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

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Abstract

We find analyst coverage has a significant negative impact on corporate political investment, which suggests analyst pressure effects outweigh analyst benefits to investment from information asymmetry reduction. Analyst preferences for reduced predation risk and future earnings stability induce political spending reductions in firms facing high financial constraints and high competition. However, these pressure effects are offset by beneficial information asymmetry reductions in innovative industries and by takeover protections that enable long-term investment and reduce the threat of predation. We establish causality primarily by using a difference-in-differences approach around the exogenous reduction in analyst coverage due to brokerage merger and closure events. We further confirm our results using an instrumental variable approach in a two-stage least squares model and a systems generalized method of moments estimation of linear dynamic panel data model. For robustness, we confirm that our results are not driven by short-term earnings management and are not driven by potentially confounding information flow or preferences for political investments. Using our main identification strategy and a matched sample, we find that an exogenous reduction in analyst coverage causes a 28.3% increase in political investments over a three-year window post-event.

JEL Classification: *D72, G24, G34*

Keywords: Financial Analysts, Asymmetric Information, Managerial Myopia, Political Contributions, Lobbying

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Abstract

We find analyst coverage has a significant negative impact on corporate political investment, which suggests analyst pressure effects outweigh analyst benefits to investment from information asymmetry reduction. Analyst preferences for reduced predation risk and future earnings stability induce political spending reductions in firms facing high financial constraints and high competition. However, these pressure effects are offset by beneficial information asymmetry reductions in innovative industries and by takeover protections that enable long-term investment and reduce the threat of predation. We establish causality primarily by using a difference-in-differences approach around the exogenous reduction in analyst coverage due to brokerage merger and closure events. We further confirm our results using an instrumental variable approach in a two-stage least squares model and a systems generalized method of moments estimation of linear dynamic panel data model. For robustness, we confirm that our results are not driven by short-term earnings management and are not driven by potentially confounding information flow or preferences for political investments. Using our main identification strategy and a matched sample, we find that an exogenous reduction in analyst coverage causes a 28.3% increase in political investments over a three-year window post-event.

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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)). The rise in intangible spending also explains most of the increase in corporate cash holdings as precautionary savings to ensure liquidity for future investment opportunities. Intangible investment spending is inherently long-term and focused on growth and innovative development (Corrado and Hulten (2010)). It is commonly known to consist of R&D spending, advertising (to build brand recognition and customer loyalty), and SG&A expenditures on employee training (which creates organization capital). It also consists of other SG&A components such as charitable contributions and political investments to build long-term relationships with politicians and lobbyist organizations (Snyder (1992), Hillman and Hitt (1999), Correia (2014)).

Intangible investment is a long and uncertain process. Therefore, due to the threat of expropriation, 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)). We use corporate political investment (CPI) as an example of intangible spending and find analyst coverage has a significant negative impact on CPI, which suggests analyst pressure effects outweigh analyst benefits to intangible spending from information asymmetry reduction.

Our findings address two hypotheses that have emerged regarding the impact of analyst coverage on intangible spending. The pressure hypothesis suggests that an increase in financial reporting can raise the probability of temporary value reductions due to increased investor awareness of adverse conditions such as low or missed earnings (Graham, Harvey, and Rajgopal (2005); de Jong et al. (2013)). Analyst information can also 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. Both of these can create moral hazard issues by pressuring managers to myopically underinvest in long-term assets (He and Tian (2013)) in order to maintain high and stable short-term earnings (Roychowdhury, Shroff, and Verdi (2019)) or to stabilize cash levels in the event of a price war. In addition to public awareness issues, pressure can also result from analyst preferences for forecast accuracy and optimistic price targets (Jackson (2005); Ertimur, Muslu, and Zhang (2011)). Barron et al. (2002)) notes that high intangibles make the analyst's job harder, whereas low intangible investment improves their forecast accuracy. Surveys support the pressure hypothesis, as Graham, Harvey, and Rajgopal (2005) present evidence that 78% of CFOs will sacrifice long-term value to better meet analyst's earnings targets. Their study notes the impact that analysts have on this CFO myopia, stating that CFOs often say analysts "viciously turn on you when you fail to come in line with their projections." They mention, "Many CFOs deplore the culture of giving earnings guidance and meeting or beating the guided number. They argue that such a culture inhibits managers from thinking about long-term growth…" This does not necessarily imply short-term earnings management either, as Zang (2012) notes that real earnings management is difficult to use in the short-term.

However, many studies call into question the effectiveness of the pressure hypothesis. Billett, Garfinkel, and Yu (2017) support an information hypothesis and argue that the ability of analyst coverage to reduce information asymmetries plays a more dominant role than any myopic analyst pressures. Related studies have come to similar conclusions. For example, Derrien and Kecskés (2013) find that an increase in analyst coverage reduces information asymmetries, reduces the cost of capital, and increases R&D investment. Analyst information can be particularly beneficial for R&D intensive firms (Palmon and Yezegel (2012)) and especially because it promotes efficient investment (Guo, Pérez-Castrillo, and Toldrà-Simats (2019)).

These two views may be in conflict because of differences between internal and external investments. For example, Guo, Pérez-Castrillo, and Toldrà-Simats (2019) note that analyst pressure reduces internal R&D, while analyst effects on information asymmetry increase both internal and external innovation. This suggests pressure and information effects can offset each other for internal spending, and information alone works to increase innovation externally.

