Political Sentiment and Predictable Returns*

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Abstract – This study examines the impact of a changing political environment on the stock market. We find that as the political climate changes, there are systematic shifts in the portfolio compositions of investors, which generates predictable patterns in stock returns. A trading strategy that attempts to exploit this predictability pattern generates an annualized risk-adjusted performance of about six percent during the 1939 to 2011 period. The evidence of predictability spans an economically meaningful segment of the market (17-27%) and is somewhat stronger during the more recent time period. Return predictability is 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 high attention months surrounding the elections and years one and four of the Presidential term when the level of political awareness is higher. Overall, our results establish a strong link between politics and financial markets.

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Abstract – This study examines the impact of changing political environment on the stock market. We find that as the political climate changes, there are systematic shifts in the portfolio compositions of investors, which generates predictable patterns in stock returns. A trading strategy that attempts to exploit this predictability pattern generates an annualized risk-adjusted performance of about six percent during the 1939 to 2011 period. The evidence of predictability spans an economically meaningful segment of the market (17-27%) and is somewhat stronger during the more recent time period. Return predictability is 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 high attention months surrounding the elections and years one and four of the Presidential term when the level of political awareness is higher. Overall, our results establish a strong link between politics and financial markets.

1. Introduction

The level of interest in financial markets typically rises in the period surrounding the Presidential elections. The popular press often talks about implications of changing political climate on portfolio composition. There is also considerable interest in predicting the market reaction following the election outcome.[1] Both retail and relatively more sophisticated institutional investors try to identify stocks that could benefit from the Party policies and those that may be adversely affected. And there is likely to be considerable heterogeneity in the portfolio decisions of different groups of investors.

Some investors may be uniformly more optimistic about the entire market instead of certain segments of the market. For example, investors who support the Republican Party may become

[1]For example, see Hill (2012), Zweig (2012), and Hulbert (2012).

more optimistic about the entire market and increase their holdings of risky assets if they expect the Republican Party to come to power. In contrast, investors who associate more strongly with the Democratic Party may be systematically more pessimistic about the markets and the economy. These investors may exhibit a "flight toward safety" and reduce the riskiness of their portfolios.[2]

Beyond this optimism channel, irrespective of their political affiliation, some sophisticated investors could engage in hedging and try to identify market segments that may benefit from the policies of the Party that is expected to win. The hedging motivation may be stronger among sophisticated institutional investors, while retail investors may be more susceptible to changing optimism as the political environment changes. The demand shifts induced by the optimism and hedging channels could be stronger during times when people pay more attention to the political environment and their political awareness is higher (e.g., around Presidential elections).

Even during other periods, as the political climate changes, investors may react to those changes and alter the composition of their portfolios. Due to these systematic shifts in investors' portfolio decisions, certain segments of the market may get mispriced and generate predictable patterns in stock returns. In this paper, we examine whether systematic shifts in the portfolio compositions of investors induced by the optimism, hedging, and attention channels generate predictable patterns in stock prices.

Although market participants often talk about the impact of politics on the markets, there is no consensus among them 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. We compute the political betas of all firms and industries with respect to the Republican and Democratic Parties. The

[2]In a recent Allianz Life survey, a significant proportion of individuals (about 40%) in the 55 to 65 age group mention that they would choose more conservative portfolio if the opposing Party wins the election. 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.

beta captures the sensitivity of returns to the changing political climate. For example, a stock or an industry has large positive Republican beta if in the past its returns react more strongly when the Republican Party comes to power.

Using the new measures of political betas of firms and industries, we demonstrate that returns in segments of the market with high political betas are predictable. A Long-Short trading strategy that attempts to exploit this predictability pattern generates an annualized characteristic-adjusted return of 5.57 percent during the 1939 to 2011 period. As we vary the portfolio holding periods, we find that the performance of our trading strategy declines. This evidence is consistent with our conjecture that systematic investor demand induced by changing political climate generates mispricing, which eventually gets corrected through the action of arbitrageurs.

Our evidence of predictability spans an economically meaningful segment of the market (about 17-27% of the total market capitalization) and is somewhat stronger in the recent time period. For example, during the 1976 to 2011 period, the Long-Short strategy generates an annualized characteristic-adjusted performance of 7.06 percent.

We also demonstrate that our findings are robust to the choice of the asset pricing models used to adjust for risk. For example, even when we use conditional factor models that take into account time-varying exposures to risk, the Long-Short strategy generates significant alphas. Further, 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 high attention months surrounding the elections and years one and four of Presidential term when the level of political awareness is higher.

These findings contribute to the growing finance literature that examines the link between politics and the stock market. For example, Santa-Clara and Valkanov (2003) demonstrate that the stock market performs better during the Democratic Presidency. Cooper, Gulen, and

Ovtchinnikov (2010) find that politically-connected firms earn higher returns. Similarly, 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. Pastor and Veronesi (2012) show that political uncertainty induces a higher risk premium, especially when the economic conditions are poor. More recently, Belo, Gala, and Li (2012) demonstrate that firms with greater exposure to government spending earn higher returns during Democratic Presidencies and lower average returns during Republican Presidencies.

Unlike these previous studies that focus mainly on the impact of political environment on firm cash-flows, we examine the impact of political climate on asset returns through the investor demand channel. In particular, we show that certain segments of the market are mispriced during periods of high political awareness and this mispricing eventually gets corrected in about six months.

Our results do not merely reflect the findings from these earlier studies since we find evidence of return predictability in high and low government spending states as well as in high and low political alignment states. We also find evidence of predictability during both Republican and Democratic Presidential terms. Overall, our findings suggest that the predictability in returns generated by the cash-flow channel and the investor demand channel are likely to operate simultaneously and during different time periods.

Beyond the literature on politics and finance, our paper extends the recent 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 (2012) 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 arbi-

trageurs eventually correct this mispricing. Our key innovation is to recognize the heterogeneity in the sentiment levels of investors. Specifically, we examine the effects of Republican and Democratic sentiments instead of the aggregate market sentiment.

The rest of the paper is organized as follows. We describe the main data sources and the estimation method in the next section. We present evidence of return predictability in Section 3 and identify the predictability channels in Section 4. We conclude in Section 5 with a brief discussion.

2. Data and Methods

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

2.1. Main Data Sources

We use data from multiple sources. The data on stock returns are from the Center for Research on Security Prices (CRSP). We only consider common stocks with share codes of 10 and 11. The returns of 48 value-weighted Fama-French industry portfolios are from Ken French's data library.

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 or 11. We also obtain 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 from Ken French's data library. Both daily and monthly stock returns from CRSP are available for the December 1925 to December 2011 period. Daily returns for Fama-French 48 industry portfolio returns are available from July 1963

to December 2011 and monthly returns range from July 1926 to December 2011.

We also compute book-to-market ratios for each listed U.S. firm in our sample, using data obtained from Compustat. 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 six-month lag between measurement and observation periods. The annual Compustat data are available from 1950 to 2011.

We obtain the Daniel, Grinblatt, Titman, and Wermers (1997) characteristic-adjustment stock assignments and benchmark portfolio returns from Russ Wermers' web site. The benchmark returns are available from 1975 to 2011. We use the Daniel, Grinblatt, Titman, and Wermers (1997) method to augment the stock assignments and benchmark portfolio returns back to January 1939 using historical book equity data.

Last, we obtain the Lettau and Ludvigson (2001) *cay* measure from Sydney Ludvigson's web site, National Bureau of Economic Research (NBER) recession indicators from the NBER web site, and data on Presidential election outcomes from the CQ Press Voting and Elections Collection.

2.2. Political Sensitivity Based Industry Portfolios

We estimate the political sensitivity of each stock and each industry portfolio. The industry-level political sensitivity portfolios are formed as follows. Each month, for each industry, we regress the past 15 years' (180 months') excess Fama French 48 industry returns on the excess market return and a Presidential Party indicator. Abramowitz (1988, 2008) documents predictability of Presidential election outcomes, showing that outcomes can be predicted using information available at the end of June in election years (GDP growth, approval rating, and whether it is the incumbent party's first term in office). We exploit this predictability by setting the Presidential Party indicator such that it reflects the winning party of the November election in the preceding

August, September, and October of the election year.[3] Specifically, we estimate the following time-series regression:

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

We then sort industries on the political party coefficient, calling industries with large positive (negative) coefficient Republican (Democrat) industries. We sort the industries into portfolios as follows. If the presidential party for the current month is Republican (Democrat), then we sort the industries on political party coefficient in descending (ascending) order and use the top 5 industries to form the long portfolio and the bottom 5 industries to form the short portfolio. The remaining industries are split equally among portfolios 2, 3, and 4. Portfolios are value-weighted using industry market capitalization at the beginning of the month and are held for one month.

2.3. Political Sensitivity Based Stock Portfolios

To obtain stock-level political sensitivity estimates, for each stock, each month, we regress past excess returns on the excess market return and the interaction between a Presidential Party indicator and four term-period indicators. The Presidential Party indicator variable is equal to one when the Presidential Party was Republican and zero during Democratic Presidential periods. Again, we exploit the predictability of Presidential election outcomes by setting the Presidential Party indicator such that it reflects the winning party of the November election in the preceding August, September, and October of the election year. The term-period indicators are respectively set equal to one during each August - July period of a four-year Presidential

[3]We verify in unreported tests that the predictability we document is not dependent on exploiting the predictability in Presidential election outcomes.

term. Specifically, we estimate the following time-series regression:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i \left(r_{mkt,t} - r_{f,t}\right) + \sum_{j=1}^{4} \left[\theta_{i,j} \left(Period_{j,t} \times RepubDummy_t\right)\right] + \varepsilon_{i,t} \tag{2}$$

To increase the accuracy of identifying political sensitivity, we apply several filters. We only keep stocks with at least 50 monthly observations to ensure proper identification, limit the maximum observation window to 480 months of past returns to guard against stale partisan effects that are no longer relevant, and end the estimation window at the end of the previous Party's time in power to ensure we are identifying political effects and not just momentum in stock returns. Each month we take those stocks with above-median political sensitivity t-statistic and sort those stocks into portfolios. If the Presidential Party for the current month is Republican (Democrat), then we sort the stocks on political Party coefficient in descending (ascending) order and use the top quintile of stocks to form the long portfolio and the bottom quintile to form the short portfolio. Portfolios are value-weighted using market capitalization at the beginning of the month and are held for one month.

2.4. Characteristics of Political Sensitivity Sorted Portfolios

Table 1 reports the descriptive characteristics of industry and stock portfolios defined using the political sensitivity return prediction model. Panel A reports mean size (log market capitalization), book-to-market ratio, returns over the previous six 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 Hong and Kacperczyk (2009) method as stocks in the Tobacco, Guns, and Alcohol industries among the 48 Fama and French (1997) industries. For both the industry and stock portfolios in Panel A, we can see that average size and book-to-market ratios across portfolios are relatively constant, and that past returns increase with expected returns according to our political sensitivity prediction model. 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.

