -0.0532 | (-0.88) | -0.0536 | (-0.88) |
| $Speech_{Both}$*Sin-stocks | 0.0538 | (0.57) | 0.0523 | (0.56) | 0.0435 | (0.47) |
| $Speech_{Dem}$ | -0.1679 | (-1.11) | -0.1829 | (-1.22) | | |
| $Speech_{Rep}$ | -0.0259 | (-0.27) | -0.0330 | (-0.34) | | |
| $Speech_{Both}$ | 0.0067 | (0.05) | 0.0022 | (0.01) | | |
| Sin-stocks | 0.0155 | (0.98) | 0.0149 | (0.94) | 0.0153 | (0.96) |
| Mktrf | | | -0.0963*** | (-2.76) | | |
| Smb | | | 0.1553** | (1.99) | | |
| Hml | | | 0.0181 | (0.22) | | |
| Mom | | | 0.0018 | (0.05) | | |
| Controls | Yes | | Yes | | Yes | |
| Date F.E. | No | | No | | Yes | |
| N | 156,768 | | 156,768 | | 156,768 | |
| $R^2$ | 0.0160 | | 0.0203 | | 0.6073 | |

## Table IX
## Speech Content and Trading Volume

This table presents coefficient estimates and their corresponding t-statistics that measure the impact of a one-percent increase in the speech content variable on the detrended daily log NYSE volume at time *t+1*. In all estimations, I include similar control variables as in Table II. To obtain robust standard errors, I use a Newey and West (1987) variance/covariance matrix, which accounts for heteroskedasticity and autocorrelation up to five lags. *, ** and *** measure significance at the 10%, 5%, and 1% level, respectively.

| | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat | Coef. | t-stat |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Government spending | -0.0046 | (-0.27) | -0.0046 | (-0.26) | | | | |
| Taxes | -0.0013 | (-1.05) | -0.0010 | (-0.78) | | | | |
| Fiscal policy | | | | | -0.0014 | (-1.15) | -0.0010 | (-0.83) |
| Monetary policy | 0.0157* | (1.93) | 0.0167** | (2.07) | 0.0152* | (1.92) | 0.0161** | (2.03) |
| National security | 0.0002 | (0.09) | 0.0003 | (0.12) | 0.0002 | (0.10) | 0.0003 | (0.13) |
| Entitlement programs | 0.0117** | (2.01) | | | 0.0115* | (1.94) | | |
| Healthcare | | | 0.0022 | (1.32) | | | 0.0021 | (1.24) |
| Trade policy | 0.0221** | (2.41) | 0.0208** | (2.24) | 0.0216** | (2.33) | 0.0202** | (2.18) |
| Regulation | 0.0095 | (1.00) | 0.0074 | (0.78) | 0.0096 | (1.01) | 0.0076 | (0.78) |
| Sovereign debt | 0.0099 | (0.08) | 0.0005 | (0.00) | 0.0107 | (0.09) | 0.0016 | (0.01) |
| Negative tone | -0.0029*** | (-2.63) | -0.0026** | (-2.27) | -0.0029*** | (-2.64) | -0.0026** | (-2.29) |
| \|Negative tone\| | 0.0022* | (1.76) | 0.0020 | (1.53) | 0.0022* | (1.75) | 0.0020 | (1.53) |
| Controls | Yes | | Yes | | Yes | | Yes | |
| N | 3,266 | | 3,266 | | 3,266 | | 3,266 | |
| $R^2$ | 0.3140 | | 0.3134 | | 0.3139 | | 0.3134 | |

**Table X**
## Trade Policy Information and Export-Oriented Firms

This table examines whether political speeches that contain trade policy information influence the stock returns and stock turnover of export-oriented firms. Individual stock turnover is equal to the daily volume divided by the number of outstanding shares. Panel A presents the summary statistics, whereas Panel B shows the results of the regression specification. In the regression specifications, I include similar control variables as in equation (1). Due to the inclusion of date fixed effects, Carhart's (1997) four factors and the control variables related to policy-specific information and linguistic tone are omitted from the regression specifications. To improve readability, all coefficient estimates are multiplied by 100. In all regression specifications, I include as control variables similar stock characteristics (i.e., five lags of excess stock returns, five lags of the detrended log of the daily stock volume and five lags of detrended squared return residuals) and political factors as in equation (1). To account for heteroscedasticity and autocorrelation, I cluster standard errors at the level of the trading day. *, ** and *** measure significance at the 10%, 5%, and 1% level, respectively.

