Under-Reaction to Political Information and Price Momentum*

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Abstract – This study examines 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. During the 1939 to 2011 period, 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 eliminates all momentum profits. Further, our political sensitivity based factor (POL) explains 23-25% (38-40%) of monthly stock (industry) momentum alphas, and generates large increases in time-series R^2s for the momentum factor. This incremental explanatory power is especially strong 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.

Keywords: Price momentum, political environment, market under-reaction, trading strategies.

JEL classification: G12, G14.

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1. Introduction

Momentum in stock returns is perhaps one of the most robust empirical patterns identified in the recent asset pricing literature. While there is general agreement in the literature that momentum profits are large and pervasive (e.g., Asness, Moskowitz, and Pedersen (2013)), there is still 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, 2013) propose risk-based explanations of momentum profits. In contrast, 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 study, 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, firms with environmental-friendly policies may expect to benefit from the policies of the Democratic party, while industries such as defense, tobacco, guns, etc. 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. And if investors incorporate news about a potential shift in the political environment with some delay, either because the outcome is not certain or they 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 a number of 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, due to 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, firms and industries that have underperformed in the past but are expected to benefit from the new political regime would begin to gradually rise following the change in political regime. Similarly, firms that have performed well would begin a gradual downward trend following the change in the political environment if the new party is expected to affect them adversely. Overall, our main conjecture is that around political events, changes in the political climate would induce momentum in stock prices. More generally, we posit that even during other time periods, time-variation in the political environment would generate 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 (2013) show that investors adjust their portfolios following changes in the political environment. In particular, Addoum and Kumar (2013) 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. While they show that these portfolio reallocations in turn generate short-term predictability in stock and industry returns, Addoum and Kumar (2013) do not examine the impact of shifts in the political environment on momentum profits.

Our paper links this literature with that on 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 under-reaction 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 (2013) 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 3.26% (6.76%) on an annual basis during the 1939 to 2011 sample period. Further, 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. This evidence indicates that the profitability of the momentum strategy depends critically on the sensitivity of firms to the changing political climate.

In additional tests, we investigate the ability of a political sensitivity based factor (POL) to explain the time-variation in momentum profits. The POL factor 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 the returns of our political sensitivity factor (POL) portfolio.

The incremental explanatory power of our political sensitivity measure is economically meaningful as it eliminates approximately 23-25% of monthly momentum alphas during the 1939 to 2011 period.

We also examine the relation between returns to the political sensitivity factor 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 the political sensitivity factor. Specifically, we show that approximately 38-40% of industry momentum alphas can be attributed to time-varying political sensitivity of industry portfolios.[1]

To better understand the relation between political cycles and momentum returns, we consider distinct sub-periods surrounding elections in which the party in power changes and stays the same. Consistent with our main conjecture, we find that the explanatory power of political sensitivity is especially strong during sub-periods in which there is a change in power and the political environment changes considerably.

We 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), as well as lagged market return moments as in Cooper et al. (2004). We find that our political sensitivity based factor not only survives the inclusion of all momentum predictors proposed in the extant literature, but it has greater explanatory power than all of these predictors combined.

Collectively, our findings contribute to the finance literature that attempts to understand the

[1]We also examine the potential relation between political sensitivity and earnings momentum returns at both the firm- and industry-levels. We find that the political sensitivity factor 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.

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, while Stivers and Sun (2010) advance the cross-sectional dispersion of returns as an important determinant of momentum. More recently, Daniel and Moskowitz (2013) relate momentum to market crashes and stock market volatility, while Asness et al. (2013) consider an extensive set of macroeconomic and liquidity controls.

Our paper 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, which suggest that 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.

While investor under-reaction 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 under-react. In contrast, we show that investor under-reaction to political information can explain a significant portion of the time-series variation in momentum returns.

The rest of the paper is organized as follows. In Section 2, we describe our data and the method for constructing momentum and political portfolios. Section 3 presents the main empirical results. Sections 4 and 5 present evidence from additional robustness tests and we also consider alternative explanations for our key findings. Section 6 concludes with a brief summary.

2. Data and Methods

In this section, we briefly describe our data, and summarize the methods used for measuring the political sensitivity of firms and industries.

2.1. 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, historical book equity data, forty-eight SIC industry classifications, as well as forty-eight industry monthly value-weighted portfolio returns from Kenneth French's data library. Investor sentiment data are from Jeffrey Wurgler's web page, and the liquidity factor is from Lubos Pastor's web site.

We obtain National Bureau of Economic Research (NBER) recession indicators from the NBER web site, and data on Presidential election outcomes from the CQ Press Voting and Elections Collection. Data on consumption growth, industrial production growth, default spreads, term spreads, and 3 month T-bills are from the St. Louis Federal Reserve web site (FRED). The default spread is defined as the difference in yields between BAA and AAA rated corporate bond portfolios from Moody's. The term spread is defined as the difference in yields between the AAA bond portfolio and the 1-month T-bill from Kenneth French's web site. Finally, the market dividend-yield is from Robert Shiller's web site.

2.2. 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 (2013). The estimation process is summarized below 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.[2] Specifically, we estimate the following time-series regression:

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

In this equation, the Presidential party indicator variable ($RepubInd_t$) is equal to one when the Presidential party is Republican and zero during Democratic Presidential periods. We define the Presidential party indicator variable based on national election outcomes. Though 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 (2013) find that congressional control has little impact on the effects associated with the President's partisan ties. Further, our market-based measure of political sensitivity is available for a long sample period and provides evidence suggesting 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, while a negative θ_i estimate indicates that the industry (stock) earns higher returns when the President is a Democrat.

Addoum and Kumar (2013) show that the political sensitivity estimates effectively capture industry-level partisan ties. For example, industries such as Tobacco, Pharmaceuticals, and Finance are typically estimated as being favored during Republican presidencies and unfavored during Democratic presidencies. On the other hand, the Healthcare and Construction indus-

[2] We choose a 15-year rolling window in order to ensure that there is always a change in Presidential party-affiliation during the window. In unreported tests, we verify that our main results are unaffected by alternative rolling window lengths.

tries are generally favored during Democratic presidencies and unfavored otherwise. Further, 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)). There is also significant time-variation in estimated industry-level political sensitivities. For example, Addoum and Kumar (2013) 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.

In our main empirical tests, we use these 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 these 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 political environment have higher θ_i^c when the President is a Republican and industries that are politically favored by the Democratic political environment have higher θ_i^c when the President is a Democrat.

Using the θ_i^c estimates, each month, we sort industries in descending order. We use the top five industries to form the 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), while 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. Portfolios are value-weighted using industry market capitalization at the beginning of the month. The portfolio composition is fixed for one month.

We use the political favorites and unfavorites portfolios to create a political sensitivity factor (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 political sensitivity based portfolios by sorting firms into deciles.

2.3. 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 ten equally-weighted portfolios for the subsequent six months.[3] 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 for the subsequent six months.[4] 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.[5]

3. Main Empirical Results

The main goal of our paper 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 substantially large portion of momentum profits. Before proceeding with the standard time-series and cross-sectional tests, we provide direct evidence of the relation between political sensitivity and

[3] 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 et al. (2003), Griffin et al. (2003), Liu and Zhang (2008) among others.

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

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

momentum profits using the political composition of momentum portfolios.

3.1. Sorting Results

To assess the relation between political climate and price momentum, we first perform univariate sorts using the conditional political sensitivity measure. Table 1 shows 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 1 are comparable to previous studies. According to Table 1, monthly average returns are monotonically increasing across political sensitivity portfolios, and the political sensitivity spread (favorites-minus-unfavorites) is 0.564% at the industry-level, and 0.431% at the firm-level. These numbers are statistically significant, and very similar to the results in Tables 1 and 3 of Addoum and Kumar (2013). Average returns for the momentum spread (winners-minus-losers) at the industry-level are 0.532% per month (t-statistic = 5.15),[6] while at the stock-level, average returns for the momentum spread are 0.827% per month (t-statistic = 5.27).[7] Finally, the momentum and political sensitivity spreads are positively correlated both at the industry and stock-levels.

Moskowitz and Grinblatt (1999) find that stock-level momentum profits depend on the short leg of the strategy, while at the industry-level, momentum profits can be attributed to the long leg of the strategy. Our estimates in Table 1 suggest that both at the industry and stock-levels, momentum profits mainly originate from the short leg of the strategy, even though this finding

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

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

is more pronounced for individual stocks. Investing in portfolio 5 of stock momentum and shorting losers yields a profit of 0.602%, while holding winners and shorting portfolio 6 of stock momentum yields a profit of 0.206%. In contrast, at the industry-level, winners-minus-portfolio 3 yields an average profit of 0.212%, while portfolio 3-minus-losers yields an average profit of 0.320%. Unlike momentum, profits for the political sentiment portfolio mainly originate from the long leg of the strategy.[8] This finding is important for the implementability of the politics-based trading strategy as well as its profits net of transaction costs.

The evidence in Moskowitz and Grinblatt (1999) that industry momentum subsumes momentum at the stock-level has been questioned by Chordia and Shivakumar (2002) and Grundy and Martin (2001). Since a number of papers suggest that stock and industry momentum are likely to be different phenomena,[9] we present empirical results for both stocks and industries in order to better understand the relation between the political climate and momentum at the stock- and industry-levels.

3.2. Political Sensitivity and Momentum: Baseline Estimates

For the next test, we separately sort all firms into ten momentum portfolios and ten political sensitivity portfolios. Within the winners portfolio, we only pick firms that also belong to the political favorites portfolio, while among the loser firms we only pick those 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 follow a similar methodology for industries as well.

The performance of the politically consistent momentum strategy is then compared to the standard momentum strategy (winners-minus-losers) and to the politically inconsistent momen-

[8] Industry-level: favorites-minus-political portfolio 3 = 0.334%, political portfolio 3-minus-unfavorites = 0.231%; stock-level: favorites-minus-portfolio 6 = 0.262%, portfolio 5-minus-unfavorites = 0.116%.

[9] Chordia and Shivakumar (2002), Grundy and Martin (2001), Lewellen (2002).

tum strategy. For the latter strategy, we long winner firms (industries) that also belong to the unfavorites portfolio, and short loser firms (industries) that also belong to the favorites portfolio.

Table 2 shows unconditional sample means for the three momentum strategies: standard, politically consistent, and politically inconsistent. At the industry-level, monthly returns for the politically consistent momentum strategy (winners/favorites-minus-losers/unfavorites) are, on average, twice as large as returns for the standard momentum strategy (1.095% vs. 0.532%). In contrast, the average monthly return for the politically inconsistent momentum strategy is negative and statistically insignificant.

