Financial Management

Underreaction to Political Information and Price Momentum

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In this study, we examine whether momentum in stock prices is induced by changes in the political environment. We find that momentum profits are concentrated among politically sensitive firms and industries. From 1939 to 2016, a trading strategy with a long position in winner portfolios (industries or firms) that are politically unfavored and a short position in losers that are politically favored does not generate significant momentum profits. Furthermore, our political-sensitivity-based long-short portfolio explains 23% to 27% (42% to 43%) of monthly stock (industry) momentum alphas. This explanatory power is concentrated around presidential elections, when the level of political activity is high. Collectively, our results suggest that investor underreaction to political information generates momentum in stock and industry returns.

Momentum in stock returns is perhaps one of the most robust empirical patterns identified in the recent asset pricing literature. Although there is general agreement in the literature that momentum profits are large and pervasive (e.g., Asness, Moskowitz, and Pedersen, 2013), there is considerable debate about the economic determinants of momentum in stock returns. On the one hand, Berk, Green, and Naik (1999), Johnson (2002), Sagi and Seasholes (2007), and Liu and Zhang (2008, 2014) propose risk-based explanations of momentum profits. On the other hand, Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), and Grinblatt and Han (2005) posit that momentum in returns is driven by underreaction to news. Moreover, Hong, Lim, and Stein (2000) demonstrate that slow information diffusion is an important driver of momentum in stock returns.

In this article, we identify a new economic mechanism that generates momentum in stock prices. Specifically, we posit that sensitivity of firms and industries to a changing political environment is an important driver of momentum in returns. Our key insight is that certain types of firms and industries are more likely to benefit from the policies of the Republican or the Democratic party. Similarly, certain market segments may be more adversely affected by specific party policies. For example, environmentally friendly firms may expect to benefit from the policies of the Democratic party, whereas industries such as defense, tobacco, and guns may be favored by a Republican regime.

If shifts in the political climate can be predicted, the stock prices of certain firms and industries would start to rise or fall in anticipation of a shift in the political climate. If investors incorporate

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news about a potential shift in the political environment with some delay, because either the outcome is not certain or the investors are slower to respond to perceived changes in the economic environment, stock prices may not adjust immediately. This adjustment process may extend over several weeks or even months.

Investors may find interpretation of news tied to the political cycle difficult for several reasons. First, investors may perceive the party in power to be only a noisy signal of economic policies and hence may not anticipate differences over partisan cycles. Second, because of the relatively small sample of presidential cycles, investors may find it difficult to identify the systematic effects associated with the party in power. Finally, such systematic effects may be time varying, making the problem of identifying and interpreting new political information especially difficult for investors.

Given the potential delay in the interpretation of new political information, valuations of firms and industries that are expected to benefit from the new political regime should gradually rise surrounding the change in ruling party. Similarly, if the new party is expected to affect other firms adversely, these firms' valuations should gradually decline following the change in the political environment. Overall, our main conjecture is that around political events, changes in the political climate induce momentum in stock prices.[1] More generally, we posit that even during other periods, time variation in the political environment generates time-varying momentum profits. This key conjecture is motivated by a growing literature in finance that establishes a link between the political environment and stock market returns.

Specifically, Cooper, Gulen, and Ovtchinnikov (2010), Belo, Gala, and Li (2013), and Kim, Pantzalis, and Park (2012) provide evidence of return predictability induced by political connections, government spending, and geography-based political alignment, respectively. The political climate is also an important determinant of investors' portfolio decisions. For example, Bonaparte, Kumar, and Page (2012) and Addoum and Kumar (2016) show that investors adjust their portfolios following changes in the political environment. In particular, Addoum and Kumar (2016) demonstrate that retail and institutional investors gradually tilt their portfolios toward stocks in politically favored industries when there is a change in the presidential party. Although they show that these portfolio reallocations in turn generate short-term predictability in stock and industry returns, Addoum and Kumar (2016) do not examine the impact of shifts in the political environment on momentum profits.

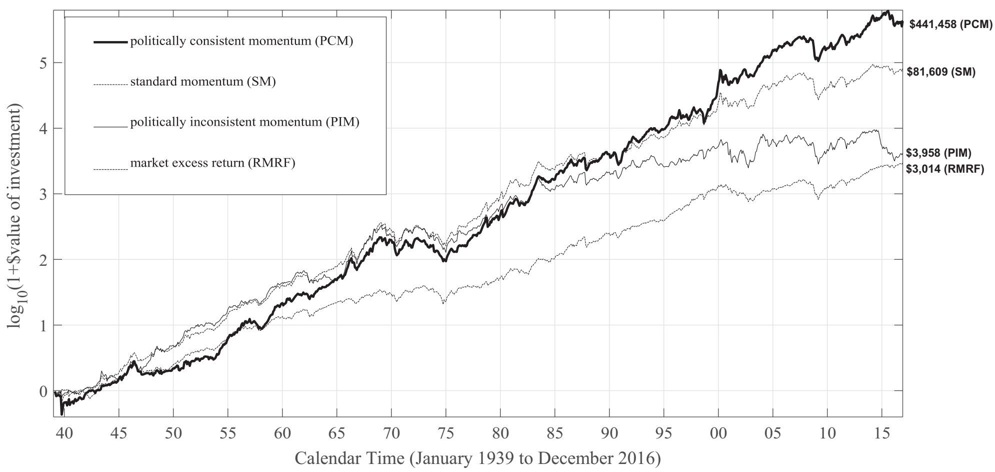
Our article links this growing literature on politics to the literature on price momentum and demonstrates that momentum profits are influenced by the political climate. In our empirical analysis, we identify politically sensitive firms and industries and show that a large part of momentum profits can be attributed to underreaction to political information. Specifically, we construct a long-short portfolio based on political sensitivity estimates of firms and industries. We measure political sensitivity using the Addoum and Kumar (2016) method and classify momentum winner and loser portfolios into politically consistent (i.e., favored) and politically inconsistent (i.e., unfavored) categories.

We find that the politically consistent momentum strategy, which takes a long position in stocks (industries) that are both winners and politically favored and a short position in stocks (industries) that are both losers and politically unfavored, outperforms the standard momentum strategy by 5.04% (2.01%) on an annual basis during our 1939-2016 sample period. Furthermore,

[1] To help build intuition for this mechanism, we conduct a case study examining the evolution of industry momentum portfolio components in the months following the 2016 presidential election. We show that the resulting change in the political environment induced a gradual shift in momentum decile portfolio classifications, with some momentum winners even becoming losers (and vice versa) in the six to nine months after the election. See Appendix A for details.

Figure 1. Cumulative Gains for Different Momentum Portfolios

This figure presents cumulative monthly log-returns for investing in: (1) the politically consistent momentum portfolio, (2) the standard momentum portfolio, (3) the politically inconsistent momentum portfolio, and (4) the market excess return portfolio. The *y*-axis shows cumulative log returns for each portfolio. On the right side of the plot, we present final dollar values for each of the four long-short strategies.



the politically inconsistent momentum strategy, which has a long position in stocks (industries) that are winners but politically unfavored and a short position in stocks (industries) that are losers but politically favored, generates returns that are statistically indistinguishable from zero.

Figure 1 highlights the importance of political sensitivity in momentum returns. We find that during 1939-2016, a $1 investment in the politically consistent momentum strategy grows to more than five times the value of $1 invested in the standard momentum strategy and more than 100 times the value of $1 invested in the politically inconsistent momentum strategy. This evidence indicates that the profitability of the momentum strategy depends critically on the sensitivity of firms to the changing political climate. When the political environment is misaligned with the winner and loser portfolios, the momentum strategy yields economically insignificant profits.

In additional tests, we investigate the ability of a political-sensitivity-based long-short portfolio (POL) to explain the time variation in momentum profits. POL represents the difference between the value-weighted returns of a portfolio of firms that are expected to benefit from the new political environment and the value-weighted returns of firms that are expected to be most adversely affected by the new political environment. In the presence of several additional asset pricing factors, we find that a large portion of the time-series of momentum profits can be explained by the time variation in POL returns. The incremental explanatory power of our political sensitivity measure is economically meaningful as it eliminates approximately 23% to 27% of monthly momentum alphas during 1939-2016.

We also examine the relation between returns to POL and a momentum strategy formed using industry returns. Moskowitz and Grinblatt (1999) suggest that industry momentum drives much of the momentum profits in stocks. In turn, we find that a significant portion of industry momentum alphas can be explained by POL. Specifically, we show that approximately 42% to 43% of industry momentum alphas can be attributed to time-varying political sensitivity of industry portfolios.[2]

To better understand the relation between political cycles and momentum returns, we consider subperiods around elections in which the party in power changes or stays the same. Consistent with our main conjecture, we find that the explanatory power of political sensitivity is especially strong during subperiods in which there is a change in power and the political environment changes considerably.[3]

Collectively, our findings contribute to the finance literature that attempts to understand the origins of momentum returns. Chordia and Shivakumar (2002) posit that momentum returns can be explained by a set of macroeconomic predictors. Cooper et al. (2004) relate momentum to prior stock market movements. Avramov et al. (2007) show that momentum is related to credit ratings, and Stivers and Sun (2010) advance the cross-sectional dispersion of returns as an important determinant of momentum. More recently, Daniel and Moskowitz (2016) relate momentum to market crashes and stock market volatility, and Asness et al. (2013) consider an extensive set of macroeconomic and liquidity controls.

Our article contributes to this literature by demonstrating that shifts in the political climate are an important determinant of momentum returns. In particular, our results provide empirical support for behavioral theories that suggest momentum in stock returns is driven by investor underreaction to news. Our key innovation is to demonstrate that changes in the political climate are an important source of such news, which originates outside of financial markets. Although investor underreaction to new information is one of the most prominent explanations for momentum, previous studies do not typically identify the actual sources of information to which investors underreact. In contrast, we show that investor underreaction to political information can explain a significant portion of the time-series variation in momentum returns.

The rest of the article is organized as follows. In Section I, we describe our data and the method for constructing momentum and political portfolios. Section II presents the main empirical results. Section III presents evidence from additional robustness tests and tests of alternative explanations for our key findings. Section IV concludes with a brief summary.

[2] We also examine the potential relation between political sensitivity and earnings momentum returns at both the firm and industry levels. We find that POL explains an economically and statistically insignificant portion of earnings momentum returns. This evidence is consistent with the findings of Chan, Jegadeesh, and Lakonishok (1996) and suggests that earnings and price momentum signals capture distinct sources of information about future returns. See Section III.C for details.