Panel A: Summary statistics

| | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Stock turnover | 8,809,966 | 0.0122 | 0.0290 | 0 | 0.2333 |
| Exports | 8,809,966 | 0.0048 | 0.0405 | 0 | 0.9982 |

Panel B: The effect of trade policy information on the stock returns and turnover of export-oriented firms

| | Stock return$_{t+1}$ | | Stock turnover$_{t+1}$ | |
|---|---|---|---|---|
| | Coef. | t-stat | Coef. | t-stat |
| | (1) | (2) | (3) | (4) |
| Trade policy*Exports | 0.3235 | (1.12) | 0.4384*** | (2.61) |
| Exports | -0.0339 | (-0.60) | -0.3639*** | (-13.84) |
| Controls | Yes | | Yes | |
| Firm F.E. | Yes | | Yes | |
| Date F.E. | Yes | | Yes | |
| N | 8,809,966 | | 8,809,966 | |
| $R^2$ | 0.1086 | | 0.5583 | |

## Table XI
## Robustness Tests

This table shows the coefficient estimates and their corresponding t-statistics for several robustness tests. In Panel A, I conduct a falsification test where I include in my regression specification lead values of *Speech*. In Panel B, I use as dependent variable the logarithm of the daily frequency that the major television networks mention the names of presidential candidates. In Panel C, I present coefficient estimates when I winsorize stock market returns at 1% and 99% level. In Panel D, I use as dependent variable the equally-weighted instead of value-weighted excess returns. Panel E presents coefficient estimates when I use as dependent variable the value-weighted excess return of all CRSP firms listed on the NYSE, Nasdaq or AMEX. In Panel F, I consider only the speeches of presidential candidates who are assumed to be their party's nominee. In all estimations, I include similar control variables as in Table II. To obtain robust standard errors, I use a Newey and West (1987) variance/covariance matrix, which accounts for heteroskedasticity and autocorrelation up to five lags. *, ** and *** measure significance at the 10%, 5%, and 1% level, respectively.

Panel A: Falsification test

| | Coef. | t-stat |
|---|---|---|
| | (1) | (2) |
| $Speech_{t+2}$ | 0.0004 | (0.41) |
| $Speech_{t+1}$ | 0.0007 | (0.65) |
| $Speech_{t}$ | 0.0023*** | (2.64) |
| Controls | Yes | |
| N | 3,266 | |
| $R^2$ | 0.2204 | |

Panel B: Television coverage

| | Coef. | t-stat |
|---|---|---|
| | (1) | (2) |
| $Speech_{t}$ | 0.2545** | (2.10) |
| Controls | Yes | |
| N | 252 | |
| $R^2$ | 0.4986 | |

Panel C: Winsorized excess returns at 1% and 99% level

| | Coef. | t-stat |
|---|---|---|
| | (1) | (2) |
| $Speech_{t}$ | 0.0019** | (2.52) |
| Controls | Yes | |
| N | 3,266 | |
| $R^2$ | 0.2512 | |

**Table XI**—*Continued*

| Panel D: Equally-weighted NYSE excess returns | | |
|---|---|---|
| | Coef. | t-stat |
| | (1) | (2) |
| $Speech_t$ | 0.0026*** | (2.82) |
| Controls | Yes | |
| N | 3,266 | |
| $R^2$ | 0.1997 | |
| **Panel E: NYSE, NASDAQ and AMEX excess returns** | | |
| | Coef. | t-stat |
| | (1) | (2) |
| $Speech_t$ | 0.0026*** | (2.96) |
| Controls | Yes | |
| N | 3,266 | |
| $R^2$ | 0.2189 | |
| **Panel F: Presumptive nominee speeches** | | |
| | Coef. | t-stat |
| | (1) | (2) |
| $Speech_t$ | 0.0019* | (1.94) |
| Controls | Yes | |
| N | 3,266 | |
| $R^2$ | 0.2192 | |