Our paper addresses this debate by being the first study to examine the impact of analyst coverage on CPI, which represents an often-overlooked type of intangible investment spending. We use the three major forms of corporate political spending that occur at the start of our sample period: 1) lobbying, 2) soft money, and 3) political action committee (PAC) contributions.[1] Borghesi and Chang (2015) note that CPI and R&D are complementary and work synergistically to promote long term innovation, which positions CPI as a unique alternative long-term investment (Snyder (1992)) to the commonly used R&D measure. CPI offers additional advantages, as it 1) is less recognizable as a form of real earnings management and 2) is likely less susceptible to adjustment costs (Anderson, Banker, and Janakiraman (2003); Brown and Petersen (2011)). This should allow firms to adjust CPI temporarily or more permanently when faced with adverse economic conditions. We discuss these advantages in greater detail in Section 2.

We begin our study by examining the impact of sell-side analyst coverage on various measures of CPI. We find a negative relationship between analyst coverage and 1) lobbying and soft money (LSM), 2) PAC contributions, and 3) the number of candidates supported by a firm's PAC. This evidence is consistent with the pressure view, which suggests that analysts induce a reduction in long-term intangible spending. However, there are several possible endogenous relationships between the choice of analyst coverage by a brokerage firm and the firm's choice to invest 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"

[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.

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 corporate political contributions using three different identification strategies from both the analyst literature and the corporate governance literature. Our first and primary identification strategy utilizes the 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 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

[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.

flow between management and the public is key to our result. 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. We find that our results are robust to each of these tests.

We then examine what channels may be driving our results that support the pressure hypothesis. To narrow down potential channels, we first determine whether short-term earnings management is a driver. The negative relationship between analyst coverage and CPI could simply result from sudden and destructive short-term earnings management needs 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 earnings management (Roychowdhury (2006)). Our results hold after this exclusion, suggesting that earnings management is not a driver.

For our first channel, we argue that there is a chain of causality from financial analysts increasing firm disclosures (Irani and Oesch (2013)), to greater disclosure increasing predation risk for financially constrained firms (Bernard (2016)), and to predation risk increasing the value of cash holdings in financially constrained firms (Bolton and Scharfstein (1990); Haushalter, Klasa, and Maxwell (2007)). This would suggest analyst pressure would induce financially constrained firms to increase short-term liquidity over long-term investment, thus providing motivation for CPI cuts. We find that reduced analyst coverage leads to higher CPI under various measures of financial constraints. Competition represents a second channel 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 risk (Bolton and Scharfstein (1990). We find that reduced analyst coverage leads to significantly higher CPI only in firms facing high competition. Finally, we would expect that the negative relationship between analyst coverage and CPI would be strong in less innovative firms that are less efficient at innovation (Clarke, Dass, and Patel (2015)) and would represent a third channel. We find support for this and also for firms with strong shareholder rights where there is less "tolerance for failure" (Manso (2011)) and managers are more exposed to short-term pressure.

We structure the remainder of this paper as follows. Section 2 further describes our main measure as well as related literature. Section 3 describes our sample selection and reports summary statistics. Section 4 presents the baseline results and introduces our identification methodologies and results. Section 5 concludes.

2 Motivation and Relevance of CPI

While not a major expense for most firms, CPI provides several important advantages in determining whether analyst pressure or information effects have the greater impact on intangible investment. First, CPI provides a discrete means for firms 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, and CFOs must find discrete ways to conduct REM. Similarly, Graham, Harvey, and Rajgopal (2005) find that managers prefer REM to accruals management (AM) because it is less likely to be detected and scrutinized by auditors and regulators, and REM has become more common than AM since SOX (Cohen, Dey, and Lys (2008)). CPI adjustments can be particularly discrete, as Bebchuk and Jackson (2012) note that identifying political contributions can be notoriously difficult for stakeholders unless firms directly choose to voluntarily disclose the information. Furthermore, managers have more flexibility to cut intangibles if necessary 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 both analyst information and pressure effects because it is less susceptible than other intangibles to adjustment problems. For example, R&D and many intangible components of SG&A consist largely of salaries to key employees that cannot be reduced without the potential exit of such key employees. These departures would result in the loss of training, skills, and other organizational capital that would be costly to replace and could end up benefiting competitors. In contrast, CPI likely suffers less from this adjustment problem because it involves relationship bonds between the firm and political incumbents or lobbyist organizations. This creates implicit contracts of cooperation (Snyder (1992), Hillman and Hitt (1999)) and builds valuable long-term relationship capital between the two groups (Hillman and Hitt (1999); Correia (2014)). This relationship capital fosters the ability of 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)).

Third, changes to CPI would likely precede changes in R&D and other intangible spending. Government policy uncertainty is negatively related to innovation (Bhattacharya et al. (2017)). CPI should lead any change in innovative spending after a change in analyst coverage because CPI can help reduce policy uncertainty regarding whether certain innovations are feasible based on regulations and government policy decisions (Ovtchinnikov, Reza, and Wu (2020)). Firms cannot commit to long-term tangible or intangible investment spending without a favorable political and regulatory framework in place to support those investments.

3 Data and Descriptive Statistics

Our full sample ranges from 2001 to 2010.[3] 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

[3] 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.

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 as a result 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.[4] 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.

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

[4] We do not exclude financials and utilities from our DiD regressions, but simply present a model showing that their exclusion actually makes our results stronger and that analysts have little influence on discouraging political contributions in these industries.

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 information hypothesis and the pressure hypothesis produce opposing outcomes, the following tests will help us narrow our analysis by identifying one of these views as the dominant effect. For example, if it turns out that the information hypothesis drives our results, we 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. This would suggest an increase in intangible investments (including CPI) and would imply that a reduction in asymmetric information drives our results. On the other hand, a negative relationship between analyst coverage and CPI would suggest support for the pressure 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 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:

$$CPI_{i,t+1} = \beta_0 + \beta_1 ANALYST\ COVERAGE_{i,t} + \beta_2 FIRM\_CTRLS_{i,t} + \beta_k YEAR_t + \beta_j FIRM_i + \varepsilon_{it} \quad (1)$$

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, or 2) PAC contributions plus the total annual LSM expenditures made by the firm. 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.

