Analyst Effects on Intangible Investment: Evidence from Corporate Political Investments*

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Abstract

Using brokerage merger and closure events, we address how analysts affect intangible investment using a novel measure of intangibles – corporate political investments (CPI). While other common proxies for intangibles represent firm benefits, CPI typically represents agency problems and provides a different perspective for our study. We find a negative relationship between analyst coverage and CPI, with a 28.3% increase in CPI over a three-year window after a quasi-exogenous analyst reduction. Analyst monitoring preferences for reduced predation risk, future earnings stability, and reduced agency costs induce CPI reductions in firms facing high financial constraints and high competition. Our findings question prior studies indicating analyst myopic pressure decreases innovative output, as analyst information production favors trade secrets over patenting. We find analyst coverage is positively related to firm valuation and non-patent based measures of innovative efficiency in financially constrained firms.

JEL Classification: *D72, E22, G24, O32*

Keywords: Financial Analysts, Intangible Capital, Monitoring, Political Contributions, Lobbying

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Abstract

Using brokerage merger and closure events, we address how analysts affect intangible investment using a novel measure of intangibles – corporate political investments (CPI). While other common proxies for intangibles represent firm benefits, CPI typically represents agency problems and provides a different perspective for our study. We find a negative relationship between analyst coverage and CPI, with a 28.3% increase in CPI over a three-year window after a quasi-exogenous analyst reduction. Analyst monitoring preferences for reduced predation risk, future earnings stability, and reduced agency costs induce CPI reductions in firms facing high financial constraints and high competition. Our findings question prior studies indicating analyst myopic pressure decreases innovative output, as analyst information production favors trade secrets over patenting. We find analyst coverage is positively related to firm valuation and non-patent based measures of innovative efficiency in financially constrained firms.

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1 Introduction

How do sell-side analysts impact spending on intangible assets? This question is salient today, as the share of intangible capital in the U.S. economy has been growing rapidly in recent decades and now represents up to 60% of total capital growth (Corrado et al. (2018)). Intangible investment is a long, uncertain process exposing the manager to significant risk of appropriation during temporary setbacks. Therefore, prudent managers tend to make only partial information disclosures about the innovations they are developing (e.g., Rawson (2021)), and thus firms with substantial intangibles are subject to a larger relative degree of information asymmetry. Since analysts produce information, they can have a significant impact on firms with high intangibles (Barth, Kasznik, and McNichols (2001); Barron et al. (2002); Banker et al. (2019)). However, prior studies disagree over whether analysts provide beneficial improvements to firm value as monitors, create harmful myopic pressures, or otherwise influence firm performance and value. Most studies on intangible investment focus on beneficial intangibles (Corrado and Hulten (2010)) as measured by R&D spending, advertising (to build brand recognition and customer loyalty), and SG&A expenditures on employee training (which creates organization capital). In contrast, our study focuses on agency-related intangible spending.

We address two main hypotheses that have emerged regarding the impact of analyst coverage on agency intangibles. The monitoring hypothesis suggests analyst coverage is negatively related to agency intangibles for two reasons. First, information asymmetry is greater in firms with significant intangible assets (Aboody and Lev (2000); Barth, Kasznik, and McNichols (2001); Barron et al. (2002); Banker et al. (2019)). Analyst information can reveal resource diversion by management for private benefits, which should lead management to cut agency-related spending to maintain good relationships with stakeholders (Billett, Garfinkel, and Yu (2017)). Second, analyst information can increase predation risks (Bolton and Scharfstein (1990); Bernard (2016)) by exposing financial or other strategic weaknesses and encouraging deep-pocketed competing firms to lower prices to force the firm into distress. In response, managers would likely cut wasteful agency-related spending in preparation for a price war. This would be especially important for financially constrained firms, as predation and takeover risks would force managers to build precautionary savings and cash holdings to deter the threats (Chen, Harford, and Lin (2015)). Even though this hypothesis increases firm threats, financial stabilization is likely to produce a net long-term benefit for the firm.

On the other hand, consistent with a certification hypothesis, analysts could extend greater credibility to a firm and create a positive relationship with agency intangibles. Analyst information produces improved stock price estimates, which is especially valuable in high-intangible firms with inherently greater information asymmetries (Palmon and Yezegel (2011)). This aids investors in price discovery and has a direct impact on reducing costs from capital providers. However, even without the production of information, placing a price target on a firm indicates the willingness of the analyst to invest their reputation in the firm and creates a positive signaling effect (e.g., Leland and Pyle (1977)) similar to the IPO certification hypothesis of Booth and Smith (1986) and the production of audited financials in financially constrained firms (Roychowdhury, Shroff, and Verdi (2019) (Section 2.1.2)). This provides credibility to the firm and represents a mechanism explaining how analyst coverage reduces a firm's borrowing costs (Derrien and Kecskes (2013); Derrien Kecskes and Mansi (2016)). It could also allow the firm to invest more in R&D (Palmon and Yezegel (2012). However, this certification benefit from analyst coverage could inadvertently produce an increase in agency intangibles; that is, the financial stability brought about by analyst certification could allow management to selectively reduce information supply and hide agency spending.

Our paper addresses this debate by being the first study to examine the impact of analyst coverage on corporate political investment (CPI), which represents a unique and overlooked type of intangible investment. We use the three major forms of CPI that occur at the start of our sample period: 1) lobbying, 2) soft money, and 3) political action committee (PAC) contributions.[1] In contrast to prior studies examining beneficial intangible assets, our study provides a unique perspective because CPI is often related to agency problems (Fan, Wong, and Zhang (2007); Chaney, Faccio, and Parsley (2011); Coates (2012); Cao, Fernando, Tripathy, and Upadhyay (2018)). Our paper finds that a reduction in analyst coverage leads to an increase in future CPI over a three-year window post-event. Analyst monitoring preferences for reduced predation risk, future earnings stability, and reduced agency costs induce CPI reductions in firms facing high financial constraints and high competition. We also find that analyst coverage relates positively to firm valuation and non-patent based measures of innovative efficiency in financially constrained firms. These results are consistent with our monitoring hypothesis.

However, there are several possible endogenous relationships between the choice of analyst coverage by a brokerage firm and a manager's choice to engage in CPI. For example, "omitted variable bias" could result from unobservable firm heterogeneity related to both analyst coverage and a firm's CPI. Controlling for firm fixed effects can help, but that assumes current explanatory variable observations are independent of past values of the dependent variable (Wintoki, Linck, and Netter (2012)). In addition, "simultaneity bias" could exist if a firm's ability to attract analyst coverage directly relates to the firm's political investments.[2]

For these reasons, we address endogeneity and confirm the negative impact of analyst coverage on CPI using three different identification strategies from both the analyst literature and the corporate governance literature. Our first and primary identification strategy utilizes the quasi-exogenous loss of analyst coverage from both brokerage mergers (Hong and Kacperczyk (2010)) and brokerage closures (Kelly and Ljungqvist (2012)). However, while brokerage mergers and

[1] Lobbying represents donations to organizations to influence legislation, soft money represents donations to national political parties for general expenses and advertising, while PAC contributions are made by individuals connected to the firm (with fundraising costs paid for by the firm) and can be used to directly support political candidates. We also consider the number of political candidates supported by a firm's PAC.

[2] This primarily refers to accounting-based performance measures. Jiang, Kumar, and Law (2016) find that equity analysts usually have moderate political preferences, reducing concerns about personal biases.

closures are used extensively to examine analyst effects, an asymmetric effect between analyst increases and decreases is possible. We thus apply two more methods of identification. Our second identification strategy utilizes a systems generalized method of moments (GMM) estimation of linear dynamic panel data model to address the variable changes in both analyst coverage and political contributions over time and considers both increases and decreases in analyst coverage. This method also addresses both unobserved heterogeneity and simultaneity, and in addition uses "internal" instruments derived from past values of variables within the panel to address "serial correlation biases". Serial correlation bias has been commonly ignored in the corporate governance literature, and this GMM model has been used to address the issue (Wintoki, Linck, and Netter (2012); O'Connor and Rafferty (2012)).

In our third identification strategy, we apply a two stage least squares instrumental variable test to alternatively address omitted variable and simultaneity bias. This method has been used extensively in prior analyst literature (Yu (2008); He and Tian (2013)) and uses "external" instruments related to expected analyst coverage that capture the change in brokerage house size. The size of a brokerage house typically depends on profitability and growth in internal funds, and thus should not be related to the political contributions of firms it covers or could cover.

We next employ a battery of robustness tests to check the validity of our prior findings. The impact of analysts on the quality of disclosures (Irani and Oesch (2013)) and on information flow between management and the public is key to our results. Therefore, we first control for four sets of potentially confounding regulators of information flow: 1) analyst ability, 2) firm complexity (Li (2008)), 3) disclosure readability (Li (2008), Loughran and McDonald (2011)), and 4) firm age and Delaware incorporation (Li (2008)). We then control for potentially confounding factors affecting a firm's propensity to invest in CPI, which include: 1) political influence and state tax intensity, 3) in-house lobbying and degree of industry innovation and litigation, and 4) shareholder rights.[3] We find that our results are robust to each of these tests.

Although our prior results support monitoring over certification, the myopic pressure hypothesis (He and Tian (2013)) also suggests analyst coverage would be negatively related to CPI similar to monitoring. We present a literature review arguing against myopic pressure, and then we perform several tests to further show that monitoring and not myopic pressure is driving our results as follows. First, we determine whether real earnings management (REM) is a driver. The negative relationship between analyst coverage and CPI could result from sudden and destructive REM driven by myopic pressure and not be related to predation risk or precautionary savings to establish long-term earnings stability. Consequently, we exclude firm-year observations more likely to experience REM (Roychowdhury (2006)). Our results hold after this exclusion, suggesting that REM is not a driver, which favors the monitoring hypothesis over myopic pressure.

Second, we argue that there is a chain of causality from financial analysts increasing firm information (Irani and Oesch (2013)), to greater information increasing predation and takeover risks for financially constrained firms (Bernard (2016)), and to predation and takeover risks increasing the value of cash holdings in financially constrained firms (Bolton and Scharfstein (1990); Haushalter, Klasa, and Maxwell (2007)). In this scenario, analysts encourage financially constrained firms to increase short-term liquidity and precautionary savings via responsible cuts to long-term spending. Supporting this argument, we find that analyst coverage is negatively associated with CPI under various measures of financial constraints, suggesting a prudent firm response and favoring the monitoring hypothesis over the myopic pressure hypothesis. Third, competition represents another mechanism and serves as an alternative proxy for financial constraints by limiting funding sources (Moritzen and Schandlbauer (2020)), raising debt costs (Valta (2012)) and increasing predation risks (Bolton and Scharfstein (1990)). We find that analyst

[3] In the Internet Appendix, we alternatively examine how two related factors affecting the value of CPI to management – 1) varying benefits per CPI dollar invested and 2) entrenchment – reduce the ability of analysts to affect management in subsample analysis. As these two effects merely weaken our results, we conclude that our results are robust to factors that could limit analyst influence on CPI.

coverage is negatively associated with CPI only in firms facing greater competition. Finally, we validate our results by showing that analyst coverage relates positively to innovative efficiency in financially constrained firms using the RQ measure of Cooper, Knott, and Yang (2021). Their study notes that RQ is more closely associated with firm value than patent-based innovation efficiency measures, and they make direct contradictions to the findings of He and Tian (2013).

We structure the remainder of our paper as follows. Section 2 discusses our motivation, related literature, and our main measure. Section 3 describes our sample selection and reports summary statistics. Section 4 presents the baseline results, introduces our identification methodologies, and provides robustness tests for the monitoring vs. certification hypothesis. Section 5 disentangles our monitoring hypothesis from the myopic pressure hypothesis. Section 6 concludes.

2 Motivation and Literature Review

2.1 CPI as an Agency Cost, and Why Analysts Might Oppose Its Use

While most studies examining the impact of analysts on intangible investment have used standard measures of beneficial intangibles such as R&D and advertisements, CPI often represents an agency cost and provides a different perspective on how analysts affect agency-related firm spending. CPI represents spending by managers used to build long-term relationships with politicians and lobbyist organizations (Snyder (1992), Hillman and Hitt (1999)). Many studies suggest CPI creates two main negative outcomes by 1) imposing significant agency costs over time and 2) creating general harm to an industry.

Studies supporting the first outcome find that political connections can lead to inefficient investments meant to protect managers (Duchin and Sosyura (2012); Bertrand, Kramarz, Schoar, and Thesmar (2018)) and a lower probability of CEO replacement after poor performance (Cao, Pan, Qian, and Tian (2017)). These connections could also allow reduced disclosures and protection for fraudulent firm activity (Chaney, Faccio, and Parsley (2011); Yu and Yu (2011);

Borisov, Goldman, and Gupta (2016)). For example, Jagolinzer, Larcker, Ormazabal, and Taylor (2020) find that officers and directors of banks with political connections make informed insider trades ahead of TARP payments, suggesting management is helping the firm as a whole procure government benefits while also extracting private benefits from minority shareholders. Although this may seem like a perverse benefit to shareholders, ultimately such an outcome is not likely to create long term value within a market and may lead to costly legal penalties or regulatory fines in the long run. For example, Heese, Khan, and Ramanna (2017) find that firms with political connections are more likely to receive comment letters from the SEC.

The second outcome considers that sell-side financial analysts usually represent large investment firms with diverse holdings. Even when political contributions provide shareholder benefits to an individual donating firm (thus suggesting analyst support), it can produce a net shareholder loss in the industry due to generalized effects it produces on financial reporting quality and investment efficiency (Fan, Wong, and Zhang (2007); Chaney, Faccio, and Parsley (2011); Cao, Fernando, Tripathy, and Upadhyay (2018)). CPI can also reduce competition by creating barriers to entry, securing asymmetric subsidies to firms (via subsidized lending or tax relief), or otherwise restricting laissez-faire free market behavior (Coates (2012)). This "analyst diverse portfolio" view suggests that analysts would not be supportive of political contributions in one firm to the detriment of the other firms they cover and to their investment firm employer.

2.2 Relevance of CPI as a Measure of Analyst Influence on Intangibles

Anecdotal evidence suggests CPI firms are concerned by analyst monitoring efforts. For example, Enron was one of the most fraudulent firms in recent decades and was also one of the most active in making political contributions. Enron had an analyst following, but when analyst John Olson provided less than positive recommendations, Enron successfully coerced Merrill Lynch to fire the analyst in a now infamous example of firm opposition to analyst monitoring.

Despite this well-known example, it is more likely firms cannot retaliate and that they adjust spending when faced with analyst influence. CPI provides two unique features that allow its flexible use by managers needing to reduce costs. First, CPI provides a discrete means for managers to conduct real earnings management (REM) or adjust precautionary savings. For example, de Jong et al. (2013) present survey evidence that analysts favor stable earnings but do not favor REM. CPI adjustments can help in this regard because they are particularly discrete, as Bebchuk and Jackson (2012) note that identifying political contributions can be extremely difficult for stakeholders unless firms directly choose to voluntarily disclose the information. Furthermore, managers have more flexibility to cut these intangibles because they do not capitalize these expenditures on the balance sheet, and thus there is no balance sheet penalty when cuts are made.

Second, CPI is likely to be more responsive to analyst effects because it is less susceptible than other intangibles to adjustment costs (Anderson, Banker, and Janakiraman (2003); Brown and Petersen (2011)). For example, R&D and many intangible components of SG&A consist largely of salaries to key employees that cannot be reduced without encouraging their potential exit. These departures would result in the loss of training, skills, and other organizational capital that would be costly to replace and could affect a firm's competitive position. In contrast, CPI likely suffers less from this adjustment problem because it involves relationship bonds between management and political incumbents or lobbyist organizations. This creates implicit contracts of cooperation (Snyder (1992), Hillman and Hitt (1999)) that result in valuable long-term relationships between the groups. This relationship allows firms to provide explanations (e.g., financial hardships faced by the firm) to skip or reduce such payments. In addition, most of these funds are directed to broad-based PACs or multi-client lobbying firms that would not be as dependent on steady revenue streams from one source (Strickland (2019)).

3 Data and Descriptive Statistics

Our full sample ranges from 2001 to 2010.[4] Although lobbying data is first reported in 1998, our sample period is set to the period after the Regulation Fair Disclosure Act of 2000 (Reg FD), when managers are prohibited from selectively disclosing nonpublic information to analysts. Sampling prior to Reg FD could bias our sample, as management during this era could have more effectively placed implicit pressure on analysts, distorting their incentives and affecting their governance role (Yu (2008)). We also end our sample period in 2010 to avoid the subsequent impact of "dark money" contributions after this time. Dark money represents political spending funneled through a tax-exempt nonprofit registered under Section 501 of the Internal Revenue Code. As noted by the Center for Responsive Politics (CRP), these organizations generally do not have to disclose donors to the general public and can engage in political activities as long as this activity is not what they do in the majority of their time (Bebchuk and Jackson (2012); Coates (2012)). Dark money began to proliferate partly because of *FEC v. Wisconsin Right to Life* in 2008 and more importantly due to *Citizens United v. FEC* in 2010. Although CPI data is officially reported after this period, it is possible that money funneled through more hidden means could skew the meaning of more recent, more public CPI data.