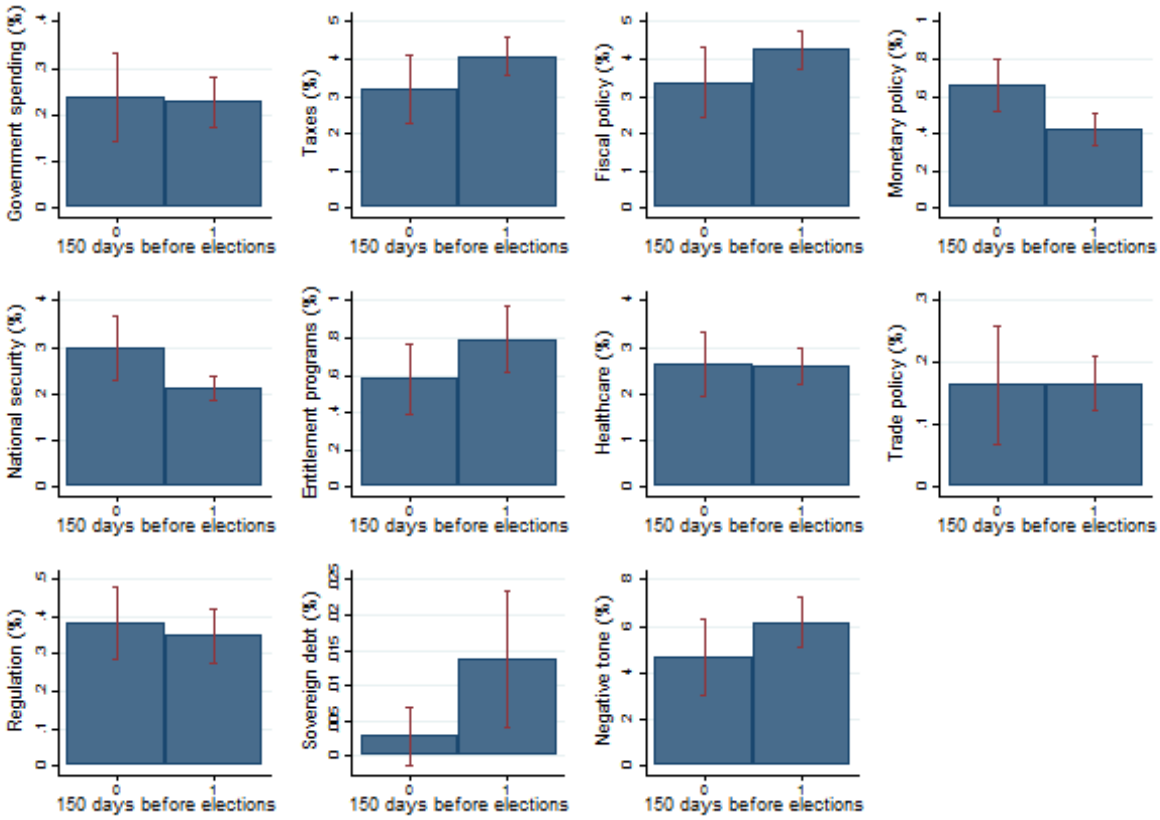


**Figure 1. Variation in the Content of Political Speeches during the Campaigns.** This figure shows whether the content of speeches varies between the first and second half of their campaign. Each graph represents either the level of policy-specific information or the negative tone of the speech. The red spikes show the upper and lower bound of each variable in a 95% confidence interval.

# Appendix

*A1. Summary statistics*

Table A.I presents the summary statistics for all the variables of main regression specification. In particular, Panel A and Panel B displays the summary statistics of the market and political characteristics, respectively. In Panel C, I present information about the content-specific variables, and Panel D shows the statistics for the industry-level measures of government exposure and political sensitivity.

*A2. Political uncertainty and speech content*

Presidential candidates often follow different campaign strategies, which depend on their personal style and the issues of public interest. Consistent with this view, Table I shows that the speech content can be significantly different across candidates. In this section, I examine whether the content of political speeches is also associated with the level of political uncertainty.