Panel B reports the five most prevalent industries in the Long and Short portfolios across Republican and Democrat Presidencies. For industry portfolios, prevalence is measured by the number of months an industry is classified into a given portfolio over the estimation period. For individual stocks, prevalence is measured by the time-series average market capitalization weight of industry stocks in a given portfolio over the estimation period. Examination of Panel B further validates the intuition of Panel A, with traditionally Republican industries such as Tobacco, Pharmaceuticals, and Finance-related industries consistently populating the Long portfolios during Republican Presidencies and Short portfolios during Democrat Presidencies. Further, traditionally Democrat industries such as Health-care and Construction populate the Long portfolios during Democrat Presidencies and Short portfolios during Republican Presidencies.

3. Evidence of Return Predictability

Our empirical analysis is based on the key premise that the demands of certain types of stocks vary systematically with the political climate. In particular, investors may systematically alter their holdings of certain types of stocks due to systematic shifts in optimism induced by the changing political climate or due to the hedging demand. Both the optimism- and hedging-induced demands are likely to be stronger during periods when people pay more attention to the national politics. If the demand shifts of politically-sensitive investors aggregate and arbitrage forces are limited, those demand shifts could alter stock prices and generate predictable patterns in returns. In this section, we test this main conjecture using industry- and stock-level portfolios.

3.1. Graphical Evidence

To begin, we present the time-series of the annual return of the Long-Short portfolio obtained using value-weighted Fama and French (1997) 48-industry portfolios. The sample period is from January 1939 to December 2011. The bar plot shows that politically-sensitive industries outperform less politically-sensitive industries and this pattern is not concentrated in any particular time-period. In 54 out of 73 years, the annual performance differential is positive. When we compare the performance of our Long and Short portfolios with the market portfolio and the risk free asset, as expected, we find that the Long portfolio earns significantly higher return than the market (see Figure 2). In contrast, the Short portfolio under-performs the market.

These performance patterns are qualitatively very similar if we use characteristic-adjusted returns to measure portfolio performance or consider stock-based portfolios. Overall, the graphical evidence suggests that the performance of our political sensitivity based Long-Short portfolio is robust and economically significant.

3.2. Sorting Results: Industry Portfolios

Next, we perform univariate sorts using the political sensitivity estimates of industry portfolios to further assess the relation between political climate and stock returns. We report the performance of six portfolios defined using our political sensitivity return prediction model: (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 to 4, which represent the value-weighted portfolios of the remaining industries sorted into terciles based on predicted returns in the next month.

The results are presented in Table 2. In Panel A, we report the raw and characteristic-

adjusted portfolio returns for the full-sample period from January 1939 to December 2011 and two sub-periods covering January 1939 to December 1975 and January 1976 to December 2011. The characteristic-adjusted returns are computed using the Daniel, Grinblatt, Titman, and Wermers (1997) method. 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 political betas. Industry portfolios in the lowest beta quintile earns an average raw monthly return of 0.721%, while industries in the highest beta quintile earns 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 performance differential during the full-sample period is $0.464 \times 12 = 5.57\%$, which is still economically large. Examining the performance estimates for the sub-periods, we find a similar pattern across both sub-periods, although the pattern is stronger during the more recent sub-period. During the 1939 to 1975 period, the annualized characteristic-adjusted performance differential is $0.344 \times 12 = 4.13\%$. During the more recent 1976 to 2011 sub-period, the Long-Short performance differential increases to $0.588 \times 12 = 7.06\%$. This evidence suggests that the impact of political climate on financial markets has become stronger over time. Alternatively, this finding could reflect the fact that our political beta estimates become more precise during the recent sub-period as the beta estimation window increases.

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

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. 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 2, we report the average monthly market shares for our quintile portfolios for both raw and characteristic-adjusted return portfolios. We find that Long and Short portfolios cover an economically meaningful segment of the market (17-27%).

3.3. Sorting Results: Stock Portfolios

Our main analysis uses industry portfolios to ensure that our political beta estimates are less noisy. Nevertheless, for robustness, we repeat the main analysis using stock-based portfolios instead of industry-based portfolios. We form portfolio using the political sensitivity return prediction model applied to individual stocks. As before, we define six political sensitivity based portfolios and report their performance estimates in Table 3.

We find the same monotonic pattern as before when we measure performance using raw return. The characteristic-adjusted portfolio returns do not increase monotonically but the qualitative patterns are very similar. The Long portfolio outperforms the Short portfolio and this pattern is stronger during the more recent time period. Specifically, during the 1952 to 2011 full-sample period, the Long-Short portfolio earns an annualized characteristic-adjusted return of $0.323 \times 12 = 3.88\%$. Further, the sub-period estimates indicate that this performance differential is insignificant during the 1952 to 1980 sub-period and is considerably stronger during the 1981 to 2011 period (annualized performance differential = 6.64%, t-statistic = 3.22).

The standard deviation and Sharpe ratio patterns in Panel B are also qualitatively similar

to the evidence obtained using industry-based portfolios. The extreme portfolios have higher volatility levels but the Sharpe ratio exhibits a monotonically increasing pattern. The evidence in Panel C shows that stock-based portfolios cover a larger segment of the market (17% versus 27%). Last, the results in Panel D of Table 3 indicate that the political sensitivity based portfolios typically contain over 100 stocks. Thus, our results are unlikely to reflect the abnormal behavior of stocks in some small and economically inconsequential segment of the market.

3.4. Predictability Around Incumbent versus Challenger Victories

In the next set of tests, we investigate whether our evidence of predictability is stronger during certain types of transitions. In particular, we examine whether predictability in returns is stronger when the challenger is victorious. Table 4 presents the performance estimates of industry portfolios defined using the political sensitivity return prediction model, conditioning on the outcome of the Presidential elections. 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 four-year 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.

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 0.222% (t-statistic = 1.68) and 0.781% (t-statistic = 4.00), respectively. 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 tran-

sitions are 0.589% (t-statistic = 2.34) and 0.973% (t-statistic = 3.30), 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 3. We plot the cumulative characteristic-adjusted returns over the 48 months surrounding elections in which there is a change in 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 $t-2$ and up until July of year $t+2$.

Consistent with the dominant role of elections in which the incumbent party is replaced, we find that the returns to the Long and Short portfolios respectively increase and decrease prior to the change in power. As the election nears, the cumulative Long portfolio returns begin to decrease, and continue decreasing over the next 24 months. Conversely, the cumulative Short portfolio returns increase steadily over the next 24 months. In contrast, the other three portfolios exhibit no sensitivity to the changing political climate around the election period.

3.5. Factor Model Estimates

All our results so far are based on raw or characteristic-adjusted returns. To better account for portfolio risk, we examine the performance of political sensitivity based trading strategies using various unconditional and conditional factor models to obtain risk-adjusted performance. 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 unconditional factor model estimates are reported in Table 5. Panel A reports the estimates for industry based portfolios, while Panel B reports the estimates for stock based portfolios. For industry based portfolios, 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. For stock based portfolios, the estimation period is from August 1952 to December 2011, except for models including the liquidity factor (LIQ), in which the estimation period is from August 1962 to December 2011.

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 (see Panel A). For example, the monthly six-factor alpha (t-statistic) estimates for Long, Short, and Long−Short portfolios are 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 six percent 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. The performance estimates are also significant when we consider stock based portfolios (see Panel B).

To ensure that the abnormal performance estimates political sensitivity based trading strategies do not merely 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 Long, Short, Long-Short portfolios using three conditional asset pricing models, which allow portfolio exposures to U.S. systematic risk factors to vary with the U.S. business cycle. The factor models contain some combination of the following factors and interactions among them: 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)), an NBER Recession indicator (REC), and the Lettau and Ludvigson (2001) *cay* measure. 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 estimation period for each regression is indicated at the top of each column. All specifications including the *cay* measure end in September 2011.

We report the conditional alpha estimates and factor exposures in Table 6. The results indicate that the alpha estimates remain equally strong when we use conditional factor models to account for portfolio risk. For example, the alpha estimates of the Long-Short portfolio when we use the conditional model with NBER recession interactions,the Lettau and Ludvigson (2001) conditional model, and the extended conditional model are 0.544, 0.551, and 0.583, respectively. These estimates are somewhat stronger than the unconditional factor model alpha estimate of 0.498. Further, the statistical significance of these alpha estimates increase when we use conditional factor models to account for risk. We find a qualitatively similar pattern when we obtain the conditional factor model alpha estimates of stock based portfolios.

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. In the next section, we show explicitly that the abnormal performance of Long-Short portfolios reflect mispricing that eventually get corrected in about six months.

3.6. Fama-MacBeth Regression Estimates

In the last set of baseline tests, we estimate Fama and MacBeth (1973) type regressions. We estimate both industry- and stock-level regressions. The dependent variable is the monthly industry or stock return and the main explanatory variable is the lagged political beta. The regres-

sion specification also includes several firm 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 six-month return, value-weighted log market capitalization of industry-firms at the beginning of the previous month, and value-weighted book-to-market ratio of industry-firms available six months prior. We report the time-series averages of the coefficient estimates from monthly cross-sectional regressions and the t-statistics are based on these monthly coefficient estimates. The t-statistics reported in parentheses below the estimates are computed using the Newey and West (1987) adjusted standard errors. The estimation period is from July 1963 to December 2011.

The regression estimates are reported in Table 7. Both industry- and stock-level results portray a consistent picture. Industries and stocks with higher political sensitivity earn higher returns even in the presence of all other control variables. In the industry-level regressions, the political beta has an estimate of 1.026 and the t-statistic is 2.46. In economic terms, a one standard deviation shift in the political beta is associated with a $1.026\times = 0.099 = 0.102\%$ shift in the industry portfolio return in the following month (see Column (3)). The economic significance of the stock-level regression estimates reported in Column (6) is similar. A one standard deviation shift in the political beta is associated with a $6.791\times = 0.021 = 0.143\%$ shift in the next month's stock return.

Overall, the estimates from Fama and MacBeth (1973) type regressions provide additional support for our main hypothesis. We show that the political sensitivity of firms and 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.

4. Main Predictability Channel

Our evidence so far indicates that the changing political climate has an economically meaningful impact on the stock market. In this section, we examine whether this link reflects the systematic shifts in the portfolio compositions of certain investor groups. A variety of factors (e.g., partisan-based optimism, hedging motives, etc.) could influence the systematic shifts in the portfolio composition of investors. We do not precisely identify those factors but rather show that the joint effects of those factors generate systematic mispricing in certain segments of the market, which eventually get correct due to the actions of arbitrageurs.

Our goal is not to establish that systematic shifts in investor demand is the only channel through which the political environment influences stock prices. Clearly, the changing political environment could influence the market through its impact on firm profitability. We want show that (i) the cash-flow channel is unlikely to fully explain our findings and (ii) the investor demand channel plays an economically significant role for asset prices that is captured by our novel political sensitivity estimation method.