We exclude financial and utilities firms from our baseline results due to the potential impact of high government regulations for these industries.[5] We obtain firm-level financial and stock return data from COMPUSTAT and the Center for Research in Security Prices (CRSP). The main explanatory variable is a firm's analyst coverage (*Analyst Coverage*). We obtain analyst information from the Institutional Brokers Estimate System (I/B/E/S) summary file. We obtain political contribution data from the Center for Responsive Politics and from the Federal Election Commission. We describe these datasets in more detail in the next section. We manually match political contributions data from both sources annually by firm name to Compustat and account for annual name changes over time using Compustat historical firm name data.

[4] This is a similar period to the closely related paper by Chen, Harford, and Lin (2015), whose dataset ranges from 1999 to 2011. Our matched sample uses data from 1998 to 2010 to form a seven-year window around brokerage merger and closure events that occurred between 2001 and 2007.

[5] We address the impact of regulated firms in our identification strategies in later sections.

3.1 Political Contributions Data

We obtain both lobbying and soft money datasets for our sample period from the Center for Responsive Politics (CRP), while we obtain PAC contribution data from the Federal Election Commission. A PAC is organized to raise money to support or defeat political candidates. While soft money contributions and lobbying expenditures come entirely from the corporate treasury, individuals connected to the firm make PAC contributions and thus represent a broad range of stakeholder interests in political contributions. However, firms will typically pay the fundraising costs associated with the promotion of the firm's PAC, which can still be quite substantial and in some cases almost 50% of total PAC funds (Coates (2012)). Thus, shareholders still bear a significant portion of the costs associated with PAC spending, and for that reason we consider PAC funds to be another measure of corporate political spending. Indeed, Hill et al. (2013) find that managers use lobbying and PAC contributions as complementary sources of funds. Despite this, the CRP notes a low correlation between PAC contributions and lobbying behavior. We evaluate the combined effects of all three datasets, and in many of our analyses, we also separate out the effects of LSM vs. PAC for robustness.

We examine two measures built from PAC contribution data: political donations and the number of supported candidates in the year following each election (Cooper, Gulen, and Ovtchinnikov (2010)). To obtain PAC contributions information, we download data on biennial corporate political contributions (representing every two-year election cycle) directly from the Federal Election Commission's (FEC) detailed committee and political candidate summary contribution files. The PAC file provides data on how much each firm donates in contributions to political candidates and campaigns. The detailed file provides contribution-by-contribution data for each candidate. It records all contributions by individuals in excess of $200 and includes their affiliation (company name), date of the contribution, amount, and the destination committee. We merge the PAC data with accounting data from Compustat by manually matching each observation by firm name.

Lobbying represents the strategic transmission of corporate funds to influence legislation. Lobbying data has been available to the CRP from the Senate Office of Public Records (SOPR) since 1998. The Lobbying Disclosure Act of 1995 requires any organization whose lobbying expenditures exceed $20,000 semiannually to register with the clerk of the House of Representatives and the Secretary of the Senate within 45 days of contacting the lobbying group.

Companies make soft money contributions directly and these represent unlimited campaign gifts to national political parties. They are used for general party administrative expenses and non-specific advertising (voter registration drives, "get out the vote" campaigns, etc.). The Bipartisan Campaign Reform Act of November 6, 2002 banned soft money contributions. Although this happened during the middle of our sample period, soft money has little impact on our results and our findings are similar even when soft money is excluded from our tests. "527 Committee" donations largely replaced soft money contributions after their ban and after McConnell v. FEC in December 2003. We exclude "527 Committee" contributions from our sample because 1) they appeared midway through our sample period and likely had a lagged impact, 2) the matched samples formed around even the last brokerage merger and closure events in 2007 barely covered the period in 2004 when FECs grew in prominence, and 3) they are a much smaller dataset that likely would have had little impact on our results.

3.2 Summary Statistics

Table 1 presents firm-level summary statistics of all dependent and explanatory variables we use for this study. The main sample consists of 12,813 firm-year observations. The total lobbying, soft money, and PAC contributions average $135,780 annually, whereas the median is zero. While the size of PAC contributions appears low at first glance, there are several reasons why this does not affect the validity of our results. First, only a small percentage of firms utilize CPI in a major way, and the impact of analyst effects on CPI is concentrated in these firms. This is true for many studies focusing on long-term intangibles. For example, the closely related study by He and Tian (2013) notes in the summary statistics that the median number of both patents and

R&D spending for their sample is zero. We also ensure outliers from the limited group of CPI firms do not drive our results by winsorizing at the 1% level. Second, the majority of our results utilize a matched sample, which mitigates the effect of this limited CPI data. The matched sample requires firms to have made CPI investments at some point during the sample period. As shown in Table 3 Panel B, matched sample firm-years have CPI investments just under $1 million on average for both the treatment and control groups. Finally, we employ a wide variety of additional endogeneity tests to address any other biases our limited CPI firm sample might cause. Furthermore, our results remain valid because we center our study on analyst information effects and not economic magnitudes.

We also consider the number of supported candidates and find that the average number of supported candidates is approximately 18, with a median of zero. The average number of analysts covering firms in our sample is around 10, with a median of 9. We also note that most firms utilizing CPI are fairly mature with a median firm age of 23 years and a median CEO age of 56 years. These firms have very low CEO ownership (0.3% at the median) but very high institutional ownership (72.7% at the median). Throughout our analysis, we utilize controls from both the financial analyst literature and the political science literature related to CPI (He and Tian (2013); Correia (2014); Billett, Garfinkel, and Yu (2017); Cao et al. (2018). Appendix A contains definitions of all variables.

4 Methodology and Results

We begin our study by examining the relationship between analyst coverage and various measures of CPI. Since the monitoring and certification hypotheses produce opposing outcomes, the following tests will help us narrow our analysis by identifying which of these two views is dominant. For example, if it turns out that the certification hypothesis drives our results, we would expect to see analyst coverage positively related to CPI. Prior studies find that the information shared by analysts helps reduce information asymmetries and thus lowers the cost of capital On the other hand, a negative relationship between analyst coverage and CPI would suggest support for the monitoring hypothesis. We address this debate in the following sections.

4.1 Baseline Regressions

Our analysis starts by examining the baseline relationship between analyst coverage and various measures of CPI: 1) LSM contributions, 2) PAC contributions, and 3) the number of candidates supported by a firm's PAC. Because the CRP suggests there is a low correlation between lobbying and PAC contributions, we separate out donations from PACs for robustness to determine if there is a differential effect.

We estimate the following regression to examine the relationship between analyst coverage and our measures of CPI:

$$
\begin{aligned}
CPI_{i,t+1} = {} & \beta_0 + \beta_1 ANALYST\ COVERAGE_{i,t} + \beta_2 FIRM\_CTRLS_{i,t} \\
& + \beta_k YEAR_t + \beta_j FIRM_i + \varepsilon_{it}
\end{aligned}
\tag{1}
$$

Where *i* and *t* represent firm and year. We define *CPI* as the natural logarithm of the dollar amount of 1) campaign contributions made by a firm's PAC during the most recent election cycle, 2) PAC contributions plus the total annual LSM expenditures made by the firm, or 3) number of political candidates supported. 1 and 2 are over an election cycle and 3 is over the next fiscal year. We measure *ANALYST COVERAGE* as the mean number of estimates from the 12 monthly earnings forecasts a firm receives over the fiscal year. *FIRM_CTRLS* is a vector of control variables of accounting characteristics that includes firm size (assets), leverage, market to book ratios, return on assets, capital expenditures, return volatility, and firm age. We also add variables relating to management characteristics (CEO age, ownership, and tenure years) or other parties exerting monitoring influence (independent directors, percentage of institutional holdings) as additional controls in some models. *YEAR* represents year fixed effects and *FIRM* stands for firm fixed effects.

Table 2 reports these regressions on the main explanatory variable, *ANALYST COVERAGE*, and other firm-level control variables in a pooled OLS regression with year and firm fixed effects. Our sample runs from 1996 to 2010 when considering PAC and the number of candidates. However, it begins in 1998 when including lobbying as that is the first year lobbying data is available.[6] In models (1), (2), (4), and (5), the coefficient on *ANALYST COVERAGE* is negative and obtains statistical significance at the 1% and 5% level, suggesting a negative correlation between analyst coverage and political contributions. The addition of firm fixed effects helps reduce potential bias from the endogeneity problem of omitted variables. This implies that time-invariant unobserved firm characteristics may be important factors in examining the relationship between analyst coverage and a firm's CPI.

In addition to the results obtained for *CPI* in the previous analysis, we follow Cooper, Gulen, and Ovtchinnikov (2010) and consider the number of candidates supported by a firm's PAC as an alternative measure of the degree of firm political spending in models (3) and (6) of Table 2. We estimate the following regression to examine the effect of analyst coverage on this measure of a firm's CPI practice:

$$\text{NUM\_CND}_{i,t+1} = \beta_0 + \beta_1\text{ANALYST COVERAGE}_{i,t} + \beta_2\text{FIRM\_CTRLS}_{i,t} + \beta_k\text{YEAR}_t + \beta_j\text{FIRM}_i + \varepsilon_{it} \quad (2)$$

where *NUM_CND* is the natural logarithm of the number of candidates supported by a firm's PAC during the most recent election cycle, and the rest of the regression is defined as in equation (1). The sign on the coefficient of *ANALYST COVERAGE* in models (3) and (6) is negative and statistically significant at the 1% and 5% levels, respectively, suggesting a negative association between analyst coverage and the number of supported candidates as in the other models in Table 2,[7] showing that analyst coverage is strongly and negatively associated with CPI and related

[6] Our results are robust to limiting the sample range to 2001 through 2010 as we do in later tests to avoid potential bias from results before Reg FD became effective in 2000.

[7] The results remain significant when we require the donations for each candidate to exceed $1,000. This reduces the concern of including a relatively weak relationship between the contributing firm and a candidate in our analysis.

measures. Overall, this baseline evidence is not consistent with the certification hypothesis and instead suggests that analyst coverage reduces CPI via the monitoring hypothesis.

4.2 Monitoring vs Certification: Identification Strategies

The results from our baseline models with firm fixed effects mitigate the concern of the omitted variable problem. However, there is still concern that a firm's CPI and analyst coverage can be jointly determined through some unobserved common factors. Chen, Harford, and Lin (2015) cite studies that find analysts tend to cover firms that are higher quality or face less information asymmetry. Therefore, we employ multiple empirical strategies to alleviate various endogeneity concerns in the following sections.

4.2.1 Brokerage Mergers and Closures

Our first strategy employs quasi-natural experiments, using brokerage closures and mergers as shocks that quasi-exogenously reduce analyst coverage of a firm. Prior studies document that brokerage closures and mergers occur over time and across industries and these events lead to the loss of analysts of firms regardless of those firms' policies (Hong and Kacperczyk (2010); Kelly and Ljungqvist (2012); He and Tian (2013); and Billett, Garfinkel, and Yu (2017).[8] In a difference-in-differences framework, we identify firms that lose analysts due to the brokerage closures and mergers as the treatment sample firms. Conversely, control sample firms are those that do not lose analysts.

Panel A of Table 3 examines the full sample in a DiD framework. We utilize a) PAC contributions and b) LSM contributions as our dependent variables. We add control variables from

[8] We follow closely the methodologies used in He and Tian (2013), except that we include both 1) Treat and Post and 2) fixed effects for cross sectional units and time periods in our regression model similar to Irani and Oesch (2013) and Billett, Garfinkel, and Yu (2017). Our results are also robust to the exclusion of 1) fixed effects or 2) Treat and Post in favor of using only fixed effects as in Bourveau, Lou, and Wang (2018) Section 5.1. We also cluster standard errors at the deal level following He and Tian (2013), but our results are robust to clustering by firm as in Billett, Garfinkel, and Yu (2017).

Hong and Kacperczyk (2010) for market capitalization, book-to-market, and past returns.[9] While many prior studies on political contributions utilize PAC donations as their main measure of contributions by firms, it is possible that this measure is biased because the costs of PAC donations are only partially borne by shareholders. However, LSM expenditures are direct corporate payments and are thus fully borne by shareholders. By utilizing both types of contributions as alternative measures, our test results provide further robustness. We obtain positive and statistically significant full sample results from the impact of a quasi-exogenous analyst reduction event on both PAC contributions and LSM contributions in all models. In terms of economic significance, these results suggest the quasi-exogenous loss of an analyst causes a firm to generate 17% more PAC contributions and 36% more LSM contributions (in rows 1 and 3, respectively) over a three-year window than a similar firm without any loss of analyst coverage.

For robustness we examine highly regulated industries (e.g., the financial and utility sectors). These industries are more dependent on government policies and should respond more strongly to analyst influence because 1) they tend to have higher levels of political contributions, and 2) the political capital established in these industries should allow them to more easily reduce contributions when financially necessary without the imposition of adjustment costs. Rows 3 and 6 of Panel A include only financials and utilities firms and show more strongly positive and significant results within these industries, supporting these arguments. Nevertheless, our Panel A findings hold for unregulated industries in untabulated results.

Panels B through E examine a matched sample in a DiD framework. We first create a matched sample similar to Hong and Kacperczyk (2010) using market capitalization terciles, book-to-market ratio terciles, past returns terciles, and analyst coverage terciles. This helps address concerns of bias due to firm size, as analysts tend to cover larger firms. Cooper, Gulen, and Ovtchinnikov (2010) note that politicians find it most favorable to provide support for larger firms because those firms generate greater tax revenue and supply more local jobs. We also match by

[9] We add stock return volatility and stock turnover as additional controls following Kelly and Ljungqvist (2012) in untabulated results, where we obtain similar positive and statistically significant outcomes.

Fama-French 49 industries, as political contributions are often highly industry specific and aimed at changing industry-level regulations.[10]

To perform a valid difference-in-differences test, we follow He and Tian (2013) and show that (1) pre-event trends in both groups are similar, and (2) the treatment and control groups are not significantly different. We first examine condition (1) in Figure 1 by showing that the parallel trends assumption is satisfied in the pre-event period. The difference between treatment and control groups is constant prior to the quasi-exogenous loss of analyst coverage in the treatment group, thus isolating the change in contributions to the effect of analyst coverage. We then examine condition (2) in Panel B of Table 3 by showing that our treatment and control samples are insignificantly different post-match when considering CPI and our key matching parameters in the first five rows. Together with numerous prior studies validating the use of this quasi-exogenous shock for related variables, these results provide evidence supporting the parallel trends assumption for CPI. Panel C of Table 3 shows the results of our difference-in-differences estimation using this matched sample. We use 1) combined LSM and PAC contributions, 2) LSM contributions only, and 3) PAC contributions only as our dependent variables and obtain positive and statistically significant results in all three cases, confirming our results found using the full sample.

Panel C also compares treatment-control pairs on an equal basis, which is necessary to allow us to better determine economic significance as discussed in Section 5.1.3 of He and Tian (2013)).[11] We find that a quasi-exogenous analyst loss increases CPI, measured by LSM and PAC, by 28.3% over a three-year window. Our results are similar in magnitude to the full sample and to the innovation outcomes of He and Tian (2013), who find that a quasi-exogenous analyst loss results in an 18.2% increase in patenting over the same three-year window and identification strategy.

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[10] In unreported results, we also conduct a simple match by firm size quantiles (total assets), fiscal year, and industry (Fama-French 49 industries) and obtain similar DiD results.

[11] For example, a firm spending $50,000 on CPI would likely see a very different percentage impact from a similar firm spending $800,000 on CPI based on the same one-analyst decrease from a brokerage merger/closure.

It is possible that subsets of the data over time could be driving our results. He and Tian (2013) note that most of the brokerage mergers and closures occur in 2001 and 2002 after the collapse of the internet bubble. This could bias our sample if the results are driven mainly by firms facing economic hardship after the collapse. Following these studies, we a) include only matching years 2001 and 2002 in the first model to show their effects, and b) exclude matching years 2001 and 2002 in the second model in Panel D of Table 3. Results are positive and significant in both cases, suggesting that economic effects from the decline are not driving the results.

We next determine whether long-term trends toward greater political contributions may be driving the post-treatment increase in contributions in our regressions, instead of our results being driven by the quasi-exogenous analyst reductions. Therefore, in Panel E of Table 3 we implement various placebo tests to isolate the effect of the analyst reductions. Models (1) and (2) shift the events backward in time by 5 years and 3 years, respectively, while models (3) and (4) shift the events forward by 3 years and 5 years, respectively. Although we start our main regression matched sample years in 2001 to avoid the effects of Reg FD, we shift our starting matched sample years back to 1996 and 1998, respectively, to allow for a larger sample size. Models (3) and (4) both use 2001 as the starting matched sample year to allow a larger sample size, as limitations on contribution data after 2010 would limit our sample size. Models (1), (3), and (5) are insignificant, while model (2) is actually slightly negatively significant, suggesting our results are not being driven by long-term trends in political contributions. In sum, our matched sample results in Panels B through E confirm our full sample results in Panel A, suggesting analyst coverage relates negatively to CPI and rejecting the information asymmetry hypothesis.

