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Do Industries' Political Profiles Affect Their Portfolio Return Performance?

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by

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DEDICATION

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

The political profiles of an industry influence its performance due to its impact on industry-level investor sentiment and idiosyncratic risk. I form eight comprehensive political profile portfolios after double sorting on industry-level: (1) political geography proxied by political alignment, (2) corporate political strategies (CPS), proxied by donations to political action committees & lobbying expenditures, (3) and government interference, proxied by dependence on procurement contracts & federal regulations, and exhibit that an industries' political profiles impact its returns. Industries with high political alignment, concentrated corporate political strategies, and low government interference, deemed the *high-performance portfolio*, earn an annualized alpha of 10.3428%, significantly out-performing the market. The results hold in a cross-sectional setting, as industries in the *high-performance portfolio*, earn a 10.338% higher return than the base group. Mispricing is reduced in the short-term in the *high-performance portfolio*, but prices revert in the medium and long-term. Industries in the *high-performance portfolio* are more likely to experience positive earnings surprises, and investors tend to under-react to the bad news of firms in the *high-performance portfolio*. In addition, investor sentiment and idiosyncratic risk is substantially higher for those industries. The political profile impact on stock returns is distinct and substantially stronger than other political factors known to predict returns.

CHAPTER 1: DO INDUSTRIES' POLITICAL PROFILES AFFECT THEIR PORTFOLIO RETURN PERFORMANCE?

1. Introduction

The influence of U.S. politics on corporate performance has been a long-standing topic of interest in the financial literature. Firms are exposed to policy risk emanating from shifts in three general components: political agendas, legislative activity, and regulations. In the U.S., policy agendas are often uncertain due to the short-tenure of elected officials: Representatives (2 years), Senators (6 years), and President (4 years). Although there are 'deep-colored' states where elections were historically predictable, recent elections have shown flips in a number of states that tend to vote along the same party lines (e.g. Georgia, Ohio, Arizona). Elected officials tout a number of planned achievements prior to each election to sway the public, but these objectives can be quickly adjusted or even abandoned, without support from their comrades, as legislators within the state and across the nation must work together to pass effective laws. In terms of implementing bill changes, a 66% majority in both the (state) House and Senate chambers, as well as the president's (governor's) signature is necessary to pass federal (state) laws. As politicians become disproportionally aligned, the policy uncertainty emanating from changes in legislative activity increases. Last, executive departments and agencies attempt to control the quality of economic competition through the enforcement of regulations. According to the U.S. government website regulations.gov, "If an agency believes a rulemaking is warranted, the agency then proposes their findings to Congress or to the President in order to receive authority to issue a regulation." Once the regulation is approved, agencies will implement the rules and adjust as they see fit. Although regulatory changes are made by a separate entity from those passing legislation, the appointment of the heads of government agencies are done by the President, illustrating how convoluted the U.S. political system is.

Political geography can also add to the level of exposure to policy risk that a corporation faces. Firms are inherently exposed to different levels of political risk, simply based on the state location of their headquarters. Companies located in 'redder' (bluer) states during a Republican (Democratic) presidency, or alternatively phrased, states with higher political alignment, are more likely to face legislation changes, making them more exposed to policy uncertainty (Kim et al. 2012). Corporations can attempt to put their footprint on legislation to avoid unforeseen changes in policy by either donating to political action committees (PACs) or lobbying for or against bills. Alternatively, it is possible that corporations located in highly aligned states benefit from favorable economic environments, as a result of politicians passing laws that benefit their constituents (Kim et al. 2012; Cohen, Diether, & Malloy (2013). As the political climate increases in polarization, firms must carefully consider pushes for certain bills or donations towards politicians, that may impact their returns. Generally, politicians attempt to stay on the positive side on the climate of opinion, which can make certain industries more prone to legislative changes.

The federal government also has the power to impact businesses through procurement contract offerings, only further encouraging firms to get their 'feet wet' in the political sea. The growing impact of outside influences, has raised serious concerns as to whether the U.S. government and its elected officials are acting in the best interest of the greater public, as opposed to benefitting wealthy political players. Some of these wealthiest players are public corporations, that ultimately maintain political relationships, to improve their performance.

Typically, political activity (regulation, legislation, etc.) impacts markets at the industry-wide level. Cohen et. al (2013) examine the voting records of legislators and find that industries classified as beneficiaries of the vote, earn abnormal returns. The authors choose to analyze industry returns, as "*very rarely can a legislator put language into a bill that solely affects an individual firm*." Furthermore, according to US Open Secrets, a majority of powerful lobby groups are formed at industry level, including the: Dairy Farmers of America, Alliance of Automobile Manufacturers, General Aviation Manufacturer's Association, and Investment Company Institute. Therefore, in order to properly attribute the impact of legislation, regulation, and general policy uncertainty to corporate performance, empirical examinations should concentrate on industry-level returns.

A number of prior studies that examine industry abnormal performance have not considered the impact of political risk. Hou & Robinson (2006) find industries with greater competition in sales, perform better. The authors utilize a Herfindahl index (Hirschman 1945, Herfindahl 1950) to proxy for the level of sales competition in each industry, and find that more competitive (concentrated) industries earn higher (lower) returns. They attribute the abnormal returns of competitive industries to higher innovation risk or higher distress risk. Dellavigna & Pollet (2007) examine the relationship between demographics and industry performance and display certain sectors are age-sensitive. Boudoukh, Richardson, & Whitelaw (1994) find that non-cyclical (cyclical) industries perform better during periods of inflation. More recently, Bustamante & Donangelo (2017) examine the relationship between product market competition and industry performance and surprisingly find that higher product market competition decreases markup prices, and ultimately industry returns, in opposition to Hou & Robinson (2006).

Although, the aforementioned studies neglect the possible impact that politics can have on industry performance, a number of articles have analyzed the firm-level or industry-level impacts of individual components of political risks but have not examined all measures comprehensively. American corporations have a multitude of avenues to influence the political landscape. First, an inherent political risk that all corporations face comes from the state location of their headquarters. The political geography or location of corporate headquarters relative to powerful politicians can expose a firm to different levels of policy uncertainty, as legislation can be more or less likely to face resistance in traditionally left-aligned or right-leaning states. A state is viewed as maintaining powerful politicians if its officials are in tight alignment with each other, and the presidential party in power (MS/AL during Republican presidency; CA/NY during Democratic presidency). Prior studies show that corporate proximity to political power impacts returns. Kim, Pantzalis, and Park (2012) comprise a political alignment index and show that corporations headquartered in states with leading politicians (senators and representatives) that are in high alignment with the presidential party, earn higher returns. As stated, firms can participate in corporate political strategies through donating to PACs or incurring lobbying expenditures. Obviously, corporations expect a return for their political engagement and prior literature has provided evidence that connections to elected officials have meaningful impacts on the bottom line (Cooper, Gulen, and Ovtchinikov, 2010; Fisman, 2001; Fowler, 2006). Similarly, recent papers have shown that corporate lobbying is associated with an increase in investment and profit (Boubakri, Guedhami, Mishra, and Saffar, 2012; and Minnick and Noga, 2017). At the same token, the federal government has the power to inhibit or increase business in various industries through regulation enforcement or federal procurement contract engagement. Aabo et al. (2016) demonstrate that political interference can exacerbate market segmentation and local bias leading to an exaggerated "only game in town" effect.

In terms of procurement contracts, a number of papers have also discovered that a high dependence on government contracts can positively affect corporate growth or investment (SEAF 2007, Ngo 2010, Luechinger and Moser 2019, & Hebous and Zimmerman 2021). Previous literature has also found that fewer regulations or de-regulation can lead to improved performance (Nicoletti and Scarpetta, 2003; Alesina, Ardagna, Nicoletti, and Schiantarelli, 2003). However, there are also a number of papers displaying that an increase in regulations can enhance competition, and ultimately, performance (Su and Fleisher, 1998; Bandeira et al., 2000; Bassinini and Ernst, 2002).

Although studies have looked at the aforementioned corporate-political influences individually, it is important to examine the different dimensions in conjunction, to make conclusive statements about their possible impacts on corporate performance. Also consequential, political influence, whether it be elected officials, legislation, regulation (etc.), typically does not impact a single firm, but rather has an industry-wide effect. Appropriately, I construct eight political profile portfolios after triple-sorting industries annually, based on industry-level (low vs. high) political alignment, (concentrated vs. wide-spread) corporate political strategies, and (low vs. high) government interference, and study its impact on industry performance over the period of 2001-2020. Industries falling into the high political alignment-concentrated corporate political strategies-low government interference portfolio, or the *high-performance portfolio*, display substantially higher performance, earning an annualized alpha of 10.3428%. Furthermore, I display those industries with high political alignment, concentrated corporate political strategies, and low government interference, earn a 10.338% higher return than the base group of industries. The empirical regressions utilize the Fama-French 5-factor asset pricing models and the results are robust, holding across cross-sectional and time-series settings.

The alphas or abnormal returns produced could be a result of those industries being exposed to greater risk (a risk factor not accounted for in the Fama-French or other asset-pricing models), or that these industries are mispriced from their true values. I assume that the Fama-French model is correctly set, without failure to account for an unknown risk factor, and conduct analyses demonstrating that mispricing drives the alphas of industries in the *high-performance portfolio*. First, I display that prices in the *high-performance portfolio* revert in the long-term which is consistent with the mispricing literature (DeBondt & Thaler 1985). There is also litany of literature suggesting that investor sentiment and idiosyncratic risk are underlying factors in driving prices away from their fundamental values, which could explain the abnormal performance of industries (Barberis et al. 1998; Grossman et al. 2007; Sampson et al. 2002; Pontiff 2006, Merton 1987, Shleifer and Vishny 1997)[1]. Investor sentiment or their pre-ordained beliefs impact how they view the release of earnings announcements and other firm-specific news. If investors have strong pre-held beliefs on industries with certain political characteristics, they may under or over-react to a particular news event or a series of earnings announcements, leading to prices that are unrepresentative of corporate fundamentals. In fact, in the final section of the mispricing examinations, I investigate the earnings surprises and the stock price reaction to those earnings announcements. I find that not only are positive earnings surprises more prevalent in the *high-performance portfolio*, but also that investors tend to under-react to the bad news of those

[1] I also examine whether financial analyst disagreement drives excess returns. The inability of financial analysts to come to a consensus on particular stocks suggests there is information opaqueness existent, which exacerbates mispricing (Diether, Malloy, Scherbina 2002; Johnson 2004).

industries. Idiosyncratic risk can also increase mispricing when investor sentiment is high (Suh 2003; Wu et al. 2017). Hence, I examine the levels of idiosyncratic risk that the industries in the *high-performance portfolio* are exposed to and compare it to the rest of the sample.

As expected, I find that industries in the *high-performance portfolio* experience significantly higher levels of investor sentiment and unsystematic risk, implying that mispricing is driving abnormal returns. What makes these group of industries special? As mentioned previously, the U.S. political setting is convoluted. Policy risk emanates from changes in the political agenda, legislation, or government interference. It can be difficult for investors to make sense of political agendas if an industry is exposed to large shifts in all three of these components. In turn, it appears that the *high-performance portfolio* contains industries exposed to high political alignment, concentrated corporate political strategy activity, and low government interference. These industries are in proximity to political power, based on the headquarter location, and exposed to high policy risk. It is also important to note that the political profiles of outside influences, corporate political strategies and government interference, in the *high-performance portfolio* are below the median, or in other words, weak. In sum, if elected officials pass laws that present a favorable economic environment to local industries, high levels of activity through political strategies or government interference, weaken the impact of the policies passed. This concoction of characteristics allow industries to perform well despite their exposure to political risk, as they are less likely to face unforeseen changes in law or regulation, whose impacts may be difficult to determine.

I close the paper with a number of robustness examinations that include a deeper analysis into the specific firms, industries, and periods driving performance. First, I examine the impact of dropping conglomerates, as large firms are better tuned with dealing with industry exposure to policy uncertainty due to their many lines of business (Fan et al. 2020). Unsurprisingly, I find that the abnormal performance of the industries in the high-performance portfolio vanishes, after dropping conglomerates. Last, to ensure the validity of the political profile portfolio effect does not succumb to the spurious performance of an industry experiencing ‘happy times’, I drop various industries and years from the sample. In the final tests, I confirm that the abnormal returns are not driven by a particular industry, specific year, or presidential party in power.

The lasting contributions of this work serve academicians, investors, and economic/financial analysts interested in examining the impact of politics on corporate returns. In terms of scholarly papers, I expand on previous work examining the impact of corporate political activity by including a thorough analysis of political profiles, differentiable from previous measures used in the literature. I display that the political profiles of an industry have a profound impact on its performance. Next, this work addresses the most well-cited political measures on ‘policy uncertainty in the literature and its impact on stock returns (Kim et al. 2012, Baker et al. 2016, Hassan et al. 2019). Kim et al. (2012) display that firms with high policy uncertainty, proxied by political alignment, earn higher returns. Baker (et al. 2016) develop an economic policy uncertainty measure from leading U.S. newspapers using textual analysis, and display that stock volatility increases, while investment, employment, and output decrease during times of high economic uncertainty. Hassan et al. (2019) create a political risk measure using the dialogue from executive earning calls, and find that corporations with high political risk reduce investment and hiring, and actively lobby and donate to politicians. I display industries with higher policy uncertainty, proxied by political alignment, perform better, but only in a setting where the industry maintains concentrated political strategies and has low government interference. Accordingly, this work also contributes to the existing literature regarding corporate political strategies’ (Faccio

2006, Cooper et al. 2010, Cohen et al. 2013, etc.), and government interference's (Goldman et al. 2013, Scarpetta 2000, etc.) impact on returns. Portfolio holders can also benefit from these findings, by investing in industries with political profiles that are associated with higher performance. Market participants can generate substantial profit by investing in industries with the political characteristics of the *high-performance portfolio*. Furthermore, the trading strategy is straightforward, as the alphas generated do not rely on shorting any industries and do not require frequent re-calibration. Last, macroeconomists and financial analysts gain insight on which industry political characteristics spur growth and what elements drive mispricing, allowing them to make more reliable forecasts.

The remainder of the paper is structured as follows: Section 2 details the financial literature regarding asset pricing models, political measures, and potential drivers of mispricing. Section 3 describes the data-collection process and methodology for generating the political profiles. Section 4 discusses the performance results of the political profiles using univariate analysis and time-series and cross-sectional regressions. Section 5 details the drivers of mispricing: investor sentiment, unsystematic risk, and earnings surprises, and discusses other political measures in the literature. Section 6 displays the various robustness tests. Section 7 concludes.

2. Asset Pricing Models and Politics

2.1 Fama-French Factors

The financial literature consistently scours for factors that exhibit evidence of explaining stock prices. Among the most notable factors in the financial literature are five seminal predictors, utilized as inputs in the Fama-French 5 factor model (Fama & French 2015). The five factors include a(n): (1) market factor, (2) size factor, (3) book-to-market equity factor, (4) profitability factor, and (5) investment factor. After long-standing debate regarding the explanatory power of the market factor in the CAPM model, in 1992, Eugene Fama and Kenneth French display evidence that the market *B*s of the Sharpe-Lintner asset pricing models (Sharpe 1964; Lintner 1965) are insufficient in explaining the cross-section of returns. They also find evidence that variables that appeared to have no unique standing in asset-pricing, most notably, size and book-to-market equity, showed reliable power in explaining returns. This led to the identification of three common risk factors in the returns of stocks: an overall market factor, an additional factor related to size (SMB), and an additional factor related to book-to-market equity (HML) (Fama and French 1993). The authors supplement the market factor by constructing portfolios that mimic risk factors related to size and book-to-equity, and demonstrate that these 3 risk factors, known as the Fama-French 3-factor model, explain the differences in average returns.

Several models have suggested additional risk factors to complement the Fama-French 3-factor model in explaining expected returns, such as an accruals factor (Sloan 1996), a net-share issues factor (Ikenberry, Lakonishok, and Vermaelen 1995; Loughran and Ritter 1995), a labor income factor (Jagannathan and Wang 1996), a momentum factor (Jegadeesh and Titman 1993) factor, a liquidity risk factor (Pastor and Stambaugh 2003), and a volatility factor (Ang et al. 2006). However, despite the wide-range of propositions, nearly two decades later, Fama-French supplemented their three-factor model, with two distinct factors derived from the dividend discount model (Miller and Modigliani 1961), profitability (RMW) and investment (CMA), and designated it the Fama-French 5-factor model (Fama-French 2015). However, because of so much wide-spread debate regarding mispricing and left-out anomalies, empirical models often supplement the five Fama-French factors with controls of firm characteristics that display the ability to explain the cross-section average returns. Some of these characteristics include leverage

(Bhandari 1988), R&D expenditure (Chan et al. 1990), short-term return (lag), long-term return (momentum), and stock turnover (Rouwenhorst 1999). Political influence is another important risk to consider and has the ability to explain corporate performance. A number of papers have created political measures in hopes of shedding light on possible mispricing or omitted variables in asset-pricing models (Baker, Bloom, and Davis 2016; Addoum and Kumar 2016; Hassan et al. 2019, etc.).

2.2 Political Measures

Before reviewing the literature on the three political characteristics (political geography, corporate political strategies, government interference) used as distinguishers in generating the political profile portfolios, I describe a number of the most well-cited political measures in the literature.

First, Kim et al. (2012) design a political alignment variable that proxies for corporate proximity to political power, and finds that firms that are located in states with highly aligned politicians, earn higher returns. They attribute their findings to high policy uncertainty (due to lower resistance of passing legislation in highly aligned states, but are unable to rule out indirect advantages, such as political connectedness). Politically powerful officials are identified as elected officials who are most able to influence the legislature. Bills in states must be passed through both the state-level senate and House of Representatives, before either being signed by the governor or allowed by him/her into law without signature. There is also the possibility that a law passes without the governor's approval, if the majority of the state senate and house vote to over-ride the veto of the governor. Similarly, federal bills must be passed through both chambers of Congress and then signed into law by the president. Typically, federal bills have a stronger impact on corporate performance than state bills and typically have industry-wide effects (Cohen and Malloy 2010). Due to the nature of the U.S. political system, new laws have a higher likelihood of passing in states where legislatures are highly aligned with each other, as well as the presidential party in power. In turn, corporations will be exposed to various levels of policy uncertainty, due to their geographical location on the political map. At the same time, politicians in states with aligned legislature may shape policies that provide opportunities for local constituents to prosper. Put together, this implies that corporations in strong red states like Alabama or Mississippi, either will be exposed to higher policy uncertainty or presented with more favorable growth opportunities, during a Republican presidency than corporations in California or Vermont. Political alignment, alongside corporate political strategies (PAC/lobby) and government interference (federal contracts/regulations), is one of the three political measures used in this study to construct the eight 2x2x2 political profiles. I demonstrate that political profiles affect the performances of industries and distinguish the measure from previous variables introduced in the literature.

Most relatable to this paper, Addoum and Kumar (2016) argue that certain industries perform better based on the presidential party in power and create a political sensitivity variable that proxies for shifts in the political climate. They suggest that investors try and pinpoint industries that benefit from the policies of the winning presidential party, designating certain industries as political 'losers' and 'winners.' In addition, they argue that systematic differences in the political preferences of investors during various administrations, can generate heterogeneity in portfolio holdings. The authors argue that the systematic shifts in portfolios accompanied by changes in political sentiment, can accumulate to a point where securities are persistently mispriced due to the capital constraints of arbitragers. They find that a trading strategy that longs the top 5 industries and shorts the bottom 5 industries during each presidential term, earns a reliable profit. This work identifies a strong pattern regarding politically sensitive industries, but does not ascribe the specific political characteristics of industries, such as legislation or regulation level, as drivers of returns. Instead, the authors attribute their findings to a shift in investor sentiment during presidential terms. The empirical tests in this work identify the specific political profile that drives performance. The political profile effect is robust to different time periods, industries, and party lines across the first two decades in the 21st century. Furthermore, the political profile predictor is substantially stronger in economic magnitude, than the political sensitivity variable. I compare the measures in time-series and cross-sectional settings and find consistent results.

Next, and arguably the most notable paper regarding policy uncertainty, Baker et al. (2016), design an economic policy uncertainty (EPU) variable using the frequency of the mentioning of key terms such as 'legislation', 'regulation', and 'uncertainty', in 10 leading U.S. newspapers. The authors find that higher levels of economic policy uncertainty are associated with greater stock price volatility and reduced investment in certain policy-sensitive sectors of the market. Their EPU measures are robust, and highly correlated to other policy uncertainty measures obtained from: Beige Books, corporate 10-K filings, and daily moves in the S&P. Beige Books are published roughly eight times a year and illustrate the perspectives and concerns of businesses to 12 Federal Reserve banks, and put an enhanced focus on sovereign debt and regulation concerns. The authors also examined the frequency of the mentioning of policy terms in the 'risk factors' section of SEC 10-K filings. Directly quoted from the risk-factor section of 10-Ks *"If any of the following risks actually occurs, our business, financial condition, results of operation, cash flow and prospects could be materially and adversely affected. As a result, the trading price of our common stock could decline."* Finally, Baker et al. (2016) analyze the frequency of policy term mentions in Wall Street Journal and New-York Times articles that cover large daily moves in the stock price (the day immediately following the jump). The authors validate their measure by finding a strong correlation in the annual frequency of daily stock price jumps attributed to policy uncertainty from their EPU variables. The EPU variable is a market-month measure, in other words all U.S. firms have the same EPU measure each month, making it difficult to apply in a setting examining whether the political characteristics of various industries impact performance.[2] Regardless, to cover all corners, I examine the relationship between the EPU and political profile measures used throughout this paper, and find no significant correlation.

