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Contents

Abstract

Using U.S. Department of Justice data on political corruption convictions, I examine how political corruption affects firms' earnings management. I find that companies headquartered in more corrupt states manipulate earnings downwards. The findings are robust to six alternative corruption measures, the restatement analysis, the accounting policy analysis, the instrumental variable approach, the difference-in-differences analysis, and an event study. In addition, I find that the effect of corruption on earnings management is more pronounced for firms whose operations concentrate in their headquarter states and for firms without political connections, but is not significant for firms on the edge of missing earnings benchmarks or firms facing tight debt covenants. In sum, my findings suggest that firms respond to corruption by managing earnings downwards.

Keywords: Earnings Management, Political Corruption, Rent Seeking

JEL Classification: M41; G38

1. Introduction

Political corruption is pervasive and the U.S. is not immune to this problem. In its 2012 Global State of Mind Report, Gallup reports that the percentage of adults who perceive corruption as a widespread problem in their government is greater than 50%, for 108 out of 129 countries. The percentage for the U.S. stands at 73%[1]. Consistent with these statistics, there are plenty of anecdotal evidence of political corruption in the U.S. For example, Don Siegelman, the former Alabama governor, appointed the CEO of HealthSouth to a state regulatory board after taking a bribe of $500,000. For another example, several officials of the Defense Logistics Agency awarded government contracts to United Logistic in exchange for $800,000.

How does political corruption affect firms' accounting choices? Given the pervasiveness of political corruption, this is an important question that has implications for academics, regulators and the public. However, this question has received scant attention from prior literature, and I attempt to address this gap.

Following Butler et al. (2009), I define political corruption as agency issues between elected or appointed government officials and their constituents, which manifest in rent-seeking by government officials. Public officials can extract rents from firms through the threat of additional regulations and targeted taxation (McChesney, 1987). According to the positive accounting theory (Watts and Zimmerman, 1986), downward earnings management weakens the argument for such government actions, and shields firms from the rent-seeking of corrupt officials. Besides, if corrupt officials directly solicit bribes, the amount of bribe is subject to a firm's profitability (Svensson, 2003). Therefore, I hypothesize that firms facing high corruption are incentivized to manipulate earnings downwards.

[1] The report is available at http://www.gallup.com/file/poll/165497/GlobalStateMind_Report_10-13_mh.pdf.

This hypothesis is not without tension. Numerous studies have shown that political favors increase firm value (Fisman, 2001; Faccio et al., 2006; Claessens et al., 2008; Goldman, et al., 2009; Duchin and Sosyura, 2012; Tahoun, 2014), and corruption offers opportunities for firms to bribe their way into an advantageous position. Expenses related to illicit dealings with government officials are likely hidden from the public (Gul, 2006). Since these expenses can't be reasonably expected by investors, they are likely to result in actual earnings falling short of the market's expectation. To avoid these negative surprises, firms have incentives to manipulate earnings upwards.

Using a sample of 56,096 observations, I take the question to the data. To measure corruption, I follow the common practice in related economics and finance literature (Fredricksson et al., 2003; Glaeser and Saks 2006; Butler et al., 2009; Campante and Do, 2014; Smith 2016). Specifically, I obtain U.S. Department of Justice data on the number of corruption convictions involving public officials in each of the 94 federal judicial districts in the U.S. I aggregate the cases to the state level. The number of convictions *per capita* in each state (i.e., the variable *Corruption*) is used as the main measure of political corruption. A higher value indicates a more corrupt environment.

In my main test, I measure earnings management with performance-matched discretionary accrual. I regress it on *Corruption* and a battery of control variables. My control variables include general firm characteristics, firm characteristics associated with capital market incentives and contracts-based incentives, and state characteristics related with local corruption.

The results show that a one standard deviation increase in *Corruption* is associated with a reduction of 2.1 percentage points in performance-matched discretionary accrual. This effect is economically significant, considering that the mean value of discretionary accrual in the sample is only -2.4 percentage points. Overall, the results are consistent with the hypothesis.