In Table 2, we estimate a regression of *CPI* and the number of candidates supported by the PAC 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.[5] In models (1), (2), (4), and

[5] 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.

(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:

$$\begin{aligned} NUM\_CND_{i,t+1} = {} & \beta_0 + \beta_1 ANALYST\ COVERAGE_{i,t} + \beta_2 FIRM\_CTRLS_{i,t} \\ & + \beta_k YEAR_t + \beta_j FIRM_i + \varepsilon_{it} \end{aligned} \tag{2}$$

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,[6] showing that analyst coverage is strongly and negatively associated with CPI and related measures. Overall, this baseline evidence does not support the information hypothesis and instead suggests that analyst coverage reduces CPI via the pressure hypothesis.

4.2 Information vs. Pressure: 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

[6] 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.

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 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).[7] 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 Hong and Kacperczyk (2010) for market capitalization, book-to-market, and past returns.[8] 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

[7] 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).

[8] 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.

alternative measures, our test results provide further robustness. We obtain positive and statistically significant full sample results from the impact of an exogenous analyst reduction event on both PAC contributions and LSM contributions in all models. In terms of economic significance, these results suggest the 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.

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 Fama-French 49 industries, as political contributions are often highly industry specific and aimed at changing industry-level regulations.[9]

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 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 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

[9] 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.

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)).[10] We find that an exogenous analyst loss increases CPI 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 an exogenous analyst loss results in an 18.2% increase in patenting over the same three-year window and identification strategy.

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. In addition, highly regulated industries (e.g., the financial and utility industries) are much more dependent on government policies and may respond differently to analyst pressure in terms of their political contributions. Therefore, in the third model of Panel D we exclude financials and utilities from our matched sample. Our results are more strongly positive and statistically significant when excluding these industries. In fact, in untabulated results we find that analysts have no statistically significant effect on political contributions in these industries, likely because the benefit from political involvement outweighs the costs due to analyst pressure.

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

[10] 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.

driven by the 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.[11]

4.2.2 Instrumental Variables Approach

[11] 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.

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 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.

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 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:

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

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,[12] 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));[13] 4) firm age and Delaware incorporation. Approximately half of the corporations incorporate in

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

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

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

Similar to Table 5, in Table 6 we address potentially confounding political factors impacting a firm's propensity to engage in CPI. 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 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.

4.4 CPI Reductions in Firms Facing Financial and Competitive Risks

In the next three sub-sections, we examine empirically whether analyst pressure reduces financial risks via CPI reductions and whether pressure effects drive the results. These sections are partly motivated by Zang (2012), who examines earnings management subject to varying financial constraints, marginal tax rates, and competition.[14]

4.4.1 Excluding the Impact of Short-Term Earnings Management

The negative relationship between analyst coverage and CPI in our main model could be due in large part to myopic 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 like those involving accruals management. In other words, they are more likely to reflect a longer-term shift toward precautionary savings. 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 short-term earnings management 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

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

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 is strongly significant, suggesting precautionary savings is predominant and short-term earnings management is not a significant driver of our results.

4.4.2 Financial Constraints

We next examine whether varying levels of financial constraints drive the negative relationship between analyst coverage and CPI. We identify three primary reasons why analyst coverage is likely to reduce CPI in financially constrained firms based on prior literature. First, analyst coverage increases firm disclosures (Irani and Oesch (2013)). This in turn increases the likelihood of predation risk in financially constrained firms (Bernard (2016)), and predation risk raises the value of cash holdings in financially constrained firms (Bolton and Scharfstein (1990); Haushalter, Klasa, and Maxwell (2007)). 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. Thus, managers facing pressure from analyst information disclosures would likely seek cuts in CPI before they cut R&D. Because of the long-term relationship capital built by CPI (Snyder (1992), Hillman and Hitt (1999), Correia (2014)), CPI could be reduced without incurring significant adjustment costs in order to stabilize other investments. Third, analysts prefer both forecast accuracy and optimistic price targets (Jackson (2005); Ertimur, Muslu, and Zhang (2011)). Predation risk would threaten both goals, inducing analysts to place additional pressure on managers to make cuts.

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)). We utilize our matched sample in a DiD framework around brokerage mergers and closures similar to Table 3. 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 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.[15] 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 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.

4.4.3 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 firms facing high competition may cut CPI expenditures for this purpose 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

[15] 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)).

added disclosure can 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. An increase in analyst coverage would push back against this, improving disclosure (Irani and Oesch (2013)) and forcing the firm to reduce predation risk via other means, such as stabilizing their financial situation by cutting CPI.

