Political Sentiment and Predictable Returns

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This study shows that shifts in political climate influence stock prices. As the party in power changes, there are systematic changes in the industry-level composition of investor portfolios, which weaken arbitrage forces and generate predictable patterns in industry returns. A trading strategy that attempts to exploit demand-based return predictability generates an annualized risk-adjusted performance of 6% during the 1939 to 2011 period. This evidence of predictability spans 17%−27% of the market and is stronger during periods of political transition. Our demand-based predictability pattern is distinct from cash flow-based predictability identified in the recent literature. (*JEL* G02, G10, G11, G14, G18)

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There is considerable interest among academics, as well as practitioners, in predicting the stock market behavior around the presidential elections.[1] Both retail and relatively more sophisticated institutional investors try to identify stocks and industries that could benefit from the policies of the winning party, as well as market segments that may be adversely affected. Based on these predictions about political "winners" and "losers," investors may systematically alter their stock holdings in certain segments of the market.[2] Some investors may be uniformly more optimistic about the entire market or certain segments of the market that they overweight in their portfolios.

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[1] See Santa-Clara and Valkanov (2003), Hill (2012), Zweig (2012), and Hulbert (2012).

[2] For example, in May of 2008, 6 months before the presidential election, Jim Cramer, host of CNBC's Mad Money, wrote an article in New York Magazine titled "The Presidential Portfolio." In the article, Cramer states that the secret to investing in the period around presidential elections is "to identify the individual sectors and stocks that will rise and fall under each hypothetical administration." He goes on to suggest that oil industry stocks would suffer under an Obama administration, but that solar and wind power companies would benefit. Further, Cramer suggests that an Obama win would hurt pharmaceuticals. In contrast, he states that a McCain

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People's beliefs about the potential impact of the political climate on financial markets and the overall economy is likely to vary. For example, using data from a Gallup survey administered early in President Obama's first term, Jones (2009) finds that although respondents across the political spectrum agreed that the economy was in recession, there was significant disparity in views on where the economy was headed over the next 12 months. Whereas 85% of Democrat respondents felt that the economy would improve, only 50% of Republicans felt the same, with 18% of Republicans expecting the economy to decline further.

In a similar manner, systematic differences in the political preferences of investors (e.g., Hong and Kostovetsky 2012; Bonaparte, Kumar, and Page 2012) could generate considerable heterogeneity in the portfolio decisions of various investor groups. Specifically, investors who support the Democratic Party may become more optimistic about the market and increase their holdings of risky assets if they expect the Democratic Party to come to power. In contrast, during these periods, investors who associate more strongly with the Republican Party may be systematically more pessimistic about financial markets and the aggregate economy. These investors may exhibit a "flight toward safety" and reduce the riskiness of their portfolios when the president belongs to the Democratic Party. Overall, because of differences in perceptions about the market and the aggregate economy, investors would exhibit systematic differences in their portfolio reallocations as the political climate changes.[3]

If systematic shifts in investors' portfolio holdings that accompany changes in the political environment aggregate to a volume that overwhelms the capital constraints of arbitrageurs, they could generate mispricing in certain segments of the market.[4] Further, systematic portfolio reallocations could translate to increased turnover and volatility in the months surrounding presidential elections. In turn, increased volatility would represent increased risk in the positions and eventual payoffs of arbitrageurs, especially those with relatively short investment horizons (e.g., De Long et al. 1990; Gromb and Vayanos 2010). As a result, the power of arbitrage would weaken. Policy uncertainty

presidency would help the nuclear power and defense industries. Finally, Cramer instills a sense of urgency in his readers, directing them to place their bets "before the big gains and losses have been taken."

Similarly, ahead of the 2012 election, Larry McDonald, a political risk expert, managing director, and head of U.S. Macro Strategy at Societe Generale, gave television interviews with Fox Business and CNBC in which he outlined investment strategies under which investors could make money following either an Obama or a Romney win. Terming these strategies the "Obama portfolio" and the "Romney portfolio," McDonald suggested that if President Obama were to win, investors should buy HMO, insurance, food manufacturer, and alcohol stocks. In contrast, if Romney were to win, McDonald suggested that investors should buy stocks in the financial, medical devices, and defense industries.

[3] Consistent with these findings, a significant proportion of respondents (about 40%) in the 55 to 65 age group of a recent Allianz Life survey mention that they would choose a more conservative portfolio if the opposing party wins the election. Also, using brokerage data, Bonaparte, Kumar, and Page (2012) show that when the political climate is aligned with the political identity of investors, they increase portfolio allocations to risky assets.

[4] By "mispricing," we mean that there are predictable patterns in returns that cannot be explained by existing multifactor asset pricing models used to account for systematic risk.

following shifts in the political environment could further deter arbitrageurs from taking positions in the market.

Motivated by these observations, in this paper, we conjecture that there will be predictable patterns in the returns of politically sensitive firms and industries that can be identified *ex ante*. Specifically, systematic shifts in the portfolio compositions of investors induced by changes in the political climate (i.e., political sentiment) would generate predictable return patterns. The correlated demand shifts of politically-sensitive investors would move prices away from fundamental values, and the subsequent adjustment to fair values will be sluggish due to the reduced power of arbitrage forces. This prediction is motivated by economic models, which posit that the two key ingredients necessary for generating predictability in any economic setting are the existence of systematic demand shocks and limits to arbitrage (e.g., Shleifer 1986; Baker and Wurgler 2006; Gromb and Vayanos 2010).

For example, while optimistic Democrat investors may choose to buy healthcare stocks when a Democrat comes to power, pessimistic Republicans may choose to sell their holdings in tobacco stocks at the same time. Further, some sophisticated investors, as a hedge against the opposite party to their own coming to power, may choose to buy stocks that are in industries they feel will be favored by the new regime. This correlated trading behavior may drive prices away from fundamentals among stocks in politically sensitive industries such as healthcare and tobacco. Arbitrageurs may struggle to quickly and completely eliminate this mispricing owing to the high political uncertainty and accompanying return volatility surrounding presidential elections.[5]

Although market participants often talk about the potential effect of political environment on financial markets, there is no consensus about how to identify stocks and industries that would benefit from the election outcome. We propose a novel method for identifying those market segments that are more likely to be influenced by changes in the political climate. Specifically, we estimate the political-sensitivity of all industries with respect to the Republican and Democratic Parties on a 15-year rolling basis. These estimates capture the return sensitivity of industry segments to the changing political climate. In particular, according to our political-sensitivity estimate, an industry has greater sensitivity to the presidential party if its returns more strongly correspond (either positively or negatively) with the party in power.

Using the political-sensitivity estimates, we demonstrate that returns in segments of the market with greater political-sensitivity to either the Republican or Democratic Party are predictable. This evidence of predictability spans an economically meaningful segment of the market (about 17%−27% of the total

[5] Although there is likely to be some divergence of opinions on the effect of a given candidate's victory on a particular industry's fortunes, investors are likely to be influenced by the opinions of authorities in the media. Thus, the trading activity of institutional and retail investors in politically sensitive sectors is likely to be correlated around presidential elections. In Section 3.1, using portfolio holdings of retail and institutional investors, we provide additional evidence of systematic demand shifts induced by changes in the political environment.

market capitalization). A Long−Short trading strategy that attempts to exploit this predictability pattern generates an annualized characteristic-adjusted return of 5.57% during the 1939 to 2011 period. This evidence of predictability is stronger in the recent time period, perhaps because political parties have become more polarized (e.g., Poole and Rosenthal 1997; 2001). During the 1976 to 2011 period, the Long−Short strategy generates an annualized characteristic-adjusted performance of 7.06%.

These findings are robust to the choice of the asset pricing models used to adjust for risk. Even when we use conditional factor models that take into account time-varying exposures to risk, the Long−Short strategy generates economically significant alphas.

We conduct a battery of tests to confirm that our evidence of predictability is driven by systematic shifts in investor demand. First, we illustrate that our evidence of predictability is much stronger (almost twice as strong) in the months surrounding elections in which the challenger party is victorious. Second, we show that the predictability patterns are stronger during months surrounding the elections and years 1 and 4 of presidential terms when the level of political awareness is higher. This evidence is consistent with the conjecture that systematic investor demand induced by changing political climate generates mispricing, which eventually gets corrected through the action of arbitrageurs.

Beyond these return-based tests, we examine the portfolios of retail and institutional investors directly to determine whether they alter their portfolio holdings as the political climate changes. Consistent with our demand-induced predictability hypothesis, we find that the relative holdings of Republican (Democrat)-favored industries are higher around elections in which the power switches to the Republican (Democratic) Party. These portfolio shifts are stronger among retail investors, mutual funds, and investment companies in comparison to bank trusts, insurance companies, and pension and endowment funds.

To establish the link between investors' portfolio rebalancing and return predictability, we also examine the level of trading, volatility, and short interest in various segments of the market. We find that the level of trading increases when there is a change in presidential party, leading to increased volatility. In turn, this increased volatility can translate to increased risk in the positions and eventual payoffs to arbitrageurs. We find direct evidence of a coincident exit or reduction of arbitrage capital from the market. Specifically, we find that arbitrageurs alter their trading behavior in the months surrounding presidential elections, reducing active trades against the potential mispricing generated by investors' reallocations.

We perform several tests to ensure further that our evidence of demand induced return predictability is distinct from the evidence of predictability induced by actual shifts in firm cash flows or perceptions of shifts in cash-flows associated with the changing political climate. The goal of these tests is not to illustrate that systematic shifts in investor demand is the only channel through which changes in political climate could influence stock prices. Clearly, the changing political environment could influence the market through its potential effect on firm profitability. We want to demonstrate that the investor-demand channel plays an economically significant role for asset prices that is captured by our novel political-sensitivity estimation method and the cash flow channel is unlikely to fully explain those findings.[6]

First, we demonstrate that our findings are distinct from the evidence in Belo, Gala, and Li (2013), who find that firms with greater industry-level exposure to government spending earn higher returns during Democratic presidencies. We calculate their industry-level measure of exposure to government spending using input-output tables from the Bureau of Economic Analysis, and find that our results are not driven by firms that have high exposure to government spending. Our results are actually stronger among firms with lower exposure to government spending. In addition, we find that our results hold for firms located in low as well as high government spending states.

Next, we show that our evidence of return predictability is stronger during presidential election periods and in years 1 and 4 of the presidential term when investor attention is likely to be higher. In contrast, Belo, Gala, and Li (2013) find that their evidence of cash flow-based predictability is stronger during the 2 middle years of the presidential term as the policy uncertainty is resolved. This timing difference suggests that the channel driving the predictability we document is distinct from that documented by Belo, Gala, and Li (2013).

Last, we provide evidence of predictability during both Republican and Democratic presidential terms, which suggests that our results do not somehow reflect the presidential puzzle identified in Santa-Clara and Valkanov (2003). In addition, we show that our evidence of return predictability is distinct from the known relation between political connections and stock returns (Cooper, Gulen, and Ovtchinnikov 2010). We also establish that our results do not reflect the findings in Kim, Pantzalis, and Park (2012), who show that firms located in U.S. states that are more politically aligned with the presidential party earn higher average returns. We find evidence of return predictability in both high- and low-political-alignment states.

In additional tests, we directly estimate the sensitivity of industry cash flows to the presidential party and examine the performance of double-sorted portfolios using cash flow-based and return-based political-sensitivity measures. We form conditional cash flow- and return-based hedge portfolios,

[6] Whereas investor demand is likely to be driven by perceived changes in expected cash flows during a new administration, investors' perceptions in the months surrounding an election may not always reflect the eventual outcomes of firms in politically sensitive industries. For example, in a Wall Street Journal article, Harder (2015) asserts that when President Obama first took office in 2009, he was expected to be an adversary of oil and gas companies. However, not only has he been less adversarial than initially feared, but his repeal of the 40-year-old ban on oil exports is seen as a significant boon to the industry. Further, even within an industry, there is likely to be substantial heterogeneity across firms in eventual outcomes during a president's time in office.

and find that for all return-based political-sensitivity groups, the difference between the returns of the long and short cash flow-based political-sensitivity portfolios is statistically insignificant. In contrast, we find that across all three cash flow-based political-sensitivity groups, the Long−Short return-based political-sensitivity portfolio returns are economically and statistically significant. These results further suggest that the return predictability we document is not driven by rational expectations related to the sensitivity of industry cash flows to the presidential party.

Taken together, these findings contribute to the growing finance literature that examines the link between politics and the stock market (e.g., Santa-Clara and Valkanov 2003; Cooper, Gulen, and Ovtchinnikov 2010; Belo, Gala, and Li 2013; Kim, Pantzalis, and Park 2012). We extend the evidence from these previous studies that focus mainly on the impact of political environment on firm cash flows and we examine the effect of political environment on asset returns through the investor-demand channel. We show that political sentiment generates mispricing in certain segments of the market, especially during periods of high political awareness.

More recently, Pastor and Veronesi (2013) show that political uncertainty induces a higher risk premium, especially when the economic conditions are poor. Moreover, they conjecture that stocks should be more volatile and exhibit higher correlation when political uncertainty is high. They present evidence supporting these predictions using the political uncertainty measure of Baker, Bloom, and Davis (2013), which tends to spike around presidential elections. Given these spikes, our evidence of industry-level predictability is consistent with both the volatility and correlation predictions of Pastor and Veronesi (2013). Further, our political-sensitivity measure offers the additional insight of predicting which industries will experience positive and negative abnormal returns during the months surrounding presidential elections.

Beyond the literature on politics and finance, our paper extends the literature on return predictability. For example, Cohen and Frazzini (2008) show that customer-supplier links can be used to identify predictable patterns in stock returns. Similarly, Korniotis and Kumar (2013) show that local economic conditions can be used to predict the returns of local stock returns, especially in regions with strong local bias. Our paper identifies a new predictability mechanism and provides evidence of return predictability in a different segment of the market.

More broadly, our results provide support for behavioral asset pricing models, which posit that investor sentiment moves prices away from the fundamental values and the actions of arbitrageurs eventually correct this mispricing (e.g., De Long et al. 1990; Baker and Wurgler 2006). Our key innovation is to recognize the heterogeneity in the sentiment levels of investors along the political dimension. Specifically, we examine the asset pricing effects of Republican and Democratic sentiments instead of the aggregate market-wide sentiment.

1. Data and Methods

In this section, we describe the various data sets used in the empirical analysis. We also summarize the methods used for measuring political-sensitivity of industries.

1.1 Main data sources

We use data from multiple sources. We obtain daily and monthly stock returns, stock prices, shares outstanding, and Standard Industry Classification (SIC) codes from the Center for Research on Security Prices (CRSP). We consider only common shares, restricting the sample to observations with share codes 10 and 11. Both daily and monthly stock returns from CRSP are available for the December 1925 to December 2011 period.

The monthly Fama-French factor returns, historical book-equity data, forty-eight SIC industry classifications, and forty-eight industry daily and monthly value-weighted portfolio returns are from Kenneth French's data library. The daily returns for the forty-eight Fama and French (1997) industry portfolio returns are available from July 1963 to December 2011, and monthly industry portfolio returns are available from July 1926 to December 2011.

We use data from Compustat to compute book-to-market ratios for each listed U.S. firm in our sample. Book-to-market ratio is calculated as the ratio of year-end book equity plus balance sheet deferred taxes to year-end market equity, with an assumed 6-month lag between measurement and observation periods. The annual Compustat data are available from 1950 to 2011.

We obtain the Daniel et al. (1997) characteristic-adjustment stock assignments and benchmark portfolio returns from Russ Wermers's website. Because the benchmark returns are available only from 1975 to 2011, we use the Daniel et al. (1997) method to generate stock assignments and benchmark portfolio returns back to January 1939 using historical book-equity data.[7] We use these stock assignments and benchmark portfolio returns to calculate characteristic-adjusted returns at the stock level. We then use the forty-eight SIC industry classifications to calculate value-weighted Fama-French forty-eight industry-portfolio characteristic-adjusted returns.