To test whether the results are indeed related to rent-seeking by corrupt officials, I conduct several subsample analyses. Public officials have higher ability to seek rents from companies that mainly operate in their jurisdictions, because these firms face higher costs to shift operations to non-corrupt states than geographically dispersed firms (Bai et al., 2015). Therefore, I expect that the impact of local political corruption on earnings management is more pronounced for geographically concentrated firms. I test this expectation by dividing the sample into two subsamples based on their geographic concentration. Consistent with my expectation, the effect of corruption on discretionary accruals is indeed more significant for firms with more concentrated operations.

Firms without political connections are more vulnerable to expropriations by politicians, such as bribe solicitations (Clarke and Xu, 2004). Thus, I predict that the impact of political corruption on earnings management is more pronounced for these firms. Following Cooper et al. (2010) and Kim and Zhang (2015), I use the establishment of corporate political action committee (PAC) to identify political connection, and my empirical results lend support to my prediction.

There is a tension between the costs of downward earnings management and the benefits of downward earnings management (Bova, 2013). Compared with companies that are faced with lower costs of downward earnings management, companies faced with higher costs of downward earnings management are less likely to do so. I test this prediction by diving the sample into two subsamples based on their costs of downward earnings management. Following prior literature (i.e., DeFond and Jiambalvo, 1994; Skinner and Sloan, 2002), I deem firms on the edge of missing earnings benchmarks or facing tight debt covenants as firms with high costs of downward earnings management. I find that the effect of political corruption on discretionary accrual is not pronounced for these firms.

The results are robust to six alternative political corruption measures that are suggested by prior literature. These first three measures are the number of corruption conviction cases per government employee, the *per capita* corrupt convictions weighted by firms' operations in each state, and the raw number of corruption convictions, respectively. The next three measures are respectively based on the ranking of the state in the 2013 BGA-Alper Integrity Index, the ranking of the state in the 2012 State Integrity Investigation, and the perception of the level of corruption by State House reporters.

I also test whether my conclusion is robust by focusing on an alternative measure of earnings management, i.e. restatement. I find that companies located in more corrupt states are more likely to understate their earnings. Then, I continue to study how political corruption affects corporate accounting policy choices. I document that companies headquartered in more corrupt states are more likely to choose accelerated depreciation method and their depreciation reserves are higher. Although these companies do not differ from other companies in the likelihood of choosing LIFO as the primary inventory valuation method, they do report higher LIFO reserves. My findings are consistent with the notion that companies located in more corrupt areas report lower earnings.

To address the endogeneity concern and establish a causal relation between political corruption and downward earnings management, I adopt an instrumental variable approach. The instrumental variable (IV) is the isolation of state capital from its populace. Campante and Do (2014) show that states with isolated capital cities are more corrupt, because politicians in isolated capital cities are less effectively monitored by the public. This instrumental variable is positively related with political corruption but is unlikely to be correlated with local firms' earnings management except through the channel of corruption. I find that the relation between instrumented corruption and discretionary accrual remains negative and significant.

In addition, I conduct a difference-in-differences test by focusing on firms that move between corrupt and non-corrupt states. A state is deemed as corrupt (non-corrupt), if its time-series mean value of *Corruption* is above (below) the median of all the states. For each treatment firm (i.e., a firm that moves between corrupt and non-corrupt states), I match it to a control company (i.e., a firm that does not move) that is in the same 2-digit SIC industry, located in the same state, and with most similar ROA. The results show that treatment firms that move to a more (less) corrupt state experience a decline (an increase) in discretionary accruals, relative to control firms.

Besides, I provide some evidence by studying how a high-profile corruption case affects firms' discretionary accruals. High-profile corruption cases help deter the rent-seeking behaviors of local politicians, by elevating their assessment of the likelihood of being caught and penalized. Consistent with my expectation, I find that companies located in Alabama increase their discretionary accruals after a former Alabama governor was sent to prison, and decrease their discretionary accruals after the person was released in advance.

One alternative explanation is that my findings reflect the relation between political corruption and tax avoidance (Ayyagari et al., 2014), which is achieved through downward earnings management (Chen and Daley, 1996). To test this alternative hypothesis, I test how political corruption affects book-tax difference. I find that political corruption does not significantly affect book-tax difference, suggesting that the alternative explanation is unlikely.

Another alternative explanation is that my measure of corruption may be a proxy for state party affiliation, since party affiliation may affect the Department of Justice's decision to prosecute a case (Meier and Holbrook, 1992). To test this alternative hypothesis, I conduct a subsample analysis based on state party affiliation. The results suggest that the negative relation between political corruption and discretionary accrual is unlikely to be affected by state party affiliation.