Finally, we also examine whether there is a nonlinear effect from the loss of analyst coverage on CPI. The loss of an analyst should have a bigger impact on firms with overall fewer analysts covering them before the shock. Following He and Tian (2013) in their Table 3 Panel C, we examine this for our full sample in rows 5 through 7 of Panel A. We find that for each group of increasing analyst coverage, both the magnitude of the coefficient and statistical significance decline, resulting in no significance at the standard levels for the group greater than 25 analysts.

Similarly, we examine this for our matched sample in rows 4 through 6 of Panel C. As in the full sample, the magnitude of the DID coefficient declines for each group of increasing analyst coverage, losing significance for the groups of 20 or greater analysts. Overall, these results suggest the impact of analyst coverage on CPI is stronger for firms covered by fewer analysts.[12]

4.2.2 Instrumental Variables Approach

Even though the use of analyst reductions via brokerage mergers and closures have been widely used in prior literature examining analyst effects, it is possible that analyst reductions have asymmetric effects on firms relative to the effects of analyst increases. Although our main identification strategy considers the quasi-exogenous loss of analyst coverage from brokerage mergers or closures, brokerage houses will often add or eliminate analysts based on their own financial situation. Such changes in analyst coverage are unlikely related to CPI decisions by firms. This provides us with another plausible exogenous variation in analyst coverage that we can use to examine firm political contributions. Following Yu (2008) and He and Tian (2013), we create an instrumental variable called expected coverage to use in a two-stage least squares (2SLS) regression.

We employ expected coverage as an instrument for analyst coverage in the first stage, as shown in model (1) of Table 4 Panel A. The results show a positive and statistically significant effect at the 1% level of expected coverage on analyst coverage. The level of significance also suggests that the instrument is not weak. In models (2), (3), and (4), we observe negative and significant results in our second stage for PAC contributions, total CPI contributions (LSM and PAC), and the number of candidates, respectively. These results confirm our findings from the brokerage merger and closure tests.

[12] We do not report PAC regression results for varying analyst coverage in Table 3 Panel A due to insignificant results. Similarly, we use higher cutoffs for analyst coverage groups in Panel C versus Panel A to avoid insignificance; however, coefficient magnitudes are similar in Panel C if we use cutoffs close to Panel A.

4.2.3 Dynamic Panel Systems GMM Estimation

We next examine the generalized method of moments estimation of linear dynamic panel data (Wintoki, Linck, and Netter (2012)) to address similar endogeneity issues and to verify our results hold for both analyst increases and decreases. Prior studies in corporate governance and political contributions have suffered from these issues of endogeneity and such have only recently begun to be addressed in the literature (Wintoki, Linck, and Netter (2012), O'Connor and Rafferty (2012)). Following Wintoki, Linck, and Netter (2012), we estimate the following models to examine the causal effect of analyst coverage on our measures of a firm's political contributions:

$$\begin{aligned} POL\_CON_{i,t+1} = {} & \beta_0 + \beta_1 ANALYST\ COVERAGE_{i,t} \\ & + \sum_{J=2}^{\eta} \beta_2 FIRM\_CTRLS_{i,t} + \beta_3 POL\_CON_{i,t} \\ & + \beta_4 POL\_CON_{i,t-1} + \beta_k YEAR_t + \beta_j FIRM_i + \varepsilon_{it} \end{aligned} \tag{3}$$

Panel B of Table 4 presents the results of the dynamic panel system GMM using measures of a firm's PAC contributions, total CPI contributions (LSM and PAC), and the number of candidates, respectively. Similar to the prior tests, the relationship between analyst coverage and a firm's political contributions remains significantly negative. The AR (1) and AR (2) tests for first-order and second-order serial correlations in the first-differenced residuals show that the null hypothesis of no serial correlation cannot be rejected. The Hansen test of over-identifying restrictions test results in a p-value of 0.103-0.241, suggesting that our instruments are reasonably valid; i.e., they are uncorrelated with the disturbance term. These two additional tests confirm our baseline and difference-in-differences results of the negative relationship between analyst coverage and a firm's political contributions.

4.3 Robustness to Potentially Confounding Factors

Although CPI represents a parallel outbound information flow to government policy makers from corporate management, we are not concerned that this dual information flow creates a confounding substitution effect with analyst information for the following reasons. CPI firms provide information to politicians jointly with financial gifts to emphasize their regulatory policy needs regarding innovation (Hillman and Hitt (1999)). As noted in the motivation section of the paper, this information flow should precede innovation (negating any impact on shareholders), as innovative spending or changes in innovative spending will not occur until a favorable regulatory framework is in place. Politicians would likely not know or care about analyst information geared toward future earnings and cash flows. In the next sections, we consider other factors that may bias our main DiD model. We examine the effects on our sample of potentially confounding factors 1) affecting the information environment and 2) affecting political contributions.

4.3.1 Factors Influencing a Firm's Information Environment

Despite our matching methodology that replicates prior studies covering shocks to analyst coverage, the significance of the interaction term in our DiD regression may be capturing systematic differences in information-related characteristics between the treatment and control groups. For robustness, we address this concern as motivated by Section 5.1 in Billett, Garfinkel, and Yu (2017). As they note, managers often provide their own earnings forecasts, and analyst coverage loss may lead them to make forecasts more often. This may assist the remaining analysts and thus eliminate the supposed negative impact on information. To examine this concern, we conduct similar tests, partitioning our sample conditional on decreasing or increasing analyst forecast dispersion between the 3-year pre- and post-event period around the brokerage merger or closure and rerun our DiD model. We then repeat the procedure using analyst forecast error and report the results in Table 5 Panel A. Similar to Billett, Garfinkel, and Yu (2017), we find that our results remain significant when analyst forecast dispersion/error is increasing. This verifies that manager efforts to counter information loss due to the drop in analyst coverage are not able to eliminate the increase in asymmetric information from a brokerage merger/closure event, and so it directly links the change in CPI levels to information asymmetry.

Following prior difference-in-differences literature,[13] we add additional controls to our main DiD model in Table 5 Panel B to address other factors that may be affecting the information environment. Specifically, we control for the following: 1) the ability of the analyst cohort covering the firm, which we proxy by the presence of all-star analyst coverage both before and after the event; 2) the complexity in the financial statements as measured by the number of non-missing items, special items, and business segments (Li (2008)); 3) measures of report readability using gross 10-K file size (Loughran and McDonald (2011)) and the FOG index (Li (2008));[14] 4) firm age and Delaware incorporation. Approximately half of the corporations incorporate in Delaware and their manager-friendly corporate legal system likely appeals to firms engaging in political contributions that some stakeholders consider controversial (as our results show with the strong significance of this variable). Overall, we find that our main interaction term remains positive and highly significant throughout these tests, suggesting that analyst information effects drive the impact of brokerage merger/closures on CPI.

4.3.2 Factors Influencing Political Contributions

We address potentially confounding political factors impacting a firm's propensity to engage in CPI in Table 6. Models (1) through (3) utilize our main DiD tests with lobbying, soft money, and PAC as the dependent variables. In model (1) we also control for whether the firm is incorporated in a state evenly divided by political parties (battleground state) or whether the firm's headquarter state will face high state taxes (state tax climate). Model (2) adds in-house lobbyist presence, the litigation risk of the industry as proxied by Francis, Philbrick, and Schipper (1994), and the classification of an innovative industry following Hirshleifer, Low, and Teoh (2012). Model (3) adds the entrenchment index of Gompers, Ishii, and Metrick (2003). We find that higher state taxes are positively and significantly associated with CPI, as firms often seek to find political relief for heavy corporate tax burdens (as discussed in a later section). We also find that the

[13] See for example Bourveau, Lou, and Wang (2018) Section 5.1.

[14] In a related study using brokerage merger/closure data, Irani and Oesch (2013) use similar report readability tests.

presence of an in-house lobbyist is positively and significantly associated with CPI. This is not surprising, as firms often employ in-house lobbyists when they are highly engaged with political entities and need a readily available contact for frequent usage. We also find that FPS industries (which face higher litigation risk) are negatively associated with CPI. This may be because CPI remains controversial and may adversely affect litigation risk and settlement amounts. Overall, we find that the results on the interaction term hold with the addition of these controls. We repeat this analysis in models (4) through (6) using only lobbying and soft money as the dependent variable. This eliminates any potential bias from including PAC contribution expenses only partially borne by the firm. The results on the interaction term hold for these models.

In the Internet Appendix, we alternatively employ subsample analysis and find that 1) high benefits per CPI dollar invested and 2) entrenched managers limit the ability of analysts to affect management spending on CPI. These two factors suggest analysts have difficulty in persuading CPI reductions when the agency-related benefits are large. However, overall these results show that our findings are robust to factors that could limit analyst influence on CPI.

5 Monitoring vs. Myopic Pressure

Although our prior results support the monitoring hypothesis, the myopic pressure hypothesis (He and Tian (2013)) similarly suggests analyst coverage would be negatively related to CPI. We present a literature review in the next section favoring monitoring over myopic pressure, and then we perform several tests to show that monitoring and not myopic pressure is driving our results by considering the impact of financial risks on the relationship between analyst coverage and CPI.

5.1 Monitoring vs. Myopic Pressure: A Discussion of Prior Literature

A negative relationship between analyst coverage and CPI could indicate either analyst monitoring or myopic pressure. He and Tian (2013) invoke the myopic pressure argument and suggest analyst coverage presents a “dark side” by pressuring firms to reduce innovative output, an inefficient outcome. While they rule out several existing explanations for the reduction in output and isolate an analyst effect, they do not identify a specific mechanism through which analysts reduce innovative output. They ultimately conclude (without evidence) that managers innovate less after increased analyst coverage because investors impose a penalty (negative returns) on firms facing an earnings miss, resulting in a negative impact on manager reputation.

We think there is evidence for alternative explanations to their myopic pressure conclusions. First, earnings management could be a plausible driver as they suggest, but results from related literature are mixed. Irani and Oesch (2016) argue that analysts deter accruals management while encouraging REM. However, Roychowdhury, Shroff, and Verdi (2019) note that REM is lower in the presence of sophisticated investors, and Chen, Harford, and Lin (2015) find a negative causal effect of analyst coverage on REM. In fact, we find that REM is not a significant driver of analyst effects on CPI in our sample. Second, Mann (2018) notes that patents are often used for collateral, and innovative firms with lower analyst coverage may feel more compelled to develop patents in order to signal innovative progress to secure financing and avoid undervaluation that could increase takeover threats. Analyst coverage reduces debt costs and overall capital costs (Derrien and Kecskes (2013); Derrien, Kecskes, and Mansi (2016)) and could provide a substitute for the need to produce patents. Thus, the decrease in patent output reported by He and Tian (2013) might simply identify firms that no longer need to secure financing through patent filings. Clarke, Dass, and Patel (2015) find that analysts reduce innovation only in firms with patents that are not cited. This suggests that there may be frivolous patenting used for financing purposes. Therefore, analyst reductions in this type of patenting would not represent myopic pressure.[15]

[15] The concentration of our results in financially constrained firms support this argument, as these firms would face predation and takeover risks and would feel the need to file patents in order to secure financing. In untabulated results, we also find that analysts induce CPI cuts mostly among weak patent firms.

Third, patenting could increase proprietary information spillovers to competitors. Roychowdhury, Shroff, and Verdi (2019) notes that firms do not like to report information directly because of proprietary costs of disclosure. Firms may have to patent to obtain financing (Mann (2018)), but details in the patent filing can provide valuable leaks to competitors who might seek to "build upon" or "build around" the firm's patent (Glaeser (2018)). Analyst certification could replace the need for patenting to establish financial credibility. In this scenario, a decrease in patenting would not indicate a reduction in innovative output, but it would instead signal that the firm prefers to retain trade secrets in response to analyst concerns over proprietary information leakage. Finally, there could be measurement error in innovation output. Cooper, Knott, and Yang (2021) develop an RQ innovation measure that captures the output to R&D investments more accurately than patent or citation counts. They argue that traditional patent-based measures of innovation output may be inaccurate for several reasons: 1) one-half of publicly traded firms invest in R&D without ever patenting, 2) R&D spending increases with the scale of the firm but patent intensity does not, 3) RQ correlates more reliably to firm value than patent-based measures. In fact, they even replicate He and Tian (2013) using an IV model and find that while analysts do seem to induce lower patent-based innovative efficiency, they do not cause lower RQ efficiency. This supports their measurement error hypothesis. Similarly, we find an insignificant effect of analysts on patent-based measures of innovation and a positive relationship with RQ, especially in financially constrained firms. In conclusion, all of these arguments favoring monitoring. In the following sections, we present additional evidence that monitoring is driving our results and not myopic pressure.

5.2 Excluding the Impact of Real Earnings Management

While many studies find analyst coverage is negatively associated with REM (Chen, Harford, and Lin (2015); Roychowdhury, Shroff, and Verdi (2019)), the negative relationship between analyst coverage and CPI in our main model could be due to myopic pressure driving short-term earnings management, as Irani and Oesch (2016) find that analyst coverage is positively associated with REM. However, because REM must be implemented well before an earnings release (Zang (2012)), cuts in CPI are not likely to be part of a short-term repeating earnings management strategy brought about by analyst pressure to meet earnings targets. In other words, CPI cuts are more likely to reflect a longer-term shift toward precautionary savings driven by monitoring. This may be especially true for financially constrained firms, as Denis and Sibilkov (2010) find that firms facing financial constraints spend the bulk of cash raised on existing investment projects and face difficulty building cash reserves, suggesting that a repeating earnings management strategy is less likely.

We examine the impact of REM on our results by excluding firm-year observations that are likely to experience short-term manipulation of earnings. Roychowdhury (2006) finds that earnings management is more likely for firms that barely beat earnings, and they use a cutoff of 0 to 0.005 (0 to 0.5%) return on assets (ROA) to identify these firms; however, the exclusion of this range barely impacts our sample. Roychowdhury (2006) notes that earnings management also occurs above their 0.5% cutoff, although higher levels may introduce noise and contain a higher proportion of firm-years in which earnings were not manipulated. To determine a potential wider range and extend the power of our test, we generate histograms in Figure 2 of the number of firm-year observations with ROA levels just above the zero-threshold similar to Roychowdhury (2006). While we detect the spike between zero and 0.005 in Figure 2 Panel B verifying prior studies, the additional abnormal spike in an otherwise normal distribution of ROA levels that occurs around 0.03 shows that our cutoff can likely be extended higher.

In Panels A and B of Table 7 we identify firm-years that barely beat earnings as having at the match year 1) a positive ROA that meets/just beats zero dollar earnings (ROA) by up to a certain percentage, and 2) that increase ROA from the prior year up to a certain percentage. We repeat our main DiD model excluding firm-year observations with earnings ranging up to 0.005 (0.5%) of ROA levels/change following Roychowdhury (2006), and we additionally exclude firm-year observations with earnings up to 0.01, 0.03, and 0.05, respectively. Throughout all of the tests our interaction term remains positive and strongly significant, suggesting precautionary savings due to monitoring is predominant and REM due to myopic pressure is not a significant driver of our results.

5.3 Financial Constraints

We next examine whether varying levels of financial constraints drive the negative relationship between analyst coverage and CPI. We identify two primary reasons why analyst coverage is likely to reduce CPI in financially constrained firms based on prior literature. First, analyst coverage reduces information asymmetry and reveals details of weaknesses causing the firm's financial constraints. This in turn increases the likelihood of predation risk (Bernard (2016)), and predation risk raises the value of cash holdings in financially constrained firms (Bolton and Scharfstein (1990); Haushalter, Klasa, and Maxwell (2007)). Monitoring would lead responsible managers to make cuts to increase financial stability. Second, managers would seek to raise cash first from sources where the lowest costs are incurred. This is difficult in high intangibles firms which inherently have many long-term expenditures with high adjustment costs. Firms facing large financing frictions rely heavily on their cash holdings to smooth R&D (Brown and Petersen (2011)), and R&D cuts can impose high adjustment costs relative to CPI. Myopic pressure would drive cuts in any intangible regardless of adjustment costs; however, monitoring would favor cuts in CPI before R&D. Because CPI creates long-term relationship capital (Snyder (1992), Hillman and Hitt (1999)), CPI could likely be reduced without incurring significant adjustment costs in order to stabilize other investments.

For these reasons, we test the impact of analyst coverage reductions on lobbying, soft money, and PAC for varying levels of financial constraints in Table 8 similar to subsample tests in related studies (Irani and Oesch (2013, 2016)). These sections are partly motivated by Zang (2012), who examines earnings management subject to varying financial constraints, marginal tax rates, and competition.[16] Similar to Table 3, we utilize our matched sample in a DiD framework

[16] While these sections examine CPI from a cost perspective and assume a fixed benefit per CPI dollar, we also find that analyst coverage reduces CPI more in firms with lower benefits per CPI dollar. Results are available upon request.

around brokerage mergers and closures in Panel A and our full sample in Panel B. In models 1 through 4 of Panel A, we examine the impact of analyst coverage reductions on lobbying, soft money, and PAC contributions after dividing the sample at the match year into low and high quantiles by the four financial constraint variables of Hoberg and Maksimovic (2015). These measures categorize firms according to the risk of delaying their investments due to liquidity measures. Models 1 through 4 separate the sample into low and high groups by 1) their primary delay measure, 2) liquidity constrained firms that also plan to issue equity, 3) liquidity constrained firms that also plan to issue debt, and 4) liquidity constrained firms that also plan to issue private equity. The additional issuances in models 2 through 4 suggest a strong desire to alleviate liquidity problems. All four models show that analyst coverage reductions lead to reduced CPI only for firms facing high financial constraints with no significance in the low financial constraint groups. For robustness, we also divide our sample into quantiles in model 5 using the KZ index of Lamont, Polk, and Saaá-Requejo (2001). We find similar significant results only for firms facing high financial constraints, with no significance in the lower group. In Panel B, we repeat models (1) and (2) of Panel A and find similar results for the full sample. While our results mainly support monitoring, we find a positive relationship between analyst coverage and CPI in the non-financially constrained sample, suggesting some support for the certification hypothesis.