Third, Hassan et al. (2019), use similar computational linguistics to Song et al. (2008) and Baker et al. (2016), but focus on individual firms' uncertainty, rather than aggregate economic risk. They create a political risk variable that captures the portion of shareholder earnings calls attributed to political risks. Management view earnings calls, designated communications between the firm and various participants, as a channel to express their outlook on the company's future. In developing their measure, the authors state that they "*quantify the political risk faced by a given firm at a given point in time based on the share of conversations on conference calls that centers on risks associated with politics in general and with specific political topics*." Hassan et al. (2019) argue that their quarterly earnings call measure serves as a strong proxy for the political risk a company faces at various points in time. They find that corporations exposed to high political risk experience greater stock price volatility and retrench investment and employment. They also suggest that corporations 'actively' mitigate political risk by donating to PACs or lobbying, and that most of the activity is done by large firms because they capitalize more of the gain from

[2] It is more appropriate to use a policy uncertainty variable emanating from individual corporate exposure to political risk, rather than the level of market-wide policy uncertainty. To that end, I utilize an individual firm political risk (PRisk) measure (Hassan et al. 2019) that is similar in nature to economic policy uncertainty (EPU) in Baker et al. (2016).

swaying political decisions (Olson 1965). The authors find that their measure is highly correlated to Baker et al. (2016) EPU measure and sector-level proxies on dependence on government spending. I incorporate the political risk (PRisk) measure throughout various examinations to analyze whether it is associated with mispricing or with any opportunities for arbitrage, and to see whether it has any significant relationship with the political profiles. In terms of performance implications, I find no significant ability of PRisk to generate alphas or predict expected returns in time-series and cross-sectional examinations. In addition, I find no substantial relationship between the political profiles measure and PRisk: after splitting industries into their various political profile portfolios, there is no substantial difference in the PRisk that each portfolio faces.

In addition to the aforementioned studies, other political uncertainty measures that are popular in the literature stem from disagreement in inflation forecasts (Bomberger 1996), political elections (Jens 2017, Colak et al. 2017, Gao et al. 2019), and legislative activities (Kim et al. 2019). Bail et al. (2021) builds off of Bomberger (1996) by creating a variable based on the disagreement in sentiment among social media users, through analyzing the mentions of various firms and politicians online, and find that the measure is associated with greater stock price volatility. Jens (2017) uses gubernational elections as a source of uncertainty; the author finds that corporate investment drops and firms delay seasoned equity offerings, prior to elections. Kim et al. (2019) work with legislative activity or corporate political strategies data, to design a policy uncertainty measure using firms that 1) have former politicians on their corporate board, 2) make PAC contributions, and 3) lobby. The authors find that active political strategies are associated with greater firm idiosyncratic risk, making real options more value-relevant in uncertain environments. However, articles utilizing legislative changes and elections changes as exogenous shocks to policy uncertainty do face shortcomings (Lei et al. 2020), including: (1) political elections and legislative activities only affect the surrounding region/states, (2) there has been no clear guidance provided on the window where uncertainty is particularly high, and (3) policy uncertainty is affected by numerous other factors outside legislative and electoral changes (government response to COVID-19). Due to the nature of their construction, other political measures that do not succumb to these issues include Baker et al. (2016), Hassan et al. (2019), and Huang et al. (2015), who capture global political crises as a proxy for uncertainty.

Although prior studies have distributed exorbitant knowledge regarding the impact of policy uncertainty on the corporate world, examining uncertainty in conjunction with other political characteristics such as lobbying activity, PAC donations, regulation enforcement, and procurement contract dependence on corporations' or industries' performance has not been addressed. Corporations will be exposed to different levels of political uncertainty in different time periods due to the economic cycle/global crises, but uncertainty also is derived from legislation or regulation changes, dependence on federal contracts, and changes to the parties in power. The structure of the U.S political system allows for firms to maintain political connections through donating to political action committees (PACs) or lobbying against bills. Furthermore, certain industries are exposed to higher levels of business risk due to dependence on government contracts or exposure to federal regulations. Lastly, corporate headquarter locations may expose firms to different levels of policy uncertainty as federal government policy agendas shift their focus following elections. Thus, in order attribute the impact of politics on industry-level performance, it is crucial to consider multiple elements of an industry's political profiles, such as its political connectedness, degree of regulation, dependence on government contracts, and political geography.

As mentioned, prior studies have analyzed firm-level consequences of the above but have not examined all measures comprehensively, or at the industry level. Given the fact that political agendas, policies, and legislative activities are geared toward industries rather than individual firms, this study fills an important gap in the literature. In order to make definitive conclusions regarding the relationship between industry performance and its political characteristics, I form 2x2x2 political profile portfolios using three measures (1) political alignment, (2) corporate political strategy activity (3) government interference level. I sort industries into eight political profiles using the annual median values of each measure and examine the research question: *Does an industry's political profiles affect its portfolio return performance?*

2.3 Corporate Political Strategies

Money talks in U.S. elections, and corporations are a driving force. In fact, corporate influence has grown so large that there has been a push among select politicians for increased regulation on the sources of funds, however, the tie between businesses and politics in the U.S. only seems to be strengthening as time passes. U.S. corporations have the option to engage in political strategies with the hopes of minimizing political risk, and ultimately, improving performance. Corporate political strategies include donations to political action committees (PACs) and expenditures on lobbying, both of which, are important dimensions of political influence. Each PAC raises money for a candidate in hopes of winning a particular election. Most PACs represent corporations, labor unions, or ideological interests that solicit funds from the group's employees or members, and make contributions in the name of the PAC to candidates and political parties. PACs can raise up to $5,000 to a candidate's committee each election, as well as up to $15,000 annually to a national party committee, and $5,000 to a different PAC. Recently introduced in 2010, the Super PAC further strengthened the grip that corporations had on U.S.

elections. Super PACs have no limit on the sources of funds used on independent expenditures in federal races, although these funds cannot be used to make donations to candidates or committees. Super PACs are not considered in this paper, but they are mentioned, to emphasize the influence corporations can have on shaping the U.S. political field.

Several different measures have been utilized to capture the impact of corporate political action committee ties on stock prices including, total dollar amount donated to PACs per industry, number of candidates supported by an industry, percentage of firms contributing per industry, among others (Roberts 1990, Fowler 2006, Ansolabahere et al. 2004, Jayachandaran 2006, etc.). Although a number of these measures can be used, I base the creation of the PAC-Herfindahl variable off of two highly cited papers in American political finance. First, Kroszner and Strattman (1998) investigate interest group competition in Congress, particularly in the financial services committee. They find that interest groups are rewarded with legislative efforts akin to their wishes, because of their high contributions to committee members. Similar to this paper, the authors utilize a Herfindahl-Hirschman Index (HHI)[3] measure to capture PAC activity, but focus on the dollar amount of donations. The authors also display that the concentration of a committee's PAC donations increases with the seniority of committee members, as they build (or tarnish, depending on the perspective) their reputation in Congress. Cooper (et al. 2010), construct variables measuring PAC contributions from 1979-2004, and find that the measures are in positive and significant correlation with future stock return performance. The authors develop a PAC measure by summing up the number of candidates that a firm supports, over a multi-year window. They demonstrate that the number of supported candidates has a statistically significant and positive

[3] The HHI measure is a standard measure utilized in the industrial organization literature and was developed by Hirschman (1945) & Herfindahl (1950).

relation with future abnormal returns, and that donating to representative members may be more effective. They also demonstrate that Republican candidates receive a higher amount of donations in total dollars and receive contributions from a larger number of firms. Despite soliciting more donations, the 'Democrat' effect on abnormal returns is stronger, suggesting that Democratic candidates cater to their donors with more favorable policies. The Herfindahl-PAC measures used in this paper combine the motivations of the measures in Cooper et al. (2010), who uses the number of candidates supported by PACs as a proxy for political ties, and Kroszner et al. (1998) who introduces the use of the HHI as a proxy for political connections.

A great depth of literature has examined the relationship between political connections and corporate rewards. Roberts (1990) examines stock market reactions in response to the death of Henry "Scoops" Jackson. The paper establishes the first strong empirical evidence of the seniority/benefit relationship, as the passing away of a prominent senator is used as an exogenous shock to the stock prices of firms, and their anticipated futures. They find that firms with political connections to Jackson, the ranking Democrat from Washington on the armed services committee, exhibited strong a -1% abnormal return the day of his death. Roberts uses a wide-array of measures to capture political ties including: firms who donated to Jackson's PAC, firms located in the state of Washington, and firms in the armed services industry. Similar to Roberts (1990), Jayachandaran (2006) examines the impact of representative Jim Jeffords leaving the Republican party to become an independent, tipping control of the senate to Democrats. He finds that firms that donate to Republicans experience a loss in stock price, almost .8% of their market capitalization. He also documents a small gain for Democrat donating firms. Fisman (2001) compares the returns of firms with different degrees of political exposure during times where there were adverse rumors regarding the health of Indonesian President Suharto. In almost every case, the returns of politically connected firms were lower than non-connected firms, suggesting that a large percentage of well-connected firms' value may be derived from political connections. Faccio (2006) accumulates evidence from over 45 countries and finds that politically connected firms see significant increases in corporate value around the time large shareholders or officials enter politics. The impact is stronger in countries with highly corrupt governments and in countries that impose restrictions on the foreign direct investment of their citizens. She also finds that connections are more wide-spread among larger firms and demonstrates that the increase in company value is greater for firms with connections to political officials that are more powerful and for firms whose large shareholders enter politics. Faccio et al. (2006) analyze the likelihood of bailouts of 450 politically connected firms across 35 different countries. They find that politically connected firms are significantly more likely to receive a bailout than their non-political counterparts. Furthermore, they find that among bailed out firms, those with political connections exhibit substantially worse performance, post bailout. Furthermore, Faccio and Parsley (2009) study the sudden deaths of politicians to analyze the possible impact on the valuations of connected firms and find that connected firms suffer a decline in market value of around 2% on average following the death of politicians. Boubakri, Guedhami, Mishra, and Saffar (2012) find that politically connected firms earn a lower cost of equity capital than their non-connected peers. Investors require a lower cost of capital from politically connected firms, implying that political ties decrease risk concerns.

As mentioned before, another way firms can establish political ties is through lobbying, which can be broadly defined as an attempt to influence government action through written or oral communication. According to the IRS, "a*n organization will be regarded as attempting to influence legislation if it contacts, or urges the public to contact, members or employees of a* *legislative body for the purpose of proposing, supporting, or opposing legislation, or if the organization advocates the adoption or rejection of legislation."* Each state has their own fine-tuned definition, but typically the process involves a lobbyist acting on behalf of another party for compensation. Billions of dollars are spent each year on lobbying in the U.S., with corporations as the primary expender. There is no limit on the amount that a corporation is allowed to spend, allowing for powerful groups to shape U.S. policy with little regard for public interest. Corporations often lobby for or against policies affecting either its own operations or the performance of their suppliers, in hopes of minimizing unfavorable policy changes. Put together, the influence that U.S. corporations have on election outcomes and proposed legislation is immense.

For consistency purposes, similar to the PAC-Herfindahl measure, I utilize a lobby-Herfindahl measure, capturing industry wide-lobbying expenditure competition as a proxy for legislative activity. Due to the nature of lobbying expenditures, one cannot utilize number of candidates in this setting, as lobbying expenditures are made by firms on bills they wish to pass or fail. Instead, one could examine the concentration in total dollar amount of lobbying expenditures or number of bills lobbied per industry, I choose the former. To the best of my knowledge, no prior paper has applied the Herfindahl to lobby expenditure, making it a novel contribution. Papers have examined the relationship between the concentration in sales (HHI) and lobbying activity. Namely, Gawande (1998) examines the free-rider problem existent in lobbying special interest groups using industry concentration. He demonstrates that lobbying spent per contributing firm increases substantially with industry sales concentration. On the other hand, Finger et al. (1982) and Gamsi et al. (1997) find that industry concentration is negatively associated with the likelihood of foreign government agency rewarding firms with favorable legislation.

A great depth of literature has examined the rewards that corporations seek in return for their expenditures. Kim (2008) investigates the determinants of lobbying expenditures and campaign contributions while assessing the returns to lobbying using panel data from the S&P 500. He finds that free-riding is prevalent in both types of corporate political strategies, but finds that management incentives and economic hardships are much more impactful for lobbying expenditures. He also displays that lobbying has a positive and significant effect on equity returns. Chen, Parsley, and Yang (2015) argue that lobbying is a more direct way for corporations to influence legislators as contributions come straight from individual corporations (rather than several firms in an industry forming a political action committee). They examine the impact of lobbying on different measures of corporate performance, including net income and operating cash flows. In their final tests they examine the excess returns of lobbying firms and find that they earn substantially higher returns than their non-lobbying counterparts. Excess returns are larger for firms that lobby most aggressively, but the impact is not necessarily due to lobbying. The authors document that an agency problem may be driving the results, as managers with more freedom may lobby more whenever they expect firm performance to be good. Hill, Kelly, Lockhart, and Van Ness (2013) find that firms with greater potential payoffs tend to lobby more aggressively, after controlling for PAC donations. They display that lobbying is positively associated with industry size, investment opportunities, and concentration, and negatively related to cash flow. Furthermore, they find that lobbying is more impactful for firms that do not contribute to PACs, as the benefit of lobbying is incremental for PAC-connected firms. Cohen et al. (2013) finds that investors can form a trading strategy that yields positive, abnormal returns based on the votes of interested legislators on a particular bill. The author argues that bills passed in the legislature affect an entire industry, not just one firm and assigns 'interested' legislators on the criteria that they operate in a state where the largest industry is affected by the bill. In addition, Minnick and Noga (2017) find that firms operating in industries with trade associations that invest in political spending benefit through lower taxes, and find that firms that politically spend themselves, pay an even lower amount in taxes.

I build on recent literature and investigate whether the concentration/competition of corporate political strategies in an industry, in conjunction with its other political characteristics, have implications on its performance.

2.4 Regulation

The ability of the U.S. government to protect competition through federal regulation, is another factor in the political realm that firms must consider. First, bills are signed into law by the president via executive order or after Congress' approval. Regulations are then issued by federal agencies, boards, and commissions and are listed in the Code of Federal Regulations (CFR). Organizations and its members can be fined, sanctioned, forced to close, and potentially jailed for violations of federal regulations. Generally, there are three categories of regulation: social, economic, and process regulations. Social regulations are intended to ensure that corporate production is made in ways that are beneficial and not harmful to public interests such as health, safety, and the environment. Economic regulations aimed to prevent firms from upping prices or entering/exiting business sectors that can cause harm to existing competition. Process regulations impose administrative and filing requirements that include income tax, immigration, social security, and procurement forms.

Theoretically, regulations should be designed to enhance corporate competition, but a number of well-detailed economic and finance articles have found that increases in regulations have pernicious effects on firms and overall macro-economic output. Djankov et al. (2002) analyze the impact of regulation of entry of start-up firms in 85 countries. They discover that heavier regulation is associated with higher corruption and unassociated with higher quality public or private goods, concluding that costly regulation is intended to benefit politicians and bureaucrats. Nicoletti and Scarpetta (2000) investigate a number of European countries and find that strict product market regulation explains reduction in performance, and the impact is stronger in those industries with a greater technological gap. Alesina et al. (2003) find that regulatory reform or de-regulation of product markets is strongly associated with an increase in investment. Dawson and Seater (2013) design a time-series measure capturing federal regulation, and find that increases in regulation are associated with lower growth rates of output. Healthy industry competition is boosted by fewer regulations; therefore, it is highly possible that industries with fewer regulations perform better.

On the other hand, other papers have also shown different views regarding the impact of government interference. Su and Fleisher (1998) find that changes in regulation, such as removal of price-caps/floors or easing of brokers' borrowing limits, increase volatility in the Chinese stock market. Bandeira et al. (2000) assert that the effect of financial liberalization on private savings is ambiguous after investigating eight developing countries. Bassinini and Ernst (2002) conduct a cross-sectional analysis among OECD countries, and find that enhancing competition in the product market, through increased regulations, while guaranteeing intellectual property, has a positive impact on innovation.

2.5 Federal Contracts

On the other hand, the federal government offers procurement contracts to vendors for the purchase of their goods and services. Billions of dollars are spent by the U.S. government each year on a wide-variety of products and services via procurement contracts. Government agencies are required to use the System for Awards Database (SAM) to advertise all contracts over $25,000. Corporations then bid on procurement contracts listed on the database, and agencies award contracts to the offers with the 'best value'. Best value can entail the corporation's history with the agency, expected differences in product quality, and existing treaties with countries or other geopolitical factors if the firm is multinational.

Prior literature has shown that corporate dependence on government contracts can crowd out investment and lower firm output, leading to decreased performance. Karpoff (et al. 1999) find that firms investigated for military procurement fraud lose almost 1.42% of their market value on average. Cohen et al. (2011) find evidence that government spending shocks substantially reduces corporate investment. Along those same lines, Cohen and Coval (2016) find that government dependent firms invest less in physical and intellectual capital. The authors also find evidence that firms awarded procurement contracts are associated with lower future sale growth. Paglia and Harjoto (2014) find that despite government contractors obtaining capital from venture and private equity firms at a higher rate, they fail to produce post-funding sales growth and employment benefits. Kong (2020) studies the impact of government spending on corporate innovation and finds that states with the government spending increases, undergo a substantial reduction in their patent and citations. Similarly, Esqueda, Ngo, and Susnjara (2019) find that government contractors have substantially lower sales growth and valuations, but the result only holds for strategically unimportant industries.

Opposingly, there are several works that argue that the government contracts are rewards typically given to firms with existing political connections. Houston et al. (2014) find evidence that U.S. firms awarded procurement contracts are rewarded with lower rates on bank loans. Furthermore, they find the cost-cutting effect is stronger for politically connected firms that are awarded procurement contracts. Hebous and Zimmerman (2021) find evidence that government revenue increases the investment of financially constrained firms. Goldman et al. (2013) demonstrate that firms with boards connected to the winning party in an election are rewarded with procurement contracts. Luechinger and Moser (2019) find that firms with a former employee serving in the Department of Defense earn roughly double the amount of procurement volume. They also find evidence that hiring former political appointees in the Department of Defense increases procurement volume. Ngo (2010) find evidence that firms that supply customers that are a part of domestic or foreign government earn higher operating income, profit margin, return on asset, and lower operating expenses than matched firms without government customers. Lichtenberg (1992) and McGowan and Vendryzk (2002) find evidence that defense contractors oversaw abnormal profitability in the mid-late 1980's.

Given that prior literature supports the notion that dependence on federal contracts suppresses investment and profitability, I expect industries with a lower dependence on federal contracts, to perform better.

2.6 Political Geography

Corporate political geography or proximity to political power is a characteristic that is often disregarded, but has been proven to impact performance. As aforementioned, corporate performance is impacted by the existence of political strategies and government interference.

However, there is a third dimension that is more difficult to navigate, exposure to policy uncertainty or discretionary corporate investment opportunities associated with proximity to political power, or political geography. The proximity of a corporation to political power varies bi-annually and by state, as the uncertainty of an administration's future policies differ upon the results of state and federal elections that occur every two years. Firms headquartered in 'red' states during a Republican administration (or in 'blue' states during a Democratic presidency), may be prone to greater policy risk or presented with better growth prospects as a result of legislation passed by politicians who are aligned (Kim et al. 2012; Ansolabahere et al. 2006).

In fact, Kim (et al. 2012) comprise a measure proxying for a local firms' proximity to political power known as PAI (political alignment index), a state-level measure of political alignment with the President's party. In turn, the authors find that corporations headquartered in high PAI states earn higher returns than firms located in low PAI states, on average. Other papers have also employed the political alignment index including, Gross (et al. 2016) which finds a positive and significant relationship between discretionary accruals or earnings management and political alignment, arguing that an increase in policy risk facilitates earnings management. Bradley (et al. 2016) find that firms located in high PAI states incur higher costs of debt. Truong (et al. 2020) also utilizes the political alignment index to demonstrate that the pricing of audits is more expensive in high PAI states due to perceived high political risk. Cordis (2021) finds that political alignment is positively and significantly correlated with corporate fraud. In this paper, I focus on political alignment on an industry-level, and examine whether industries comprised of a high percentage of high PAI firms outperform industries composed of a low percentage of high PAI firms, when considering other political characteristics (corporate political strategies, regulations, contracts). Industries comprised of firms headquartered in states that lean Republican or Democrat undergo a greater number of policy changes, which have been shown to impact its return performance (Kim et al. 2012). Therefore, I posit that politically aligned industries, or industries with a large number of firms in high PAI states, perform better than industries composed of firms that are less politically aligned.

2.7 Mispricing

Several of the different studies previously stated, detail the scholarly work of various corporate political characteristics' impact on returns and profitability. However, it is important to identify which mechanism (idiosyncratic risk, sentiment, informational asymmetry, etc.) drives the mispricing of industries with different political profiles, leaving the opportunity for investors to profit.

Policy uncertainty is the risk associated with unpredictable changes in government policy, and increases with the difficulty of assessing the preferred policies of an industry and with the likelihood that new policies can be targeted towards industries or geographic areas where firms operate (Kim et al. 2012). As mentioned previously, the authors utilize the political geography of a firm as a proxy for the policy uncertainty that it faces. Corporations located in areas where politicians are more aligned, are more likely to face unforeseen legislative changes. Several papers have also shown that rising policy uncertainty increases mispricing in markets (Bouthchkova et al. 2012, Chen et al. 2017, Jin et al. 2019; Chan et al. 2020; Fan et al. 2020; Lei et al. 2020).

Boutchkova et al. (2012) investigate local and global political risks, and their relationship with industry return volatility. They find that industries that are more dependent on contract enforcement, trade, and labor display more volatility during periods of high political risk. Unsurprisingly, increasing political uncertainty in the countries of trading partners results in greater industry volatility. The authors demonstrate that foreign election uncertainty is more related to idiosyncratic, rather than systematic risk, *"the managers of trade-dependent companies can potentially diversify political risks through an optimal selection of trading partners, the benefits of such diversification are limited."* Although investors can diversify idiosyncratic risk away through the selections of securities in their portfolio, the managers of these firms have limited opportunities to do the same, due to the finite number of foreign subsidiaries (Desai, Foley, and Hines 2008). This suggests that industries with political profiles that are more exposed to uncertainty based on their location on the political map, or political geography, may be prone to greater idiosyncratic risk. Higher levels of industry idiosyncratic risk, can initiate mispricing in markets that can lead to abnormal under/over performance. As mentioned previously, Kim et al. (2012) utilizes political geography as a proxy for the policy uncertainty that a particular corporation is exposed to, and demonstrate that firms in areas of high political alignment, earn higher returns. Given the number of papers which illustrate that policy uncertainty impacts prices, I posit that industries comprised of firms in areas of high political alignment will experience higher returns and greater mispricing.