This paper contributes to the literature in the following ways. First, this paper adds to the understanding of the effect of political costs on firms' accounting practices. The positive accounting theory predicts that companies have incentives to manipulate earnings downwards to minimize political costs (Watts and Zimmerman, 1986). While prior studies document empirical evidence of the impact from other types of political costs (Liberty and Zimmerman, 1986; Han and Wang, 1998; Johnston and Rock, 2005; Grace and Leverty, 2010; Bova 2013), the impact of political corruption has received scant attention. Given the importance and pervasiveness of political corruption, this paper addresses an important gap in the literature.

Second, this paper contributes to the literature on corruption. Prior literature in finance and economics has studied how corruption influences innovation, cost of capital, and firms' operating decisions (Butler et al., 2009; Borisov et al., 2015; Smith, 2016; Ellis et al., 2016).[2] I extend this line of enquiry to firms' accounting choices, offering results from a novel and less-explored perspective.

In addition, this paper contributes to prior research that investigates the relation between corruption and earnings quality in the international setting. Leuz et al. (2003) and Gupta et al. (2008) show that firms in countries with weaker legal enforcement (a measure partially based on a cross-country corruption index) exhibit lower earnings quality. Countries differ substantially in terms of culture and institutional features, and international studies are subject to the criticism that uncontrolled/unobservable country-specific factors account for the results. Since the sample in this paper consists of only U.S. firms that are faced with a homogenous institutional environment, the results are less exposed to the criticism. What's more, while these studies suggest that firms manipulate earnings more in countries with higher corruption, the direction of earnings management is unclear. This paper helps cover the blank.

[2] Dass et al. (2016) use unsigned discretionary accrual as a proxy for information transparency. They find that companies located in areas of high political corruption are opaquer. Their study however offers no prediction on the direction of earnings management, which is the focus of this study.

The rest of the paper proceeds as follows. Section 2 reviews prior literature and develops hypothesis. Section 3 discusses research methodology. Section 4 reports sample formation and descriptive statistics. Section 5 tests the hypothesis. Section 6 checks robustness. Section 7 concludes.

2. Literature Review and Hypothesis Development

The accounting literature has long recognized the importance of political costs on firms' accounting choices. Watts and Zimmerman (1986) hypothesize that firms facing high political costs have incentives to manipulate earnings downwards. This hypothesis has been tested in different settings. Liberty and Zimmerman (1986) examine earnings management around labor negotiations but they find no evidence that the management manipulates earnings downwards to increase its negotiation power. Jones (1991) documents that affected firms manage earnings downwards during import relief investigations by the U.S. International Trade Commission. Han and Wang (1998) show that oil companies manipulate earnings downwards to reduce their political costs during the 1990 Persian Gulf Crisis, when the rapid rising oil price raises the prospects of wind-fall taxes on oil firms. Johnston and Rock (2005) find that firms under investigation by the government for potential environmental damages manage earnings downwards to minimize their future clean-up and transaction costs. Bova (2013) reports that unionized firms are more likely to miss analysts' consensus forecasts, consistent with that unionized firms seek to lower the threat of wage increases by manipulating profitability signals. Overall, the empirical evidence so far predominantly supports the positive accounting theory that managers deem downward earnings management an effective way to reduce the political costs.

Public officials can extract rents from firms through the threat of regulations and targeted taxation (McChesney, 1987), imposing additional costs on these firms. Svensson (2003) suggests that the amount of bribe is determined in a bargaining process between a rent-maximizing public official and a firm. The firm's higher profitability reduces its bargaining power, since the official can require a higher amount of bribe and the firm can afford to pay the bribe. In sum, firms have incentives to manage earnings downwards, because poor financial results offer powerful arguments against additional regulations, taxations, and bribe solicitations.

Downward earnings management is not costless. Companies that disappoint the capital market will face negative capital market consequences (Skinner and Sloan, 2002). A tension exists between the costs of downward earnings management and the benefits of downward earnings management (Bova, 2013). So, companies located in less corrupt areas, who are faced with lower risk of expropriation by corrupt officials, have less incentive to manipulate earnings downwards.