We obtain the Lettau and Ludvigson (2001) *cay* measure from Sydney Ludvigson's website and National Bureau of Economic Research (NBER) recession indicators from the NBER website. The data on presidential election outcomes are from the CQ Press Voting and Elections Collection.[8]

In our robustness tests, we use data on industry-level exposure to government spending, firm HQ state-level political alignment, and data on corporate

[7] We verify the accuracy of our generated stock assignments and benchmark portfolio returns over the 1975 to 2011 period using the data from Russ Wermers's website.

[8] The CQ Press Voting and Elections Collection provides outcome and voting data for presidential and congressional elections. The collection dates back to 1824 for presidential and House elections, and to 1908 for Senate elections. The data is publicly available at: http://library.cqpress.com/elections/index.php.

political contributions to political action committees (PACs), as well as personal political contributions of firm executives. We use the Belo, Gala, and Li (2013) method to calculate industry-level exposure to government spending. Specifically, we use federal, state, and local government transaction data from the Bureau of Economic Analysis (BEA) Input-Output tables to calculate the government spending exposure for each of the forty-eight Fama and French (1997) industry portfolios. The BEA input-output tables are publicly available for the period from 1955 to 2011 and are updated at 5-year intervals. Following Belo, Gala, and Li (2013), each month we calculate the government spending exposure for each of the forty-eight Fama and French (1997) industry portfolios using the most recent publicly available Input-Output table.

We use the political alignment index (PAI) developed in Kim, Pantzalis, and Park (2012), which measures the degree of political alignment between a state's leading politicians and the presidential party, directly from the authors.[9] This measure is available from 1950 to 2008. We measure firms' political connectedness, as in Cooper, Gulen, and Ovtchinnikov (2010), using data on corporate political contributions to PACs made available by the Federal Election Commission (FEC). These data are available from 1979 to 2006. Finally, following Hutton, Jiang, and Kumar (2014), we identify the political orientation of firm managers using data on their personal contributions to political candidates. These data are also made available by the FEC, and they cover the period from 1992 to 2008.

1.2 Estimating political sensitivity of industries

We estimate the political sensitivity of each industry portfolio. The industry-level political-sensitivity estimates are obtained using a conditional version of the specification used in Santa-Clara and Valkanov (2003). Each month, for each of the forty-eight Fama and French (1997) industry portfolios, we regress the excess industry returns during the past 15 years (180 months) on the excess market return and a presidential party indicator. Specifically, we estimate the following time-series regression:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i \left(r_{mkt,t} - r_{f,t} \right) + \theta_i RepubDummy_t + \varepsilon_{i,t}. \tag{1}$$

In this equation, the presidential party indicator variable ($RepubDummy_t$) is equal to one when the presidential party is Republican and zero during Democratic presidential periods.[10]

We define the Republican dummy variable based on the findings in Abramowitz (1988, 2008), who demonstrates that presidential election

[9] We thank Chris Pantzalis for sharing the PAI data with us.

[10] We also estimate political sensitivities with respect to Senate and House party indicators. These indicators are based on whether the Republican Party holds the majority in the Senate or House, respectively. Similar to Santa-Clara and Valkanov (2003), we find that the results based on these measures are statistically and economically insignificant, suggesting that the executive branch has a much stronger effect on political sentiment than the legislative branch of government, perhaps because it is more salient.

outcomes can be predicted with high accuracy. The set of election predictors include the following measures available at the end of June in election years: GDP growth, presidential approval rating, and whether it is the incumbent party's first term in office.[11] We exploit this known predictability of election outcomes by setting the presidential party indicator such that it reflects the winning party of the November election in August, September, and October of the election year. This approach allows the model to capture potential swings in industry returns that occur in anticipation of the November election outcome.

For robustness, we verify that our key results are not dependent upon our ability to exploit this known predictability in presidential election outcomes. We find similar results when the Republican dummy is set to one starting in the month of December after the Republican Party wins the election (i.e., almost an entire month after the election outcome is known).

Our focus is on the θ_i estimate, which captures the political-sensitivity of an industry.[12] A positive θ_i estimate indicates that the industry earns higher average returns during Republican presidential terms, whereas a negative θ_i estimate indicates that the industry earns higher returns when the president is a Democrat. In our main empirical tests, we use these political-sensitivity estimates to define different types of political-sensitivity based portfolios.[13]

We measure political sensitivity using rolling windows to allow for time-variation in both the magnitude and direction of the political-sensitivity estimates. Our choice of a 15-year (180 month) window is motivated by the need to have at least one party change during the estimation period.[14] After the

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[11] We verify the efficacy of the election prediction model in our sample. Beginning with the 1952 election, we model the popular vote as a function of GDP growth over the first two quarters of the election year, the incumbent's June approval rating, and whether it is the incumbent party's first term in office. We use data from past elections to fit this model. Then, using known values of these predictors in the year of the current election, we predict the winner. We find that the model's prediction is correct for every election except the 1988 Republican win.

[12] In Appendix Table A.1, we use a short sample of *direct* political sentiment measures to validate our key assumption that the return-based political-sensitivity measures can capture the effects of partisan-based shifts in investor sentiment. We find that the return-based political-sensitivity estimates capture the effects of political sentiment on stock returns reasonably well.

[13] While our focus is on the political-sensitivity of domestic industry returns to changes in the U.S. political environment, we also consider international portfolios. Specifically, we collect level-6 classification industries from Datastream International for the following countries: Australia, Canada, France, Germany, Japan, and the United Kingdom. We then estimate the political-sensitivity of each country-specific industry portfolio to that country's party in power (left- or right-leaning), and subsequently form portfolios in a manner identical to that in the main results of our paper. In addition, we estimate the political-sensitivity of international industry portfolio returns to the U.S. presidential party. We find that the domestic political-sensitivity estimates do not yield significant predictability in any of the six countries. However, we find that in three out of six instances, the U.S.-based political-sensitivity estimates produce an economically profitable trading strategy, which is also statistically significant at the 5% level. Further, in two of the remaining three countries, there is evidence of predictability at the 10% level of statistical significance.

[14] This constraint also motivates our choice of measuring political-sensitivity at the industry-level. Specifically, industry portfolios have valid return observations over long periods of time. In contrast, this is not true for many stocks in the CRSP universe. For such stocks with insufficient observations, we would be forced to either discard them from analysis or come up with an *ad-hoc* alternative measure of political sensitivity. Evidence from the style investing literature (e.g., Barberis and Shleifer 2003), which shows that investors tend to categorize stocks into different styles and invest depending on the relative performance of these styles, suggests that our industry-level approach is reasonable.

1952 presidential election, there is always a change of party in power during any given 15-year period. Before the 1952 election, a Democratic president occupied the White House for 20 years following the 1932 election. To deal with this exception, we hold the political-sensitivity estimates constant during the last 5 years of this period (i.e., from 1948 to 1952).[15]

1.3 Construction of political-sensitivity sorted portfolios

We use the political-sensitivity estimates θ_i to define a variety of industry-based political-sensitivity portfolios. To facilitate the construction of these portfolios, we first define a *conditional* political-sensitivity measure θ_i^c using these θ_i estimates. Specifically, $\theta_i^c = \theta_i$ when the president belongs to the Republican Party and $\theta_i^c = -\theta_i$ when the president is a Democrat. This transformation ensures that industries that are politically favored by the Republican political environment have higher θ_i^c when the president is a Republican, and industries that are politically favored by the Democratic political environment have higher θ_i^c when the president is a Democrat.

Using the θ_i^c estimates, each month, we sort industries in descending order. We use the top-five industries to form the Long portfolio and the bottom-five industries to form the Short portfolio.[16] The Long portfolio contains industries that are most favored by the existing political climate (Republican or Democrat), whereas the Short portfolio contains industries that are least favored by the existing political climate. The remaining thirty-eight industries are split equally among portfolios 2, 3, and 4.[17] Portfolios are value-weighted using industry market capitalization at the beginning of the month. We re-sort industries and form portfolios monthly.

1.4 Characteristics of political-sensitivity sorted portfolios

Table 1 reports the descriptive characteristics of industry portfolios defined using our political-sensitivity-based return-prediction model. Panel A reports the mean conditional political-sensitivity, size (log market capitalization), book-to-market ratio, returns over the previous 6 months with a 1-month lag, and the concentration of sin stocks in each portfolio as a proportion of total portfolio market capitalization. Sin stocks are defined using the Hong and Kacperczyk (2009) method as stocks in the Tobacco, Guns, and Alcohol industries among the forty-eight Fama and French (1997) industries.

We find that there is significant variation in conditional political-sensitivity across the portfolios. Further, we find that average size and book-to-market

[15] In untabulated results, we verify that our main results are not affected by this choice. Our results are similar if we focus on the post-1952 sample period.

[16] We experiment with alternative extreme portfolio sizes and find similar results. See Table 4, Panel C.

[17] Before July 1969, classifying firms according to the Fama and French (1997) SIC-code classifications yields fewer than forty-eight industries. Between January 1939 and June 1963, there are forty-three industries in total and thirty-three industries sorted across the three middle portfolios. Between July 1963 and June 1969, there are forty-seven industries in total and thirty-seven industries sorted across the three middle portfolios.

Table 1
Political-sensitivity portfolios: Descriptive characteristics

Panel A: Portfolio characteristics

Portfolio	Pol. sensitivity	Size	Book-to-market	Lag 6m return	Sin stocks (%)
1 (Short)	−3.649	13.616	0.350	4.141	6.252
2	−1.120	14.257	0.400	5.191	2.843
3	0.079	14.274	0.382	6.723	1.085
4	1.097	14.324	0.363	7.794	2.479
5 (Long)	2.779	14.115	0.329	11.531	7.191

Panel B: Top-five industries

Ranking	Republican long	Republican short	Democratic long	Democratic short
1	Tobacco	Construction	Electronic chips	Finance
2	Candy & soda	Real estate	Real estate	Business supplies
3	Lab equipment	Precious metals	Construction	Aircraft
4	Boxes	Healthcare	Oil	Tobacco
5	Food products	Textiles	Books	Computers

This table reports descriptive characteristics for portfolios defined using the political-sensitivity return-prediction model. We report the characteristics of five industry (stock) portfolios: (i) the "Short" portfolio, which is a value-weighted portfolio of the five industries predicted to have the lowest returns in the next month; (ii) the "Long" portfolio, which is a value-weighted portfolio of the five industries predicted to have the highest returns in the next month; and (iii)−(v) portfolios 2−4, value-weighted portfolios of the remaining industries sorted into terciles based on predicted returns in the next month. Panel A reports mean conditional political-sensitivity, size (log market capitalization), book-to-market ratio, returns over the previous 6 months with a 1-month lag, and the concentration of sin stocks in each portfolio (as a proportion of total portfolio market capitalization). Sin stocks are defined as stocks in the Fama-French forty-eight Tobacco, Guns, and Alcohol industries, as in Hong and Kostovetsky (2012). Industry portfolio measures are calculated as the value-weighted average among individual stocks. Panel B reports the five most prevalent industries in the Long and Short portfolios across Republican and Democratic presidencies. Prevalence is measured by the number of months an industry is classified into a given portfolio over the estimation period. The estimation period for industries is from January 1939 to December 2011.

ratios across the portfolios are similar, and that past returns increase with expected returns according to our political-sensitivity prediction model.[18] Also, consistent with the partisan nature of the propensity to hold sin stocks documented in Hong and Kostovetsky (2012), we find that Tobacco, Guns, and Alcohol industries are sorted into the Short and Long portfolios with higher frequency than into the other three portfolios.

To provide further insights into the composition of the conditional political-sensitivity portfolios, panel B reports the five most prevalent industries in the Long and Short portfolios across Republican and Democratic presidencies.

[18] Naturally, this pattern may raise the potential concern that our political-sensitivity prediction model is somehow repackaging momentum returns. We address this concern in three ways. First, in a related paper, Addoum et al. (2016) show that holding the political-sensitivity measure constant for successive one year periods, which effectively purges political sensitivities of price momentum information, still yields a political-sensitivity hedge portfolio return that can explain a significant portion of momentum alphas. In other words, political-sensitivity explains momentum returns, and not the other way around. Second, Addoum et al. (2016) show that in November of switching-party election years, a period that we show is the most profitable for the political-sensitivity hedge portfolio, past returns are actually monotonically decreasing across the political-sensitivity portfolios instead of increasing. Third, throughout the paper we report characteristic-adjusted hedge portfolio returns, in addition to presenting factor model regressions where we control for momentum returns and Fama and MacBeth (1973) cross-sectional regressions where we control for past returns. Overall, we conclude that our political-sensitivity prediction model does not indirectly reflect the known evidence on price momentum.

Prevalence is measured by the number of months an industry is classified into a given portfolio over the estimation period.

We find that the political-sensitivity of industries vary over time. Appendix Table A.2 outlines the top-five politically sensitive industries favored respectively by Democrats and Republicans during each party administration during our sample period. The table shows that there is significant variation in the composition of politically sensitive portfolios across presidential administrations.[19] For example, whereas the Coal industry was favored by Democrats early in the sample period, it is among the top Republican industries from 2009 to 2011. Overall, these results suggest that our industry-level political-sensitivity estimates are reasonable.

2. Evidence of Predictable Returns

Our return predictability analysis is based on the key premise that the investor demand for certain types of stocks varies systematically with the political climate. In particular, we posit that investors systematically alter their holdings of certain types of stocks because of changes in the political climate. If the demand shifts of these politically sensitive investors aggregate to a volume that overwhelms the capital constraints of arbitrageurs, the systematic shifts in investors' portfolio holdings could generate mispricing in certain segments of the market and predictable patterns in stock returns. Further, during periods of increased political uncertainty, arbitrage forces may weaken as arbitrageurs may choose to stay on the sidelines until the uncertainty is resolved. The incremental volatility around presidential elections could further deter arbitrageurs.

Overall, because of the joint effects of correlated demand shifts of politically-sensitive investors and reduced arbitrage forces, returns are likely to be predictable in politically sensitive segments of the markets. In this section, we test this main conjecture using industry portfolios sorted on the basis of our new measures of political-sensitivity.

2.1 Political climate induced demand shifts

Before presenting the results from our returns-based tests, we provide direct evidence of political climate-induced demand shifts using the portfolio holdings of different groups of investors. The goal of this analysis is to investigate whether retail and institutional investors change the composition of their

[19] Though there is significant variation in the composition of politically sensitive portfolios across presidential administrations, the composition of portfolios is relatively stable during a given administration. Specifically, a given industry currently in the Long (Short) portfolio transitions out of the portfolio with average frequency of 7.65% (7.01%) in the next month. These transitions are more prevalent during the 6 months surrounding presidential elections. During these months, a given industry in the Long (Short) portfolio exits the portfolio in the following month with average frequency of 14.07% (14.26%).

portfolios as the political climate changes in a manner that could generate the return predictability patterns we document.

If the return predictability is driven by the demand channel, demand for firms and industries that are predicted to perform well during a Republican presidency should increase when the presidential affiliation shifts from the Democratic to the Republican Party. Similarly, the demand for firms and industries that are predicted to perform well during a Democratic presidency should increase when the presidential affiliation shifts from the Republican to the Democratic Party. Thus, shifts in investor holdings coincident with changes in the party affiliation of the president can provide *direct* evidence of the demand-based channel-driven return predictability among politically sensitive industries and firms.

To measure changes in investor demand, we calculate the relative Republican−Democrat portfolio weight for various investor groups such as retail investors, mutual funds, investment companies, bank trusts, insurance companies, and pension and endowment funds. The relative Republican−Democrat portfolio weight is defined as the difference between end-of-period holdings in Republican and Democrat industries (Rep − Dem) divided by the sum of end-of-period aggregate holdings in Republican and Democrat industries (Rep + Dem). This measure varies between −1 and +1, with negative values indicating a tilt towards holdings in industries that have tended to perform better under a Democratic president, and positive values indicating a portfolio tilted toward stocks in industries that have exhibited higher returns when the president is a Republican. A relative Republican−Democrat portfolio weight of zero indicates a portfolio that is neutral on the dimension of our political-sensitivity measure.