Other papers illustrate the impact of policy uncertainty on corporate returns including, Chen et al. (2017), which investigates the impact of economic policy uncertainty on the time-series variation of China's expected stock returns. The authors find that policy uncertainty predicts negative future returns and posit that the mispricing is hard to be eliminated due to the stringent short-sale constraints in the Chinese market. Although the U.S. market does not maintain the same restrictions on short-selling, the average American investor will not be able to bear the full brunt of costs that come with profiting through shorting strategies. Even in the event that investors are able to accurately identify a group of industries that can be taken advantage of through arbitrage strategies, short-selling constraints will limit their ability to collect "all the marbles". Next, Jin et al. (2019) examine the impact of economic policy uncertainty on stock price crash risk and find a positive impact, surprisingly. Although the effect reverses later, the impact is more prominent for state-owned enterprises. They also find that the impact is more imminent for firms with higher informational asymmetry and with greater investor disagreement. The authors suggest economic policy uncertainty impacts prices through two demeanors: management's concealment of bad news, and investors' heterogenous beliefs (sentiment). Mispricing impacts should be heightened in industries more affected by policy uncertainty as a result of those industries being more attractive to investors with fixed psychological beliefs, ex-ante. Similar to Chen et al. (2019) mispricing is difficult to fully eliminate due to the high transaction costs associated with arbitrage.

Fan et al. (2020) examine the impact of economic policy uncertainty on business distribution operations between parent companies and their subsidiaries in the Chinese market. They find that operations have a negative relationship with policy uncertainty and that state-owned enterprises are more likely to distribute under uncertain conditions, similar to Jin et al. (2019). This suggests that large, conglomerate, firms with many subsidiaries are better suited to deal with periods of policy uncertainty than small firms, as they can utilize their sub-parts to sustain value in the event that one of their lines of business performs poorly. In this paper, I examine changes in the abnormal returns after dropping conglomerates from the sample and find that excluding large firms dissipates the alphas in the *high-performance portfolio*.

Chan et al. (2020) finds that economic policy uncertainty (EPU) increases the cost of raising equity capital, particularly when the economy is in a weak-state. They find that a one standard deviation increase, in the Baker et al. (2016) EPU index, is associated with a 43 basis point increase in the price discount of seasoned equity offerings. The authors show that the EPU effect on seasoned equity offering discounts is stronger for firms with greater dependence on government spending. Their findings suggest that industries with higher dependence on federal contracts, are more negatively impacted during periods of high policy instability.

Financial analyst forecasts and corporate disclosures can be impacted by policy uncertainty, leading to the heightening of information asymmetry (Lei and Luo 2020). Lei and Luo conduct a comprehensive study of 51 different articles focusing on policy uncertainty, corporate disclosure, and information asymmetry. The authors find that corporations strategically change their practices during times of increased policy uncertainty, accelerating the mispricing of stocks from their inherent values. Corporate disclosures are an important piece in promoting information asymmetry, and efforts to distort the accuracies of the financial standings of various institutions, hinders the efficiency of markets. There is substantial evidence displaying that policy uncertainty has negative impacts on firm disclosure. Zhang (2006) suggests that policy uncertainty reduces the level of reliable firm information and Jiang et al. (2020) finds that the tone of corporate disclosure is more negative and uncertain in periods where policy uncertainty is high. Pitrioski et al. (2015) find that politically affiliated firms suppress negative information in response to major political events. Bail et al. (2018) find that politically connected and dependent firms reduce their reporting quality during periods of high uncertainty. Cui et al. (2020) find that policy uncertainty increases firms earning management. However, as noted in Lei et al. (2020), corporations may adjust their real activities during periods of high policy uncertainty, which dampens the importance and accuracy of company disclosures. Bonaime et al. (2018) finds that political and regulatory uncertainty are highly negatively associated with mergers and acquisitions. They find that the impact is consistent with the real option channel, as the effect is less exacerbated for reversable deals and that policy uncertainty increases the target's negotiation power. Julio and Yook (2012) investigate investment levels during election years and non-election years, and find that investment is substantially higher in non-election years. Their findings suggest that corporations refrain from investment until electoral policy uncertainty is resolved. On a similar note, Colak et al. (2017) finds that fewer IPOs originate from a state in the year where there is a gubernational election and that the effect is more prominent for firms dependent on government contracts. Industries exposed to higher levels of policy uncertainty may have limited accuracy on their financial analyst forecasts leading to increased information asymmetry and opportunities for arbitrage. In other words, corporations will be encouraged to tamper with their financial statements when the futures of policies are uncertain, leading inaccurate valuations and unreliable recommendations from analysts. Because prior literature suggests that industries with greater mispricing may be driven by analyst forecasts that are more widely dispersed, I posit that forecast dispersions will be higher in the portfolios that display evidence of under-performing or beating the market. Counter to the literature, in un-tabulated analyses, I find that the financial analyst forecast disagreements are substantially lower for industries that display evidence of abnormal returns. After negating that analyst disagreements are driving the prices away of industries in the *high-performance profile*, I examine other elements commonly discussed to shift prices, such as investor sentiment and idiosyncratic risk.

Investor sentiment, or how investors form beliefs, also plays a direct role in the pricing of securities (Barberis, Shleifer, and Vishny 1998). As stated in their seminal work, Barberis et al. (1998) further the work of Griffin and Terversky (1992) which illustrates that investors pay too much thought to the strength of evidence (changes in returns, earnings, corporate announcements) rather than its statistical weight when making forecasts. Barberis et al. (1998) display that there are two persistent regularities in investor psychology: underreaction of stock prices to a particular news event, such as earnings announcements, and overreaction of stock prices to a sequence of good or bad news events. They suggest that stock prices slowly incorporate all news information, leading to overpriced or underpriced stocks eventually reverting back to their mean value. Several works have concurred that sentiment plays a role in mispricing (Loughran and McDonald 2011; Chopin and Darrat 2000; Miwa 2016, Stambaugh et al. 2015 etc.). Grossman et al. (2007) examine 74 ADRs across 9 countries and find that price deviation is higher for those with higher transaction costs and in periods where the U.S. T-Bill rate is high, suggesting that U.S. consumer sentiment drives the prices. Consumer sentiment has been used as a proxy for investor sentiment (Simpson and Ramchander 2002) who find that sentiment levels, influence closed-end funding. Miwa (2016) analyzes market-wide sentiment and its influence on mispricing. The author finds that mispricing is high when market-wide sentiment is bullish, as investors aggressively pursue high-growth "winner" stocks. Sought out stocks with stronger-predicted growth experience higher negative forecast revisions and decreased subsequent stock returns, specifically after periods where investor sentiment is high. Finally, Stambaugh et al. (2015) adds two mispricing factors to the size and market factors and find that their model performs better than traditional four and five-factor models. They find that investor sentiment predicts the mispricing factors, particularly in the short-term. Given that several papers provide substantial evidence on the psychological biases of investors and its persistent impact on prices, I posit that the level of sentiment is higher for industries in the political profile portfolio that earns abnormal returns. After establishing the political profiles of industries associated with abnormal performance, I compare the sentiment of the industries in the *high-performance portfolio* to the remainder of the sample, to assess whether investor sentiment is driving mispricing. Consistent with the literature, I find that investor sentiment is substantially higher in the *high-performance portfolio*, indicating that investors' pre-held beliefs are stronger for industries with a certain set of political characteristics.

It is also possible that idiosyncratic risk may be an additional driver of mispricing. Pontiff (2006) states that idiosyncratic risk is a holding cost that investors must bear and is unrelated to future stock returns of other assets, and cannot be hedged away. Merton (1987) suggests that in the presence of informed investors, market participants have a fixed budget, implying that securities with higher firm-specific risk are rationally priced to earn higher expected returns when markets are segmented. However, Shleifer and Vishny (1997), determine that idiosyncratic risk hinders arbitrage, as some stocks with high idiosyncratic risk may be overpriced, and that mispricing cannot be eliminated by arbitrage due to the risk of shorting. De Jong et al. (2009) examine dual-listed companies and find that idiosyncratic risk hinders arbitrage opportunities, leading to large abnormal returns. Ang et al. (2006) finds that a strong negative relationship between future cross-sectional stock returns, and idiosyncratic risk. Similar to Grossman et al. (2007) and Suh (2003), Wu, Hao, and Lu (2017) examine the impact of investor sentiment and idiosyncratic risk on the mispricing of American Depository Receipts. The authors find that idiosyncratic risk impact on mispricing increases when local investor sentiment is high, suggesting that firm-specific risk plays a key role relative to investor sentiment. The authors conclude that investor sentiment impacts mispricing through idiosyncratic risk. Stambaugh et al. (2015) finds that the relationship between idiosyncratic volatility and expected returns is negative for overpriced stocks, especially for stocks that are difficult to short, but positive among underpriced stocks. Noise traders act more irrationally when market investor sentiment is high. Hence, some institutional investors may shy away from trading when sentiment is high due to higher holding costs, causing mispricing to persist. A number of papers demonstrate that not only does idiosyncratic risk impact prices, but also show that it can combine with investor sentiment to drive prices even further away from their fundamental values. Therefore, I posit the level of idiosyncratic risk in the *high-performance portfolio* should be substantially higher than the remainder of the sample.

Some arbitragers may look at periods of high sentiment as an opportunity for profit, but the unpredictable nature of investor sentiment makes it difficult for mispricing to be fully eliminated. The political uncertainty delineating from the profiles of a corporation certainly can impact the level of sentiment it is exposed to. In fact, Hassan et al. (2019) develop a political sentiment measure, PSentiment, based on textual linguistics techniques that are similar to their political risk measure, PRisk. The authors find that corporations experience positive (negative) stock returns when measures of political sentiment are high (low). In turn, they also find that political sentiment is negatively correlated with political risk, indicating that public sentiment is highly pessimistic during times of high political risk. Firms tend to hire and invest significantly more during periods of low uncertainty (Pindyck 1988; Bloom, Bond, and Van Reenen 2007). Hassan et al. 2019), both of which are positive pieces of information that firms should be encouraged to disclose. The authors also find that corporations that are optimistic regarding the prospects of favorable legislation, tend to lobby and donate to PACs significantly more. This suggests that those industries exposed to higher policy uncertainty, would have more sparse contributions to political candidates and lobbying expenditures, due to their negative forecasts. Industries that foresee positive changes in legislation, will most likely have wide-spread activity across the corporations in that industry, or political competition, rather than political activity being concentrated amongst a small group of firms. Prior literature has stressed the importance of the level of concentration and competition of industry characteristics, such as political connections and sales, on returns (Kroszner et al. 1998, Hou et al. 2006). Following this line of logic, industries that foresee negative policy changes due to higher policy uncertainty, will have little political strategy activity amongst a small group of firms, opening up the corporation to murky disclosure practices, inaccurate financial forecasts, and increased investor sentiment, all of which amplify mispricing. In other words, those industries that face greater policy uncertainty will have concentrated corporate political strategies and experience greater mispricing.

In this paper, I identify the political profiles of industries associated with out-performing the market by splitting them into portfolios based off their political characteristics, and demonstrate that mispricing drives the disparity. I utilize three political characteristics to develop the portfolios: political geography, corporate political strategies (PAC/lobby), and government interference (regulation/federal contract). As mentioned previously, I posit that industries that experience abnormal performance will be those located in areas of greater political uncertainty or alignment and those with concentrated political strategies. Given that the literature is relatively split regarding the impact of contract and regulations on corporate performance, I have no strict hypothesis on whether industries exposed to low or high government interference, experience greater mispricing. I utilize univariate analysis and multi-variate regressions to illustrate that those industries in areas of high political alignment, with concentrated corporate political strategies, and exposed to low government interference, designated the *high-performance portfolio*, experience abnormal returns and experience significantly higher levels of investor sentiment and greater idiosyncratic risk, implying that mispricing drives the effect. I conduct several robustness examinations that display the impact is not due to a particular industry, year, or presidential administration. Last, I display that conglomerate firms play a large role in driving abnormal returns as their exclusion, substantially reduces the performance of the *high-performance* portfolio.

In the next section, I describe the sources of data and methodology for generating the political profile portfolios.

3. Data and Methodology of Political Profiles

3.1 Data Collection

Data is obtained from a variety of sources. Shares outstanding and daily, weekly, and monthly stock price data are taken from CRSP. Accounting measures used to control for industry characteristics, are obtained from COMPUSTAT. Details regarding corporate political strategies are taken from the Center of Respective Politics (CRP). To proxy for industry regulation level, I download regulation data from quantgov.com, which lists the annual number of regulations for each NAICS industry, according to the code of Federal Regulations. A small number of observations are lost when re-classifying industries from NAICS to SIC. Federal procurement information is taken from usopensecrets.com. Industry classification information (SIC) and the Fama-French factors are obtained from the Kenneth French website. I restrict the sample to share codes 10 and 11. The time period of the sample is 2001-2020.

Industry portfolios after generated after classifying each corporation to one of the forty-nine Fama-French industries, by SIC code, and taking the value-weighted average of the individual returns.[4] I include several firm characteristics and take the equal-weighted average, in order to form industry controls. I control for firm size using total assets or market equity. Market equity is lagged and calculated as the stock price at the end of June multiplied by the number of shares outstanding (Fama and French 1993). Book equity is calculated according to Grullon et al. (2012) as stockholder's equity minus preferred stock plus balance sheet deferred taxes and investment tax

[4] Only CRSP SIC codes are considered (COMPUSTAT SIC codes are disregarded), due to discrepancies between the datasets (Kahle and Walkling 1996).

credit (if available) minus post-retirement benefits (if available). If stockholder's equity is missing, I use common equity (if available) plus preferred stock par value (if available). If these variables are missing, I simply use book assets less liabilities. I include the sales-Herfindahl of each industry to account for competition (Hou and Robinson 2006). Leverage is defined as the ratio of total book liabilities to total market value of a firm (market equity plus total assets minus book equity). I include corporate R&D expense, scaled by total assets, to control for industry-level innovation. I control for industry-level turnover as investors may be more attracted to trade in specific industries at various points of time in the sample. Stock turnover is calculated as monthly stock volume divided by number of shares at the end of the month (Addoum and Kumar 2016).[5] Last, I include momentum (m-12, m-2) and lag (m-1) measures to control for short-term reversal and momentum trading based-strategies.

3.2 Composition of Political Profiles

Industries are sorted into 2x2x2 (eight) portfolios by the median values of each component of the political profiles: political alignment, corporate political strategies, and government interference. First, industries are sorted annually into low and high groups of political alignment, based on the median industry value-weighted PAI, following Kim et al. (2012).[6] In order to capture industry-level political competition, proxied by corporate political strategies, I use a variation of the Herfindahl measure introduced by Hou et al. (2006), which captures industry sales concentration. The respective equations for the PAC-Herfindahl and Lobby-Herfindahl measures are:

[5] Industry turnover is the value-weighted average of the stocks' turnover in each industry.
[6] Political alignment is calculated according to Kim et al. (2012), and proxies for a local firms' proximity to political power. The Political Alignment Index (PAI) is a state-level measure of political alignment with the President's party.

$$PAC\text{-}Herfindahl_j = \sum_{i=1}^{I} c_{ij}^2 \quad (1a) \qquad\qquad Lobby\text{-}Herfindahl_j = \sum_{i=1}^{I} l_{ij}^2 \quad (1b)$$

where c_{ij} represents the number of candidates supported by firm i in industry j, and l_{ij} represents the dollar amount of lobbying expenditures made by firm i in industry j.[7] Herfindahl measures are scaled from 0-1, with low levels implying that the respective industry has wide-spread political connections across a multitude of firms. For example, a PAC-Herfindahl value of .30, well below the mean of .3722, indicates that the industry has wide-spread (as opposed to concentrated) donations to candidates. At the same token, high Herfindahl scores indicate that the industry's political connections are concentrated amongst a small group of firms. I take the sum of the PAC-Herfindahl and Lobby-Herfindahl measures and label the measure as CPS-Herfindahl (1c), in order to account for industry-level corporate political strategies. Similar to industry-level political alignment, I sort industries annually into wide-spread and concentrated corporate political strategy portfolios, based on the median of CPS-Herfindahl.

$$CPS\text{-}Herfindahl_j = PAC\text{-}Herfindahl_j + Lobby\text{-}Herfindahl_j \quad (1c)$$

Last, I sort industries into low and high government interference portfolios, based on the median value of total procurement dollars awarded to an industry each year, scaled by market equity. I also include regulations (along with procurement contracts) in the government interference measure, in additional tests, and find that the results are consistent. Empirical examinations that include regulations as part of interference, sort industries by the median value of the annual number of federal regulations.[8]

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[7] To rule out the influence of potential data errors, I perform the above calculations each year for each industry, and then average the values over the past 3 years (Hou et al. 2006).

[8] The *interference* measure (for tests including contracts and regulation) is taken as the sum of the log of industry regulations and log of contract dollars scaled by market equity. Industries are then sorted into low and high government interference portfolios, based on the median value of *interference*.

In sum, there are eight political profile portfolios: (1) Low PAI – Wide Spread CPS – Low Interference, (2) Low PAI – Wide Spread CPS – High Interference, (3) Low PAI – Concentrated CPS – Low Interference, (4) Low PAI – Concentrated CPS – High Interference, (5) High PAI – Wide Spread CPS – Low Interference, (6) High PAI – Wide Spread CPS – High Interference, (7) High PAI – Concentrated CPS – Low Interference, and (8) High PAI – Concentrated CPS – High Interference.

The descriptive statistics of the various measures used throughout the tests are listed in Table 1. Panel A details industry monthly return summary statistics. There are 10,927 monthly industry return observations in the final sample. A few industry-month portfolios are missing for a variety of reasons.[9] The mean of industry monthly returns is 1.0060%, or 12.072% per year. The measures are relatively widely dispersed with a standard deviation of 8.4068. Returns in the 5th percentile hover around -12.4405%, while returns in the 95th percentile are listed at 13.346%. The industry lag (m-1) return is slightly less, with a mean of .9932%, while the momentum (m-12, m-2) averages at 9.5504%. Just below, Panel B details the annual political measures used in empirical examinations. There are 911 annual observations in the final sample, which matches the number of monthly return observations (10,927 observations/12 months). The average (median) number of candidates supported by PACs per industry is 290 (163). The p5 and p95 values of 0 candidates and 1,182 candidates indicate that corporate donations to political candidates up for election, are widely distributed across industries. The Herfindahl-PAC measure, calculated by number of candidates, hovers around an average (median) of .3772 (.2951) and a standard deviation of .2707. Hence, two-thirds of the Herfindahl-PAC observations fall in the range of .1065 and .6479.

9 1) CRSP does not have available returns for certain industry-month observations. 2) COMPUSTAT annual data has some missing characteristics for a small number of industries. 3) More industries are dropped when merging regulation data from quantgov (classified by NAICS) to the final sample (classified by SIC).

Similarly, the Lobby-Herfindahl measure, calculated by dollar expenditures, averages at .3907 and has a median of .3333. The standard deviation of .2615 indicates that 66.7% of observations are in the bracket of .1292 and .6522. The similar nature of the corporate political strategies' statistics limits the potential of skewed assessment. The Herfindahl-CPS measure (.7629 mean) is simply the sum of the Herfindahl-PAC and Herfindahl-Lobby measures. The average annual dollar contracts awarded to an industry is a whopping $2.74 trillion, with a median of $19.6 billion, indicating that large value contracts are driving the mean upwards. The same can be said for regulations which has a mean (median) of 12,992 (4,590) regulations per year. Panel C details the industry characteristics at the bottommost part of Table 1. First shown is the Herfindahl-Sales measure, estimated according to Hou et al. (2006), which has a mean of .1794. Industry book-to-market ratio proxies for industry profitability and has a mean of .4996. To control for industry size, I include the log of total industry market equity and the log of total industry assets, which have means of 13.2655, and 6.6317. Leverage, R&D/Assets, and turnover have means of .4162, .0323, and .7271.

Panel A of Table 2 includes the correlation measures of monthly industry returns and the various political measurements. Interestingly, industry political alignment is the only political measure that is significantly correlated with industry returns. Both value-weighted and equal-weighted political alignment are positively and significantly correlated at the 1% level with industry returns, with coefficients of .0529 and .0578. Industry returns show no significant relationship with the other political measures capturing industry-level corporate political strategies, government contract dependence, or regulation activity. This gives preliminary evidence that political geography is the sole political profile driving industry returns. In order to discover whether corporate political strategies, government contracts, or regulations can play a part in enhancing or diminishing the impact that political alignment has on industry returns, the political proxies must be examined comprehensively. Therefore, these correlation measures, only provide a small picture of the impact of various political measures on industry-level corporate returns. Panel B of Table 2 shows the relationship between monthly industry returns and control variables. Unsurprisingly industry returns have a significantly positive correlation with B/M and negative relationship with industry assets and leverage, consistent with prior literature.

In Table 3, I list the annual distribution of industries for each of the eight political profiles. This table provides insight into which group of industries are responsible for propelling returns. Industries are relatively split across the eight portfolios, ensuring that firms are properly distributed. In order to avoid the possibility of data errors, I enforce requirements of (1) at least two firms per industry each month and (2) each industry must appear in at least four out of the five presidential terms in the sample. Any industry observations that do not meet this criterion, are dropped from the sample. Proven in later empirical examinations, column (7), the high PAI – concentrated CPS – low interference portfolio, lists the industries with consistent evidence of outperforming the market (*high-performance portfolio*). The majority of industries in the *high-performance* portfolio include: Beer, Smoke, Books, Ships, Other, and PerSv. The industries in this political profile may be outperforming the market because they are more are susceptible to mispricing as a result of investor belief in a particular industry.