We conduct this test in Table 8 Panel C-1 utilizing various measures of industry competition in subsample tests similar to related studies (Irani and Oesch (2013, 2016)). Models (1) and (2) divide the sample at the match year into low and high quantiles by the 1) fixed industry classification (FIC) Herfindahl measure of Hoberg and Phillips (2016)[16] that is similar in divisions to a three-digit SIC code and 2) by the industry competitor frequency. Models (3) and (4) repeat these tests using the text-based network industry classification (TNIC) measure for the Herfindahl Index from Hoberg and Phillips (2016). For robustness, 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 quantiles of models (2) and (4), the magnitude of the coefficients are slightly smaller. We strengthen the findings in these two models in Panel C-2, where we rerun our results excluding PAC contributions from the dependent variable (since PAC costs are only partially borne by the firm). In this panel, we find strong and positive statistical significance in the high competition quantiles of models (2) and (4) along with all of the other models except for model (5), which in this case has a higher coefficient

[16] We thank Gerard Hoberg for making these Herfindahl measures available on his website.

value but is insignificant. Because competition induces financial pressure on firms, these results provide additional support for the pressure view and further confirm our financial constraints findings. It is also possible that there is no significance in the low competition group due to anti-competition benefits provided by CPI and manager desires to resist analyst pressure and preserve CPI levels to maintain those benefits. Prior literature suggests firms lobby to increase regulation and barriers to entry for new firms, thus reducing competitive pressure (Coates (2012)).

4.5 CPI Investment Commitment Given Varying Dedication to Innovation

In this section, we examine how analyst coverage reductions affect CPI when considering the innovative focus of a firm and their commitment to long-term investment. Although our primary findings support the pressure view (He and Tian (2013)), the information view argues that analyst information production and distribution may be especially helpful for innovative firms with high levels of intangible investment. Analyst recommendations reduce the high information asymmetry inherent to these firms and can help to "certify" the viability of firms with high levels of long-term innovative investments not revealed to the public due to the threat of expropriation (Palmon and Yezegel (2012); Guo, Pérez-Castrillo, and Toldrà-Simats (2019)). This can encourage greater investment, reduced costs of capital, and improved valuations. Guo, Pérez-Castrillo, and Toldrà-Simats (2019) conclude their study by noting that although analyst pressure leads to cuts in internal R&D, analyst information production offsets this pressure and encourages efficient investments in internal innovation. For these reasons, we expect pressure effects to be strongest in less innovative industry firms where beneficial reductions in information asymmetry are less likely from analyst coverage and no offsetting effect occurs.

In Table 9 Panel A we examine the impact of analyst coverage on CPI using our brokerage merger and closure matched sample in subsample tests similar to related studies (Irani and Oesch (2013, 2016)). We divide the sample into innovative and non-innovative firms based on the innovative industry classification of Hirshleifer, Low, and Teoh (2012). Models 1 and 2 divide the sample by match year into low and high quantiles by the innovative industry classification of

Hirshleifer, Low, and Teoh (2012). To reduce the concern of bias due to our sample observations being concentrated in the high quantile, in models 3 and 4 we divide the sample by match year into 1) the bottom 3 quartiles of firms by innovative industry classification and 2) the top quartile, respectively. Using the full seven-year event window, we find that an exogenous analyst reduction event exhibits a positive and statistically significant association with CPI (analyst coverage is negatively associated with CPI) only in less innovative industries. Since innovation is a slow, long-term process, it is possible that there is a lagged reaction to innovative spending measures. Firms' reaction functions would likely be dependent on their innovation focus. Thus, we also exclude the event year (year 0) and recalculate our models in the second row of Table 9 Panel A. We find the results for less innovative industries become even stronger.

For all of the innovative industry models both including and excluding the event year, we do not find any analyst effect on CPI. Because innovative firms are inherently less transparent and are difficult for investors to value, analyst pressure effects might be offset by analyst information as suggested by Guo, Pérez-Castrillo, and Toldrà-Simats (2019). It is also possible that analyst pressure effects are stronger in less innovative firms because they are less efficient at innovation (Clarke, Dass, and Patel (2015)), suggesting the need for a monitoring role. Relatedly, Cao et al. (2018) find that lobbying is only positively associated with firm performance in growth firms, while Mathur et al. (2013) suggest lobbying is beneficial in innovative firms but is an agency cost in other firms.

We next consider an alternative commitment device to long-term investment. For firms with strong shareholder rights (low ATP), many of the same arguments suggesting analyst coverage would be negatively related to CPI should still apply. In contrast, for firms with weak shareholder rights (high ATP) a large literature suggests analysts might approve of CPI for three reasons. First, Daines and Klausner (2001) note that ATP supports the bargaining power of a target firm when faced with a takeover threat. Competition normally maximizes the bid price of acquirers, but when only one acquirer is active, the presence of ATP can help the target firm increase the negotiated price. The maintenance of CPI in the high ATP group could be used to support legislation preserving the antitakeover measures providing this bargaining power. Analysts who would like to see the price of their firms high and stable would also likely support managers on this. Second, Daines and Klausner (2001) note that ATP allows managers to extract private benefits. Although sometimes considered an agency problem, analysts might support this in certain cases. For example, Manso (2011) argues that innovative managers should be given a "tolerance for failure" to allow them to take long-term risks. Third, it is also possible that analysts simply do not have the ability to influence high ATP firms. Antitakeover laws are strongly promoted by lobbying (Karpoff and Wittry (2018)), suggesting managers would be highly resistant to analyst pressure on CPI. In addition, 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 pressure either 1) encourages CPI or 2) does not affect CPI in high ATP firms.

In Table 9 Panel B 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. 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 an 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).

While the significance in the low ATP quantile is suggestive of analyst pressure reducing CPI only in less innovative firms, we seek to disentangle further this finding by exploring the complementary effect between ATP protection and innovation. For example, Ovtchinnikov, Reza, and Wu (2020) find that political contributions reduce innovation uncertainty and might encourage firms to maintain CPI levels if they have made high prior levels of innovative investments. We test for this in Panel C. We double sort first by low vs. high innovative industries (Hirshleifer, Low, and Teoh (2012)) and second by our three measures of entrenchment. In all three double sorts, we find that the negative and significant relationship between analyst coverage and CPI is strongest in firms with both low ATP protection and in less innovative industries. In contrast, the high ATP / high innovation quadrant is the only one to show no significance.