4.1. Is the Evidence of Predictability Distinct?

To begin, we examine whether our evidence of investor demand induced return predictability is distinct from the evidence of predictability induced by the shifts in firm cash-flows associated with the changing political climate. First, we show that our findings are distinct from the evidence in Belo, Gala, and Li (2012) who demonstrate that firms with greater exposure to government spending earn higher returns during Democratic Presidencies and lower average returns during Republican Presidencies. As shown in Panel A of Table 10, we show that our results are not driven by firms with high exposure to government spending, and are actually stronger among firms with lower exposure to government spending. Further, as shown in Panel B of Table 8, we find that our results hold for firms located in low government spending as

well as high government spending states, where low (high) federal spending states are defined as those below (above) the median per capita federal spending across all U.S. states. Again, our results are stronger for firms located in low government spending states. These findings suggest that our results are unlikely to reflect the effects of firms' exposures to government spending. It is likely that the two effects operate simultaneously and during different time periods.

Next, we ensure 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. 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. Low (high) PAI states are defined as those below (above) the median PAI across all U.S. states each year. As shown in Panel C of Table 8, we find evidence of return predictability in both high and low political alignment states. Again, our results are stronger for firms located in regions with low political alignment. This evidence suggests that our results are unlikely to reflect the potential cash flow effects that emerge from alignment between state and federal political environments.

Last, as shown in Panel A of Table 9, we find evidence of return predictability during both Republican and Democratic Presidential terms. Thus, our results do not somehow reflect the Presidential puzzle identified in Santa-Clara and Valkanov (2003), who demonstrate that the stock market performs better during the Democratic Presidency. Further, as shown in Panel B of Table 9, we find that our results hold during sub-periods in which the Senate, House of Representative, and White House are controlled by the same party (unified Congress and White House), and otherwise (divided Congress and White House). Overall, these sub-sample and sub-period results suggest that our evidence of predictability is novel. The predictability in returns generated by the cash-flow channel that is highlighted in related studies and the investor demand channel that is the focus of our paper are likely to operate simultaneously and during

different time periods.

4.2. Graphical Evidence of Mispricing and Correction

In our next test, we examine the performance of the Long-Short portfolio as the holding period increases. If the abnormal performance of the Long-Short portfolio reflects mispricing that eventually gets corrected, the performance estimates would become weaker as the holding period increases. The speed with which the Long-Short performance differential declines would indicate the effectiveness of arbitrage forces that correct the mispricing captured by our political sensitivity based portfolios.

Figure 4 shows the effect of varying portfolio holding periods on average monthly characteristic-adjusted returns (solid line) to the political sensitivity portfolio formed using value-weighted Fama and French (1997) 48 industry portfolios. We also show the two standard error bars (dashed lines). Consistent with the mispricing hypothesis, we find that the characteristic-adjusted performance of the Long−Short portfolio declines gradually as the holding period increases. Beyond six months, the performance differential is no longer distinguishable from zero. This declining trend in the performance estimates is consistent with the mispricing explanation and indicates that most of the mispricing is corrected in about six months.

We provide an alternative perspective on the mispricing and correction pattern. Figure 5 shows the effect of varying portfolio formation periods on average monthly characteristic-adjusted returns (solid line) to the political sensitivity portfolio formed using value-weighted Fama and French (1997) 48 industry portfolios. We also show the two standard error bars (dashed lines). Again, consistent with the mispricing hypothesis, we find that the characteristic-adjusted performance of the Long-Short portfolio declines gradually as the formation period increases, with the performance differential indistinguishable from zero beyond about 12 months.

4.3. Validation Tests using Direct Sentiment Measures

Next, we use a short sample of direct political sentiment measures to validate our key assumption that our political betas reflect 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.[4] The difference in the optimism levels of Republicans and Democrats is likely to capture the relative political sentiment of Republicans over Democrats.

Using these direct measures of investor optimism or sentiment, we estimate the political sentiment betas 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 betas, we first calculate a five-month moving average of the Republican-Democrat optimism spread. Next, using this measure, we regress monthly industry and stock 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 five industries or quintile of stocks that are predicted to have the lowest returns in the next month, (ii) the "Long" portfolio, which is a value-weighted portfolio of five industries or quintile of stocks 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 or stocks sorted into terciles based on predicted returns in the next month.

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 portfolio betas of stocks and industries. Specifically, considering the two ranking methods, we calculate rates of portfolio coincidence across double-sorted political sensitivity portfolios. Table 10 reports rates (percentages) of portfolio coincidence across these double-sorted political

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

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.

The results from both panels demonstrate that the political 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. Among individual stocks, the coincidence rates are again clustered along the diagonal, though with slightly more variance in the level of misclassification than among industries. However, in both the equal- and value-weighted results, coincidence levels between Long and Short portfolio rankings using the two ranking methods are very high, with zero misclassification of Long (Short) stocks into the Short (Long) category. These findings suggest that our return-based political betas capture the effects of political sentiment reasonably well.

4.4. Predictability Patterns Across the Presidential Term

In this section, we examine whether our evidence of return predictability varies systematically across the four 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 time periods, the political awareness among investors is higher and, therefore, optimism or hedging based demands are likely to be stronger. In contrast, Belo, Gala, and Li (2012) find that their evidence of cash-flow based predictability is stronger during the two middle years of the Presidential term as the policy uncertainty is resolved.

Table 11 reports the performance estimates of Long-Short industry portfolios defined using the political sensitivity return prediction model, 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 February 1 to January 31 of the following year, while the predictive term-years are 6-month forward-looking, running from August 1 to July 31 of the following year. We find that our results are spread throughout the Presidential term and stronger in years 1 and 4 when investor attention is likely to be higher. This evidence is consistent with our investor demand based explanation for the observed predictability in returns.

4.5. Predictability During High Attention Periods

To further examine the role of investor attention on return predictability, we explicitly identify high attention periods and examine whether the evidence of predictability is stronger during high attention periods. High political attention periods are defined as months surrounding the November presidential election. Low political attention 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 11, Panel B indicate that our evidence of predictability is significantly stronger during the high-attention periods. In contrast, during the low-attention periods around the mid-term elections, the evidence of predictability is significantly weaker.

This finding is consistent with the investor demand based explanation for predictability.

4.6. Turnover and Volatility Regression Estimates

In the next set of tests, we explicitly examine the level of trading during the high attention periods. If our evidence of predictability is indeed induced by the systematic shifts in the demands of investors, the turnover levels should be higher during high attention periods, especially if the challenger Party wins the election. Further, the high turnover levels would be associated with higher levels of return volatility.

Table 12 reports the estimates from panel regressions of monthly asset turnover (Panel A) and monthly asset return volatility (Panel B) on an indicator for high attention periods and its interaction with an indicator for elections in which there is a change in Presidential party. The high political attention period indicator takes the value one for months falling within one year (i.e., ± 6 months) of a presidential election. For individual stocks, turnover is calculated as monthly stock volume divided by shares outstanding at the end of the month, while for industry portfolios, turnover is calculated as the value-weighted average of component-industry stocks' turnovers during each month. For both individual stocks and industry portfolios, volatility is calculated as the standard deviation of daily returns during the month.

To account for short-term reversal and momentum-based trading effects, in later specifications, we also control for asset returns in the previous month, as well as the six-months prior to that. Last, we include asset-term fixed effects in all specifications, giving our coefficient estimates a within-term time-series interpretation. The turnover and volatility regression estimates are reported in Table 12.

The turnover regression estimates reported in Panel A suggest that during the high attention period surrounding elections in which the incumbent party wins, turnover is generally higher than at other times during the political cycle. The statistical significance of this effect increases

as we add controls for short-term contrarian and momentum trading. Further, the effect of the high attention period is especially strong when we consider elections in which there is a change in Presidential party, with estimated economic magnitudes 6 to 8 times larger among industries and 2.5 to 4.5 times larger among individual stocks. 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 (6.13% for industries, and 8.28% for individual stocks).

The volatility regression estimates reported in Panel B yield additional insights to those of the turnover estimates in Panel A. We find that during the high attention period surrounding elections in which the incumbent is the victor, a period associated with slightly increased 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, high attention periods are associated with a sharp increase in monthly volatility. Once again, these effects are economically significant when compared to unconditional monthly volatility levels (1.17% for industries, and 3.26% for individual stocks).

Overall, the turnover and volatility regressions suggest that the level of trading increases significantly during periods of high political awareness. In conjunction with our prior evidence of stronger return predictability during these periods, this evidence provides additional support for our main conjecture. During periods of high political awareness, increased trading levels increase volatility and generate short-term mispricing, which eventually get corrected in about six months. While part of the increase in trading could reflect changes in anticipation of future cash flows, most of the abnormal trading levels cannot be tied to higher future cash-flows.

4.7. Direct Test of Cash-Flow Predictability

In the last set of tests, we focus on the cash-flow channel and directly examine whether trading activity and return predictability around Presidential elections are driven by rational expectations of future operating performance. We estimate Fama and MacBeth (1973) type regressions of h-quarter ahead operating performance at the industry- and stock-level. The dependent variable is the h-quarter ahead industry or firm return on assets and the main explanatory variable is the political sensitivity measure interacted with high and low political-attention period indicators. We calculate return on assets as operating income before extraordinary items and accrued interest divided by the book value of total assets at the end of each quarter. We define the high-attention period as the ± 4 quarters surrounding Presidential elections and the low-attention period as the complement of this.

Following Fama and French (2000), Vuolteenaho (2002), and Hou and Robinson (2006), the regression specification also includes several firm characteristics known to explain operating performance. This set includes the ratio of market value to book value of assets, an indicator variable for non-dividend-paying firms, and the ratio of dividends to book equity, as well as current-quarter return on assets.

We report the time-series averages of the coefficient estimates from monthly cross-sectional regressions. We also report the average difference between political sensitivity coefficient estimates across high and low political-attention periods. The t-statistics reported in parentheses are computed using Newey and West (1987) adjusted standard errors. The estimation period is from January 1970 to December 2011 for h-quarter ahead prediction with $h = 1$. For each $h > 1$, the estimation period decreases by $h - 1$ quarters.

We report the regression estimates in Table 13. The results at both the industry- (Panel A) and stock-level (Panel B) tell a consistent story. For all horizons within one year, we fail to reject the null hypothesis that the political sensitivity measure has equal predictive power for

future operating performance during high and low political-attention periods. This is in direct contrast to our earlier result that return predictability is strongest during the periods surrounding Presidential elections. We find similar results when considering operating performance at longer horizons in the future (8- and 12-quarters ahead).

We note that the political sensitivity measure is considerably more precise in forecasting earnings among stocks than at the industry-level. Again, this in contrast to the return predictability results, which are equally strong at the industry-level. Together with the disappearing portfolio returns shown in Figure 4, we interpret this as evidence of overreaction around Presidential elections spurring broad trading and swings in asset prices at the industry-level. This is eventually corrected by the actions of arbitrageurs, as heterogeneity within industries is impounded into prices across individual stocks.