[3] We also consider whether the link between POL and momentum returns extends to international markets. In particular, we combine monthly return data for Level 6 classification industries from Datastream International with national election results from the Comparative Political Data Set made available by the Institute of Political Science at the University of Bern for the following countries: Canada, France, Germany, Japan, the United Kingdom, and the United States. We then estimate the political sensitivity of each country-specific industry portfolio to the country's party in power (left or right leaning). We also estimate the political sensitivity of foreign industry portfolios to the party in power in the United States. Using these sets of political sensitivity estimates, we find that only the US-based political sensitivity estimates yield significant predictability. Furthermore, we find that this predictability is concentrated in Canada, France, and the United Kingdom, countries where momentum is known to be profitable (Chui, Titman, and Wei, 2010; Asness et al., 2013). In Japan, where momentum performs poorly, the predictability results are relatively weak. Overall, this analysis suggests that the link between the political environment and momentum returns that we document in the United States may extend to other countries. We leave a closer examination of this conjecture for future research.

I. Data and Methods

A. Main Data Sources

We obtain monthly stock returns, stock prices, and shares outstanding from the Center for Research in Security Prices (CRSP), and Standard Industry Classification (SIC) codes from Compustat. We consider only common shares, restricting the sample to observations with share codes 10 or 11. We also obtain monthly Fama-French factor returns, 48 SIC industry classifications, and 48 industry monthly value-weighted portfolio returns from Kenneth French's data library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Investor sentiment data are from Jeffrey Wurgler's Web page (http://people.stern.nyu.edu/jwurgler/), and market liquidity data are from Lubos Pastor's Web site (http://faculty.chicagobooth.edu/lubos.pastor/research/). Finally, we obtain National Bureau of Economic Research (NBER) recession indicators from the NBER Web site (http://www.nber.org/cycles.html), and data on presidential election outcomes from the CQ Press Voting and Elections Collection.

B. Identifying Politically Favored Firms and Industries

To identify firms and industries that are politically favored, we construct a measure of political sensitivity at the stock and industry levels using the method proposed in Addoum and Kumar (2016). The estimation process is summarized for industry portfolios.

Each month, for each of the 48 Fama and French (1997) industry portfolios, we regress excess industry returns during the past 15 years (180 months) on excess market returns and a presidential party indicator. Specifically, we estimate the following time-series regression:

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

In this equation, the presidential party indicator variable ($RepubInd_t$) is equal to one when the presidential party is Republican and zero when it is Democratic. We define the presidential party indicator variable based on national election outcomes. Although the political environment depends on factors beyond the presidential party (e.g., the president's approval rating, congressional control, and lobbying activities), our simple approach is motivated by past studies of politics and the macroeconomy. In particular, Santa-Clara and Valkanov (2003) and Addoum and Kumar (2016) find that congressional control has little impact on the effects associated with the president's partisan ties. Furthermore, our market-based measure of political sensitivity is available for a long sample period and provides evidence that investors underreact to even highly salient information captured by the presidential party.

We measure political sensitivity using rolling windows to allow for time variation in both the magnitude and direction of our political sensitivity estimates. Our focus is on the θ_i estimate, which captures the political sensitivity of an industry or of a single stock. A positive θ_i estimate indicates that the industry (stock) earns higher average returns during Republican presidential terms, and a negative θ_i estimate indicates that the industry (stock) earns higher returns during Democratic presidential terms.

We choose a 15-year rolling window to ensure that there is always a change in presidential party affiliation during the window.[4] To quickly incorporate industries that did not exist at the

[4] After the 1952 election, there is always a change in presidential party during a given 15-year period. However, a Democrat was president for 20 years following the 1932 election. We hold the political sensitivity estimates constant for the final five years of this period to deal with this exception.

beginning of the sample into the study, we impose a minimum 12-year window that widens up to 15 years and then rolls forward thereafter. Thus, because our sample returns begin in 1927, we begin forming portfolios in 1939. In unreported tests, we verify that our main results are unaffected by alternative rolling window lengths.

In our main empirical tests, we use these look-ahead bias-free political sensitivity estimates to define politically favored and unfavored portfolios. To facilitate the construction of these portfolios, we first define a conditional political sensitivity measure θ_i^c using the θ_i estimates. Specifically, $\theta_i^c = \theta_i$ when the president in the current month is a Republican and $\theta_i^c = -\theta_i$ when the president is a Democrat. This transformation ensures that industries that are politically favored by the Republican (Democratic) political environment have higher θ_i^c when the president is a Republican (Democrat).

C. Construction of Political Sensitivity Portfolios

Using the θ_i^c estimates, each month, we sort industries in descending order. We use the top five industries to form the political favorites portfolio and the bottom five industries to form the political unfavorites portfolio. The favorites portfolio contains industries that are most favored by the existing political climate (Republican or Democrat), and the unfavorites portfolio contains industries that are least favored by the existing political climate. The remaining industries are split equally among portfolios 2, 3, and 4. The portfolio composition is fixed for one month.

We use the political favorites and unfavorites portfolios to create POL by holding a long position in the favorites portfolio and shorting the unfavorites portfolio. In a similar manner, we consider the entire universe of CRSP stocks and assign political sensitivities based on each firm's SIC industry. In this case, we form POL by sorting firms into deciles.

In Appendix B, we show that the political sensitivity estimates effectively capture industry-level partisan ties. For example, industries such as tobacco, coal, and shipping are generally favored during Republican presidencies and unfavored during Democratic presidencies. Conversely, real estate and construction industries are generally favored during Democratic presidencies and unfavored otherwise. Furthermore, sin stocks in the tobacco, guns, and alcohol industries are disproportionately classified as politically sensitive, consistent with these industries' partisan nature (e.g., Hong and Kacperczyk, 2009).

Generally, the political sensitivity estimates appear to be consistent with our priors about politically favored industries. However, we also find significant time variation in the estimated industry-level political sensitivities. For example, we find that industries such as agriculture and coal are favored by Democratic administrations early in the sample, but that this relation reverses in more recent periods.

Overall, the evidence in Appendix B supports the hypothesis that investors may not be able to immediately identify and interpret the systematic effects of a new political regime's policies on stock prices. In turn, this underreaction generates persistence in returns that can potentially explain momentum in stock prices.

D. Construction of Momentum Portfolios

To construct stock-level momentum portfolios, we follow Jegadeesh and Titman (1993) and sort all stocks at the beginning of every month on the basis of their past six-month returns and hold the resulting 10 equally weighted portfolios for the subsequent six months.[5] To construct

[5] The 6/6 strategy is probably the most common in the momentum literature (see also Jegadeesh and Titman, 1993; Conrad and Kaul, 1998; Moskowitz and Grinblatt, 1999; Hong et al., 2000; Ahn, Conrad, and Dittmar, 2003; Griffin, Ji, and Martin, 2003; Liu and Zhang, 2008).

industry-level momentum portfolios, we follow Moskowitz and Grinblatt (1999) and sort all 48 Fama-French industries into quintiles at the beginning of every month on the basis of their past six-month returns, and hold the resulting five portfolios for the subsequent six months.[6] To avoid potential microstructure biases (e.g., bid-ask bounce, price pressure, lead-lag reaction effects, and short-term reversal), we skip one month between the end of the ranking period and the beginning of the holding period.[7]

II. Main Empirical Results

The main goal of our article is to show that changes in the political environment alter expected returns and generate predictable patterns in stock returns, which in turn account for a substantial portion of momentum profits. Before proceeding with time-series and cross-sectional tests, we provide direct evidence of the relation between political sensitivity and momentum profits using the political composition of momentum portfolios.

A. Sorting Results

To assess the relation between political climate and price momentum, we first perform univariate sorts using the conditional political sensitivity measure. Table I presents descriptive statistics for political sensitivity and momentum portfolios at the industry (Panel A) and stock (Panel B) levels. By construction, the political sensitivity measure is monotonically increasing across political sensitivity portfolios. Interestingly, momentum portfolios also exhibit a less pronounced monotonic pattern in their political sensitivities, suggesting a link between political sensitivity and momentum returns.

Momentum and political sensitivity profit estimates reported in Table I are comparable to previous studies. Monthly average returns are monotonically increasing across political sensitivity portfolios, and the political sensitivity spread (favorites minus unfavorites) is 0.58% at the industry level and 0.52% at the firm level. These numbers are statistically significant and similar to the results in tables 1 and 3 of Addoum and Kumar (2016). Average returns for the momentum spread (winners minus losers) at the industry level are 0.54% per month (t-statistic $= 5.10$), and at the stock level are 0.78% per month (t-statistic $= 6.56$).[8,9] Finally, the momentum and political sensitivity spreads are positively correlated at both the industry and stock levels.

Moskowitz and Grinblatt (1999) find that at the stock level, momentum profits depend on the short leg of the strategy, whereas at the industry level, momentum profits depend on the long leg of the strategy. Our estimates in Table I suggest that both at the industry and stock levels, momentum profits mainly originate from the short leg of the strategy, though this finding is more pronounced for individual stocks. Investing in portfolio 5 of stock momentum and shorting losers yields a profit of 0.58%, whereas holding winners and shorting portfolio 6 of stock momentum yields a profit of 0.15%. In contrast, at the industry level, winners-minus-portfolio 3 yields an average profit of 0.21%, whereas portfolio 3-minus-losers yields an average profit of 0.33%.

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[6] In untabulated robustness tests, we verify that our key results also hold for value-weighted momentum portfolios. These results are available upon request.

[7] Skipping a month is also common in this literature (see Jegadeesh, 1990; Lehmann, 1990; Jegadeesh and Titman, 1993; Moskowitz and Grinblatt, 1999; Grundy and Martin, 2001; Griffin et al., 2003; Liu and Zhang, 2008).

[8] In Jegadeesh and Titman (1993), the average stock momentum spread is 1.21%.

[9] In Moskowitz and Grinblatt (1999), industry momentum returns are 0.40% per month for the 6/6 momentum strategy, and in Grundy and Martin (2001) industry momentum returns are 0.78%.