The above discussion gives rise to the following hypothesis.

H1: Compared to companies located in less corrupt states, companies located in more corrupt states manipulate earnings downwards.

This hypothesis is not without tension. Shleifer and Vishny (1994) argue that corruption is an efficient arrangement, which allows firms to cut through bureaucracies. According to this view, it is optimal for firms to purchase political favors through bribes. There is plenty of evidence that political favors increase firm value. Fisman (2001) documents that politically dependent companies in Indonesia under President Suharto experience significant drops in value when there are negative rumors related to Suharto's health, suggesting the benefit of political support. Subsequent studies show that politically favored firms are more likely to be bailed out (Faccio et al., 2006; Duchin and Sosyura, 2012), experience higher returns (Claessens et al., 2008; Goldman et al., 2009), win more government contracts (Tahoun, 2014), and are less likely to be the targets of the SEC's enforcement actions (Correia, 2014). These evidences help buttress the case that bribing corrupt officials is an optimal choice for managers seeking to maximize shareholder value.

If firms indeed pay bribes to corrupt officials, I expect that these illicit expenditures are more substantial for firms facing a higher level of corruption. Since these expenditures can't be revealed to the public (Gul, 2006), they can't be reasonably anticipated by investors and likely result in actual earning falling short of investors' expectations. Therefore, firms have incentives to manipulate earnings upwards to avoid the shortfall. This argument predicts that firms in more corrupt areas manipulate earnings upwards.

3. Research Design

3.1 Baseline Model

I test whether firms in more corrupt states choose to manipulate earnings downwards by running the following OLS regression:

$$DA_{ist} = \alpha_0 + \alpha_1 Corruption_{st} + \alpha_2 Firm\ Characteristics_{ist} + \alpha_3 State\ Characteristics_{st} + Industry\ FE + Year\ FE + \varepsilon_{ist}\ (1),$$

The dependent variable DA_{ist} is discretionary accrual of firm *i* in year *t*. The independent variable is $Corruption_{st}$, a measure of the local corruption level in state s in year *t*. The details of these two variables are provided in Section 3.2 and Section 3.3. The model includes a set of firm characteristics that affect earnings management, as well as state characteristics that may be related with local corruption.

The model includes industry fixed effects, as some industries are more vulnerable to political corruption (Svensson, 2003). It also includes year fixed effects, so as to capture the economic-wide shocks. Since the independent variable (*Corruption*) is measured at state-year level, I cluster the standard errors by state-year (Butler et al., 2009)[3].

3.2 Measure of Earnings Management

I follow Kothari et al. (2005) and use the performance-matched discretionary accruals as a proxy for earnings management. Specifically, I run the modified Jones (1991) model as described in Dechow et al. (1995) for each two digit SIC-year combination as follows:

$$\frac{ACCRUAL_{it}}{ASSETS_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{ASSETS_{i,t-1}} + \beta_2 \frac{\Delta REV_{it} - \Delta AR_{it}}{ASSETS_{i,t-1}} + \beta_3 \frac{PPE_{it}}{ASSETS_{i,t-1}} + \varepsilon_{it} \text{ (2)},$$

where ACCRUAL is accruals, computed as earnings before extraordinary items and discontinued operations minus cash flow from operating activities from the statement of cash flows (Hribar and Collins, 2002; Cohen et al., 2008). ASSET is total assets, REV is total revenue, AR is accounts receivable, and PPE is gross property, plant, and equipment.

To measure accruals more accurately, I follow the method of Reichelt and Wang (2010) and use all the available observations from Compustat U.S. universe to estimate Equation (2). The residual from Equation (2) is the discretionary accrual measure. Following Kothari et al. (2005), I calculate firm *i*'s performance-matched discretionary accrual in year *t* as firm *i*'s discretionary accrual minus the discretionary accrual of the firm from the same industry-year combination with the closest ROA.

[3] If I cluster the standard errors by state and year, the results still hold.