5. Summary and Conclusion

Casual observation of financial markets suggests that the changing political climate influence various financial market outcomes. For example, the political climate may influence the cash flows of firms directly or it could affect the portfolio composition of investors systematically. In this study, we 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 segments of the market with high political betas are predictable. A Long-Short trading strategy that attempts to exploit this predictability pattern generates an annualized risk-adjusted returns of 5.57 percent during the 1939 to 2011 period. Our evidence of predictability covers an economically meaningful segment of the market (about 17-27% of the total market capitalization) and is somewhat stronger in the recent time period. For example, during the 1976 to 2011 period, the Long-Short strategy generates an annualized risk-adjusted performance of 7.06 percent.

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 high attention months surrounding the elections and years one and four of Presidential term when the level of political awareness is higher. As we vary the portfolio holding periods, we find that the performance of our trading strategy declines. This evidence is consistent with our conjecture that systematic investor demand induced by changing political climate generates mispricing, which eventually gets corrected through the action of arbitrageurs.

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 the election period could generate momentum in the 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 impact of political climate varies geographically across the U.S. states. In particular, changes in political climate would influence asset prices more strongly in states weaker economic conditions because the political sensitivity is likely to be stronger in those states.

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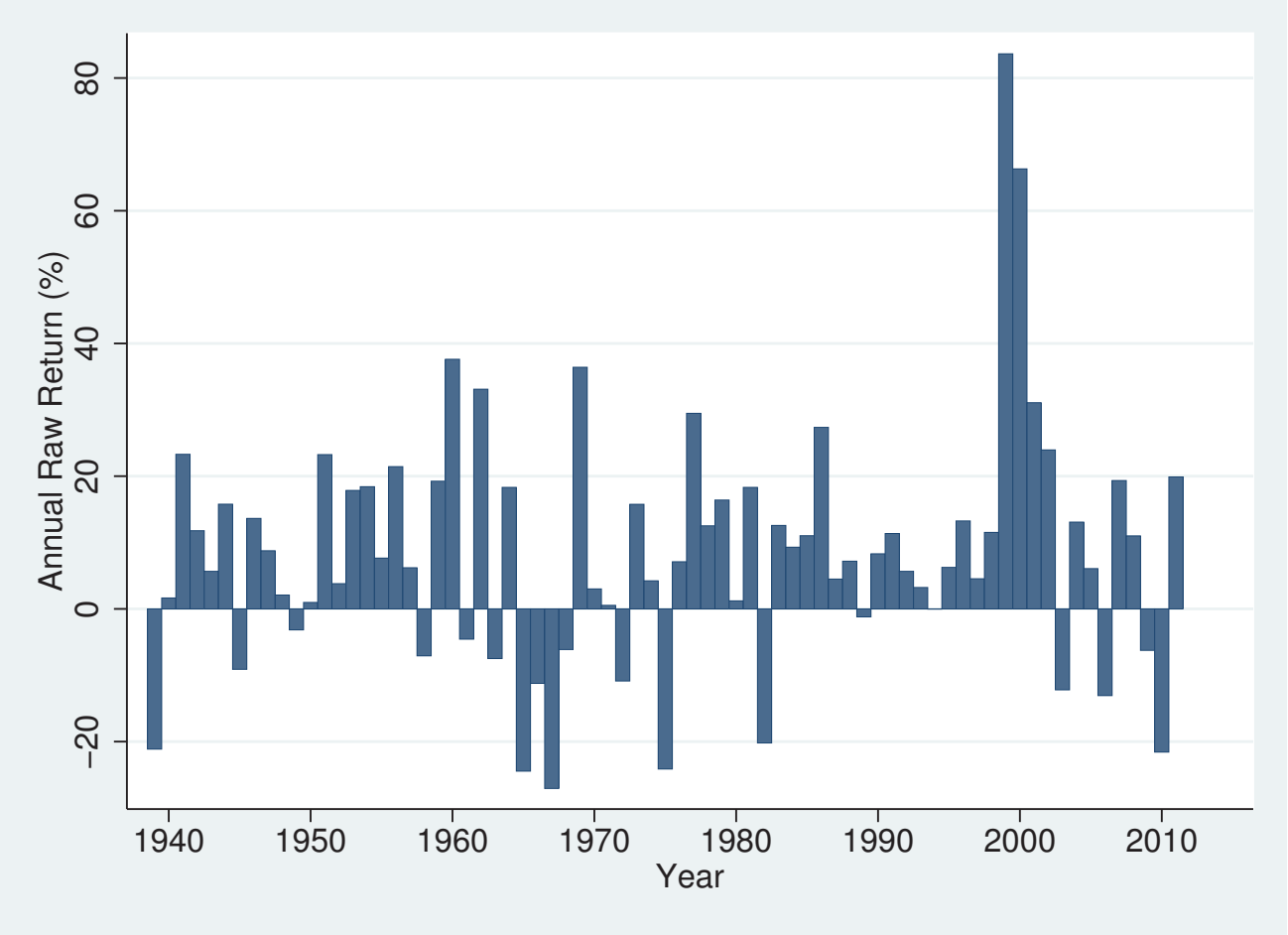
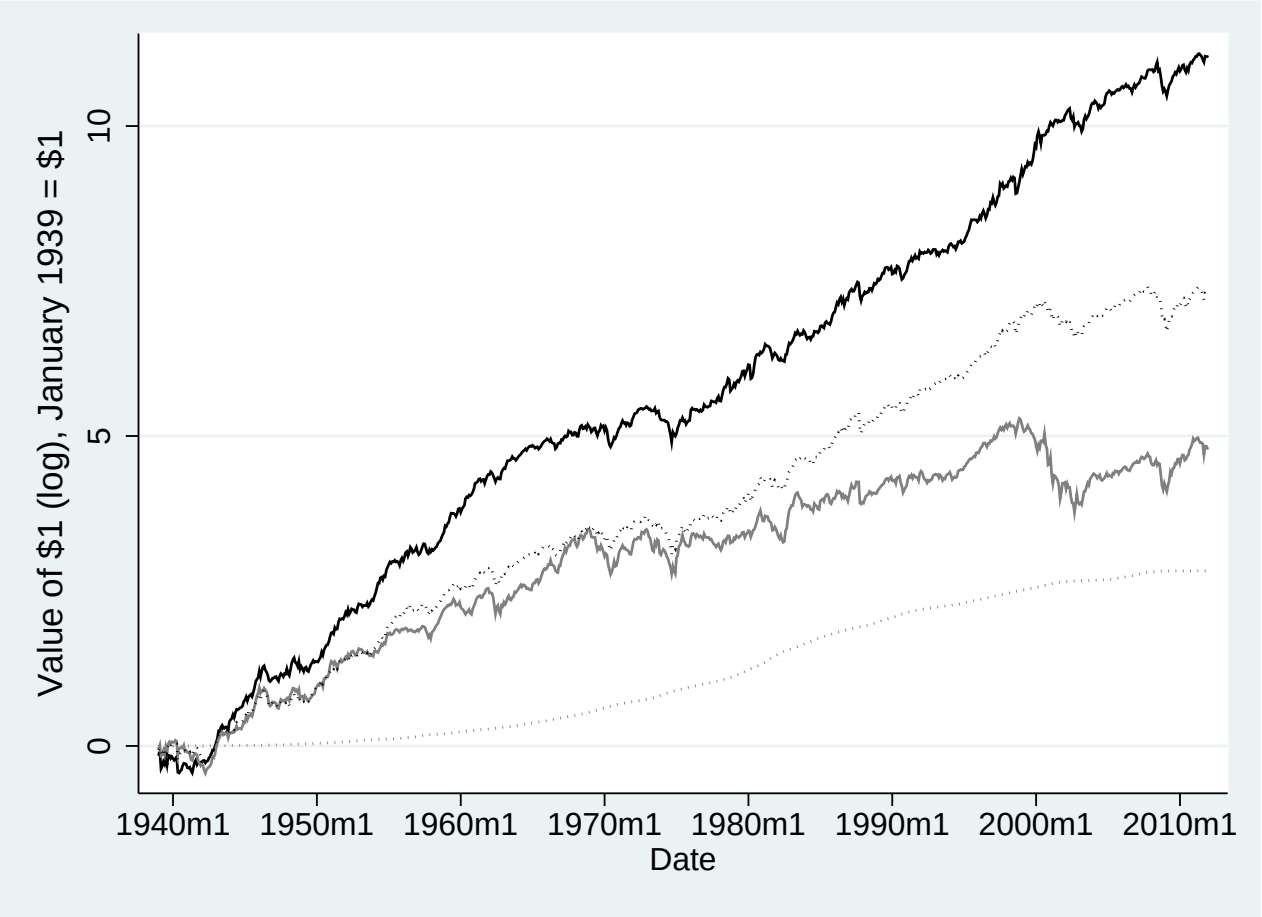
Figure 1: Political Sensitivity Based Industry Portfolio: Annual Returns



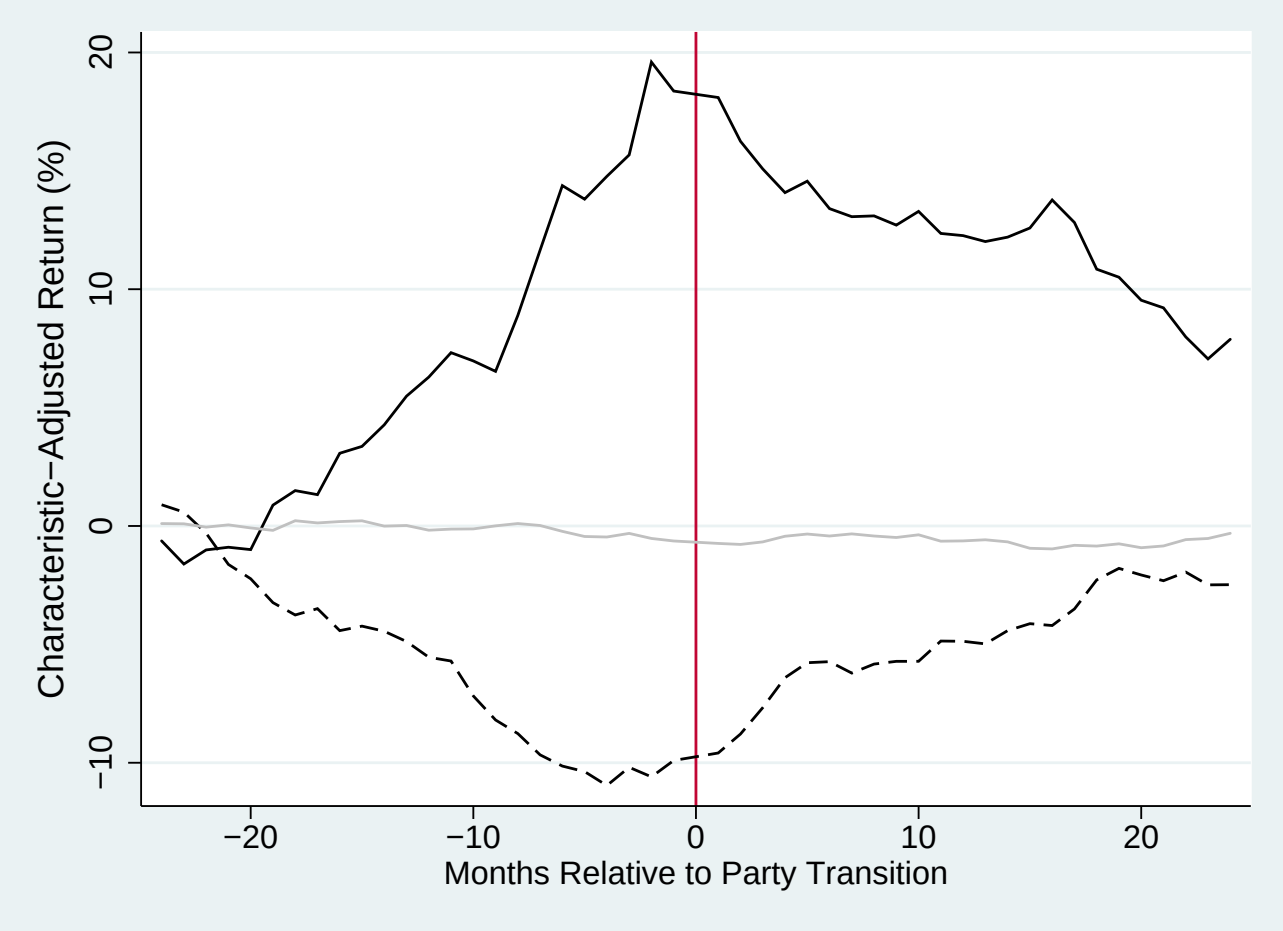
This figure shows the annual returns of the political sensitivity based Long-Short portfolio formed using value-weighted Fama and French (1997) 48 industry portfolios. The construction of the portfolios is described in Section 2.2. The sample period is from January 1939 to December 2011.