In Panel C, we examine the impact of analyst coverage reductions on CPI given varying levels of business taxes in the firm's headquarter state. We use various measures from the Panel Database on Incentives and Taxes (PDIT) from the W.E. Upjohn Institute for Employment Research, which covers 33 states and 45 industries between 1990 and 2016.[17] Model 1 divides the sample at the match year into low and high quantiles by the total state level business taxes levied on a firm, which is the sum of the three primary state business taxes a firm has to pay as follows: 1) business property taxes, 2) business sales taxes, and 3) corporate income taxes. Model 2

[17] We believe this variation in state tax levels is quasi-exogenous based on prior literature. Very few firms change their headquarter location and they are not likely to do so merely in response to changes in state taxes. It is also unlikely that firms choose their initial location simply due to state tax levels, as at the median they are only 13.7% of total income taxes and vary considerably over time (Heider and Ljungqvist (2015)).

replicates model 1 but subtracts state subsidies from the nominal total state level business tax rate. Models 3, 4, and 5 replicate model 1 but divide the sample by the business property tax subcomponent, the business sales tax subcomponent, and the state corporate income tax subcomponent, respectively. We find that analyst coverage reduction leads to lower CPI in the high business tax liability quantiles across all models. While we obtain significance in two of the low business tax quantiles, the coefficient estimates are smaller than in the high tax quantiles for each case.

5.4 Firm Competition

We also examine the impact of analyst coverage on CPI for different levels of product market competition. Competition is an alternative proxy for financial constraints, as it can lead to lower profit margins, more competition for sources of funds (Moritzen and Schandlbauer (2020)), and higher debt costs (Valta (2012)). While competition in general is considered healthy for an industry, stronger, well-funded firms can try to undercut their weaker industry rivals via product market predation (Bolton and Scharfstein (1990), Haushalter, Klasa, and Maxwell (2007); Hoberg, Phillips, and Prabhala (2014)). These studies show that predation risk leads to an increase in precautionary cash holdings, and it suggests prudent firms facing high competition may cut CPI expenditures due to monitoring given increased analyst coverage. However, it is not clear that managers would first choose to cut long-term spending to reduce the risk of predation. Because information disclosures increase predation risks (Bernard (2016)), managers may decide to reduce the number and quality of disclosures instead. Supporting this notion, Mattei and Platikanova (2017) find that greater competitive threats lower disclosure quality. They note that this also reduces analyst forecast accuracy, which would not be desirable to analysts. Monitoring suggests analysts would push back against this and favor more responsible means to reduce predation risk such as stabilizing their financial situation by cutting CPI.

We conduct this test in Table 8 Panel D utilizing various measures of industry competition in subsample tests similar to related studies (Irani and Oesch (2013, 2016)). Models (1) and (3) divide the sample at the match year into low and high quantiles using the text-based network industry classification (TNIC) measure of Hoberg and Phillips (2016) that is similar in divisions to a three-digit SIC code, while models (2) and (4) divide similarly by the TNIC industry competitor frequency. We also divide the sample by the annual frequency of firms within their census designated 4-digit NAICS industry as identified by the Small Business Administration based on similar measures in Bailey and Thomas (2017) and Billett, Garfinkel, and Yu (2017). Keil (2017) finds that census-based industry data is a better measure of competition than Compustat measures because it also includes private firms.

In all five models, we find positive and statistical significance in the high competition quantile. While we also find positive significance in the low competition quantile of model (4), the magnitude of the coefficient is slightly smaller. These results confirm our financial constraints findings and provide support for the monitoring hypothesis.

5.5 Impact of Analysts on Innovative Efficiency

In this section, we examine the impact of analyst coverage on overall innovative efficiency in financially constrained firms 1) to validate our prior financial constraint support for monitoring and 2) to provide further evidence for monitoring based on the efficiency of innovative output. Cooper, Knott, and Yang (2021) directly question the myopic pressure conclusions of He and Tian (2013) and suggest analysts don't actually reduce innovation. They provide evidence using their RQ measure of innovative output.

In Table 9 Panel A we find that analyst coverage is positively related to RQ innovative efficiency and the Bartlett and Partnoy (2020) measure of Tobin's Q. We use the full sample for these tests, as Cooper, Knott, and Yang (2021) note that an advantage of RQ is greater coverage throughout most firms in the Compustat universe. Models (2) and (3) show that the analyst impact on RQ is concentrated in firm-year with CPI spending, further validating our monitoring hypothesis. Although we do not find a negative relationship with patent-based innovation measures based on Hirshleifer, Hsu, and Li (2013) following Cooper, Knott, and Yang (2021), our insignificant results in models (4) and (5) are consistent with the argument that patenting drops as analyst coverage increases and provides a certification benefit.[18] In Panel B we find a positive and significant relationship within the highest quartile of financially constrained firms, consistent with our argument that financially constrained firms will be more impacted by a need to stabilize future spending needs. Panels C and D provide further robustness to Panel B (and to Table 8) and find that analyst coverage is positively related to RQ innovative efficiency and Bartlett and Partnoy (2020) Tobin's Q within the top quantile of alternative financial constraint measures. These measures are defined by 1) the total state business tax measure of the Panel Database on Incentives and Taxes (PDIT) from the W.E. Upjohn Institute and 2) the Herfindahl index constructed from the text-based network industry classification (TNIC) of Hoberg and Phillips (2016). The lower quantiles are insignificant except within Panel D Model (3), which has a smaller coefficient than Model (4). Taken together, these results provide additional robustness for our financial constraints findings on monitoring, and they provide support for monitoring based on future firm innovative efficiency and valuation.

6 Conclusion

We examine the impact of sell-side analyst coverage on intangible investments (as proxied by corporate political investments (CPI)) and analyze two competing hypotheses: monitoring and certification. The monitoring hypothesis argues that analysts cause reductions in CPI as they draw attention to CPI agency costs and financial shortcomings. These might increase predation and takeover risks, forcing managers to cut wasteful spending to build precautionary savings. The net effect of improved financial stability would be beneficial to the firm long-term. In contrast, the certification hypothesis argues that increasing analyst coverage provides enhanced credibility to a firm. This would improve financial stability and provide a substitute for voluntary disclosures

[18] Innovative investment may take more than one year to generate patent output, biasing our findings. However, in untabulated tests we repeat Panel A and examine the 3-year period post-brokerage merger/closure and find similar results.

used previously to build financial credibility. Together, this would lead to improved financials coupled with lower firm disclosures, which could provide cover to management to increase agency-related intangible spending like CPI.

We find that analyst coverage is negatively associated with CPI, supporting the monitoring hypothesis in our first battery of tests. We use a wide variety of CPI measures (lobbying, soft money, PAC contributions, and number of candidates supported by a PAC) and identification strategies (brokerage mergers/closures, two-stage least squares using expected analyst coverage, and dynamic panel models). We also employ a wide variety of robustness tests controlling for additional factors that may impact analyst coverage effects on CPI and find that our results hold.

We then consider an alternative hypothesis to monitoring. The myopic pressure hypothesis argues that analysts exert pressure on managers to meet short-term earnings targets at the expense of long-term investment and value creation. Both the monitoring and myopic pressure hypotheses are consistent with a negative relationship between CPI and analyst coverage. To disentangle the two hypotheses, we first present extensive literature providing support for monitoring over myopic pressure. Second, we find that real earnings management (REM) does not drive analyst effects on CPI. This is relevant because the myopic pressure argument predicates on analysts pressuring management to favor short-term outcomes. Third, we find that analysts are negatively associated with CPI in financially constrained firms. This result supports monitoring primarily because 1) analyst information exposes firm failures and weaknesses, 2) these weaknesses increase predation and takeover risks, and 3) firms cut wasteful spending to build cash reserves to alleviate these risks. In addition, CPI is less susceptible to adjustment costs compared to R&D because of the relationships it builds, thus it can be reduced without harming the firm when cash needs are high. We find similar results when examining competition as an alternative measure of financial constraints. Finally, the literature documents a negative relationship between analyst coverage and patents, an intangible asset. However, this relationship might be spurious because both facilitate financing. Patents act as collateral (Mann (2018)), and analyst coverage reduces debt and overall capital costs. In addition, Cooper, Knott, and Yang (2021) present evidence that patent-based measures may be inaccurate. We find a positive relationship between analyst coverage and 1) the RQ innovative efficiency measure of Cooper, Knott, and Yang (2021) and 2) firm valuation. Overall, our findings support monitoring over myopia.

In sum, our study provides a new perspective on the extensive debate over how analyst coverage affects high-intangible firms by uniquely considering an intangible often representing agency costs. In addition, given the Supreme Court verdict on *Citizens United* in 2010 which enables additional growth in CPI usage by firms, the importance of studying analyst effects on CPI has become even more relevant.

References

Aboody, David, and Baruch Lev. "Information asymmetry, R&D, and insider gains." *The journal of Finance* 55.6 (2000): 2747-2766.

Anderson, Mark C., Rajiv D. Banker, and Surya N. Janakiraman, 2003, Are Selling, General, and Administrative Costs “Sticky”?, *Journal of Accounting Research* 41, 47–63.

Bailey, James B., and Diana W. Thomas, 2017, Regulating away competition: the effect of regulation on entrepreneurship and employment, *Journal of Regulatory Economics* 52, 237–254.

Barron, Orie E., Donal Byard, Charles Kile, and Edward J. Riedl, 2002, High-Technology Intangibles and Analysts’ Forecasts, *Journal of Accounting Research* 40, 289–312.

Barth, Mary E., Ron Kasznik, and Maureen F. McNichols, 2001, Analyst Coverage and Intangible Assets, *Journal of Accounting Research* 39, 1–34.

Bartlett, Robert, and Frank Partnoy. "The Misuse of Tobin's q." *Vand. L. Rev.* 73 (2020): 353.

Bebchuk, Lucian Arye, and Robert J. Jackson, 2012, Shining Light on Corporate Political Spending, *Georgetown Law Journal* 101, 923.

Bernard, Darren, 2016, Is the risk of product market predation a cost of disclosure?, *Journal of Accounting and Economics* 62, 305–325.

Bertrand, Marianne, Francis Kramarz, Antoinette Schoar, and David Thesmar. "The cost of political connections." *Review of Finance* 22, no. 3 (2018): 849-876.

Billett, Matthew T., Jon A. Garfinkel, and Miaomiao Yu, 2017, The effect of asymmetric information on product market outcomes, *Journal of Financial Economics* 123, 357–376.

Bolton, Patrick, and David S. Scharfstein, 1990, A theory of predation based on agency problems in financial contracting, *The American economic review*, 93–106.

Borisov, Alexander, Eitan Goldman, and Nandini Gupta. "The corporate value of (corrupt) lobbying." *The Review of Financial Studies* 29.4 (2016): 1039-1071.

Bourveau, Thomas, Yun Lou, and Rencheng Wang. "Shareholder litigation and corporate disclosure: Evidence from derivative lawsuits." *Journal of Accounting Research* 56.3 (2018): 797-842.

Brown, James R., and Bruce C. Petersen, 2011, Cash holdings and R&D smoothing, *Journal of Corporate Finance* 17, 694–709.

Cao, Zhiyan, Guy D. Fernando, Arindam Tripathy, and Arun Upadhyay, 2018, The economics of corporate lobbying, *Journal of Corporate Finance* 49, 54–80.

Cao, Xiaping, Xiaofei Pan, Meijun Qian, and Gary Gang Tian. "Political capital and CEO entrenchment: Evidence from CEO turnover in Chinese non-SOEs." *Journal of Corporate Finance* 42 (2017): 1-14.

Chaney, Paul K., Mara Faccio, and David Parsley. "The quality of accounting information in politically connected firms." *Journal of Accounting and Economics* 51.1-2 (2011): 58-76.

Chen, Tao, Jarrad Harford, and Chen Lin, 2015, Do analysts matter for governance? Evidence from natural experiments, *Journal of Financial Economics* 115, 383–410.

Clarke, Jonathan, Nishant Dass, and Ajay Patel, 2015, When Do Analysts Impede Innovation?*, *SSRN Electronic Journal*.

Coates, John C., 2012, *Citizens United* and Corporate Politics, Governance, and Value, *Journal of Empirical Legal Studies* 9, 657–696.

Cooper, Michael J., Huseyin Gulen, and Alexei V. Ovtchinnikov, 2010, Corporate Political Contributions and Stock Returns, *The Journal of Finance* 65, 687–724.

Cooper, Michael, Anne Marie Knott, and Wenhao Yang. "RQ innovative efficiency and firm value." *Journal of Financial and Quantitative Analysis* (2021): 1-46.

Corrado, Carol A, and Charles R Hulten, 2010, How Do You Measure a “Technological Revolution”?, *American Economic Review* 100, 99–104.

Corrado, Carol, Jonathan Haskel, Cecilia Jona-Lasinio, and Massimiliano Iommi, 2018, Intangible investment in the EU and US before and since the Great Recession and its contribution to productivity growth, *Journal of Infrastructure, Policy and Development* 2, 11.

Cremers, K. J. Martijn, and Vinay B. Nair, 2005, Governance Mechanisms and Equity Prices, *The Journal of Finance* 60, 2859–2894.

Daines, Robert, and Michael Klausner, 2001, Do IPO Charters Maximize Firm Value? Antitakeover Protection in IPOs, *Journal of Law, Economics, and Organization* 17, 83–120.

Duchin, Ran, and Denis Sosyura. "The politics of government investment." *Journal of Financial Economics* 106.1 (2012): 24-48.

De Jong, Abe, Gerard Mertens, Marieke van der Poel, and Ronald van Dijk, 2013, How does earnings management influence investor’s perceptions of firm value? Survey evidence from financial analysts, *Review of Accounting Studies*.

Denis, David J., and Valeriy Sibilkov, 2010, Financial Constraints, Investment, and the Value of Cash Holdings, *Review of Financial Studies* 23, 247–269.

Derrien, François, and Ambrus Kecskés, 2013, The Real Effects of Financial Shocks: Evidence from Exogenous Changes in Analyst Coverage, *The Journal of Finance* 68, 1407–1440.

Derrien, François, Ambrus Kecskés, and Sattar A. Mansi. "Information asymmetry, the cost of debt, and credit events: Evidence from quasi-random analyst disappearances." *Journal of Corporate Finance* 39 (2016): 295-311.

Duchin, Ran, and Denis Sosyura. "The politics of government investment." *Journal of Financial Economics* 106.1 (2012): 24-48.

Fan, J.P., Wong, T.J. and Zhang, T., 2007. Politically connected CEOs, corporate governance, and Post-IPO performance of China's newly partially privatized firms. *Journal of Financial Economics*, 84(2), pp.330-357.

Francis, Jennifer, Donna Philbrick, and Katherine Schipper, 1994, Shareholder Litigation and Corporate Disclosures, *Journal of Accounting Research* 32, 137.

Glaeser, Stephen. "The effects of proprietary information on corporate disclosure and transparency: Evidence from trade secrets." *Journal of Accounting and Economics* 66.1 (2018): 163-193.

Gompers, Paul, Joy Ishii, and Andrew Metrick, 2003, Corporate Governance and Equity Prices, *The Quarterly Journal of Economics* 118, 107–156.

Haushalter, D, S Klasa, and W Maxwell, 2007, The influence of product market dynamics on a firm's cash holdings and hedging behavior, *Journal of Financial Economics* 84, 797–825.

He, Jie (Jack), and Xuan Tian, 2013, The dark side of analyst coverage: The case of innovation, *Journal of Financial Economics* 109, 856–878.

Heese, Khan, and Ramanna (2017) Heese, Jonas, Mozaffar Khan, and Karthik Ramanna. "Is the SEC captured? Evidence from comment-letter reviews." *Journal of Accounting and Economics* 64.1 (2017): 98-122.

Heider, Florian, and Alexander Ljungqvist, 2015, As certain as debt and taxes: Estimating the tax sensitivity of leverage from state tax changes, *Journal of Financial Economics* 118, 684–712.

Hill, Matthew D., G. Wayne Kelly, G. Brandon Lockhart, and Robert A. Van Ness, 2013, Determinants and Effects of Corporate Lobbying, *Financial Management* 42, 931–957.

Hillman, Amy J., and Michael A. Hitt, 1999, Corporate Political Strategy Formulation: A Model of Approach, Participation, and Strategy Decisions, *Academy of Management Review* 24, 825–842.

Hirshleifer, David, Angie Low, and Siew Hong Teoh, 2012, Are Overconfident CEOs Better Innovators?, *The Journal of Finance* 67, 1457–1498.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li. "Innovative efficiency and stock returns." *Journal of financial economics* 107.3 (2013): 632-654.