The sixth column represents the political profile portfolio associated with the second highest returns throughout the empirical examinations, the high PAI, wide-spread CPS, and high interference political profile portfolio. Interestingly, this portfolio is associated with high-tech as the three out of the top four industries include the Telecom, Software, and Chips industries. These group of industries are primarily located in areas of high PAI, are subject to high government interference through regulation and procurement contract, and maintain wide-spread connections to politicians through corporate political strategies. The political profiles that show the strongest evidence of under-performance (in later tests), are the low PAI-concentrated CPS-low interference and low PAI-wide spread CPS-high interference portfolios. The most popular industries in the portfolios are the agriculture and guns industries, and the business service and electric equipment industries.

In the next set of tests, I examine the political profiles and industry returns in univariate and regression settings, in order to solidify evidence that the industries in the high PAI – concentrated CPS – low interference portfolio, out-perform the market.

4. Political Profiles and Returns

4.1 Univariate

Panel A of Table 4 displays the results of the univariate tests, listing the mean values of the different components of returns for each portfolio. As can be seen in column (7), both industry monthly value-weighted and equal-weighted returns are highest in the High PAI-Concentrated CPS-Low Interference portfolio with means of 1.6756% and 1.6253% per month (~20% per year). It is also interesting to note that the momentum and lag measures are also highest in this portfolio with average values of 15.4242% and 1.5768%. Put together, this column provides preliminary evidence that the group of industries with High PAI-Concentrated CPS-Low Interference political characteristics, show evidence of earning higher returns than the market. Looking deeper into the components of the table, three out of the four political portfolios with High PAI, rank the highest in terms of value-weighted returns (1.6756%, 1.0977%, 1.0101%). As mentioned previously and detailed in Table 2, political alignment is the only political measure significantly correlated to PAI.

Both tables' results imply that PAI is the political measure driving industry returns, while, the other political measures (corporate political strategies, contracts, and regulation) allow for a setting for the PAI effect on returns to be stronger. On the other hand, industry monthly returns are lowest in column (3), the Low PAI-Wide spread CPS-Low Interference portfolio, as the value-weighted average of .3206% is significantly lower than the remainder of the sample.

Panels B and C list the means for the annual political measures and industry control characteristics, for each of the eight political profile portfolios. Unsurprisingly, in panel B, the political alignment is highest in the Low PAI - Wide spread CPS - Low Interference portfolio, suggesting that it is the primary factor driving returns. The mean of Herfindahl-CPS is also highest in column 7, illustrating that these group of industries have the most concentrated political strategies in the sample. Looking at the political Herfindahl measures more closely, the *Herfindahl-lobby* measure is substantially higher in column 7, than that of all other columns, implying that a small group of firms in this portfolio incur lobby expenditures. The procurement contract amount, scaled by market equity, and regulation restrictions are lowest in column 7, with an average hovering around $60,000. The mean number of industry regulations for this political profile was 7,641, the second lowest average among political profiles. Overall, the results of Panel B indicate that extreme political settings (highly concentrated corporate political strategies, low government contract, and low regulations) allow for the impact of political alignment impact on industry returns, to be the strongest.

Moving to Panel C, industry sales concentration, captured by Herfindahl-Sales, is highest in column 7, indicating the majority of sales are made by a small group of firms in the portfolio. This indicates that a higher concentration in sales is associated with higher returns, consistent with Bustamante & Donangelo (2017). Market equity and total assets have their highest values in column 7, indicating that large firms are prevalent in the high PAI – concentrated CPS – low interference portfolio. R&D expenditure is lowest in column 7, indicating that these group of industries do not spend a high number of resources on the future development of products.

The results in Panel A of Table 4 indicate that industries in the high PAI – concentrated CPS – low interference portfolio, earn stock returns that are sizably above industries in the seven other political profile portfolios. However, no implications can be made regarding the performance of industries in the high-performance portfolio until we examine the impact in a time-series setting and control for market-factors. Do industries in the high PAI – concentrated CPS – low interference portfolio beat market estimates on a consistent basis over the time-period of 2001-2020? Can investors earn a profit by investing in the industries in the high PAI – concentrated CPS – low interference portfolio? I aim to resolve the following questions in the sub-section below.

4.2 Time-Series: OLS Regressions

After establishing that industries in the high PAI-concentrated CPS-low interference portfolio earn the highest returns in the sample, I turn to examinations that examine the performance of political profiles and whether it can predict future returns. To that end, I examine the association between industry returns and industry political profiles in time-series and cross-sectional regressions. I split the sample into the eight political profile portfolios, and first, run OLS time-series regressions of the monthly value-weighted industry returns in each political profile, on the FF-5 monthly factors. This methodology enables the examination of the sensitivity of returns for the political profile portfolios dummies over a period that spans across multiple presidential administrations, to ensure the effect is not driven by a particular party in power, or a particular industry.

$$R_i - R_f = \alpha + B_1(R_m - R_f) + B_2SMB + B_3HML + B_4RMW + B_5CMA \quad (2)$$

Industries categorized into political portfolios associated with out-performing the market, are illustrated by alphas that are positive, and economically and statistically significant. Panel A of Table 5 shows that two portfolios, columns (6), and (7), display evidence of out-performing the market with 5% statistical significance. The alpha in column (7), the High PAI–Concentrated CPS–Low Interference portfolio, has that has the highest statistical and economic power, and is the primary portfolio that is robust to a multitude of tests. The coefficient of the alpha is .7785, which equates to an abnormal performance that is substantial, at 9.342% per year. The results in Panel A of Table 5 confirm that industries with high – concentrated – low political characteristics perform better, and the impact is not subject to party affiliation. Hence, I designate the industries in column (7) as the *high-performance portfolio*. The performance of the High PAI – Wide Spread CPS – High Interference portfolio is also noteworthy, with an annualized alpha of 4.1496%, and is significant at the 5% level. Unsurprisingly, in Panel A of Table 4, the high - wide spread - high portfolio had the second highest value-weighted industry return average at 1.0977% per month or 13.1724% per year, indicating that these group of industries also display consistent evidence of earning high returns.

Panel B of Table 5, runs the same regressions as Panel A, but includes regulations as part of the government interference measure. The results are consistent, as the alphas in column (6) and (7) display values indicating abnormal performance. Industries in the *high-performance portfolio* earn an annualized alpha that is quite substantial in economic magnitude, with a value of 10.3428%. The alpha in column (6), the high PAI-wide spread CPS-high interference portfolio, has a coefficient of .3881, translating to a 4.6572% annual measure. Both panels of Table 5 indicate that the political profile impact is not trivial. In fact, trading on industries in the High PAI-concentrated CPS-low interference portfolio or the *high-performance portfolio*, can earn investors an annualized alpha of over 10%.

Investors can realistically replicate the trading strategy with low cost and little additional research. It is important to mention that the alphas generated in Table 5 do not depend on shorting any stock or frequent recalibration of portfolios. The political profile trading strategy relies on investing in industries based off their annual political characteristics.[10] Investors will only need to recalibrate their portfolios at the beginning of each year, or preferably immediately after the election, limiting their costs of transactions. Each year, investors should long industries located in states with highly aligned legislatures with the presidential party in power, with political strategies concentrated among a small number of firms, and with a low possibility of exposure to government interference to experience an easy profit. Investors can simply invest index funds or ETFs with the political characteristics mentioned, to generate a reliable and substantial annualized alpha of 10.3428%. In the next section, I examine whether the relationship between industries' political profiles and their portfolio returns holds in a cross-sectional setting.

4.3 Cross-Sectional: Fama-MacBeth Regressions

In the next batch of tests, Fama-MacBeth regressions are run to determine whether the relationship holds in a cross-sectional setting. I include various measures known to predict cross-sectional returns including: the Fama-French factors in the 5-factor model, industry lagged returns, and industry momentum. I also control for the remainder of political profiles through political profile dummies. In un-tabulated results, I control for a variety of measures listed in Panel C of

[10] Political action committee, lobbying expenditure, federal contract and regulation data are calculated on an annual basis. Political alignment is calculated bi-annually, as U.S. elections occur every two years, generally in November. To accurately account for political profiles impact on industries' returns, portfolios are sorted based on their annual political characteristics.

Table 1, Herfindahl-Sales, book-to-market, size, leverage, R&D, and turnover, and find that the results are consistent.

Table 6 lists the results of the Fama-MacBeth regressions. Panel A excludes regulations as part of government interference, while panel B includes regulations. Column (1) controls for the political profiles, the 5-FF monthly factor loadings. Column (2) controls for momentum and lag, in addition to the set of variables controlled for in column (1). Both panels display that the coefficient of the high PAI–concentrated CPS–low interference portfolio dummy (7) is highly significant in both columns. In panel A, the results in the left (right) column indicate that the difference in returns between the high-concentrated-low group and the base group is .8204% (.7563%) per month, or 9.8448% (9.0756%) per year. Panel B of Table 5 shows that the difference in returns between the high PAI-concentrated CPS-low interference group and the base group is 10.338% (7.512%) per year.

Similar to Table 5, the magnitude of the annualized coefficients in Table 6, are meaningful for industry returns. Political alignment appears to drive industry returns, while sparse political strategies, and minimal government interference allow for the impact on returns to be more effective. The impact spans across multiple industries and years where different parties in power. The political profiles of an industry are important determinants into the variation of its expected returns, and the impact is distinct from common firm characteristics known to predict returns.

Identifying the political profiles associated with higher returns is important, but a deeper discussion into their individual roles in driving performance is needed to understand the root causes of abnormal performance. As illustrated in the correlation table and univariate analysis, the political profile driving returns appears to be political alignment. Political alignment is the only political measure that is significantly related to returns. All other political measures are insignificant, which does not mean that their influence on returns is unimportant, but rather indirect. Hence, comprehensive political profiles are formed to determine the set of political characteristics allowing for the political alignment impact on returns to be enhanced. I also find in the univariate analysis that industry excess returns are substantially higher in the four high-political alignment profiles, than they are in the four low-political alignment profiles. As detailed in Kim et al. (2012) corporations with high political alignment can be exposed to greater policy uncertainty (higher likelihood of legislative change) or presented with greater investment opportunities (officials pass favorable policies for constituents). Industries with greater policy uncertainty require higher excess returns, but may not perform better on a consistent basis- unless the political environment presents a favorable setting for firms to take advantage of the uncertainty, possibly through real options. Similarly, if certain industries are presented with favorable investment opportunities (because of their geographic location), it is important to determine whether the existence of wide-spread interference or minimal political strategies influence the materialization of these favorable policies on performance. It appears that a political environment of concentrated political strategies and low government interference, or low political activity, allows industries to take advantage of higher policy uncertainty or investment opportunities consistently. The time-series and cross-sectional regressions illustrate those industries with concentrated corporate political strategies and low government interference, allow for the (high) political alignment effect on performance to flourish, and is deemed the *high-performance portfolio*.

As mentioned previously, the tests ran up to this point should satisfy investors looking to make a profit on the market. The time-series and cross-sectional results are consistent in magnitude and significance, and the trading strategy is easy to implement. Political alignment appears to drive industry performance, while the other political characteristics serve an important purpose in allowing the impact to materialize. In the next section, I analyze several tests supporting the argument that mispricing appears to drive abnormal returns by examining reversals, sentiment, idiosyncratic risk, and reactions to earnings announcements. I also conduct an analysis comparing the impact of political profiles with other established variables in the literature.

5. Mispricing and Other Political Factors

5.1 Short-term, Medium-term, and Long-term Returns

Industries in the high-performance portfolio generate substantially higher alphas, implying that these group of firms may either be temporarily mispriced due to various factors such as the possibility of higher investor sentiment or idiosyncratic risk or permanently mispriced due to a political risk factor unaccounted for in the Fama-French asset pricing model.

To help address this dilemma, I first investigate the persistence of the superior performance of industries in the high PAI - concentrated CPS - low interference portfolio, by examining short-term (-1,0), medium-term (-12,-2), and long-term (-36,-13) returns (Jegadeesh 1990; DeBondt & Thaler, 1985; Jegadeesh & Titman, 1993). I incorporate these three mispricing proxies to investigate whether the mispricing effect is reduced or more pronounced during various terms of length. I run OLS regressions of industry monthly excess returns on the following variables of interest: portfolio dummy * short-term returns, portfolio dummy * medium-term returns, portfolio dummy * long-term returns. Portfolio dummy is set to 1 if an observation falls in the *high-performance portfolio* in a given year. I also control for the five factors (*Rm-Rf*, *SMB*, *HML*, *RMW, and CMA*) in the Fama-French model, log(market equity), and log(book-to-market ratio).

The results of the OLS regressions on the previous variables mentioned, are displayed in Table 7. First, the coefficient on the portfolio dummy variable is positive and statistically significant at the 1% level, in agreement with prior results indicating that the industries in the high PAI – concentrated CPS – low interference portfolio, display superior performance. The coefficient on the short-term return variable is negative and significant at the 10% level in both columns, consistent with the short-term reversal effect documented in the literature (Jegadeesh 1990). Moving to the interaction terms, interestingly, the coefficient of the portfolio dummy * short-term variable flips to a positive value, with high statistical significance at the 1% level. This suggests that the mispricing effect is effectively minimized in the short-term for industries that fall into the *high-performance portfolio*. I then investigate whether, positive long-term returns of industries in the *high-performance portfolio* predict negative performance, as suggested by the mispricing literature (DeBondt & Thaler 1985). As expected, the coefficients on both portfolio dummy * medium-term returns and portfolio dummy * long-term returns, are negative and highly significant at the 1% or 5% level, in line with the long-term reversal effect. In sum, the results suggest that the prices revert only in the medium and long-run for industries in the *high-performance portfolio*.

5.2 Risk and Sentiment

To further the argument that prices are temporarily mispriced, I identify investor sentiment and idiosyncratic risk, elements that may be the driving forces behind straying prices away from their fundamental values in the *high-performance portfolio*. Specifically, I compare the time-varying levels of unsystematic risk and sentiment of the industries in the *high-performance portfolio* and the remainder of the sample. As discussed in the literature review, the behavioral attributes of investors can lead to over or under reaction to firm-specific information resulting in a push of prices away from their fundamentals (Barberis et al.1998; Daniel et al, 1998; Hong and Stein, 1999). In other words, investors' beliefs or sentiment may cause them to inaccurately value stock, causing them to under or overreact to new information, generating mispricing. Furthermore, investors may over-demand compensation for industries with higher firm-specific risk, causing prices to deviate further (Li et al. 2008). Therefore, proving whether unsystematic risk or investor sentiment is significantly higher in the *high-performance portfolio*, would lend credence to the mispricing argument.

Table 8 and figure 1 display the levels of total risk, systematic risk, and unsystematic risk. Total risk is calculated as the annual variance of daily industry returns. Unsystematic risk is obtained as the annual variance of the daily residuals obtained from regressing the FF-5 factors on daily industry returns each year for the *high-performance portfolio* and the remainder of the sample. Systematic risk is set equal to the difference between total risk and unsystematic risk. As can be seen in panel A, the volatility of industry returns is higher in the *high-performance portfolio*. Panels B and C display the values of systematic risk and unsystematic risk for the profiles. Industries in the *high-performance portfolio* are exposed to substantially higher idiosyncratic risk than the remainder of the sample. As can be seen in the difference column, the results are relatively consistent through time, as there are only three years (2001, 2012, 2019) where the difference between the unsystematic risk of the *high-performance portfolio* and the remainder of the sample is negative. The mean of the annual industry idiosyncratic risk in the *high-performance portfolio* (.0352) is almost 150% higher than that of the remainder of the sample (.0202). The industries in the *high-performance portfolio* display high levels of unsystematic risk and also appear to experience more of a roller coaster ride, as the variance measures are twice as volatile. Unsurprisingly, the difference in systematic risk between the *high-performance portfolio* and all other political profiles portfolios is negligible in magnitude. Put together, table 7 and figure 1, specifically panel C, affirm that abnormal performance is associated with greater likelihood of mispricing because industries are exposed to greater idiosyncratic risk and investors require higher returns for more risk. In the next set of tests, I investigate whether investor sentiment plays a part in the political profile effect. Investors may hold strong pre-ordained beliefs of industries with the political characteristics of the *high-performance portfolio*. Prior literature has shown that investor sentiment is proportionally affected by idiosyncratic risk (Wu et al. 2017), and when both of these levels are high, stock prices are driven even further away from their fundamentals.

The previous set of tests established that firm-specific news events hit industries in the *high-performance portfolio* harder. If investor sentiment is also higher for industries in the *high-performance portfolio*, their prices will deviate even further from their fundamental values when adverse firm-specific news arises, further enhancing the mispricing effect. Table 9 displays quarterly investor sentiment, standardized by its standard deviation (Hassan et al. 2019), for the *high-performance portfolio* and the remainder of the sample. Once again, examining whether investors pre-ordained beliefs are stronger for industries that perform better, would suggest that the alphas they generate are associated with mispricing as a result of investors over/under-reacting to firm-specific news. As can be seen, investor sentiment is not only higher for industries in the *high-performance portfolio*, but the difference in sentiment of .0346 is statistically significant at the 1% level. Table 8 confirms that investors form stronger biases for industries with high political alignment, concentrated corporate political strategies, and low government interference.

Table 9 shows that investors have strong biases and take a longer time to update their beliefs when new information is released on industries in the *high-performance portfolio*. Additionally, Table 8/figure 1 display that these same industries are already more affected by changes in firm-specific news, because their unsystematic risk is substantially higher. In sum, it appears that the true drivers of returns are two elements of mispricing, as industries with political characteristics in the *high-performance portfolio* experience high levels of investor sentiment and idiosyncratic risk.

5.3 Earnings Surprises and Cumulative Abnormal Returns

After establishing that idiosyncratic risk and investor sentiment are substantially higher in the *high-performance portfolio*, I examine whether these group of industries are more likely to experience positive earnings surprises. Establishing that prices of firms in industries in the *high-performance portfolio* tend to beat analysts' forecast, can help explain why this group of industries deliver superior performance, especially when investor sentiment is high. To address this point, I first compute individual firm earnings surprises by scaling the difference between the actual EPS and the median of the most recent forecasted EPS from all analysts, by the stock price from 5 trading days ago (Meng et al. 2023). I then compute the values at the industry-year level, by taking the annual average of the quarterly earnings surprises of the firms in each industry. Afterwards, I sort industries into annual quintiles based off their earnings surprises ranks, which are displayed in Figure 2. Industries in the high-performance portfolio have an average rank of 3.15 compared to an average rank of 2.9307 for the remainder of the sample, and the difference is significant at the 1% level. The graph suggests that industries in the *high-performance portfolio* experience positive news' earnings surprises at a much higher rate. In the next paragraph, I examine the stock price reaction to good and bad earnings surprises, to help determine whether the alphas are driven by investors over-reacting to good news or under-reacting to bad news.

I first calculate the immediate stock price reaction to earnings announcement dates, using cumulative abnormal returns (0,1). In Panel A of Table 10, I conduct a univariate analysis comparing the CARs (as well as various analyst control measures) of firms in industries in the *high-performance portfolio* and the remainder of the sample. As can be seen, in the third column, cumulative abnormal returns are significantly lower, in the *high-performance portfolio*, as the difference in returns over the two-day window equates to .0711%. Although industries in the *high-performance portfolio* are more likely to have positive earnings surprises (as shown in Figure 2), the stock prices of these firms show a weaker reaction in the immediate term, to the remainder of the sample. Earnings volatility is also greater, by .0486%, in the *high-performance portfolio*. The differences of (1) the number of analysts covering an industry and (2) the reporting lag between industries in the *high-performance portfolio* and the remainder of the sample, are not economically significant.

I then combine the analyses in Figure 2 and Panel A of Table 10, in order to investigate the immediate stock price reaction to good/bad earnings surprises. To further the argument that investor sentiment is stronger among industries with political characteristics that fall into the *high-performance portfolio*, I investigate the immediate stock price reaction to positive/negative earnings announcements. If investor sentiment is driving the alphas generated by the high-performance portfolio, firms in industries in the high-performance portfolio should display stronger (weaker) immediate stock price reactions to good (bad) news. Accordingly, in Panel B, I conduct a multivariate analysis analyzing the immediate stock price reaction to good/bad earnings announcements, following equation (3). Similar to Figure 2, I sort industries into quintiles based on their earnings surprises and form a good (bad) news dummy if an industry falls in the top (bottom) quarter of earnings surprises, in a given quarter. The independent variables of interest include the interaction term of portfolio dummy and good news (bad news).

$$CAR = \beta_0 + \beta_1 \textit{ Portfolio dummy} + \beta_2 \textit{ Good news} + \beta_3 \textit{ Bad news}$$

$$+ \beta_4 \textit{ Portfolio dummy} * \textit{Good news} + \beta_5 \textit{ Portfolio dummy} * \textit{Bad news} + \textit{Controls} \quad (3)$$

Assuring, the coefficient of the portfolio dummy * bad news variable is negative and statistically significant at the 10% level, lending credence to the argument that investors tend to under-react to the bad news of firms in industries falling into the *high-performance portfolio*. In other words, investors have a stronger belief that industries in the *high-performance portfolio* can overcome a quarter of disappointed earnings, compared to other industries. These results suggest that investors view industries with a mix of certain political characteristics, those industries with high PAI – concentrated CPS – low government interference, as a 'rebuff' to bad-news. In the final section of the main set of tests, I compare the 'political profiles' classification to popular political variables used in the literature.