3.3 Measure of Political Corruption

The main political corruption measure, *Corruption*, is the number of corruption convictions divided by the number of population (in 100,000s) in the state. The U.S. Department of Justice Public Integrity Section (PIN) reports annual public corruption conviction numbers for the 94 U.S. federal district courts in its yearly *Report to Congress on the Activities and Operations of the Public Integrity Section*[4]. Most convicted cases are handled by the U.S. Attorney's Office in the originating district, while some are handled by PIN directly. The crimes reported include bribery, extortion, election scandals, conspiracy, and criminal conflicts of interest. As discussed in Smith (2016), the data do not allow researchers to identify cases directly impacting firms. Therefore, I implicitly assume that a higher number of conviction cases in a district reflects a more corruption culture that firms in the district have to face.

The data are used widely in finance and economics literature to measure corruption in the U.S. (Fredricksson et al. 2003; Glaeser and Saks 2006, Butler et al. 2009; Campante and Do, 2014; Smith 2016). The researchers suggest that the data are objective and verifiable, and therefore they are superior to survey data.

One plausible concern with the data is that a corruption conviction depends on not only the existence of corruption, but also the detection of the misdeed. In fact, a lower number of convicted cases could reflect the absence of strong oversight and effective law enforcement, rather than a less corrupt environment in the particular area. This concern can be alleviated in the following ways. First, Glaeser and Saks (2006) argue that the federal judicial system, which is responsible for most cases, should be above the influence of local corruption and therefore, the enforcement is more or less equal across the country. Second, Smith (2016)

[4] If, in the rare cases, the number of convictions in a district is missing, I use the average number of convictions in the adjacent years as the conviction number for the missing year.

shows that the number of convictions is aligned with intuition and anecdotal evidence in identifying the most and least corrupt areas in the U.S. Third, I test the robustness of the results by using survey-based measures of corruption. The results continue to hold.

Since a state may have more than one districts, I aggregate the number of convicted cases to the state level. I then standardize the number by the state population data obtained from the U.S. Census Bureau.

Appendix B reports summary statistics for *Corruption* by state for the period from 1987 to 2011. As indicated by the mean values of *Corruption*, Washing D.C., Louisiana, North Dakota, and Mississippi are the most corrupt states, while Oregon, New Hampshire, Utah, and Washington are the least corrupt ones. The value of *Corruption* for Washington D.C. is exceptionally high. This is not surprising, since D.C. is a political centre with fewer residents. The regression results remain similar, if I remove all the firms located in D.C. from my sample.

I provide a visual illustration of *Corruption* in Figure 1. I calculate the mean value of *Corruption* in each state across the sample period, and plot these values in the map. Figure 1 shows that there is a significant variation in *Corruption* across different states. The figure also suggests that there is no obvious geographic cluster in terms of political corruption.

3.4 Control variables

I control for *Ln(total assets)*, as larger firms are more politically visible (Watts and Zimmerman, 1986). I control for *CFO* (cash flow from operating activities scaled by lagged total assets) and *ROA* (income before extraordinary items divided by lagged total assets) to capture the effect of firm performance on discretionary accruals (e.g., Kothari et al., 2005). I control for *R&D* (research and development expenses divided by lagged total assets), because firms with high R&D expenditure suffer from information asymmetry and have the incentive to signal good accounting quality (Aboody and Lev, 2000; Godfrey and Hamilton, 2005). Following the suggestions by prior studies (Bebchuk et al., 2011; Koh and Reeb, 2015), I set missing *R&D* as zero and include a dummy variable *R&D missing*, which equals 1 when R&D is reported as missing in Compustat, and 0 otherwise.

I control for *Acquisition*, an indicator for M&A involvement, because acquisitive activities have a significant influence on financial accounting (Ali and Zhang, 2015). I also control for *Issuance*, an indicator for external financing, because companies may manipulate earnings upwards before external financing (Teoh et al., 1998; DuCharme et al., 2004; Carter et al., 2007).

I control for *Institution* (the percentage of shares held by institutional investors) and *Ln(Analyst)* (the logged number of analysts covering the firm), *Big N* (an indicator for Big N auditor) and *Leverage* (long-term debt plus debt in current liabilities, divided by lagged total assets), because institutional investors, analysts, auditors and debt holders could impede earnings management (Matsumoto, 2002; Yu, 2008; Francis and Krishnan, 1999; Khan and Watts, 2009).

I control for *Tight covenant* (an indicator for proximity to debt covenant violation) and *Meet/Beat* (an indicator for meeting or beating earnings benchmarks by a small margin), as managers may manipulate earnings to avoid debt covenant violation and to meet or beat earnings benchmarks (DeFond and Jiambalvo, 1994; Sweeney, 1994; Burgstahler and Dichev, 1997; Graham et al., 2005).