Changes in the relative Republican−Democrat portfolio weight can be driven by changes in both the price of securities in a given investor's portfolio (i.e., passive changes), changes in the securities held in the investor's portfolio (i.e., active changes), or a combination of both. Because we are interested in identifying investors' active reallocations that are coincident with shifts in the presidential party, we adopt the approach of Kumar (2009) and hold the prices of stocks constant over windows surrounding presidential elections. This procedure eliminates the mechanical effects of passive portfolio reallocations while maintaining relative value-weights across securities.

For retail investors, monthly data are from a large U.S. discount brokerage firm.[20] For institutional investors, quarterly holdings data come from the Thomson Reuters 13-f institutional holdings database. We also use Brian Bushee's institutional investor classification data to correctly classify funds in the Thomson Reuters database.[21]

[20] See Barber and Odean (2000) for additional details about the brokerage data.

[21] The data are publicly available from Brian Bushee's website (http://acct3.wharton.upenn.edu/faculty/bushee/).

For the retail investors sample, we aggregate holdings across all individuals residing in a given state, and run within-state panel regressions using monthly observations over the sample period from November 1991 to October 1993. To eliminate the mechanical effects of price changes over the observation window, we set the price of each stock equal to its average price during the sample period.

For the sample of institutional investor holdings, we estimate fund-level panel regressions. The institutional sample spans the ± 12 months surrounding elections in which there was a change in presidential party (1992, 2000, and 2008). We eliminate the mechanical effects of price changes by setting the price of stocks equal to their average price during the 24-month sample period surrounding each of these elections. Further, we include fund-election fixed effects to isolate changes in holdings of politically sensitive securities around elections in which the presidential party switches. Finally, we also vary the size of the observation window around elections. In panel A, we present estimates using a subsample of observations spanning the $\pm$ 6 months surrounding presidential elections, whereas in panel B, we present estimates using all observations.

Table 2 reports the coefficient estimates from demand shift panel regressions. In these regressions, the relative Republican−Democrat portfolio weight is the dependent variable and the Republican president indicator is the main independent variable. We find that, on average, the relative holdings of Republican- (Democrat-) favored industries is higher in the 6 months after an election in which the party in power switches to the Republican (Democratic) Party for retail investors, mutual funds, and investment companies (see panel A). In contrast, bank trusts, insurance companies, and pension and endowment funds do not quickly react to the change in the party in power.[22] Focusing on the larger ± 12-month window in panel B reveals that the rebalancing trades of retail investors, mutual funds, and investment companies are eventually absorbed to some extent by bank trusts and pension and endowment funds. Taken together, these results provide direct evidence of the trading channel through which political sentiment can generate predictable patterns in stock returns.[23]

Next, we assess the economic importance of the trading volume generated by each of the investor groups. Specifically, we calculate the total active

[22] This evidence is consistent with the relatively long-term investment objectives of these investor groups. In particular, bank trusts, insurance companies, and pension and endowment funds would likely be more interested in immunizing their long-term liabilities than in responding to the results of presidential elections when making portfolio decisions.

[23] Because we hold stock prices fixed over the sample period, the rebalancing results are driven by changes in the number of shares held by investors. This admits the possibility that higher portfolio allocations among retail investors, mutual funds, and investment companies could be driven by an increase (decrease) in the number of shares outstanding of politically favored (unfavored) firms (e.g., because of strategic IPOs or SEOs). We address this possibility by removing stocks that have a change in the number of shares outstanding during the ± 12-month analysis window, and verify that our results are qualitatively unchanged. We thank an anonymous referee for pointing this out.

Table 2
Investor holdings regression estimates

Panel A: ± 6 months surrounding party-switch elections	Retail investors	Mutual funds	Investment companies	Bank trusts	Insurance companies	Pensions & endowments
Republican president	0.190	0.052	0.076	−0.010	0.008	0.003
	(6.16)	(12.56)	(3.35)	(−1.41)	(0.44)	(0.21)
State FE	Yes	No	No	No	No	No
Fund-election FE	No	Yes	Yes	Yes	Yes	Yes
N obs	969	16,036	629	2,240	750	1,985
Adj R^2	0.141	0.851	0.883	0.969	0.924	0.854
Panel B: ± 12 months surrounding party-switch elections						
Republican president	0.122	0.048	0.050	−0.028	−0.008	−0.027
	(3.88)	(14.38)	(3.00)	(−3.93)	(−0.54)	(−2.90)
State FE	Yes	No	No	No	No	No
Fund-election FE	No	Yes	Yes	Yes	Yes	Yes
N obs	1,785	22,998	1,395	4,950	1,671	4,496
Adj R^2	0.188	0.832	0.818	0.915	0.836	0.776
Panel C: Implied Republican-Democrat rebalancing						
Number of states/funds	51	4,666	109	476	123	520
Average portfolio value	37.280M	1.152B	23.701B	9.032B	8.627B	3.820B
Rep + Dem allocation (%)	20.380	26.785	23.082	23.340	24.405	28.357
Rep-Dem reallocation ($ B), ±6m	0.074	74.867	45.319	−10.034	2.072	1.690
Rep-Dem reallocation ($ B), ±12m	0.047	69.108	29.815	−28.096	−2.072	−15.209

This table reports coefficient estimates from panel regressions of the relative Republican-Democrat portfolio weight on a Republican president indicator variable. We calculate the relative Republican-Democrat portfolio weight as the difference between month-end holdings in republican and democrat industries (Rep − Dem) divided by the sum of month-end holdings in republican and democrat industries (Rep + Dem). For the Retail Investors sample, we aggregate holdings across all individuals residing in a given state using investor data from a large U.S. discount brokerage firm, and run within-state panel regressions using monthly observations over the sample period from November 1991 to October 1993. For all other investor classifications, we run fund-level panel regressions with fund-election fixed effects. The sample consists of quarterly observations and spans the ±12 months surrounding elections in which there was a change in presidential party (1992, 2000, and 2008). In panel A, we present estimates using a subsample of observations spanning the ±6 months surrounding presidential elections. In panel B, we present estimates using all observations spanning the ±12 months surrounding presidential elections. In panel C, we calculate the total active reallocations between holdings in politically sensitive industries implied by the estimates in panels A and B. For each investor group, we multiply the average change in the relative Republican-Democrat portfolio weight estimated in panels A and B by the total assets in republican and democrat industries held by the investor group. For ease of interpretation, we adjust the total assets into real terms (2012 dollars). The t-statistics computed using state(fund)-level clustered standard errors are reported in parentheses below the estimates.

reallocations between holdings in politically sensitive industries implied by the estimates in panels A and B. For each investor group, we multiply the average change in the relative Republican-Democrat portfolio weight estimated in panels A and B by the total assets in Republican and Democrat industries held by the investor group. For ease of interpretation, we adjust the total assets into real terms (2012 dollars). This calculation yields an estimate of the total active reallocations between holdings in Republican and Democrat industries coincident with a change in the party affiliation of the president.

We find that the aggregate rebalancing activity is large in magnitude. In particular, we find that among retail investors in our brokerage data sample, the implied total rebalancing from Democrat to Republican industries when the presidential party affiliation changes from Democrat to Republican amounts to \$74 million in the 6 months surrounding an election.[24]

Turning to 13F institutional investors, we find implied aggregate rebalancing of much larger magnitude. For example, among mutual funds, we find that the implied rebalancing aggregates to almost \$76 billion in the 6 months surrounding a presidential election, and that only about \$6 billion of this is reversed when we expand the observation window to the surrounding 12 months. Further, investment companies' rebalancing totals over \$45 billion in the 6 months following an election in which there is a change in power, with about two-thirds of these reallocations remaining in place in the 12 months following an election. We find that bank trusts, insurance companies, pensions, and endowments absorb some, but not all, of these trades, with total opposite-signed rebalancing of about \$45 billion in the twelve months surrounding an election. Overall, we find that net rebalancing across 13F investor groups totals about \$114 billion in the 6 months surrounding a presidential election, and remains at \$55 billion in the 12 months surrounding an election.

We acknowledge that our sample of investors does not capture the full extent of trading in the market. However, within our sample, the net demand for politically sensitive stocks with opposite partisan ties appears to be large when the party affiliation of the president switches. Still, we do not claim that this alone generates return predictability. Instead, our conjecture is that political uncertainty deters arbitrageurs from absorbing the net flows between politically sensitive stocks and industries. We test this conjecture next.

2.2 Increased limits to arbitrage

In the next set of tests, we provide evidence that the power of arbitrage forces weaken when investors rebalance their portfolio holdings. In particular, we show that during presidential election periods in which there is a change in the presidential party, the level of trading and return volatility increases. Such increases in volatility can translate into increased risks in the positions and eventual payoffs of arbitrageurs, especially those with relatively short investment horizons (e.g., De Long et al. 1990; Gromb and Vayanos 2010).[25]

2.2.1 Turnover and volatility regression estimates. In our first test of the limits to arbitrage, we explicitly examine the level of trading and volatility

[24] We do not attempt to quantify the aggregate reallocations of all U.S. retail investors implied by extrapolating this estimate. Instead, we argue that the brokerage sample represents the actions of retail traders and that the trading patterns we identify can influence stock returns. This is consistent with the approach and findings of the prior literature, which shows that there is a strong correlation between retail trading and stock returns (e.g., Kumar and Lee 2006; Barber, Odean, and Zhu 2009).

[25] In untabulated results, we find that the policy and macroeconomic uncertainty measures of Baker, Bloom, and Davis (2013) and Jurado, Ludvigson, and Ng (2015), respectively, increase significantly during these periods. This finding also suggests that such periods can be characterized as having increased risks for arbitrageurs.

Table 3
Turnover and volatility regression estimates

Panel A: Industry turnover

	(1)	(2)	(3)
Presidential election	0.326	−0.292	−0.278
	(4.75)	(−4.27)	(−4.01)
Pres. election × new party		1.551	1.557
		(7.63)	(7.62)
Pres. election × $\|\theta_c\|$			−0.008
			(−2.30)
Pres. election × new party × $\|\theta_c\|$			−0.004
			(−1.27)
Abs. cond. pol. sensitivity ($\|\theta_c\|$)			0.005
			(1.10)
Lag 1m return	−0.012	−0.009	−0.009
	(−1.83)	(−1.49)	(−1.50)
Lag 6m return	0.002	0.002	0.002
	(0.96)	(1.28)	(1.25)
Asset-term FE	Yes	Yes	Yes
N obs	39,584	39,584	39,584
Adj R^2	0.858	0.862	0.862
Panel B: Industry volatility			
Presidential election	0.178	−0.827	−1.368
	(0.47)	(−4.01)	(−2.09)
Pres. election × new party		1.765	2.157
		(7.55)	(3.10)
Pres. election × $\|\theta_c\|$			−0.346
			(−0.39)
Pres. election × new party × $\|\theta_c\|$			0.161
			(0.55)
Abs. cond. pol. sensitivity ($\|\theta_c\|$)			0.683
			(3.89)
ARCH(1) coefficient	0.290	0.274	0.268
	(17.19)	(17.18)	(17.49)
GARCH(1) coefficient	0.650	0.539	0.488
	(17.96)	(14.32)	(18.99)
Avg N obs	12,179	12,179	12,179

(*continued*)

during presidential election periods. Systematic shifts in demand during the months surrounding presidential elections could lead to higher turnover levels, especially if the challenger party wins the election. Moreover, higher turnover during these periods could be associated with higher levels of volatility, which would limit the activity of arbitrageurs (e.g., Gromb and Vayanos 2010).

Table 3, panel A, reports the estimates from panel regressions of monthly industry turnover on an indicator for presidential election periods and its interaction with an indicator for elections in which there is a change in presidential party. The presidential election period indicator takes the value one for months falling within 9 months (i.e., ± 9 months) of a presidential election. Industry portfolio turnover is calculated as the value-weighted average of component-industry stocks' turnovers during each month. Stock turnover is

Table 3
Continued

Panel C: Short interest ratio

	(1)	(2)	(3)
Cond. pol. sensitivity (θ_c)	0.053	0.053	0.060
	(11.56)	(11.56)	(14.12)
θ_c × presidential election	−0.081	−0.043	−0.040
	(−9.27)	(−4.68)	(−4.60)
θ_c × presidential election × new party		−0.081	−0.036
		(−5.29)	(−2.42)
Institutional ownership			5.911
			(85.49)
3m turnover			1.186
			(9.89)
12m return volatility			0.241
			(1.32)
Convertible securities indicator			0.895
			(61.15)
Exchange FE	No	No	Yes
Month FE	Yes	Yes	Yes
N obs	1,521,361	1,521,361	1,521,361
Adj R^2	0.270	0.270	0.391

Panel A reports estimates from panel regressions of monthly asset turnover on the following regressors: an indicator for presidential election periods, a new presidential party indicator, absolute conditional political-sensitivity, the return over the previous month, and the return over the 6 months ending at the beginning of the previous month. All regressions in panel A are estimated using time-series variation within presidential terms (asset-term fixed effects). The presidential election period indicator takes the value one for months falling within 9 months (±9 months) of a presidential election, and zero otherwise. The new presidential party indicator takes the value one during presidential election periods surrounding elections in which the party of the incumbent president loses the election. Industry turnover is calculated as the value-weighted average of industry stocks' turnovers during each month. The t-statistics computed using industry-term cluster-robust standard errors are reported in parentheses below the estimates. The estimation period in panel A is from January 1964 to December 2011. Panel B reports the estimates from multivariate GARCH volatility models. Daily industry returns are regressed on the Carhart (1997) four factors, with the conditional volatility following a GARCH(1,1) process. Conditional heteroskedasticity is captured by including the presidential election period indicator, the new party indicator, and absolute conditional political-sensitivity in the conditional volatility equation. For brevity, we report the cross-sectional average of coefficients and z-statistics from the volatility equation in panel B. The estimation period in panel B is from July 1, 1963 to December 30, 2011. Panel C reports estimates from regressions of stock-level short ratio on conditional political-sensitivity, the presidential election period indicator, and the new presidential party indicator. All regressions in panel C include a full set of month fixed effects. Short ratio is calculated as the ratio of short interest at the mid-month reporting date to the number of shares outstanding. The t-statistics computed using standard errors clustered at the stock-level are reported in parentheses below the estimates. The estimation period in panel C is from January 1988 to December 2011.

calculated as monthly stock volume divided by shares outstanding at the end of the month.

We also include an interaction between the absolute conditional political-sensitivity and the presidential election period indicator. This term measures whether changes in turnover surrounding presidential elections are different for politically sensitive industries. Further, we include a triple interaction between the presidential election indicator, the new party indicator, and the absolute value of the conditional political-sensitivity. Similarly, this term measures whether the effects of presidential elections in which there is a change in party are different for politically sensitive industries.

Beyond these variables of interest, to account for short-term reversal and momentum-based trading effects, we control for asset returns in the previous month, as well as the 6 months before that. We also include asset-term fixed effects in all specifications, which gives our coefficient estimates a within-term time-series interpretation.

The turnover regression estimates reported in panel A suggest that during the period surrounding presidential elections in which the incumbent party wins, turnover is generally higher than at other times during the political cycle. Further, the effect of the presidential election period is especially strong when we consider elections in which there is a change in the presidential party, with estimated economic magnitudes that are about 5-times larger. Not only do we find large differential magnitudes between elections in which incumbents and challengers are the eventual victors, but the estimates for new-party elections are also economically large relative to unconditional average monthly turnover. Finally, in Column 3, we find that the increase in turnover in the months surrounding new-party elections is not concentrated only among stocks in politically sensitive industries. Instead, the statistically insignificant $|\theta_c|$ triple interaction term indicates that the large increase in turnover is relatively constant across industries.