Table I. Performance of Political and Momentum Portfolios

This table reports monthly performance for political and momentum portfolios. To construct stock-i level political portfolios, we sort all stocks at the beginning of every month based on their conditional political sensitivity (θ^c estimates in Equation (1)) and hold the resulting 10 equally weighted portfolios for one month. To construct industry-level political portfolios, we sort all 48 Fama-French industries at the beginning of every month on the basis of their conditional political sensitivity and hold the resulting five portfolios for one month. The unfavorite portfolio at the industry level is an equally weighted portfolio of the five industries having the lowest political sensitivity, whereas the favorite portfolio consists of the five industries having the highest political sensitivity. Industry-level political portfolios 2, 3, and 4 are equally weighted portfolios of the remaining industries sorted into terciles based on their political sensitivity. POL is created by holding the favorite portfolio and shorting the unfavorite portfolio. To construct stock-level momentum portfolios, we follow Jegadeesh and Titman (1993) and sort all stocks at the beginning of every month on the basis of their past six-month returns and hold the resulting 10 equally weighted portfolios for the subsequent six months. To construct industry-level momentum portfolios, we follow Moskowitz and Grinblatt (1999) and sort all Fama-French 48 industries at the beginning of every month on the basis of their past six-month returns and hold the resulting five portfolios (same group classification as for political portfolios) for the subsequent six months. To avoid potential microstructure biases, we skip one month between the end of the ranking period and the beginning of the holding period. The correlations of each pair of favored-minus-unfavored (F–U) political portfolio and winner-minus-loser (W–L) momentum portfolio (MOM) are also reported. The t-statistics are adjusted for autocorrelation and heteroskedasticity using the Newey and West (1987) correction method and are reported in parentheses. The estimation period is from January 1939 to December 2016.

	Political Portfolios				Momentum Portfolios		
	Pol. Sensitivity	Raw Return	Sharpe Ratio		Pol. Sensitivity	Raw Return	Sharpe Ratio
Panel A. Fama-French 48 Industries							
Unfavorite	−2.61	0.76	0.27	Loser	−0.28	0.76	0.29
2	−0.86	0.91	0.43	2	−0.10	0.95	0.45
3	0.05	1.07	0.57	3	0.00	1.09	0.58
4	0.89	1.18	0.64	4	0.13	1.13	0.61
Favorite	2.17	1.34	0.68	Winner	0.12	1.30	0.68
F–U (POL)		0.58	0.23	W–L (MOM)		0.54	0.24
		(3.95)				(5.10)	
Corr(F–U,W–L) = 0.47							
Panel B. Individual Stocks							
Unfavorite	−1.98	0.96	0.34	Loser	−0.08	0.65	0.16
2	−0.92	0.94	0.35	2	−0.07	1.01	0.40
3	−0.58	1.18	0.53	3	−0.06	1.19	0.56
4	−0.34	1.00	0.40	4	−0.03	1.20	0.62
5	−0.11	1.10	0.50	5	−0.03	1.23	0.68
6	0.19	1.25	0.57	6	−0.02	1.28	0.73
7	0.51	1.15	0.51	7	−0.01	1.27	0.73
8	0.77	1.41	0.67	8	−0.01	1.30	0.72
9	1.01	1.33	0.61	9	−0.01	1.44	0.76
Favorite	1.64	1.48	0.64	Winner	−0.02	1.43	0.60
F–U (POL)		0.52	0.21	W–L (MOM)		0.78	0.41
		(3.86)				(6.56)	
Corr(F–U,W–L) = 0.37							

The evidence in Moskowitz and Grinblatt (1999) that industry momentum subsumes stock momentum is questioned by Chordia and Shivakumar (2002) and Grundy and Martin (2001). Because several studies suggest that stock and industry momentum are likely to be different phenomena (e.g., see Grundy and Martin, 2001; Chordia and Shivakumar, 2002; Lewellen, 2002), we present empirical results for both stocks and industries to better understand the relation between the political climate and momentum at the stock and industry levels.

B. Political Sensitivity and Momentum: Baseline Estimates

For the next test, we sort all firms into 10 momentum portfolios and 10 political sensitivity portfolios. Within the winners portfolio, we pick only firms that also belong to the political favorites portfolio, whereas within the losers portfolio, we pick only firms that also belong to the political unfavorites portfolio. Our trading strategy consists of holding a long position in winner/favorite firms and shorting loser/unfavorite firms. We label this a politically consistent momentum strategy, and we use a similar method for industries.

We then compare the performance of the politically consistent momentum strategy to the standard momentum strategy (winners-minus-losers) and to the politically inconsistent momentum strategy. To construct the politically inconsistent momentum portfolio, we long winner firms (industries) that also belong to the unfavorites portfolio, and short loser firms (industries) that also belong to the favorites portfolio.

Panel A of Table II presents performance estimates for the three momentum strategies: standard, politically consistent, and politically inconsistent. At the industry level, average monthly returns for the politically consistent momentum strategy (winners/favorites-minus-losers/unfavorites) exceed those of the standard momentum strategy by 0.16% (0.70% vs. 0.54%). In contrast, the average monthly return for the politically inconsistent momentum strategy is statistically indistinguishable from zero.

More pronounced results hold for individual stocks. On average, the stock-level politically consistent momentum strategy performs better than the traditional momentum strategy. The average monthly returns are 1.19% and 0.78%, respectively. In contrast, the politically inconsistent momentum strategy yields average returns that are close to zero.

To account for portfolio characteristics, we also calculate the Fama-French three-factor alpha for each strategy. Similar to the unconditional mean results at the industry level, the politically consistent momentum strategy has an alpha of 1.02%, whereas the standard momentum strategy has an alpha of 0.64%. Again, the politically inconsistent strategy yields an alpha indistinguishable from zero. We find almost identical patterns among stock-level momentum strategies.

Furthermore, we find that returns to the standard and politically consistent momentum strategies, using both individual stocks and industry returns as base assets, are largely driven by the short leg. This is consistent with the findings of Avramov et al. (2007, 2013) and Stambaugh, Yu, and Yuan (2012). In particular, the loser portfolio alpha of the politically consistent strategy is about 40% larger in magnitude (−0.60% vs. 0.43%) than that of the winner portfolio for industry-level momentum. At the stock level, the alpha of the politically consistent loser portfolio has a magnitude more than twice that of the winner portfolio (−0.99% vs. 0.46%).

To summarize the findings reported in Panel A of Table II, Figure 1 shows the cumulative monthly log-returns for the various momentum portfolios. We find that during 1939-2016, the dollar value of holding the politically consistent momentum portfolio is more than five times larger than the final dollar value from holding the traditional momentum portfolio: \$441,458 versus \$81,609. In contrast, the value of the politically inconsistent momentum portfolio (\$3,958) is more than 100 times smaller than that of the politically consistent momentum strategy.

Table II. Performance of Politically Enhanced Momentum Strategies

This table reports monthly performance for three types of momentum strategies: standard momentum, politically consistent momentum, and politically inconsistent momentum. The standard momentum strategy invests in winners and short-sells losers. The politically consistent momentum strategy invests in an equally weighted portfolio of momentum winners, which are also political favorites, and short-sells an equally weighted portfolio of momentum losers, which are also political unfavorites. The politically inconsistent momentum strategy invests in an equally weighted portfolio of momentum winners, which are also political unfavorites, and shorts an equally weighted portfolio of momentum losers, which are also political favorites. W–L is winners-minus-lowers, Alpha is the abnormal return adjusted by the Fama-French three-factor model, and SR is the Sharpe ratio. The *t*-statistics are adjusted for autocorrelation and heteroskedasticity and are reported in parentheses. The estimation period is from January 1939 to December 2016.

	Fama-French 48 Industries			Individual Stocks		
	Standard Mom.	Pol. Consist. Mom.	Pol. Inconsist. Mom	Standard Mom.	Pol. Consist. Mom.	Pol. Inconsist. Mom
	Panel A. Full Sample Performance					
Winner (excess)	0.99	1.14	0.62	1.13	1.36	0.88
	(5.54)	(5.30)	(2.71)	(4.69)	(5.07)	(3.29)
Loser (excess)	0.46	0.44	0.56	0.35	0.17	0.77
	(2.40)	(1.64)	(2.77)	(1.32)	(0.58)	(2.70)
W–L	0.54	0.70	0.06	0.78	1.19	0.11
	(5.10)	(2.99)	(0.31)	(6.56)	(5.63)	(0.58)
Winner (alpha)	0.26	0.43	−0.16	0.21	0.46	−0.11
	(3.91)	(3.12)	(−1.05)	(2.91)	(3.64)	(−0.88)
Loser (alpha)	−0.38	−0.60	−0.24	−0.74	−0.99	−0.28
	(−4.78)	(−2.96)	(−1.77)	(−8.27)	(−7.12)	(−2.20)
W–L (alpha)	0.64	1.02	0.08	0.95	1.45	0.17
	(6.05)	(3.81)	(0.40)	(7.96)	(6.99)	(0.88)
SR	0.24	0.19	−0.14	0.41	0.50	−0.14
	Panel B. Conditional Performance Around Presidential Elections					
Switch. party	0.52	0.77	0.07	0.67	1.20	−0.19
	(3.51)	(2.27)	(0.28)	(3.93)	(3.94)	(−0.75)
9-mo. postelec.	0.31	0.47	−0.92	0.60	1.50	−0.52
	(1.04)	(0.65)	(−2.30)	(1.70)	(3.25)	(−1.13)

Collectively, our results in Panel A of Table II and Figure 1 suggest that if we create momentum portfolios relying exclusively on politically unfavored winners (long leg) and politically favored losers (short leg), winners-minus-losers profits disappear completely. In contrast, the politically consistent momentum strategy significantly outperforms the standard momentum strategy, at both the industry and stock levels. These findings suggest that a substantial component of momentum strategies can be attributed to changes in the political climate.

C. Performance Estimates When Political Intensity Is High

To shed additional light on the interplay between political climate and momentum, we focus on periods around presidential elections. Although election outcomes can be accurately predicted before November of the election year (Abramowitz, 1988, 2008), our hypothesis is that election years are periods of political uncertainty. Moreover, political uncertainty may be only partially resolved by election outcomes. Investors may remain uncertain about the new economic agenda until at least a few months into a new presidency, even if an incumbent candidate is reelected. We posit that during these periods of high political uncertainty, the political sensitivity of firms and industries becomes even more important for momentum profits than during normal times.

Panel B of Table II shows that during the switching-party years, the politically consistent strategy outperforms the standard momentum strategy by 0.25% (the full-sample difference is 0.17%) and the politically inconsistent strategy generates average returns close to zero. At the stock level, the outperformance of the politically consistent strategy over the standard strategy amounts to 0.53% (the full-sample difference is 0.41%) and the politically inconsistent strategy yields negative profits.

Next, we focus on the first nine months after presidential elections, when the level of political activity/news should be high. Similar to the switching-party subsample results, we find that the politically consistent strategy outperforms standard momentum by 0.15% at the industry level and by 0.90% at the stock level.[10]

D. Performance Estimates Using Various Factor Models

So far, we have presented performance estimates of politically enhanced momentum strategies using different types of sorts. Next, we use various factor models to test the ability of our political portfolio (POL) to explain momentum in stock prices.