5 Conclusion

We examine the effect of sell-side analyst coverage on intangible investments (as proxied by corporate political investments (CPI)) and test two competing hypotheses. The information hypothesis argues that increasing analyst coverage should improve the information environment, thereby lowering the cost of capital and increasing long-term intangible investments like CPI. In contrast, the pressure hypothesis argues that analyst information production can increase predation risks when negative financial or strategic conditions are revealed, forcing managers to make cuts to increase liquidity. Analyst preferences for forecast accuracy and the maintenance of price targets would also lead analysts to pressure managers to cut CPI to reduce predation risks.

We find that analyst coverage is negatively associated with CPI, supporting the pressure 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 next explore a financial constraints channel through which analyst coverage is negatively associated with CPI. We find that analysts favor CPI cuts in financially constrained firms because a reduction in CPI spending increases cash reserves which reduce 1) predation risk and 2) the risk of incurring adjustment costs in the event of an adverse financial shock. CPI is less susceptible to adjustment costs compared to R&D and other long term spending because of the relationship capital it builds, thus it can be reduced when cash-level needs are high (as in the case for a financially constrained firm). We find similar results when examining competition as an alternative measure of financial constraints.

We then find that the negative relationship between analyst coverage and CPI is confined to firms in less innovative industries and with lower antitakeover protection. Less innovative firms are not as efficient at innovation (Clarke, Dass, and Patel (2015)) and would face lower costs when making CPI cuts. Presence in an innovative industry and high antitakeover protection are proxies for firms with a long-term investment commitment. Entrenchment can allow stable prices (Daines and Klausner (2001)) by providing bargaining power in merger negotiations and a tolerance for innovative failure, both of which would be favorable to analysts. Our results support the Guo, Pérez-Castrillo, and Toldrà-Simats (2019) finding of an offsetting effect between analyst pressure and information production in highly innovative firms. We also find that antitakeover protection and innovative industry presence function as complements in a way that affects the impact of analyst coverage on CPI. 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.

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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 and 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	
Tot 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	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 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 (2015). 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 (2015). 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 (2015). 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 (2015). 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 Saaá-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 / Sales / Corp Income Tax	State tax liability from business-related property / sales / corporate income taxes. *(Source: Panel Database on Incentives and Taxes (PDIT), W.E. Upjohn Institute for Employment Research)*
Herfindahl	Herfindahl index following Hoberg and Phillips (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 (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)*
BCF Index	Entrenchment index constructed following Bebchuk, Cohen, and Ferrell (2008). *(Source: ISS Riskmetrics)*
ATI Index	Antitakeover index of Cremers and Nair (2005). Identical to the delay subindex of Gompers, Ishii, and Metrick (2003) and composed of (blankcheck + cboard + lspmt + lwcnst). *(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 litigous industry; zero otherwise. *(Source: Francis, Philbrick, and Schipper (1994))*
Battle vs. 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)*

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)

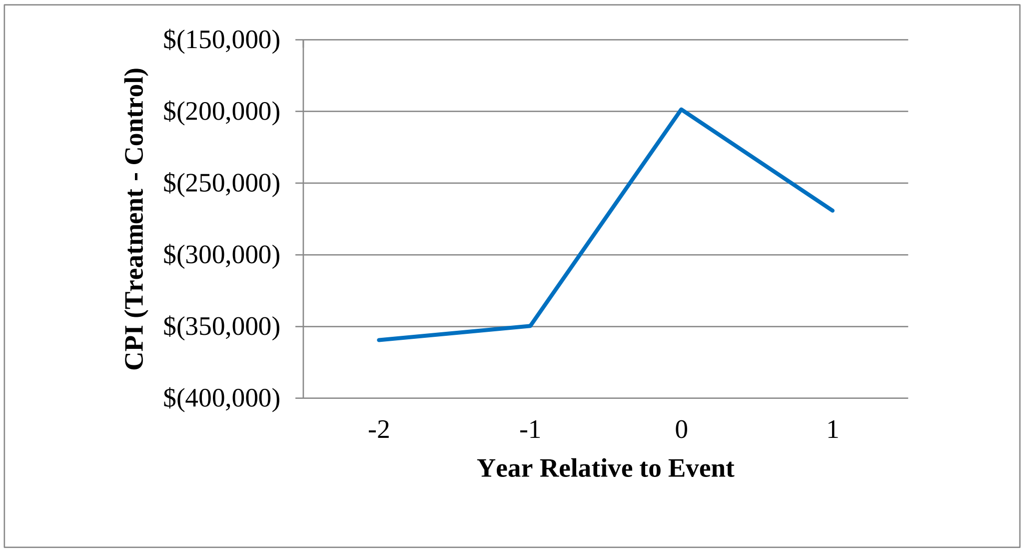
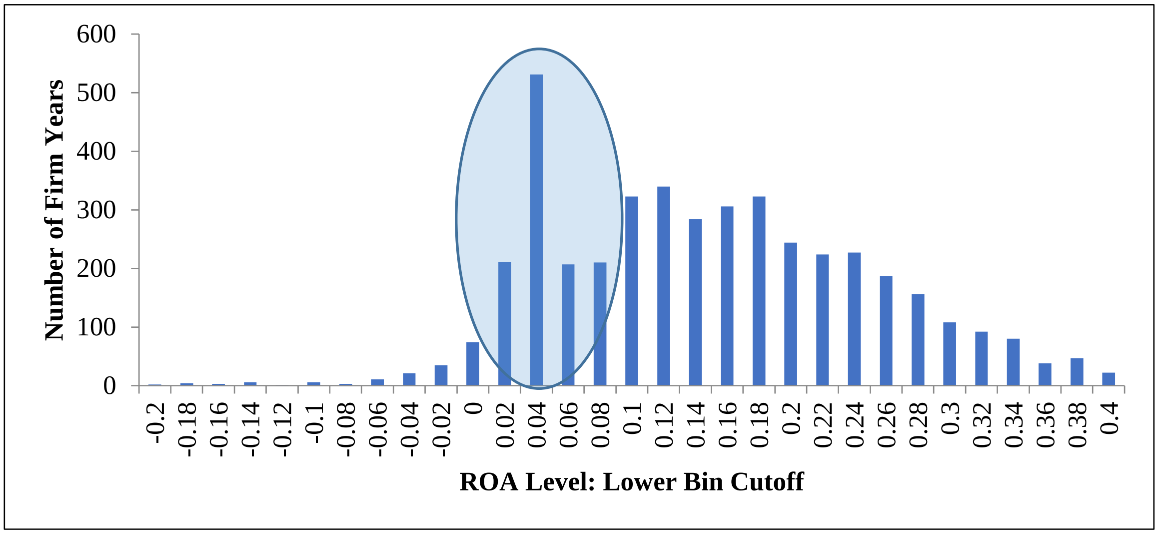