In panel B of Table 3, we report estimates from the multivariate GARCH volatility model of Bollerslev (1990), implementing the general event-induced volatility framework of Savickas (2003). Specifically, we regress daily industry returns on the Carhart (1997) four factors, with the conditional volatility following a GARCH(1,1) process. We capture conditional heteroskedasticity during presidential election periods by including the presidential election period dummy and its interaction with the new party indicator. We also include the absolute value of the conditional political-sensitivity, as well as interactions with the presidential election period and new party indicators. For brevity, we report only the average coefficient estimates and z-statistics from the volatility equation.

The volatility regression estimates reported in panel B yield additional insights. We find that during the presidential election period surrounding elections in which the incumbent is the victor, a period associated with slightly decreased trading, volatility is generally lower than at other times during the presidential term. However, we find that when considering elections in which the challenging party wins, presidential election periods are associated with a sharp increase in monthly volatility. Once again, these effects are economically significant when compared with the unconditional monthly volatility levels. Further, we find that while politically sensitive industries exhibit higher return volatility unconditionally, the increase in volatility surrounding elections in which there is a change in presidential party is relatively uniform across industries.

Overall, the turnover and volatility regressions suggest that the level of trading increases significantly during the months surrounding elections in which there is a change in presidential party. In addition, these increased trading levels increase volatility.[26] Further, the fact that the increases in trading activity and volatility are independent of industries' political sensitivities suggests that political uncertainty following a change in presidential party may deter arbitrageurs from participating in the financial market. Coupled with the systematic demand shifts of retail investors, mutual funds, and investment companies during this period, an exit of arbitrage capital can potentially generate short-term mispricing.

2.2.2 Short interest ratio regression estimates.. Our results thus far suggest that a large group of investors shift their holdings toward stocks in politically favored industries when there are changes in the presidential party. In turn, this finding suggests that stocks in politically favored industries could be subject to demand-induced price pressure that would normally be counteracted quickly by arbitrageurs. However, this price pressure may generate systematic mispricing if investors' reallocations surrounding elections aggregate to a volume of trades that overwhelm the capital constraints of arbitrageurs or if the increased volatility of returns surrounding elections is accompanied by an exit of arbitrage capital from the market. In our next set of tests, we examine the collective actions of short-sellers and provide evidence supporting the second channel, the exit of arbitrage capital.

To examine the actions of arbitrageurs among politically sensitive stocks, we adopt the technique proposed by Hanson and Sunderam (2014). Specifically, we examine the cross-sectional distribution of short interest across stocks in politically sensitive industries, and how this distribution changes over time. We posit that if arbitrageurs actively short-sell stocks that are potentially priced above their fundamental values, then the cross-sectional distribution of short interest will be an increasing function of our conditional political-sensitivity measure (θ_c). Further, if arbitrageurs actively trade against the mispricing generated by portfolio rebalancing, then the outstanding short interest among stocks in politically favored industries would increase around elections. However, if increased volatility surrounding presidential elections affects short sellers' actions, then this relation would be dampened or even reversed during these periods.

Table 3, panel C, reports the estimates from panel regressions of monthly short interest ratio on conditional political-sensitivity (θ_c), the interaction between θ^c and a presidential election period indicator, and a double interaction term between θ_c, the presidential election period indicator, and a new party indicator. The presidential election period and new party indicators are defined as in panels A and B of Table 3. Short interest ratio is calculated as the ratio

[26] This finding is consistent with those of Kelly, Pastor, and Veronesi (2015), who document that political uncertainty is priced in equity options, and that options whose lives span elections tend to be more expensive.

of short interest at the mid-month reporting date to the number of shares outstanding.

To control for previously documented determinants of short interest (e.g., Hanson and Sunderam 2014), we include controls for institutional ownership, 3-month turnover, 12-month return volatility, and a dummy variable indicating whether a firm has convertibles securities outstanding. We also include a full set of month fixed effects in all specifications, which gives our coefficient estimates a cross-sectional interpretation.[27]

The short interest ratio regression estimates suggest that market participants short-sell a larger proportion of the shares of firms in politically favored industries. However, we find that this relation is significantly weaker during months surrounding presidential elections. Further, the dampening effect associated with the presidential election period is especially strong during elections in which there is a change in the presidential party. Finally, the estimates in Column 3 suggest that this pattern cannot be explained by known determinants of short interest.

Overall, the short interest ratio estimates indicate that arbitrageurs do not actively trade against potential mispricing generated by investors' reallocations surrounding elections in which there is a change in presidential party. This finding suggests that investor reallocations coinciding with changes in the party in the White House can generate demand-based mispricing that may not immediately get corrected by arbitrageurs. Consequently, we should observe return predictability patterns in politically sensitive segments of the market.

2.3 Sorting results: Industry portfolios

To assess the relation between political climate and stock returns, we first perform univariate sorts using the conditional political-sensitivity estimates of forty-eight Fama and French (1997) industry portfolios. We report the performance of the following six portfolios, defined using the conditional political-sensitivity estimates: (i) the "Short" portfolio, which is a value-weighted portfolio of the five industries with lowest conditional political-sensitivity estimates and are predicted to have the lowest returns in the next month, (ii) the "Long" portfolio, which is a value-weighted portfolio of the five industries with highest conditional political-sensitivity estimates and predicted to have the highest returns in the next month, (iii) the "Long−Short" portfolio, which captures the difference in the returns of the Long and Short portfolios, and (iv−vi) portfolios 2 to 4, which represent the value-weighted portfolios of the remaining industries sorted into terciles based on predicted returns in the next month.[28]

[27] Because of the inclusion of month fixed effects, we do not include the presidential election period indicator.

[28] In untabulated results, we also consider the role of geography-based political-sensitivity. Specifically, we form state portfolios by grouping firms sharing a common headquarters state. We then calculate value-weighted state

Table 4
Political-sensitivity based portfolios: Performance estimates

Panel A: Portfolio performance estimates

	Sample period					
	1939–2011		1939–1975		1976–2011	
Portfolio	Raw return	Char-adj return	Raw return	Char-adj return	Raw return	Char-adj return
1 (Short)	0.721	−0.154	0.883	−0.073	0.554	−0.237
	(3.36)	(−1.90)	(2.97)	(−0.76)	(1.79)	(−1.82)
2	0.903	−0.066	0.864	−0.059	0.942	−0.073
	(5.20)	(−1.87)	(3.78)	(−1.31)	(3.61)	(−1.35)
3	0.949	−0.003	0.844	−0.037	1.057	0.031
	(5.90)	(−0.13)	(3.78)	(−1.21)	(4.57)	(0.70)
4	1.040	0.045	0.898	0.007	1.186	0.084
	(6.47)	(1.29)	(4.13)	(0.16)	(5.02)	(1.53)
5 (Long)	1.423	0.310	1.320	0.270	1.528	0.351
	(7.84)	(4.24)	(5.21)	(2.78)	(5.88)	(3.21)
Long-Short	0.702	0.464	0.437	0.344	0.974	0.588
	(4.09)	(3.95)	(2.17)	(2.36)	(3.51)	(3.19)
N months	876	876	444	444	432	432

Panel B: Portfolio performance characteristics

Portfolio	Std dev	Sharpe ratio	Std dev	Sharpe ratio	Std dev	Sharpe ratio
1 (Short)	5.858	0.068	5.572	0.120	6.132	0.019
2	4.789	0.121	4.552	0.143	5.027	0.101
3	4.454	0.140	4.293	0.147	4.618	0.134
4	4.545	0.158	4.334	0.158	4.757	0.158
5 (Long)	5.397	0.204	5.127	0.216	5.667	0.193
Long-Short	4.924	0.143	4.121	0.106	5.623	0.173

Panel C: Estimates using alternative extreme portfolio sizes

	Extreme portfolio size					
	3 Industries		7 Industries		10 Industries	
Portfolio	Raw return	Char-adj return	Raw return	Char-adj return	Raw return	Char-adj return
1 (Short)	0.732	−0.093	0.741	−0.138	0.824	−0.095
2	0.911	−0.056	0.944	−0.043	0.922	−0.062
3	0.926	−0.019	0.945	−0.006	0.955	0.006
4	1.102	0.090	1.048	0.067	1.007	0.040
5 (Long)	1.418	0.229	1.285	0.174	1.277	0.184
Long-Short	0.686	0.322	0.545	0.311	0.452	0.279
	(3.05)	(2.09)	(3.56)	(3.09)	(3.28)	(3.36)

(*continued*)

The portfolio performance estimates are presented in Table 4. In panel A, we report the raw and characteristic-adjusted portfolio returns for the full-sample covering the period from January 1939 to December 2011 and two subperiods of roughly equal length, which span from January 1939 to December 1975 and January 1976 to December 2011. The characteristic-adjusted portfolio

portfolio returns and estimate the sensitivity of state portfolio returns to the party in power. We perform a double-sort based on the political-sensitivity of each firm's industry and the political-sensitivity of each firm's headquarters state. The evidence from the double-sort suggests that there is an interaction between industry-based and geography-based political sensitivities, with the industry-based sensitivities being more important for return predictability.

Table 4
Continued

Panel D: Average monthly portfolio market shares

	Sample Period					
	1939–2011		1939–1975		1976–2011	
Portfolio	Raw return	Char-adj return	Raw return	Char-adj return	Raw return	Char-adj return
1 (Short)	7.524	7.413	6.279	6.115	8.804	8.748
2	25.803	25.638	25.730	25.432	25.881	25.851
3	32.614	33.452	34.582	36.224	30.591	30.602
4	24.093	24.119	23.754	23.847	24.441	24.398
5 (Long)	9.964	9.377	9.654	8.381	10.283	10.401

This table reports performance estimates of trading strategies defined using the political-sensitivity return-prediction model. Component returns are those of value-weighted Fama-French forty-eight industry portfolios. We report the performance of six portfolios: (i) the "Short" portfolio, which is a value-weighted portfolio of the five industries predicted to have the lowest returns in the next month; (ii) the "Long" portfolio, which is a value-weighted portfolio of the five industries predicted to have the highest returns in the next month; (iii) the "Long−Short" portfolio, which captures the difference in the returns of the Long and Short portfolios; and (iv)-(vi) portfolios 2−4, value-weighted portfolios of the remaining industries sorted into terciles based on predicted returns in the next month. In panel A, we report raw and characteristic-adjusted portfolio returns over three periods: January 1939−December 2011, January 1939−December 1975, and January 1976−December 2011. Characteristic-adjusted returns are computed using the method of Daniel et al. (1997). The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. In panel B, we report the standard deviation and Sharpe ratio for each portfolio over the three periods. In panel C, report raw and characteristic-adjusted portfolio returns as in panel A, but with a varying number of industries in the Long and Short portfolios. The estimation period in panel C is from January 1939 to December 2011. In panel D, we report the average monthly market shares across portfolios for the raw and characteristic-adjusted retun portfolios.

returns are computed using the Daniel et al. (1997) method.[29] The t-statistics computed using Newey and West (1987) adjusted standard errors are reported in parentheses below the estimates.

Consistent with our key conjecture, we find that portfolio returns increase monotonically with conditional political-sensitivity. Industry portfolios in the lowest conditional political-sensitivity quintile earn an average raw monthly return of 0.721%, while industries in the highest beta quintile earn an average raw monthly return of 1.423%. The monthly difference of 0.702% is significant, both statistically (t-statistic $=4.09$) and economically. During the 73-year sample period, the Long−Short portfolio earns an annualized return of 8.42%. This pattern is very similar when we use characteristic-adjusted returns to measure performance. The annualized characteristic-adjusted performance differential during the full-sample period is $0.464\times 12=5.57\%$, which is still economically large.[30]

[29] Specifically, we construct characteristic-adjusted industry portfolio returns by matching each stock, in each quarter, to one of 125 ($5\times 5\times 5$) benchmark portfolios on the dimensions of size, book-to-market ratio, and momentum, as in Daniel et al. (1997). We then calculate the return of each stock, each month, in excess of the corresponding passive portfolio return. We aggregate stock-level excess returns to the industry-level using the SIC code definitions of the forty-eight Fama and French (1997) industry portfolios available from Kenneth French's website.

[30] In untabulated tests, we follow the approach of Grundy and Martin (2001) and assess how trading costs affect these results. Specifically, we calculate the levels of roundtrip transaction costs that would render the trading

Examining the performance estimates for the subperiods, we find a similar pattern across both subperiods, although the pattern is stronger during the more recent subperiod. During the 1939 to 1975 period, the annualized characteristic-adjusted performance differential is $0.344 \times 12 = 4.13\%$. But during the 1976 to 2011 subperiod, the Long−Short performance differential increases to $0.588 \times 12 = 7.06\%$. This evidence suggests that the effect of political climate on financial markets has become stronger over time, perhaps because the political parties have become more polarized in recent years.

When we explicitly examine the riskiness of the industry-based conditional political-sensitivity portfolios, we find that the extreme quintile portfolios (i.e., our Long and Short portfolios) have higher standard deviations (see panel B). However, the Sharpe ratio increases monotonically just like the raw and characteristic-adjusted portfolio returns. The pattern is similar for the full sample period, as well as the two subperiods.

We ensure that our baseline results are robust. When we vary the number of industries in the extreme portfolios, we find qualitatively similar results. As expected, the performance of the Long−Short portfolio weakens when we increase the number of industries in the extreme portfolios (see panel C). However, the performance differential remains economically significant (differential = 0.279%; t-statistic = 3.36) even when we have ten industries in the extreme portfolios.

We also investigate whether our evidence of predictability covers a significant segment of the market. In panel D of Table 4, we report the average monthly market shares for our quintile portfolios for both raw and characteristic-adjusted return portfolios. We find that the Long and Short portfolios cover an economically meaningful segment of the market (17%−27%).

For additional robustness, Figure 1 presents the year-by-year return of the conditional political-sensitivity-based Long−Short portfolio for the full sample period (1939−2011). The bar plot indicates that politically-sensitive industries out-perform less politically-sensitive industries in 54 out of 73 years. These performance patterns are similar when we use characteristic-adjusted returns to measure portfolio performance. For brevity, we do not report those results. The graphical evidence suggests that the performance of our political-sensitivity based Long−Short portfolio is robust and not concentrated in any particular period.[31]

strategy returns statistically insignificant at the 5% level or would completely dominate the trading strategy returns. We find that the raw (characteristic-adjusted) Long−Short trading strategy returns remain statistically significant at the 5% level after roundtrip transaction costs up to 1.93% (1.20%). Further, the trading strategy remains profitable on average up to roundtrip transaction costs of 3.76% (2.44%). These estimates suggest that the predictability we document does not exist because of a high-turnover trading strategy that is economically unsustainable for arbitrageurs.

31 While the years 1999 and 2000 exhibit the strongest Long−Short portfolio returns, they do not drive the results. Specifically, when we exclude observations in 1999 and 2000 from the sample, the average Long−Short portfolio return is 0.546% (t-statistic = 3.78).

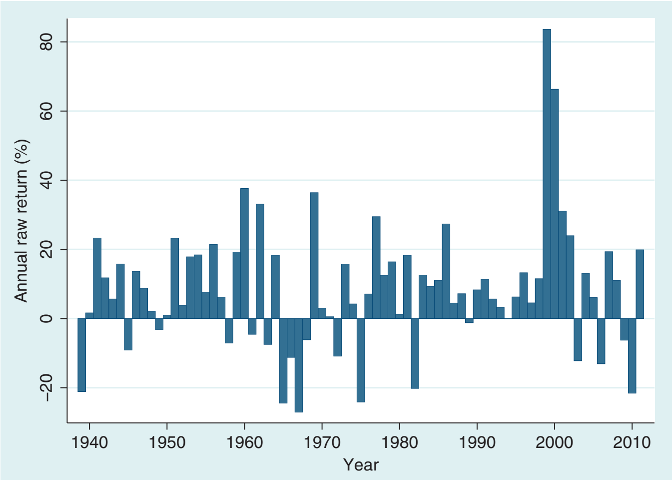

Figure 1
Political-sensitivity-based industry portfolio: Annual returns
This figure shows the annual returns of the political-sensitivity-based Long−Short portfolio formed using value-weighted Fama and French (1997) forty-eight industry portfolios. The construction of the portfolios is described in Section 2.2. The sample period is from January 1939 to December 2011.