Similar results, although less pronounced, hold for individual stocks. On average, the politically consistent momentum strategy at the stock-level performs better than the traditional momentum strategy: The average monthly returns are 1.099% and 0.827%, respectively. In contrast, the politically inconsistent momentum strategy yields almost zero profits.

The unconditional means above do not account for portfolio characteristics. Following Moskowitz and Grinblatt (1999), we adjust portfolio returns using the Daniel et al. (1997) characteristic-based method (hereafter, DGTW). Again, we find that at the industry-level, the politically consistent momentum strategy yields average DGTW-adjusted returns that are twice as large as the DGTW-adjusted returns for the standard momentum strategy: 0.724% versus 0.342%, respectively. In contrast, the average DGTW adjusted return for the politically inconsistent momentum strategy is negative and statistically insignificant.

At the stock-level, the politically consistent momentum strategy still improves upon the standard momentum strategy, since DGTW-adjusted returns are 0.505% and 0.420% respectively, while the politically inconsistent strategy yields almost zero characteristic-adjusted returns. These results suggest that we could create zero-investment portfolios focusing on winners/favorites and winners/unfavorites, without even considering loser portfolios, and still obtain an average monthly DGTW-adjusted profit of 0.360% at the industry-level, and 0.196% at the stock-level.[10]

To summarize the findings reported in Table 2, Figure 1 shows the cumulative monthly log-returns for the various momentum portfolios. We find that during the 1939 to 2011 period, the dollar value of holding the politically consistent winners portfolio is three times larger than the final dollar value from holding the traditional winners portfolio: $74,281 versus $24,103. In contrast, the losses relative to the risk-free asset for the politically consistent losers portfolio are more than twice the losses for the traditional losers portfolio. Similar results hold when we consider characteristic-adjusted returns.

Collectively, our results in Table 2 and Figure 1 suggest that if we create momentum portfolios relying exclusively on politically unfavored winners (long leg) and politically favored losers (short leg), then winners-minus-losers profits at the stock-level disappear, and even turn negative at the industry-level. In contrast, profits from the politically consistent momentum strategy at the industry-level are more than double the profits from the traditional industry momentum strategy. Similar results hold for the politically consistent momentum strategy at the stock-level. These findings suggest that a substantial component of momentum strategies can be attributed to changes in the political climate.

3.3. 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 prior to November of the election year, our hypothesis is that election years are periods of political turmoil and uncertainty. Moreover, political uncertainty is only partially resolved by election outcomes. Even if the incumbent candidate gets re-elected, investors remain quite uncertain about the new economic agenda until at least a few months into the new Presidency.

[10] Similar results hold when we form double-sorted portfolios based on past performance and political sensitivity. See appendix Table A1.

We posit that during these periods of high political uncertainty, the political sensitivity of firms and industries would become even more important for momentum profits than normal times.

Figures 2, 3, and 4 focus on the average performance of political and momentum portfolios during the one-year period around these switching-party years. More specifically, Figure 2 shows the cumulative returns for political and momentum portfolios around switching-party years. As expected, politically consistent winners earn, on average, almost twice the returns of standard winners (21.41% and 11.04%). In contrast, politically inconsistent losers (losers but favorites) perform better than politically inconsistent winners (winners but unfavorites). Consistent with our conjecture, the evidence in Figure 2 suggests that, around election years, political sensitivity becomes more important and can even reverse the sign of momentum profits.

Figures 3 and 4 provide additional evidence on how momentum profits are affected by the political climate around election years. According to Figure 3, the tendency of past winners to keep on winning in the near future is more pronounced for winner firms (industries) that are also politically favored than for winner firms (industries) that are politically unfavored. Similarly, Figure 4 shows that the tendency of past losers to continue losing in the medium term is more pronounced for losers/unfavorites than for losers/favorites. More importantly, comparing the two figures, we find that, around election years, losers/favorites earn higher returns than winners/unfavorites, which implies that the momentum profits for the politically inconsistent momentum portfolios are reversed.

3.4. Performance Estimates During Other Sub-Periods

Table 3 further examines the performance of the three momentum strategies (standard, politically consistent, and politically inconsistent) during other sub-periods. We find that the politically consistent momentum strategy (winners/favorites) yields higher profits than the standard momentum strategy across almost all sub-periods, and this finding is more pronounced at the industry-level than at the stock-level.

An interesting result in Table 3 is that, despite strong evidence of momentum crashes (Daniel and Moskowitz (2013)), 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, both at the stock- and industry-levels. During NBER recessions, we also find that standard momentum performs better than the politically consistent momentum strategy, 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 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 sub-samples. The fact that in January, momentum profits are negative and standard momentum performs better than political momentum is consistent with a number of results showing that contrarian strategies yield positive profits in the month of January.[11]

The most important take-away from Table 3 is that the politically consistent momentum strategy outperforms the traditional strategy in almost all sub-periods. In contrast, the politically inconsistent momentum strategy yields negative profits at the industry-level, and low or zero profits at the stock-level during most sub-periods.[12]

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

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

Given the higher profitability of the politically consistent momentum strategy, we shed additional light on its time-series behavior. Figure 5 plots the time-series of returns for the politically consistent momentum strategy. The grey line shows raw returns, and the dark line is the 12-month moving average of monthly returns from January 1926 through December 2011. It is interesting to note that the time-series variation in the politically consistent momentum has increased tremendously during the 2000's, particularly around the dot-com bubble and the recent financial crisis of 2008. During the latter crisis, the politically consistent momentum strategy crashed, yielding monthly returns as low as -60%. This finding is in line with the results in Daniel and Moskowitz (2013) on momentum crashes, and highlights the link between political sensitivity and momentum returns.

Finally, Tables A1 and 4 show that market capitalization and book-to-market ratios are very similar across politically enhanced momentum portfolios, both at 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.

3.5. 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 factor to explain momentum in stock prices.

Table 5 reports the risk-adjusted performance estimates for winner-minus-loser momentum (MOM) strategies at the industry (Panel A) and stock-levels (Panel B). 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 (DeBondt and Thaler (1985), Jegadeesh (1990), Conrad and Kaul (1998)), as well as our political factor (POL) of favorites-minus-unfavorites.

Results in Table 5 imply that neither the traditional Fama-French factors nor the reversal factors can successfully explain momentum.[13] Similar findings have been previously reported in Fama and French (1996). Further, Moskowitz and Grinblatt (1999) suggest that since 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 5 are consistent with previous findings. For example, similar to Jegadeesh and Titman (2001), we find that the CAPM alpha at the stock-level is 0.902% and that the Fama-French stock-level alpha is 1.011%. At the industry-level, we find that the CAPM alpha is 0.556% and the Fama-French alpha is 0.621%.

Comparing results in Tables 1 and 5, we conclude that risk-adjusting returns with the CAPM or Fama-French models actually exacerbates the momentum puzzle.[14] However, including the political factor POL in any linear model (CAPM, FF, or FF+LTR+STR) leads to an economically meaningful and statistically significant reduction in the alphas relative to models that do not include the political factor.[15] The declines in alphas are approximately 40% at the industry-level and 30% at the stock-level. Further, these alpha drops are statistically significant at reasonable confidence levels, with t-statistics ranging from 2.34 to 4.40.[16]

In addition to significant alpha drops, the fit of the linear factor model also improves when we add the political factor. As shown in Table 5, the political factor can explain approximately 25.0% of the time-series variation in momentum returns at the stock-level, and 22.5% at the industry-level. Furthermore, the political factor causes R^2's to increase by 20% relative to the other models, which can only explain 3.6% and 9.8% of the variation in industry and stock momentum, respectively.

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

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

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

[16] The t-statistic for testing the significance in alpha drops is derived in appendix section A.1.

To better understand the magnitude of the improvement in model fit due to the inclusion of the political factor, we note that the majority of explanatory factors proposed in the literature imply coefficients of determination that are quite low. 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 can explain from 3% to 10% of momentum profits. The Stivers and Sun (2010) model of cross-sectional dispersion can explain up to 7.5% of momentum profits. Finally, the conditional CAPM model of Daniel and Moskowitz (2013) yields R^2's around 28.5% at the stock-level.[17]

3.6. Factor Model Estimates During Sub-Periods

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 5, but now we focus on momentum returns during two important sub-periods: (i) a six-year time window around switching party elections, and (ii) the first nine months after elections. Table 6 reports the risk-adjusted performance estimates for momentum strategies during these specific sub-periods. Momentum returns have been adjusted using the three factor Fama-French model with and without the political factor. To save space, Table 6 shows results for the three-factor specification augmented by the political sentiment factor. The estimates for

[17] The market illiquidity model in Avramov et al. (2013) can explain around 25% of the time-series variation in momentum profits. However, this is a marginal improvement if we believe their findings that the standard Fama-French model can explain 23% of the variation in momentum.

the standard three-factor specification are omitted.

When we focus on six-year time windows around switching-party elections, the explanatory power of the political factor increases substantially. At the stock-level, including the political factor in the Fama-French model causes the alpha to decrease by approximately 40%, from 0.974 to 0.601, and this drop is statistically significant. Moreover, the R^2 increases from 0.037 for the three-factor model to 0.290 for the augmented model (3FF+POL).

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

At the industry level, the political factor is economically significant both around switching-party years as well as around non-switching party years. In both sub-periods, the political factor loads positively and statistically significantly, while the increase in R^2 is 20% around switching years and 14% around non-switching years. Nevertheless, during switching party years, the alpha drop due to the inclusion of the political factor in the model is far more pronounced (drop = 0.296, t-statistic = 3.01) than during non-switching party years (drop = 0.088, t-statistic = 2.46).

Taken together, the evidence in Table 6 indicates that the political factor becomes particularly important for stock-level momentum around switching party years, while industry momentum depends on the political factor during both switching and non-switching years. This finding likely reflects the fact that equity returns at the stock-level are particularly noisy. Therefore, the effects of the political factor on returns are best identified during periods when this factor is particularly important, i.e., during switching party years or during the first few months of a presidency. Industry returns, on the other hand, are not as noisy due to aggregation. Therefore, the impact of the political factor on returns can be identified during normal times as well.

Our second sub-period analysis focuses on a nine-month period after elections. At the stock-level, the four-factor model with political sentiment is characterized by a statistically significant drop in alpha and an increase in overall fit by 17.6% relative to the Fama-French three-factor model. Even though the four-factor alpha is statistically insignificant during the first nine months sub-sample, once we go beyond the first nine months of the presidency, the four-factor alpha becomes economically and statistically significant (estimate = 0.866, t-statistic = 5.53).

At the industry-level, the performance of the political factor is similar during the first nine months and beyond the first nine months sub-sample. In both sub-samples, the inclusion of the political factor causes the R^2 to increase by 20.2% and 20.4%, respectively, relative to the three-factor model. Also, in both sub-periods, there is a substantial decrease in alphas relative to the three factor model: 0.222 (t-statistic = 3.10) and 0.231 (t-statistic = 3.53), respectively. However, the alpha for the four-factor model (3FF+POL) is statistically insignificant during the first nine months sub-sample, while after the first nine months, the alpha estimate becomes statistically significant.