Hoberg, Gerard, and Vojislav Maksimovic, 2015, Redefining Financial Constraints: A Text-Based Analysis, *The Review of Financial Studies* 28, 1312–1352.

Hoberg, Gerard, and Gordon Phillips, 2016, Text-Based Network Industries and Endogenous Product Differentiation, *Journal of Political Economy* 124, 1423–1465.

Hoberg, Gerard, Gordon Phillips, and Nagpurnanand Prabhala, 2014, Product Market Threats, Payouts, and Financial Flexibility, *The Journal of Finance* 69, 293–324.

Hong, H., and M. Kacperczyk, 2010, Competition and Bias, *The Quarterly Journal of Economics* 125, 1683–1725.

Irani, Rustom M., and David Oesch, 2013, Monitoring and corporate disclosure: Evidence from a natural experiment, *Journal of Financial Economics* 109, 398–418.

Irani, Rustom M., and David Oesch, 2016, Analyst Coverage and Real Earnings Management: Quasi-Experimental Evidence, *Journal of Financial and Quantitative Analysis* 51, 589–627.

Jagolinzer, Alan D., David F. Larcker, Gaizka Ormazabal, and Daniel J. Taylor. "Political connections and the informativeness of insider trades." *The Journal of Finance* 75, no. 4 (2020): 1833-1876.

Jiang, Danling, Alok Kumar, and Kelvin K. F. Law, 2016, Political contributions and analyst behavior, *Review of Accounting Studies* 21, 37–88.

Keil, Jan, 2017, The trouble with approximating industry concentration from Compustat, *Journal of Corporate Finance* 45, 467–479.

Kelly, Bryan, and Alexander Ljungqvist, 2012, Testing Asymmetric-Information Asset Pricing Models, *Review of Financial Studies* 25, 1366–1413.

Lamont, Owen, Christopher Polk, and Jesús Saaá-Requejo, 2001, Financial Constraints and Stock Returns, *Review of Financial Studies* 14, 529–554.

Leland, Hayne E., and David H. Pyle. "Informational asymmetries, financial structure, and financial intermediation." *The journal of Finance* 32.2 (1977): 371-387.

Li, Feng, 2008, Annual report readability, current earnings, and earnings persistence, *Journal of Accounting and Economics* 45, 221–247.

Loughran, Tim, and Bill McDonald, 2011, When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks, *The Journal of Finance* 66, 35–65.

Mann, William. "Creditor rights and innovation: Evidence from patent collateral." *Journal of Financial Economics* 130.1 (2018): 25-47.

Mattei, Marco Maria, and Petya Platikanova, 2017, Do product market threats affect analyst forecast precision?, *Review of Accounting Studies* 22, 1628–1665.

Moritzen, Mark Raun, and Alexander Schandlbauer, 2020, The impact of competition and time-to-finance on corporate cash holdings, *Journal of Corporate Finance* 65, 101502.

O'Connor, Matthew, and Matthew Rafferty, 2012, Corporate Governance and Innovation, *Journal of Financial and Quantitative Analysis* 47, 397–413.

Palmon, Dan, and Ari Yezegel, 2012, R&D Intensity and the Value of Analysts' Recommendations, *Contemporary Accounting Research* 29, 621–654.

Rawson, Caleb, 2021, Manager perception and proprietary investment disclosure, *Review of Accounting Studies*.

Roychowdhury, Sugata, 2006, Earnings management through real activities manipulation, *Journal of Accounting and Economics* 42, 335–370.

Roychowdhury, Sugata, Nemit Shroff, and Rodrigo S. Verdi, 2019, The effects of financial reporting and disclosure on corporate investment: A review, *Journal of Accounting and Economics* 68, 101246.

Snyder, James M., 1992, Long-Term Investing in Politicians; Or, Give Early, Give Often, *The Journal of Law and Economics* 35, 15–43.

Strickland, James. "America's crowded statehouses: measuring and explaining lobbying in the US states." *State Politics & Policy Quarterly* 19.3 (2019): 351-374.

Valta, Philip, 2012, Competition and the cost of debt, *Journal of Financial Economics* 105, 661–682.

Wintoki, M. Babajide, James S. Linck, and Jeffry M. Netter, 2012, Endogeneity and the dynamics of internal corporate governance, *Journal of Financial Economics* 105, 581–606.

Yu, Fang (Frank), 2008, Analyst coverage and earnings management, *Journal of Financial Economics* 88, 245–271.

Yu, Frank, and Xiaoyun Yu, 2011, Corporate Lobbying and Fraud Detection, *Journal of Financial and Quantitative Analysis* 46, 1865–1891.

Zang, Amy Y., 2012, Evidence on the Trade-Off between Real Activities Manipulation and Accrual-Based Earnings Management, *The Accounting Review* 87, 675–703.

Appendix: Variable Descriptions

Political Contribution Variables	
PAC	Campaign contributions made by a firm's political action committee during the most recent election cycle. *(Source: Center for Responsive Politics)*
Lobbying	Lobbying expenditures by the corporation over a given fiscal year. Dataset begins in 1998 after the Lobbying Disclosure Act of 1995 required these expenditures to be publicly reported. *(Source: Center for Responsive Politics)*
Soft Money	Contributions by the corporation to political parties (not specific candidates) by fiscal year. Dataset ends in 2002 after its ban by the Bipartisan Campaign Reform Act (BCRA) of 2002. *(Source: Center for Responsive Politics)*
Number of candidates	Number of candidates supported by a firm with PAC contributions during the most recent election cycle. *(Source: Center for Responsive Politics)*

Analyst Coverage Variables	
Coverage	Arithmetic mean of the monthly earnings forecasts for firm *i* over the fiscal year. *(Source: Institutional Brokers' Estimate System (IBES) Summary File)*
Broker Event	Indicator variable equal to one if a reduction in analyst coverage occurred during the fiscal year due to either 1) a merger between brokerages simultaneously providing analyst coverage for the firm, or 2) the closure of a brokerage providing analyst coverage for the firm; zero otherwise. *(Source: Institutional Brokers' Estimate System (IBES), Broker Translation File)*
Expected Coverage	Variation in analyst coverage by fiscal year resulting from a change in brokerage house size (constructed following Yu (2008); He, Tian (2013)). *(Source: Institutional Brokers' Estimate System (IBES) Summary File)*
All-Star Analyst	Equals 1 if at least one all-star analyst (as identified in *Institutional Investors*) covers the firm in the year before and after the brokerage merger or closure; zero otherwise. *(Source: Institutional Investors magazine)*
Forecast Dispersion	Standard deviation of analyst estimates per fiscal year scaled by the absolute value of the mean analyst estimates per fiscal year. *(Source: Institutional Brokers' Estimate System (IBES))*
Forecast Error	(Mean analyst estimate per fiscal year minus actual earnings) / (Absolute value of mean analyst estimate per fiscal year). *(Source: Institutional Brokers' Estimate System (IBES))*

Firm and Manager Characteristics	
Total Assets	Total book value of assets (at) ($ millions) measured at the end of fiscal year t. *(Source: Compustat)*
Leverage	(Long-term debt (dltt) plus debt in current liabilities(dlc)) / Total assets (at)) measured at the end of fiscal year t. *(Source: Compustat)*
ROA	(Net income (ni)/Total assets (at)) measured at the end of fiscal year t. *(Source: Compustat)*
Capex	(Capital expenditures (capx)/ Total assets(at)) measured at the end of fiscal year t. *(Source: Compustat)*
Volatility	Standard deviation of weekly (Thursday through the following Wednesday) market excess returns (over the equal weight CRSP return portfolio) during the prior rolling 1-year period measured at the end of fiscal year t. Two months prior data is required or the variable is set to missing. *(Source: CRSP)*
Stock Turnover	Average of (monthly volume (vol) / Shares outstanding (shrout)) per fiscal year measured at the end of fiscal year t. *(Source: CRSP)*
Firm Age	Age since the IPO in years measured at the end of fiscal year t. *(Source: CRSP, Compustat, SDC, Jay Ritter's website)*

High CEO Tenure	Indicator variable equal to one if the number of years as CEO of the firm (measured at the end of fiscal year t) is above the sample median; zero otherwise. *(Source: Execucomp)*
CEO Ownership	Percentage of total shares held by the CEO measured at the end of fiscal year t. *(Source: Thompson Reuters and Execucomp)*
CEO Age	Age of the CEO measured at the end of fiscal year t. *(Source: ExecuComp)*
Indep Directors	(Number of independent (outside) directors/Total board members) measured at the end of fiscal year t. *(Source: ISS Riskmetrics)*
Inst Holdings	(Institutional shares held / Total shares outstanding) during fiscal year t, averaged over four quarters. *(Source: Thompson Reuters 13F Filings)*
$Return_{t-1}$	Lagged 12-month returns including dividends (ret) measured at the end of fiscal year t. *(Source: CRSP)*
M/B Ratio	Market capitalization of the firm ((prc*shrout) / total assets (at)) measured at the end of fiscal year t. *(Source: CRSP, Compustat)*
Market Cap	Market capitalization defined as (price (prc) * shares outstanding (shrout)) measured at the end of fiscal year t. *(Source: CRSP)*
Non-Missing Items	Number of non-missing items. *(Source: Compustat)*
Special Items	Amount of special items scaled by the book value of assets. *(Source: Compustat)*
Business Segments	Number of reported business segments. *(Source: Compustat Segments - historical)*
Delaware Incorp	Equals 1 if the state in which the firm is incorporated is Delaware; zero otherwise. *(Source: Compustat).*

Miscellaneous Variables	
Gross File Size	Gross digital file size (kilobyte) in 10-k or 10-k40 disclosures. *(Source: Loughran and McDonald (2011))*
Fog Index	Readability of the 10-k using the Gunning Fog Index Readability Formula. *(Source: Li (2008))*
In-House Lobbyist	Equals 1 if the firm employs a lobbyist in the same state of the firm headquarters; zero if the firm employs an external lobbyist in Washington, D.C., in other states, or has no employed lobbyist. *(Source: Washington Representatives Study (Organized Interests in Washington Politics) - 1981, 1991, 2001, 2006, 2011. Inter-university Consortium for Political and Social Research)*
Delay	Delaycon financial constraints measure from Hoberg and Maksimovic (2014). Firms with higher values are more similar to a set of firms known to be at risk of delaying their investments due to issues with liquidity. *(Source: Hoberg and Maksimovic Data Library)*
Equity Delay	Equitydelaycon financial constraints measure from Hoberg and Maksimovic (2014). Firms with higher values are more similar to a set of firms that (A) are at risk of delaying their investments due to liquidity issues and (B) that indicate plans to issue equity. *(Source: Hoberg and Maksimovic Data Library)*
Debt Delay	Debtdelaycon financial constraints measure from Hoberg and Maksimovic (2014). Firms with higher values are more similar to a set of firms that (A) are at risk of delaying their investments due to liquidity issues and (B) that indicate plans to issue debt. *(Source: Hoberg and Maksimovic Data Library)*
Private Delay	Privdelaycon financial constraints measure from Hoberg and Maksimovic (2014). Firms with higher values are more similar to a set of firms that (A) are at risk of delaying their investments due to liquidity issues and (B) that indicate plans to issue private placements. *(Source: Hoberg and Maksimovic Data Library)*
KZ Index	Kaplan and Zingales financial constraints index constructed following Lamont, Polk, and Saa-Requejo (2001) and calculated as KZ = 0.283Q - 1.002CF/K + 3.139Debt/Capital - 39.368Div/K - 1.315Cash/K. Q = total assets + (fiscal year end price x common shares outstanding) - common equity - deferred tax / property, plant, and equipment. CF/K = (income before extraordinary items + depreciation) / property, plant and equipment$)_{t-1}$. Debt/Capital = (long-term debt + debt in current liabilities) / (long-term debt + debt in current liabilities + stockholder's equity). Div/K = (dividends common + dividends preferred) / property, plant and equipment$)_{t-1}$. Cash/K = cash holdings and short-term investments / property, plant and equipment$)_{t-1}$. *(Source: Compustat)*

Tot (Net) Bus Tax	Total state business tax liability including imports and exports (net of imports and exports). Includes both import and export industries for the state and adds business related property tax, sales tax, and corporate income tax. *(Source: Panel Database on Incentives and Taxes (PDIT), W.E. Upjohn Institute for Employment Research)*
Bus Prop Tax	State tax liability from business-related property taxes. *(Source: Panel Database on Incentives and Taxes (PDIT), W.E. Upjohn Institute for Employment Research)*
Bus Sales Tax	State tax liability from business-related sales tax. *(Source: Panel Database on Incentives and Taxes (PDIT), W.E. Upjohn Institute for Employment Research)*
Corp Income Tax	State tax liability from business-related corporate income tax. *(Source: Panel Database on Incentives and Taxes (PDIT), W.E. Upjohn Institute for Employment Research)*
Hoberg and Phillips Herfindahl	Herfindahl index following Hoberg and Phillips (2010, 2016), ranging from 0 to 10,000. Uses fixed industry classifications (FIC) based on icode300 or text-based network industry classifications (TNIC). *(Source: Hoberg and Phillips Data Library)*
Competitor Frequency	Count of total firms in an FIC or TNIC industry following Hoberg and Phillips (2010, 2016). *(Source: Hoberg and Phillips Data Library)*
Census Ind Comps	Number of public and private firms (total competitors) per fiscal year and 4 digit NAICS code. *(Source: Census Bureau data from the Small Business Administration database)*
GIM Index	Shareholder rights index constructed following Gompers, Ishii, and Metrick (2003). *(Source: ISS Riskmetrics)*
Innovative Industries	An indicator variable equal to one for the top half of industries by their innovative activity following Hirshleifer, Low, and Teoh (2012).
FPS Industries	Equals 1 if the firm is in a more litigious industry; zero otherwise. *(Source: Francis, Philbrik, and Schipper (1994))*
Battle v Partisan	Partitions by the Citizen Ideology measure per state and year, which ranges from 0 (very conservative) to 100 (very liberal). Equals 1 if in middle two quartiles (battleground), zero if top or bottom quartile (partisan). *(Source: Berry et al. (2010); Richard Fording's website)*
RQ Innov Effic	Research Quotient of the output elasticity of R&D, defined as the percent increase in revenue from a 1% increase in R&D. *(Source: Cooper, Knott, and Yang (2021)).*
HHL Innov Effic - Patents	Log of firm patent filing count scaled by R&D spending in the current and prior four lagged years and depreciated 20% per year. *(Source: Hirshleifer, Hsu, and Li (2013)).*
HHL Innov Effic - Citations	Log of firm citation count scaled by the deflate method and tech categories following Hall, Jaffe, and Trajtenberg (2001), then scaled by R&D spending the current and prior four lagged years depreciated 20% per year. *(Source: Hirshleifer, Hsu, and Li (2013)).*
B&P Tobin's Q	Log of the book value of assets plus the market value of equity minus the book value of equity and deferred taxes. *(Source: Bartlett and Partnoy (2020)).*

Fig.1. CPI Trends Around a Brokerage Merger/Closure Event

This figure shows corporate political investment trends in the years before and after a brokerage merger/closure event in our matched sample. CPI spending in our treatment sample net of the control group is plotted for 1) the two years before the event year and 2) the event year and the year after the event.