Table III reports the risk-adjusted performance estimates for winner-minus-loser momentum (MOM) strategies at the industry (Panel A) and stock (Panel B) levels. The returns for MOM strategies are regressed on the three Fama-French factors (Fama and French, 1992), the short-term reversal factor (Jegadeesh, 1990; Conrad and Kaul, 1998), the long-term reversal factor (De Bondt and Thaler, 1985; Jegadeesh, 1990; Conrad and Kaul, 1998), as well as our political portfolio (POL) of favorites-minus-unfavorites.[11]

Results in Table III imply that neither the traditional Fama-French factors nor the reversal factors can successfully explain momentum.[12] Similar findings are previously reported in Fama and French (1996). Further, Moskowitz and Grinblatt (1999) suggest that because momentum and long-term reversal are not related, we should be skeptical about behavioral theories that link the two stylized facts.

The magnitude and statistical significance of alpha estimates in Table III are consistent with previous findings. For example, similar to Jegadeesh and Titman (2001), we find that the capital asset pricing model (CAPM) alpha at the stock level is 0.81% and that the Fama-French stock-level alpha is 0.95%. At the industry level, we find that the CAPM alpha is 0.57% and the Fama-French alpha is 0.64%.

[10] We further examine the performance of the standard and political momentum strategies during various subperiods in Appendix C.

[11] In untabulated tests, we also consider a host of additional asset pricing factors and macroeconomic predictors to assess the robustness of our results. In particular, we consider macroeconomic variables proposed by Chordia and Shivakumar (2002) and Liu and Zhang (2008). We also include the liquidity factor of Pastor and Stambaugh (2003), the lagged investor sentiment measure of Baker and Wurgler (2006), and lagged market return moments as in Cooper, Gutierrez, and Hameed (2004). We find that POL survives the inclusion of these momentum predictors proposed in the literature.

[12] Nevertheless, the coefficient for short-term reversal is statistically significant, at both the stock and industry levels, suggesting that short-term reversal might be linked to momentum.

Table III. Factor Model Estimates: Time-Series

This table reports risk-adjusted performance estimates for the winner-minus-loser momentum strategy. Component returns are those of equally weighted Fama-French 48-industry portfolios (Panel A) and individual stocks (Panel B). The set of factors includes market excess return (RMRF), size (SMB (i.e., small-minus-big)), value (HML (i.e., high-minus-low)), short-term reversal (STR), long-term reversal (LTR), and the zero-investment political portfolio (POL) at the industry (Panel A) and stock (Panel B) levels. The *t*-statistics are adjusted for autocorrelation and heteroskedasticity and are reported in parentheses. Alpha drop is the decrease in alpha due to the inclusion of POL in the linear model. The estimation period is from January 1939 to December 2016.

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Industry Momentum			
Alpha	0.56	0.32	0.64	0.37	0.73	0.42
	(5.35)	(3.21)	(6.05)	(3.70)	(6.41)	(3.69)
RMRF	−0.04	−0.01	−0.05	−0.03	−0.03	−0.01
	(−0.92)	(−0.34)	(−1.19)	(−0.80)	(−0.92)	(−0.33)
SMB			0.00	0.05	0.04	0.06
			(0.04)	(0.94)	(0.85)	(0.89)
HML			−0.17	−0.10	−0.14	−0.11
			(−2.12)	(−1.65)	(−3.11)	(−1.57)
STR					−0.18	−0.09
					(−4.53)	(−1.39)
LTR					−0.03	0.03
					(−0.54)	(0.44)
POL		0.38		0.37		0.37
		(8.84)		(9.00)		(8.12)
Adj. R^2	0.00	0.22	0.02	0.22	0.04	0.23
N (months)	936	936	936	936	936	936
Alpha drop	0.24		0.27		0.30	
	(4.01)		(3.95)		(2.46)	
			Panel B. Stock Momentum			
Alpha	0.81	0.59	0.95	0.71	1.13	0.86
	(7.62)	(4.91)	(7.96)	(5.37)	(8.36)	(5.75)
RMRF	−0.06	−0.04	−0.03	−0.01	0.03	0.04
	(−0.88)	(−0.74)	(−0.67)	(−0.13)	(0.57)	(0.89)
SMB			−0.17	−0.21	−0.16	−0.21
			(−1.19)	(−1.87)	(−1.35)	(−2.01)
HML			−0.30	−0.23	−0.33	−0.28
			(−2.01)	(−1.84)	(−2.31)	(−2.27)
STR					−0.35	−0.27
					(−3.48)	(−2.88)
LTR					0.13	0.13
					(1.27)	(1.52)
POL		0.41		0.40		0.36
		(5.75)		(5.00)		(4.52)
Adj. R^2	0.00	0.14	0.06	0.18	0.12	0.22
N (months)	936	936	936	936	936	936
Alpha drop	0.22		0.24		0.26	
	(2.67)		(3.07)		(1.84)	

Comparing results in Tables I and III, we conclude that risk-adjusted returns using the CAPM or Fama and French (1992) model actually exacerbate the momentum puzzle.[13] However, including POL in any linear model (CAPM, Fama-French three-factor, or Fama-French three-factor plus long-term and short-term reversals) leads to an economically meaningful and statistically significant reduction in the alphas relative to models that do not include POL.[14] The declines in alphas are more than 40% at the industry level and close to 30% at the stock level. Furthermore, these alpha drops are statistically significant at reasonable confidence levels, with t-statistics ranging from 1.84 to 4.01.[15]

In addition to significant alpha drops, the fit of the linear factor model also improves when we add POL. For instance, as shown in Table III, the Fama-French three-factor model augmented with POL can explain approximately 22.4% of the time-series variation in momentum returns at the stock level and 18.5% at the industry level, whereas the Fama-French three factors alone explain only 5.8% and 2.0% of the variation in stock and industry momentum, respectively.

To better understand the magnitude of the improvement in model fit due to the inclusion of the political portfolio, we note that the majority of explanatory factors proposed in the literature imply coefficients of determination that are low.[16] For example, in Griffin et al. (2003), the proposed macroeconomic risks model yields adjusted R^2's ranging from -1.60% to 7.8%, with almost half of them being negative. The macroeconomic model proposed in Asness et al. (2013) has an R^2 of 5.9%. In Cooper et al. (2004), the lagged market returns and the squared lagged market returns explain from 3% to 10% of momentum profits. The Stivers and Sun (2010) model of cross-sectional dispersion explains up to 7.5% of momentum profits. Finally, the conditional CAPM model of Daniel and Moskowitz (2016) yields R^2's around 28.5% at the stock level.[17]

E. Fama-MacBeth Regression Estimates

So far, the analysis has focused on the time-series dynamics of momentum at the stock and industry levels. In this section, we employ the Fama and MacBeth (1973) method to examine how the political environment interacts with prior stock performance to explain the cross-section of returns.

Each month, we estimate cross-sectional regressions of excess returns on the following variables: winner-favorite indicator, winner indicator, returns over the previous month, returns over the previous six months (skipping the most recent month), firm characteristics (size and book-to-market), and stock-level Fama-French three-factor betas calculated over the previous month. The winner-favorite indicator is equal to $+1$ for firms that are both a momentum winner and a political favorite, -1 for firms that are a momentum loser and a political unfavorite, and 0 for all other firms. The winner indicator is equal to $+1$ for firms that are a momentum winner, -1 for firms that are a momentum loser, and 0 for all other firms.

[13] Grundy and Martin (2001) and Ahn et al. (2003) also find that the CAPM and Fama-French three-factor model yield alphas that are higher than the unconditional mean of the momentum strategy.

[14] Lyandres et al. (2008) also use alpha drops to assess the explanatory power of their model.

[15] The t-statistic for testing the significance in alpha drops is derived in Appendix D.

[16] Despite this fact, we do not claim that underreaction to political information is the only driver of momentum returns. We simply argue that it is an important driver of momentum returns, and one that likely coexists alongside other drivers documented in the literature.

[17] The market illiquidity model in Avramov, Cheng, and Hameed (2016a) explains around 25% of the time-series variation in momentum profits. However, this is a marginal improvement in light of their finding that the standard Fama-French three-factor model explains 23% of the variation in momentum profits.

Table IV. Stock- and Industry-Level Fama-MacBeth Regressions

This table reports estimates from Fama and MacBeth (1973) regressions. Asset returns are from the Fama-French 48 value-weighted industry portfolios, and all individual stocks in the sample. We regress monthly excess returns on the following variables: winner-favorite indicator, winner indicator, returns over the previous month, returns over the previous six months skipping the most recent month, size, book-to-market, and Fama-French three-factor betas (i.e., Beta_RMRF, Beta_SMB, and Beta_HML) calculated over the previous 60 months. The winner-favorite indicator is equal to +1 if the asset is a momentum winner and a political favorite, −1 if the asset is a momentum loser and a political unfavorite, and 0 otherwise. The winner indicator is equal to +1 if the asset is a momentum winner, −1 if it is a momentum loser, and 0 otherwise. Avg. adj. R^2 is the time-series average of the cross-sectional adjusted R^2 for each month. The *t*-statistics are adjusted for autocorrelation and heteroskedasticity and are reported in parentheses. The estimation period is from January 1962 to December 2015.

	Dependent Variable: Monthly Excess Return							
	Fama-French 48 Industries			Individual Stocks				
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Winner-favorite indicator	0.34	0.30	0.27	0.41	0.42	0.40	0.35	0.29
	(2.16)	(2.13)	(1.96)	(3.21)	(3.34)	(3.33)	(2.98)	(3.44)
Winner indicator	0.22	0.17	0.13	0.25	0.26	0.22	0.29	0.27
	(3.43)	(2.50)	(2.02)	(3.39)	(3.44)	(3.46)	(5.09)	(6.42)
Lagged return		0.06	0.05		−0.04	−0.04	−0.05	−0.06
		(4.92)	(4.71)		(−10.26)	(−10.44)	(−11.21)	(−13.57)
Lagged 6-mo. return			0.01			0.00	0.00	0.00
			(1.09)			(0.93)	(1.72)	(1.88)
Size							−0.05	−0.02
							(−1.34)	(−0.58)
Book-to-market							0.40	0.29
							(5.79)	(7.27)
Beta_RMRF								0.17
								(0.80)
Beta_SMB								0.22
								(1.54)
Beta_HML								0.02
								(0.12)
Constant	0.56	0.58	0.37	0.72	0.72	0.66	1.27	0.42
	(2.72)	(2.96)	(1.95)	(2.86)	(2.76)	(2.63)	(1.38)	(0.73)
Avg. adj. R^2	0.11	0.17	0.23	0.01	0.02	0.02	0.04	0.13
Avg. no. of obs./month	47	47	47	3,203	3,203	3,203	3,203	3,203

The estimation results in Table IV show that the winner-favorite variable remains statistically significant even when we control for past performance through the lagged returns and the winner indicator. For instance, when an industry transitions from the loser-unfavorite portfolio to the winner-favorite portfolio, it earns 0.54% higher returns on average. Likewise, a stock earns 0.71% higher returns when it transitions from the loser-unfavorite portfolio to the winner-favorite portfolio. The winner-favorite indicator retains its economic and statistical significance, albeit less pronounced, even after controlling for risk exposures using traditional factor betas as well as firm characteristics.