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 the political factor is concentrated around party-switching years, and decreases as we go beyond the first nine months following an election. This finding can be explained by the fact that equity returns at the stock-level are particularly 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 the political factor at the industry level may reflect the diversification of idiosyncratic noise in industry portfolios.

3.7. Fama-MacBeth Regression Estimates

So far, the analysis has focused on the time-series dynamics of momentum (MOM) at the stock- and industry-levels. In this section, we employ the Fama and MacBeth (1973) methodology to examine how 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 six months (skipping the most recent month), Fama-French three-factor betas calculated using daily returns over the previous month, as well as firm characteristics (size and B/M). The winner-favorite indicator is set to $+1$ for firms that are both a momentum winner and a political favorite, set to -1 for firms that are a momentum loser and a political unfavorite, and set to 0 for all other firms. The winner indicator is equal to $+1$ if a firm is a momentum winner, equal -1 if it is a momentum loser, and equal to 0 otherwise.

Estimation results in Table 7 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 one, it earns 0.604% higher returns on average. Likewise, a stock earns 0.464% higher returns when it transitions from the loser/unfavorite portfolio to the winner/favorite group. The winner/favorite indicator retains its economic and statistical significance, although less pronounced, even after controlling for risk exposures using traditional factor betas as well as firm characteristics attenuates the effect of the winner/favorite indicator. 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 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" factor (Jagannathan and Wan (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 political environment and price momentum. Specifically, during switching-party years or during the first few months of a new presidency, the importance of the political factor 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, the under-reaction to the new political information creates an upward price trend among favorites and a downward trend among unfavorites. Through this under-reaction channel, shifts in the political environment generate persistence in returns and can explain a significant part of time-variation in momentum profits.

4. Robustness Tests and Alternative Explanations

Our main empirical results demonstrate that the profitability of the momentum strategy is sensitive to the political environment. Specifically, firms that are momentum winners but political unfavorites deliver lower average returns than firms that are momentum losers but political favorites. In this section, we perform a number of additional tests to ensure that these findings are orthogonal to the effects of known determinants of price momentum.

4.1. Political Factor 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:

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

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

These equations are very similar to the specification in equation (1), but now the Presidential party indicator is 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 8 indicate that neither the House- nor the Senate-based political factor is able to explain an economically significant portion of momentum returns. For example, the alpha-drop due to the inclusion of the President-based political factor (0.218, t-statistic = 4.40) is three to seven times larger than the alpha-drop due to the House- or Senate-based political factors (0.070 and 0.036, respectively). Moreover, when we pool all of the political factors together, much of the significance of the Senate- and House-based political factors is subsumed by the original political factor based on the Presidential party. This evidence indicates that our Presidential party indicator is able to capture the political environment better that other related measures.

4.2. Political Environment or Macroeconomic Risks?

An important strand of the momentum literature addresses the momentum phenomenon using risk-based or characteristic-based explanations. For instance, Bansal, Dittmar, and Lundblad (2005) associate momentum profits with a long-run risk component in dividends. Further, Liu and Zhang (2013) use a partial equilibrium production model to identify the source of this higher long-run risk exposure in terms of cashflows (sales-to-capital, investment-to-capital, etc.). In a similar manner, Chordia and Shivakumar (2002) and Liu and Zhang (2008) associate momentum profits with macroeconomic risks.

In this section, we show that our political factor has incremental ability to explain momentum profits even after we account for an exhaustive set of control variables that have recently appeared in the literature. In fact, we show that the political factor is the only statistically significant factor in explaining momentum profits.

For the first robustness test, we regress momentum profits on the three-factor Fama-French model augmented by a set of macroeconomic variables that have been previously considered in Chordia and Shivakumar (2002): the default spread, the yield on three-month T-bills, the term spread, and the value-weighted market dividend yield. Following Avramov et al. (2013), we control for the lagged market liquidity factor of Pastor and Stambaugh (2003), the lagged Baker-Wurgler (Baker and Wurgler (2006)) investor sentiment, and lagged market volatility. We also consider industrial production growth as in Liu and Zhang (2008), lagged market returns, market returns squared, and a down-market indicator[18] from Cooper et al. (2004) as well as the cross-sectional dispersion in returns from Stivers and Sun (2010). Finally, we control for long-run consumption growth as in Bansal et al. (2005) and Asness et al. (2013).[19]

[18] Daniel and Moskowitz (2013) also consider lagged market volatility, market returns, and a lagged down market indicator.

[19] Asness et al. (2013) also consider quarterly GDP growth and additional liquidity measures. In our case, since we focus on monthly data we cannot use GDP growth. Nevertheless, GDP growth should be captured by industrial production. Also, the Pastor and Stambaugh (2003) liquidity factor included in our specification should be able to capture the liquidity measures in Asness et al. (2013).

Table 9 shows that these additional control variables do not improve the fit of the three-factor model. More importantly, our political factor remains statistically and economically significant even after controlling for all these momentum determinants. Specifically, accounting for the political factor increases the overall fit of the model by 21% at the industry level and 20% at the stock level, whereas the inclusion of all other variables leaves the R^2 of the standard factor model from Table 5 virtually unchanged.

Overall, the results in this section indicate that the political factor has superior explanatory power to a wide set of macroeconomic variables. This does not necessarily mean that macroeconomic factors are irrelevant for momentum profits. Rather, our findings suggest that the political factor is a significant determinant of the time-series variation in momentum profits, over and above the effects of macroeconomic risks, liquidity, down-market states, and market volatility.

4.3. Do We Simply Repackage Momentum?

One potential concern about our empirical strategy is that political sensitivity based portfolios might simply be a relabeling of momentum portfolios. We address this issue in Table 10. In Panel A, for each industry and each stock, we use the political sensitivity estimates from July of the election year, and keep them constant until July of the following year. Given that momentum portfolios are formed based on past six month performance, by keeping the political sensitivity constant for a year, we are essentially accounting for any momentum information that might be embedded in our political portfolios.

The results in Panel A of Table 10, in which political sensitivity is kept constant, are almost identical to the results in Table 5 where we estimate political sensitivity every month. The model with the political factor explains approximately 21% of the time-series variation of the momentum strategy at the industry-level and 28% at the stock-level. Hence, the overall fit of the four-factor model (3FF+POL) is almost one order of magnitude higher than the explanatory power of the model without the political factor. Further, even when political sensitivities are kept constant, the inclusion of the political factor in the Fama-French model generates alpha drops that are economically and statistically significant.

Panel B in Table 10 addresses the relabeling of momentum concern in a more direct way. If political portfolios were essentially a relabeling of momentum portfolios, then both past as well as future six month returns would be monotonically increasing across political portfolios. This is not the case in Panel B of Table 10, which focuses on past and future six-month returns for political portfolios around November of switching-party election years. Both at the stock- and industry-levels, previous six-month returns are actually monotonically decreasing across political portfolios, while there is no clear pattern in future six-month returns. Based on the results from Table 10, we conclude that our political portfolios do not repackage momentum, and instead provide new insights into the economic mechanism that drives return predictability.

4.4. Other Political Sensitivity Measures

Throughout the paper, 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 propose an alternative model that measures political sensitivity, while controlling for past performance. More specifically, we estimate political sensitivity using the following specification

$$\begin{aligned} r_{i,t} - r_{f,t} = \alpha_i + \beta_i \left(r_{mkt,t} - r_{f,t} \right) + \theta_i^* RepubInd_t \\ + \sum_{j=2}^{12} \beta_j r_{i,t-j} + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

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

The results in Table 11 for the alternative political sensitivity measure are almost identical to the baseline results reported in Tables 5 and 6. The alternative political sentiment factor is economically and statistically significant across all sub-periods, both at the stock- and the industry-levels. Further, by adding the alternative political sensitivity measure in the three-factor model, there is a substantial improvement in the overall fit: R^2's increase by 17.4% at the industry-level (from 2.8% to 20.3%) and by 20.9% at the stock-level (from 3.7% to 24.6%).

These increases in R^2 are also combined with significant drops in alphas. During switching-party years, the industry alpha decreases by 0.236% (from 0.611% to 0.375%), and the stock alpha decreases by 0.331% (from 0.973% to 0.642%) in relation to models without the political sensitivity. On the basis of results in Table 11, we conclude that our political sensitivity measure is not somehow contaminated by past returns.

4.5. Additional Robustness Checks

In addition to the set of 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. Further, 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 equal to zero. In all cases, we find results that are similar to those presented in the paper. Finally, we also test the relationship between political sensitivity and earnings momentum, and find that the political sensitivity factor explains an economically and statistically insignificant portion of earnings momentum returns. This evidence is consistent with the findings of Chan, Jegadeesh, and Lakonishok (1996), who conclude that price momentum and earnings momentum are two different phenomena.

Overall, our 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 the political factor carries over to the full cross-section of stock returns. These findings are robust to a wide set of alternative methodologies and control specifications. Next, we examine the specific mechanism through which political information affects momentum profits.

5. Momentum Decomposition

In the last set of tests, we use the momentum decomposition procedure (Jegadeesh and Titman (1993), Moskowitz and Grinblatt (1999)) to identify the main channel though which the political environment influences momentum profits. First, we assume that stock returns are generated by a linear factor model as follows

$$r_{i,t} = r_{f,t} + \sum_{j=1}^{K} \beta_{i,j} f_{j,t} + \epsilon_{i,t}, \tag{5}$$

where $f_{j,t}$ are factors and $\epsilon_{i,t}$ are firm or industry specific effects. For the political sensitivity model summarized in equation (1), $f_{1,t}$ is the excess market returns and $f_{2,t}$ is the Republican indicator.

If $\bar{r}_t$ is the cross-sectional mean for stock returns at time t, then the momentum strategy implies that there is a time interval h such that

$$\mathbb{E}[(r_{i,t+h} - \bar{r}_{t+h})(r_{i,t} - \bar{r}_t)] > 0. \tag{6}$$

Given the linear structure of the factor model in (5), then average momentum profits across N stocks are equal to[20]

$$\frac{1}{N}\sum_{i=1}^{N}\mathbb{E}[(r_{i,t+h}-\bar{r}_{t+h})(r_{i,t}-\bar{r}_t)] = \sigma_\mu^2 + \sum_{j=1}^{K}\sigma_{\beta_j}^2 Cov(f_{j,t+h}, f_{j,t}) + \frac{1}{N}\sum_{i=1}^{N} Cov(\epsilon_{i,t+h}, \epsilon_{i,t}), \quad (7)$$

where σ_μ^2 is the cross-section variance in expected returns, and $\sigma_{\beta_j}^2$ are the cross-sectional variances in factor loadings. Equation (7) implies that momentum profits can be decomposed into three parts: cross-sectional variance, factor autocovariance, and residual autocovariance. We study the importance of each component using the results in Table 12.