Figure 2: Relative Performance of Political Sensitivity Based Industry Portfolio



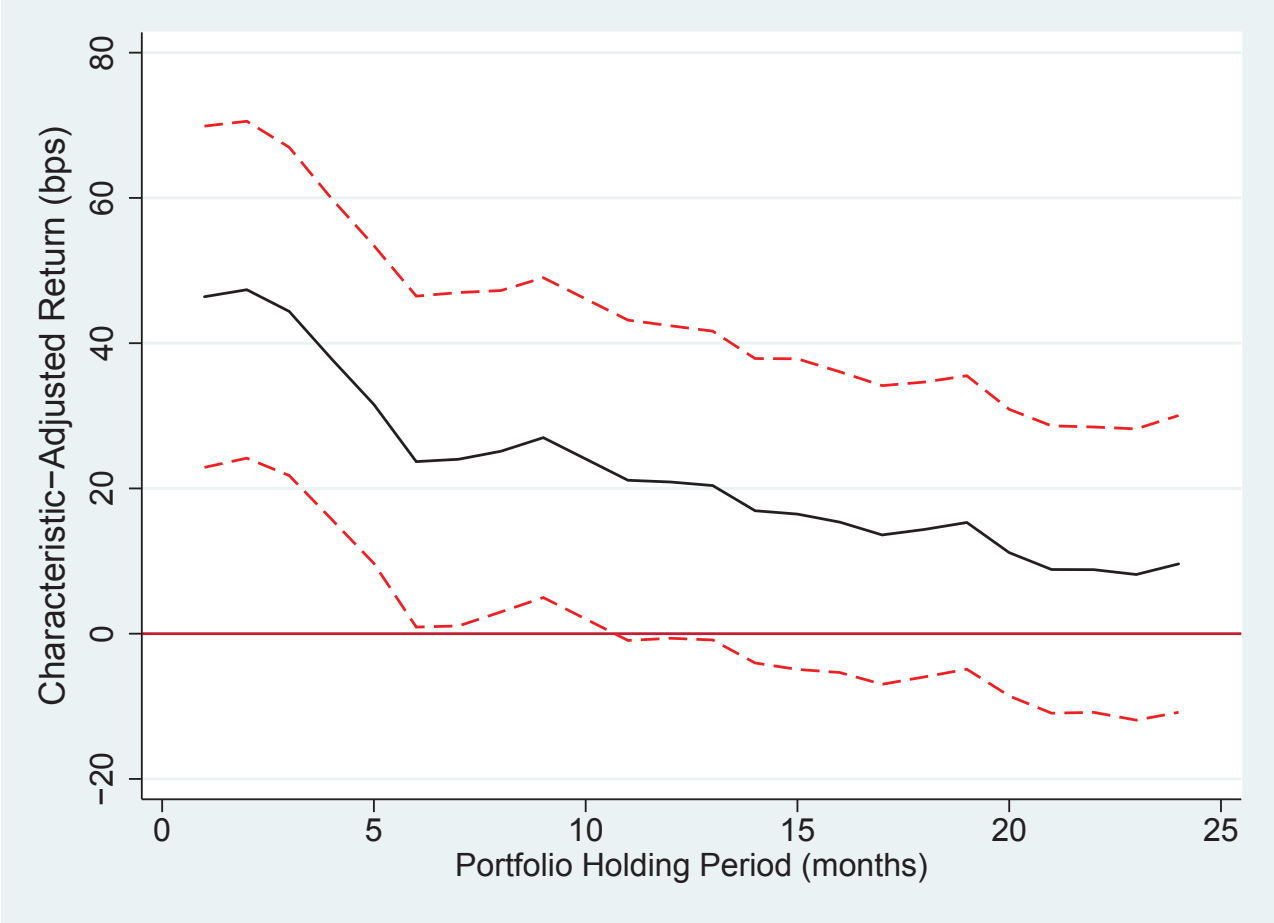
This figure shows the relative performance of political sensitivity based Long and Short portfolio formed using value-weighted Fama and French (1997) 48 industry portfolios. The performance of the aggregate stock market and the risk free asset are also shown. Long portfolio = dark solid, Short portfolio = light solid, Market portfolio = dark dashed, Risk free asset = light dashed. The sample period is from January 1939 to December 2011.

Figure 3: Cumulative Returns Surrounding Party Transitions



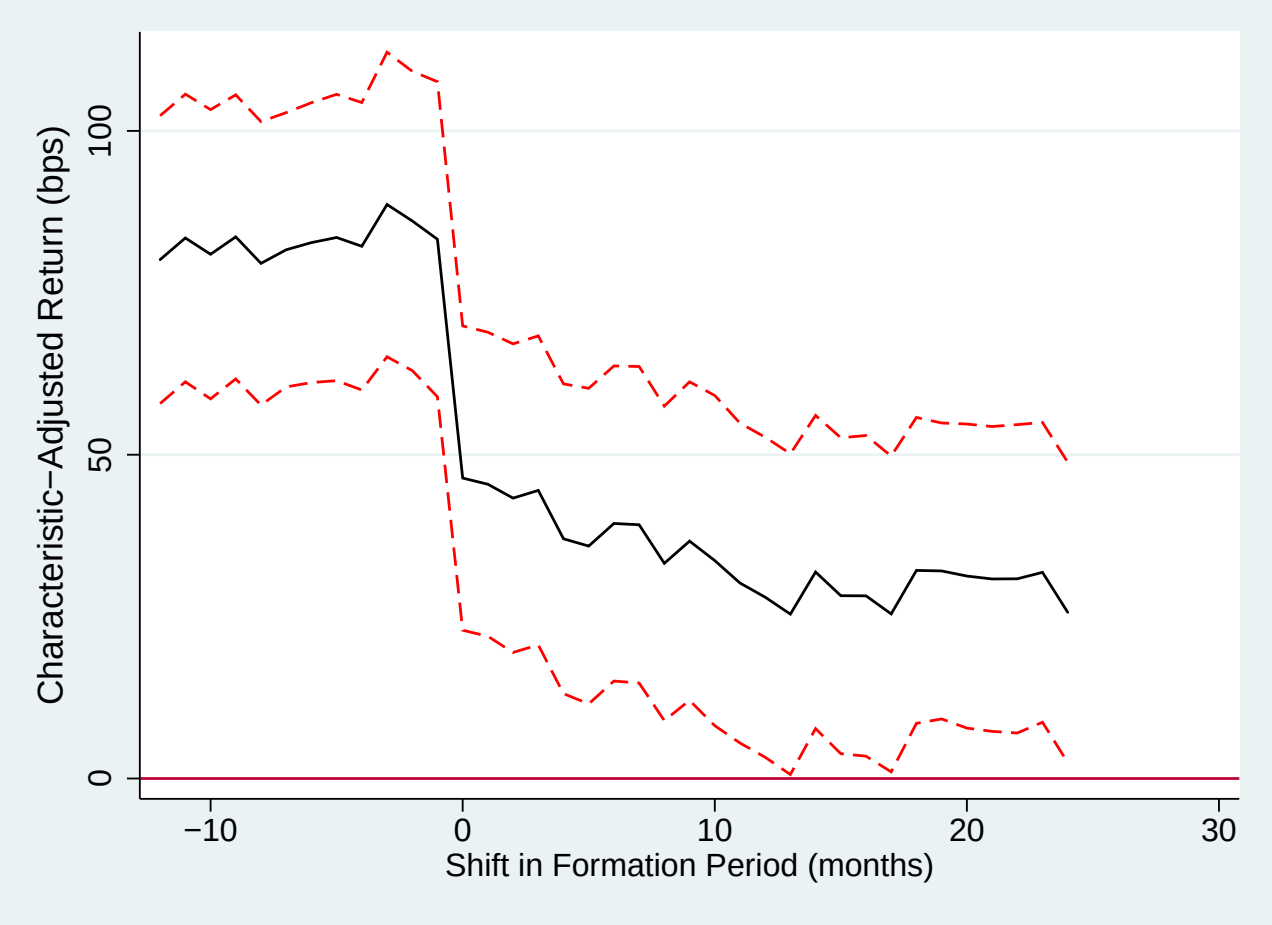
This figure displays cumulative characteristic-adjusted returns over the 48 months surrounding elections in which there is a change in presidential party. Cumulative returns are plotted for the long portfolio (dark solid line), the short portfolio (dark dashed line), and the average across the other 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 August of year $t-2$ and up until July of year $t+2$. Characteristic-adjusted returns are computed using the method of Daniel, Grinblatt, Titman, and Wermers (1997). The estimation period is from January 1939 to December 2011.

Figure 4: The Effect of Varying Portfolio Holding Periods



This figure shows the effect of varying portfolio holding periods on average monthly characteristic-adjusted returns (solid line) to the political sensitivity portfolio formed using value-weighted Fama and French (1997) 48 industry portfolios. Also shown are the two standard error bars (dashed lines). Characteristic-adjusted returns are computed using the method of Daniel, Grinblatt, Titman, and Wermers (1997). The estimation period is from January 1939 to December 2011.