5.4 Other Political Factors

In this section I compare the political profile effect to two other political factors commonly used in the literature, conditional political sensitivity (Addoum and Kumar, 2016) and PRisk (Hassan et al. 2019).[11] Addoum et al. (2016) develop a political sensitivity measure based on the five industries that earn highest and lowest returns when a particular presidential administration is in power. The authors find that investors can generate a substantial profit utilizing an arbitrage trading strategy based on the conditional political sensitivity variable. On the other hand, Hassan

[11] Economic policy uncertainty or EPU (Baker et al. 2016) was also examined. In un-tabulated tests, EPU is uncorrelated with industry returns. It is difficult to implement EPU in a regression-setting due to the nature of the variable (same monthly value for each firm).

et al. (2019) develop a political risk measure based the frequency that ‘risk’, ‘policy’, ‘legislature’, and other words centered on risk and political topics, are used during earnings calls. They find that firms with higher political risk (PRisk) retrench hiring and investment and are more likely to participate in corporate political strategies, but do not make any implications of PRisk’s influence on expected returns. Table 11 lists OLS times-series regressions of industry monthly returns on various political factors and industry controls, with year-month fixed effects and clustering by year-month and industry. The coefficient of conditional political sensitivity of .2284% is statistically significant at the 1% level, which suggests that the variable is able to positively predict returns for the next month. On the other hand, the PRisk effect is not statistically different from zero, indicating it has little association with returns. In column (3), the High-Concentrated-Low dummy coefficient is almost four time higher than the magnitude of conditional political sensitivity, demonstrating that the political profile effect is more impactful. Table 11 concludes that certain industries garner higher returns during presidential administrations, but incorporating the level of political activity on all fronts, can lead to more fruitful predictions on the impact of politics on expected returns.

Last, in Figure 3, I examine the annual PRisk values for the *high-performance portfolio* and the remainder of the sample. Industries in the *high-performance portfolio* may be exposed to higher political risk if their corporate executives speak on political topics more frequently during earnings calls. Looking at the graph, up until about 2011, the PRisk of the *high-performance portfolio* was substantially higher, especially during the financial crisis period. However, from 2011-2020 the difference in PRisk is negligible between both groups. Overall, the results suggest that PRisk does not appear to drive the higher returns associated with industries in the high PAI-concentrated CPS-low interference portfolio.

In terms of political measure predicting returns, implementing a trading strategy following the political profile methodology generates almost twice as large of a profit as the conditional political sensitivity impact in Addoum et al. (2016). The strategies have negligible differences in complexity of implementation and transaction costs. Although the strategy in Addoum et al. (2016) requires recalibration every presidential election (rather than every year), their strategy does involve a long-short effort, partially off-setting the difference in transaction costs. The political profile impact is also distinct from political measures used in Hassan et al. (2019), as industries in the *high-performance portfolio* experience similar levels of PRisk in the past decade. Political alignment, a proxy for firm exposure to legislative policy uncertainty, seems to be unrelated to PRisk, corporations' frequency of mentioning 'political risks' during earning calls. Prior literature has demonstrated that investors require higher returns because of higher uncertainty in future legislation (Kim et al. 2012). In addition, political alignment shows consistent evidence of driving returns, across the univariate and multi-variate tests, suggesting that it is a more appropriate proxy for policy uncertainty in this setting. In terms of investors, the political profile effect is strong and reliable. For academicians, in comparison to other political measures, industries political profiles are a distinct and formidable measure.

In the last section, I confirm the relationship between political profiles and industry returns is not vulnerable to data errors (e.g. a particular time period or industry driving performance). To do so, I conduct various robustness tests that analyze the industries in the high PAI-concentrated CPS-low interference portfolio across various time frames. I also include a final examination where I demonstrate that conglomerates are driving the abnormal returns in the *high-performance portfolio*.

6. Robustness

6.1 Industries

I examine the industries driving returns by splitting the sample in two groups, the and all other political profiles. Panel A (B) of figure 4 and table 12 display the average value-weighted returns (equal-weighted returns) of each industry. The industries with the highest value-weighted returns in the high PAI-concentrated CPS-low interference political profile portfolio include the beer (3.9562%), toys (3.3598%), steel (2.8188%), wholesale (2.7360%), and fabric products (2.8959%) industries. Similarly, the industries with the highest equal-weighted returns in the *high-performance portfolio* are the toys (4.3191%), wholesale (3.7566%), beer (3.4958%), guns (2.9176%), and steel (2.2598%) industries. In terms of the other group, all seven other political profiles, the industries with the highest value-weighted and equal-weighted returns are the personal services and gun industries.

The industries earning the lowest returns for the *high-performance portfolio* include the textiles, real estate, paper and food industries, all of which, have negative returns. The industries with the largest difference in value-weighted returns between the two political profile groups include the textiles (6.3038%), beer (3.9562%), toys (3.3598%), fabric products (2.8959%), and steel (2.8188%) industries. The group of industries with the largest difference in equal-weighted returns also include the textiles (4.9529%), toys (3.5938%), and beer (2.3623%) industries, indicating that these group of industries may drive abnormal performance.

After identifying specific industries, that earn the highest returns in the high PAI-concentrated CPS-low interference portfolio, I conduct additional tests to ensure the results are robust. More pointedly, to exclude the possibility that one industry is driving returns, I re-run the OLS regressions in Table 5, but drop various industries.

Table 15 drops a variety of industries in the *high-performance portfolio* that may be driving abnormal performance. Industries excluded include those with the most prevalent distribution in the *high-performance portfolio* (Table 3), the highest average returns in the *high-performance portfolio* (Table 12/Figure 4), and the highest difference in average returns between the *high-performance portfolio* and the remainder of the sample (Table 10/Figure 1). In total nine industries are dropped: Beer, Books, Fabric products, Other, Ships, Smoke, Steel, Toys, and Wholesale. The statistical and economical magnitude of the alphas remain quite consistent across all panels, and hover around the .7785 coefficient in Table 5, indicating that no particular industry is responsible for the abnormal performance of the high PAI-concentrated CPS-low interference portfolio. Similarly, the alphas in the high PAI- wide spread CPS-high interference portfolio are almost unchanged in magnitude to the Table 5 alpha of .3458%. The results in Table 15 mirror that of Table 5, confirming that the political profile effect is robust to the exclusion of various industries. If certain industries are infeasible to trade at a particular time, investors can be comforted by the fact that the effect will not be dissipated.

6.2 Year & Presidential Term

The next tests listed in Table 13 (14) and graphically displayed in figure 5 (6), split returns by year (presidential term), in order to examine whether a particular year (presidential administration) disproportionately impacts performance. Panel A displays the annual averages of the monthly value-weighted returns, while panel B displays the annual averages of the monthly equal-weighted returns. Unsurprisingly, the year with the highest value-weighted and equal-weighted returns for both groups is 2009, the year immediately following the financial crisis. Shown in panel A of Table 13, the mean of monthly value-weighted returns was 6.2559% in 2013, nearly 2% higher than any other year. The second and third highest monthly returns for the *high-performance portfolio* occurred in 2013 and the year preceding the financial crisis, 2006, with means of 4.3323% and 3.3829%. The equal-weighted returns are also highest in the years 2003 (4.2763%), 2009 (6.0202%), and 2013 (4.6875%) for the *high-performance portfolio*. These preliminary results indicate that value-weighted returns in the *high-performance portfolio* is dispersed across presidential terms, as the top three return-earning years occur under different administrations. On the other hand, the years averaging negative returns include the financial crisis years (2007 and 2008) and 2018 with values of -.7788%, -3.743%, and -.6297%. The results in panel B, are relatively consistent, as the same group of years (2003, 2009, 2013) have the highest average monthly equal-weighted returns for both groups.

Table 14 and figure 6 display the value-weighted and equal-weighted returns by presidential term for the *high-performance portfolio*, and the remainder of the sample. The industries in the *high-performance portfolio* see their highest value-weighted returns earned in the first Obama term postdating the Great Recession, with a monthly average of 2.6664%. The second term under the Obama administration, and the first term of the bush administration both saw monthly returns average above 2.10%, indicating that returns were not substantially lower during these terms. The second Bush term is the only term averaging a negative monthly return, due to the financial crisis in 2007-2008. In Panel B, the equal-weighted monthly returns for the *high-performance portfolio* are highest in the first Bush presidential term, with an average of 2.8305%.

Table 16 drops each presidential term in order to examine whether a particular administration enabled a political environment that is responsible for the majority of abnormal performance. The financial crisis is dropped in panel F, in order to examine how abnormal performance was impacted by the Great Recession. Similar to before, the annualized alphas are relatively consistent to Table 5. In terms of presidencies, the alpha is largest after dropping the sample of Bush (term 2), with an annualized alpha of 10.5084%. As noted previously, the Bush term included the financial crisis years, both of which experienced negative industry returns. Continuing along the same lines, after dropping the years 2007 and 2008 in panel F, the annualized alpha makes a considerable jump to 11.84%.

The results in sub-section 6.1 and 6.2 illustrate that the political profile effect is robust to different industries and time-periods. Investors will not be affected by the fear of missing out on if they experience periods of financial constraints, because the magnitude of profit is robust to different years. Furthermore, the impact is unrelated to the party in power, and can be implemented under any presidency. The results suggests that both parties in the legislative and executive branch, pass policies that affect different industries' performance in similar ways. The impact is consistent across all presidential administrations, and varies across party lines, as the sample includes two republican and two democratic presidencies.

6.3 Conglomerates

In the last set of robustness tests, I turn my attention to conglomerates. Large firms operating in different industries may skew the results in two directions. First, excluding conglomerates puts a narrowed focus on 'pure' industry corporations, which may enhance performance results for the high PAI-concentrated CPS-low interference political profile. Corporations operating in multiple industries, may be negatively affecting the *high-performance portfolio* return because their business segments are exposed to different levels of corporate political strategies and interference. Alternatively, it is also possible that leaving out conglomerates may significantly alter which political profile is associated with abnormal performance, as conglomerates are typically responsible for the bulk of corporate political strategies and procurement contracts. Therefore, leaving out large corporations that dictate the majority of political activity can completely change the set of political profiles that allow for abnormal performance. Furthermore, as shown in the examinations and discussed earlier, industries with high policy uncertainty (high political alignment) perform better in the event that industry political activity (political strategies & government interference) is low. Large, politically-active corporations in industries with low political activity will have more sway on policies, and may be more likely to experience abnormal returns, from their passing. Although political activity influences corporations at the industry level, large firms tend to benefit more from periods of policy uncertainty due to their many lines of business and large capital (Fan et al. 2020). Ergo, dropping conglomerates may cause abnormal performance to dissipate or disappear completely.

Table 17 presents the results of OLS regressions utilizing industry monthly returns as the dependent variable and the 5-FF monthly factors as regressors, similar to Table 5. Panel A excludes conglomerates, defined as corporations operating in more than one business segment (COMPUSTAT). Panel B negates 'super conglomerates', defined as those corporations operating in two or more business segments. Interestingly, the alpha in column (7), the *high-performance portfolio*, loses all statistical power and significantly drops in economic magnitude, in both panels. This result is quite surprising as it indicates that conglomerates in the *high-performance portfolio* drive the abnormal performance. It is important to note that market equity and total assets maintained their largest means in the *high-performance portfolio*, emphasizing the role of large firms in this political profile. Also important to note, the performance of the low PAI-wide spread

CPS-high interference political profile portfolio soars after excluding conglomerates, while the performance of the high PAI-wide spread CPS-high interference portfolio, does not change much. The results in columns (2 and 6) illustrate positive and significant annualized alphas of 7.5396% and 6.6012%, the highest of the bunch. In sum, the results of Table 17 indicate that conglomerates drive performance as their exclusion causes the significance of the alphas of industries in the high-profile portfolio to disappear. Without conglomerates, the set of political characteristics associated with abnormal performance appears to be more reliant on wide-spread corporate political strategies and high government interference, rather than political alignment.

7. Conclusion

This research examines whether the comprehensive political profiles of an industry affect its portfolio return performance. Political profiles must be looked at comprehensively, as isolated examinations of these characteristics can lead to spurious conclusions. Typically, political activity impacts corporations at the industry level (Cohen et al. 2013). Accordingly, I separate industries into eight portfolios, after triple-sorting them into portfolio based on the median of three political profiles: (a) political alignment, (b) corporate political strategies, and (c) government interference. I demonstrate that industries that fall into the high political alignment-concentrated corporate political strategies-low government interference portfolio, display powerful and consistent evidence of positive, abnormal performance.

I utilize time-series regressions to analyze the performance implications to investors that care to earn a profit through replicating the political profile trading strategy. I illustrate those industries with high political alignment, concentrated corporate political strategies, and low government interference, or the *high-performance portfolio*, out-perform the market, substantially at almost 10.3428% per year. The results are robust to a multitude of regressions, implying that the relationship between industries' political profiles and their performance is not spurious. In cross-sectional Fama-MacBeth examinations, I display those industries falling into the *high-performance portfolio* earn a 10.338% higher return than the base group of industries.

It also appears political alignment is the primary political profile driving excess returns, while the other profiles form a setting to enhance the effect. I first demonstrate through correlation analysis that industry returns are only significantly associated with political alignment and no other political measures. Likewise, in the univariate analysis, the returns of portfolios with high political alignment are substantially greater than the portfolios with low political alignment. However, the returns still vary across the portfolios with high political alignment, indicating that the industry-level concentration of political strategies and low government intervention allow for the political alignment impact on industry returns to flourish.

I then conduct analyses to determine the underlying factors driving returns. Mispricing appears to drive the abnormal returns associated with industries' political profiles, and the impact is substantially higher than that of other political factors known to predict returns. Specifically, I examine levels of sentiment and idiosyncratic risk in the *high-performance portfolio*, to see whether they play a part in driving prices away from their fundamental values. I display those industries in the *high-performance portfolio*, demonstrate substantially higher levels of unsystematic risk, averaging a value almost 150% greater than the remainder of the sample. Idiosyncratic risk also appears to be substantially more unstable in the *high-performance portfolio*. Both of these results indicate that industries in this portfolio are more greatly impacted by positive and negative industry-specific events, which may cause investors to have stronger pre-held beliefs on the corporations falling into the *high-performance portfolio*, making prices unrepresentative of industries' financials. In turn, I illustrate through univariate analysis that the level of sentiment is significantly greater in the *high-performance portfolio*, illustrating that mispricing appears to drive the alphas.

The performance of the *high-performance portfolio* is not driven by a particular industry, year, political party, or president. Multiple robustness tests are conducted that drop the highest return-earning industries and presidential terms in the *high-performance portfolios*, to ensure the results are not reliant on a time-frame or industry. I conduct a final analysis where I drop conglomerates from the sample. Large firms are better able to deal with policy uncertainty and possibly take advantage of greater investment opportunities, and excluding them may cause the performance impact to weaken. I find this to be the case, as the abnormal returns of the *high-performance portfolio*, disappear after conglomerates are excluded.

The contributions of this paper apply to academicians, traders, practitioners, and policy makers. First, the impact of this works fits into the vast literature examining the relationship between political activity and corporate performance. I demonstrate that political alignment drives industry returns, and discuss how it fits into the policy uncertainty literature (Baker et al. 2016; Hassan et al. 2019). I also contribute to the corporate political strategies literature (Faccio 2006, Fowler 2006, etc.) and the government interference literature (Goldman et al. 2013; Nicoletti et al. 2003). Second, the trading strategies are easy to implement for investors who are looking to earn sizable profits on the market. The political profile trading strategy requires annual recalibration and does not involve any shorting positions, limiting transaction costs. Furthermore, the alpha earned is immense at over 10%, and does not depend on a particular year, political party, or industry. Investors can profit off this strategy using minimal research, as data on all these political measures are publicly available. Next, financial analysts and economic advisors also gain knowledge from the findings of this paper. Analysts may be better able to price securities in industries in the *high-performance portfolio*, after identifying the factors leading to drifts in prices. Economic advisors to corporations can also show managers the stock price performance in relation to the exposure of political risks at various points in times, leading to the better timing of large projects. Policymakers also can determine, for better or worse, donors that they can impact more directly. Policy uncertainty in industries with low political activity (industries with low government interference and concentrated corporate political strategies) appear to affect conglomerate performance in a positive fashion. Legislators may be more motivated to pass policies for large donors in industries with low political activity if it can solicit them more donations (because those corporations know that they have larger influence).

One of the limitations of this study include the absence of direct analysis on specific policies passed, and their impacts on performance. Although I illustrated the political setting for industries to profit, it is also important to examine the language on lobbying bills and regulations, to determine the kind of policies that affect industries more directly. Another limitation includes that there is no pinpointing of firm assets that could be driving returns for conglomerates, such as real options. Real options are mechanisms that could be driving the performance of the *high-performance portfolio*. Industries with projects that are able to be delayed or aborted may be better attuned to dealing with uncertainty emanating from political geography. Other papers have shown that political geography has implications on real options, (Douidar, Pantzalis, and Park 2022). Additional analysis is necessary to determine whether industries in the h*igh-performance portfolio* are better able to exercise and profit off of real options, leading to greater abnormal returns.

Table 1: Descriptive Statistics

Table 1 displays the descriptive statistics of the variables utilized in empirical examinations. Panel A includes industry monthly returns. Panel B lists the statistics for various political measures. Panel C shows the statistics of industry characteristics.

Variable	Mean	Standard Deviation	Skewness	p5	p50	p95	N
Panel A: Returns							
Monthly Return	1.0060	8.4068	0.2144	-12.4405	1.2826	13.3446	10,927
Momentum (m-12,m-2)	9.5504	28.5949	-0.3193	-38.8931	11.8023	48.2637	10,927
Lag (m-1)	0.9932	8.4226	0.1996	-12.4660	1.2752	13.3618	10,927
Panel B: Political Measures							
Value-weighted PAI	0.4914	0.1902	0.0697	0.1787	0.4943	0.8111	911
Equal-weighted PAI	0.5059	0.1304	0.1186	0.3027	0.5098	0.7288	911
# of candidates supported by PACs	290	366	1.7338	0	163	1,182	911
Herfindahl-PAC	0.3722	0.2707	0.8224	0.0000	0.2951	1.0000	911
Total ($) lobby expenditures	$9,655,634	$17,800,000	3.4812	$0	$2,781,381	$45,100,000	911
Herfindahl-Lobby	0.3907	0.2615	0.6976	0.0000	0.3333	0.9792	911
Herfindahl-Corporate political strategies (CPS)	0.7629	0.4422	0.5673	0.1816	0.6897	1.5954	911
Total ($) contract awarded	$2,740,000,000,000	10,300,000,000,000	5.0637	$23,400,000	$ 19,600,000,000	$ 18,700,000,000,000	911
Regulations	12,992	19,504	1.940546	394	4,590	60,876	784
Panel C: Controls							
Herfindahl-Sales	0.1794	0.1675	2.1501	0.0317	0.1144	0.5502	911
Log(B/M)	0.4996	0.1557	0.6277	0.2851	0.4749	0.7782	911
Size (Log(ME))	13.2655	0.8861	-0.0564	11.7717	13.2584	14.6929	911
Asset (Log(Total Assets))	6.6317	0.9305	0.1038	5.1630	6.6543	8.2234	911
Leverage	0.4162	0.1755	7.2357	0.2101	0.4065	0.6358	911
R&D/Asset	0.0323	0.0529	3.3076	0.0002	0.0118	0.1168	911
Turnover	0.7271	9.7197	28.5841	0.0061	0.0750	1.4605	911

Table 2: Correlation

Table 2 displays the correlation matrix. Panel A describes the relationship between industry returns and industry political measures. Panel B illustrates the relationship between industry returns and industry control characteristics.

Panel A: Political Measures								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Returns	1.0000							
(2) Value-weighted PAI	0.0529***	1.0000						
	(0.0000)							
(3) Equal-weighted PAI	0.0578***	0.8287***	1.0000					
	(0.0000)	(0.0000)						
(4) Herfindahl-PAC	0.0072	-0.1010***	-0.1306***	1.0000				
	(0.4530)	(0.0000)	(0.0000)					
(5) Herfindahl-Lobby	0.0063	0.0570***	0.0130	0.3817***	1.0000			
	(0.5125)	(0.0000)	(0.1735)	(0.0000)				
(6) Herfindahl-CPS	0.0081	-0.0281***	-0.0722***	0.8376***	0.8246***	1.0000		
	(0.3973)	(0.0033)	(0.0000)	(0.0000)	(0.0000)			
(7) Total Contract $ / ME	0.0106	-0.0594***	-0.0383***	-0.0630***	-0.0004	-0.0388***	1.0000	
	(0.2657)	(0.0000)	(0.0001)	(0.0000)	(0.9647)	(0.0000)		
(8) Regulations	-0.0011	0.0239**	-0.0079	-0.1102***	-0.0521***	-0.0971***	-0.1290***	1.0000
	(0.9164)	(0.0273)	(0.4628)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Panel B: Controls								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Returns	1.0000							
(2) Herfindahl- Sales	0.0020	1.0000						
	(0.8315)							
(3) Book-to-Market	0.0730***	0.0222**	1.0000					
	(0.0000)	(0.0205)						
(4) Size	-0.0127	-0.0406***	-0.4144***	1.0000				
	(0.1837)	(0.0000)	(0.0000)					
(5) Assets	0.0173*	-0.0500***	0.0188**	0.8656***	1.0000			
	(0.0708)	(0.0000)	(0.0492)	(0.0000)				
(6) Leverage	-0.0273***	-0.0235**	0.3111***	0.1008***	0.3650***	1.0000		
	(0.0044)	(0.0141)	(0.0000)	(0.0000)	(0.0000)			
(7) R&D	-0.0112	-0.1006***	-0.3501***	-0.1648***	-0.4178***	-0.3602***	1.0000	
	(0.2414)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
(8) Turnover	-0.0083	0.0182*	0.0693***	-0.0482***	-0.0093	0.0297***	-0.0537***	1.0000
	(0.3883)	(0.0570)	(0.0000)	(0.0000)	(0.3297)	(0.0019)	(0.0000)	

Table 3: Distribution of Political Profiles

Table 3 displays the mean value of the annual distribution of industries in each of the eight political profile portfolios.