First, Panel A indicates that the cross-sectional variance in expected returns at the stock-level may account for a significant part of momentum,[21] although at the industry-level, the cross-sectional variance in expected returns is almost zero.[22] These estimates are consistent with the evidence in Conrad and Kaul (1998) for stock-level momentum, and Moskowitz and Grinblatt (1999) for industry momentum. They also indicate that industry- and stock-level momentum phenomena may be distinct and driven by different economic mechanisms.

Another important finding in Panel A of Table 12 is that the cross-sectional dispersion in expected returns increases significantly during switching party years and during the first 12 months after an election.[23] During these politically important periods, the cross-sectional volatility of expected returns almost doubles at the industry-level (from 0.907% to 2.072%) and increases significantly at the stock-level (from 19.961% to 34.872%).

Consistent with previous results, Panel B in Table 12 shows that the traditional asset pricing factors (RMRF, SMB, HML) exhibit almost no autocorrelation.[24] This finding does not imply

[20] Conrad and Kaul (1998), Moskowitz and Grinblatt (1999).

[21] At the stock-level, the cross-sectional variance for expected returns at the semi-annual frequency is approximately 0.04, while the semi-annual momentum profits from Table 1 are approximately 0.05.

[22] At the industry-level, the cross-sectional variance for expected returns at the semi-annual frequency is approximately 0.0001, while the semi-annual momentum profits from Table 1 are 0.03.

[23] Here we consider 12 months after the election instead of 9 months as we did before because returns in Table 11 are calculated on a semi-annual frequency, and thus we can only consider 6-month, 12-month, 18-month intervals.

[24] Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999) find similar results.

that asset pricing factors are not persistent. It only means that the Fama-French specification includes factors that are serially uncorrelated. The political factor at the industry-level is also serially uncorrelated, since the autocorrelation is 0.057 with a p-value of 0.480. However, at the stock-level, the autocorrelation for the political factor is 0.160, which is much larger than the autocorrelations for the rest of the factors. Further, the political indicator is very persistent, since the autocorrelation is 0.88 and statistically significant. Based on these findings, it appears that the persistence of the political indicator or the persistence of the political factor at the stock-level could explain part of the momentum phenomenon.

Last, Panel B shows results for the third momentum component: idiosyncratic shocks (residuals). Industry residuals have been estimated according to equation (1). Out of the 48 residual autocorrelations, only two are lower than 5%. This result is in line with Moskowitz and Grinblatt (1999) who assume that industry residuals are serially uncorrelated. Moreover, this result shows that the autocovariances of industry residuals cannot explain industry momentum. At the stock-level, we find that residuals exhibit, on average, stronger autocorrelation patterns than industry residuals, yet the magnitudes of these autocorrelations cannot fully explain momentum either. Overall, only 2 out of the 48 residual autocorrelations are statistically significant at the industry-level, and only 290 out of the 4650 residual autocorrelations are statistically significant at the stock-level.

In addition to the above decomposition results, it is interesting to explore the cashflow versus discount rate channel through which the political factor affects momentum. For this analysis, we cite the results in Addoum and Kumar (2013), who also estimate the sensitivity of industry-level average earnings to the Presidential party. They find that forming portfolios on these earnings-based sensitivities does not yield profitable long-short strategy returns. Further, they find that a 3×3 double-sort on the returns-based and earnings-based political sensitivity measures yields consistently profitable returns on the returns-based dimension and returns that are consistently indistinguishable from zero on the earnings-based dimension. This analysis is complimentary to our momentum decomposition results above, and suggests that political information operates through the discount rate channel rather than the cashflow channel.

Collectively, the evidence in Table 12 suggests that during periods of political unrest, the cross-sectional variance of stock returns increases, and this may explain some of our results. Nevertheless, the cross-sectional variance is important for stock momentum but not for industry-level momentum. Further, unlike traditional asset pricing factors, the political indicator is quite persistent, while the political factor exhibits some persistence at the stock-level. This persistence can partially explain why our political factor is effective in explaining momentum profits. Examining the third component of momentum profits, we find that neither industry nor stock momentum can be attributed to the autocorrelation of industry- or stock-specific shocks.

6. Summary and Conclusion

Momentum is one of the most well studied regularities in the asset pricing literature. Contrary to the majority of stylized phenomena in asset markets, momentum has remained robust long after its discovery (Jegadeesh and Titman (2001)). However, the economic mechanism that induces momentum in stock prices is not fully understood.

In this study, we show that changes in political environment can explain an economically significant part of the time-series variation in momentum profits, even after controlling for effects of a large set of variables that have been previously linked to momentum. Including the political factor in asset pricing models leads to a significant drops 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, our political factor has significant explanatory power during periods of political unrest, i.e., around switching-party years, and during the first few months of a new presidency.

When we decompose momentum profits into various components, we find that the explanatory power of the political factor is likely to originate from two sources: an increase in the cross-sectional variance of expected returns during politically important periods, and the persistence of the presidency indicator. 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.

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Figure 1
Cumulative Gains for Different Momentum Portfolios

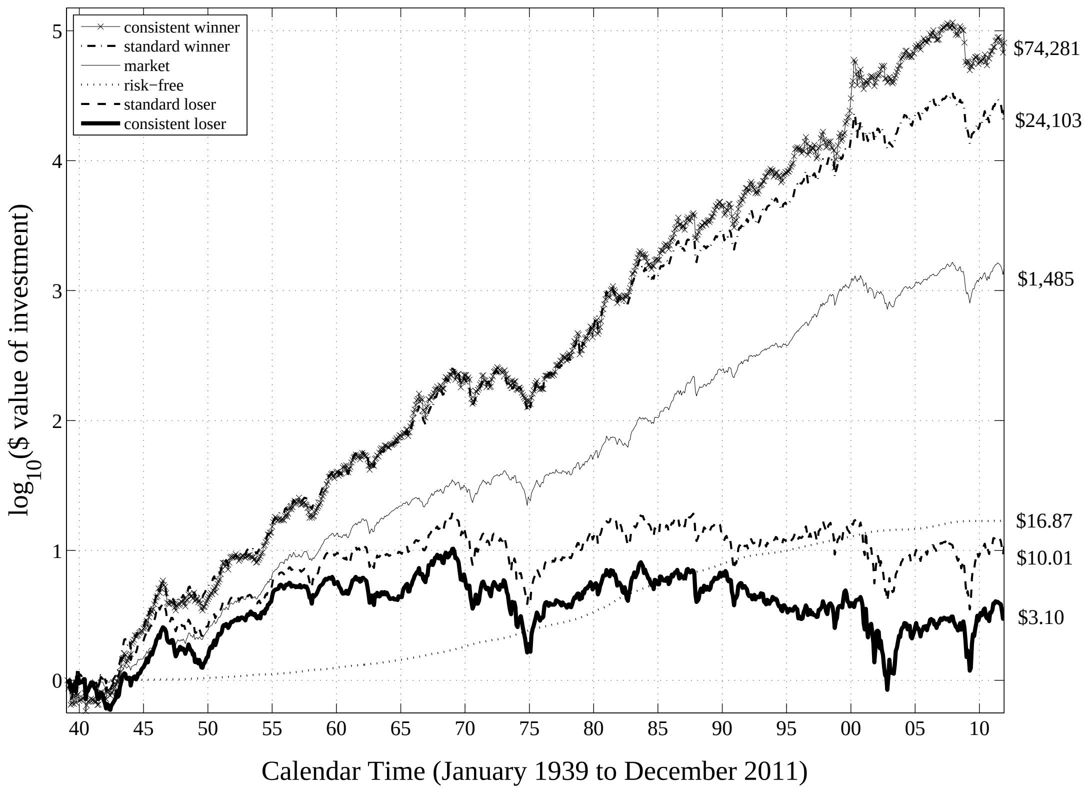

Figure 1 presents cumulative monthly log-returns for investing in: (1) the risk-free asset; (2) the CRSP value-weighted market index; (3) the politically consistent winner portfolio (winners/favorites); (4) the politically consistent loser portfolio (losers/unfavorites); (5) the standard momentum winners portfolio; and (6) the standard momentum losers portfolio. The y-axis shows cumulative log_{10} returns for each portfolio. On the right side of the plot, we also present final dollar values for each of the six assets.