The finding that the winner-favorite indicator variable has additional explanatory power in the cross-section of expected returns, even after controlling for past returns, additional risk exposures, and firm characteristics, provides strong support for our key conjecture that the political environment is an economically important determinant of momentum in stock prices. Moreover, the fact that the winner-favorite indicator remains significant after controlling for firm characteristics implies that the winner-favorite indicator is not a "useless" characteristic (Jagannathan and Wang, 1998).

Collectively, our empirical results provide new insights into the economic mechanism behind part of the momentum phenomenon. The results are consistent with our key conjecture and allow us to establish a link between the political environment and price momentum. Specifically, during switching-party years or during the first few months of a new presidency, the importance of POL increases, and so does its ability to explain momentum profits. It is precisely during these periods that investors form new expectations about firms and industries that are most likely to be favored by the new political party. Investors start investing in these new political favorites (stocks or industries) and shy away from the new political unfavorites.

Thus, election outcomes generate new information associated with changes in the political status of favorite and unfavorite firms and industries around election years. Investors do not incorporate this information in their portfolio decisions immediately. The new favorites are included in their portfolios gradually, and the selling of new unfavorites is also spread out over time. Consequently, underreaction to the new political information creates an upward price trend among favorites and a downward trend among unfavorites. Through this underreaction channel, shifts in the political environment generate persistence in returns and can explain a significant amount of time variation in momentum profits.

III. Robustness Tests and Alternative Explanations

Our main empirical results demonstrate that the profitability of the momentum strategy is sensitive to the political environment. In this section, we perform additional tests to ensure that these findings are orthogonal to the effects of known determinants of price momentum.

A. Political Portfolios Based on House and Senate Majorities

The political sensitivity measure in Equation (1) focuses on the political affiliation of the president. As a robustness check, we also measure the sensitivity of industry returns to the party that controls the Senate and the House of Representatives. Specifically, we run the following time-series regressions:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i \left(r_{mkt,t} - r_{f,t}\right) + \theta_i^S RepubSenate_t + e_{i,t}, \tag{2}$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i \left(r_{mkt,t} - r_{f,t}\right) + \theta_i^H RepubHouse_t + e_{i,t}. \tag{3}$$

These equations are similar to the specification in Equation (1), but with the presidential party indicator replaced by Senate and House party indicators (*RepubSenate* and *RepubHouse*), depending on whether the Republican Party holds the majority in the Senate and House, respectively. Using these additional political sensitivity measures, we form portfolios at the industry and stock levels, and examine the degree to which the returns of these portfolios are able to explain momentum returns.

The results reported in Table V indicate that neither the Senate- nor House-based political long-short portfolio is able to explain an economically significant portion of momentum returns.

Table V. Factor Model Estimates: House and Senate Majority

This table reports risk-adjusted performance estimates for the winner-minus-loser momentum strategy. Returns have been risk-adjusted with the Fama-French three-factor model (i.e., RMRF, SMB, and HML), and the Fama-French three-factor model augmented with three alternative measures of the political long-short portfolio. POL_presid is the benchmark political portfolio based on the political affiliation of the president. POL_senate is the political portfolio based on the party that holds the majority in the Senate, and POL_house is the political portfolio based on the party that controls the House. Component returns correspond to equally weighted Fama-French 48-industry portfolios (Panel A) and individual stocks (Panel B). The *t*-statistics are adjusted for autocorrelation and heteroskedasticity and are reported in parentheses. Alpha drop is the decrease in alpha due to the inclusion of POL in the linear model. The estimation period is from January 1939 to December 2016.

	(1)	(2)	(3)	(4)	(5)
Panel A. Industry Momentum					
Alpha	0.64	0.37	0.58	0.53	0.33
	(6.05)	(3.70)	(5.21)	(5.17)	(3.34)
RMRF	−0.05	−0.03	−0.04	−0.06	−0.03
	(−1.19)	(−0.80)	(−0.92)	(−1.40)	(−0.91)
SMB	0.00	0.05	−0.01	−0.01	0.03
	(0.04)	(0.94)	(−0.17)	(−0.22)	(0.57)
HML	−0.17	−0.10	−0.14	−0.05	−0.03
	(−2.12)	(−1.65)	(−1.94)	(−0.73)	(−0.60)
POL_presid		0.37			0.32
		(9.00)			(7.79)
POL_senate			0.19		0.05
			(3.16)		(1.18)
POL_house				0.36	0.20
				(5.60)	(3.46)
Adj. R^2	0.02	0.22	0.06	0.13	0.27
N (months)	936	936	936	936	936
Alpha drop		0.27	0.06	0.11	0.31
		(3.95)	(2.86)	(3.81)	
Panel B. Stock Momentum					
Alpha	0.95	0.71	0.85	0.90	0.65
	(7.96)	(5.37)	(7.56)	(7.43)	(5.39)
RMRF	−0.03	−0.01	−0.03	−0.03	−0.01
	(−0.67)	(−0.13)	(−0.65)	(−0.54)	(−0.22)
SMB	−0.17	−0.21	−0.19	−0.17	−0.23
	(−1.19)	(−1.87)	(−1.60)	(−1.35)	(−2.17)
HML	−0.30	−0.23	−0.25	−0.26	−0.21
	(−2.01)	(−1.84)	(−1.79)	(−1.91)	(−1.71)
POL_presid		0.40			0.39
		(5.00)			(4.47)
POL_senate			0.20		0.20
			(2.03)		(3.14)
POL_house				0.11	−0.09
				(1.05)	(−1.35)
Adj. R^2	0.06	0.18	0.09	0.07	0.20
N (months)	936	936	936	936	936
Alpha drop		0.24	0.10	0.05	0.30
		(3.07)	(1.71)	(0.78)	

For example, the alpha-drop due to the inclusion of the president-based political portfolio (0.27, t-statistic $= 3.95$) is two to five times larger than the alpha-drop due to the Senate- or House-based political portfolios (0.06 and 0.11, respectively). Moreover, when we pool all of the political long-short portfolios together, much of the significance of the Senate- and House-based political portfolios is subsumed by the original political portfolio based on the presidential party. This evidence indicates that the presidential party-based political portfolio is able to capture the political environment better than other related measures.[18]

B. Political Environment or Sentiment, Liquidity, and Market States?

An important strand of the momentum literature documents that momentum profits are concentrated during periods of high sentiment (Antoniou, Doukas, and Subrahmanyam, 2013), high liquidity (Avramov, Cheng, and Hameed, 2016b), and positive market states (Cooper et al., 2004). In our final set of tests, we examine the performance of the standard momentum strategy and that of our politically consistent and inconsistent momentum strategies conditional on these state variables. Specifically, we split our sample based on above- and below-median realizations of (1) the investor sentiment index of Baker and Wurgler (2006) and (2) the aggregate liquidity measure of Pastor and Stambaugh (2003). We also split the sample based on whether cumulative market returns over the past two years are positive or negative, as in Cooper et al. (2004). In each case, we compute and report the conditional performance of the standard and political momentum strategies in Table VI.

First, our results for the standard stock-level momentum strategy are consistent with the literature. In particular, we find that the standard stock-level strategy yields an average monthly return of 1.10% (t-statistic $= 6.55$) in periods of high investor sentiment, compared to 0.68% (t-statistic $=$ 2.48) in periods of low investor sentiment. Similarly, the strategy yields returns that are higher during periods of high liquidity (1.03%, t-statistic $= 5.94$ vs. 0.74%, t-statistic $= 2.65$) and during positive market states (0.91%, t-statistic $= 8.48$ vs. -0.03%, t-statistic $= -0.05$).

Second, we note that these conditional results are similar for the industry momentum strategy when it comes to periods of positive versus negative market states. However, the relation between aggregate liquidity and industry momentum returns is weaker than for stock-level momentum. Furthermore, we find that the sign of the relation between momentum returns and investor sentiment changes when using industry returns as base assets. Specifically, industry momentum returns are economically larger during periods of low investor sentiment (0.69%, t-statistic $=$ 2.85) than during periods of high investor sentiment (0.50%, t-statistic $= 3.02$).

To understand these differences, we examine the conditional performance of the politically consistent and inconsistent momentum strategies. In particular, we find that among both the industry- and stock-level politically consistent strategies, returns are higher in periods of high sentiment, high liquidity, and positive market states. Specifically, we find that the politically consistent stock-level momentum strategy yields an average monthly return of 2.04% (t-statistic $=$ 6.65) in periods of high market liquidity compared to 1.05% (t-statistic $= 2.38$) in periods of low market liquidity. In periods of high investor sentiment, the strategy yields an average monthly return of 1.96% (t-statistic $= 5.83$) compared to 1.10% (t-statistic $= 2.87$) during periods of low investor sentiment. Finally, during positive market states, the politically consistent stock-level momentum strategy yields an average monthly return of 1.45% (t-statistic $= 7.10$) but during negative market states yields an insignificant negative monthly return. Similar patterns that line up with the literature emerge from the politically consistent industry-level strategy.

[18] We find similar results using an alternative model that measures political sensitivity while controlling for past performance. See Appendix E for details.

Table VI. Performance of Politically Enhanced Momentum Strategies: Sentiment, Liquidity, and Market States

This table reports monthly performance for three types of momentum strategies: standard momentum, politically consistent momentum, and politically inconsistent momentum. The standard momentum strategy invests in winners and short-sells losers. We examine the performance of each momentum strategy conditional on the levels of market liquidity and market sentiment, as well as on market states. Specifically, we split our sample based on above- and below-median realizations of (1) the investor sentiment index of Baker and Wurgler (2006) and (2) the aggregate liquidity measure of Pastor and Stambaugh (2003). We also split the sample based on whether cumulative market returns over the past two years are positive or negative, as in Cooper, Gutierrez, and Hameed (2004). The *t*-statistics are adjusted for autocorrelation and heteroskedasticity and are reported in parentheses. The estimation period is from January 1939 to December 2016.