Fig. 2. Earnings Management Around the Zero Threshold

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)

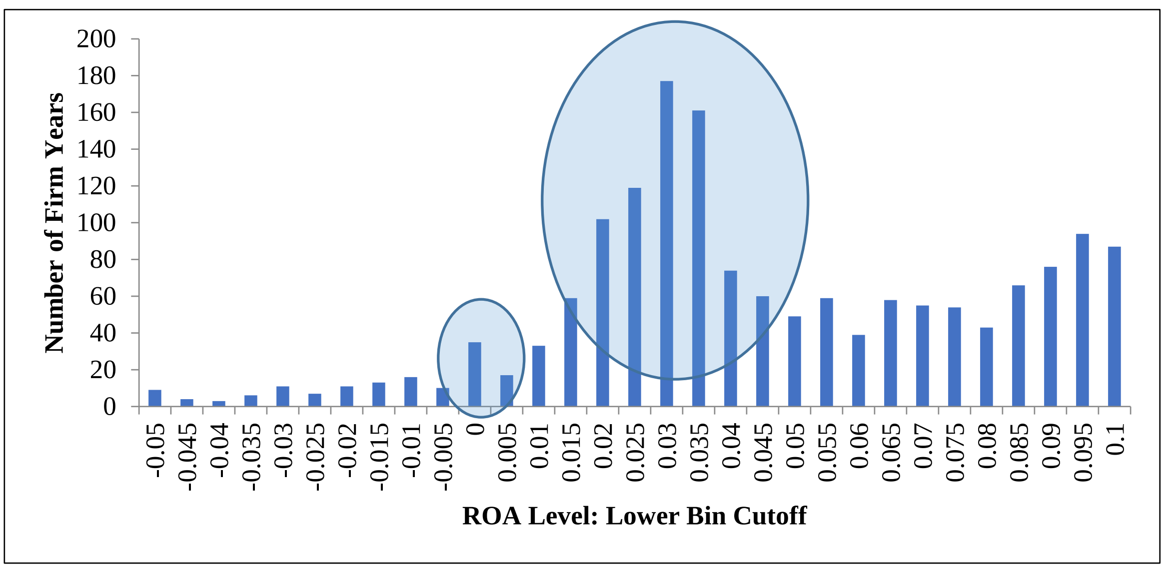


Table 1. Firm Level Descriptive Statistics

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 an 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	(2)	(3)	(4)
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***	0.368***	0.337***	0.420**
	(0.000)	(0.001)	(0.004)	(0.016)
Treat	-0.137	-0.103	-0.094	-0.237
	(0.204)	(0.283)	(0.310)	(0.151)
Post	-0.037	-0.101	-0.044	-0.155
	(0.717)	(0.438)	(0.713)	(0.420)
All-Star Analyst	0.008	0.058	0.098	0.078
	(0.861)	(0.408)	(0.257)	(0.444)
Non-Missing Items$_{t-1}$		0.005	0.00814*	0.0110***
		(0.279)	(0.058)	(0.002)
Special Items$_{t-1}$		24.400	-57.900	27.000
		(0.424)	(0.439)	(0.683)
Business Segments$_{t-1}$		0.0279*	0.020	0.022
		(0.091)	(0.157)	(0.111)
Gross File Size$_{t-1}$			0.047	0.026
			(0.231)	(0.372)
Fog Index$_{t-1}$			-0.017	-0.017
			(0.610)	(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
	(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	Post x Treat	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	Post x Treat	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. 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 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 Saaá-Requejo (2001). We report the coefficients of the interaction term in the matched sample DiD model. The dependent variable is the log of the combination of firm lobbying, soft money, and PAC contributions. Panel B 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. We report the coefficients of the interaction term in the matched sample DiD model. The dependent variable is the log of the combination of firm lobbying, soft money, and PAC contributions. Panels C-1 and C-2 divide 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. Panel C-1 model (1) divides the sample into low and high competition quantiles using the inverse of the Herfindahl index constructed from the fixed industry classification (FIC) of Hoberg and Phillips (2016), while model (2) divides the sample by FIC industry competitor frequency. Models (3) and (4) repeat models (1) and (2) using the text-based network industry classification (TNIC) that is similar to a 3-digit SIC code. Model (5) divides the sample using the match-year level of Census based industry classifications from the Small Business Administration. We report the coefficients of the interaction term in the matched sample DiD model. The dependent variable is the log of the combination of firm lobbying, soft money, and PAC contributions. Panel C-2 repeats panel C-1 using the log of the combination of firm 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 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	Delay	Equity Delay	Debt Delay	Private Delay	KZ Index
	(1)	(2)	(3)	(4)	(5)
Low	0.188	0.181	0.042	0.106	0.139
	(0.312)	(0.396)	(0.653)	(0.500)	(0.259)
High	0.225*	0.311**	0.321*	0.374**	0.394**
	(0.087)	(0.041)	(0.077)	(0.015)	(0.040)
Firm/Yr/Deal FE	Yes	Yes	Yes	Yes	Yes