2.4 Salience and predictability

In the next set of tests, we investigate whether our evidence of predictability is stronger during certain types of political transitions. In particular, we examine whether predictability in returns is stronger when the challenger is victorious. These tests are motivated by the observation that elections in which the incumbent party is expected to lose attract greater national attention and, consequently, the political environment is likely to be more salient among investors. Therefore, if the predictability patterns we document are driven by systematic shifts in investor demand, the evidence of predictability would be stronger around elections in which the challenger wins.

Table 5 presents the performance estimates of industry-based conditional political-sensitivity portfolios, where we condition on the outcome of the presidential elections. In panel A, we report portfolio returns during periods surrounding presidential elections in which the incumbent president's party wins or loses. Incumbent- (challenger-) victory periods are defined as the 18-month (±9 months) periods surrounding elections in which the incumbent president's party wins (loses). In panels B and C, we further analyze challenger- and incumbent-victories, reporting portfolio returns for Republican-to-Democrat and Democrat-to-Republican transitions.[32]

[32] As a robustness check, we also conduct the analysis in Table 5 using alternative ±3-, 6-, and 12-month windows surrounding elections. These results are presented in Appendix Table A.3, and they indicate that the basic conclusions of the analysis in Table 5 hold regardless of the length of the observation window.

Table 5
Trading strategy performance estimates: Incumbent versus challenger victories

Panel A: Incumbent- vs. challenger-victory

	Incumbent party victorious		Challenger party victorious	
Portfolio	Raw return	Char-adj return	Raw return	Char-adj return
1 (Short)	0.797	−0.037	−0.180	−0.228
	(2.47)	(−0.31)	(−0.33)	(−1.19)
2	1.001	−0.073	0.231	−0.097
	(3.82)	(−1.26)	(0.46)	(−0.94)
3	1.010	−0.027	0.592	−0.001
	(4.06)	(−0.61)	(1.48)	(−0.01)
4	1.209	0.087	0.586	−0.028
	(4.22)	(1.53)	(1.42)	(−0.25)
5 (Long)	1.462	0.242	1.122	0.591
	(4.08)	(1.64)	(2.29)	(2.45)
Long-Short	0.665	0.280	1.303	0.819
	(2.21)	(1.31)	(2.46)	(2.65)
N months	180	180	144	144

Panel B: Conditional party transitions

	Republican to Democrat		Democrat to Republican	
Portfolio	Raw return	Char-adj return	Raw return	Char-adj return
1 (Short)	−0.050	−0.181	−0.311	−0.274
	(−0.06)	(−0.69)	(−0.36)	(−1.24)
2	0.139	−0.161	0.323	−0.034
	(0.14)	(−0.95)	(0.59)	(−0.28)
3	0.450	−0.088	0.734	0.086
	(0.63)	(−0.73)	(1.63)	(0.78)
4	0.526	−0.033	0.645	−0.023
	(0.72)	(−0.35)	(1.46)	(−0.13)
5 (Long)	0.975	0.592	1.269	0.590
	(1.36)	(1.79)	(2.18)	(1.54)
Long-Short	1.024	0.773	1.581	0.865
	(1.74)	(1.83)	(1.84)	(2.00)
N months	72	72	72	72

(*continued*)

Consistent with our main conjecture, we find that the Long−Short portfolio earns significantly higher returns when the challenger party is victorious (see panel A). The average monthly characteristic-adjusted returns for the incumbent and challenger victories are 0.280% (t-statistic = 1.31) and 0.819% (t-statistic = 2.65), respectively.[33] The results reported in panel B indicate that while the performance estimates are significant for both Republican-to-Democrat and Democrat-to-Republican transitions, they are considerably higher when a Republican candidate wins the election. The average monthly characteristic-adjusted returns for Republican-to-Democrat and Democrat-to-Republican transitions are 0.773% (t-statistic = 1.83) and 0.865% (t-statistic = 2.00),

33 We also split the sample of challenger victories on the basis of close versus blowout elections. We find that our evidence of predictability is stronger in the months surrounding close elections than in periods surrounding blowouts. Specifically, the monthly Long−Short portfolio return is 1.730% (t-statistic = 2.27) for close elections versus 0.590% (t-statistic = 1.15) for blowout elections.

Table 5
Continued

Panel C: Conditional incumbent victories

	Republican to Republican		Democrat to Democrat	
Portfolio	Raw return	Char-adj return	Raw return	Char-adj return
1 (Short)	0.789	0.155	0.806	−0.230
	(1.75)	(0.92)	(1.78)	(−1.44)
2	0.960	−0.084	1.042	−0.062
	(2.89)	(−0.96)	(2.70)	(−0.78)
3	0.905	−0.039	1.114	−0.014
	(2.91)	(−0.61)	(3.03)	(−0.26)
4	1.173	0.124	1.245	0.051
	(3.26)	(1.40)	(2.84)	(0.74)
5 (Long)	1.469	0.239	1.455	0.245
	(3.91)	(1.38)	(2.45)	(1.09)
Long-Short	0.680	0.084	0.649	0.475
	(1.63)	(0.34)	(1.61)	(1.46)
N months	90	90	90	90

This table reports performance estimates of portfolios defined using the political-sensitivity return-prediction model, conditioning on the outcome of presidential elections. Component returns are those of value-weighted Fama-French forty-eight industry portfolios. We report raw and characteristic-adjusted portfolio returns in all panels. In panel A, we report portfolio returns over periods surrounding presidential elections in which the incumbent president's party wins or loses. Incumbent- (challenger-) victory periods are defined as the 18 months (±9 months) surrounding elections in which the incumbent president's party wins (loses). The estimation period is from January 1939 to July 2009. In panel B, we further analyze challenger-victories, reporting portfolio returns for Republican-to-Democrat and Democrat-to-Republican transitions. In panel C, we further analyze incumbent-victories, reporting portfolio returns for Republican-to-Republican and Democrat-to-Democrat transitions. Characteristic-adjusted returns are computed using the method of Daniel et al. (1997). The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates.

respectively. In contrast, when the incumbent is victorious, the performance estimates are stronger when the President is affiliated with the Democratic Party.

These conditional performance estimates suggest that the stock market's sensitivity to the political climate is influenced by the election outcome. In particular, the cross-sectional differences in returns are more pronounced when the election outcome changes the political climate significantly. We show the effect of party transitions graphically in Figure 2. We plot the cumulative characteristic-adjusted returns over the 24 months surrounding elections in which there is a change in the presidential party. We plot cumulative returns for the Long portfolio (dark solid line), the Short portfolio (dark dashed line), and the average across the other three portfolios (light solid line). For each election in which the incumbent president's party loses, the portfolios are fixed as of July of the election year t and cumulative returns are calculated for the three portfolios beginning in August of year $t-1$ and up until July of year $t+1$.

Consistent with the dominant role of elections in which the incumbent party is replaced, we find that the returns of the Long and Short portfolios, respectively, increase and decrease before the change in power. As the election nears, the cumulative Long portfolio returns begin to decrease. Conversely, the cumulative Short portfolio returns begin to increase. In both

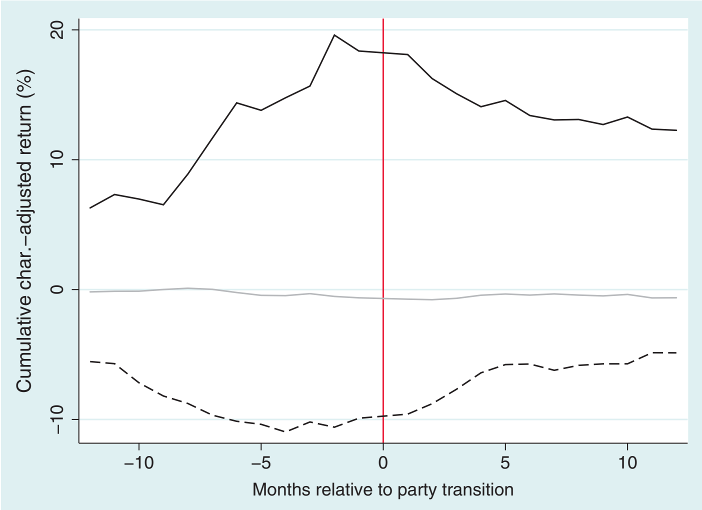

Figure 2
Cumulative returns surrounding party transitions
This figure displays cumulative characteristic-adjusted returns over the 24 (±12) months surrounding elections in which there is a change in presidential party. Cumulative returns are plotted for the long portfolio (dark solid line), the short portfolio (dark dashed line), and the average across the other three portfolios (light solid line). For each election in which the incumbent president's party loses, the portfolios are fixed as of July of the election year t. Cumulative returns are calculated for all portfolios beginning in November of year $t-1$ and up until October of year $t+1$. Characteristic-adjusted returns are computed using the method of Daniel et al. (1997). The estimation period is from January 1939 to December 2011.

cases, the cumulative return profiles begin to flatten out after about 4−5 months, indicating that politically sensitive industries no longer earn significant abnormal returns. In contrast to the Long and Short portfolios, the other three portfolios exhibit no sensitivity to the changing political climate around the election period.

2.5 Political connections and return predictability

In this section, we investigate whether our evidence of predictability varies with political connections of firms and industries. Cooper, Gulen, and Ovtchinnikov (2010) show that politically connected firms, those that make contributions to political action committees (PACs), exhibit high future abnormal returns. We want to ensure that our results do not merely reflect the known predictive ability of political connections.

Following the approach of Cooper, Gulen, and Ovtchinnikov (2010), we classify firms that make a contribution to a PAC (regardless of party affiliation) in a given year as politically connected, and classify the remaining firms as politically unconnected.[34] We compute the performance of our conditional

[34] The vast majority of firms that contribute to PACs give money to PACs affiliated with both parties. We have also considered classifying firms as leaning toward the Democratic or Republican party, based on which party's

political-sensitivity portfolios for both subsamples of firms. The sample period is from 1979 to 2006. During this period, of the 19,157 firms in the CRSP universe, 1,446 firms comprising, on average, 41.23% of the total market value are politically connected.

Despite the shortened sample period, we find that our results are significant for both politically connected and unconnected firms. In untabulated results, we find that the monthly raw Long−Short portfolio return is 1.138% (t-statistic = 3.37) among the subsample of politically connected firms and 1.034% (t-statistic = 2.67) among the subsample of politically unconnected firms. The monthly characteristic-adjusted Long−Short portfolio returns are 0.764% (t-statistic = 3.11) for politically connected firms and 0.493% (t-statistic = 2.17) for politically unconnected firms. The difference between the characteristic-adjusted returns for these two groups is 0.271%, which is statistically insignificant (t-statistic = 1.35).

We also calculate characteristic-adjusted portfolio returns for the subsamples of politically connected firms with above- and below-median PAC donations in a given year. We find that the monthly difference in returns between these two groups is 0.145% and statistically insignificant (t-statistic = 0.43). These performance estimates indicate that our evidence of predictability is distinct from the known link between political connections and stock returns.

2.6 Factor model estimates

All of our results so far are based on raw or characteristic-adjusted returns. To better account for differences in the riskiness of conditional political-sensitivity portfolios, we examine the risk-adjusted performance of political-sensitivity-based trading strategies using various unconditional and conditional factor models. These extended factor models allow us to control for the effects of additional factors and also allow the factor sensitivity to vary over time.

The unconditional factor model estimates are reported in Table 6. The unconditional factor models contain some combination of the market factor (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), short-term reversal factor (STR), long-term reversal factor (LTR), and the liquidity (LIQ) factor. The estimation period is from January 1939 to December 2011, except for the models that include the liquidity factor (LIQ), where the estimation period is from August 1962 to December 2011.

We find that the performance of political-sensitivity-based industry portfolios remain economically significant even when we include a large number of factors in the risk adjustment models. For example, the monthly six-factor alpha (t-statistic) estimates for Long, Short, and Long−Short portfolios are

PACs they contribute more money to. We find that the Long−Short portfolio returns constructed using firms in the two groups are neither statistically nor economically different. Further, we have also considered classifying firm-level party affiliation based on the net political contributions of firm executives. Similarly, we find that the evidence of predictability does not statistically differ between firms with Democrat- and Republican-leaning executives.

Table 6
Political-sensitivity-based portfolios: Factor model estimates

	Long	Short	L−S	Long	Short	L−S	Long	Short	L−S	Long	Short	L−S
Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	0.479	−0.289	0.768	0.295	−0.130	0.425	0.373	−0.165	0.539	0.368	−0.130	0.498
	(4.48)	(−2.60)	(4.40)	(2.76)	(−1.17)	(2.46)	(3.42)	(−1.22)	(2.67)	(2.95)	(−0.75)	(1.97)
RMRF	1.014	1.121	−0.107	1.009	1.060	−0.052	1.018	1.055	−0.037	0.962	1.035	−0.072
	(29.52)	(28.53)	(−1.67)	(31.00)	(30.33)	(−0.96)	(30.65)	(28.73)	(−0.65)	(26.76)	(21.81)	(−1.05)
SMB				0.132	0.176	−0.045	0.192	0.163	0.029	0.181	0.187	−0.005
				(2.55)	(1.82)	(−0.33)	(3.67)	(1.86)	(0.24)	(3.14)	(2.01)	(−0.04)
HML				0.019	−0.036	0.055	0.086	−0.047	0.133	−0.013	−0.098	0.085
				(0.33)	(−0.40)	(0.44)	(1.35)	(−0.43)	(0.85)	(−0.16)	(−0.75)	(0.43)
UMD				0.212	−0.204	0.416	0.192	−0.194	0.386	0.168	−0.254	0.422
				(5.23)	(−3.29)	(4.61)	(4.91)	(−3.21)	(4.41)	(3.68)	(−3.92)	(4.26)
STR							−0.113	0.050	−0.162	−0.086	0.055	−0.141
							(−2.28)	(0.73)	(−1.57)	(−1.43)	(0.66)	(−1.09)
LTR							−0.138	0.021	−0.159	−0.170	−0.016	−0.154
							(−2.08)	(0.23)	(−1.16)	(−1.93)	(−0.14)	(−0.85)
LIQ										0.019	0.014	0.005
										(0.74)	(0.38)	(0.09)
Adj R^2	0.689	0.715	0.008	0.715	0.740	0.113	0.720	0.740	0.125	0.708	0.732	0.143
N months	876	876	876	876	876	876	876	876	876	593	593	593

This table reports factor model risk-adjusted performance estimates of trading strategies defined using the political-sensitivity return-prediction model. Component returns are those of value-weighted Fama-French forty-eight industry portfolios. We consider the estimates of (i) the "Long" portfolio, which is a value-weighted portfolio of the five industries predicted to have the highest returns in the next month; (ii) the "Short" portfolio, which is a value-weighted portfolio of the five industries predicted to have the lowest returns in the next month; and (iii) the "Long−Short" portfolio, which captures the difference in the returns of the Long and Short portfolios. The factor models contain some combination of the following factors: the market excess return (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), two reversal factors (short-term reversal [STR] and long-term reversal [LTR]), and the liquidity factor (LIQ). The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from January 1939 to December 2011, except for models including the liquidity factor (LIQ), in which the estimation period is from August 1962 to December 2011.