	Fama-French 48 Industries			Individual Stocks		
	Standard Mom.	Pol. Consist. Mom.	Pol. Inconsist. Mom.	Standard Mom.	Pol. Consist. Mom.	Pol. Inconsist. Mom.
High sentiment	0.50	1.23	−0.37	1.10	2.04	−0.09
	(3.02)	(3.25)	(−0.97)	(6.55)	(6.65)	(−0.30)
Low sentiment	0.69	0.71	0.40	0.68	1.05	0.10
	(2.85)	(1.39)	(1.12)	(2.48)	(2.38)	(0.24)
High liquidity	0.64	1.56	−0.26	1.03	1.96	0.17
	(3.89)	(4.04)	(−0.74)	(5.94)	(5.83)	(0.58)
Low liquidity	0.54	0.39	0.30	0.74	1.10	−0.27
	(2.42)	(0.87)	(0.83)	(2.65)	(2.87)	(−0.77)
Positive states	0.59	0.95	0.04	0.91	1.45	0.11
	(5.94)	(4.28)	(0.21)	(8.48)	(7.10)	(0.59)
Negative states	0.21	−0.75	0.16	−0.03	−0.35	0.10
	(0.50)	(−0.82)	(0.29)	(−0.05)	(−0.47)	(0.16)

In contrast, we find that these patterns are weakened and often reversed when considering the conditional performance of politically inconsistent momentum strategy returns at both the industry and stock levels. Furthermore, both the industry- and stock-level politically inconsistent strategies yield insignificant profits across periods of high and low market liquidity, high and low investor sentiment, and positive and negative market states.

C. Additional Robustness Checks

In addition to the tests described above, we further examine the validity of our results by repeating all of the analysis using value-weighted returns, as well as alternative rolling-window specifications for estimating political sensitivity. Furthermore, we sort industries and firms into political sensitivity portfolios based on the *t*-statistics of the corresponding θ estimates from Equation (1). In addition, we set political sensitivities that are not significant to zero. In all cases, we find results that are similar to those presented in this article.

Finally, we test the relation between political sensitivity and earnings momentum, and find that POL explains an economically and statistically insignificant portion of earnings momentum returns (see Appendix F for details). This evidence is consistent with the findings of Chan et al. (1996), who conclude that price momentum and earnings momentum are two different phenomena.

Overall, these results suggest that political information can explain an important part of the time-series variation in returns to the momentum factor, and that the significance of POL carries over to the full cross-section of stock returns. These findings are robust to a wide set of alternative methodologies and control specifications.

IV. Summary and Conclusion

In this study, we show that the profitability of the momentum strategy depends critically on the political sensitivity of firms and industries. Specifically, when the political environment is misaligned with the winner and loser portfolios, the momentum strategy yields economically insignificant profits. Changes in the political environment can explain an economically significant amount of the time-series variation in momentum profits, even after controlling for the effects of a large set of variables that have been linked to momentum. Including the political long-short portfolio in asset pricing models leads to a significant drop in alphas, and to R^2's that are considerably larger than previous momentum models.

Our results are particularly strong for industry momentum. At the stock level, POL has significant explanatory power during periods of political unrest, that is, around switching-party elections, and during the first few months of a new presidency. Collectively, these results suggest that shifts in political climate affect momentum profits. Specifically, investor underreaction to information embedded in a changing political environment generates momentum in both stock and industry returns. In broader terms, our findings provide support for behavioral theories, which suggest that underreaction to news generates momentum in returns.

Appendix A: Case Study—2016 Presidential Election

To help build intuition for the mechanism underlying the empirical findings, we conduct a case study examining the evolution of industry momentum portfolio components following the 2016 presidential election (we focus on industries because this yields clearer intuition than individual stocks). Specifically, for each of the top and bottom 10 industries, as ranked by momentum formation period returns over the six months before the election (skipping a month), we examine how the average ranking of these industries changes at each three-month interval over the nine months after the election.

Panel A of Table A1 shows results for the 10 industries with the lowest momentum formation period returns going into the 2016 presidential elections. The standard industry momentum strategy sorts these industries into the first and second decile portfolios on the loser side. Moreover, given the persistence in returns that generates the momentum anomaly, we expect these industries to continue to underperform (Moskowitz and Grinblatt, 1999) and to continue to be classified as loser industries following the election.

By construction, the average momentum portfolio ranking for the loser industries in Table A1 is 1.5 at election time. However, the average political sensitivity ranking of these industries is relatively high (4.8). Consistent with the political sensitivity rankings, we find that in the months following the 2016 election, there is a rapid change in the loser portfolios' momentum rankings. Specifically, we find that the average momentum ranking of industries that were considered losers at election time increases from 1.5 to 4.3 just three months after the election. Six months after the election, the average momentum ranking of the initial loser industries increases to 5.6, and further increases to 6.2 nine months after the election. This finding shows that industries that are

Table A1. Case Study: 2016 Presidential Election

This table reports the evolution of industry-level momentum decile portfolio rankings over the nine months following the 2016 election (at three-month intervals) for each of the top and bottom 10 industries, as ranked by momentum formation period returns over the six months before the election (skipping a month). Panel A (Panel B) shows results for the 10 Fama-French 48 industries with the lowest (highest) momentum formation period returns at the beginning of November 2016. We also report political sensitivity portfolio rankings for each industry at the beginning of November 2016.

Industry	Momentum Portfolio, Election	Political Sensitivity Portfolio, Election	Momentum Portfolio, 3-Month Postelection	Momentum Portfolio, 6-Month Postelection	Momentum Portfolio, 9-Month Postelection
Panel A. Momentum Losers as of November 1, 2016					
Apparel	1	7	1	1	5
Candy & soda	1	1	1	2	5
Real estate	1	7	6	8	9
Restaurants, hotels, motels	1	5	5	7	9
Recreation	1	3	4	5	5
Textiles	2	3	3	2	8
Automobiles and trucks	2	2	8	7	5
Other industries	2	4	6	6	2
Tobacco products	2	7	2	9	10
Personal services	2	9	7	9	4
Average	1.5	4.8	4.3	5.6	6.2
Panel B. Momentum Winners as of November 1, 2016					
Petroleum and natural gas	9	10	6	1	1
Electronic equipment	9	5	9	9	9
Agriculture	9	10	3	6	8
Computers	9	8	8	6	6
Machinery	9	8	9	8	9
Fabricated products	10	9	9	10	7
Medical equipment	10	5	1	3	10
Shipping containers	10	9	7	2	8
Precious metals	10	5	1	1	1
Coal	10	10	10	1	1
Average	9.5	7.9	6.3	4.7	6

classified as losers at election time quickly move out of the loser category following the switch in presidential party affiliation.

Examining the evolution of individual industries' rankings also reveals interesting patterns. For example, the tobacco and personal services industries, both categorized as loser industries assigned to portfolio 2 at election time, move to winner portfolio 9 just six months after the election. Moreover, the tobacco industry ends up in winner portfolio 10 nine months after the election. Similarly, the real estate industry, assigned to loser portfolio 1 at election time, moves into winner portfolio 8 six months after the election, and into winner portfolio 9 nine months after the election. Overall, we find that of the 10 industries that were classified in loser portfolios 1 and 2 at election time, 4 end up in the top three winner portfolios and another 4 move to the median portfolio nine months after the election. In contrast, only 1 industry remains in the bottom three loser portfolios nine months after the election. The finding that 40% of the industries that were losers at election time end up in the top three winner portfolios nine months later is an extreme one. This is because, in our entire sample, the unconditional probability of an industry moving from loser portfolios 1 and 2 to the top three winner portfolios within nine months is just 5.4%.

Panel B of Table A1 reveals similar patterns among the 10 industries classified as winners going into the 2016 election. By construction, these 10 winner industries have an average momentum portfolio ranking of 9.5. However, these rankings quickly change over the following nine months. Specifically, their average decile ranking drops to 6.3 three months after the election, and then to 4.7 six months after the election. Nine months after the election, the average momentum ranking of the initial winner industries is 6.0.

The evolution of portfolio classifications among several individual industries that are classified as winners at election time also stands out. For example, we find that the precious metals industry, classified in winner portfolio 10 at election time, moves into loser portfolio 1 just three months after the election and remains there up to nine months after the election. Note that the precious metals industry is assigned to political sensitivity portfolio 5 at election time. This ranking indicates a worse performance for the gold industry than its election-time momentum ranking. Similarly, the petroleum and coal industries, respectively classified in winner portfolios 9 and 10 at election time, both end up in loser portfolio 1 six months after the election and remain there three months later. Again, this type of extreme movement from winners to losers is rare in our sample. In particular, we find that the unconditional probability of an industry moving from the top two winner portfolios to any of the bottom three loser portfolios six months later is only 5.3%.

Overall, our case study of the 2016 presidential election yields evidence consistent with our main conjecture. In particular, we find that a change in the political environment induces a gradual but significant shift in momentum decile portfolio classifications, with several momentum winners becoming losers (and vice versa) in the six to nine months following the 2016 presidential election.

Appendix B: Politically Favored Industries

This table shows the most politically favored industries across all presidencies from 1939 to 2016. Panel A shows the most favored industries by the Democratic party and Panel B shows the most favored industries by the Republican party. Industries are classified into favored and unfavored based on the method described in Section I.C.