To examine whether presidential candidates adjust the content of their political speeches when there is a closely contested election race, I use as dependent variables the content-specific variables constructed in Sections 2.3 and 2.4. To capture the impact of political uncertainty on the content of political speeches, I construct the dummy variable $|Polls_{Dem\text{-}Rep}|_{Low}$ ($|ElectionMkt_{Dem\text{-}Rep}|_{Low}$) that is equal to one when the absolute value of $Polls_{Dem\text{-}Rep}$ ($ElectionMkt_{Dem\text{-}Rep}$) is lower than its median value during the campaign period, otherwise zero.

Table A.II presents my results. I find that political speeches contain more information about monetary policy, national security, entitlement programs and healthcare when the likelihood of winning the election is similar across candidates. During these periods, candidates also choose to decrease their negative tone. These results remain robust when, instead of using the election poll data, I use the IEM data to capture the political uncertainty.

Overall, these findings suggest that presidential candidates choose the content of their speeches not only based on the issues of public interest but also based on whether the likelihood of winning the election is similar to the one of their opponent.

## Table A.I
## Summary Statistics

This table shows the summary statistics for all the variables of my main regression specifications. Panel A presents summary statistics of market characteristics. $R_t$ is equal to the value-weighted return of all CRSP firms listed on the NYSE minus the one month Treasury Bill expressed in terms of daily returns. To proxy for *Volatility*, I use the detrended squared NYSE residuals and to proxy for *Volume* I use the detrended daily log NYSE volume. Panel B shows summary statistics for the political and campaign variables. *Speech* is equal to one if a presidential candidate gave a speech that date. $Pres_{Dem}$ is a dummy variable equal to one when the President is member of the Democratic party. $Poll_{Dem\text{-}Rep}$ is equal to the daily difference of national polls between the Democratic and the Republican candidate (measured in percentage points). Polls are available from January 1 until the election day of each election year. Due to the limited availability data, the 2004 election poll data are available from 9th March until the election date of that year. $Poll_{Dem\text{-}Rep}$ is equal to zero for the post-election period. $ElectionMkt_{Dem\text{-}Rep}$ is equal to the daily difference of the Iowa Electronic Market (IEM) prices between the Democratic and the Republican candidate. Data from IEM are available from January 1 until the election day of each election year, except of the 2004 data that are available from June 1. *TVcoverage* is equal to the total number of times that the major TV networks mention the names of the two presidential candidates. Panel C presents information about the policy-specific information and the tone of candidate speeches. When there are not any political speeches at a specific date, the text-based variables are equal to zero. Panel D shows the summary statistics for the government exposure and political sensitivity of industries.

Panel A: Market characteristics

| | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| $R_t$ | 3,273 | -0.0044 | 0.0139 | -0.0958 | 0.1112 |
| Volatility | 3,273 | 0.0000 | 0.0005 | -0.0022 | 0.0126 |
| Volume | 3,273 | 0.0012 | 0.2199 | -1.5394 | 1.2314 |

Panel B: Political and campaign characteristics

| | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Speech | 3,273 | 0.1375 | 0.3444 | 0.0000 | 1.0000 |
| $Pres_{Dem}$ | 3,273 | 0.6120 | 0.4874 | 0.0000 | 1.0000 |
| $Poll_{Dem\text{-}Rep}$ | 3,273 | 0.6248 | 1.9114 | -7.6000 | 11.4000 |
| $ElectionMkt_{Dem\text{-}Rep}$ | 3,273 | 0.0530 | 0.1393 | -0.9580 | 0.9880 |
| TVcoverage | 252 | 5,196 | 2,150 | 374 | 11,456 |

Panel C: Policy-specific information and textual tone

| | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Government spending | 3,273 | 0.0003 | 0.0021 | 0.0000 | 0.0604 |
| Taxes | 3,273 | 0.0051 | 0.0229 | 0.0000 | 0.7059 |
| Fiscal policy | 3,273 | 0.0054 | 0.0235 | 0.0000 | 0.7059 |
| Monetary policy | 3,273 | 0.0007 | 0.0035 | 0.0000 | 0.0652 |
| National security | 3,273 | 0.0034 | 0.0149 | 0.0000 | 0.4151 |
| Entitlement programs | 3,273 | 0.0010 | 0.0058 | 0.0000 | 0.1772 |
| Healthcare | 3,273 | 0.0036 | 0.0170 | 0.0000 | 0.4419 |