Industry	Low PAI Wide-Spread CPS Low Interference	Low PAI Wide-Spread CPS High Interference	Low PAI Concentrated CPS Low Interference	Low PAI Concentrated CPS High Interference	High PAI Wide-Spread CPS Low Interference	High PAI Wide-Spread CPS High Interference	High PAI Concentrated CPS Low Interference	High PAI Concentrated CPS High Interference
Aero	0.00%	30.00%	0.00%	30.00%	0.00%	30.00%	0.00%	10.00%
Agriculture	25.00%	0.00%	41.67%	0.00%	25.00%	0.00%	8.33%	0.00%
Autos	0.00%	25.00%	0.00%	55.00%	0.00%	0.00%	0.00%	20.00%
Banks	5.00%	5.00%	30.00%	15.00%	10.00%	15.00%	10.00%	10.00%
Beer	0.00%	0.00%	12.50%	0.00%	6.25%	0.00%	81.25%	0.00%
BldMt	5.00%	10.00%	0.00%	50.00%	0.00%	5.00%	0.00%	30.00%
Books	10.00%	0.00%	20.00%	0.00%	5.00%	0.00%	65.00%	0.00%
Boxes	0.00%	0.00%	5.00%	50.00%	5.00%	10.00%	0.00%	30.00%
BusSv	0.00%	65.00%	0.00%	0.00%	0.00%	35.00%	0.00%	0.00%
Chems	30.00%	5.00%	0.00%	0.00%	65.00%	0.00%	0.00%	0.00%
Chips	0.00%	40.00%	0.00%	20.00%	0.00%	40.00%	0.00%	0.00%
Clths	5.00%	0.00%	25.00%	10.00%	0.00%	0.00%	10.00%	50.00%
Cnstr	0.00%	5.00%	0.00%	35.00%	0.00%	10.00%	0.00%	50.00%
Drugs	55.00%	5.00%	0.00%	0.00%	40.00%	0.00%	0.00%	0.00%
ElcEq	0.00%	55.00%	0.00%	5.00%	5.00%	35.00%	0.00%	0.00%
FabPr	0.00%	20.00%	0.00%	10.00%	10.00%	40.00%	5.00%	15.00%
Fin	40.00%	0.00%	20.00%	0.00%	30.00%	0.00%	10.00%	0.00%
Food	5.00%	30.00%	0.00%	5.00%	25.00%	30.00%	5.00%	0.00%
Fun	18.75%	0.00%	31.25%	0.00%	25.00%	0.00%	25.00%	0.00%
Guns	0.00%	0.00%	47.37%	10.53%	0.00%	0.00%	15.79%	26.32%
Hardw	0.00%	25.00%	10.00%	25.00%	0.00%	10.00%	15.00%	15.00%
Hlth	10.00%	35.00%	0.00%	0.00%	10.00%	45.00%	0.00%	0.00%
Hshld	0.00%	15.00%	5.00%	10.00%	5.00%	20.00%	10.00%	35.00%
Insur	55.00%	20.00%	0.00%	0.00%	25.00%	0.00%	0.00%	0.00%
LabEq	0.00%	10.00%	10.00%	55.00%	0.00%	10.00%	0.00%	15.00%
Mach	10.00%	45.00%	0.00%	0.00%	15.00%	30.00%	0.00%	0.00%
Meals	25.00%	0.00%	20.00%	0.00%	30.00%	0.00%	25.00%	0.00%
MedEq	65.00%	0.00%	5.00%	0.00%	30.00%	0.00%	0.00%	0.00%
Mines	0.00%	0.00%	25.00%	20.00%	0.00%	0.00%	15.00%	40.00%
Oil	35.00%	5.00%	0.00%	0.00%	50.00%	10.00%	0.00%	0.00%
Other	0.00%	0.00%	40.00%	0.00%	0.00%	0.00%	55.00%	5.00%
Paper	5.00%	0.00%	15.00%	25.00%	10.00%	5.00%	10.00%	30.00%
PerSv	30.00%	0.00%	15.00%	5.00%	5.00%	0.00%	45.00%	0.00%
RlEst	5.56%	0.00%	44.44%	16.67%	11.11%	0.00%	11.11%	11.11%
Rtail	60.00%	0.00%	0.00%	0.00%	20.00%	0.00%	15.00%	5.00%

Table 3 (Continued)

Industry	Low PAI Wide-Spread CPS Low Interference	Low PAI Wide-Spread CPS High Interference	Low PAI Concentrated CPS Low Interference	Low PAI Concentrated CPS High Interference	High PAI Wide-Spread CPS Low Interference	High PAI Wide-Spread CPS High Interference	High PAI Concentrated CPS Low Interference	High PAI Concentrated CPS High Interference
Rubbr	10.00%	0.00%	15.00%	30.00%	5.00%	0.00%	5.00%	35.00%
Ships	0.00%	0.00%	12.50%	31.25%	0.00%	0.00%	56.25%	0.00%
Smoke	11.11%	0.00%	11.11%	0.00%	0.00%	0.00%	77.78%	0.00%
Soda	0.00%	0.00%	55.00%	5.00%	10.00%	0.00%	10.00%	20.00%
Softw	5.00%	45.00%	0.00%	10.00%	0.00%	40.00%	0.00%	0.00%
Steel	5.00%	5.00%	35.00%	5.00%	15.00%	5.00%	25.00%	5.00%
Telcm	15.00%	20.00%	0.00%	0.00%	5.00%	60.00%	0.00%	0.00%
Toys	0.00%	0.00%	20.00%	40.00%	0.00%	0.00%	5.00%	35.00%
Trans	11.76%	23.53%	0.00%	0.00%	41.18%	23.53%	0.00%	0.00%
Txtls	5.00%	0.00%	45.00%	0.00%	30.00%	10.00%	5.00%	5.00%
Util	52.63%	0.00%	0.00%	0.00%	15.79%	31.58%	0.00%	0.00%
Whlsl	0.00%	35.00%	0.00%	10.00%	15.00%	30.00%	5.00%	5.00%

Table 4: Univariate

Table 4 displays the univariate results for each of the eight political profile portfolios. Panel A displays the mean values of various return monthly measures. Panel B displays the mean values of the annual political measures. Panel C displays the mean values of industry control measures.

	Low PAI Wide-Spread CPS Low Interference	Low PAI Wide-Spread CPS High Interference	Low PAI Concentrated CPS Low Interference	Low PAI Concentrated CPS High Interference	High PAI Wide-Spread CPS Low Interference	High PAI Wide-Spread CPS High Interference	High PAI Concentrated CPS Low Interference	High PAI Concentrated CPS High Interference
Panel A: Returns								
Value-weighted Return	0.9644***	0.8706***	0.5012**	1.0121***	0.9166***	1.0977***	1.6756***	1.0101***
	(4.53)	(4.41)	(1.98)	(4.95)	(3.76)	(5.20)	(6.35)	(4.61)
Equal-weighted Return	0.9883***	1.0443***	0.6689***	1.3131***	1.0904***	1.2268***	1.6253***	1.2807***
	(4.34)	(5.09)	(2.71)	(6.23)	(4.81)	(5.72)	(6.26)	(5.57)
Momentum (m-2,m-12)	8.4820***	7.3896***	5.1826***	10.9091***	10.6421***	9.1650***	15.4242***	9.1809***
	(11.30)	(11.02)	(6.52)	(16.95)	(13.47)	(13.24)	(15.77)	(11.69)
Lag (m-1)	0.8623***	0.8305***	0.5410**	1.0227***	1.0479***	1.0447***	1.5768***	1.0273***
	(4.04)	(4.21)	(2.14)	(4.96)	(4.26)	(4.91)	(6.00)	(4.71)
N	1,423	1,380	1,392	1,380	1,380	1,380	1,392	1,200
Panel B: Political Measures								
Value-weighted PAI	0.3852***	0.3532***	0.3304***	0.3367***	0.6257***	0.6130***	0.6618***	0.6497***
	(35.58)	(30.34)	(28.49)	(29.40)	(58.07)	(54.82)	(51.20)	(50.50)
Herfindahl-CPS	0.4056***	0.4386***	1.1529***	1.0518***	0.4432***	0.4048***	1.1408***	1.1176***
	(22.98)	(22.96)	(36.42)	(31.66)	(23.90)	(21.17)	(37.67)	(36.63)
Herfindahl-PAC	0.1919***	0.2139***	0.5727***	0.5419***	0.1919***	0.2038***	0.5222***	0.5676***
	(14.54)	(17.66)	(21.47)	(22.23)	(14.62)	(18.47)	(23.02)	(22.75)
Herfindahl-Lobby	0.2137***	0.2247***	0.5803***	0.5099***	0.2512***	0.2010***	0.6185***	0.5500***
	(18.14)	(19.08)	(25.58)	(25.09)	(19.28)	(16.70)	(25.76)	(21.12)
Total Contract $ / ME	255,760.9063***	5.5443e+07***	105,177.3672***	6.4943e+07***	275,864.6250***	4.0666e+07***	59,811.1328***	1.5471e+07***
	(3.99)	(4.93)	(6.80)	(4.77)	(6.10)	(4.97)	(6.25)	(2.75)
Regulations	8,142.2217***	19,405.3086***	6,959.2783***	11,398.9707***	11,919.9004***	21,312.0645***	7,641.1982***	17,044.1211***
	(6.09)	(8.13)	(6.26)	(6.88)	(6.02)	(8.11)	(6.74)	(7.57)
N	119	115	116	115	115	115	116	100

Table 4 (Continued)

Panel C: Controls								
	Low PAI Wide-Spread CPS Low Interference	Low PAI Wide-Spread CPS High Interference	Low PAI Concentrated CPS Low Interference	Low PAI Concentrated CPS High Interference	High PAI Wide-Spread CPS Low Interference	High PAI Wide-Spread CPS High Interference	High PAI Concentrated CPS Low Interference	High PAI Concentrated CPS High Interference
Herfindahl-Sales	0.1090***	0.1226***	0.2850***	0.1730***	0.1438***	0.1263***	0.3021***	0.1731***
	(7.98)	(13.60)	(16.58)	(15.17)	(8.77)	(13.35)	(14.67)	(14.71)
Log(B/M)	0.4848***	0.4823***	0.5078***	0.4836***	0.5229***	0.5239***	0.4949***	0.4966***
	(33.28)	(39.05)	(28.58)	(40.71)	(36.19)	(36.69)	(31.30)	(34.66)
Log(ME)	13.4422***	13.0169***	13.2134***	13.2359***	13.2834***	13.1178***	13.5298***	13.2781***
	(177.91)	(160.33)	(142.32)	(182.50)	(179.01)	(143.05)	(152.14)	(179.52)
Log(Asset)	6.7751***	6.3124***	6.6061***	6.5924***	6.7006***	6.5278***	6.8875***	6.6467***
	(63.18)	(67.14)	(84.29)	(83.15)	(77.26)	(70.11)	(98.33)	(99.04)
Leverage	0.4214***	0.4145***	0.4195***	0.4093***	0.4240***	0.4181***	0.4169***	0.4042***
	(29.02)	(14.35)	(36.19)	(18.79)	(35.11)	(34.79)	(44.83)	(37.84)
R&D/Asset	0.0483***	0.0480***	0.0180***	0.0365***	0.0354***	0.0338***	0.0140***	0.0230***
	(5.96)	(10.79)	(7.61)	(10.12)	(5.35)	(9.94)	(5.68)	(5.44)
Turnover	0.3710***	0.1304***	0.6732***	0.0891***	2.8803	0.6728**	0.7179***	0.2304***
	(3.17)	(5.81)	(2.90)	(9.89)	(1.15)	(2.16)	(4.34)	(3.91)
N	119	115	116	115	115	115	116	100

Table 5: Performance of Political Profiles- OLS

Table 5 displays the results of ordinary least squares time-series regressions, after sorting industries into the eight political profiles. The dependent variable is the monthly value-weighted excess industry return. The coefficients and t-statistic (parenthesis) of each variable are displayed. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

	Dependent Variable: Returns							
	Panel A: No Regulations							
	Low PAI Wide-Spread CPS Low Interference	Low PAI Wide-Spread CPS High Interference	Low PAI Concentrated CPS Low Interference	Low PAI Concentrated CPS High Interference	High PAI Wide-Spread CPS Low Interference	High PAI Wide-Spread CPS High Interference	High PAI Concentrated CPS Low Interference	High PAI Concentrated CPS High Interference
Alpha	0.3342*	0.2503*	-0.3066	0.1607	0.1787	0.3458**	0.7785***	0.1223
	(1.86)	(1.77)	(-1.43)	(1.16)	(0.82)	(1.99)	(3.27)	(0.72)
Mktrf	0.9797***	1.0275***	1.1221***	1.2166***	1.0179***	0.9550***	1.0653***	1.0584***
	(21.67)	(28.57)	(21.09)	(34.54)	(18.41)	(21.64)	(17.56)	(24.77)
Smb	0.1841**	0.3097***	0.4140***	0.3231***	0.3210***	0.5547***	0.4951***	0.4713***
	(2.56)	(5.47)	(4.85)	(5.83)	(3.69)	(7.99)	(5.16)	(6.94)
Hml	0.1710**	-0.2470***	0.1244	-0.0884	0.0427	-0.0175	0.0943	0.1338*
	(2.27)	(-4.15)	(1.39)	(-1.51)	(0.47)	(-0.24)	(0.94)	(1.88)
Rmw	-0.1566*	-0.3796***	-0.0225	-0.0616	0.0622	0.0493	0.2543**	0.2454***
	(-1.72)	(-5.29)	(-0.21)	(-0.88)	(0.56)	(0.56)	(2.06)	(2.85)
Cma	0.0633	0.0037	-0.0234	0.0853	-0.0069	-0.0163	0.1734	0.1028
	(0.56)	(0.04)	(-0.17)	(0.99)	(-0.05)	(-0.15)	(1.14)	(0.97)
Observations	1,423	1,380	1,392	1,380	1,380	1,380	1,392	1,200
R-squared	0.366	0.544	0.364	0.591	0.291	0.397	0.275	0.466

Table 5 (Continued)

	Dependent Variable: Returns							
	Panel B: Regulations Included							
	Low PAI Wide-Spread CPS Low Interference	Low PAI Wide-Spread CPS High Interference	Low PAI Concentrated CPS Low Interference	Low PAI Concentrated CPS High Interference	High PAI Wide-Spread CPS Low Interference	High PAI Wide-Spread CPS High Interference	High PAI Concentrated CPS Low Interference	High PAI Concentrated CPS High Interference
Alpha	0.1650	0.2926*	-0.1334	0.0626	0.2776	0.3881**	0.8619**	-0.0087
	(0.98)	(1.90)	(-0.56)	(0.35)	(1.13)	(1.99)	(2.55)	(-0.04)
Mktrf	1.0365***	0.9854***	1.1449***	1.2331***	1.0914***	0.8722***	1.0383***	1.1324***
	(23.86)	(25.00)	(19.43)	(27.24)	(17.77)	(17.41)	(12.18)	(19.81)
Smb	0.2534***	0.2761***	0.3939***	0.2682***	0.2512***	0.6089***	0.5691***	0.5590***
	(3.75)	(4.44)	(4.23)	(3.76)	(2.59)	(7.76)	(4.07)	(6.15)
Hml	0.0884	-0.1933***	-0.0993	-0.0323	0.1051	-0.1129	-0.0440	0.1494
	(1.23)	(-2.97)	(-1.01)	(-0.43)	(1.03)	(-1.35)	(-0.31)	(1.58)
Rmw	-0.2895***	-0.3581***	-0.2044*	-0.0323	0.0759	0.0618	0.1196	0.3413***
	(-3.37)	(-4.57)	(-1.73)	(-0.36)	(0.61)	(0.61)	(0.67)	(2.97)
Cma	-0.0227	0.0296	0.1046	0.0441	0.0822	-0.2010	0.4827**	0.1102
	(-0.21)	(0.31)	(0.72)	(0.40)	(0.54)	(-1.63)	(2.17)	(0.78)
Observations	1,447	1,344	1,080	1,152	1,176	1,140	1,028	1,020
R-squared	0.426	0.476	0.393	0.513	0.303	0.358	0.207	0.399

Table 6: Political Profiles & Expected Returns- Fama-MacBeth

Table 6 displays the results after running Fama-MacBeth cross-sectional regressions, after sorting industries into the eight political profile portfolios. The dependent variable is the monthly value-weighted excess industry return. The coefficients and t-statistic (parenthesis) of each variable are displayed. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

	Dependent Variable = Returns	
	Panel A: No Regulations	
	All Industries	All Industries
Low-Wide Spread-High	-0.3576	-0.3581
	(-1.64)	(-1.51)
Low-Concentrated-Low	-0.5347*	-0.4568
	(-1.87)	(-1.57)
Low-Concentrated-High	-0.1228	-0.1802
	(-0.52)	(-0.75)
High-Wide Spread-Low	0.0113	-0.0800
	(0.04)	(-0.30)
High-Wide Spread-High	0.0424	-0.0210
	(0.17)	(-0.09)
High-Concentrated-Low	0.8204***	0.7563***
	(2.96)	(2.74)
High-Concentrated-High	-0.2388	-0.2702
	(-0.91)	(-1.04)
B_{mktrf}	0.2503	0.0713
	(0.73)	(0.20)
B_{smb}	0.1055	0.1011
	(0.47)	(0.44)
B_{hml}	-0.2201	-0.1934
	(-0.92)	(-0.79)
B_{rmw}	0.2166	0.2266
	(1.18)	(1.26)
B_{cma}	-0.1916	-0.1044
	(-0.96)	(-0.51)
Momentum		0.0058
		(0.93)
Lag		0.0062
		(0.29)
Constant	0.7024*	0.6737*
	(1.90)	(1.82)
Observations	10,927	10,927
R-squared	0.320	0.430
# of Months	240	240

Table 6 (Continued)

	Dependent Variable = Returns	
	Panel B: Regulations Included	
	All Industries	All Industries
Low-Wide Spread-High	0.2526	0.1026
	(1.14)	(0.43)
Low-Concentrated-Low	-0.0595	0.0378
	(-0.20)	(0.13)
Low-Concentrated-High	0.2200	0.2215
	(0.92)	(0.87)
High-Wide Spread-Low	0.5399*	0.2866
	(1.83)	(1.09)
High-Wide Spread-High	0.5862**	0.3958
	(2.10)	(1.52)
High-Concentrated-Low	0.8615***	0.6260***
	(2.63)	(2.10)
High-Concentrated-High	0.2957	0.0921
	(1.09)	(0.34)
B_{mktrf}	0.0137	-0.4429
	(0.03)	(-1.08)
B_{smb}	0.1491	0.1956
	(0.56)	(0.75)
B_{hml}	0.0326	0.0023
	(0.12)	(0.01)
B_{rmw}	0.3364	0.3062
	(1.56)	(1.44)
B_{cma}	-0.0729	-0.0691
	(-0.32)	(-0.33)
Momentum		0.0078
		(1.22)
Lag		0.0010
		(0.04)
Constant	0.5123	0.7679*
	(1.21)	(1.85)
Observations	9,387	9,387
R-squared	0.374	0.493
# of Months	240	240

Table 7: Political Profiles & Short, Medium, and Long-Term Returns - OLS

Table 7 displays the results after running ordinary least square regressions of industry monthly value-weighted excess returns on High-Concentrated-Low political profile dummy's interaction with various mispricing proxies: short-term reversals, momentum, and long-term reversals. The coefficients and t-statistic (parenthesis) of each variable are displayed. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Dependent Variable = Industry Returns		
Portfolio Dummy	1.1961***	1.2125***
	(4.82)	(4.86)
Industry Short-term Returns (-1,0)	-0.0149*	-0.0158*
	(-1.67)	(-1.77)
Industry Medium-term Returns (-12,-2)	0.0007	0.0022
	(0.25)	(0.80)
Industry Long-term Returns (-36,-13)	-0.0002	0.0013
	(-0.08)	(0.72)
Industry Short-term Returns * Portfolio Dummy	0.0800***	0.0795***
	(3.59)	(3.57)
Industry Medium-term Returns * Portfolio Dummy	-0.0187***	-0.0186***
	(-2.79)	(-2.78)
Industry Long-term Returns * Portfolio Dummy	-0.0102**	-0.0099**
	(-2.35)	(-2.29)
mktrf	1.0536***	1.0527***
	(62.39)	(62.13)
smb	0.3798***	0.3715***
	(14.13)	(13.76)
hml	0.0318	0.0324
	(1.13)	(1.15)
rmw	-0.0098	-0.0124
	(-0.29)	(-0.36)
cma	0.0409	0.0269
	(0.98)	(0.64)
Log(B/M)		-0.1175
		(-1.46)
Log(ME)		1.1853***
		(2.60)
Constant	0.1485*	1.0727
	(1.73)	(0.92)
Observations	10,927	10,927
R-squared	0.386	0.386

Table 8: Risk by Year

Table 8 displays various measures of risk by year for the High PAI – Concentrated CPS – Low Interference portfolio and the remainder of the sample. Panel A displays total risk, calculated as the annual variance of daily returns. Panel B displays the systematic risk, set to the difference between total risk and unsystematic risk. Panel C displays unsystematic risk, computed as the annual variance of the daily residuals obtained from time-series regressions of daily returns on the 5 Fama-French factors.