		1	2	3	4	5
				Panel A. Top 5 Democratic Industries		
1939–1952:	Roosevelt/Truman (Dem)	Electronic chips	Agriculture	Pharmaceuticals	Insurance	Wholesale
1953–1960:	Eisenhower (Rep)	Construction	Agriculture	Coal	Textiles	Wholesale
1961–1968:	Kennedy/Johnson (Dem)	Construction	Mining	Oil	Transportation	Textiles
1969–1976:	Nixon/Ford (Rep)	Construction	Personal services	Rubbers & plastics	Textiles	Real estate
1977–1980:	Carter (Dem)	Personal services	Real estate	Construction	Books & printing	Business services
1981–1992:	Reagan/Bush (Rep)	Healthcare	Precious metals	Construction	Real estate	Fabricated products
1993–2000:	Clinton (Dem)	Electronic chips	Computers	Precious metals	Shipbuilding	Real estate
2001–2008:	Bush (Rep)	Computers	Electronic chips	Pharmaceuticals	Aircraft	Communication
2009–2016:	Obama (Dem)	Pharmaceuticals	Books & printing	Computers	Communication	Beer & liquor
				Panel B. Top 5 Republican Industries		
1939–1952:	Roosevelt/Truman (Dem)	Paper	Banking	Oil	Communication	Real estate
1953–1960:	Eisenhower (Rep)	Lab equipment	Aircraft	Computers	Rubbers & plastics	Entertainment
1961–1968:	Kennedy/Johnson (Dem)	Recreation	Personal services	Lab equipment	Books & printing	Computers
1969–1976:	Nixon/Ford (Rep)	Recreation	Tobacco	Pharmaceuticals	Defense	Communication
1977–1980:	Carter (Dem)	Coal	Chemicals	Tobacco	Communication	Steel
1981–1992:	Reagan/Bush (Rep)	Candy & soda	Retail	Food products	Communication	Automobiles
1993–2000:	Clinton (Dem)	Tobacco	Textiles	Food products	Shipping	Retail
2001–2008:	Bush (Rep)	Textiles	Shipping	Precious metals	Recreation	Mining
2009–2016:	Obama (Dem)	Coal	Mining	Agriculture	Shipping	Precious metals

Appendix C: Additional Robustness Tests

C1. Performance Estimates during Various Subperiods

Table C1 examines the performance of the three momentum strategies (standard, politically consistent, and politically inconsistent) during other subperiods. We find that the politically consistent momentum strategy (winners-favorites) yields higher profits than the standard momentum strategy across most subperiods, and this finding is more pronounced at the industry level than at the stock level.

An interesting result in Table C1 is that despite strong evidence of momentum crashes (Daniel and Moskowitz, 2016), momentum seems to be a recession-proof strategy. On average, profits for the politically consistent and standard momentum strategies remain positive during expansions as well as during recessions, at both the stock and industry levels. During NBER recessions, we also find that standard momentum performs better than the politically consistent momentum strategy at the stock level, though the differences are not statistically significant. These results are consistent with Griffin et al. (2003), who find that momentum profits are positive during good

Table C1. Performance of the Politically Enhanced Momentum Strategies: Subperiod Analysis

This table reports monthly performance in various subperiods for the three types of momentum strategies: standard momentum, politically consistent momentum (Consist. Pol. Env.), and politically inconsistent momentum (Inconsist. Pol. Env.). Expansionary and recessionary periods are according to the National Bureau of Economic Research. The *t*-statistics are adjusted for autocorrelation and heteroskedasticity and are reported in parentheses. The estimation period is from January 1939 to December 2016.

	Fama-French 48 Industries			Individual Stocks		
	Standard	Consist. Pol. Env.	Inconsist. Pol. Env.	Standard	Consist. Pol. Env.	Inconsist. Pol. Env.
Exclud. switch. party	0.57	0.59	0.05	0.96	1.17	0.61
	(3.97)	(2.18)	(0.14)	(6.06)	(4.60)	(2.51)
Exclud. 9-mo. postelec.	0.59	0.76	0.30	0.82	1.11	0.27
	(5.42)	(3.26)	(1.40)	(7.10)	(4.71)	(1.31)
Exclud. ± 9-mo. elec.	0.67	0.75	0.50	0.79	1.14	0.31
	(5.33)	(2.75)	(1.94)	(5.81)	(4.09)	(1.31)
Non-January	0.63	0.88	0.13	1.09	1.52	0.38
	(5.54)	(3.56)	(0.64)	(8.27)	(6.89)	(2.02)
January	−0.46	−1.21	−0.69	−2.64	−2.52	−2.92
	(−1.14)	(−1.35)	(−0.93)	(−4.13)	(−2.74)	(−4.69)
Expansion	0.55	0.71	0.06	0.85	1.37	0.13
	(5.28)	(3.26)	(0.31)	(7.76)	(6.05)	(0.68)
Recession	0.42	0.63	0.03	0.34	0.07	−0.03
	(1.12)	(0.62)	(0.06)	(0.69)	(0.12)	(−0.44)
1941-1950	0.57	0.08	0.58	0.74	0.76	0.91
1951-1960	0.37	0.12	0.00	0.75	0.92	0.46
1961-1970	0.78	1.43	0.30	0.81	0.93	0.56
1971-1980	0.74	1.26	−0.29	0.70	0.67	−0.06
1981-1990	0.34	0.85	−0.24	1.45	1.87	0.87
1991-2000	0.85	1.58	0.49	1.46	2.99	−0.77
2001-2007	0.60	0.65	0.00	0.54	0.94	0.30

Table C2. Characteristics of Momentum and Political Portfolios

This table shows the average size (log market capitalization) and book-to-market ratios of political and momentum portfolios at the stock and industry levels. The construction of both sets of portfolios is identical to that in Table C2. The sample period is from January 1962 to December 2015.

Portfolio	Size	Book-to-Market	Portfolio	Size	Book-to-Market
		Panel A. Fama-French 48 Industries			
Unfavorite	13.13	0.56	Winner/favorite	13.64	0.59
2	13.34	0.62	Loser/unfavorite	12.96	0.62
3	13.45	0.61	Winner/unfavorite	13.34	0.57
4	13.49	0.64	Loser/favorite	13.29	0.64
Favorite	13.58	0.56			
		Panel B. Individual Stocks			
Unfavorite	18.39	0.83	Winner/favorite	18.53	0.61
2	18.47	0.89	Loser/unfavorite	17.78	0.96
3	18.45	0.89	Winner/unfavorite	18.25	0.66
4	18.63	0.84	Loser/favorite	17.66	0.88
5	18.61	0.90			
6	18.59	0.81			
7	18.68	0.88			
8	18.83	0.91			
9	18.61	0.92			
Favorite	18.61	0.78			

and bad states of the economy. Similarly, Avramov et al. (2007) also find positive, but statistically insignificant, profits during recessions. In contrast, Chordia and Shivakumar (2002) find that momentum strategies yield negative but statistically insignificant returns during recessions over the 1926-1994 sample period.

We also observe that January is not a good month to implement momentum strategies. During this month, momentum spreads are negative across all momentum strategies (standard, consistent, and inconsistent) and across all subsamples. The fact that in January, momentum profits are negative and standard momentum performs better than political momentum is consistent with results showing that contrarian strategies yield positive profits in January.[19]

The most important take-away from Table C1 is that the politically consistent momentum strategy outperforms the traditional strategy in almost all subperiods. In contrast, the politically inconsistent momentum strategy yields profits that are close to zero or negative at both the industry and stock levels.[20]

Finally, Table C2 shows that market capitalization and book-to-market ratios are similar across politically enhanced momentum portfolios, at both the industry and stock levels. This evidence indicates that the politically enhanced momentum strategy is not related to firm characteristics such as size or value.

[19] Jegadeesh and Titman (1993, 2001), Grundy and Martin (2001), Chordia and Shivakumar (2002), and Avramov et al. (2007) all document that January is a bad month for momentum strategies. According to Grundy and Martin (2001), if returns are adjusted for market and size, the negative January effect on momentum disappears.

[20] The difference between the standard and the politically consistent momentum strategies during 2001-2007 is not statistically significant.

C2. Factor Model Estimates during Subperiods

The analysis in the previous section pools together periods of intense political activity with normal times. However, not all periods carry equal political weight. For instance, we expect that during election years, switching-party elections, or during the first few months of a new presidency, the political climate may have a greater impact on asset prices.

To examine the importance of political climate for momentum in returns, we repeat the analysis in Table III, but now we focus on momentum returns during two important subperiods: (1) a six-year window around switching-party elections and (2) the first nine months after elections. Table C3 reports risk-adjusted performance estimates for momentum strategies during these subperiods. Momentum returns are adjusted using the three-factor Fama-French model with and without POL. To save space, Table C3 shows results for the three-factor

Table C3. Factor Model Estimates: Subperiod Analysis

This table reports risk-adjusted performance for the winner-minus-loser momentum strategy. Returns are risk-adjusted with the Fama-French three-factor model, and the Fama-French three-factor model augmented with augmented with the political factor (POL). Beta estimates and *t*-statistics for the three-factor model are omitted. The analysis includes returns for the first nine months after an election, where we assume that election outcomes are resolved in November of election years. This table also focuses on returns during a six-year window centered around the starting month of switching-party years (±3 years around January after switching-party elections). Component returns correspond to equally weighted Fama-French 48-industry portfolios (Panel A) and individual stocks (Panel B). The *t*-statistics are adjusted for autocorrelation and heteroskedasticity and are reported in parentheses. Adj. R^2 increase is the increase in the adjusted R^2 due to the inclusion of POL in the Fama-French three-factor model. Alpha drop is the decrease in alpha due to the inclusion of POL in the Fama-French three-factor model. The estimation period is from January 1939 to December 2016.

	Switch. Party	Nonswitch. Party	First 9-Mo. Postelec.	After 9-Mo. Postelec.
		Panel A. Industry Momentum		
Alpha	0.31	0.40	0.20	0.42
	(2.39)	(2.56)	(0.83)	(3.91)
POL	0.39	0.29	0.34	0.37
	(8.05)	(3.96)	(3.48)	(8.07)
Adj. R^2 Increase	0.22	0.10	0.12	0.21
Alpha drop	0.33	0.10	0.34	0.24
	(3.05)	(1.52)	(1.26)	(3.63)
N (months)	588	348	187	749
		Panel B. Stock Momentum		
Alpha	0.47	0.99	0.34	0.80
	(2.84)	(5.34)	(0.89)	(6.41)
POL	0.48	0.04	0.52	0.31
	(5.71)	(0.44)	(3.86)	(4.08)
Adj. R^2 Increase	0.21	−0.00	0.14	0.08
Alpha drop	0.36	0.01	0.53	0.15
	(2.73)	(0.16)	(1.17)	(2.71)
N (months)	588	348	187	749

specification augmented by POL. The estimates for the standard three-factor specification are omitted.

When we focus on six-year windows around switching-party elections, the explanatory power of POL increases substantially. At the stock level, including the political factor in the Fama-French model causes the alpha to decrease by almost 40%, from 0.84 to 0.47, and this drop is statistically significant. Moreover, the R^2 increases from 0.05 for the three-factor model to 0.25 for the augmented four-factor model (Fama-French three-factor model plus POL).

However, consistent with our conjecture, when we consider six-year periods around nonswitching-party years, the addition of POL does not improve the performance of the Fama-French factor model. The alpha drop is economically and statistically insignificant, and the R^2 actually decreases relative to the standard Fama-French three-factor model.

At the industry level, POL is economically significant around both the switching-party years and the nonswitching-party years. In both subperiods, POL is positive and statistically significant, and the increase in R^2 is 22% around switching years and 10% around nonswitching years. Nevertheless, the alpha drop is far more pronounced during switching-party years (drop = 0.33, t-statistic = 3.05) than during nonswitching-party years (drop = 0.10, t-statistic = 1.52).