	Dependent Variable: Lobbying, Soft Money, and PAC				
Panel B. Total State Business Tax Liability	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 (0.387)	0.287* (0.056)	0.109 (0.406)	0.183 (0.176)	0.193* (0.055)
High	0.335*** (0.006)	0.295** (0.042)	0.427*** (0.001)	0.271** (0.024)	0.326*** (0.004)
Firm/Yr/Deal FE	Yes	Yes	Yes	Yes	Yes

	Dependent Variable: Lobbying, Soft Money, and PAC				
Panel C-1. Competition	FIC Industry	FIC Comp Frequency	TNIC Industry	TNIC Comp Frequency	Census Industry Comp
	(1)	(2)	(3)	(4)	(5)
Low	0.109 (0.353)	0.279** (0.045)	0.261 (0.114)	0.281* (0.066)	0.189 (0.133)
High	0.402*** (0.005)	0.282** (0.019)	0.321** (0.026)	0.316* (0.058)	0.350* (0.073)
Firm/Yr/Deal FE	Yes	Yes	Yes	Yes	Yes

	Dependent Variable: Lobbying and Soft Money				
Panel C-2. Competition	FIC Industry	FIC Comp Frequency	TNIC Industry	TNIC Comp Frequency	Census Industry Comp
	(1)	(2)	(3)	(4)	(5)
Low	0.081 (0.490)	0.099 (0.547)	0.186 (0.200)	0.179 (0.347)	0.169 (0.181)
High	0.360** (0.042)	0.387** (0.023)	0.384** (0.029)	0.398** (0.018)	0.298 (0.227)
Firm/Yr/Deal FE	Yes	Yes	Yes	Yes	Yes

Table 9. Factors Affecting a Firm's Long-Term 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 factors influencing a firm's long-term investment commitment. 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. Panel A models (1) and (2) divide the sample at the match year into low and high quantiles by the innovative industry classification of Hirshleifer, Low, and Teoh (2012). Models (3) and (4) divide the sample at the match year into the bottom three quartiles of firms by innovative industry classification and the top quartile, respectively. The first row of results uses the full seven years in our matched sample window, while the second row of results excludes the event year (year 0). Panel B models (1) through (3) 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 (2008), and the antitakeover (ATI) index of Cremers and Nair (2005), respectively. Panel C double sorts dividing the sample by the match year on a) high vs. low quantiles of innovative industries as in Panel A and b) the three entrenchment measures in Panel B, respectively. 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. Innovative Industries	Low Innovative Quantile	High Innovative Quantile	Low Innovative Quartiles	High Innovative Quartile
	(1)	(2)	(3)	(4)
Incl Event Yr	0.664**	0.145	0.374***	0.053
	(0.022)	(0.104)	(0.000)	(0.755)
Observations	382	1,413	1,151	644
Adj Rsq	0.912	0.896	0.895	0.892
Excl Event Yr	0.778***	0.135	0.388***	0.081
	(0.006)	(0.205)	(0.000)	(0.687)
Observations	331	1,208	991	548
Adj Rsq	0.907	0.888	0.888	0.883
Firm/Yr/Deal FE	Yes	Yes	Yes	Yes

	Low Entrenchment			High Entrenchment		
Panel B. Low vs. High Entrenchment	GIM Index	BCF Index	ATI Index	GIM Index	BCF Index	ATI Index
	(1)	(2)	(3)	(4)	(5)	(6)
Low Entrenchment	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

Panel C. Entrenchment & Innovation	GIM Index		BCF Index		ATI Index	
	Low Innov	High Innov	Low Innov	High Innov	Low Innov	High Innov
	(1)	(2)	(3)	(4)	(5)	(6)
Low Entrenchment	1.230**	0.257*	0.784*	0.250**	0.905*	0.234*
	(0.026)	(0.062)	(0.070)	(0.039)	(0.066)	(0.090)
High Entrenchment	0.401	0.162	0.434	0.016	0.491*	0.038
	(0.125)	(0.147)	(0.330)	(0.895)	(0.090)	(0.732)
Firm/Yr/Deal FE	Yes	Yes	Yes	Yes	Yes	Yes

Supplementary Appendix

to accompany

Analyst Effects on Intangible Investment: Evidence from Corporate Political Investments

March 29, 2022

B. Supplementary Appendix

In this Supplementary Appendix, we show that our results are concentrated in firms that would likely receive smaller returns from CPI and would thus be more likely to reduce CPI as the result of analyst pressure effects, further supporting the pressure 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 Economic Importance of CPI and 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, as 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 firms may be resistant to analyst pressure because they receive abnormally strong 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 pressure affects a firm's CPI spending given a variance in the benefits of CPI. Just as Guo, Pérez-Castrillo, and Toldrà-Simats (2019) find that analyst pressure to decrease R&D can be offset by analyst information that increases R&D, it is likely that managers receiving particularly strong CPI benefits per dollar of CPI investment might be more resistant to analyst pressure, creating another offsetting effect. Analysts should also be more likely to favor CPI in these situations.