**Table A.I**—*Continued*

| | | | | | |
|---|---|---|---|---|---|
| Regulation | 3,273 | 0.0005 | 0.0026 | 0.0000 | 0.0408 |
| Trade policy | 3,273 | 0.0002 | 0.0019 | 0.0000 | 0.0703 |
| Sovereign debt | 3,273 | 0.0000 | 0.0002 | 0.0000 | 0.0062 |
| Negative tone | 3,273 | 0.0079 | 0.0426 | -0.3571 | 0.5417 |
| Panel D: Government exposure and political sensitivity | | | | | |
| | Obs. | Mean | Std. Dev. | Min | Max |
| Government exposure | 96,720 | 0.1823 | 0.1702 | 0.0000 | 0.9375 |
| PolSens | 157,104 | 0.5426 | 0.9316 | -2.2173 | 6.4895 |

## Table A.II
## Closely Contested Election Race and Speech Content

This table presents coefficient estimates and their corresponding t-statistics when I examine how political uncertainty influences the content of political speeches. In Panel A, I measure high political uncertainty by constructing a dummy variable (i.e., $|Polls_{Dem\text{-}Rep}|_{Low}$) that is equal to one when the absolute value of $Polls_{Dem\text{-}Rep}$ is lower than its median value during the pre-election period, otherwise zero. Similarly, in Panel B I construct a dummy variable (i.e., $|ElectionMkt_{Dem\text{-}Rep}|_{Low}$) that is equal to one when the absolute value of $ElectionMkt_{Dem\text{-}Rep}$ is lower than its median value during the pre-election period, otherwise zero. In all estimations, I include similar control variables as in Table II. To obtain robust standard errors, I use a Newey and West (1987) variance/covariance matrix, which accounts for heteroskedasticity and autocorrelation up to five lags. *, ** and *** measure significance at the 10%, 5%, and 1% level, respectively.

| Panel A: Polls and speech content | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Government spending | Taxes | Fiscal policy | Monetary policy | National security | Entitlement programs | Healthcare | Trade policy | Regulation | Sovereign debt | Negative tone |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| $\|Polls_{Dem\text{-}Rep}\|_{Low}$ | -0.0128 | -0.2158 | -0.2112 | 0.1715*** | 0.3623* | 0.0128 | 0.5170** | -0.0354 | -0.0031 | 0.0018 | -1.0872* |
| | (-0.43) | (-0.60) | (-0.57) | (3.25) | (1.83) | (0.14) | (2.32) | (-0.97) | (-0.07) | (0.52) | (-1.77) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 |
| $R^2$ | 0.0982 | 0.1936 | 0.2025 | 0.2158 | 0.1928 | 0.1161 | 0.1575 | 0.0545 | 0.1299 | 0.0203 | 0.2058 |
| Panel B: Iowa electronic market and speech content | | | | | | | | | | | |
| | Government spending | Taxes | Fiscal policy | Monetary policy | National security | Entitlement programs | Healthcare | Trade policy | Regulation | Sovereign debt | Negative tone |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
| $\|ElectionMkt_{Dem\text{-}Rep}\|_{Low}$ | -0.0117 | -0.0282 | -0.0554 | 0.1695*** | 0.4208** | 0.1908** | 0.9864*** | -0.0101 | 0.0048 | -0.0040 | -1.3269** |
| | (-0.45) | (-0.08) | (-0.15) | (3.75) | (2.23) | (2.03) | (4.66) | (-0.44) | (0.11) | (-1.13) | (-2.24) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 | 3,266 |
| $R^2$ | 0.0982 | 0.1931 | 0.2021 | 0.2145 | 0.1938 | 0.1221 | 0.1709 | 0.0526 | 0.1299 | 0.0215 | 0.2073 |