Avg Lobbying, Soft Money, and PAC by Event-Year (Treatment - Control)

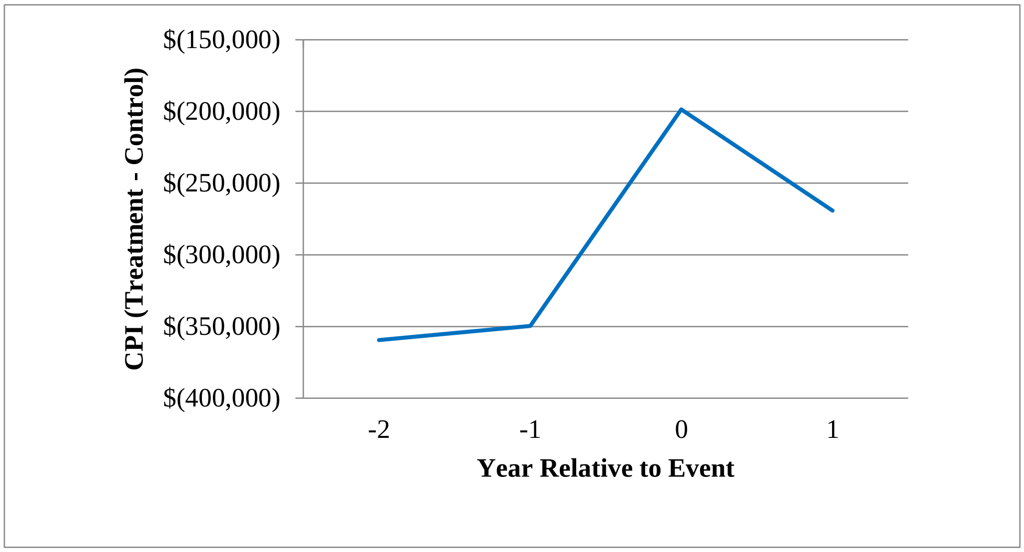
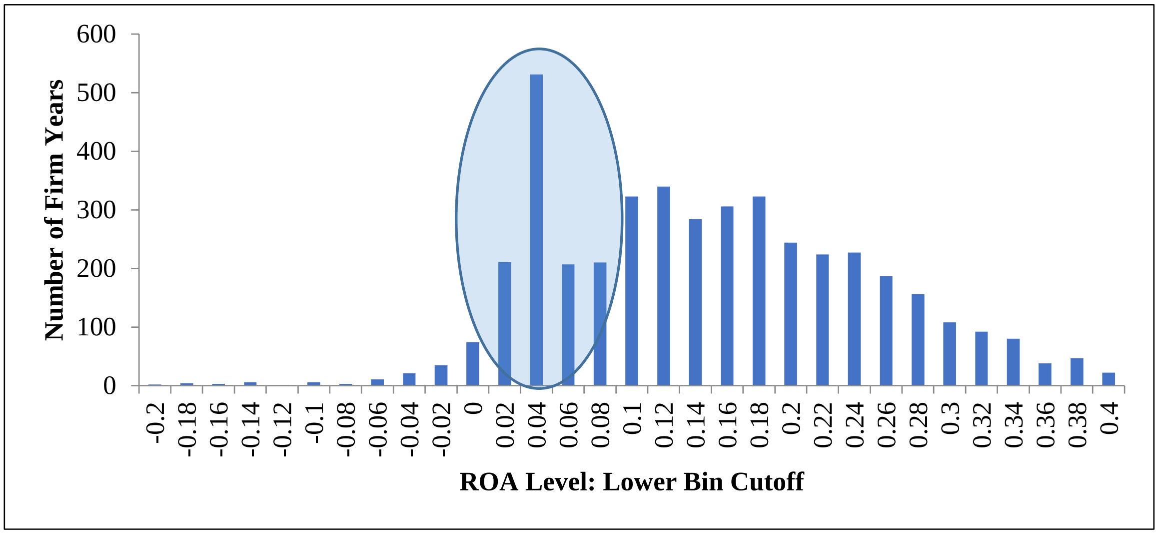


Fig. 2. Earnings Management Around the Zero Threshold

This figure shows histograms of the number of firm years per ROA earnings interval over the period 2001-2010. Panel A presents intervals with a width of 0.02, while Panel B presents intervals with a width of 0.005. X-axis labels represent the ROA level at the lower end of each interval (bin). The figure is built from our full matched sample containing 4,437 observations (includes observations missing CPI values) and is truncated at both ends.

Panel A: Wide Earnings Management Range (-0.2 to 0.4)



Panel B: Narrow Earnings Management Range (-.05 to 0.1)

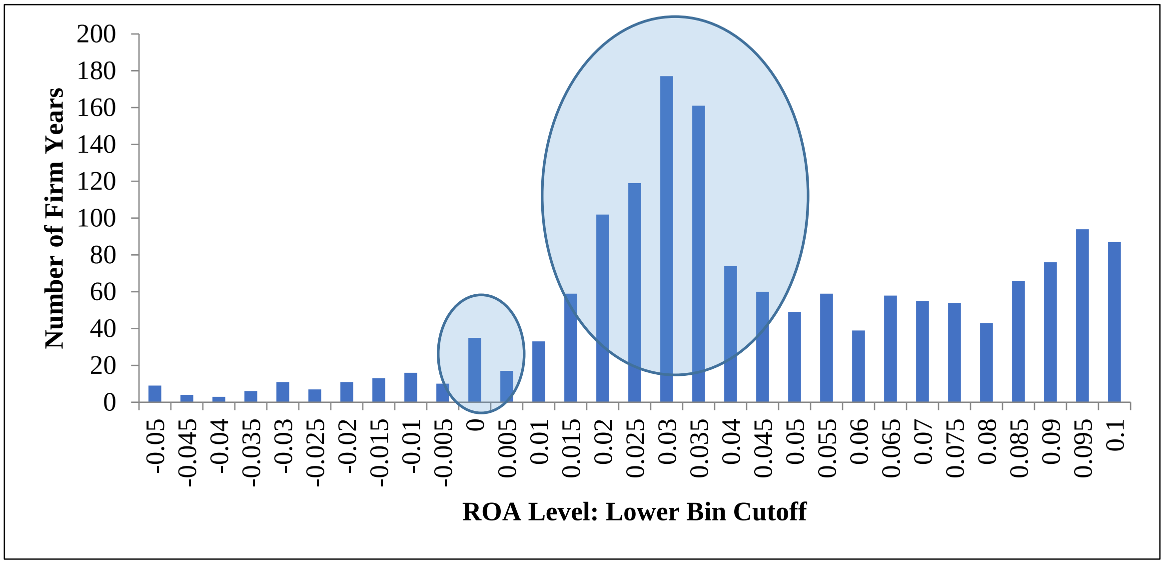


Table 1. Firm Level Descriptive Statistics

This table reports summary statistics for various firm-year variables from fiscal years 1996 to 2010. Appendix A reports definitions of all variables.

Variables	N	Mean	Std. Dev	25% Perc.	Median	75% Perc.
PAC ($)	12,813	24,503	84,466	0	0	10,500
PAC, Lobbying, Soft Money ($)	11,795	135,780	965,626	0	0	12,000
Number of candidates	12,732	18.34	56.69	0	0	8
Analyst Coverage	12,813	10.44	7.290	5	9	15
Total Assets ($ millions)	12,813	7,124	13,191	636.0	1,802	6,259
Leverage	12,813	0.224	0.192	0.055	0.210	0.341
Market to Book	12,813	1.497	0.829	0.827	1.227	1.987
ROA	12,813	0.141	0.094	0.089	0.135	0.191
Capex	12,813	0.054	0.055	0.019	0.038	0.069
Volatility	12,813	0.312	0.190	0.155	0.266	0.433
Firm Age	12,813	27.96	16.89	13	23	43
High CEO Tenure	10,079	0.490	0.500	0	0	1
CEO Age	10,079	56.02	6.992	51	56	60
CEO Ownership	10,079	0.021	0.056	0.001	0.003	0.112
Independent Directors	10,079	0.704	0.163	0.600	0.733	0.833
Institutional Holdings	10,079	0.681	0.257	0.566	0.727	0.853

Table 2. Analyst Coverage and Political Contributions

This table shows the results of OLS regressions estimating the impact of analyst coverage on various proxies for firm political contributions. Models (1), (3), (4), and (6) utilize the sample of firms from 1996 to 2010. Models (2), and (5) utilize the sample of firms from 1998 to 2010. The dependent variable in Models (1) and (4) is the natural logarithm of one plus the dollar amount of campaign donations made by a firm's PAC during the most recent election cycle. The dependent variable in Models (2) and (5) is the natural logarithm of one plus the dollar amount of lobbying, soft money, and PAC contributions during the most recent election cycle. The dependent variable in Models (3) and (6) is the natural logarithm of one plus the number of candidates supported by a firm over a given fiscal year. All models include year and firm fixed effects. Definitions of all variables are reported in Appendix A. Standard errors are clustered at the firm level and t-statistics are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

	Dependent Variable					
	PAC_{t+1}	$(PAC \& LSM)_{t+1}$	Number of $candidates_{t+1}$	PAC_{t+1}	$(PAC \& LSM)_{t+1}$	Number of $candidates_{t+1}$
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log Analyst Coverage	-0.254***	-0.187***	-0.066***	-0.224**	-0.177**	-0.051**
	(-2.83)	(-2.68)	(-2.71)	(-2.26)	(-2.21)	(-2.33)
Log Total Assets	0.622***	0.478***	0.211***	0.748***	0.624***	0.249***
	(5.15)	(3.86)	(4.94)	(4.94)	(4.04)	(4.70)
Leverage	-0.485*	-0.558**	-0.247**	-0.767**	-0.940**	-0.402***
	(-1.75)	(-1.98)	(-2.45)	(-2.06)	(-2.52)	(-3.05)
Market to Book	0.038	0.029	-0.006	0.006	-0.007	-0.027
	(0.59)	(0.38)	(-0.26)	(0.07)	(-0.07)	(-0.97)
ROA	0.306	-0.074	0.073	0.732	0.176	0.193
	(0.56)	(-0.13)	(0.47)	(1.05)	(0.24)	(0.93)
Capex	1.090	1.116	0.361	0.192	0.179	0.100
	(1.34)	(1.38)	(1.35)	(0.21)	(0.19)	(0.33)
Volatility	-0.369**	-0.281	-0.132**	-0.319*	-0.140	-0.131**
	(-2.19)	(-1.54)	(-2.36)	(-1.66)	(-0.66)	(-1.99)
Log Firm Age	-0.079	0.826**	-0.183	-0.140	0.775*	-0.209
	(-0.22)	(2.24)	(-1.42)	(-0.31)	(1.82)	(-1.30)
High CEO Tenure				-0.001	0.003	0.039
				(-0.01)	(0.03)	(1.24)
Log CEO Age				0.026	0.267	0.009
				(0.12)	(1.23)	(0.12)
CEO Ownership				0.014	0.019**	0.004*
				(1.42)	(2.10)	(1.72)
Independent Directors				0.392	0.167	0.091
				(1.09)	(0.42)	(0.69)
Institutional Holdings				-0.396	0.199	-0.199
				(-1.13)	(0.59)	(-1.61)
Constant	-0.755	-2.857*	0.226	-1.416	-4.943**	0.156
	(-0.50)	(-1.85)	(0.42)	(-0.66)	(-2.31)	(0.21)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,813	11,795	12,732	10,079	9,235	10,015
R-squared	0.0425	0.0421	0.0415	0.0481	0.0498	0.0481

Table 3. Causal Effect of Analyst Coverage on Political Contributions: Difference in Differences Models

This table shows the effect of a quasi-exogenous reduction in analyst coverage on lobbying, soft money, and PAC contributions in a difference in difference (DiD) estimation using brokerage merger or closure events. Panel A shows full sample DiD regression results for the interaction term between a) the occurrence of a merger or closure event and b) the year the event takes place. The dependent variable includes either a) PAC or b) Lobbying and soft money (LSM) contributions. Various control variables relating to the occurrence of a brokerage merger or closure event are also added for robustness. C1 represents control variables for market capitalization, book-to-market ratio, and past one-year returns following Hong and Kacperczyk (2010). For the LSM regressions including C1 we show the results for varying levels of analyst coverage. Panels B through E utilize a 2001-2007 event year (1998-2010 total year) sample matched between political contributions and brokerage related variables over a seven-year window (from -3 to +3 years around a brokerage merger or closure event). Brokerage closure treatment firms are those covered by a closing brokerage in which analyst coverage drops by one. Brokerage merger treatment firms are those covered by both the target and acquiring brokerage and in which analyst coverage drops by one. The portfolio of control firms is created by a 4 to 1 matching of candidate control firms to treatment firms by the closest analyst coverage in the matching year on terciles of a) market capitalization, b) book-to-market, c) average monthly stock returns, and d) number of analyst following in the year prior to the event (t-1) as per Hong and Kacperczyk (2010). Panel B reports post-match univariate differences in means between the treatment and control sample. Gross file size is in millions. Panel C reports the matched sample DiD regression results with a dependent variable consisting of the cumulative sum of political contributions during the event year and three post event years of a) lobbying, soft money, and PAC contributions, b) Lobbying and soft money contributions only, and c) PAC contributions only. We also separate the sample into varying levels of analyst coverage. Panel D reports subsample tests limiting the matched sample to a) only event years 2001 and 2002, b) event years excluding 2001 and 2002, and c) treatment and control firms from the financials or utilities sector, respectively. Panel E exhibits robustness tests matching placebo brokerage merger and closure events to a matched sample as in Panel C. The events are shifted a) five years before the actual event, b) 3 years before the actual event, c) 3 years after the actual event, and d) 5 years after the actual event. Firm, year, and deal fixed effects are used in all models, and robust standard errors are clustered at the firm level for the full sample and at the deal level for the matched sample. *,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Difference-in-Differences: Full Sample Estimates	Treat *post	P-value	Obs	Adj Rsq
	(1)	(2)	(3)	(4)
PAC	0.170**	0.012	32,654	0.016
PAC w/C1	0.132*	0.059	28,218	0.105
LSM	0.359***	0.007	7,147	0.014
LSM w/C1	0.341**	0.012	6,664	0.136
LSM w/C1, Analysts <=10	0.750**	0.011	3,035	0.047
LSM w/C1, 10 < Analysts <=25	0.331*	0.057	3,294	0.083
LSM w/C, Analysts > 25	0.342	0.486	693	0.219

Panel B. Post-Match Differences Between Treatment and Control Sample	Treat	Control	% Bias	P-value
	(1)	(2)	(3)	(4)
Lobbying, Soft Money, and PAC Contributions	780,000	920,000	-7.0	0.411
Analyst Coverage	15.169	14.570	7.3	0.204
Market Capitalization ($ millions)	14,208	16,393	-5.4	0.350
Book-to-Market	3.655	3.744	-2.4	0.680
Past One-year Returns	0.096	0.124	-6.1	0.284
Non-Missing Items	309.420	303.760	11.0	0.054**
Special Items	-50.568	-86.782	5.5	0.380
Business Segments	3.052	3.461	-14.0	0.031**
Gross File Size	1.200	1.200	2.4	0.690
Fog Index	19.581	19.418	9.9	0.098*
Firm Age	13.005	12.587	5.9	0.428
Delaware Incorporation	0.528	0.533	-1.0	0.854
Battle vs. Partisan	0.542	0.496	9.2	0.108
State Tax Climate	0.050	0.051	-11.8	0.044**
In-house Lobbyist	0.090	0.072	6.4	0.257
FPS Industry	0.452	0.429	4.7	0.409
Innovative Industry	0.785	0.799	-3.4	0.552
GIM Index	9.145	8.914	8.8	0.198

Panel C. Difference-in-Differences: Matched Sample Estimates	Treat *post	P-value	Obs	Adj Rsq
	(1)	(2)	(3)	(4)
PAC	0.167**	0.012	1,137	0.858
LSM	0.243**	0.020	1,475	0.861
LSM & PAC	0.283***	0.000	1,835	0.888
LSM & PAC, Analysts <20	0.287**	0.050	1,154	0.895
LSM & PAC, 20 <= Analysts <=30	0.200	0.251	643	0.857
LSM & PAC, Analysts > 30	0.157	0.580	132	0.956

Panel D. Difference-in-Differences: Subsample Tests	Treat *post	P-value	Obs	Adj Rsq
	(1)	(2)	(3)	(4)
Including only 2001 and 2002	0.387**	0.049	598	0.902
Excluding 2001 and 2002	0.238**	0.010	1,237	0.887
Excluding Financials and Utilities	0.348***	0.001	1,421	0.867

Panel E. Difference-in-Differences: Placebo Tests	Treat *post	P-value	Obs	Adj Rsq
	(1)	(2)	(3)	(4)
Event - 5 years	0.202	0.423	580	0.807
Event - 3 years	-0.298*	0.097	387	0.892
Event + 3 years	-0.086	0.846	424	0.898
Event + 5 years	0.0373	0.799	456	0.902

Table 4. Causal Effect of Analyst Coverage on Political Contributions: Alternative Models

This table shows the effect of analyst coverage on lobbying, soft money, and PAC contributions from fiscal year 2001 to 2010. Panel A presents the results of 2SLS regressions of the measures of firm lobbying, soft money, and PAC contributions as well as the number of candidates on analyst coverage. Expected Coverage is an instrumental variable which captures the variation in analyst coverage given a change in brokerage house size (Yu (2008); He and Tian (2013)). Log Analyst Coverage (Instrumented) is the predicted value of Log Analyst Coverage obtained in the first stage model. Panel B presents the results of the dynamic panel system GMM using measures of political spending and analyst coverage. The dependent variable is the natural logarithm of the total dollar amount of firm lobbying, soft money, and PAC contributions as well as the number of candidates over a given year. The AR(1) and AR(2) tests are tests for first-order and second-order serial correlation in the first-differenced residuals, under the null of no serial correlation. The Hansen test of over-identifying restrictions is a test with the joint null hypothesis to determine if instrumental variables are valid; i.e. uncorrelated with error terms. We use lagged two-to four-periods as instruments for endogenous variables. Standard errors are clustered at the firm level and t-statistics are shown in parentheses. Statistical significance at the 1%, 5%, and 10% level is indicated by ***, **, and *, respectively.