Figure 5: The Effect of Varying Portfolio Formation Periods



This figure shows the effect of varying portfolio formation periods on average monthly characteristic-adjusted returns (solid line) to the political sensitivity portfolio formed using value-weighted Fama French 48 industry portfolios. A negative (positive) shift in formation period corresponds to early (delayed) formation of the Long and Short portfolios. A shift of zero is equivalent to the standard portfolio formation procedure. Also shown are ±2 standard error bars (dashed lines). Characteristic-adjusted returns are computed using the method of Daniel, Grinblatt, Titman, and Wermers (1997). The estimation period is from January 1939 to December 2011.

Table 1
Political Sensitivity Portfolios: Descriptive Characteristics

Panel A: Portfolio Characteristics

	FF 48 Industries				Individual Stocks			
Portfolio	Size	Book:Market	Lag 6m Return	Sin Stocks (%)	Size	Book:Market	Lag 6m Return	Sin Stocks (%)
1 (Short)	13.616	0.350	4.141	6.252	14.455	0.535	6.587	1.060
2	14.257	0.400	5.191	2.843	14.883	0.579	5.948	2.751
3	14.274	0.382	6.723	1.085	15.050	0.613	5.582	1.757
4	14.324	0.363	7.794	2.479	14.919	0.586	6.272	1.267
5 (Long)	14.115	0.329	11.531	7.191	14.283	0.561	8.124	0.625

Panel B: Top 5 Industries

	FF 48 Industries				Individual Stocks			
Ranking	Republican Long	Republican Short	Democrat Long	Democrat Short	Republican Long	Republican Short	Democrat Long	Democrat Short
1	Tobacco	Construction	Electronic Chips	Finance	Automobiles	Oil	Oil	Computers
2	Candy & Soda	Real Estate	Real Estate	Business Supplies	Retail	Electronic Chips	Business Services	Banking
3	Lab Equipment	Precious Metals	Construction	Aircraft	Pharmaceuticals	Healthcare	Aircraft	Automobiles
4	Boxes	Healthcare	Oil	Tobacco	Computers	Machinery	Electronic Chips	Pharmaceuticals
5	Food Products	Textiles	Books	Computers	Consumer Goods	Transportation	Transportation	Insurance

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 (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, iii) - v) portfolios 2 - 4, value-weighted portfolios of the remaining industries (quintiles of stocks) sorted into terciles based on predicted returns in the next month. Panel A reports mean size (log market capitalization), book-to-market ratio, returns over the previous six 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 48 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 Democrat presidencies. For industry portfolios, prevalence is measured by the number of months an industry is classified into a given portfolio over the estimation period. For individual stocks, prevalence is measured by the time-series average market capitalization weight of industry stocks in a given portfolio over the estimation period. The estimation period for industries is from January 1939 to December 2011, and for individual stocks is from January 1960 to December 2011.

Table 2

Political Sensitivity Industry Portfolios: Performance

Panel A: Portfolio Returns

	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 (Excess raw returns)

	Sample Period					
	1939 - 2011		1939 - 1975		1976 - 2011	
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: 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)

Panel D: Average Monthly Portfolio Market Shares

	Sample Period					
	1939 - 2011		1939 - 1975		1976 - 2011	
Portfolio	Raw Portfolios	Char-Adj Portfolios	Raw Portfolios	Char-Adj Portfolios	Raw Portfolios	Char-Adj Portfolios
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 48 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 time periods: January 1939 - December 2011, January 1939 - December 1975, and January 1976 - December 2011. Characteristic-adjusted returns are computed using the method of Daniel, Grinblatt, Titman, and Wermers (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 time 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 retrun portfolios.

Table 3
Political Sensitivity Stock Portfolios: Performance

Panel A: Portfolio Returns

	Sample Period					
	1952-2011		1952-1980		1981-2011	
Portfolio	Raw Return	Char-Adj Return	Raw Return	Char-Adj Return	Raw Return	Char-Adj Return
1 (Short)	0.735	-0.097	0.991	0.075	0.502	-0.254
	(3.06)	(-1.37)	(3.28)	(0.85)	(1.39)	(-2.41)
2	0.781	-0.169	0.787	-0.109	0.775	-0.224
	(4.01)	(-3.06)	(3.16)	(-1.85)	(2.68)	(-2.49)
3	0.938	0.011	0.929	-0.037	0.946	0.056
	(5.33)	(0.21)	(3.93)	(-0.58)	(3.73)	(0.68)
4	1.026	0.045	1.106	0.088	0.953	0.005
	(5.16)	(0.76)	(4.00)	(1.11)	(3.41)	(0.06)
5 (Long)	1.251	0.227	1.351	0.148	1.160	0.298
	(5.40)	(2.74)	(4.46)	(1.69)	(3.37)	(2.23)
Long - Short	0.516	0.323	0.360	0.073	0.659	0.553
	(3.48)	(2.94)	(1.98)	(0.58)	(2.89)	(3.22)
N months	713	713	341	341	372	372

Panel B: Portfolio Performance Characteristics (Excess raw returns)

	Sample Period					
	1952-2011		1952-1980		1981-2011	
Portfolio	Std Dev	Sharpe Ratio	Std Dev	Sharpe Ratio	Std Dev	Sharpe Ratio
1 (Short)	6.083	0.057	5.389	0.116	6.652	0.015
2	4.885	0.081	4.403	0.095	5.294	0.070
3	4.531	0.122	4.223	0.133	4.801	0.113
4	5.008	0.128	4.919	0.150	5.092	0.108
5 (Long)	5.729	0.151	5.344	0.184	6.066	0.125
Long - Short	3.783	0.136	3.466	0.104	4.050	0.163

Panel C: Average Monthly Portfolio Market Shares

	Sample Period					
	1952-2011		1952-1980		1981-2011	
Portfolio	Raw Portfolios	Char-Adj Portfolios	Raw Portfolios	Char-Adj Portfolios	Raw Portfolios	Char-Adj Portfolios
1 (Short)	13.319	13.450	13.427	13.907	13.219	13.031
2	24.635	24.994	27.888	28.665	21.653	21.629
3	25.424	26.024	24.394	25.515	26.368	26.489
4	22.181	21.599	18.775	17.463	25.303	25.391
5 (Long)	14.442	13.933	15.516	14.449	13.458	13.461

Panel D: Number of Stocks in Monthly Quintile Portfolios

	Sample Period					
	1952-2011		1952-1980		1981-2011	
Measure	Raw Portfolios	Char-Adj Portfolios	Raw Portfolios	Char-Adj Portfolios	Raw Portfolios	Char-Adj Portfolios
Mean	121.1	107.8	63.7	51.7	173.7	159.3
Std Dev	68.9	64.5	28.0	25.4	50.8	42.9
Min	33	28	33	28	71	69
Max	295	258	251	204	295	258

This table reports performance estimates of trading strategies defined using the political sensitivity return prediction model. Component returns are those of individual stocks. We report the performance of five value-weighted quintile portfolios, where stocks are sorted into quintiles based on predicted returns in the next month. Stocks in the "Short" ("Long") portfolio are predicted to have the lowest (highest) returns in the next month, and the "Long - Short" portfolio captures the difference in the returns of the Long and Short portfolios. In Panel A, we report raw and characteristic-adjusted portfolio returns over three time periods: August 1952 - December 2011, August 1952 - December 1980, and January 1981 - December 2011. Characteristic-adjusted returns are computed using the method of Daniel, Grinblatt, Titman, and Wermers (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 time periods. In Panel C, we report the average monthly market shares across portfolios for the raw and characteristic-adjusted return portfolios. In Panel D, we report statistics on the number of individual stocks in each quintile for the raw and characteristic-adjusted return portfolios.

Table 4
Political Sensitivity Industry Portfolios: Incumbent vs. 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)	1.007	-0.029	0.387	-0.288
	(3.93)	(-0.31)	(1.10)	(-2.06)
2	1.127	0.000	0.601	-0.168
	(5.76)	(0.01)	(2.10)	(-2.93)
3	0.969	-0.051	0.937	0.057
	(4.63)	(-1.65)	(3.81)	(1.16)
4	1.098	0.025	0.990	0.074
	(5.15)	(0.62)	(4.14)	(1.24)
5 (Long)	1.314	0.193	1.583	0.469
	(5.43)	(2.25)	(5.61)	(3.83)
Long - Short	0.307	0.222	1.196	0.757
	(1.71)	(1.68)	(3.82)	(3.77)
N months	478	478	384	384

	Panel B: Conditional Party Transitions			
	Republican to Democrat		Democrat to Republican	
Portfolio	Raw Return	Char-Adj Return	Raw Return	Char-Adj Return
1 (Short)	0.668	-0.130	0.106	-0.445
	(1.44)	(-0.76)	(0.20)	(-2.07)
2	0.559	-0.200	0.643	-0.136
	(1.29)	(-2.44)	(1.86)	(-1.75)
3	0.894	0.032	0.980	0.082
	(2.40)	(0.48)	(3.07)	(1.13)
4	0.989	0.078	0.992	0.070
	(2.64)	(1.10)	(3.30)	(0.71)
5 (Long)	1.474	0.494	1.693	0.444
	(3.92)	(2.98)	(3.97)	(2.46)
Long - Short	0.806	0.624	1.587	0.889
	(2.54)	(2.54)	(3.02)	(2.88)
N months	192	192	192	192

	Panel C: Conditional Incumbent Victories			
	Republican to Republican		Democrat to Democrat	
Portfolio	Raw Return	Char-Adj Return	Raw Return	Char-Adj Return
1 (Short)	0.810	-0.034	1.206	-0.023
	(2.09)	(-0.27)	(3.58)	(-0.17)
2	1.093	0.014	1.162	-0.014
	(3.88)	(0.22)	(4.19)	(-0.30)
3	0.883	-0.066	1.056	-0.035
	(2.80)	(-1.26)	(3.89)	(-1.04)
4	0.994	0.036	1.203	0.014
	(3.26)	(0.58)	(4.00)	(0.27)
5 (Long)	1.165	0.105	1.464	0.282
	(3.56)	(1.12)	(4.03)	(2.01)
Long - Short	0.355	0.139	0.258	0.305
	(1.40)	(0.80)	(0.97)	(1.50)
N months	240	240	238	238

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 48 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 four years (+/- 24 months) surrounding elections in which the incumbent president's party wins (loses). The estimation period is from January 1939 to October 2010. In Panel B, we further analyze challenger-victories, reporting portfolio returns for Repulican-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, Grinblatt, Titman, and Wermers (1997). The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates.