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 short-term 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 analysts would not favor a reduction in 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 a temporary reduction in CPI without a loss in benefits (or even permanently reduced if firms can convince their recipients of their dire financial need to make reductions). Thus, if the pressure view holds and especially if there is also a lower granting of favors in partisan states, we might 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 Panel A 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 our predictions.

We next examine the impact of differential levels of long-term investments on our results from Panel A. As noted in early sections, prior research suggests political contributions reduce the uncertainty of innovation (Ovtchinnikov, Reza, and Wu (2020)) and thus might provide a complementary effect and greater benefits for firms that have invested heavily in innovation. The joint benefits of politicians granting more favors in battleground states with the benefits of CPI for high innovation companies should greatly reduce the likelihood of a significant negative relationship between analyst coverage and CPI in firms experiencing both, and it should shift the impact to the opposite quadrant. To prepare our tests, in Panel B we double sort first by partisan vs. battleground states, and second by low vs. high innovative industries (Hirshleifer, Low, and Teoh (2012)). Models (1) and (2) utilize lobbying, soft money, and PAC as the dependent variable, while models (3) and (4) use lobbying and soft money only. We find that for both sorts the models are more economically and statistically significant in firms headquartered in partisan states and operating in low innovation industries, confirming prior predictions and suggesting a complementary effect.

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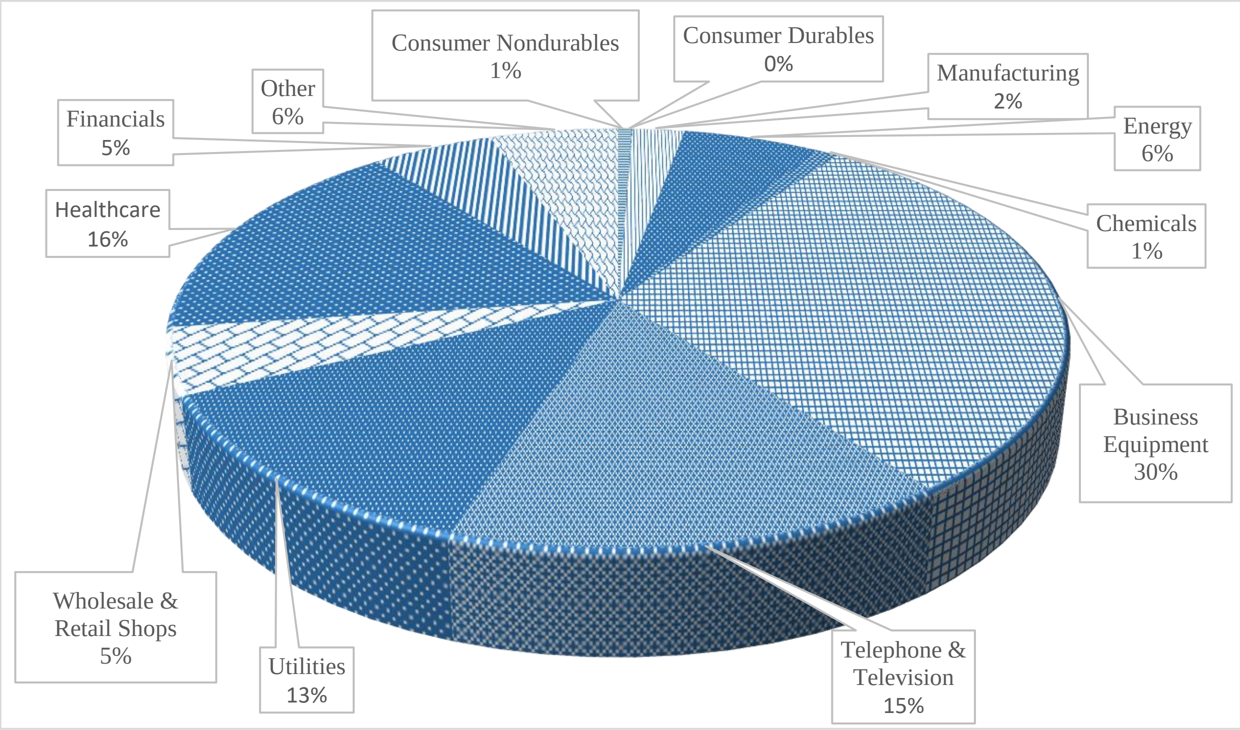
Fig. B.1. Matched Sample - Fama French 12 Industry

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 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 et al. (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. Panel A 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. Panel B double sorts dividing the sample by the match year on a) partisan vs. battleground quantiles of the Citizen Ideology measure and b) high vs. low quantiles of innovative industries (Hirshleifer, Low, and Teoh (2012)). 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. 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.

	Lobbying, Soft Money, and PAC		Lobbying and Soft Money	
Panel A. Partisan vs. Battleground States	Including Event Year	Excluding Event Year	Including Event Year	Excluding Event Year
	(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

	Lobbying, Soft Money, and PAC		Lobbying and Soft Money	
Panel B. Double Sort Citizen Ideol and Innov Ind	Low Innovind	High Innovind	Low Innovind	High Innovind
	(1)	(2)	(3)	(4)
Partisan States	1.037** (0.025)	0.093 (0.499)	0.535*** (0.000)	0.297** (0.030)
Battleground States	0.014 (0.968)	0.156 (0.369)	-0.070 (0.843)	0.083 (0.637)
Firm / Yr / Deal FE	Yes	Yes	Yes	Yes