Panel A: Two-stage least squares (2SLS)

	Log Analyst Coverage $_t$	PAC $_{t+1}$	(PAC, Lobbying, & Soft Money) $_{t+1}$	Number of candidates $_{t+1}$
	First stage	Second stage		
Variables	(1)	(2)	(3)	(4)
Log Analyst Coverage (Instrumented)		-0.880***	-0.608**	-0.157**
		(-3.50)	(2.24)	(1.96)
Expected Coverage	0.400***			
	(18.76)			
Controls (Table 2 - Model 1)	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes
Observations	12,589	11,359	11,371	11,300
R-squared	0.5773	0.2052	0.1125	0.2539

Panel B: Dynamic Panel GMM Estimates

	PAC $_{t+1}$	(PAC, Lobbying, & Soft Money) $_{t+1}$	Number of candidates $_{t+1}$
Variables	(1)	(2)	(3)
Log Analyst Coverage	-0.529**	-0.388**	-0.313***
	(-1.98)	(2.44)	(3.38)
Controls (Table 2 - Model 1)	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
Observations	9,896	9,906	9,841
AR (1) test (p-value)	0.000	0.000	0.000
AR (2) test (p-value)	0.230	0.961	0.319
Hansen test (p-value)	0.241	0.160	0.103

Table 5. Potentially Confounding Factors Influencing a Firm's Information Environment

This table examines the relationship between analyst coverage reductions through brokerage merger/closure events and CPI (lobbying, soft money, and PAC) controlling for potentially confounding factors affecting a firm's information environment. The sample covers 1,835 firm-year observations between fiscal year 1998 and 2010, matching on brokerage merger and closure events from 2001 to 2007. The matched sample is created in a [-3,+3] year window around each event. Construction of the treatment and control samples is described in the text. Panel A reports difference-in-differences (DiD) test results on CPI conditional on increases or decreases in analyst forecast dispersion (models 1 and 2) and forecast error (models 3 and 4) between the 3 years before and the 3 years after a brokerage merger/closure event. Panel B controls for information environment variables in a multivariate framework within our main model. It reports the DiD results on CPI when controlling for the following: 1) analyst ability, 2) firm complexity, 3) firm disclosure readability, and 4) firm age and Delaware incorporation. Variable definitions are reported in Appendix A, and continuous variables are winsorized at the 1% and 99% level. Special items and gross file size both multiplied by 1 million to show coefficients. We report P-values in parentheses. Firm, year, and deal fixed effects are applied as specified, and robust standard errors are clustered at the deal level. *,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Analyst Forecast Dispersion / Bias	Forecast Dispersion Decreasing	Forecast Dispersion Increasing	Forecast Error Decreasing	Forecast Error Increasing
	(1)	(2)	(3)	(4)
Treat * Post	0.250	0.324*	0.192	0.342***
(LSM and PAC)	(0.218)	(0.068)	(0.285)	(0.003)
Firm/Yr/Deal FE	Yes	Yes	Yes	Yes
Obs	660	913	771	802
Adj Rsq	0.888	0.879	0.873	0.884

Panel B. Potentially Confounding Information Factors	Analyst Ability	Ability and Complexity	Ability, Complexity, and Readability	Additional Factors
	(1)	(2)	(3)	(4)
Treat * Post	0.280*** (0.000)	0.368*** (0.001)	0.337*** (0.004)	0.420** (0.016)
Treat	-0.137 (0.204)	-0.103 (0.283)	-0.094 (0.310)	-0.237 (0.151)
Post	-0.037 (0.717)	-0.101 (0.438)	-0.044 (0.713)	-0.155 (0.420)
All-Star Analyst	0.008 (0.861)	0.058 (0.408)	0.098 (0.257)	0.078 (0.444)
Non-Missing Items$_{t-1}$		0.005 (0.279)	0.00814* (0.058)	0.0110*** (0.002)
Special Items$_{t-1}$		24.400 (0.424)	-57.900 (0.439)	27.000 (0.683)
Business Segments$_{t-1}$		0.0279* (0.091)	0.020 (0.157)	0.022 (0.111)
Gross File Size$_{t-1}$			0.047 (0.231)	0.026 (0.372)
Fog Index$_{t-1}$			-0.017 (0.610)	-0.017 (0.679)
Firm Age$_{t-1}$				0.013 (0.743)
Delaware Incorporation$_{t-1}$				0.469*** (0.000)
Firm/Yr/Deal FE	Yes	Yes	Yes	Yes
Obs	1,835	1,443	1,259	824
Adj Rsq	0.888	0.857	0.849	0.859

Table 6. Potentially Confounding Factors Influencing a Firm's CPI Efforts

This table examines the relationship between analyst coverage reductions through brokerage merger/closure events and CPI (lobbying, soft money, and PAC) controlling for potentially confounding factors affecting a firm's propensity to make political contributions. The sample covers 1,835 firm-year observations between fiscal year 1998 and 2010, matching on brokerage merger and closure events from 2001 to 2007. The matched sample is created in a [-3,+3] year window around each event. Construction of the treatment and control samples is described in the text. The table controls for political environment variables in a multivariate framework within our main model. It reports the DiD results on CPI when controlling for the following: 1) political connections or state tax climate (total gross state business tax liability), 2) usage of an in-house lobbyist and rankings of industries based on innovation or litigation, and 3) degree of entrenchment. Models (1) through (3) use the log of the combination of firm lobbying, soft money, and PAC contributions as the dependent variable, while models (4) through (6) use the log of the combination of lobbying and soft money only. Variable definitions are reported in Appendix A, and continuous variables are winsorized at the 1% and 99% level. We report P-values in parentheses. Firm, year, and deal fixed effects are applied as specified, and robust standard errors are clustered at the deal level. *,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

	Lobbying, Soft Money, and PAC			Lobbying and Soft Money		
	Political Influence State Tax	In-house Lobby & Industry	Entrench	Political Influence State Tax	In-house Lobby & Industry	Entrench
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Treat * Post	0.267***	0.269***	0.313***	0.224**	0.223**	0.275*
	(0.001)	(0.001)	(0.001)	(0.026)	(0.023)	(0.051)
Treat	-0.154	-0.204**	-0.182*	-0.169	-0.167	-0.141
	(0.156)	(0.033)	(0.052)	(0.117)	(0.119)	(0.161)
Post	-0.019	-0.042	-0.130	-0.022	-0.023	-0.139
	(0.856)	(0.684)	(0.238)	(0.841)	(0.834)	(0.287)
Battle vs. Partisan$_{t-1}$	0.030	-0.032	0.019	-0.123	-0.133	-0.059
	(0.846)	(0.795)	(0.915)	(0.142)	(0.128)	(0.649)
State Tax Climate$_{t-1}$	18.320*	10.940	11.830	12.68**	12.28**	17.54**
	(0.088)	(0.207)	(0.383)	(0.019)	(0.017)	(0.034)
In-house Lobbyist$_{t-1}$		0.505***	1.524***		0.322**	1.626***
		(0.003)	(0.005)		(0.018)	(0.005)
FPS Industry		-2.693***	-3.707***		-2.436***	-3.688***
		(0.000)	(0.000)		(0.000)	(0.000)
Innovative Industry		-0.281	-0.520		-0.520	-0.352
		(0.458)	(0.175)		(0.377)	(0.322)
GIM Index$_{t-1}$			-0.030			-0.047
			(0.623)			(0.296)
Firm/Yr/Deal FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1,704	1,664	1,088	1,382	1,371	901
Adj Rsq	0.888	0.899	0.916	0.869	0.870	0.892

Table 7. Excluding Suspected Short-Term Earnings Management

This table examines the relationship between analyst coverage reductions through brokerage merger/closure events and CPI (lobbying, soft money, and PAC) after excluding firm-year observations in which real earnings management is likely. The pre-exclusion sample covers 1,835 firm-year observations between fiscal year 1998 and 2010, matching on brokerage merger and closure events from 2001 to 2007. The matched sample is created in a [-3,+3] year window around each event. Construction of the treatment and control samples is described in the text. Panels A and B exclude firm-year observations that during the match year 1) meet/just beat zero dollar earnings by up to 5%, or 2) increase earnings (ROA) by up to 5%, respectively. Four earnings ranges are excluded between the zero threshold and 0.5%, 1%, 3%, and 5%, respectively. The 0.5% cutoff follows prior literature (Roychowdhury (2006); Zang (2012)); for robustness, we extend the cutoff up to 5% based on evidence in Figure 2 and suggestions in Roychowdhury (2006) that earnings management likely occurs above the 0.5% level. The dependent variable in both panels is the log of the combination of firm lobbying, soft money, and PAC contributions for the first four interaction terms, and the log of lobbying and soft money only for the latter four interaction terms. We report the coefficients of the interaction term in the matched sample DiD model. Variable definitions are reported in Appendix A, and continuous variables are winsorized at the 1% and 99% level. We report P-values in parentheses. Firm, year, and deal fixed effects are applied in all tests, and robust standard errors are clustered at the deal level. *,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Levels of ROA	Earnings Range to Exclude	Treat x Post	P-value	Observations	Adjusted R-squared
LSM and PAC	0 - .005	0.282***	(0.000)	1,830	0.888
	0 - .010	0.278***	(0.001)	1,818	0.888
	0 - .030	0.321***	(0.000)	1,731	0.882
	0 - .050	0.315***	(0.001)	1,639	0.879
LSM Only	0 - .005	0.242**	(0.022)	1,471	0.861
	0 - .010	0.243**	(0.020)	1,464	0.862
	0 - .030	0.261**	(0.019)	1,425	0.861
	0 - .050	0.230**	(0.028)	1,369	0.874

Panel B. Change in ROA	Earnings Range to Exclude	Treat x Post	P-value	Observations	Adjusted R-squared
LSM and PAC	0 - .005	0.285***	(0.000)	1,810	0.887
	0 - .010	0.286***	(0.000)	1,796	0.887
	0 - .030	0.294***	(0.000)	1,728	0.886
	0 - .050	0.310***	(0.000)	1,690	0.887
LSM Only	0 - .005	0.226**	(0.024)	1,452	0.862
	0 - .010	0.230**	(0.022)	1,443	0.863
	0 - .030	0.233**	(0.023)	1,396	0.862
	0 - .050	0.237**	(0.024)	1,365	0.863

Table 8. Financial Constraints and Competition

This table examines the relationship between analyst coverage reductions through brokerage merger/closure events and CPI (lobbying, soft money, and PAC) after dividing the sample into separate quantiles by various measures of financial constraints and competition. Panels A, C, and D report the coefficient of the interaction term using the matched sample, which covers 1,835 firm-years between fiscal year 1998 and 2010 and matches on brokerage merger and closure events from 2001 to 2007. The matched sample is created in a [-3,+3] year window around each event. Construction of the treatment and control samples is described in the text. Panel A models (1) through (4) divide the sample by the match year into low and high quantiles by the four financial constraint variables of Hoberg and Maksimovic (2015) as follows: 1) Firms at higher risk of delaying investments due to liquidity problems (delay firms), 2) delay firms that plan to issue equity to likely relieve their liquidity problems, 3) delay firms that plan to issue debt to likely relieve their liquidity problems, and 4) delay firms that plan to issue private placements to likely relieve their liquidity problems . Model (5) divides the sample at the match year into low and high quantiles using the Kaplan-Zingales (KZ) index of Lamont, Polk, and Saa-Requejo (2001). Panel B uses the full sample and divides the sample into low and high terciles by the first two financial constraint measures of Panel A. Panel C divides the sample by the match year into low and high quantiles given varying state-level business tax climates from the Panel Database on Incentives and Taxes (PDIT) from the W.E. Upjohn Institute for Employment Research. Models (1) through (5) divide the sample by the total state level of business taxes for 45 industries, the total state level of business taxes net of state-provided business subsidies, the state-level business property tax subcomponent, the state-level business sales tax subcomponent, and the state-level corporate income tax subcomponent, respectively. Panel D divides the sample by the match year into low and high quantiles given varying measures of competition from Hoberg and Phillips (2016) and from census data. Models (1) and (3) divide the sample into low and high competition quantiles using the inverse of the Herfindahl index constructed from the text-based network industry classification (TNIC) of Hoberg and Phillips (2016) that is similar to a 3-digit SIC code, while models (2) and (4) divide the sample by TNIC industry competitor frequency. Model (5) divides the sample using the match-year level of Census based industry classifications from the Small Business Administration. The dependent variable in all models is the log of the combination of firm lobbying, soft money, and PAC contributions (LSM & PAC) unless specified for lobbying and soft money only (LSM). Variable definitions are reported in Appendix A, and continuous variables are winsorized at the 1% and 99% level. We report P-values in parentheses. Firm, year, and deal fixed effects are applied in all tests, and robust standard errors are clustered at the deal level. *,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A. Financial Constraints - Matched Sample Quantiles	Delay	Equity Delay	Debt Delay	Private Delay	KZ Index
	(1)	(2)	(3)	(4)	(5)
Low	0.188 (0.312)	0.181 (0.396)	0.042 (0.653)	0.106 (0.500)	0.139 (0.259)
High	0.225* (0.087)	0.311** (0.041)	0.321* (0.077)	0.374** (0.015)	0.394** (0.040)
Firm/Yr/Deal FE	Yes	Yes	Yes	Yes	Yes

Panel B. Financial Constraints - Full Sample Terciles	Delay		Equity Delay	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Treat * Post	-0.257*	0.236**	-0.515***	0.209***
	(0.058)	(0.019)	(0.004)	(0.008)
Controls	Yes	Yes	Yes	Yes
Firm/Year FE	Yes	Yes	Yes	Yes
Observations	1,421	1,410	1,332	1,318
R-squared	0.1834	0.1736	0.2098	0.1894

Panel C. Total State Business Tax Liability	Dependent Variable: Lobbying, Soft Money, and PAC				
	Total State Business Tax	Net State Business Tax	State Business Property Tax	State Business Sales Tax	State Corp Income Tax
	(1)	(2)	(3)	(4)	(5)
Low	0.134	0.287*	0.109	0.183	0.193*
	(0.387)	(0.056)	(0.406)	(0.176)	(0.055)
High	0.335***	0.295**	0.427***	0.271**	0.326***
	(0.006)	(0.042)	(0.001)	(0.024)	(0.004)
Firm/Yr/Deal FE	Yes	Yes	Yes	Yes	Yes

Panel D. Competition	LSM		LSM & PAC		
	TNIC Industry	TNIC Comp Frequency	TNIC Industry	TNIC Comp Frequency	Census Industry Comp
	(1)	(2)	(3)	(4)	(5)
Low	0.186	0.179	0.261	0.281*	0.189
	(0.200)	(0.347)	(0.114)	(0.066)	(0.133)
High	0.384**	0.398**	0.321**	0.316*	0.350*
	(0.029)	(0.018)	(0.026)	(0.058)	(0.073)
Firm/Yr/Deal FE	Yes	Yes	Yes	Yes	Yes

Table 9. Analyst Impact on Innovative Efficiency and Valuation

This table examines the relationship between analyst coverage reductions through brokerage merger/closure events and various innovative efficiency and valuation measures. All models show full sample DiD regression results for the interaction between a) the occurrence of a merger or closure event and b) the year the event takes place. Each model also includes control variables for market capitalization, book-to-market ratio, and past one-year returns following Hong and Kacperczyk (2010). The dependent variables in Panel A include the RQ innovative efficiency measure of Cooper, Knott, and Yang (2021) in models (1-3), the patent- and citation-based innovative efficiency measures of Hirshleifer, Hsu, and Li (2013) in models (4-5), and Bartlett and Partnoy (2020) Tobin's Q (in 000s) in model (6), respectively. Model (2) restricts the sample to firm-year observations reporting LSM or PAC contributions, while model (3) excludes firm-year observations reporting LSM or PAC contributions. Panel B repeats Panel A Model (1) dividing the sample into four quartiles using the delay-based financial constraints measure of Hoberg and Maksimovic (2015) that identifies firms at higher risk of delaying investments due to liquidity problems (delay firms). Panels C and D models (1-2) and (3-4) divide the sample into high and low quantiles by 1) the total state business tax level from the Panel Database on Incentives and Taxes (PDIT) from the W.E. Upjohn Institute for Employment Research, and 2) the Herfindahl index constructed from the text-based network industry classification (TNIC) of Hoberg and Phillips (2016) that is similar to a 3-digit SIC code, respectively. Panel C repeats Panel A Model (1) with RQ innovative efficiency as the dependent variable, while Panel D repeats Panel A Model (6) with Bartlett and Partnoy (2020) Tobin's Q (in 000s) as the dependent variable. Variable definitions are reported in Appendix A, and continuous variables are winsorized at the 1% and 99% level. We report P-values in parentheses. Firm and year fixed effects are applied in all models, and robust standard errors are clustered at the firm level. *,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Innovative Efficiency Comparisons	RQ Innov Effic			Alt Innov Effic and Valuation		
	All	LSM or PAC Presence	No LSM or PAC Presence	HHL Innov Effic - Patents	HHL Innov Effic - Citations	B&P Tobin's Q
	(1)	(2)	(3)	(4)	(5)	(6)
Treat * Post	-0.003* (0.064)	-0.005** (0.013)	-0.001 (0.710)	-0.004 (0.952)	-0.007 (0.942)	-3.273** (0.024)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,623	2,619	5,004	1,964	1,951	11,173
Adj Rsq	0.1293	0.064	0.148	0.0947	0.0708	0.0160

Panel B. Impact of Financial Constraints on RQ	Treat*post	P-value	Obs	Adj Rsq
	(1)	(2)	(3)	(4)
Q1	-0.0003	0.904	1,529	0.124
Q2	-0.0002	0.950	1,543	0.116
Q3	-0.0025	0.513	1,551	0.140
Q4	-0.0067***	0.008	1,567	0.099

Panel C. Subsample Tests - RQ	Total State Business Tax		Competition - HP TNIC Industry	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Treat * Post	-0.001 (0.759)	-0.005*** (0.006)	0.001 (0.670)	-0.005** (0.011)
Controls	Yes	Yes	Yes	Yes
Firm/Year FE	Yes	Yes	Yes	Yes
Observations	3,850	3,773	3,864	3,759
Adj Rsq	0.1360	0.1221	0.1184	0.1341

Panel D. Subsample Tests - B&P Tobin's Q	Total State Business Tax		Competition - HP TNIC Industry	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Treat * Post	-0.277 (0.280)	-7.196** (0.025)	-0.465 (0.226)	-5.633** (0.031)
Controls	Yes	Yes	Yes	Yes
Firm/Year FE	Yes	Yes	Yes	Yes
Observations	5,449	5,724	5,350	5,823
Adj Rsq	0.0744	0.0032	0.0569	0.0165

Supplementary Appendix

to accompany

Analyst Effects on Intangible Investment: Evidence from Corporate Political Investments

B. Supplementary Appendix

In this Supplementary Appendix, we show that our results are concentrated in firms in which 1) managers receive less private benefits from CPI and 2) analysts have greater ability to influence management. These tests provide further robustness to the influence of analysts on CPI through the monitoring hypothesis. We also present evidence of the dispersed distribution of our sample.