	Panel A: Total Risk			*Panel B: Systematic Risk*			*Panel C: Unsystematic Risk*		
Year	All Other Political Profiles	High PAI - Concentrated CPS - Low Interference	Difference	All Other Political Profiles	High PAI - Concentrated CPS - Low Interference	Difference	All Other Political Profiles	High PAI - Concentrated CPS - Low Interference	Difference
2001	0.0806	0.0586	-0.0220	0.0171	0.0070	-0.0101	0.0636	0.0516	-0.0120
2002	0.0677	0.0770	0.0093	0.0194	-0.0018	-0.0212	0.0483	0.0788	0.0304
2003	0.0334	0.0378	0.0043	0.0086	0.0017	-0.0070	0.0248	0.0361	0.0113
2004	0.0211	0.0506	0.0296	0.0058	0.0024	-0.0034	0.0153	0.0483	0.0330
2005	0.0162	0.0244	0.0082	0.0050	0.0024	-0.0026	0.0112	0.0220	0.0108
2006	0.0168	0.0537	0.0369	0.0060	0.0030	-0.0030	0.0108	0.0507	0.0399
2007	0.0240	0.0349	0.0110	0.0100	0.0061	-0.0039	0.0139	0.0288	0.0149
2008	0.0914	0.0952	0.0038	0.0565	0.0295	-0.0270	0.0349	0.0657	0.0308
2009	0.0555	0.0966	0.0411	0.0299	0.0253	-0.0046	0.0256	0.0713	0.0456
2010	0.0272	0.0352	0.0080	0.0155	0.0165	0.0010	0.0117	0.0187	0.0070
2011	0.0443	0.0428	-0.0014	0.0273	0.0235	-0.0038	0.0170	0.0193	0.0023
2012	0.0182	0.0163	-0.0019	0.0081	0.0063	-0.0017	0.0101	0.0099	-0.0002
2013	0.0134	0.0239	0.0105	0.0059	0.0051	-0.0008	0.0075	0.0188	0.0113
2014	0.0186	0.0306	0.0120	0.0066	0.0092	0.0026	0.0120	0.0214	0.0094
2015	0.0267	0.0314	0.0048	0.0098	0.0077	-0.0020	0.0169	0.0237	0.0068
2016	0.0235	0.0331	0.0096	0.0093	0.0048	-0.0045	0.0141	0.0283	0.0142
2017	0.0134	0.0459	0.0325	0.0027	0.0064	0.0036	0.0107	0.0396	0.0289
2018	0.0259	0.0252	-0.0006	0.0106	0.0080	-0.0026	0.0153	0.0172	0.0019
2019	0.0223	0.0195	-0.0029	0.0075	0.0070	-0.0005	0.0148	0.0124	-0.0024
2020	0.0735	0.0905	0.0170	0.0485	0.0483	-0.0002	0.0250	0.0423	0.0173

Table 9: Sentiment

Table 9 displays the mean of quarterly sentiment for the High PAI – Concentrated CPS – Low Interference portfolio and the remainder of the sample.

	All Other Political Profiles	High-Concentrated-Low	Difference
Sentiment	1.5841***	1.6187***	0.0346***
	(147.95)	(39.91)	(-108.40)
Observations	2,854	369	

Table 10: Stock Price Reaction to Earnings Announcements

Panel A of Table 10 displays a univariate analysis comparing the average cumulative abnormal return (0,1) of firms in the High-Concentrated-Low sample and the remainder of firms. Panel B of Table 10 displays OLS regression results, utilizing cumulative abnormal returns as the dependent variable. The independent variables of interest include the interactions of Portfolio dummy * Good news quintile dummy and Portfolio dummy * Bad news quintile dummy. The coefficients and t-statistic (parenthesis) of each variable are displayed. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

Panel A: Univariate Analysis			
	All Other Political Profiles	High-Concentrated-Low	Difference
Cumulative Abnormal Return (0,1)	0.2225***	0.1514	-0.0711***
	(9.42)	(1.62)	(-7.80)
Analysts	7.9365***	7.9890***	0.0525***
	(311.96)	(75.73)	(-236.23)
Reporting Lag	31.9656***	31.6552***	-0.3104***
	(702.64)	(179.96)	(-522.68)
Earnings Volatility	0.4269***	0.4755***	0.0486***
	(88.78)	(29.27)	(-59.81)
Observations	65,539	4,194	

Table 10 (Continued)

Panel B: OLS Regression Analysis		
Dependent Variable = CAR (0,1)		
Portfolio Dummy	-0.0493	-0.0483
	(-0.43)	(-0.41)
Good news (Q5) Dummy	0.0314	0.0432
	(0.42)	(0.58)
Bad news (Q1) Dummy	-0.0557	-0.0458
	(-0.90)	(-0.74)
Portfolio dummy * Good news dummy	0.0363	0.0093
	(0.12)	(0.03)
Portfolio dummy * Bad news dummy	0.3490*	0.3580*
	(1.80)	(1.85)
Log(B/M)		0.0132
		(1.00)
Log(ME)		0.1625*
		(1.92)
Analysts		0.0074*
		(1.95)
Reporting Lag		-0.0089***
		(-4.09)
Earnings Volatility		-0.0588***
		(-3.08)
Constant	0.2230***	0.2268
	(7.38)	(1.09)
Observations	69,733	69,733
R-squared	0.004	0.004
Fixed Effects	Year & Industry	Year & Industry

Table 11: Political Profile & Other Political Variables- OLS

Table 11 displays the results after running ordinary least square regressions of industry monthly returns on popular political measures and the High-Concentrated-Low political profile dummy. The coefficients and t-statistic (parenthesis) of each variable are displayed. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

	Dependent Variable: Value-weighted Returns		
Conditional Political Sensitivity	0.2284***		
	(2.85)		
PRisk		-0.1011	
		(-0.88)	
High-Concentrated-Low Dummy			0.8510***
			(3.03)
Herfindahl-Sales	0.1307	0.2613	-0.3578
	(0.36)	(0.82)	(-0.94)
Log(B/M)	1.3584	1.8183**	1.5279*
	(1.59)	(2.49)	(1.87)
Log(ME)	0.0696	0.0853	0.0211
	(0.53)	(0.62)	(0.16)
Leverage	-0.5557	-0.6680	-0.4692
	(-1.16)	(-1.34)	(-1.09)
Momentum	-0.0019	-0.0018	-0.0018
	(-0.28)	(-0.31)	(-0.27)
Lag	-0.0129	-0.0042	-0.0132
	(-0.53)	(-0.18)	(-0.56)
R&D/Asset	-0.3374	1.1775	0.3046
	(-0.30)	(0.90)	(0.28)
Turnover	-0.0174	0.0991	-0.0184
	(-1.64)	(0.22)	(-1.61)
Constant	-0.3397	-0.7262	0.1433
	(-0.18)	(-0.38)	(0.08)
Observations	10,927	9,667	10,927
R-squared	0.400	0.468	0.400
Fixed Effects	Year-month	Year-month	Year-month
Cluster	Industry & Year-month	Industry & Year-month	Industry & Year-month

Table 12: Returns by Industry

Table 12 displays the average monthly returns of the industries in the High PAI – Concentrated CPS – Low Interference portfolio and the remainder of the sample. Panel A displays the value-weighted returns. Panel B displays the equal-weighted returns.

Panel A: Value-weighted Returns

Industry	All Other Political Profiles	High PAI - Concentrated CPS - Low Interference
Agriculture	-1.4240	0.1204
Banks	0.8694	1.1283
Beer	-7.1417	3.9562
Books	-1.6759	1.8522
Clths	1.0316	1.8358
FabPr	1.0816	2.8959
Fin	0.8380	1.6986
Food	0.9266	-1.2917
Fun	0.5716	1.3574
Guns	1.4537	2.0608
Hardw	1.2599	0.8169
Hshld	0.5016	1.9377
Meals	0.9127	1.8948
Mines	0.9130	1.0404
Other	0.7433	1.6279
Paper	0.9307	-1.1962
PerSv	1.7745	1.6551
RlEst	2.2149	-1.9165
Rtail	0.9826	1.1181
Rubbr	1.0664	0.4129
Ships	1.3292	0.9367
Smoke	0.5567	1.4790
Soda	0.7627	1.9548
Steel	0.6068	2.8188
Toys	0.3228	3.3598
Txtls	1.1140	-6.3038
Whlsl	1.0049	2.7360

Table 12 (Continued)

	Panel B: Equal-weighted Returns	
Industry	All Other Political Profiles	High PAI - Concentrated CPS - Low Interference
Agriculture	-0.3441	1.0513
Banks	1.4544	0.8858
Beer	-5.8581	3.4958
Books	-1.1650	1.9755
Clths	1.7697	1.8310
FabPr	1.4506	2.2098
Fin	0.7128	2.1496
Food	1.2309	-1.6023
Fun	0.2151	0.1650
Guns	1.9563	2.9176
Hardw	1.2739	0.7592
Hshld	0.7708	2.0994
Meals	0.8951	2.1747
Mines	0.7535	0.8018
Other	0.9356	1.5706
Paper	1.1464	-1.1382
PerSv	1.6385	1.4995
RlEst	1.0006	-2.6354
Rtail	1.4797	0.3759
Rubbr	1.3896	1.3858
Ships	1.5780	1.6811
Smoke	-0.2879	1.3509
Soda	1.1163	1.7114
Steel	0.9192	2.2598
Toys	0.7454	4.3191
Txtls	0.7766	-5.7295
Whlsl	1.1031	3.7566

Table 13: Returns by Year

Table 13 displays the average monthly returns by year for the High PAI – Concentrated CPS – Low Interference portfolio and the remainder of the sample. Panel A displays the value-weighted returns. Panel B displays the equal-weighted returns.

	Panel A: Value-weighted Returns	
Year	All Other Political Profiles	High PAI - Concentrated CPS - Low Interference
2001	0.7602	1.8011
2002	-1.7132	0.3934
2003	2.9633	3.2954
2004	1.5546	3.0059
2005	0.5404	0.9411
2006	1.5204	3.3829
2007	0.3734	-0.7788
2008	-3.6692	-3.7430
2009	3.3482	6.2559
2010	1.6788	2.6087
2011	-0.0097	0.2150
2012	1.2238	1.5859
2013	2.7012	4.3323
2014	0.3358	0.8127
2015	-0.4865	1.2109
2016	1.4830	2.3584
2017	1.9307	0.9154
2018	-0.7512	-0.6297
2019	2.5899	2.4801
2020	2.0588	3.2626
	Panel B: Equal-weighted Returns	
Year	All Other Political Profiles	High PAI - Concentrated CPS - Low Interference
2001	1.7488	2.2718
2002	-1.0077	0.9627
2003	4.4868	4.2763
2004	1.9816	3.7409
2005	0.3377	0.4138
2006	1.6712	3.1280
2007	-0.1072	-1.3785
2008	-4.3257	-3.5554
2009	4.5554	6.0202
2010	2.1721	2.6379
2011	-0.5358	-0.2550
2012	1.2101	1.6698
2013	2.9733	4.6875
2014	0.2351	0.8574
2015	-0.8925	0.8658
2016	1.6433	1.4186
2017	1.6175	1.8068
2018	-0.7210	-1.1787
2019	2.2138	2.9392
2020	2.5750	1.5215

Table 14: Returns by Presidential Term

Table 14 displays the average monthly returns by presidential term for the High PAI – Concentrated CPS – Low Interference portfolio and the remainder of the sample. Panel A displays the value-weighted returns. Panel B displays the equal-weighted returns.

	Panel A: Value-weighted Returns	
Presidential Term	All Other Political Profiles	High PAI - Concentrated CPS - Low Interference
Bush (Term 1)	0.8744	2.1494
Bush (Term 2)	-0.3307	-0.0494
Obama (Term 1)	1.5623	2.6664
Obama (Term 2)	1.0189	2.1786
Trump	1.4538	1.4542

	Panel B: Equal-weighted Returns	
Presidential Term	All Other Political Profiles	High PAI - Concentrated CPS - Low Interference
Bush (Term 1)	1.7847	2.8305
Bush (Term 2)	-0.6319	-0.3480
Obama (Term 1)	1.8544	2.5182
Obama (Term 2)	1.0021	1.9573
Trump	1.4191	1.2366

Table 15: Robustness (Industry) Performance of Political Profiles- OLS

Table 15 displays the results of ordinary least squares time-series regressions, after sorting industries into the eight political profiles. Various industries are dropped in each panel. The coefficients and t-statistic (parenthesis) of each variable are displayed. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

	Dependent Variable: Value-weighted Returns							
	Low PAI Wide-Spread CPS Low Interference	Low PAI Wide-Spread CPS High Interference	Low PAI Concentrated CPS Low Interference	Low PAI Concentrated CPS High Interference	High PAI Wide-Spread CPS Low Interference	High PAI Wide-Spread CPS High Interference	High PAI Concentrated CPS Low Interference	High PAI Concentrated CPS High Interference
	Panel A: Drop Beer Industry							
Alpha	0.3342*	0.2503*	-0.1825	0.1607	0.2317	0.3458**	0.5705***	0.1223
	(1.86)	(1.77)	(-0.87)	(1.16)	(1.07)	(1.99)	(2.63)	(0.72)
	Panel B: Drop Books Industry							
Alpha	0.3299*	0.2503*	-0.2317	0.1607	0.1957	0.3458**	0.7822***	0.1223
	(1.86)	(1.77)	(-1.06)	(1.16)	(0.89)	(1.99)	(3.01)	(0.72)
	Panel C: Drop FabPr Industry							
Alpha	0.3342*	0.2970**	-0.3066	0.1543	0.1941	0.3253*	0.7808***	0.1116
	(1.86)	(2.09)	(-1.43)	(1.11)	(0.88)	(1.85)	(3.26)	(0.65)
	Panel D: Drop Other Industry							
Alpha	0.3342*	0.2503*	-0.2230	0.1607	0.1787	0.3458**	0.7561***	0.1150
	(1.86)	(1.77)	(-1.03)	(1.16)	(0.82)	(1.99)	(3.24)	(0.70)
	Panel E: Drop Ships Industry							
Alpha	0.3342*	0.2503*	-0.3043	0.1477	0.1787	0.3458**	0.8208***	0.1223
	(1.86)	(1.77)	(-1.40)	(1.03)	(0.82)	(1.99)	(3.25)	(0.72)

Table 15 (Continued)

	Dependent Variable: Value-weighted Returns							
	Low PAI Wide-Spread CPS Low Interference	Low PAI Wide-Spread CPS High Interference	Low PAI Concentrated CPS Low Interference	Low PAI Concentrated CPS High Interference	High PAI Wide-Spread CPS Low Interference	High PAI Wide-Spread CPS High Interference	High PAI Concentrated CPS Low Interference	High PAI Concentrated CPS High Interference
	Panel F: Drop Smoke Industry							
Alpha	0.3574**	0.2503*	-0.2996	0.1607	0.1787	0.3458**	0.7246***	0.1223
	(1.97)	(1.77)	(-1.38)	(1.16)	(0.82)	(1.99)	(2.79)	(0.72)
	Panel G: Drop Steel Industry							
Alpha	0.3141*	0.2752*	-0.2851	0.1787	0.1338	0.3523**	0.7860***	0.1303
	(1.74)	(1.94)	(-1.27)	(1.28)	(0.60)	(2.02)	(3.20)	(0.77)
	Panel H: Drop Toys Industry							
Alpha	0.3342*	0.2503*	-0.3148	0.2042	0.1787	0.3458**	0.7819***	0.1505
	(1.86)	(1.77)	(-1.43)	(1.45)	(0.82)	(1.99)	(3.26)	(0.84)
	Panel I: Drop Whlsl Industry							
Alpha	0.3342*	0.2455	-0.3066	0.1822	0.1814	0.3529*	0.7666***	0.1269
	(1.86)	(1.64)	(-1.43)	(1.29)	(0.81)	(1.93)	(3.20)	(0.74)

Table 16: Robustness (President Term) Performance of Political Profiles- OLS

Table 16 displays the results of ordinary least squares time-series regressions, after sorting industries into the eight political profiles. Various presidential terms are dropped in each panel. The coefficients and t-statistic (parenthesis) of each variable are displayed. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

	Dependent Variable: Value-weighted Returns							
	Low PAI Wide-Spread CPS Low Interference	Low PAI Wide-Spread CPS High Interference	Low PAI Concentrated CPS Low Interference	Low PAI Concentrated CPS High Interference	High PAI Wide-Spread CPS Low Interference	High PAI Wide-Spread CPS High Interference	High PAI Concentrated CPS Low Interference	High PAI Concentrated CPS High Interference
	Panel A: Drop Bush (Term 1)							
Alpha	0.1589	0.2247	-0.4377**	0.0936	0.3559	0.2265	0.7047***	0.0361
	(0.91)	(1.53)	(-2.13)	(0.69)	(1.56)	(1.46)	(2.85)	(0.22)
	Panel B: Drop Bush (Term 2)							
Alpha	0.2712	0.1335	-0.1136	0.0458	-0.0638	0.3827**	0.8757***	0.1062
	(1.26)	(0.78)	(-0.46)	(0.28)	(-0.25)	(1.98)	(3.30)	(0.56)
	Panel C: Drop Obama (Term 1)							
Alpha	0.3608*	0.2340	-0.3089	0.2425	0.1809	0.3663*	0.7434***	0.1568
	(1.88)	(1.44)	(-1.27)	(1.56)	(0.72)	(1.75)	(2.73)	(0.82)
	Panel D: Drop Obama (Term 2)							
Alpha	0.5703***	0.4519***	-0.2469	0.2611	0.3100	0.3492	0.7235***	0.2120
	(2.65)	(2.98)	(-1.01)	(1.57)	(1.18)	(1.61)	(2.58)	(1.04)
	Panel E: Drop Trump Term							
Alpha	0.2839	0.2344	-0.5061**	0.1576	0.1313	0.4254**	0.8521***	0.0988
	(1.36)	(1.47)	(-1.97)	(1.03)	(0.58)	(2.20)	(3.17)	(0.51)
	Panel F: Drop Financial Crisis (2007-2008)							
Alpha	0.2733	0.1493	-0.0704	0.0922	0.0539	0.3708**	0.9870***	0.1169
	(1.41)	(0.97)	(-0.31)	(0.61)	(0.24)	(2.04)	(3.95)	(0.68)

Table 17: Robustness (Conglomerate) Performance of Political Profiles- OLS

Table 17 displays the results of ordinary least squares time-series regressions, after sorting industries into the eight political profiles. Panel A excludes conglomerates from the sample. Panel B excludes super conglomerates from the sample. The coefficients and t-statistic (parenthesis) of each variable are displayed. *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance.

	Dependent Variable: Value-weighted Returns							
	Low PAI Wide-Spread CPS Low Interference	Low PAI Wide-Spread CPS High Interference	Low PAI Concentrated CPS Low Interference	Low PAI Concentrated CPS High Interference	High PAI Wide-Spread CPS Low Interference	High PAI Wide-Spread CPS High Interference	High PAI Concentrated CPS Low Interference	High PAI Concentrated CPS High Interference
	Panel A: Drop Conglomerates							
Alpha	0.4430*	0.6283***	0.1515	-0.0294	-0.1281	0.5501**	0.2831	-0.2850
	(1.87)	(2.81)	(0.41)	(-0.12)	(-0.43)	(2.14)	(0.78)	(-0.85)
Mktrf	0.9288***	1.0217***	1.0064***	1.2116***	0.9998***	1.0645***	1.0543***	1.1354***
	(15.24)	(17.84)	(10.81)	(19.32)	(13.11)	(16.26)	(11.45)	(13.87)
Smb	0.4267***	0.4285***	0.8906***	0.5588***	0.6565***	0.8643***	0.9659***	0.5441***
	(4.42)	(4.73)	(5.88)	(5.60)	(5.59)	(8.42)	(6.51)	(3.97)
Hml	0.0346	-0.4903***	-0.0314	-0.0714	-0.0611	-0.0048	-0.3037*	-0.0671
	(0.34)	(-5.24)	(-0.20)	(-0.69)	(-0.49)	(-0.04)	(-1.94)	(-0.49)
Rmw	-0.1708	-0.8724***	-0.1699	-0.1715	-0.0154	-0.1413	0.2499	0.2971*
	(-1.39)	(-7.60)	(-0.88)	(-1.37)	(-0.10)	(-1.07)	(1.28)	(1.72)
Cma	0.2273	-0.1957	0.3595	0.0186	-0.1281	-0.1770	-0.0961	0.5440**
	(1.50)	(-1.40)	(1.50)	(0.12)	(-0.70)	(-1.09)	(-0.40)	(2.52)
Observations	1,335	1,218	1,092	1,154	1,262	1,260	1,032	984
R-squared	0.256	0.431	0.207	0.394	0.225	0.340	0.218	0.243

Table 17 (Continued)

	Dependent Variable: Value-weighted Returns							
	Low PAI Wide-Spread CPS Low Interference	Low PAI Wide-Spread CPS High Interference	Low PAI Concentrated CPS Low Interference	Low PAI Concentrated CPS High Interference	High PAI Wide-Spread CPS Low Interference	High PAI Wide-Spread CPS High Interference	High PAI Concentrated CPS Low Interference	High PAI Concentrated CPS High Interference
	Panel B: Drop Super Conglomerates							
Alpha	0.4692**	0.4708**	0.0976	0.0922	-0.1344	0.3803*	0.3920	-0.0533
	(2.21)	(2.34)	(0.38)	(0.45)	(-0.51)	(1.73)	(1.30)	(-0.21)
Mktrf	0.9631***	1.0487***	0.9830***	1.2056***	1.1590***	0.9950***	1.0256***	1.1076***
	(18.00)	(20.35)	(15.30)	(22.97)	(17.06)	(17.94)	(13.26)	(17.44)
Smb	0.3771***	0.5001***	0.5758***	0.5998***	0.4540***	0.8090***	0.9294***	0.7032***
	(4.38)	(6.22)	(5.59)	(7.27)	(4.35)	(9.28)	(7.59)	(6.76)
Hml	0.1221	-0.4462***	0.1307	-0.1040	-0.0218	-0.0272	-0.0918	0.0942
	(1.37)	(-5.26)	(1.20)	(-1.20)	(-0.20)	(-0.30)	(-0.71)	(0.89)
Rmw	-0.1780*	-0.5489***	-0.0714	0.0102	0.1330	-0.1240	0.3009*	0.3633***
	(-1.65)	(-5.39)	(-0.55)	(0.10)	(1.00)	(-1.12)	(1.91)	(2.73)
Cma	0.1538	-0.0000	0.1370	0.0769	-0.0785	-0.1005	0.0594	0.3957**
	(1.14)	(-0.00)	(0.85)	(0.60)	(-0.48)	(-0.74)	(0.30)	(2.40)
Observations	1,403	1,296	1,320	1,346	1,320	1,325	1,253	1,079
R-squared	0.309	0.441	0.265	0.420	0.275	0.370	0.231	0.343