0.373 (3.42), −0.165 (−1.22), and 0.539 (2.67), respectively. The Long−Short alpha estimate translates into an annual, risk-adjusted performance of over 6% and the strategy does not rely on the ability to take a short position. When we include the liquidity factor in the model, the performance estimates decline because the sample size is reduced significantly. Nevertheless, the performance of the Long−Short portfolio is statistically and economically significant.

Across the various factor models, the only factor that appears to be important in explaining Long−Short portfolio returns is UMD. We conduct several robustness checks to ensure that our our political-sensitivity prediction model does not repackage momentum (see Footnote 18 for details).

To ensure that the abnormal performance estimates of political-sensitivity-based trading strategies do not reflect improper adjustment for time-varying exposures to systematic risks, we account for portfolio risk using various conditional factor models. Specifically, we obtain alpha estimates for the Long−Short portfolio using a number of conditional asset pricing models, which allow portfolio exposures to U.S. systematic risk factors to vary with the U.S. business cycle.

These factor models all contain the following factors: the market excess return (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), and the two reversal factors (short-term reversal (STR) and long-term reversal (LTR)). We interact these factors with the following variables: an NBER Recession indicator (REC), the Lettau and Ludvigson (2001) *cay* measure, the dividend yield of the CRSP value-weighted index (DIV), the yield on the three-month T-bill (YLD), the term spread (TERM), and the default spread (DEF). The *cay* residual is defined as the difference between current consumption (c) and its long-term value based on assets (a) and income (y). The term spread is defined as the difference between the average yields of treasury bonds with greater than 10 years to maturity and T-bills maturing in 3 months. The default spread is defined as the difference between the average yields of BAA- and AAA-rated bonds. The estimation period for each regression is indicated at the top of each column. All specifications that include the *cay* measure end in September 2011.

We report the conditional alpha estimates and factor exposures in Table 7. We report the conditional factor model estimates for the full sample period and also consider unconditional factor models estimated over the first and second halves of the full sample period. These results indicate that the alpha estimates are equally strong when we use conditional factor models to account for differences in the riskiness of political-sensitivity portfolios. For example, the alpha estimates of the Long−Short portfolio when we use the conditional model with NBER recession interactions and the Lettau and Ludvigson (2001) conditional model are 0.557 and 0.519, respectively. These estimates are comparable to the unconditional factor model alpha estimate of 0.539. Further, the statistical significance of the alpha estimates generally increases when we use conditional factor models to account for risk. For example, the alpha estimate when we include interactions between the factors and all of the conditioning variables (see Column 9) is 0.717, with a t-statistic of 3.21.

Taken together, these conditional factor model estimates indicate that the abnormal performance of our political-sensitivity-based portfolios do not capture time-varying portfolio exposures to U.S. systematic risk factors.

2.7 Fama-MacBeth regression estimates

In the last set of baseline tests, we estimate Fama and MacBeth (1973) type regressions. The dependent variable in these regressions is the monthly industry return and the main explanatory variable is the lagged conditional political-sensitivity measure. The regression specification also includes several characteristics that are known to predict the cross-sectional patterns in returns. This set includes the factor exposures from the Fama and French (1992) three-factor model calculated over the previous month, past 6-month return, value-weighted log market capitalization of industry-firms at the beginning of

Table 7
Political-sensitivity-based portfolios: Robustness of factor model estimates

Interaction variable (INT)			REC	*cay*	DIV	YLD	TERM	DEF	All
Sample	1939–1975	1976–2011	1939–2011	1952–2011	1939–2011	1939–2011	1939–2011	1939–2011	1952–2011
Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Alpha	0.481	0.640	0.557	0.519	0.541	0.548	0.556	0.513	0.717
	(2.21)	(2.10)	(2.65)	(2.20)	(2.97)	(2.71)	(2.74)	(2.55)	(3.21)
RMRF	0.011	−0.054	−0.053	−0.063	−0.111	−0.017	−0.063	0.108	−0.008
	(0.19)	(−0.69)	(−0.80)	(−1.03)	(−0.59)	(−0.20)	(−0.57)	(0.77)	(−0.03)
SMB	−0.304	0.209	0.036	−0.048	0.049	0.020	0.085	−0.208	0.092
	(−2.40)	(1.53)	(0.27)	(−0.42)	(0.16)	(0.11)	(0.47)	(−0.84)	(0.23)
HML	0.229	0.188	0.136	0.087	−0.051	0.220	0.078	−0.607	0.222
	(1.43)	(0.96)	(0.79)	(0.49)	(−0.12)	(1.17)	(0.27)	(−1.87)	(0.44)
UMD	0.198	0.435	0.379	0.467	0.728	0.388	0.356	0.588	0.557
	(1.80)	(4.19)	(3.64)	(5.08)	(3.97)	(3.35)	(2.53)	(4.04)	(2.50)
STR	−0.183	−0.115	−0.120	−0.148	−0.165	−0.195	−0.204	−0.094	−0.179
	(−1.67)	(−0.81)	(−0.99)	(−1.21)	(−0.75)	(−1.70)	(−1.27)	(−0.45)	(−0.65)
LTR	−0.293	−0.116	−0.055	−0.154	0.206	−0.189	−0.143	0.138	0.060
	(−2.26)	(−0.60)	(−0.36)	(−0.90)	(0.49)	(−1.26)	(−0.49)	(0.42)	(0.10)
RMRF × INT			0.016	0.013	0.023	−0.886	1.471	−15.782	
			(0.12)	(0.38)	(0.50)	(−0.55)	(0.34)	(−1.53)	
SMB × INT			−0.139	−0.031	−0.028	−0.033	−3.869	17.163	
			(−0.58)	(−0.58)	(−0.34)	(−0.01)	(−0.54)	(0.81)	
HML × INT			−0.034	−0.050	0.061	−2.541	3.381	68.719	
			(−0.13)	(−0.64)	(0.64)	(−0.71)	(0.30)	(3.01)	
UMD × INT			−0.019	0.051	−0.111	0.052	1.605	−13.163	
			(−0.12)	(1.50)	(−2.36)	(0.02)	(0.30)	(−1.58)	
STR × INT			−0.143	0.097	0.006	0.878	2.362	−2.715	
			(−0.83)	(1.54)	(0.12)	(0.42)	(0.39)	(−0.21)	
LTR × INT			−0.474	−0.039	−0.111	0.684	−1.256	−32.642	
			(−1.99)	(−0.57)	(−1.14)	(0.20)	(−0.11)	(−1.24)	
Adj R^2	0.154	0.140	0.135	0.151	0.152	0.121	0.120	0.160	0.246
N months	444	432	876	717	876	876	876	876	717

This table reports factor model risk-adjusted performance estimates of Long-Short trading strategies defined using the political-sensitivity return-prediction model. Component returns are those of value-weighted Fama-French forty-eight industry portfolios. The factor models contain the following factors: the market excess return (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (UMD), and two reversal factors (short-term reversal [STR] and long-term reversal [LTR]). In Columns 1 and 2, we estimate the factor models for the first- and second-half of the sample period, where we split on calendar years. In columns 3 through 8, we report estimates from conditional factor models in which each of the factors are interacted with an interaction variable (INT). INT is one of the following: an NBER recession indicator (REC), the Lettau-Ludvigson (2004) *cay* measure, the dividend yield of the CRSP value-weighted index (DIV), the yield on the 3-month T-bill (YLD), the term spread (TERM), and the default spread (DEF). The interaction variable used in each regression is indicated at the top of each column. In column 9, we include interactions between all of the factors and interaction variables. The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period for each regression is indicated at the top of each column. All specifications including the *cay* measure end in September 2011.

the previous month, and value-weighted book-to-market ratio of industry-firms available six months prior.[35]

We report the time-series averages of the coefficient estimates from monthly cross-sectional regressions and the t-statistics are based on these

[35] We also conduct the Fama and MacBeth (1973) type regression analysis at the stock-level and find very similar results. For brevity, we discuss only the industry-level analysis, and present the stock-level results in Appendix Table A.4.

Table 8
Political-sensitivity and expected returns: Fama-MacBeth regression estimates

Factor	(1)	(2)	(3)	(4)	(5)	(6)	7)
Political-sensitivity	1.669	1.339	1.026	1.073	0.977	1.179	1.219
	(3.60)	(2.96)	(2.46)	(2.47)	(2.21)	(2.59)	(2.41)
β_{RMRF}	0.874	0.439	0.748	0.617	0.776	1.124	1.089
	(0.60)	(0.31)	(0.55)	(0.45)	(0.57)	(0.86)	(0.84)
β_{SMB}	−1.020	−1.043	−0.932	−0.926	−0.901	−1.420	−1.319
	(−1.40)	(−1.49)	(−1.33)	(−1.28)	(−1.28)	(−1.86)	(−1.70)
β_{HML}	1.384	0.947	0.559	0.618	0.696	0.586	0.737
	(2.47)	(1.77)	(1.10)	(1.19)	(1.36)	(1.06)	(1.28)
Lagged 6m ret		0.015	0.015	0.012	0.014	0.015	0.013
		(2.98)	(2.91)	(2.30)	(2.78)	(2.95)	(2.59)
Size			−0.023	−0.022	−0.024	−0.035	−0.036
			(−0.64)	(−0.61)	(−0.68)	(−0.90)	(−0.91)
Book-to-market			−0.004	0.021	0.040	0.005	0.024
			(−0.02)	(0.10)	(0.20)	(0.02)	(0.11)
Government spending exposure				−0.561			−0.179
				(−0.50)			(−0.14)
Federal spending in HQ state					0.003		0.004
					(0.67)		(0.73)
Political alignment index						0.008	0.008
						(1.50)	(1.36)
Constant	0.424	0.234	0.533	0.532	0.781	0.474	0.891
	(2.46)	(1.26)	(0.88)	(0.87)	(1.28)	(0.68)	(1.23)
Avg Adj R^2	0.162	0.203	0.236	0.248	0.242	0.241	0.259
Avg N industries	46.50	46.50	46.50	46.50	46.50	46.66	46.66
N months	581	581	581	581	581	504	504

This table reports estimates from Fama-MacBeth (1973) regressions. Asset returns under consideration are those of value-weighted Fama-French forty-eight industry portfolios. We regress monthly returns on the following regressors: lagged political-sensitivity, industry Fama-French 3-factor loadings calculated using daily returns over the previous month, industry return over the previous 6 months, value-weighted log market capitalization of industry-firms at the beginning of the previous month, value-weighted book-to-market ratio of industry-firms available 6 months prior, lagged conditional government spending exposure measure of Belo, Gala, and Li (2012), value-weighted ranking of federal spending in industry-firms' headquarters states, and value-weighted political alignment index (PAI) measure of Kim, Pantzalis, and Park (2012) in industry-firms' headquarters states. We report the time-series average of cross-sectional adjusted R^2s. The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from July 1963 to December 2011 in Columns 1 through 5, and from January 1967 to December 2008 in Columns 6 and 7.

monthly coefficient estimates. The t-statistics reported in parentheses below the estimates are computed using Newey and West (1987) adjusted standard errors.

The regression estimates are reported in Columns 1 to 3 of Table 8. The estimation period is from July 1963 to December 2011. We find that industries with higher political-sensitivity earn higher returns even in the presence of all other control variables. The conditional political-sensitivity variable has an estimate of 1.026 and the t-statistic is 2.46 (see Column 3). In economic terms, a one standard-deviation shift in conditional political-sensitivity is associated with a $1.026 \times 0.099 = 0.102\%$ shift in the industry portfolio return in the following month. Further, an interdecile shift in conditional political-sensitivity is associated with a $1.026 \times 0.236 = 0.242\%$ shift in the next month's industry returns. This evidence is consistent with our main conjecture and indicates that differences in political-sensitivity are associated with meaningful differences in industry returns.

Next, we include several alternative measures of exposure to the political climate to ensure that our evidence of investor demand induced predictability is distinct from the evidence of predictability induced by shifts in firm cash flows that are associated with the changing political climate. In particular, Belo, Gala, and Li (2013) demonstrate that firms with greater exposure to government spending earn higher returns during Democratic presidencies and lower average returns during Republican presidencies. Further, Kim, Pantzalis, and Park (2012) show that firms located in U.S. states that are more politically aligned with the presidential party earn higher average returns. To ensure that our results do not reflect these findings, we include the industry-level government spending exposure measure of Belo, Gala, and Li (2013), the value-weighted ranking of federal spending in industry-firms' headquarters states, and the value-weighted political alignment index (PAI) of Kim, Pantzalis, and Park (2012) in industry-firms' headquarters states as additional regressors.[36]

The regression estimates from these additional tests are reported in Columns 4 to 7 of Table 8. The estimation period in Columns 4 and 5 is from July 1963 to December 2011. The estimation period is from January 1967 to December 2008 in Columns 6 and 7 because of limited availability of the PAI data. Our baseline results remain unchanged in the presence of alternative measures of exposure to the political climate. The coefficient estimates on the conditional political-sensitivity variable remain statistically significant in Columns 4 through 7. In particular, when all regressors are present, the conditional political-sensitivity variable has a coefficient estimate of 1.219 and the t-statistic is 2.41.[37]

Overall, the estimates from Fama and MacBeth (1973) type regressions provide additional support for our main hypothesis. We show that the political-sensitivity of industries is an important determinant of the cross-sectional variation in returns and this effect is distinct from the known effects of various firm characteristics such as market beta, firm size, book-to-market, and past performance on cross-sectional patterns in returns. Further, this effect is distinct from return predictability generated by the cash-flow channel. These findings suggest that the investor-demand channel of return predictability is likely to coexist with other predictability channels. It operates during different time periods and in different market segments.

36 Kim, Pantzalis, and Park (2012) construct the political alignment index (PAI) based on the location of firm headquarters, which measures the degree of political alignment between a state's leading politicians and the presidential party.

37 We also conduct alternative tests of whether the return predictability we document is distinct from predictability generated by the cash-flow channels highlighted in related studies. Specifically, we show that trading strategies constructed using industry-firms with low government spending exposure, headquartered in low federal spending states, and headquartered in low political alignment states remain profitable. Further, we show that our evidence of return predictability exists during both Republican and Democratic presidencies and is robust to congressional gridlock. Thus, our results do not somehow reflect the presidential puzzle identified in Santa-Clara and Valkanov (2003). See Appendix Tables A.5 and A.6 for details.

3. Return Predictability Mechanism

So far, our evidence indicates that the changing political climate has an economically meaningful effect on asset prices. In this section, we examine whether this link reflects the effects of systematic shifts in the portfolio composition of certain investor groups that are more sensitive to the political climate (i.e., political sentiment). A variety of factors (e.g., partisan-based optimism and hedging motives) could influence the systematic shifts in the portfolio composition of investors. Because of the lack of appropriate data, we cannot precisely identify all factors that affect investor demand. However, we show that demand shifts induced by the joint effects of those factors generate systematic mispricing in certain segments of the market, which is eventually corrected because of the actions of arbitrageurs.

Our goal is not to establish that systematic shifts in investor demand is the only channel through which changes in political climate could influence stock prices. Clearly, the changing political environment could influence the market through its potential impact on firm profitability. We want to establish that the investor-demand channel plays an economically significant role for asset prices that is captured by our new political-sensitivity estimation method and the cash-flow channel is unlikely to fully explain our findings. In other words, we want to demonstrate that as the political climate changes, a significant part of predictability in politically sensitive segments of the market is driven by shifts in political sentiment.

3.1 Presidential term and return predictability

In the first test, we examine whether our evidence of return predictability varies systematically across the 4 years during a presidential term. If the evidence of return predictability we document reflects the effects of investor demand, the results should be stronger in first and last years of the presidential term. During these periods, the political awareness among investors is likely to be higher and, therefore, optimism or hedging based demands are likely to be stronger. Further, any predictability induced by the cash flow channel is likely to be weak or non-existent. This conjecture is motivated by the evidence in Belo, Gala, and Li (2013), who demonstrate that the evidence of cash flow-based predictability gets stronger during the 2 middle years of the presidential term as the policy uncertainty is resolved.