Table 5
Political Sensitivity Portfolio Factor Model Estimates

	Panel A: Fama-French 48 Industries											
	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short	Long	Short	Long-Short
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	-0.0520	1.018	1.055	-0.0368	0.962	1.035	-0.0723
	(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	-0.0445	0.192	0.163	0.0293	0.181	0.187	-0.00537
				(2.55)	(1.82)	(-0.33)	(3.67)	(1.86)	(0.24)	(3.14)	(2.01)	(-0.04)
HML				0.0191	-0.0363	0.0554	0.0855	-0.0472	0.133	-0.0131	-0.0977	0.0845
				(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	0.0498	-0.162	-0.0863	0.0551	-0.141
							(-2.28)	(0.73)	(-1.57)	(-1.43)	(0.66)	(-1.09)
LTR							-0.138	0.0207	-0.159	-0.170	-0.0157	-0.154
							(-2.08)	(0.23)	(-1.16)	(-1.93)	(-0.14)	(-0.85)
LIQ										0.0188	0.0139	0.00490
										(0.74)	(0.38)	(0.09)
Adj R-sq	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 48 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.

Panel B: Individual Stocks

Factor	Long (1)	Short (2)	Long-Short (3)	Long (4)	Short (5)	Long-Short (6)	Long (7)	Short (8)	Long-Short (9)	Long (10)	Short (11)	Long-Short (12)
Alpha	0.240	-0.298	0.538	0.253	-0.0687	0.322	0.300	-0.138	0.439	0.281	-0.118	0.399
	(2.33)	(-2.69)	(3.42)	(2.55)	(-0.59)	(2.16)	(2.81)	(-1.13)	(2.87)	(2.46)	(-0.89)	(2.47)
RMRF	1.173	1.214	-0.0404	1.130	1.138	-0.00846	1.140	1.115	0.0254	1.140	1.106	0.0336
	(38.07)	(31.01)	(-0.83)	(40.66)	(38.05)	(-0.23)	(41.82)	(33.91)	(0.69)	(35.70)	(28.65)	(0.81)
SMB				0.158	0.126	0.0322	0.196	0.153	0.0435	0.229	0.160	0.0694
				(3.09)	(1.72)	(0.49)	(3.85)	(2.49)	(0.64)	(4.09)	(2.48)	(0.96)
HML				-0.0957	-0.183	0.0869	-0.0528	-0.133	0.0799	-0.0632	-0.113	0.0496
				(-1.66)	(-1.78)	(0.74)	(-0.77)	(-1.25)	(0.59)	(-0.81)	(-0.97)	(0.34)
UMD				0.0156	-0.197	0.213	0.00114	-0.172	0.173	0.00148	-0.171	0.172
				(0.50)	(-2.62)	(3.08)	(0.03)	(-2.32)	(2.82)	(0.04)	(-2.24)	(2.70)
STR							-0.0854	0.123	-0.208	-0.0838	0.136	-0.220
							(-1.79)	(1.91)	(-2.71)	(-1.69)	(2.07)	(-2.81)
LTR							-0.0892	-0.126	0.0368	-0.109	-0.134	0.0253
							(-1.54)	(-1.59)	(0.37)	(-1.73)	(-1.57)	(0.24)
LIQ										-0.0161	0.0246	-0.0407
										(-0.80)	(0.84)	(-1.16)
Adj R-sq	0.721	0.714	0.000	0.751	0.743	0.054	0.753	0.750	0.073	0.776	0.746	0.079
N months	713	713	713	713	713	713	713	713	713	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 individual stocks. We consider the estimates of i) the "Long" portfolio, which is a value-weighted portfolio of the stocks falling in the highest quintile of predicted returns in the next month, ii) the "Short" portfolio, which is a value-weighted portfolio of the stocks falling in the lowest quintile of predicted 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 August 1952 to December 2011, except for models including the liquidity factor (LIQ), in which the estimation period is from August 1962 to December 2011.

Table 6
Political Sensitivity Portfolio Factor Model Robustness

	Fama French 48 Industries							Individual Stocks						
Sample	1939-1975	1976-2011	1939-2011	1939-2011	1952-2011	1952-2011	1952-2011	1952-1980	1981-2011	1952-2011	1952-2011	1952-2011	1952-2011	1952-2011
Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Alpha	0.481	0.640	0.562	0.544	0.554	0.551	0.583	0.260	0.582	0.396	0.421	0.452	0.483	0.455
	(2.21)	(2.10)	(2.44)	(2.33)	(2.33)	(2.32)	(2.20)	(1.13)	(2.77)	(2.37)	(2.49)	(2.88)	(3.11)	(2.71)
RMRF	0.011	-0.054	-0.037	-0.048	-0.044	-0.059	-0.079	0.082	-0.008	0.027	0.006	0.026	0.039	0.029
	(0.19)	(-0.69)	(-0.68)	(-0.74)	(-0.72)	(-0.97)	(-1.14)	(1.62)	(-0.15)	(0.75)	(0.13)	(0.70)	(1.07)	(0.62)
SMB	-0.304	0.209	0.029	0.072	-0.047	-0.043	-0.012	-0.174	0.185	0.045	-0.006	0.044	0.077	0.034
	(-2.40)	(1.53)	(0.24)	(0.55)	(-0.40)	(-0.38)	(-0.09)	(-1.94)	(1.83)	(0.68)	(-0.08)	(0.67)	(1.19)	(0.46)
HML	0.229	0.188	0.131	0.179	0.073	0.086	0.138	0.246	0.061	0.083	0.040	0.083	0.098	0.060
	(1.43)	(0.96)	(0.86)	(1.08)	(0.43)	(0.50)	(0.72)	(2.20)	(0.31)	(0.63)	(0.28)	(0.63)	(0.73)	(0.40)
UMD	0.198	0.435	0.386	0.375	0.431	0.440	0.436	0.156	0.169	0.175	0.196	0.175	0.183	0.201
	(1.80)	(4.19)	(4.46)	(4.29)	(4.49)	(4.69)	(4.65)	(2.01)	(2.08)	(2.96)	(3.30)	(2.94)	(3.07)	(3.38)
STR	-0.183	-0.115	-0.162	-0.161	-0.162	-0.166	-0.168	-0.147	-0.211	-0.209	-0.215	-0.208	-0.229	-0.234
	(-1.67)	(-0.81)	(-1.48)	(-1.48)	(-1.21)	(-1.25)	(-1.27)	(-1.23)	(-2.08)	(-2.59)	(-2.66)	(-2.53)	(-2.75)	(-2.80)
LTR	-0.293	-0.116	-0.157	-0.147	-0.141	-0.155	-0.116	-0.056	0.005	0.032	0.036	0.033	0.039	0.031
	(-2.26)	(-0.60)	(-1.16)	(-1.12)	(-0.85)	(-0.92)	(-0.70)	(-0.43)	(0.04)	(0.32)	(0.37)	(0.33)	(0.40)	(0.32)
REC			-0.151	-0.024			-0.181			0.259	0.169			0.206
			(-0.34)	(-0.06)			(-0.34)			(0.65)	(0.43)			(0.53)
CAY					0.043	0.055	0.040					0.014	0.024	0.029
					(0.45)	(0.55)	(0.40)					(0.18)	(0.32)	(0.39)
RMRF x REC				0.041			0.085				0.055			0.023
				(0.34)			(0.64)				(0.69)			(0.29)
SMB x REC				-0.292			-0.196				0.255			0.225
				(-1.30)			(-0.87)				(1.91)			(1.77)
HML x REC				-0.310			-0.284				0.148			0.149
				(-1.31)			(-1.10)				(1.00)			(1.05)
RMRF x CAY						0.018	0.024						-0.013	-0.018
						(0.53)	(0.66)						(-0.52)	(-0.72)
SMB x CAY						-0.040	-0.045						0.166	0.164
						(-0.76)	(-0.82)						(5.79)	(5.80)
HML x CAY						-0.080	-0.088						-0.004	-0.002
						(-1.12)	(-1.29)						(-0.08)	(-0.05)
Adj R-sq	0.154	0.140	0.124	0.129	0.144	0.145	0.147	0.066	0.087	0.065	0.069	0.065	0.099	0.101
N months	444	432	876	876	717	717	717	341	372	713	713	710	710	710

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 48 industry portfolios and individual stocks. 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)), an NBER Recession indicator (REC), and the Lettau-Ludvigson (2004) CAY measure. 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.

Table 7

Political Sensitivity and Expected Returns: 1963 - 2011

	FF48 Industry Returns			Individual Stock Returns		
Factor	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.424	0.234	0.533	0.533	0.514	1.838
	(2.46)	(1.26)	(0.88)	(2.56)	(2.52)	(3.22)
Beta_Political	1.669	1.339	1.026	5.144	6.374	6.791
	(3.60)	(2.96)	(2.46)	(1.68)	(2.28)	(3.26)
Beta_RMRF	0.874	0.439	0.748	27.54	27.15	28.66
	(0.60)	(0.31)	(0.55)	(5.29)	(5.38)	(5.43)
Beta_SMB	-1.020	-1.043	-0.932	-1.148	-2.012	-4.598
	(-1.40)	(-1.49)	(-1.33)	(-0.51)	(-0.94)	(-2.40)
Beta_HML	1.384	0.947	0.559	-0.803	-1.005	-0.686
	(2.47)	(1.77)	(1.10)	(-0.52)	(-0.68)	(-0.49)
Lagged 6mRet		0.015	0.015		-0.537	-0.426
		(2.98)	(2.91)		(-2.93)	(-2.52)
Size			-0.023			-0.119
			(-0.64)			(-3.37)
Book-to-market			-0.004			0.136
			(-0.02)			(2.57)
Avg Adj-R-squared	0.162	0.203	0.236	0.031	0.039	0.058
N months	581	581	581	581	581	581

This table reports estimates from Fama-MacBeth (1973) regressions. Asset returns under consideration are those of value-weighted Fama-French 48 industry portfolios and individual stocks. We regress monthly returns on the following regressors: lagged political sensitivity loading, industry Fama-French 3-factor loadings calculated over the previous month, industry return over the previous six months, value-weighted log market capitalization of industry-firms at the beginning of the previous month, and value-weighted book-to-market ratio of industry-firms available six months prior. We report the time-series average of cross-sectional adjusted R-squareds. 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.

Table 8
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

	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 48 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 48 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 48 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 48 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, Grinblatt, Titman, and Wermers (1997). The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates.

Table 9

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	-0.0313
	(2.12)	(-2.15)	(2.76)	(-0.32)
2	1.011	-0.0557	0.788	-0.0770
	(4.46)	(-1.04)	(3.17)	(-1.71)
3	0.943	-0.0235	0.955	0.0176
	(4.13)	(-0.58)	(4.49)	(0.47)
4	1.081	0.0615	0.996	0.0276
	(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 48 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, Grinblatt, Titman, and Wermers (1997). The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates.