I then control for firm growth by including *Sales growth* and *M/B* (the market-to-book ratio) in the model, because high-growth firms are faced with severe penalty for missing earnings benchmarks and thus have the incentive to manipulate earnings upwards (Skinner and Sloan, 2002).

Barton and Simko (2002) show that firms with a bloated balance sheet are less capable of upward earnings manipulation. I therefore control for *NOA* (net operating assets divided by lagged sales), a measure of bloatedness of the balance sheet. I control for *Sales Volatility* (standard deviation of the ratio of total sales to total assets in the prior five years) and *Operating cycle* ([Average Inventory/(Cost of Sales/365)]+[Average Accounts Receivable/(Sales/365)]), because companies with larger operating volatility and longer operating cycle have more flexibility in earnings manipulations.

I additionally control for state characteristics. Specifically, I control for *Per capita income* (personal income *per capita*), *Education* (the percentage of labor-force residents who have finished four-year's college education), and *Hightech* (the percentage of high tech companies in the state). I calculate the percentage of high-tech firms based on the firms in Compustat U.S. universe. Prior studies show that wealthier states and better educated states are less corrupt (Glaeser and Saks, 2006), and that innovative companies are more likely to be the targets of political corruption (Murphy et al., 1993).

Detailed variable definitions are provided in Appendix A.

4. Sample Formation and Descriptive Statistics

4.1 Sample Formation

I start with all U.S. public firms in the Compustat database. I only include companies that are incorporated and headquartered in the U.S. I exclude firms in financial industries (SIC codes 6000-6999) or utility industries (SIC codes 4900-4999), as they are under different regulatory oversights. I require at least 10 observations in each industry-year combination (industry is based on a two-digit SIC code). Following Heider and Ljungqvist (2015), I use historical location and incorporation data from the SEC's EDGAR service from May 1996 onwards, and use historical location and incorporation data from the Compact Disclosure before May 1996. The SEC's EDGAR data are provided by Bill McDonald[5].

I obtain debt covenant data from the Dealscan database and institutional shareholding data from Thomson Reuters Institutional (13f) Holdings. I collect analyst coverage, analyst forecast, and actual earnings per share data from the I/B/E/S unadjusted detailed files.

I collect corruption conviction data from the Department of Justice Public Integrity Section. I obtain data on each state's personal income *per capita* from the Bureau of Economic Analysis, and state education information from the Integrated Public Use Microdata Series (Flood et al., 2015).

Following Hribar and Collins (2002)'s suggestion, I use the cash flow method to measure total accrual. The sample period starts in 1987, the year when cash flow statements became available. The sample period ends in 2011, since the Dealscan-Compustat linking is only available before 2011 (Chava and Roberts, 2008). I delete all the firm-year observations with negative book value of equity or with missing information for the variables included in Equation (1), as specified in Section 3.1. The final sample consists of 56,096 firm-year observations from 1987 to 2011.

4.2 Descriptive Statistics

Table 1 Panel A provides summary statistics for the full sample. The mean value of *DA* is -2.39 % and its median value is -0.92%. It is slightly different from zero, because not all the observations used in the estimation of discretionary accruals are included in the final sample.

[5] The data can be obtained from http://www3.nd.edu/~mcdonald/10-K_Headers/10-K_Headers.html.

The mean value of *Corruption* is 0.31, indicating that every 100,000 people are faced with 0.31 corruption convictions in an average state. The average firm in the sample has *total assets* of $1.80 billion, with an *ROA* of 0.61%, *CFO* and *R&D* of 6.75% and 6.41% of lagged total assets, respectively. About 20% (28%) of sample observations are involved in mergers and acquisitions (debt or equity issuance). On average, institutional investors hold about 49.73% of sample firms' shares and my sample firms are followed by 8.63 analysts. About 11% of the sample firms face tight debt covenants and 16% of them meet or beat earnings benchmarks by a small margin. The mean market-to-book ratio is 3.25 and the net operating assets averages about 75% of lagged sales. The mean value of sales volatility is about 21.90% and the operating cycle on average is 130.76 days. The mean value of Big N shows that 90% of sample firms are audited by Big N auditors. The states where the sample firms are headquartered have a mean personal income *per capita* of $30,800. About 15 % of firms headquartered in these states are high tech firms, and about 27% of labor-force residents in these states have finished four years' college education.