Table 9, panel A, reports the performance estimates of political-sensitivity-based Long−Short industry portfolios, conditional on the year of the presidential term. We report the characteristic-adjusted portfolio returns for both the predictive and actual years in the presidential term. The actual term-years run from November 1 to October 31 of the following year, whereas the predictive term-years are 3-month forward looking, running from August 1 to July 31 of the following year. We find that our results are stronger in years 1 and 4, when investor attention to the political environment is likely to be higher.

Table 9
Portfolio performance estimates by term years and around election periods

Panel A: Year in presidential term

	Predictive term-years (August to July)				Actual term-years (November to October)			
Portfolio	Year 1	Year 2	Year 3	Year 4	Year 1	Year 2	Year 3	Year 4
1 (Short)	−0.206	−0.331	0.130	−0.218	−0.216	−0.106	−0.160	−0.135
	(−1.49)	(−2.07)	(0.76)	(−1.37)	(−1.43)	(−0.68)	(−0.96)	(−0.91)
2	−0.030	−0.049	−0.100	−0.083	0.026	−0.069	−0.152	−0.066
	(−0.43)	(−0.64)	(−1.50)	(−1.26)	(0.37)	(−0.88)	(−2.65)	(−0.97)
3	0.010	−0.035	0.028	−0.017	−0.019	−0.061	0.105	−0.043
	(0.17)	(−0.63)	(0.54)	(−0.30)	(−0.34)	(−1.07)	(2.16)	(−0.74)
4	0.047	0.079	0.031	0.024	0.056	0.081	0.056	−0.013
	(0.64)	(1.10)	(0.45)	(0.39)	(0.80)	(1.10)	(0.88)	(−0.19)
5 (Long)	0.409	0.322	0.218	0.293	0.303	0.306	0.171	0.465
	(2.67)	(2.22)	(1.80)	(1.76)	(2.02)	(2.73)	(1.35)	(2.70)
Long-Short	0.615	0.653	0.087	0.511	0.519	0.412	0.331	0.600
	(2.73)	(2.85)	(0.36)	(2.13)	(2.35)	(1.99)	(1.42)	(2.52)
N months	216	216	223	221	216	216	226	218

Panel B: Returns across presidential election and nonelection periods

	Months surrounding presidential election				Months surrounding midterm			
Portfolio	3	6	9	12	3	6	9	12
1 (Short)	−0.351	−0.143	−0.122	−0.155	−0.176	0.130	−0.020	−0.159
	(−1.86)	(−1.10)	(−1.16)	(−1.46)	(−0.60)	(0.75)	(−0.15)	(−1.24)
2	−0.008	−0.049	−0.084	−0.016	−0.111	−0.100	−0.111	−0.095
	(−0.08)	(−0.72)	(−1.50)	(−0.31)	(−1.12)	(−1.57)	(−2.10)	(−2.00)
3	0.038	−0.025	−0.015	−0.034	0.121	0.028	0.054	0.042
	(0.46)	(−0.48)	(−0.35)	(−0.88)	(1.53)	(0.57)	(1.35)	(1.10)
4	−0.022	0.046	0.036	0.016	0.006	0.031	0.025	0.043
	(−0.21)	(0.65)	(0.66)	(0.34)	(0.06)	(0.44)	(0.44)	(0.89)
5 (Long)	0.649	0.375	0.397	0.382	0.214	0.218	0.182	0.252
	(2.42)	(2.00)	(2.92)	(3.12)	(1.10)	(1.86)	(2.03)	(3.11)
Long-Short	1.000	0.518	0.519	0.537	0.390	0.087	0.202	0.411
	(2.67)	(2.17)	(2.88)	(3.17)	(0.94)	(0.36)	(1.10)	(2.48)
N months	108	216	324	415	112	223	334	444

This table reports performance estimates of portfolios defined using the political-sensitivity return-prediction model, conditional on periods across the presidential term. Component returns are those of value-weighted Fama-French forty-eight industry portfolios. We report the performance of six portfolios: (i) the "Short" portfolio, which is a value-weighted portfolio of the five industries predicted to have the lowest returns in the next month; (ii) the "Long" portfolio, which is a value-weighted portfolio of the five industries predicted to have the highest returns in the next month; (iii) the "Long−Short portfolio, which captures the difference in the returns of the Long and Short portfolios; and (iv)−(vi) portfolios 2−4, value-weighted portfolios of the remaining industries sorted into terciles based on predicted returns in the next month. In panel A, we report characteristic-adjusted portfolio returns over predictive and actual years in the presidential term. Actual term-years run from November 1 to October 31 of the following year. Predictive term-years are 3-month forward-looking, running from August 1 to July 31 of the following year. In panel B, we report characteristic-adjusted portfolio returns over presidential election and nonelection periods. presidential election periods are defined as months surrounding the November presidential election. Presidential non-election periods are defined as months surrounding the January midterm of the sitting president 2 years after his inauguration. In each case, we consider the ±3, 6, 9, and 12 months surrounding these events. Characteristic-adjusted returns are computed using the method of Daniel et al. (1997). The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from January 1939 to December 2011.

This evidence is consistent with our investor-demand-based explanation for the observed predictability in returns. Moreover, in light of the findings in Belo, Gala, and Li (2013), this evidence further indicates that our results do not reflect cash flow-based predictability.

3.2 Predictability during presidential election periods

To examine further the effect of investor demand shifts on return predictability, we explicitly identify presidential election periods and examine whether the evidence of predictability is stronger during those periods. Presidential election periods are defined as months surrounding the November presidential election. Non-presidential election periods are defined as months surrounding the January midterm of the sitting president two years after the inauguration. In each case, we consider the 3-, 6-, 9-, and 12-month periods surrounding these events.

The results reported in Table 9, panel B, indicate that our evidence of predictability is significantly stronger during the presidential election periods. In contrast, during the non-presidential election periods, the evidence of predictability is significantly weaker. This finding provides further support to our investor-demand-based explanation for predictability.

3.3 Direct test of cash-flow predictability

In the last set of tests, we focus on the cash-flow channel directly and examine whether trading activity and return predictability around presidential elections are driven by rational expectations about future operating performance.[38] To do so, we estimate the sensitivity of industry return on assets (ROA) to shifts in the political environment and examine the performance of double-sorted portfolios using earnings-based political-sensitivity and the returns-based political-sensitivity measure estimated in Equation (1).

We calculate industry return on assets as the value-weighted average of industry-firms' operating income before extraordinary items and accrued interest divided by the book value of total assets at the end of each quarter. Each quarter, for each of the forty-eight Fama and French (1997) industry portfolios, we regress the industry return on assets during the past 15 years (60 quarters) on the presidential party indicator. The coefficient on the presidential party indicator is our measure of earnings-based political-sensitivity. Similar to the return-based political-sensitivity measure, we measure earnings-based political-sensitivity using rolling windows and calculate a *conditional* earnings-based political-sensitivity measure based on the party in power. The conditional measure is higher among industries that are favored by the current presidential party in a given month.

Each month, we classify industries into three categories based on return-based political-sensitivity (RBPS) measures. Specifically, we classify an

[38] Whereas investor demand is likely to be driven by perceived changes in expected cash flows during a new administration, investors' perceptions in the months surrounding an election may not always reflect the eventual outcomes of firms in politically sensitive industries. For example, in a Wall Street Journal article, Harder (2015) asserts that when President Obama first took office in 2009, he was expected to be an adversary of oil and gas companies. However, not only has he been less adversarial than initially feared, but his repeal of the 40-year-old ban on oil exports is seen as a significant boon to the industry. Further, even within an industry, there is likely to be substantial heterogeneity across firms in eventual outcomes during a president's time in office.

Table 10
Performance of double-sorted portfolios based on return- and earnings-based political-sensitivity measures

Portfolio	1 (low EBPS)	2	3 (high EBPS)	High − low EBPS
1 (low RBPS)	0.626	0.492	0.614	−0.013
	(1.79)	(1.35)	(1.89)	(−0.05)
2	0.944	0.992	1.095	0.151
	(3.04)	(3.81)	(3.36)	(0.61)
3 (high RBPS)	1.514	1.244	1.354	−0.159
	(4.83)	(3.93)	(4.24)	(−0.85)
High-low RBPS	0.887	0.752	0.741	
	(2.72)	(2.75)	(2.93)	

This table reports performance estimates of double-sorted portfolios defined using return-based political-sensitivity (RBPS) and earnings-based political-sensitivity (EBPS) measures. Component returns are those of value-weighted Fama and French (1997) industry portfolios. For each of the forty-eight industries, each quarter, EBPS is measured by regressing industry return on assets on the presidential party indicator over the past 15 years (60 quarters). Each month, an industry is classified as being in the low (high) RBPS category if its RBPS is below (above) the bottom (top) tercile across industries. Similarly, an industry is classified as being in the low (high) EBPS category if its EBPS is below (above) the bottom (top) tercile across industries in a given RBPS category each month. We report raw value-weighted portfolio returns over the sample period from September 1984 to December 2011. The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates.

industry as being in the low (high) RBPS category if the industry's RBPS is below (above) the bottom (top) tercile across industries. Similarly, we then classify industries in a given RBPS category into three categories based on earnings-based political-sensitivity (EBPS) measures. Within each RBPS category, we classify industries as being in the low (high) EBPS category if the industry's EBPS is below (above) the bottom (top) tercile across industries.

Table 10 reports the raw value-weighted returns for the double-sorted portfolios. We also report the returns of the "High−Low" hedge portfolio within each of the RBPS and EBPS categories. The t-statistics reported in parentheses are computed using Newey and West (1987) adjusted standard errors. The estimation period is from September 1984 to December 2011.

The estimates in Table 10 suggest that the return predictability we document is not driven by expectations related to the sensitivity of industry cash flows to the presidential party. Specifically, the difference between the returns of the long and short ROA-based political-sensitivity portfolios are statistically insignificant across all three return-based political-sensitivity portfolios. In contrast, the High−Low RBPS returns are economically and statistically significant across all three earnings-based sensitivity categories, with t-statistic ranging from 2.72 to 2.93. Taken together, these results suggest that return predictability we document is unlikely to be driven by rational expectations about future industry operating performance. Instead, our results suggest that investors' perceptions, as revealed through their trading behavior and the resultant predictability in industry returns, are shaped largely by past industry-level return sensitivity to the presidential party.

4. Summary and Conclusion

Casual observation of financial markets suggests that the changing political climate is likely to influence various financial market outcomes. In particular, the political climate could influence the cash flows of firms and it could also generate systematic shifts in the portfolio composition of investors. Changes in firm cash flows and systematic demand shifts would, in turn, influence asset prices in market segments that are politically sensitive. In this study, we focus on the investor-demand channel and show that changes in the political climate generate systematic shifts in investor demand, which influences the returns of politically sensitive firms and industries.

We first propose a novel method for identifying market segments that are more likely to be influenced by changes in the political climate. Using these measures of political-sensitivity of firms and industries, we demonstrate that returns in market segments with high political-sensitivity are predictable. We also find that systematic demand shifts induce greater turnover and volatility, which consequently make arbitrageurs more cautious and arbitrage forces less powerful. A Long−Short trading strategy that attempts to exploit demand-based predictability generates annualized risk-adjusted returns of 5.57% during the 1939 to 2011 period. This evidence of predictability covers an economically meaningful segment of the market (about 17%−27% of the total market capitalization) and is distinct from cash flow-based predictability identified in the recent literature.

Our evidence of predictability is much stronger (almost twice as strong) when the challenger party is victorious, especially when there is a transition of power from the Democratic to the Republican Party. The predictability patterns are also stronger during months surrounding presidential elections and years 1 and 4 of the presidential term when the level of political awareness is higher. This evidence is consistent with the conjecture that systematic investor demand induced by changing political climate generates mispricing, which eventually gets corrected through the action of arbitrageurs.

Overall, these results establish a strong link between politics and financial markets. In future work, it would be interesting to examine whether the changing political climate influences other dimensions of asset prices. For example, the excess investor attention and enthusiasm around elections could generate momentum in returns of individual stocks and certain industries. Thus, a significant portion of momentum profits may be concentrated in periods of increased interest in politics. Similarly, the stock market reaction to corporate events such as earnings announcements may be influenced by changes in the political climate. It is also likely that the effect of political climate varies geographically across the U.S. states. In particular, changes in political climate would influence asset prices more strongly in states with weaker economic conditions because the political-sensitivity is likely to be stronger in those states.

Appendix

A.1 Validating the Political-Sensitivity Measure

We use a short sample of direct political sentiment measures to validate our key assumption that our return-based political-sensitivity measures can capture the effects of partisan-based shifts in investor sentiment. Specifically, we use data from the UBS/Gallup Optimism Survey, which provides qualitative responses on the optimism levels of Republicans, Democrats, and Independents with respect to the stock market and economic growth.[39] The difference in the optimism levels of Republicans and Democrats is likely to capture the relative political sentiment of Republicans over Democrats.

Table A.1
Political-sensitivity portfolios: Validation test

Panel A: Equal-weighted portfolio coincidence

	UBS/Gallup ranking				
Political ranking	1 (Short)	2	3	4	5 (Long)
1 (Short)	40.000	60.000	0.000	0.000	0.000
2	25.000	41.667	33.333	0.000	0.000
3	0.000	28.571	50.000	14.286	7.142
4	0.000	0.000	25.000	58.333	16.667
5 (Long)	0.000	0.000	0.000	60.000	40.000

Panel B: Value-weighted portfolio coincidence

	UBS/Gallup ranking				
Political ranking	1 (Short)	2	3	4	5 (Long)
1 (Short)	37.719	62.281	0.000	0.000	0.000
2	44.557	30.932	24.511	0.000	0.000
3	0.000	43.923	26.257	26.662	3.158
4	0.000	0.000	45.459	50.514	4.027
5 (Long)	0.000	0.000	0.000	86.395	13.605

This table reports rates (percentages) of portfolio coincidence across double-sorted political-sensitivity portfolios. Coincidence rates are calculated such that rates for a given political ranking across UBS/Gallup rankings (across a row) sum to 100. Asset returns are those of value-weighted Fama-French forty-eight industry portfolios. The UBS/Gallup Ranking is generated by regressing monthly excess asset returns on the excess market return and the difference between Republicans' and Democrats' monthly average economic optimism measures reported by UBS/Gallup. Assets are then sorted into five portfolios: i) the "Short" portfolio, which is a value-weighted portfolio of the five industries (quintile of stocks) predicted to have the lowest returns in the next month; ii) the "Long" portfolio, which is a value-weighted portfolio of the five industries (quintile of stocks) predicted to have the highest returns in the next month; and iii)−v) portfolios 2−4, value-weighted portfolios of the remaining industries (stocks) sorted into terciles based on predicted returns in the next month. The political ranking is generated as in all previous tables using the identical estimation period. In panel A, coincidence rates are calculated as the number of assets with a particular Political-UBS/Gallup ranking combination divided by the total number of assets across all UBS/Gallup rankings holding the political ranking fixed. In panel B, coincidence rates are calculated as the market capitalization of assets with a particular Political-UBS/Gallup ranking combination divided by total market capitalization of assets across all UBS/Gallup rankings holding the Political ranking fixed. The estimation period is from February 1997 to June 2006.

[39] We cannot perform our asset pricing tests using the direct political sentiment data because they are available only for the 1997 to 2006 period.