Figure 2
Cumulative Returns for the 1Y Window around Party-Switching Elections

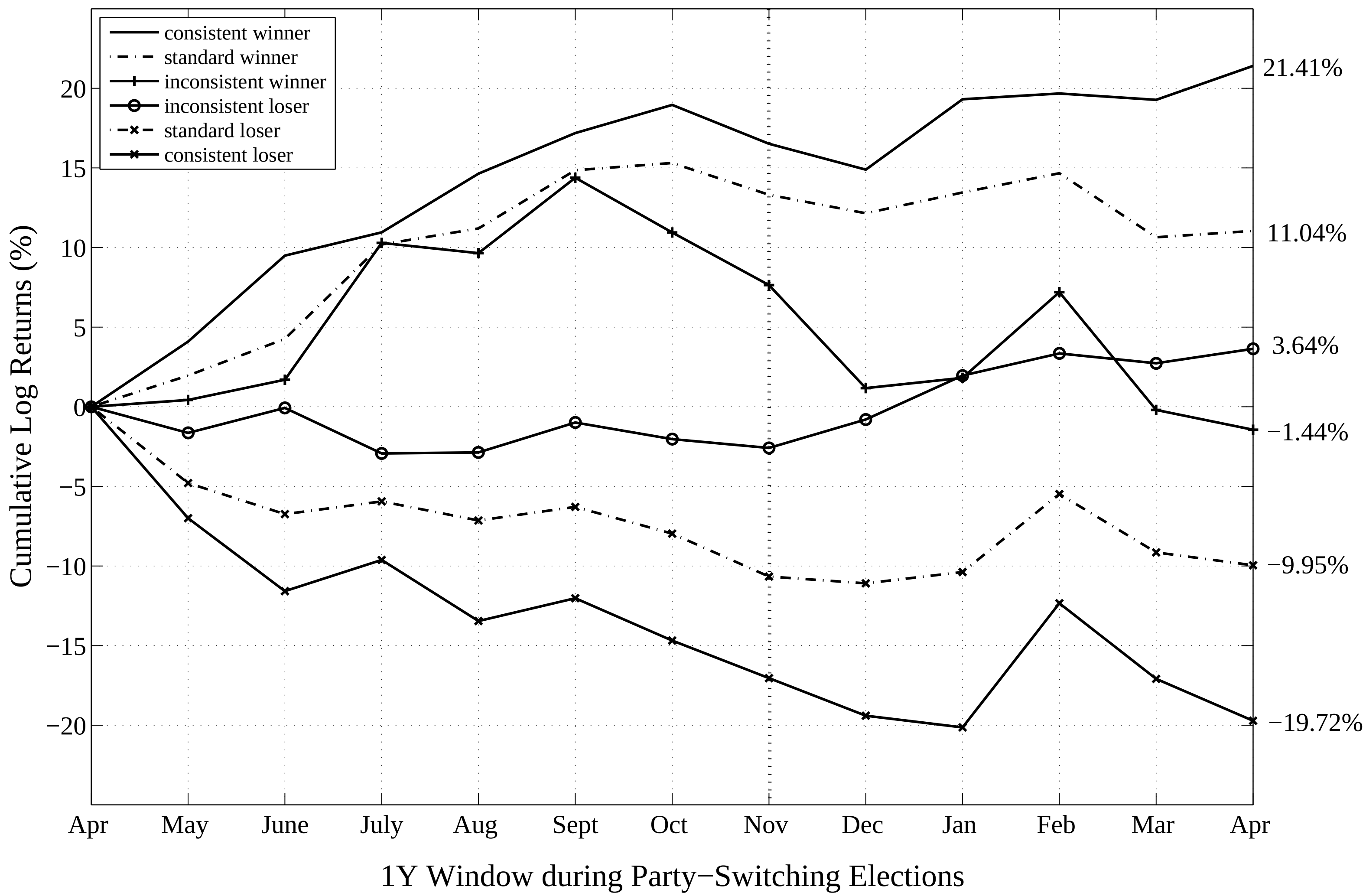

Figure 2 presents cumulative log-returns during a one-year window around party-switching elections for: (1) the politically consistent winners portfolio; (2) the standard winners portfolio excluding politically favorite and politically unfavorite stocks; (3) the politically inconsistent winners portfolio; (4) the politically consistent losers portfolio; (5) the standard losers portfolio excluding politically favorite and politically unfavorite stocks; and (6) the politically inconsistent losers portfolio. The formation time for all six portfolios is set to be November of party-switching years.

Figure 3
Cumulative Dollar Values Around Party-Switching Elections: Winner Portfolios

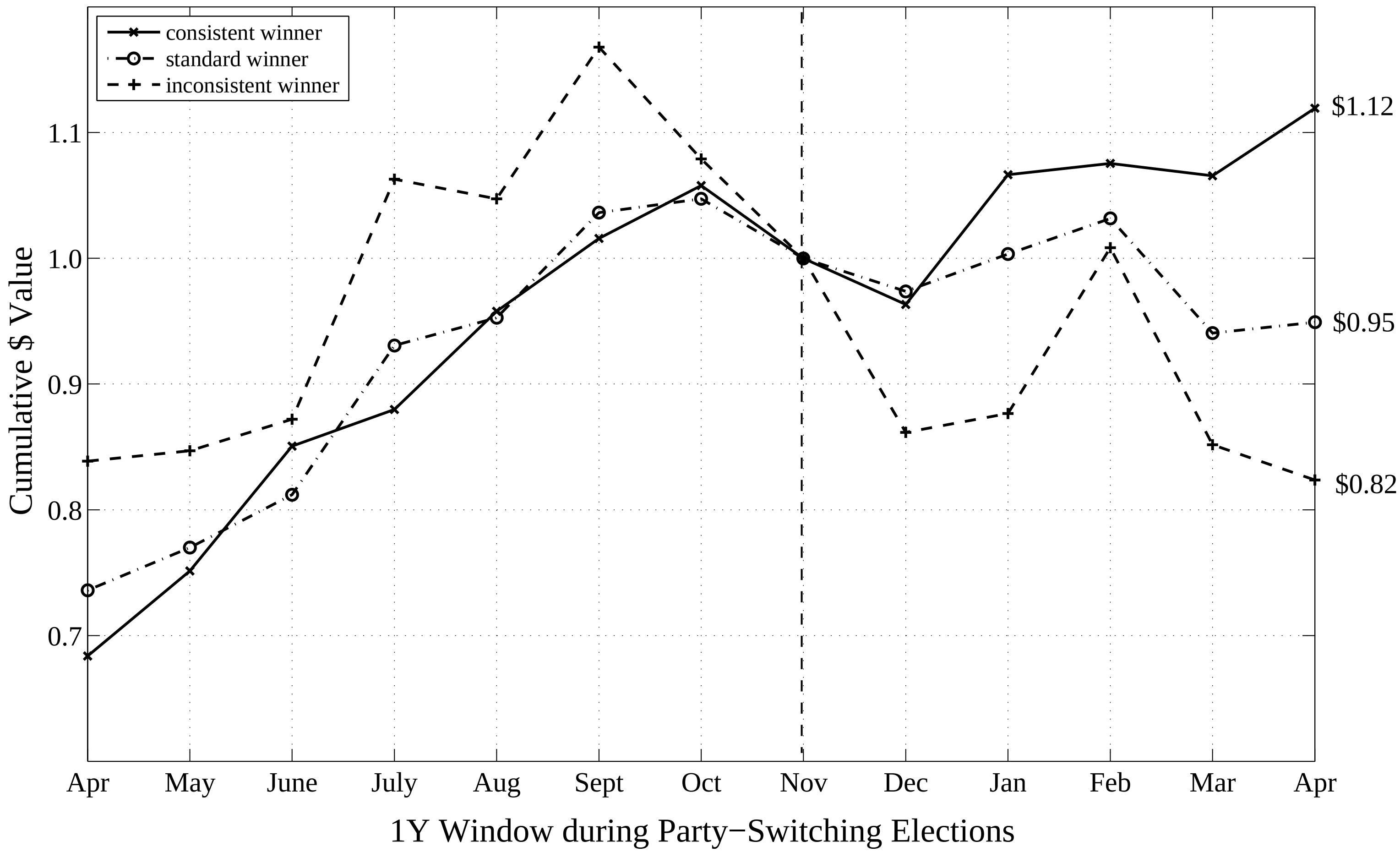

Figure 3 presents cumulative dollar values during a one-year window around party-switching elections for: (1) the politically consistent winners portfolio (winners/favorites); (2) the standard momentum winners portfolio excluding politically favorites and politically unfavorites; and (3) the politically inconsistent winners portfolio (winners/unfavorites). The formation period for all three portfolios is November of switching-party election years. The y-axis shows cumulative dollar values for each portfolio when $1 is invested in each of the portfolios at the start of November.

Figure 4
Cumulative Dollar Values Around Party-Switching Elections: Loser Portfolios

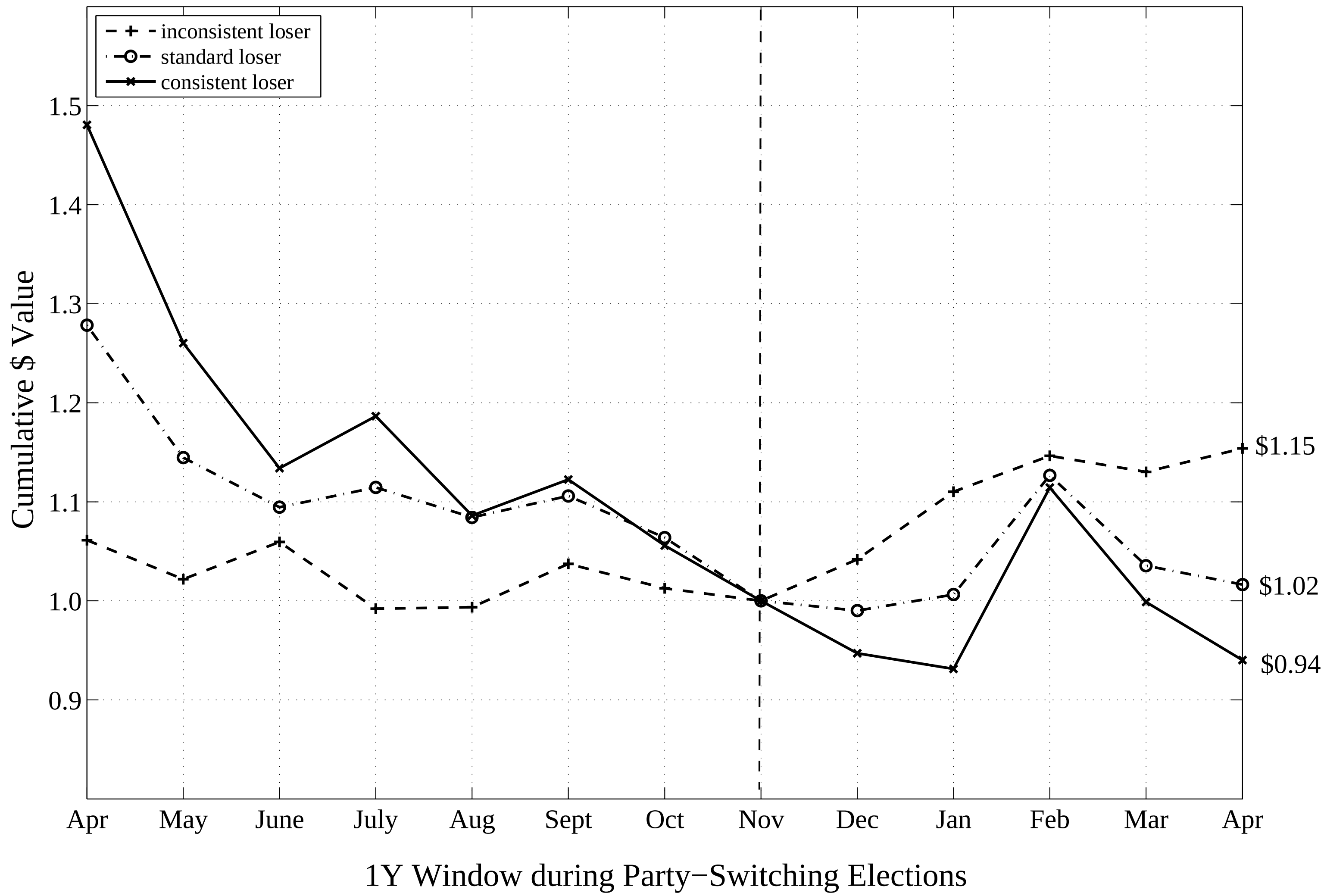

Figure 4 presents cumulative dollar values during a one-year window around party-switching elections for: (1) the politically consistent losers portfolio (losers/unfavorites); (2) the standard momentum losers portfolio excluding politically favorites and politically unfavorites; and (3) the politically inconsistent losers portfolio (losers/favorites). The formation period for all three portfolios is November of switching-party election years. The y-axis shows cumulative dollar values for each portfolio when $1 is invested in each of the portfolio at the start of November.