Table 1 Panel B provides descriptive statistics by the level of corruption. A firm-year observation is in the most corrupt (least corrupt) group, if it is in the top (bottom) quartile of all the observations. The mean value of *DA* is -1.52% in the least corrupt group, and -2.12% in the most corrupt group. The difference is significant at the 10% level. On average, companies in the most corrupt group are located in states where every 100,000 people are faced with 0.61 corruption convictions in a year, and companies in the least corrupt group are located in states where every 100,000 people are faced with only 0.11 corruption convictions in a year. The difference is significant at the 1% level.

Many variables are significantly different between the two groups. Specifically, companies in the most corrupt group are associated with higher cash flow from operations, better firm performance, lower R&D expenditure, higher market-to-book ratio, higher leverage, and are more likely to be involved in M&A activities and financing activities. These differences give rise to the need to control these variables in the analyses.

5. Empirical Results

5.1 Baseline Regression

Table 2 reports the results from estimating model (1). Column (1) reports the results where I control for all the firm-level and state-level characteristics. Column (2) shows the results after I further control for year fixed effects. Column (3) reports the results after I further include industry fixed effects.

The results in these three columns are similar. Since the model specification in Column (3) is the most comprehensive, I focus on Column (3). The coefficient on *Corruption* is -0.021, significant at the 1% level, suggesting that a one standard deviation increase in *Corruption* (0.19) is associated with -2.1% decrease in discretionary accrual. The economic magnitude is sizeable, as it is almost more than three times the mean value of ROA. The coefficients are significantly negative for *CFO*, *R&D*, *Acquisition*, *Ln(Analyst)*, and *Big N*, consistent with prior literatures, e.g., DuCharme et al. (2004), Ali and Zhang (2005), and Chen et al. (2015).

In sum, the results suggest that political corruption results in downward earnings management, consistent with H1.

5.2 Subsample Analyses

5.2.1 Geographic Concentration

I predict that the impact of corruption on earnings management is more pronounced for firms whose operations concentrate in their headquarter states. Political officials have stronger ability to seek rents, when their jurisdiction is the only place for a company's operation (Smith, 2016). Besides, geographically dispersed companies face lower costs when they shift operations to low-corrupt areas (Bai et al., 2015). The low costs of shifting increase a firm's bargaining power when it is faced with bribe solicitation (Svensson, 2003).

A firm is deemed as a concentrated (dispersed) firm if the proportion of operations in its headquarter state is above (below) sample median in the year. Following Garcia and Norli (2012) and Smith (2016), I measure the proportion of a firm's operations in each state as the number of times the state is mentioned in the firm's 10-K filing in the year divided by the total number of times all states are mentioned. The relevant data is obtained from Diego Garcia.[6] Then, I re-estimate Equation (1) for the two subsamples that are formed based on geographic concentration. Because of sample selection in Garcia and Norli (2012), the data are not available for all the companies.

Table 3 reports the results. In the subsample of geographically concentrated firms, the coefficient on *Corruption* is -0.037, significant at the 1% level. In contrast, in the subsample of geographically dispersed firms, the coefficient on *Corruption* is -0.009, much smaller in magnitude and not significant. A Chow test rejects the null hypothesis of no difference in the coefficients for concentrated and dispersed companies at the 10% level (Chow 1960).

[6] The data can be obtained from http://leeds-faculty.colorado.edu/garcia/page3.html.

Overall, the results from Table 3 suggest that the impact of political corruption on downward earnings management is stronger for firms whose operations concentrate in their headquarter states.

5.2.2 Political Connections

I predict that the impact of corruption on earnings management is less pronounced for firms with political connections. Political connections protect these firm from local officials' expropriations and these firms are less incentivized to manage earnings downwards (Clarke and Xu, 2006). Following Cooper et al. (2010) and Kim and Zhang (2015), I use the establishment of corporate political action committee (PAC) to measure political connection.