Taken together, the evidence in Table C3 indicates that POL becomes particularly important for stock-level momentum around switching party years, whereas industry momentum depends on POL during both switching and nonswitching years. This finding likely reflects the fact that equity returns at the stock level are noisy. Therefore, the effects of POL on returns are best identified during periods when this factor is particularly important, that is, during switching-party years or during the first few months of a presidency. Industry returns, however, are not as noisy because of aggregation. As a consequence, the impact of POL on returns can be identified during normal times as well.

Our second subperiod analysis focuses on a nine-month period after elections. At the stock level, the four-factor model (Fama-French three-factor model plus POL) is characterized by a statistically significant drop in alpha and an increase in overall fit by 13.6% relative to the Fama-French three-factor model. Although the four-factor alpha is statistically insignificant during the first nine months (largely because of the small sample size), the alpha drops by more than 50%. Furthermore, when going beyond the first nine months of the presidency, the four-factor alpha becomes economically and statistically significant (estimate = 0.80, t-statistic = 6.41).

At the industry level, the performance of POL is similar during the first nine months and beyond the first nine months subsample. In both subsamples, the inclusion of POL causes the R^2 to increase by 12.0% and 21.1%, respectively, relative to the three-factor model. Also, in both subperiods, there is a substantial decrease in alphas relative to the three-factor model: 0.34 (t-statistic = 1.26) and 0.24 (t-statistic = 3.63), respectively. However, the four-factor alpha is statistically insignificant during the first nine months subsample, but it becomes statistically significant after the first nine months.

Overall, when we focus on periods around presidential elections, we can better identify the effects of political climate on momentum profits, especially at the stock level. At the stock level, the explanatory power of POL is concentrated around party-switching years and decreases when moving beyond the first nine months after an election. This finding may reflect the fact that stock-level returns are relatively noisy. In contrast, the effects of political environment are long-lasting and extend beyond the election window at the industry level. The long-lasting effects of POL at the industry level may reflect the diversification of idiosyncratic noise in industry portfolios.

Appendix D: Testing Statistical Significance in Nested Ordinary Least Squares (OLS) Models

Consider the linear model:

$$y = X\beta + Z\gamma + u, E\left[uu^T\right] = \Omega,$$

and its nested counterpart:

$$y = X\beta^* + u^*, E[u^* u^{*T}] = \Omega^*.$$

We examine whether the difference between the two parameter vectors, β and β^*, is statistically different from zero.

First, define the difference between the two vectors as $d = \hat{\beta}^* - \hat{\beta}$, where $\beta\hat{\beta}^*$ are parameter estimates for the nested model, and $\beta\hat{}$ are estimates for the full model. Standard results from partitioned regressions imply that d can be expressed as:

$$d = \left(X^T X\right)^{-1} X^T y - \left[AX^T - AX^T Z\left(Z^T Z\right)^{-1} Z^T\right] y \equiv My,$$

where $A = [X^T X - X^T Z(Z^T Z)^{-1} Z^T X]^{-1}$ Because $\hat{\beta}$ and $\hat{\beta}^*$ are asymptotically normally distributed, d is as well, and its variance-covariance matrix is given by:

$$V(d) = M\Omega M^T = BX^T \Omega XB + BX^T \Omega ZC + CZ^T \Omega XB + CZ^T \Omega ZC,$$

where $B = (X^T X)^{-1} - A, andC = AX^T Z(Z^T Z)^{-1}$ The underlined parts are partitions of the variance-covariance matrix adjusted for autocorrelation and heteroskedasticity using the Newey and West (1987) method.

To test the null hypothesis that $\hat{\beta}_k^*$ in the nested model equals β_k^* in the full model, the test statistic is:

$$t_{n-2p} = \frac{d_k}{\sqrt{\mathrm{var}(d_k)}},$$

where var(d_k) is the kth diagonal element of $V(d)$, n is the number of observations, and p is the number of elements in d.

Appendix E: Alternative Political Sensitivity Measures

Throughout the article, we use the specification in (1) to estimate political sensitivity at the stock and industry levels. In this section, we address the possibility that our political sensitivity measures might somehow capture momentum effects almost mechanically, and we propose an alternative model that measures political sensitivity while controlling for past performance. More specifically, we estimate political sensitivity using the following specification:

$$\begin{aligned} r_{i,t} - r_{f,t} &= \alpha_i + \beta_i\left(r_{mkt,t} - r_{f,t}\right) + \theta_i^* RepubInd_t \\ &\quad + \sum_{j=2}^{12} \beta_j r_{i,t-j} + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_{i,t}, \end{aligned} \tag{E.1}$$

Table E1. Alpha Estimates Using Alternative Political Sensitivity Measures

This table reports risk-adjusted performance estimates for the momentum strategy (winners-minus-losers). Returns have been adjusted using the standard Fama-French three-factor model, and the Fama-French three-factor model augmented with the political factor (POL). In addition to the full sample, the analysis includes returns for the first nine months after an election (election outcomes are resolved in November), and returns from a six-year window centered around the starting month of switching-party years (±3 years around November after switching-party elections). The alternative political sentiment portfolio (POL*) is constructed using the political sensitivity model in which we control for the past 2- to 12-month returns, as well as small-minus-big (SMB) and high-minus-low (HML) factors. Component returns correspond to equally weighted Fama-French 48-industry portfolios (Panel A) and individual stocks (Panel B). The *t*-statistics are adjusted for autocorrelation and heteroskedasticity and are reported in parentheses. Adj. R^2 increase is the increase in the adjusted R^2 due to the inclusion of the political portfolio (POL*) in the Fama-French three-factor model. Alpha drop is the decrease in alpha due to the inclusion of the political portfolio (POL*) in the Fama-French three-factor model. The estimation period is from January 1939 to December 2016.

	Full Sample	Switching-Party Years	First 9-Mo. Postelec.
		Panel A. Industry Momentum	
Alpha	0.46	0.38	0.25
	(4.52)	(2.89)	(1.02)
POL*	0.36	0.40	0.39
	(8.94)	(8.36)	(3.69)
N (months)	930	588	187
Adj. R^2 increase	0.17	0.20	0.13
Alpha drop	0.20	0.26	0.28
	(4.60)	(4.09)	(2.67)
		Panel B. Stock Momentum	
Alpha	0.79	0.48	0.54
	(5.89)	(2.79)	(1.48)
POL*	0.34	0.44	0.45
	(4.15)	(5.02)	(2.99)
N (months)	930	588	187
Adj. R^2 increase	0.10	0.17	0.10
Alpha drop	0.21	0.36	0.34
	(2.59)	(2.22)	(1.71)

in which we account for 2- to 12-month past returns, size (SMB), and value (HML) factors. Using this alternative measure of political sensitivity, we repeat the analysis for both the full sample period and specific subperiods.

The results in Table E1 for the alternative political sensitivity measure are similar to the baseline results reported in Tables III and C3. The alternative political sentiment portfolio is economically and statistically significant across all subperiods, at both the stock and industry levels. Furthermore, by adding the alternative political sensitivity measure to the three-factor model, there is a substantial improvement in the overall fit: R^2's increase by 16.7% at the industry level (from 2.5% to 19.2%) and by 9.5% at the stock level (from 6.9% to 16.5%).

These increases in R^2 are also combined with significant drops in alphas. During switching-party years, the industry alpha decreases by 0.26% (from 0.64% to 0.38%), and the stock alpha decreases by 0.36% (from 0.84% to 0.48%) in relation to models without the political sensitivity measure. On the basis of results in Table E1, we conclude that our political sensitivity measure is not contaminated by past returns.

Appendix F: Time-Series Factor Model Estimates: Earnings Momentum

This table reports risk-adjusted performance estimates for the earnings momentum strategy. Component returns are those of equally weighted Fama-French 48-industry portfolios (Panel A) and individual stocks (Panel B). The set of factors includes market excess return (RMRF), size (SMB (i.e., small minus big)), value (HML (i.e., high minus low)), short-term reversal (STR), long-term reversal (LTR), as well as the zero-investment political portfolio (POL) at the industry (Panel A) and stock (Panel B) levels. The *t*-statistics are adjusted for autocorrelation and heteroskedasticity and are reported in parentheses. Alpha drop is the decrease in alpha due to the inclusion of POL in the linear model. The estimation period is from January 1972 to December 2016.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Industry Earnings Momentum						
Alpha	0.35	0.23	0.50	0.37	0.53	0.40
	(3.08)	(1.95)	(4.38)	(3.20)	(4.78)	(3.57)
RMRF	−0.09	−0.07	−0.13	−0.11	−0.11	−0.10
	(−2.00)	(−1.70)	(−3.22)	(−2.76)	(−2.46)	(−2.34)
SMB			−0.07	−0.06	−0.09	−0.09
			(−1.45)	(−1.23)	(−1.55)	(−1.62)
HML			−0.29	−0.26	−0.31	−0.30
			(−4.60)	(−4.23)	(−4.57)	(−4.54)
STR					−0.12	−0.09
					(−3.32)	(−2.39)
LTR					0.08	0.12
					(1.23)	(1.97)
POL		0.16		0.14		0.14
		(4.70)		(4.37)		(4.22)
Adj. R^2	0.02	0.12	0.12	0.19	0.15	0.21
N (months)	540	540	540	540	540	540
Alpha drop	0.13		0.13		0.13	
	(1.48)		(1.22)		(1.01)	
Panel B. Stock Earnings Momentum						
Alpha	0.79	0.71	0.90	0.81	0.92	0.83
	(12.12)	(9.13)	(13.10)	(11.42)	(12.67)	(11.18)
RMRF	−0.05	−0.04	−0.05	−0.04	−0.04	−0.03
	(−1.66)	(−1.63)	(−1.77)	(−1.52)	(−1.03)	(−0.91)
SMB			−0.18	−0.19	−0.14	−0.16
			(−4.10)	(−4.09)	(−3.54)	(−3.75)
HML			−0.19	−0.17	−0.15	−0.13
			(−3.25)	(−3.33)	(−2.58)	(−2.52)
STR					−0.07	−0.05
					(−1.70)	(−1.22)
LTR					−0.07	−0.07
					(−1.31)	(−1.40)
POL		0.09		0.09		0.09
		(2.34)		(2.88)		(2.63)
Adj. R^2	0.01	0.06	0.16	0.21	0.18	0.22
N (months)	540	540	540	540	540	540
Alpha drop	0.08		0.09		0.09	
	(0.86)		(1.06)		(0.82)	

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