Figure 5
Politically Consistent Momentum Strategy: 1939-2011

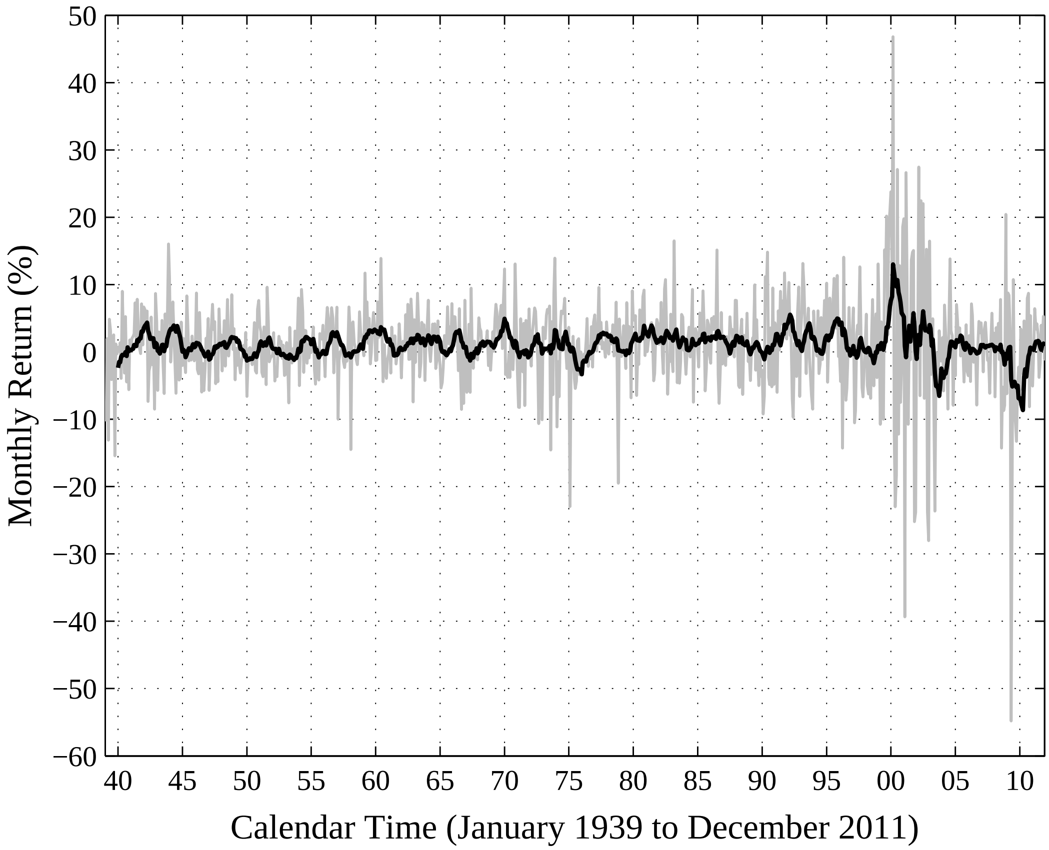

Figure 5 presents monthly returns (grey line) for the politically consistent momentum strategy and its 12-month moving average (dark line) from January 1939 to December 2011. The politically consistent momentum trading strategy holds an equally-weighted portfolio of momentum winners which are also political favorites, and shorts an equally-weighted portfolio of momentum losers which are also political unfavorites.

Table 1
Performance of Political and Momentum Portfolios

This table reports monthly performance for political and momentum portfolios. To construct stock-level political portfolios, we sort all stocks at the beginning of every month based on their conditional political sensitivity (θ_i^c estimates in Equation 1), and hold the resulting ten equally-weighted portfolios for one month. For industry-level political portfolios, we sort all Fama-French 48 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, while 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. The political (POL) factor 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 ten 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 political portfolio and winner-minus-loser momentum portfolio are also reported. t-statistics are adjusted for autocorrelation and heteroscedasticity using the Newey-West (1987) correction method. The estimation period is from January 1939 to December 2011.

Panel A: Fama-French 48 Industries

	Political Portfolios				Momentum Portfolios		
	Pol. Sensitivity	Raw Return	Sharpe Ratio		Pol. Sensitivity	Raw Return	Sharpe Ratio
Unfavorite	−1.706	0.791	0.283	Loser	−0.411	0.769	0.285
2	−0.731	0.930	0.427	2	−0.158	0.920	0.413
3	−0.105	1.022	0.504	3	−0.059	1.089	0.555
4	0.592	1.184	0.618	4	0.052	1.134	0.593
Favorite	1.356	1.356	0.667	Winner	0.114	1.301	0.656
F-U (POL)		0.564	0.207	W-L (MOM)		0.532	0.226
		(4.06)				(5.15)	
Corr(F-U,W-L)	= 0.463						

Panel B: Individual Stocks

	Political Portfolios				Momentum Portfolios		
	Pol. Sensitivity	Raw Return	Sharpe Ratio		Pol. Sensitivity	Raw Return	Sharpe Ratio
Unfavorite	−1.496	0.929	0.326	Loser	−0.100	0.551	0.102
2	−0.726	0.933	0.364	2	−0.084	0.836	0.272
3	−0.462	1.114	0.497	3	−0.069	1.019	0.416
4	−0.300	1.042	0.423	4	−0.046	1.091	0.498
5	−0.110	1.045	0.440	5	−0.023	1.153	0.584
6	0.063	1.098	0.461	6	−0.014	1.172	0.614
7	0.296	1.202	0.543	7	0.010	1.160	0.614
8	0.480	1.186	0.558	8	0.019	1.171	0.601
9	0.763	1.395	0.652	9	0.022	1.303	0.641
Favorite	1.362	1.360	0.586	Winner	0.022	1.378	0.556
F-U (POL)		0.431	0.105	W-L (MOM)		0.827	0.380
		(3.00)				(5.66)	
Corr(F-U,W-L)	= 0.434						

Table 2

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. Panel A reports raw returns for each strategy, while Panel B reports characteristic-adjusted returns for each strategy using the method of Daniel, Grinblatt, Titman, and Wermers (1997). t-statistics are adjusted for autocorrelation and heteroscedasticity. SR is the Sharpe ratio. The estimation period is from January 1939 to December 2011.

	Panel A: Raw Returns					
	Fama-French 48 Industries			Stock-Level		
	Standard Mom.	Pol. Consist. Mom.	Pol. Inconsist. Mom.	Standard Mom.	Pol. Consist. Mom.	Pol. Inconsist. Mom.
Winner	1.301	1.629	1.269	1.378	1.556	1.218
	(6.86)	(6.84)	(4.13)	(5.93)	(5.87)	(4.77)
Loser	0.769	0.534	1.360	0.551	0.457	1.130
	(3.91)	(1.93)	(4.83)	(2.12)	(1.65)	(4.19)
W-L	0.532	1.095	−0.092	0.827	1.099	0.088
	(5.15)	(4.34)	(−0.32)	(5.66)	(4.78)	(0.40)
SR	0.226	0.381	−0.208	0.380	0.401	−0.132

	Panel B: Characteristic-Adjusted Returns					
	Fama-French 48 Industries			Stock-Level		
	Standard Mom.	Pol. Consist. Mom.	Pol. Inconsist. Mom.	Standard	Pol. Consist. Mom.	Pol. Inconsist. Mom.
Winner	0.184	0.415	0.048	0.151	0.268	0.072
	(4.02)	(3.73)	(0.27)	(4.35)	(2.46)	(0.76)
Loser	−0.159	−0.309	0.153	−0.269	−0.237	−0.006
	(−2.85)	(−2.37)	(1.01)	(2.17)	(−2.09)	(−0.04)
W-L	0.342	0.724	−0.105	0.420	0.505	0.078
	(4.80)	(3.88)	(−0.46)	(4.28)	(2.91)	(0.41)

Table 3

Performance of the Politically Enhanced Momentum Strategies: Sub-Period Analysis

This table reports monthly performance for the three types of momentum strategies (standard momentum, politically consistent momentum, and politically inconsistent momentum) in various sub-periods. Expansionary and recessionary periods are according to the NBER. t-statistics are adjusted for autocorrelation and heteroscedasticity. The estimation period is from January 1939 to December 2011.

	Fama-French 48 Industries			Individual Stocks		
	Standard	Consist. Pol. Env.	Inconsist. Pol. Env.	Standard	Consist. Pol. Env.	Inconsist. Pol. Env.
Non-Jan.	0.622	1.315	0.000	1.063	1.284	0.297
	(5.63)	(4.91)	(0.00)	(6.50)	(5.14)	(1.28)
January	−0.455	−1.440	−1.079	−1.766	−0.929	−2.214
	(−1.17)	(−1.29)	(−0.83)	(−2.35)	(−1.06)	(−3.06)
Expansion	0.563	1.098	−0.125	0.917	1.271	0.159
	(5.65)	(4.46)	(−0.41)	(7.01)	(5.14)	(0.68)
Recession	0.353	1.081	0.156	0.312	0.116	−0.322
	(0.89)	(1.17)	(0.18)	(0.53)	(0.19)	(−0.39)
Switch. Party	0.510	1.250	−0.309	0.783	1.176	−0.179
	(3.49)	(3.37)	(−0.85)	(3.65)	(3.52)	(-0.59)
9mo Post Elec.	0.532	1.085	−0.092	0.827	1.099	0.088
	(5.15)	(4.34)	(−0.32)	(5.66)	(4.78)	(0.40)
1941-1950	0.574	1.120	−0.126	0.624	1.168	0.130
1950-1960	0.417	1.039	−1.035	0.775	0.917	0.397
1961-1970	0.767	1.569	0.333	0.921	1.336	0.639
1971-1980	0.682	1.555	0.224	1.039	0.918	0.624
1981-1990	0.391	1.090	−0.764	1.358	1.444	0.568
1991-2000	0.874	1.739	0.332	1.490	2.719	−0.627
2001-2007	0.586	0.496	0.375	0.353	0.397	0.062

Table 4
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 1. The sample period is from January 1939 to December 2011.