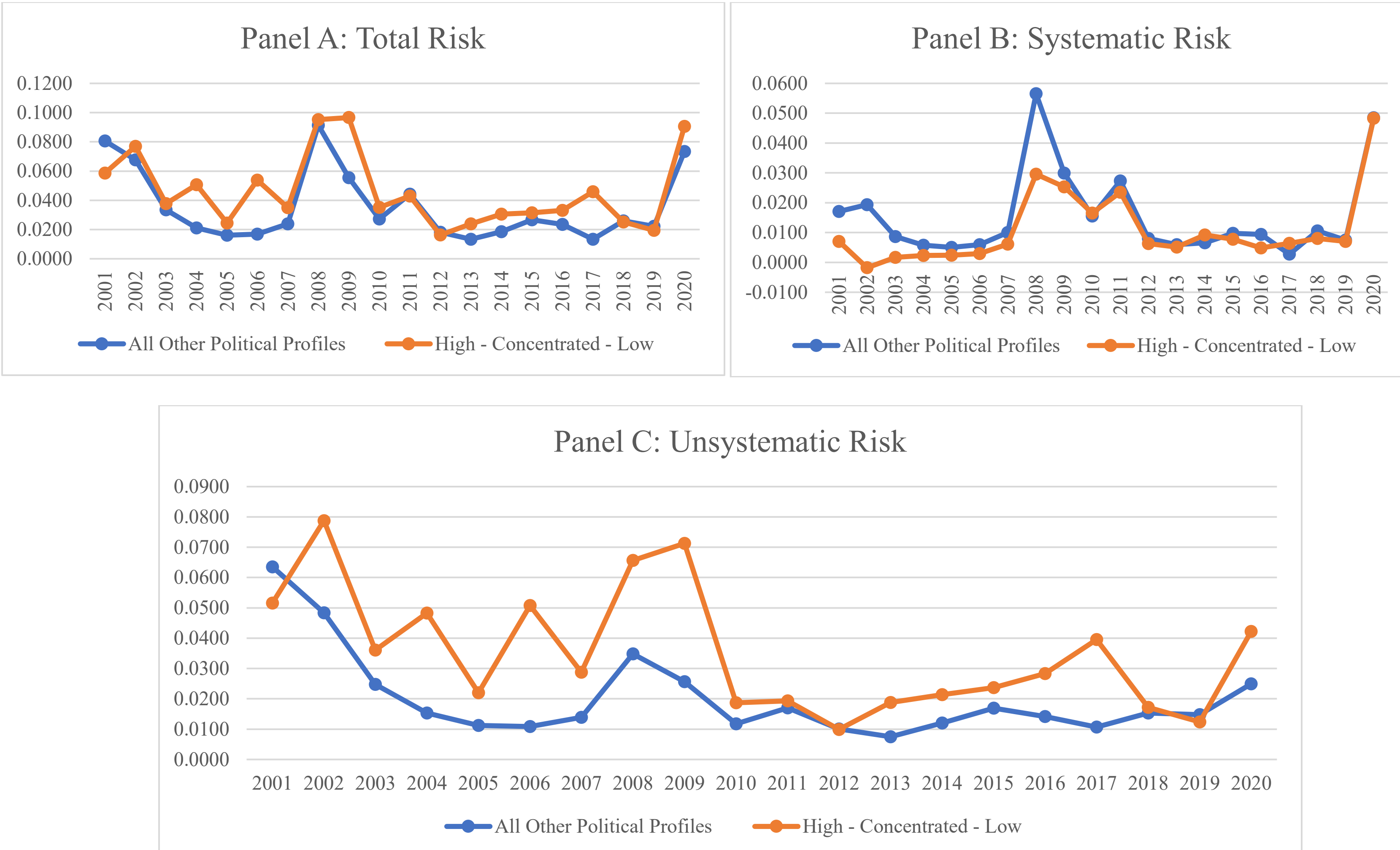


Figure 1: Risk by Year

Figure 1 displays various measures of risk by year for the High PAI – Concentrated CPS – Low Interference portfolio and the remainder of the sample. Panel A displays total risk, Panel B displays the systematic risk, and Panel C displays unsystematic risk.

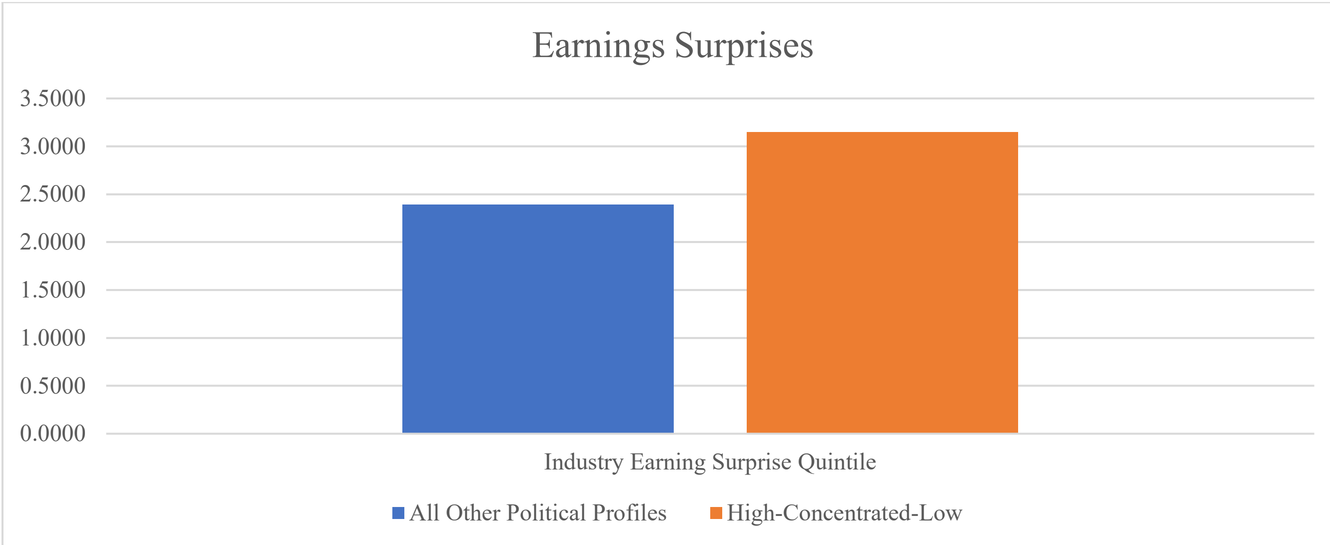


Figure 2: Earnings Surprises

Figure 2 displays the average annual industry earnings surprise quintiles in the High PAI – Concentrated CPS – Low Interference portfolio and the remainder of the sample.

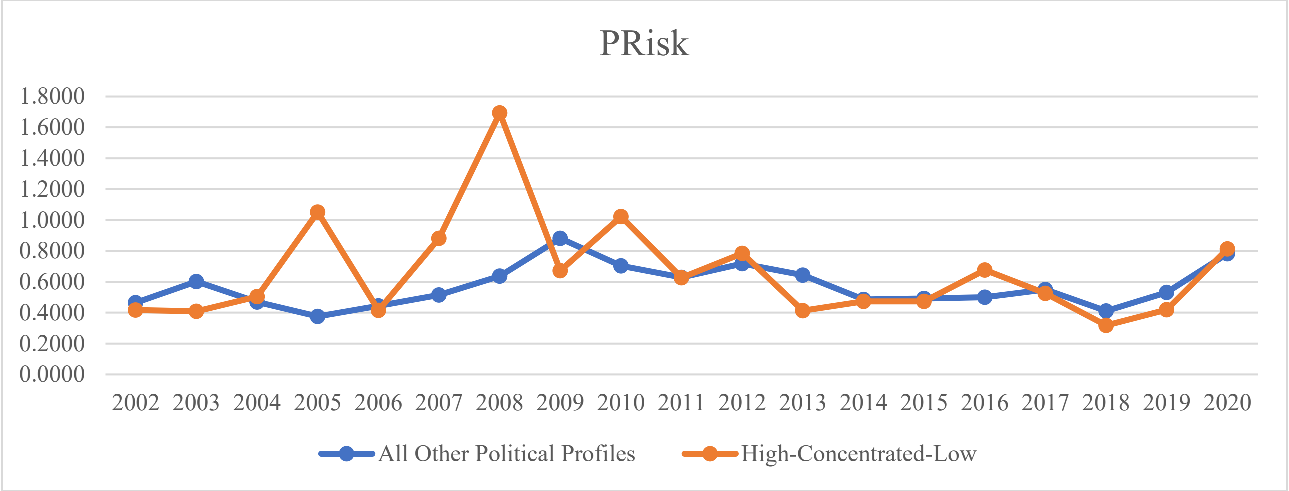
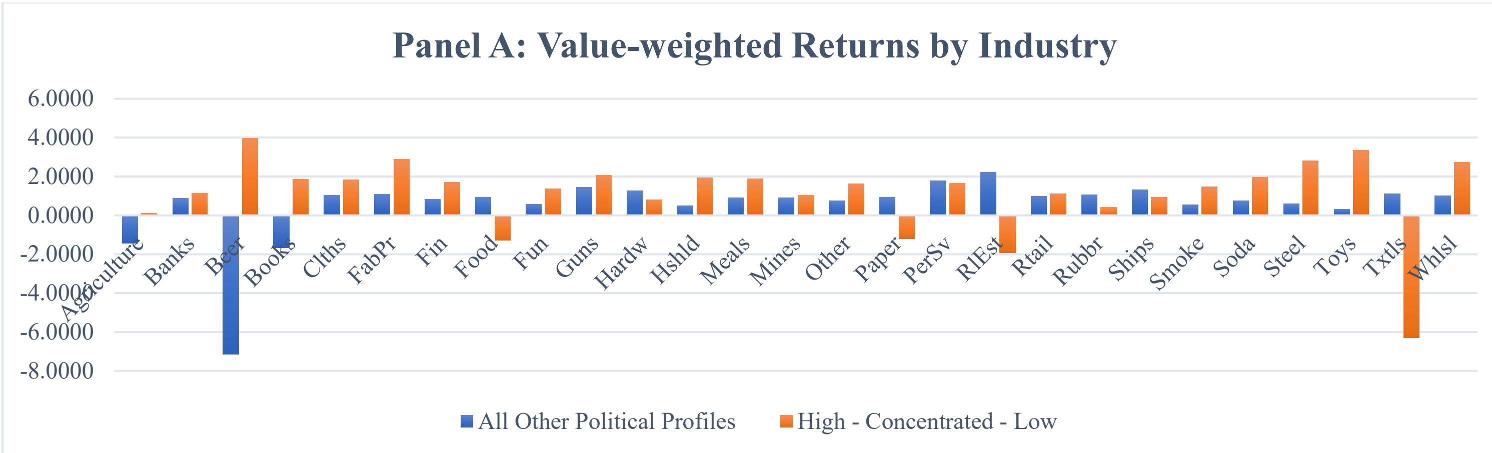


Figure 3: PRisk by Year

Figure 3 displays PRisk by year for the High PAI – Concentrated CPS – Low Interference portfolio and the remainder of the sample.



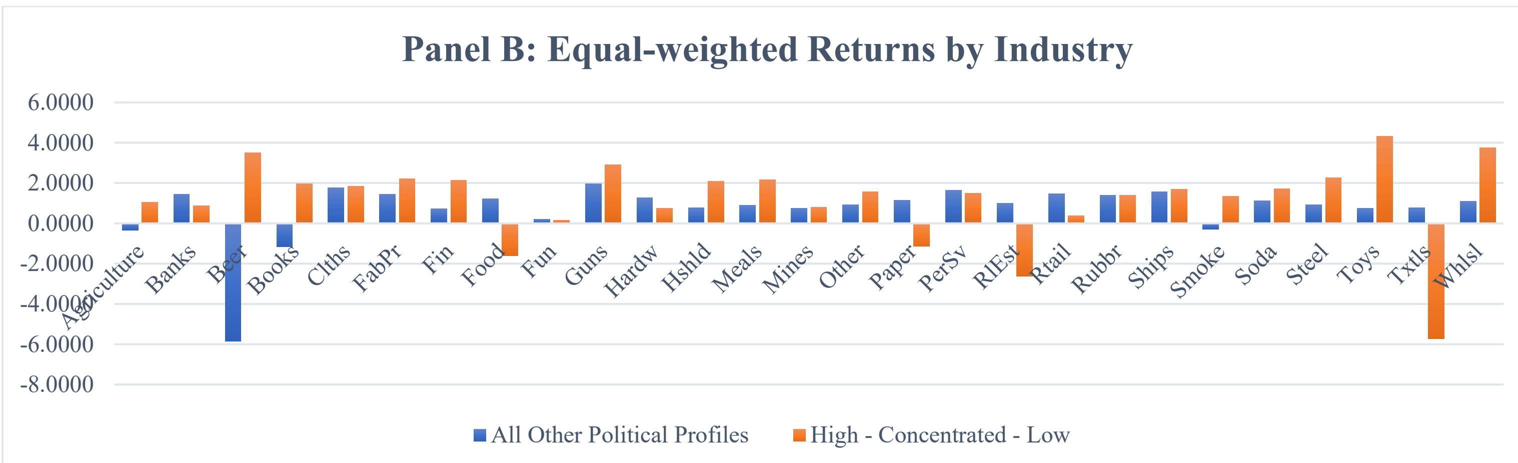
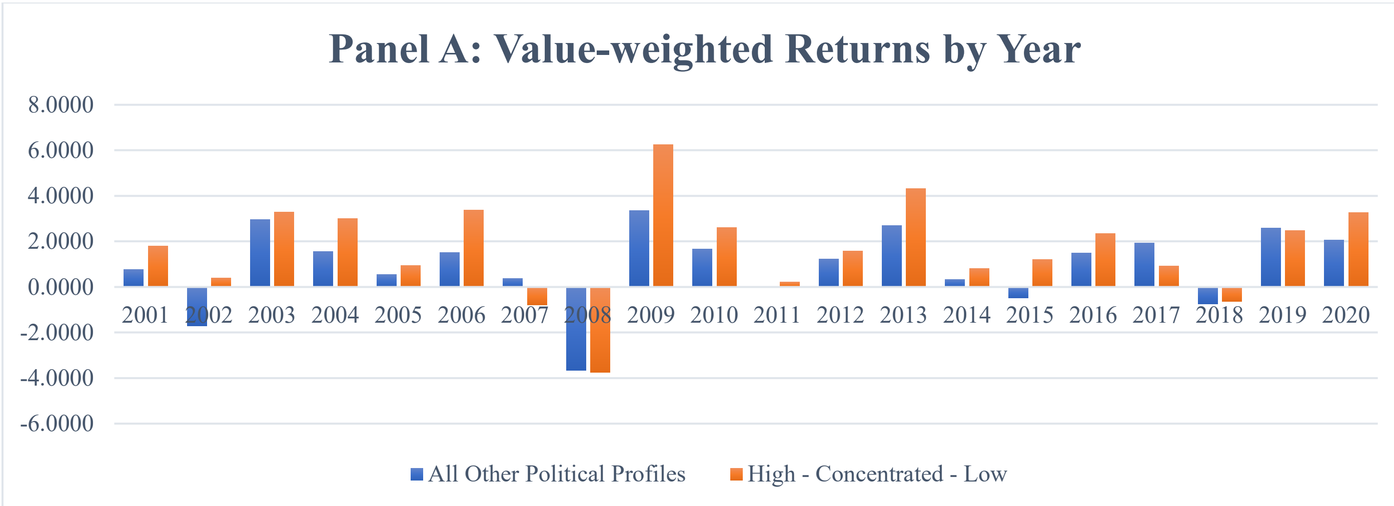


Figure 4: Returns by Industry

Figure 4 displays the average monthly returns of the industries in the High PAI – Concentrated CPS – Low Interference portfolio and the remainder of the sample. Panel A displays the value-weighted returns. Panel B displays the equal-weighted returns.



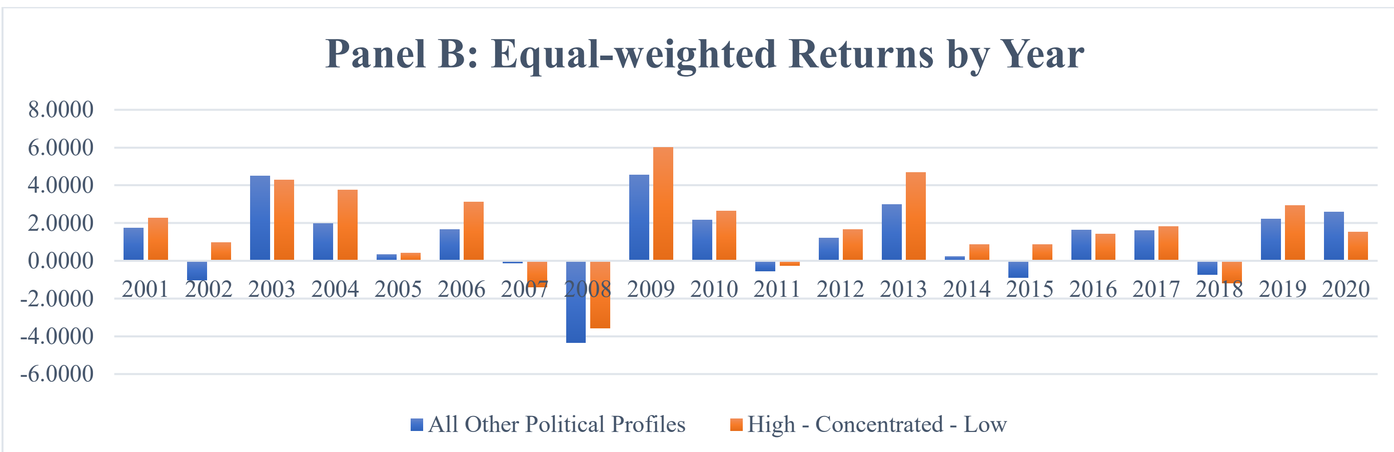
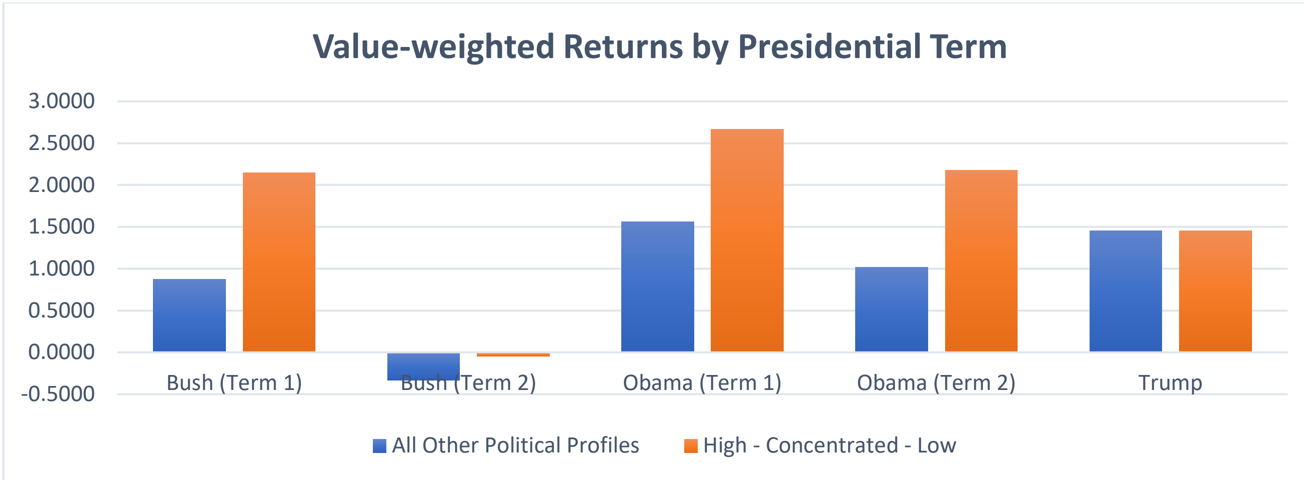


Figure 5: Returns by Year

Figure 5 displays the average monthly returns, by year, for the High PAI – Concentrated CPS – Low Interference portfolio and the remainder of the sample. Panel A displays the value-weighted returns. Panel B displays the equal-weighted returns.



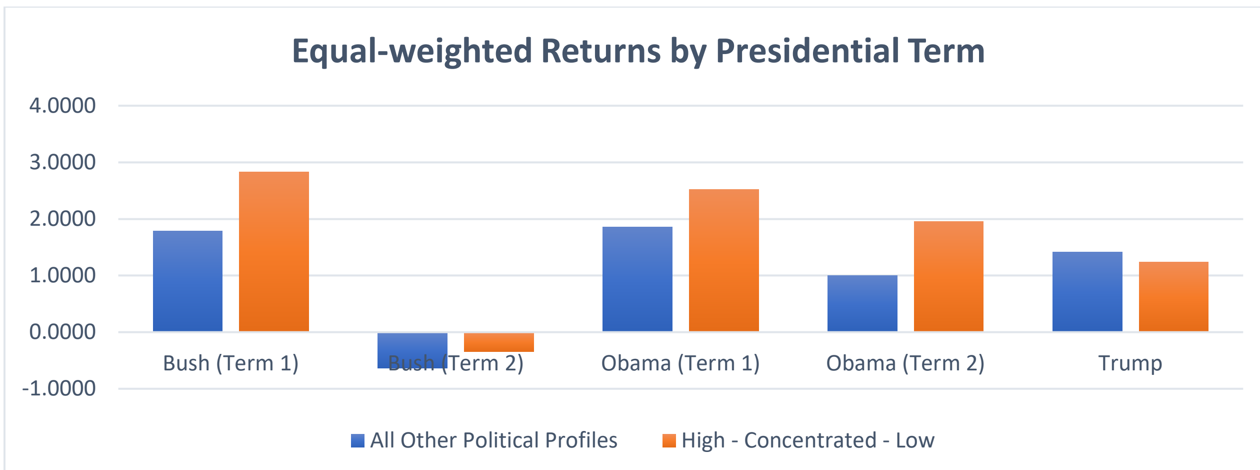


Figure 6: Returns by Presidential Term

Figure 6 displays the average monthly returns, by presidential term, for the High PAI – Concentrated CPS – Low Interference portfolio and the remainder of the sample. Panel A displays the value-weighted returns. Panel B displays the equal-weighted returns.

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