B.1 Distribution of Data Across Fama-French 12 Industries

Figure B.1 shows a summary distribution of our matched sample across Fama-French 12 industries. This figure shows that our sample is fairly well dispersed, although 45% of our contributions are from the Business Equipment or Telephone and Television industries.

B.2 Managerial Commitment to CPI Given Varying Benefits per Dollar Invested

According to the Center for Responsive Politics, corporate lobbying expenditures totaled \$1.56 billion in the year 2000, soft money expenditures totaled \$457 million, and total PAC spending was around \$287 million. While these numbers do not represent a particularly sizeable proportion of firm spending, the investment in CPI is growing. For example, lobbying expenditures more than doubled between 2000 and 2010. It is particularly noteworthy that over half of former congressional representatives work as lobbyists hired by corporations (Yu and Yu (2011)).

This evidence suggests that some managers may be resistant to analyst monitoring because they receive abnormally strong private benefits. Our tests in the main draft examine CPI only from a cost perspective and assume a fixed benefit per dollar of CPI spending. Our next test examines how analyst monitoring affects a firm's CPI spending given a variance in the benefits of CPI to the manager. It is likely that managers receiving particularly strong benefits per dollar of CPI investment might be more resistant to analyst monitoring.

Specifically, we examine whether the balance of political power in state politics affects the impact of analyst coverage on CPI. In battleground states that typically experience tight election outcomes, political contributions (directly to candidates or through indirect means to party affiliates) could be utilized to gain favors from incumbents. Prior literature has found that incumbent politicians are more willing to give up favors when faced with a close election (Ansolabehere, de Figueiredo, and Snyder (2003), Bonardi, Holburn, and Vanden Bergh (2006), Ovtchinnikov and Pantaleoni (2012)), suggesting managers would not likely reduce CPI in battleground states. In contrast, in partisan states CPI is more often long-term and persistent (Snyder (1992), Ansolabehere, Snyder, and Tripathi (2002)). This generates more relationship capital between managers and political groups, and plausibly allows at least a temporary reduction in CPI without a loss in managerial benefits (or even permanent reductions if analyst monitoring has enough of an impact). Thus, if the monitoring view holds and especially if there is also a lower granting of favors in partisan states, we expect to see a negative association between analyst coverage and CPI in firms headquartered in partisan states.

To conduct this test, in Table B.1 we divide our matched sample similar to subsample tests in related studies (Irani and Oesch (2013, 2016)) utilizing the Citizen Ideology index of Berry et al. (2010). These measures are similar to the Political Alignment Index of Kim, Pantzalis, and Park (2012). The Citizen Ideology index measures the political bias of active voters based on recent elections and produces an annual scale ranging from 0 to 100, with 0 being very conservative and 100 being very liberal. States with scores closest to 50 will tend to shift back and forth between control by conservatives or liberals, with the resulting loss of political seats for incumbent politicians in the losing party. This creates a more intense need for CPI by incumbent politicians who are struggling to remain in power when states have scores close to 50. We include the Citizen Ideology index instead of the State Government Ideology index (also from Berry et al. (2010)) because the latter measure lags the political views of voters and is backward-looking (e.g., state officials may have been elected several years ago).

We test each matched sample divided by the ideology index in a DiD framework around brokerage mergers and closures similar to the prior tests. We divide our sample between partisan and battleground states by first splitting our matched sample into quartiles based on the scores of each index for the state. We group the middle two quartiles together to identify battleground states that are more likely to switch political parties in an election and replace incumbents, and we group the highest and lowest quartiles together to identify states with an extremely partisan electorate (either very Democratic or very Republican). We identify firms as residing in partisan or battleground states based on their headquarters location. Table B.1 models (1) and (2) use lobbying, soft money, and PAC as the dependent variable, while models (3) and (4) use lobbying and soft money only. We also exclude the event year to eliminate noise in our tests. We find that our results are strongly and positively significant for all four models in partisan states, with no significance in battleground states, supporting the monitoring hypothesis.

B.3 Analyst Influence Given High Antitakeover Protection

In this section, we examine how analyst coverage affects CPI given the presence of antitakeover protection (ATP). For firms with strong shareholder rights (low ATP), many of the same arguments suggesting analyst coverage would be negatively related to CPI still apply. In contrast, for firms with weak shareholder rights (high ATP), prior literature suggests analysts might not be able to impact CPI for two reasons. First, antitakeover laws are strongly promoted by lobbying (Karpoff and Wittry (2018)), suggesting managers would be highly resistant to analyst monitoring disproving of CPI. The existence of the ATP protection would give them the means to resist analysts as well. Second, Jiraporn, Chintrakarn, and Kim (2012) argue that entrenched managers protected by staggered boards have less incentive to conceal information, reducing the beneficial impact of analysts in producing and sharing information. In sum, these studies suggest analyst monitoring cannot impact CPI in high ATP firms.

In Table B.2 we examine the impact of analyst coverage on CPI using our brokerage merger and closure matched sample and dividing the sample at the match year into low and high quantiles by various measures of entrenchment similar to subsample tests in related studies (Irani and Oesch (2013, 2016)). Specifically, we use the GIM index of Gompers, Ishii, and Metrick (2003) in models (1) and (4), the BCF index of Bebchuk, Cohen, and Ferrell (2008) in models (2) and (5), and the ATI (antitakeover) index of Cremers and Nair (2005) in models (3) and (6). We find a quasi-exogenous analyst reduction event exhibits a positive and significant association with CPI (analyst coverage is negatively associated with CPI) only in firms with low index values (higher shareholder rights).

Supplementary Appendix References

Ansolabehere, Stephen, John de Figueiredo, and James Snyder, 2003, Why Is There So Little Money in Politics?, National Bureau of Economic Research, Cambridge, MA.

Ansolabehere, Stephen, James M. Snyder, and Micky Tripathi, 2002, Are PAC Contributions and Lobbying Linked? New Evidence from the 1995 Lobby Disclosure Act, *Business and Politics* 4, 131–155.

Bebchuk, Lucian, Alma Cohen, and Allen Ferrell, 2008, What Matters in Corporate Governance?, *The Review of Financial Studies* 22, 783–827.

Berry, William D., Richard C. Fording, Evan J. Ringquist, Russell L. Hanson, and Carl E. Klarner, 2010, Measuring Citizen and Government Ideology in the U.S. States: A Re-appraisal, *State Politics & Policy Quarterly* 10, 117–135.

Bonardi, Jean-Philippe, Guy L. F. Holburn, and Richard G. Vanden Bergh, 2006, Nonmarket Strategy Performance: Evidence from U.S. Electric Utilities, *Academy of Management Journal* 49, 1209–1228.

Cremers, K. J. Martijn, and Vinay B. Nair, 2005, Governance Mechanisms and Equity Prices, *The Journal of Finance* 60, 2859–2894.

Gompers, Paul, Joy Ishii, and Andrew Metrick, 2003, Corporate Governance and Equity Prices, *The Quarterly Journal of Economics* 118, 107–156.

Irani, Rustom M., and David Oesch, 2013, Monitoring and corporate disclosure: Evidence from a natural experiment, *Journal of Financial Economics* 109, 398–418.

Irani, Rustom M., and David Oesch, 2016, Analyst Coverage and Real Earnings Management: Quasi-Experimental Evidence, *Journal of Financial and Quantitative Analysis* 51, 589–627.

Karpoff, Jonathan M., and Michael D. Wittry, 2018, Institutional and Legal Context in Natural Experiments: The Case of State Antitakeover Laws, *The Journal of Finance* 73, 657–714.

Jiraporn, Pornsit, Pandej Chintrakarn, and Young S. Kim, 2012, Analyst following, staggered boards, and managerial entrenchment, *Journal of Banking & Finance* 36, 3091–3100.

Kim, Chansog (Francis), Christos Pantzalis, and Jung Chul Park, 2012, Political geography and stock returns: The value and risk implications of proximity to political power, *Journal of Financial Economics* 106, 196–228.

Ovtchinnikov, Alexei V., and Eva Pantaleoni, 2012, Individual political contributions and firm performance, *Journal of Financial Economics* 105, 367–392.

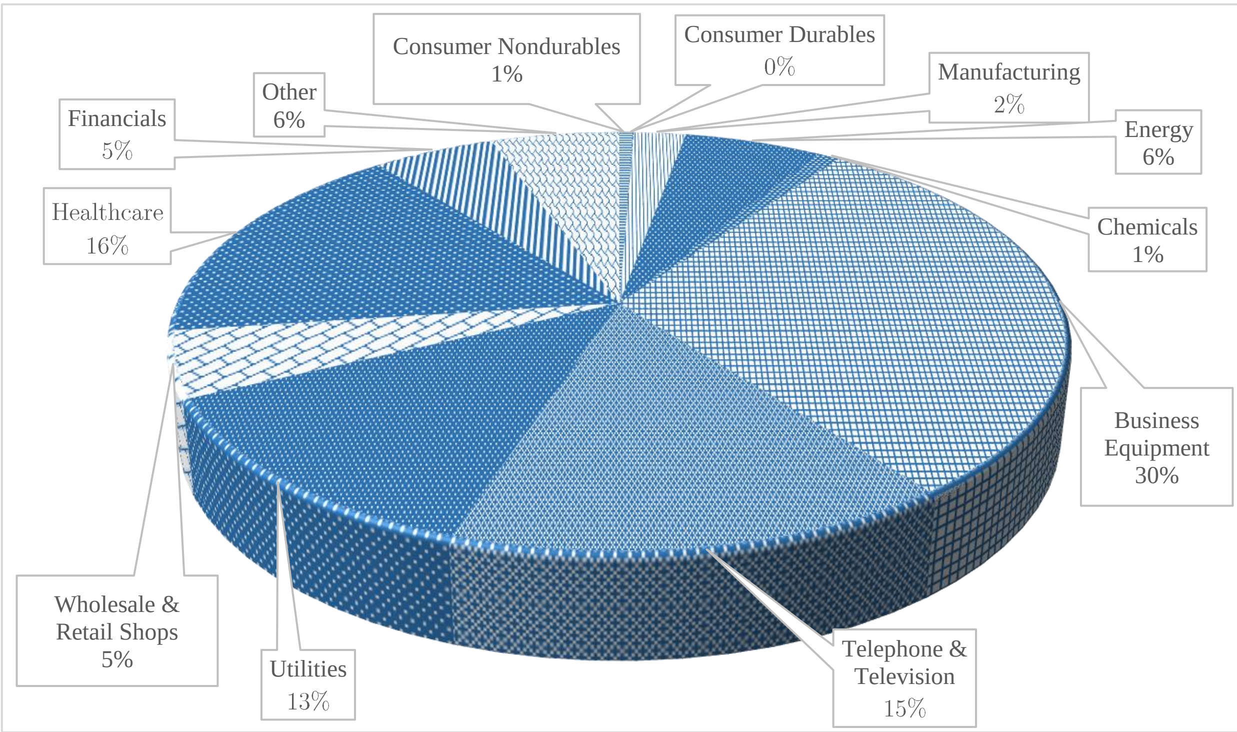
Snyder, James M., 1992, Long-Term Investing in Politicians; Or, Give Early, Give Often, *The Journal of Law and Economics* 35, 15–43.

Yu, Frank, and Xiaoyun Yu, 2011, Corporate Lobbying and Fraud Detection, *Journal of Financial and Quantitative Analysis* 46, 1865–1891.

Fig. B.1. Matched Sample - Fama French 12 Industry

This figure presents the distribution of LSM and PAC contributions by Fama-French 12 industry for our matched sample between 1998 and 2010. Panel A presents percent total contributions by Fama-French 12 industry. Panel B presents the frequency per industry for our matched sample, along with the mean, median, and total. We include all firm-year observations in our seven-year event period surrounding each quasi-exogenous reduction in analyst coverage.

Panel A: Contribution Percentage per Fama French 12 Industry



Panel B: Distribution Statistics for Matched Sample

	Frequency	Mean	Median	Total
Consumer Nondurables	25	$560,655	$607,000	$14,016,373
Consumer Durables	6	$171,800	$156,500	$1,030,800
Manufacturing	88	$607,854	$74,239	$53,491,150
Energy	99	$1,433,981	$490,000	$141,964,140
Chemicals	23	$996,931	$1,069,550	$22,929,416
Business Equipment	565	$1,266,161	$267,713	$715,380,782
Telephone and Television	61	$6,060,115	$3,574,487	$369,666,999
Utilities	217	$1,408,199	$1,000,000	$305,579,261
Wholesale and Retail Shops	244	$493,570	$150,600	$120,431,120
Healthcare	192	$2,033,581	$692,750	$390,447,603
Financials	197	$633,240	$27,000	$124,748,211
Other	118	$1,127,938	$197,500	$133,096,626
Sum	1,835		Sum	$2,392,782,481

Table B.1. State Political Balance of Power and Investment Commitment

This table examines the relationship between analyst coverage reductions through brokerage merger/closure events and CPI (lobbying, soft money, and PAC) after dividing the sample on varying headquarter state levels of political ideology based on the Citizen Ideology measure of Berry, Fording, Rinqquist, Hanson, and Klarner (2010). The main sample covers 1,835 firm-year observations between fiscal year 1998 and 2010, matching on brokerage merger and closure events from 2001 to 2007. The matched sample is created in a [-3,+3] year window around each event. Construction of the treatment and control samples is described in the text. Models (1) and (3) examine the full seven-year event period, while models (2) and (4) exclude the event year. Partisan States represent the extreme quartile states (strongly Democrat or strongly Republican) with Battleground States representing the middle two quartile states. Models (1) and (2) use the log of the combination of firm lobbying, soft money, and PAC contributions as the dependent variable, while models (3) and (4) use the log of the combination of lobbying and soft money only. Continuous variables are winsorized at the 1% and 99% level. We report P-values in parentheses. Firm, year, and deal fixed effects are applied in all tests, and robust standard errors are clustered at the deal level. *,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

	Lobbying, Soft Money, and PAC		Lobbying and Soft Money	
	Including Event Year	Excluding Event Year	Including Event Year	Excluding Event Year
Partisan vs. Battleground States	(1)	(2)	(3)	(4)
Partisan States	0.288** (0.010)	0.312** (0.023)	0.354*** (0.007)	0.392** (0.014)
Battleground States	0.190 (0.203)	0.170 (0.235)	0.097 (0.539)	0.079 (0.608)
Firm / Yr / Deal FE	Yes	Yes	Yes	Yes

Table B.2. Antitakeover Protection and Investment Commitment

This table examines the relationship between analyst coverage reductions through brokerage merger/closure events and CPI (lobbying, soft money, and PAC) after dividing the main sample into subsamples by antitakeover protection (ATP) measures. The main sample covers 1,835 firm-year observations between fiscal year 1998 and 2010, matching on brokerage merger and closure events from 2001 to 2007. The matched sample is created in a [-3,+3] year window around each event. Construction of the treatment and control samples is described in the text. The dependent variable is the log of the combination of firm lobbying, soft money, and PAC contributions. Models (1, 4), (2, 5), and (3, 6) divide the sample at the match year into low and high quantiles by the GIM index of Gompers, Ishii, and Metrick (2003), the BCF index of Bebchuk, Cohen, and Ferrell (2009), and the antitakeover (ATI) index of Cremers and Nair (2005), respectively. Continuous variables are winsorized at the 1% and 99% level. We report P-values in parentheses. Firm, year, and deal fixed effects are applied in all tests, and robust standard errors are clustered at the deal level. *,**,*** represent significance at the 10%, 5%, and 1% level, respectively.

	Low Entrenchment			High Entrenchment		
Low vs. High Entrenchment (ATP)	GIM Index	BCF Index	ATI Index	GIM Index	BCF Index	ATI Index
	(1)	(2)	(3)	(4)	(5)	(6)
Treat * Post	0.610**	0.412**	0.469**	0.188	-0.020	0.054
	(0.010)	(0.015)	(0.023)	(0.312)	(0.949)	(0.575)
Observations	530	631	585	509	550	473
Adj Rsq	0.842	0.858	0.863	0.937	0.915	0.917
Firm/Yr/Deal FE	Yes	Yes	Yes	Yes	Yes	Yes