Table A.2
Politically sensitive portfolios: Top-five industries across party administrations

	Top-five Democratic industries				
Period/presidential party	1	2	3	4	5
1939–1952: Roosevelt/Truman (Dem)	Recreation	Wholesale	Books & printing	Personal services	Oil
1953–1960: Eisenhower (Rep)	Textiles	Construction	Beer & liquor	Agriculture	Coal
1961–1968: Kennedy/Johnson (Dem)	Mining	Oil	Construction	Textiles	Transportation
1969–1976: Nixon/Ford (Rep)	Construction	Rubbers & plastics	Aircraft	Personal services	Mining
1977–1980: Carter (Dem)	Personal services	Construction	Real estate	Books & printing	Precious metals
1981–1992: Reagan/Bush (Rep)	Construction	Precious metals	Real estate	Healthcare	Personal services
1993–2000: Clinton (Dem)	Electronic chips	Real estate	Computers	Shipbuilding	Finance
2001–2008: Bush (Rep)	Computers	Electronic chips	Electrical eqmt	Communication	Pharmaceuticals
2009–2011: Obama (Dem)	Computers	Electronic chips	Pharmaceuticals	Communication	Business services

	Top-five Republican industries				
Period/presidential party	1	2	3	4	5
1939–1952: Roosevelt/Truman (Dem)	Finance	Aircraft	Paper	Rubbers & plastics	Utilities
1953–1960: Eisenhower (Rep)	Computers	Lab equipment	Aircraft	Electrical eqmt	Recreation
1961–1968: Kennedy/Johnson (Dem)	Recreation	Computers	Lab equipment	Electronic chips	Personal services
1969–1976: Nixon/Ford (Rep)	Agriculture	Tobacco	Recreation	Pharmaceuticals	Electronic chips
1977–1980: Carter (Dem)	Chemicals	Coal	Steel	Paper	Defense
1981–1992: Reagan/Bush (Rep)	Candy & soda	Retail	Food products	Paper	Consumer goods
1993–2000: Clinton (Dem)	Tobacco	Food products	Textiles	Shipping	Recreation
2001–2008: Bush (Rep)	Tobacco	Textiles	Shipping	Recreation	Precious metals
2009–2011: Obama (Dem)	Coal	Mining	Precious metals	Agriculture	Shipping

This table reports the five industries with the strongest party-specific political-sensitivity during each party administration from 1939 to 2011. Strength of party-specific political-sensitivity is measured as the number of months an industry is sorted into the Long-Short portfolio during a given administration conditional on the party in power.

Table A.3
Trading strategy performance: Incumbent versus challenger victories robustness

	Incumbent party victorious		Challenger party victorious	
Window	Raw return	Char-adj return	Raw return	Char-adj return
±3 months	0.967	0.739	1.007	1.326
	(1.82)	(1.84)	(1.01)	(2.17)
±6 months	0.516	0.248	1.207	0.855
	(1.37)	(0.87)	(1.84)	(2.08)
±9 months	0.665	0.280	1.303	0.819
	(2.21)	(1.31)	(2.46)	(2.65)
±12 months	0.564	0.245	1.532	0.952
	(2.14)	(1.24)	(3.22)	(3.44)

Panel B: Conditional party transitions

	Republican to Democrat		Democrat to Republican	
Window	Raw return	Char-adj return	Raw return	Char-adj return
±3 months	0.584	0.777	1.429	1.875
	(0.83)	(1.20)	(0.76)	(1.83)
±6 months	0.492	0.497	1.921	1.213
	(1.00)	(1.09)	(1.60)	(1.82)
±9 months	1.024	0.773	1.581	0.865
	(1.74)	(1.83)	(1.84)	(2.00)
±12 months	0.835	0.750	2.229	1.154
	(1.82)	(2.12)	(2.72)	(2.72)

Panel C: Conditional incumbent victories

	Republican to Republican		Democrat to Democrat	
Window	Raw return	Char-adj return	Raw return	Char-adj return
±3 months	0.404	0.218	1.530	1.260
	(0.50)	(0.39)	(2.12)	(1.84)
±6 months	0.721	0.148	0.311	0.348
	(1.51)	(0.48)	(0.57)	(0.76)
±9 months	0.680	0.084	0.649	0.475
	(1.63)	(0.34)	(1.61)	(1.46)
±12 months	0.632	0.128	0.497	0.361
	(1.76)	(0.53)	(1.38)	(1.22)

This table reports performance estimates of Long−Short portfolios defined using the political-sensitivity return-prediction model, conditioning on the outcome of presidential elections. The table layout and portfolio construction is identical to that described in Table 5, with two exceptions. First, we report only Long−Short portfolio performance estimates to conserve space. Second, as a robustness test, we report estimates for the performance during several observation window lengths surrounding presidential elections.

Using these direct measures of investor optimism, we estimate the political-sensitivity of all firms and industries during the 1997 to 2006 period. We generate the UBS/Gallup rankings at the end of each month during the February 1997 to June 2006 period. To obtain these political-sensitivity estimates, we first calculate a 5-month moving average of the Republican-Democrat optimism spread. Next, using this measure, we regress monthly industry excess returns on excess market returns and the Republican-Democrat optimism differential. Last, assets are sorted into five portfolios: (i) the "Short" portfolio, which is a value-weighted portfolio of the five industries that are predicted to have the lowest returns in the next month; (ii) the "Long" portfolio, which is a value-weighted portfolio of the five industries that are predicted to have the highest returns in the next month; and (iii)−(v) portfolios 2 to 4, which are value-weighted portfolios of the remaining industries sorted into terciles based on predicted returns in the next month.

Table A.4
Political-sensitivity and expected returns: Robustness of Fama-MacBeth regression estimates

	Individual returns						
Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Political-sensitivity	2.278	2.274	2.277	2.330	2.278	2.906	2.964
	(3.34)	(3.36)	(3.39)	(3.61)	(3.37)	(4.00)	(4.28)
β_{RMRF}	0.709	0.639	0.497	0.539	0.616	0.401	0.408
	(1.44)	(1.38)	(0.78)	(0.73)	(0.83)	(0.55)	(0.51)
β_{SMB}	−0.120	−0.234	−0.359	−0.375	−0.470	−0.446	−0.641
	(−0.30)	(−0.64)	(−0.97)	(−1.00)	(−1.26)	(−1.12)	(−1.64)
β_{HML}	0.339	0.338	0.314	0.523	0.341	0.266	0.474
	(1.04)	(1.07)	(0.91)	(1.49)	(0.94)	(0.69)	(1.22)
Lagged 6m Ret		0.066	0.103	0.104	0.103	0.084	0.075
		(1.67)	(2.41)	(2.40)	(2.31)	(2.21)	(1.84)
Size			−0.004	−0.005	−0.003	−0.005	−0.005
			(−0.45)	(−0.45)	(−0.35)	(−0.47)	(−0.41)
Book-to-market			0.029	0.029	0.034	0.023	0.024
			(1.63)	(1.51)	(1.70)	(1.21)	(1.19)
Government spending exposure				−0.132			−0.336
				(−0.44)			(−0.95)
Federal spending in the HQ state					−0.001		−0.001
					(−0.99)		(−1.04)
Political alignment index						0.001	0.001
						(1.72)	(1.37)
Constant	0.488	0.476	0.491	0.507	0.465	0.423	0.456
	(2.25)	(2.20)	(1.69)	(1.72)	(1.56)	(1.35)	(1.43)
Avg Adj-R^2	0.083	0.089	0.106	0.139	0.111	0.111	0.146
Avg N firms	4296.40	4296.40	3681.71	2641.65	3423.06	3649.84	2570.62
N months	581	581	581	581	581	504	504

This table reports estimates from Fama-MacBeth (1973) regressions. Asset returns under consideration are those of common stocks in the CRSP universe. We regress monthly returns on the following regressors: lagged political-sensitivity; Fama-French 3-factor loadings calculated using daily returns over the previous month; return over the previous 6 months; log market capitalization at the beginning of the previous month; book-to-market ratio available 6 months prior; lagged conditional government spending exposure measure of Belo, Gala, and Li (2012); ranking of federal spending in a firm's headquarters state; and political alignment index (PAI) measure of Kim, Pantzalis, and Park (2012) in a firm's headquarters state. We report the time-series average of cross-sectional adjusted R^2s. The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from July 1963 to December 2011 in Columns 1 through 5, and from January 1967 to December 2008 in Columns 6 and 7.

In our validation tests, we investigate whether portfolio rankings based on aggregate shifts in sentiment are captured by our portfolio formation procedure that uses indirect return-based political-sensitivity of industries. Specifically, considering the two ranking methods, we calculate rates of portfolio coincidence across double-sorted political-sensitivity portfolios. Table A.1 reports rates (in percentages) of portfolio coincidence across these double-sorted political-sensitivity portfolios. The coincidence rates are calculated such that rates for a given political ranking across UBS/Gallup rankings across a row sum to 100. In panel A, equal-weighted coincidence rates are calculated as the number of assets with a particular political-UBS/Gallup ranking combination divided by the total number of assets across all UBS/Gallup rankings holding the political ranking fixed. In panel B, value-weighted coincidence rates are calculated as the market capitalization of assets with a particular political-UBS/Gallup ranking combination divided by total market capitalization of assets across all UBS/Gallup rankings holding the political ranking fixed. Perfect coincidence between the two portfolio ranking methods would imply diagonal non-zero entries in the table.

Table A.5
Political-sensitivity industry portfolios: Robustness

Panel A: Exposure to government spending

	Low government-spending exposure		High government-spending exposure	
Portfolio	Raw return	Char-adj return	Raw return	Char-adj return
1 (Short)	0.633	−0.199	0.593	−0.169
	(2.16)	(−1.41)	(1.94)	(−1.18)
2	0.834	−0.138	0.761	−0.180
	(3.57)	(−1.37)	(3.35)	(−2.07)
3	1.057	0.058	0.996	0.001
	(4.80)	(0.70)	(4.97)	(0.01)
4	1.186	0.102	1.024	0.102
	(5.38)	(1.36)	(4.76)	(1.40)
5 (Long)	1.330	0.236	0.967	−0.081
	(5.82)	(2.11)	(4.30)	(−0.60)
Long-Short	0.697	0.436	0.373	0.088
	(3.28)	(2.47)	(1.56)	(0.44)
N months	684	684	684	684

Panel B: Federal government spending across states

	Low federal-spending states		High federal-spending states	
Portfolio	Raw return	Char-adj return	Raw return	Char-adj return
1 (Short)	0.622	−0.136	0.785	−0.088
	(2.47)	(−1.06)	(2.98)	(−0.67)
2	0.943	−0.018	0.906	−0.042
	(5.01)	(−0.37)	(4.61)	(−0.69)
3	0.998	0.035	1.005	0.007
	(5.95)	(0.88)	(5.34)	(0.14)
4	1.061	0.058	1.187	0.094
	(5.99)	(1.08)	(6.23)	(1.60)
5 (Long)	1.535	0.414	1.369	0.081
	(8.12)	(4.19)	(6.72)	(0.88)
Long-Short	0.913	0.549	0.584	0.169
	(4.35)	(3.32)	(2.88)	(1.03)
N months	744	744	744	744

(*continued*)

The results from both panels demonstrate that the political-sensitivity-based rankings and UBS/Gallup rankings are highly correlated. Among industry portfolios, the equal-weighted coincidence rates in panel A show that all non-zero coincidence rates are situated along the diagonal, or at most, one position away from the diagonal. Importantly, no industries in the Long (Short) portfolio are misclassified into the Short (Long) portfolio. The value-weighted coincidence rates in panel B provide similar intuition. These findings suggest that our return-based political-sensitivity estimates capture the effects of political sentiment on industry returns reasonably well.

Table A.5
Continued

Panel C: Political alignment with presidential party

	Low political-alignment states		High political-alignment states	
Portfolio	Raw return	Char-adj return	Raw return	Char-adj return
1 (Short)	0.445	−0.335	0.655	−0.129
	(1.38)	(−2.50)	(2.14)	(−0.88)
2	0.710	−0.158	0.670	−0.174
	(3.04)	(−2.67)	(2.86)	(−3.02)
3	0.889	0.037	1.013	0.086
	(3.86)	(0.68)	(4.55)	(1.74)
4	0.933	0.018	1.076	0.114
	(4.16)	(0.27)	(4.67)	(1.74)
5 (Long)	1.199	0.269	1.231	0.127
	(4.60)	(2.04)	(4.90)	(1.13)
Long-Short	0.754	0.604	0.576	0.256
	(2.84)	(2.91)	(2.39)	(1.36)
N months	504	504	504	504

This table reports performance estimates of double-sorted portfolios, defined using the political-sensitivity return-prediction model. Component returns are those of value-weighted Fama-French forty-eight industry portfolios. We report raw and characteristic-adjusted portfolio returns in all panels. In panel A, we condition on firms' government spending exposure, as in Belo, Gala, and Li (2012). Firms with low (high) government spending exposure are defined as those falling below (above) the median government spending exposure across all stocks each month. We recalculate the value-weighted Fama-French forty-eight industry portfolio returns using low- and high-exposure firms. The estimation period is from January 1955 to December 2011. In panel B, we condition on firms' federal government spending exposure measured using the headquarters state's ranking of per capita federal spending. Low (high) federal spending states are defined as those falling below (above) the median per capita federal spending across all U.S. states. We recalculate the value-weighted Fama-French forty-eight industry portfolio returns using low- and high-exposure firms. The estimation period is from January 1950 to December 2011. In panel C, we condition on the political alignment index (PAI) of firms' headquarters states, as in Kim, Pantzalis, and Park (2012). PAI measures the degree of political alignment between a state's leading politicians and the presidential party. Low (high) PAI states are defined as those falling below (above) the median PAI across all U.S. states each year. We recalculate the value-weighted Fama-French forty-eight industry portfolio returns using firms in low- and high-PAI states. The estimation period is from January 1967 to December 2008. Characteristic-adjusted returns are computed using the method of Daniel et al. (1997). The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates.

Table A.6
Political-sensitivity industry portfolios: Government composition

Panel A: Republican vs. Democrat presidencies

	Republican president		Democrat president	
Portfolio	Raw return	Char-adj return	Raw return	Char-adj return
1 (Short)	0.448	−0.185	0.986	−0.125
	(1.38)	(−1.82)	(3.69)	(−0.99)
2	0.787	−0.064	1.015	−0.068
	(3.39)	(−1.25)	(4.16)	(−1.41)
3	0.915	0.032	0.982	−0.038
	(3.95)	(0.73)	(4.60)	(−1.19)
4	0.981	0.112	1.097	−0.020
	(4.48)	(2.04)	(4.81)	(−0.51)
5 (Long)	1.255	0.283	1.586	0.336
	(5.07)	(2.76)	(6.06)	(3.36)
Long-Short	0.807	0.468	0.600	0.460
	(3.33)	(3.04)	(2.46)	(2.61)
N months	432	432	444	444

Panel B: Composition of government

	Divided Congress and White House		Unified Congress and White House	
Portfolio	Raw return	Char-adj return	Raw return	Char-adj return
1 (Short)	0.635	−0.271	0.811	−0.031
	(2.12)	(−2.15)	(2.76)	(−0.32)
2	1.011	−0.056	0.788	−0.077
	(4.46)	(−1.04)	(3.17)	(−1.71)
3	0.943	−0.024	0.955	0.018
	(4.13)	(−0.58)	(4.49)	(0.47)
4	1.081	0.062	0.996	0.028
	(4.78)	(1.33)	(4.55)	(0.55)
5 (Long)	1.431	0.253	1.415	0.369
	(5.59)	(2.84)	(5.62)	(3.25)
Long-Short	0.796	0.525	0.604	0.400
	(3.18)	(3.17)	(2.57)	(2.43)
N months	449	449	427	427

This table reports performance estimates of double-sorted portfolios defined using the political-sensitivity return-prediction model. Component returns are those of value-weighted Fama-French forty-eight industry portfolios. We report raw and characteristic-adjusted portfolio returns in all panels. In panel A, we split the sample based on whether the president in power was a Republican or Democrat. In panel B, we split the sample based on whether the government is unified or divided. A unified government occurs when the same party controls the House, Senate, and White House. The government is divided otherwise. Characteristic-adjusted returns are computed using the method of Daniel et al. (1997). The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates.

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