Panel A: Fama-French 48 Industries					
Portfolio	Size	Book-to-Market	Portfolio	Size	Book-to-Market
Unfavorite	11.200	0.750	Winner/Favorite	11.056	0.769
2	11.228	0.761	Loser/Unfavorite	11.068	0.920
3	11.277	0.747	Winner/Unfavorite	11.113	1.089
4	11.113	0.803	Loser/Favorite	11.031	1.134
Favorite	11.101	0.739			

Panel B: Individual Stocks					
Portfolio	Size	Book-to-Market	Portfolio	Size	Book-to-Market
Unfavorite	14.189	0.818	Winner/Favorite	14.268	0.785
2	14.400	0.974	Loser/Unfavorite	13.426	1.073
3	14.114	1.010	Winner/Unfavorite	13.442	0.705
4	14.183	1.937	Loser/Favorite	13.320	1.146
5	14.082	0.907			
6	14.145	0.816			
7	14.030	0.961			
8	14.152	0.898			
9	14.261	0.850			
Favorite	14.369	0.845			

Table 5
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 industries portfolios (Panel A) and individual stocks (Panel B). The set of factors includes market excess return (RMRF), size (SMB), value (HML), short-term reversal (STR), long-term reversal (LTR), as well as the zero-investment political portfolio (POL) at the industry (Panel A) and stock-levels (Panel B) . t-statistics are adjusted for autocorrelation and heteroscedasticity. *Alpha Drop* is the decrease in alpha due to the inclusion of the political factor (POL) in the linear model. Estimation period is January 1939 to December 2011.

	Panel A: Industry Momentum					
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.556	0.335	0.621	0.381	0.709	0.439
	(5.47)	(3.39)	(6.08)	(3.93)	(6.02)	(3.73)
RMRF	−0.040	−0.015	−0.040	−0.022	−0.014	−0.006
	(−0.83)	(−0.41)	(−0.96)	(−0.66)	(−0.30)	(−0.15)
SMB			−0.036	0.005	−0.005	0.007
			(−0.46)	(0.09)	(−0.07)	(0.11)
HML			−0.137	−0.096	−0.115	−0.103
			(−1.73)	(−1.64)	(−1.24)	(−1.45)
STR					−0.165	−0.098
					(−2.13)	(−1.41)
LTR					−0.018	0.034
					(−0.21)	(0.48)
POL		0.366		0.360		0.352
		(8.35)		(8.57)		(7.62)
Adj. R^2	0.002	0.213	0.016	0.218	0.036	0.225
N (months)	876	876	876	876	876	876
Alpha Drop	0.221		0.240		0.270	
	(3.75)		(4.40)		(2.53)	

	Panel B: Stock-Level Momentum					
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.902	0.668	1.011	0.759	1.225	0.936
	(6.74)	(4.53)	(6.95)	(4.77)	(7.61)	(5.10)
RMRF	−0.121	−0.090	−0.116	−0.064	−0.044	−0.013
	(−1.70)	(−1.57)	(−1.90)	(−1.35)	(−0.68)	(−0.25)
SMB			−0.084	−0.169	−0.073	−0.165
			(−0.51)	(−1.50)	(−0.55)	(−1.46)
HML			−0.227	−0.177	−0.259	−0.218
			(−1.32)	(−1.40)	(−1.51)	(−1.73)
STR					−0.404	−0.298
					(−3.16)	(−2.67)
LTR					0.147	0.139
					(1.18)	(1.40)
POL		0.480		0.484		0.449
		(5.52)		(5.24)		(4.66)
Adj. R^2	0.012	0.194	0.033	0.214	0.098	0.250
N (months)	876	876	876	876	876	876
Alpha Drop	0.234		0.252		0.290	
	(2.92)		(3.90)		(2.34)	

Table 6
Factor Model Estimates: Sub-Period Analysis

This table reports risk-adjusted performance for the winner-minus-loser momentum strategy. Returns have been risk-adjusted with the Fama-French three-factor model (Fama and French (1992)), and the Fama-French three-factor model augmented with the political factor. 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 time-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 industries portfolios (Panel A) and individual stocks (Panel B). t-statistics are adjusted for autocorrelation and heteroscedasticity. *Adj.* R^2 *Increase* is the increase in the adjusted R^2 due to the inclusion of the political factor (POL) in the Fama-French three-factor model.*Alpha Drop* is the decrease in alpha due to the inclusion of the political factor (POL) in the Fama-French three-factor model. The estimation period is from January 1939 to December 2011.

	Panel A: Industry Momentum			
	Switch. Party	Non-Switch. Party	First 9mo Post Elec.	After 9mo Post Elec.
Alpha	0.315	0.431	0.186	0.435
	(2.53)	(2.94)	(0.76)	(4.21)
POL	0.364	0.308	0.398	0.346
	(7.13)	(5.13)	(3.07)	(7.87)
Adj. R^2 Increase	0.202	0.141	0.202	0.204
Alpha Drop	0.296	0.088	0.222	0.231
	(3.01)	(2.46)	(3.10)	(3.53)
N months	553	323	162	714
	Panel B: Stock-Level Momentum			
	Switch. Party	Non-Switch. Party	First 9mo Post Elec.	After 9mo Post Elec.
Alpha	0.601	0.887	0.374	0.866
	(2.96)	(4.44)	(0.88)	(5.53)
POL	0.566	0.029	0.640	0.378
	(6.02)	(0.30)	(2.99)	(3.94)
Adj. R^2 Increase	0.253	−0.002	0.176	0.121
Alpha Drop	0.373	0.005	0.372	0.182
	(3.11)	(0.13)	(2.35)	(2.85)
N months	553	323	162	714

Table 7
Stock- and Industry-Level Fama-MacBeth Regressions

This table reports estimates from Fama-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, size, book-to-market, returns over the previous six months skipping the most recent one, and the Fama-French three-factor betas calculated over the previous months. The winner-favorite indicator is equal to +1 if the asset is a momentum winner and a political favorite, equals −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, equals −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. t-statistics are adjusted for autocorrelation and heteroscedasticity. The estimation period is from January 1940 to December 2011.

	Dependent Variable: Monthly Excess Return							
	Fama-French 48 Industries				Individual Stocks			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Const.	0.739	0.692	0.494	0.776	0.824	0.545	0.402	0.476
	(4.18)	(3.52)	(2.62)	(4.44)	(4.47)	(2.87)	(2.17)	(3.87)
Winner-Favorite Ind.	0.314	0.302	0.263	0.208	0.244	0.232	0.229	0.142
	(2.58)	(2.49)	(2.22)	(1.95)	(2.58)	(2.48)	(2.66)	(2.06)
Winner Ind.	0.241	0.242	0.134	0.155	0.386	0.405	0.298	0.267
	(4.47)	(4.64)	(2.41)	(2.78)	(6.89)	(7.59)	(6.25)	(7.13)
Size		0.000	0.000	0.000		0.000	0.000	0.000
		(−1.82)	(−1.80)	(−1.66)		(−2.66)	(−2.71)	(−3.05)
B/M		0.060	0.065	−0.011		0.312	0.326	0.261
		(0.047)	(0.053)	(−0.10)		(4.01)	(4.40)	(4.35)
Lagged 6mo Ret.			0.012	0.007			0.006	0.007
			(2.62)	(1.51)			(3.20)	(4.49)
Beta_RMRF				−0.187				−0.019
				(−1.04)				(−0.20)
Beta_SMB				0.028				0.000
				(0.27)				(0.01)
Beta_HML				0.152				0.089
				(1.36)				(1.73)
Avg. Adj. R^2	0.102	0.183	0.234	0.365	0.019	0.037	0.047	0.088
Avg. # Obs./Month	45	45	45	45	1421	1230	1230	1230

Table 8
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 (Fama and French (1992)), and the Fama-French three-factor model augmented with three alternative measures of the political factor. *POL_presid* is the benchmark political factor based on the political affiliation of the President. *POL_senate* is the political factor based on the party that holds the majority in the Senate, and *POL_house* is the political factor based on the party that controls the House. Component returns correspond to equally-weighted Fama-French 48 industries portfolios (Panel A) and individual stocks (Panel B). t-statistics are adjusted for autocorrelation and heteroscedasticity. *Alpha Drop* is the decrease in alpha due to the inclusion of the political factor (POL) in the linear model. Estimation period is January 1939 to December 2011.

	Panel A: Industry Momentum				
	(1)	(2)	(3)	(4)	(5)
Alpha	0.621	0.381	0.585	0.551	0.370
	(6.08)	(3.93)	(5.84)	(5.39)	(3.85)
RMRF	−0.040	−0.022	−0.037	−0.024	−0.016
	(−0.96)	(−0.66)	(−0.91)	(−0.63)	(−0.48)
SMB	−0.036	0.005	−0.040	−0.013	0.009
	(−0.46)	(0.09)	(−0.60)	(−0.21)	(0.19)
HML	−0.137	−0.096	−0.109	−0.064	−0.053
	(−1.73)	(−1.64)	(−1.50)	(−0.96)	(−0.99)
POL_presid		0.360			0.304
		(8.57)			(7.61)
POL_senate			0.239		0.071
			(5.13)		(1.53)
POL_house				0.307	0.168
				(4.56)	(2.25)
Adj. R^2	0.016	0.218	0.094	0.128	0.271
N (months)	876	876	876	876	876
Alpha Drop		0.240	0.036	0.070	0.252
		(4.40)	(6.16)	(4.17)	(7.11)

	Panel B: Stock-level Momentum				
	(1)	(2)	(3)	(4)	(5)
Alpha	1.011	0.759	0.859	0.887	0.668
	(6.95)	(4.77)	(5.80)	(6.22)	(4.23)
RMRF	−0.116	−0.064	−0.113	−0.121	−0.065
	(−1.90)	(−1.35)	(−1.92)	(−2.02)	(−1.44)
SMB	−0.084	−0.169	−0.172	−0.125	−0.228
	(−0.51)	(−1.50)	(−1.55)	(−0.96)	(2.25)
HML	−0.227	−0.177	−0.063	−0.087	−0.062
	(−1.32)	(−1.40)	(−0.44)	(−0.51)	(−0.45)
POL_president		0.484			0.447
		(5.24)			(4.36)
POL_senate			0.340		0.259
			(3.17)		(2.30)
POL_house				0.283	−0.013
				(2.22)	(−0.10)
Adj. R^2	0.033	0.214	0.102	0.068	0.251
N (months)	876	876	876	876	876
Alpha Drop		0.252	0.152	0.124	0.343
		(3.90)	(2.04)	(1.31)	(10.78)

Table 9
Factor Model Estimates: Macroeconomic Risks

This table reports time-series regressions of the winner-minus-loser momentum strategy on a combination of factors and macroeconomic predictors. Component returns are those of equally-weighted 48 Fama-French industry portfolios and individual stocks. Time-series regressions include the following factors: market excess returns RMRF, the size factor SMB, the value factor HML, and the political factor POL. We also consider a set of lagged macroeconomic variables: the default spread DEF, the yield on three-month T-bills YLD, the term spread TERM, and the value-weighted market dividend yield DIV. SENT is the Baker and Wurgler (2006) lagged investor sentiment index, VOL is the previous month daily volatility for the CRSP index, MP is one-month-ahead industrial production growth, MKT and MKT^2 are previous 36-month market returns and market returns squared. $\mathbf{I}_{MKT<0}$ is an indicator function depending on whether previous 36-month market returns are negative. RD is the cross-sectional return dispersion for the previous three months. LLR is the three-year forward cumulative consumption growth capturing the long-run risk component. t-statistics are adjusted for autocorrelation and heteroscedasticity. The estimation period is from August 1965 to December 2011.