Table 10
Political Sensitivity Portfolios: Validation Test

Panel A: Equal-weighted Portfolio Coincidence

	FF 48 Industries					Individual Stocks				
	UBS/Gallup Ranking					UBS/Gallup Ranking				
Political Ranking	1 (Short)	2	3	4	5 (Long)	1 (Short)	2	3	4	5 (Long)
1 (Short)	40.000	60.000	0.000	0.000	0.000	76.471	15.882	6.471	1.176	0.000
2	25.000	41.667	33.333	0.000	0.000	17.751	49.704	23.669	5.917	2.959
3	0.000	28.571	50.000	14.286	7.142	4.142	26.627	36.094	30.178	2.959
4	0.000	0.000	25.000	58.333	16.667	1.775	6.509	26.627	40.828	24.260
5 (Long)	0.000	0.000	0.000	60.000	40.000	0.000	1.183	7.101	21.893	69.822

Panel B: Value-weighted Portfolio Coincidence

	FF 48 Industries					Individual Stocks				
	UBS/Gallup Ranking					UBS/Gallup Ranking				
Political Ranking	1 (Short)	2	3	4	5 (Long)	1 (Short)	2	3	4	5 (Long)
1 (Short)	37.719	62.281	0.000	0.000	0.000	83.973	12.374	3.643	0.010	0.000
2	44.557	30.932	24.511	0.000	0.000	13.005	54.981	30.815	1.020	0.179
3	0.000	43.923	26.257	26.662	3.158	4.552	34.143	46.032	15.065	0.208
4	0.000	0.000	45.459	50.514	4.027	0.034	4.752	45.078	31.919	18.216
5 (Long)	0.000	0.000	0.000	86.395	13.605	0.000	0.471	9.467	27.651	62.411

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. 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.

Table 11

Political Sensitivity Industry Portfolios: Term Years and Attention Periods

	Panel A: Year in Presidential Term							
	Predictive Term-Years (August to July)				Actual Term-Years (February to January)			
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	-0.146	-0.099	-0.228	-0.152
	(-1.49)	(-2.07)	(0.76)	(-1.37)	(-1.02)	(-0.56)	(-1.40)	(-1.11)
2	-0.030	-0.049	-0.100	-0.083	0.026	-0.135	-0.128	-0.099
	(-0.43)	(-0.64)	(-1.50)	(-1.26)	(0.36)	(-1.78)	(-2.24)	(-1.41)
3	0.010	-0.035	0.028	-0.017	-0.086	0.039	0.065	-0.014
	(0.17)	(-0.63)	(0.54)	(-0.30)	(-1.58)	(0.66)	(1.30)	(-0.22)
4	0.047	0.079	0.031	0.024	0.097	0.035	0.058	-0.003
	(0.64)	(1.10)	(0.45)	(0.39)	(1.46)	(0.47)	(0.85)	(-0.04)
5 (Long)	0.409	0.322	0.218	0.293	0.227	0.254	0.264	0.511
	(2.67)	(2.22)	(1.80)	(1.76)	(1.55)	(2.19)	(1.93)	(2.79)
Long - Short	0.615	0.653	0.087	0.511	0.373	0.352	0.492	0.664
	(2.73)	(2.85)	(0.36)	(2.13)	(1.72)	(1.47)	(2.25)	(2.73)
N months	216	216	223	221	216	217	209	216

	Panel B: Returns Across Political Attention Periods							
	High Attention - Months surrounding election				Low Attention - 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 time periods across the presidential term. Component returns are those of value-weighted Fama-French 48 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 February 1 to January 31 of the following year. Predictive term-years are 6-month forward-looking, running from August 1 to July 31 of the following year. In Panel B, we report characteristic-adjusted portfolio returns over high- and low-attention periods. High political attention periods are defined as months surrounding the November presidential election. Low political attention periods are defined as months surrounding the January midterm of the sitting President two 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, Grinblatt, Titman, and Wermers (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.

Table 12
Turnover, Volatility, and High Political Attention Period

Panel A: Asset Turnover

	FF 48 Industries				Individual Stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Attention x New Party	1.241	1.210	1.195	1.161	0.458	0.493	0.435	0.471
	(4.31)	(4.08)	(4.10)	(3.85)	(4.34)	(4.72)	(4.13)	(4.51)
High Attention	0.177	0.170	0.210	0.204	0.139	0.209	0.254	0.328
	(1.60)	(1.54)	(1.93)	(1.89)	(1.91)	(2.84)	(3.38)	(4.31)
Lag 1m Return		0.038		0.040		0.070		0.072
		(3.01)		(3.03)		(19.57)		(19.70)
Lag2 6m Return			0.012	0.013			0.014	0.014
			(2.84)	(2.89)			(8.78)	(8.81)
Asset-Term FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N obs	46482	46482	46482	46482	2761781	2761781	2761781	2761781
Adj R-squared	0.755	0.757	0.756	0.758	0.021	0.026	0.024	0.030

Panel B: Asset Volatility

	FF 48 Industries				Individual Stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Attention x New Party	0.514	0.524	0.506	0.516	1.154	1.151	1.158	1.155
	(10.81)	(11.45)	(11.05)	(11.69)	(61.79)	(62.26)	(62.40)	(62.87)
High Attention	-0.214	-0.223	-0.212	-0.221	-0.307	-0.318	-0.322	-0.333
	(-14.40)	(-14.80)	(-14.22)	(-14.54)	(-38.49)	(-40.00)	(-39.87)	(-41.26)
Lag 1m Return		-0.021		-0.021		-0.010		-0.011
		(-15.53)		(-15.83)		(-45.66)		(-44.82)
Lag2 6m Return			-0.004	-0.004			-0.002	-0.002
			(-10.04)	(-10.26)			(-9.11)	(-9.13)
Asset-Term FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N obs	27576	27576	27576	27576	2913208	2913208	2913208	2913208
Adj R-squared	0.366	0.403	0.381	0.418	0.022	0.028	0.026	0.031

This table reports estimates from panel regressions of monthly asset turnover (Panel A) and monthly asset return volatility (Panel B) on the following regressors: an indicator for high political attention periods, the return over the previous month, and the return over the six months ending at the beginning of the previous month. All regressions are estimated using time series variation within presidential terms (asset-term fixed effects). The high political attention period indicator takes the value one for months falling within one year (+/- 6 months) of a presidential election, and zero otherwise. The new presidential party indicator takes the value one during high political attention periods surrounding elections in which the party of the incumbent president loses the election. For individual stocks, turnover is calculated as monthly stock volume divided by shares outstanding at the end of the month. For industry portfolios, turnover is calculated as the value-weighted average of component-industry stocks' turnovers during each month. For both individual stocks and value-weighted industry portfolios, volatility is calculated as the standard deviation of daily returns during the month. The t-statistics computed using industry-term cluster-robust standard errors are reported in parentheses below the estimates. The estimation period is from January 1964 to December 2011 for industries and January 1927 to December 2011 for individual stocks.

Table 13
Political Sensitivity, Attention Periods, and Future Operating Performance

	Panel A: FF48 Industries					
	Dependent variable: Return on Assets, *h* -quarters ahead					
Predictor	*h* = 1	*h* = 2	*h* = 3	*h* = 4	*h* = 8	*h* = 12
Constant	0.004	0.004	0.005	0.003	0.006	0.008
	(7.21)	(6.18)	(8.01)	(5.92)	(8.83)	(8.98)
Beta_Political x High Attn	0.242	0.241	0.104	-0.111	-0.208	-0.058
	(1.51)	(1.42)	(0.61)	(-0.71)	(-1.27)	(-0.40)
Beta_Political x Low Attn	0.095	0.051	-0.028	-0.084	-0.435	-0.537
	(0.67)	(0.35)	(-0.19)	(-0.62)	(-1.67)	(-1.99)
Market-to-Book Equity	1.800	1.923	1.911	0.599	0.714	0.649
	(6.46)	(6.12)	(6.06)	(3.37)	(2.40)	(2.01)
No-dividend Indicator	-0.002	-0.004	-0.003	-0.001	-0.004	-0.005
	(-1.32)	(-2.36)	(-2.06)	(-1.01)	(-2.07)	(-2.13)
Dividends-to-Book Equity	-0.054	0.105	-0.027	-0.096	-0.223	-0.335
	(-0.84)	(1.24)	(-0.31)	(-1.25)	(-2.18)	(-2.11)
ROA	0.497	0.470	0.439	0.711	0.590	0.521
	(13.09)	(13.36)	(10.92)	(19.25)	(11.96)	(10.57)
N months	167	166	165	164	160	156
Avg Adj R-squared	0.421	0.400	0.355	0.534	0.397	0.329
High - Low: Beta_Political	0.147	0.190	0.133	-0.027	0.227	0.479
	(0.66)	(0.82)	(0.59)	(-0.14)	(0.77)	(1.64)

	Panel B: Individual Stocks					
	Dependent variable: Return on Assets, *h* -quarters ahead					
Predictor	*h* = 1	*h* = 2	*h* = 3	*h* = 4	*h* = 8	*h* = 12
Constant	0.006	0.007	0.006	0.004	0.005	0.005
	(15.20)	(13.94)	(12.68)	(5.66)	(8.67)	(7.52)
Beta_Political x High Attn	0.302	0.408	0.328	0.163	0.006	-0.160
	(2.60)	(2.86)	(2.58)	(1.70)	(0.05)	(-1.45)
Beta_Political x Low Attn	0.252	0.147	0.139	0.115	-0.072	0.182
	(2.35)	(1.02)	(1.25)	(1.38)	(-0.55)	(0.87)
Market-to-Book Equity	0.745	0.775	0.859	0.487	0.561	0.563
	(3.12)	(3.18)	(3.63)	(2.55)	(2.79)	(2.11)
No-dividend Indicator	-0.009	-0.009	-0.009	-0.004	-0.005	-0.004
	(-8.91)	(-9.86)	(-9.31)	(-3.25)	(-3.86)	(-3.24)
Dividends-to-Book Equity	0.013	0.014	0.016	0.431	0.175	0.349
	(4.00)	(4.55)	(4.40)	(3.83)	(1.73)	(2.54)
ROA	0.423	0.347	0.382	0.518	0.458	0.376
	(20.23)	(10.62)	(16.08)	(19.31)	(15.70)	(6.96)
N months	167	166	165	164	160	156
Avg Adj R-squared	0.230	0.195	0.170	0.236	0.165	0.132
High - Low: Beta_Political	0.050	0.261	0.189	0.048	0.078	-0.343
	(0.32)	(1.31)	(1.09)	(0.38)	(0.44)	(-1.48)

This table reports estimates from Fama-MacBeth (1973) regressions. *h* -quarter ahead performance measures under consideration are those of value-weighted Fama-French 48 industry portfolios and individual stocks. We regress *h* -quarter ahead return on assets on the following regressors: political sensitivity interacted with high- and low-political-attention indicators, market-to-book equity ratio, an indicator for non-dividend paying stocks, and the ratio of dividends to book equity, following Fama and French (2000). We also include as a regressor return on assets in the current period, following Vuolteenaho (2002) and Hou and Robinson (2006). The high (low) political attention indicator is equal to one (zero) during the +/- 4 quarters surrounding Presidential elections, and zero (one) otherwise. Return on assets is calculated as operating income before extraordinary items and accrued interest divided by the book value of total assets at the end of each quarter. We report the time-series average of cross-sectional adjusted R-squareds. The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from January 1970 to December 2011 for *h* =1. For *h* >1, the estimation period decreases by *h* -1 quarters.