	Industry-Level Momentum		Stock-Level Momentum	
Variable	(1)	(2)	(3)	(4)
Const.	1.582	1.536	1.727	2.170
	(1.80)	(1.85)	(1.50)	(1.87)
RMRF	−0.104	−0.067	−0.231	−0.148
	(−1.67)	(−1.28)	(−2.80)	(−2.26)
SMB	0.021	0.053	0.052	−0.072
	(0.24)	(0.84)	(0.33)	(−0.67)
HML	−0.199	−0.110	−0.317	−0.209
	(−1.68)	(−1.12)	(−1.51)	(−1.58)
DEF	−0.945	−0.607	−0.786	−0.783
	(−1.74)	(−1.20)	(−0.83)	(−0.99)
YLD	0.083	0.016	0.124	0.098
	(0.77)	(0.15)	(0.66)	(0.57)
TERM	0.207	0.050	0.459	0.145
	(1.13)	(0.29)	(1.83)	(0.65)
DIV	−4.238	−1.127	−7.452	−1.144
	(−1.42)	(−0.41)	(−1.83)	(−0.37)
LIQ	0.232	0.050	−2.565	−3.437
	(0.05)	(0.01)	(−0.29)	(−0.51)
SENT	0.020	−0.041	−0.051	−0.036
	(0.10)	(−0.20)	(−0.24)	(−0.15)
VOL	−58.008	−26.808	−121.463	−129.829
	(−0.85)	(−0.41)	(−1.21)	(−1.49)
MP	−1.966	−3.650	12.997	6.505
	(−0.09)	(−0.17)	(0.45)	(0.23)
MKT	0.562	1.014	1.175	0.586
	(0.43)	(0.79)	(0.69)	(0.36)
MKT^2	−2.047	−1.214	−3.492	−0.874
	(−1.13)	(−0.68)	(−1.55)	(−0.36)
$\mathbf{I}_{MKT<0}$	0.329	0.609	0.134	0.428
	(0.52)	(1.03)	(0.16)	(0.56)
RD	−0.061	−0.153	−0.106	−0.157
	(−0.38)	(−1.12)	(−0.49)	(−0.79)
LLR	2.085	−0.062	1.366	−1.434
	(0.95)	(−0.03)	(0.43)	(−0.46)
POL		0.392		0.506
		(8.98)		(5.20)
Adj. R^2	0.040	0.255	0.071	0.272
N (months)	545	545	545	545

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Table 10
Robustness Test Results: Alternative Political Sensitivity Measure

Panel A in this table reports risk-adjusted performance 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. The analysis in focuses on returns during a six year time-window centered around the starting month of switching-party years (± 3 years around January after switching-party elections). Beta-estimates and t-statistics for the three-factor model are omitted. Results in Panel A exclude new political information: for each industry and each stock, we set the political sensitivity measure equal to the one estimated in July of the election year, and keep it constant from August of the election year up to July of the following year. In Panel B, snapshots of industry-level and stock-level political portfolios sorted on stale political sensitivity in November of the election year characterize the past six month return and forward six month return of each political portfolio. Component returns are those of equal-weighted Fama-French 48 industries portfolios and individual stocks. *t*-statistics are adjusted for autocorrelation and heteroscedasticity. *Alpha Drop* is the decrease in alpha due to the inclusion of the political factor (POL) in the Fama-French three factor model. The estimation period is from January 1939 to December 2011.

Panel A: Three-Factor Regressions in Switching-Party Years with Constant Political Sensitivity				
	Industry-Level Momentum		Stock-Level Momentum	
Alpha	0.611	0.331	0.974	0.610
	(4.70)	(2.70)	(5.44)	(3.00)
POL		0.353		0.560
		(7.40)		(5.77)
N (months)	553	553	553	553
Adj. R^2	0.028	0.212	0.037	0.284
Alpha Drop	0.280		0.364	
	(3.00)		(3.05)	

Panel B: Political Portfolios in November of Switching-Party Election Years				
	Industry-Level		Stock-Level	
Pol. Portfolio	Past 6mo Return	Fwd 6mo Return	Past 6mo Return	Fwd 6mo Return
1	14.012	9.563	9.272	0.906
2	7.620	6.703	8.092	6.227
3	7.417	6.599	9.218	5.551
4	5.272	7.474	5.317	4.301
5	3.021	11.154	9.126	4.528
6			7.137	7.168
7			8.965	5.172
8			6.973	10.058
9			1.517	10.064
10			4.118	7.574

Table 11

Alpha Estimates Using Alternative Measures for Political Sensitivity

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. 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 time-window centered around the starting month of switching-party years (±3 years around January after switching-party elections). The alternative political sentiment factor (POL*) is constructed using the political sensitivity model in which we control for the past 2-12 month returns, as well as SMB and HML factors. Component returns are those of equal-weighted Fama-French 48 industries portfolios (Panel A) and individual stocks (Panel B). t-statistics are adjusted for autocorrelation and heteroscedasticity. *Adj. R^2 Increase* is the increase in the adjusted R^2 due to the inclusion of the political factor (POL*) in the Fama-French three-factor model. *Alpha Drop* is the decrease in alpha due to the inclusion of the political factor (POL*) in the Fama-French three-factor model. Estimation period is January 1939 to December 2011.

	Panel A: Fama-French 48 Industry Momentum		
	Full Sample	Switching-Party Yrs.	First 9mo Post Elec.
Alpha	0.429	0.375	0.211
	(4.51)	(2.98)	(0.89)
POL*	0.348	0.377	0.392
	(7.43)	(6.71)	(3.06)
N (months)	864	553	162
Adj. R^2 Increase	0.156	0.171	0.146
Alpha Drop	0.178	0.236	0.198
	(5.20)	(3.65)	(3.63)

	Panel B: Stock-Level Momentum		
	Full Sample	Switching-Party Yrs.	First 9mo Post Elec.
Alpha	0.807	0.642	0.395
	(5.56)	(3.21)	(0.96)
POL*	0.425	0.532	0.600
	(4.45)	(5.21)	(2.93)
N (months)	864	553	162
Adj. R^2 Increase	0.156	0.221	0.164
Alpha Drop	0.200	0.331	0.351
	(3.44)	(2.83)	(2.43)

Table 12

Momentum Decomposition: Semi-annual Frequency

This table shows statistics from the momentum decomposition in equations (5) and (7). Panel A shows cross-sectional moments for expected returns, while Panel B shows first-order autocorrelations AC(1). μ is the cross-sectional average of the time-series expected returns. σ_μ is the cross-sectional volatility of the time-series expected returns. σ_μ *diff.* is the difference between the cross-sectional volatility during normal time sand the cross-sectional volatility during the two sub-samples: switching party years, and first 12 months post election. *Industry Residuals* and *Stock Residuals* are residuals from the regression in (1) at the stock and industry-levels. *max* is the highest autocorrelation among residual autocorrelations for the Fama-French Industry portfolios, whereas *min* is the lowest autocorrelations. *num. of p-values < 5%* is the number of p-values out of the 48 Fama-French Industry portfolios and the 4650 stocks that are statistically significant. p-value is the probability of obtaining statistics as large as the ones in this table assuming that the null hypothesis that these statistics are equal to zero is true.

Panel A: Cross-Sectional Variance for Expected Returns

	Fama-French 48 Industries			Individual Stocks		
	Full Sample	Switch. Party Yrs.	First 12mo Post Elec.	Full Sample	Switch. Party Yrs.	First 12mo Post Elec.
μ	6.696	6.832	5.825	13.378	14.416	13.445
σ_μ	0.906	1.269	2.072	19.961	24.488	34.872
N obs.	48	48	48	9748	9748	9748
σ_μ diff.		0.363	1.166		4.527	14.911
p-value		0.011	0.000		0.000	0.000

Panel B: Factor and Residual Autocorrelations

	Factor AC(1)			Industry Residual AC(1)		Stock Residual AC(1)	
	AC(1)	p-value		AC(1)	p-value	AC(1)	p-value
RMRF	0.000	0.992	max	0.257	0.002	0.691	0.006
SMB	0.075	0.358	min	−0.147	0.205	−0.729	0.005
HML	−0.014	0.856	median	0.073	0.375	0.043	0.825
$POL_{industry}$	0.057	0.480	num. of				
POL_{stock}	0.160	0.050	p-values $< 5\%$	$= 2$		$= 290$	
Republican Ind.	0.883	0.000					

A Appendix

A.1. Testing Statistical Significance in Nested OLS Models

Consider the linear model

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

and its nested counterpart

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

We would like to 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 $\hat{\beta}^*$ are parameter estimates for the nested model, and $\hat{\beta}$ are estimates for the full model. Standard results from partitioned regressions imply that d can be expressed as

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

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

$$V(d) = M\Omega M^T = B\underline{X^T\Omega X}B + B\underline{X^T\Omega Z}C + C\underline{Z^T\Omega X}B + C\underline{Z^T\Omega Z}C$$

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

If we want to test the null hypothesis that β_k^* in the nested model is equal to β_k^* in the full model, then the corresponding test statistic is

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

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.

Table A1
Performance and Characteristics of Politically Enhanced Momentum Strategies: Double-Sorted on Past Returns and Political Sensitivity

This table reports monthly performance, market capitalization, and book-to-market ratios for portfolios double-sorted on past returns and political sensitivity. Panel A shows the results for the 48 industry portfolios, and Panel B shows results for individual stocks. PS denotes political sensitivity, and PR denotes past returns. The estimation period is from January 1939 to December 2011.

Panel A: Fama-French 48 Industries

	Performance			Size			Book-to-Market		
	PS1	PS2	PS3	PS1	PS2	PS3	PS1	PS2	PS3
PR1	0.809	0.981	1.048	11.202	11.256	10.966	0.762	0.746	0.795
PR2	1.016	1.106	1.351	11.203	11.305	11.148	0.754	0.747	0.782

Panel B: Individual Stocks

	Performance			Size			Book-to-Market		
	PS1	PS2	PS3	PS1	PS2	PS3	PS1	PS2	PS3
PR1	1.074	1.063	1.308	11.004	10.847	10.913	1.968	1.325	1.491
PR2	1.039	1.055	1.442	11.622	11.552	11.642	1.167	1.012	1.088
PR3	1.180	1.386	1.614	11.263	11.344	11.478	1.109	1.006	0.972