A firm is deemed as politically connected if it registered a PAC in November of the year. I obtain the PAC data from the Federal Election Commission (FEC) Committee Master Files. The database provides the name of the company that is connected to each PAC. I then match company names from FEC to company names from Compustat by using the fuzzy merge method developed by Wasi and Flaaen (2015). I use the historical company name data provided by Bill McDonald to adjust for historical name change[7]. Then I re-estimate Equation (1) for the two subsamples that are formed based on whether the firm has a PAC. The sample consists of 56, 096 observations.

Table 4 reports the results. In the subsample of politically connected firms, the coefficient on *Corruption* is 0.005 and not significant. In contrast, in the subsample of firms without political connections, the coefficient on *Corruption* is -0.024, significant at the 1% level. The difference in the coefficients is significant at the 10% level.

[7] The data can be obtained from http://www3.nd.edu/~mcdonald/10-K_Headers/10-K_Headers.html.

Overall, the results from Table 4 lends support to the prediction that the impact of corruption on earnings management is more pronounced for firms without political connections.

5.2.3 Costs of Downward Earnings Management

Missing earnings benchmarks and violating debt covenants are both very costly (DeFond and Jiambalvo, 1994; Skinner and Sloan, 2002). Compared with companies that are faced with lower costs of downward earnings management, companies faced with higher costs of downward earnings management are less likely to manipulate earnings downwards. I therefore expect that the impact of political corruption is less pronounced for these firms.

I test this expectation by dividing the sample into two subsamples based on their costs of downward earnings manipulation. A firm is deemed with high costs of downward earnings manipulation, if it meets or beats earnings benchmarks at a small margin, of if it is faced with tight debt covenant, and is deemed with low costs otherwise. Following Cohen et al. (2008), I deem a company meets or beats earnings benchmarks by a small margin, if the net income before extraordinary items scaled by total assets lies in [0,0.005) or the change in net income before extraordinary items scaled by total assets lies in [0,0.005), or EPS beats analyst forecasts by one cent per share or less. I deem a company with tight debt covenant, if the tightest slack of the company is smaller than the sample median in the year, and equals 0 if the tightest slack of the company is larger than the sample median in the year, or if the company is not limited by debt covenant in the year, or if the company's tightest slack is negative. Following Dou et al. (2016), I measure slack as [(maximum threshold-actual) / maximum threshold] for maximum threshold covenants, and [(actual-minimum threshold)/ absolute value of minimum threshold] for minimum threshold covenants.

Table 5 report the results. In the subsample of firms with low costs of manipulating earnings downwards, the coefficient on *Corruption* is -0.024, significant at the 1% level. In contrast, in the subsample of firms with high costs of manipulating earnings downwards, the coefficient on *Corruption* is not significant. The results from Table 5 support the prediction that the impact of corruption on downward earnings management is not pronounced for firms with high costs of downward earnings manipulation.

6. Robustness checks

6.1 Alternative Measures of Corruption

6.1.1 Alternative Measures Based on Corruption Convictions

The number of political corruption convictions may be proportional to the number of officials, rather than the number of population. Following Cordis and Warren (2014), I use an alternative measure *Corruption per government employee*. This measure is calculated as the number of corruption convictions per 100,000 full-time equivalent state and local government employees[8]. I obtain the government employment data from the U.S. Census Bureau.

The main measure of corruption is based on the headquarter state and it may not capture the political corruption faced by a company that operates in several states. To address this concern, following Smith (2016), I construct *Weighted corruption*, which is the weighted average of *Corruption* in all states where the firm operates in and the weight is determined by the proportion of the firm's operations in that state. The measure of the proportion is discussed in Section 5.2.1.

[8] According to the U.S. Census Bureau, the number of full-time equivalent government employees is equal to the number of full-time government employees plus the number of part-time government employee working hours divided by the standard number of working hours of a full-time government employee.

The third measure is *Number of convictions*, calculated as the raw number of corruption convictions divided by 1,000, irrespective of the size of the population in the state.

I then re-estimate Equation (1) by replacing *Corruption* with these three alternative measures and report regression results in Table 6 Panel A. Because the operation distribution data are not available for all the companies, the sample size is smaller in Column (2). Across all the three columns, the coefficients on the alternative measures are negative and significant at least at 5% level, suggesting that the baseline regression results are robust to various alternative measures based on corruption convictions.

6.1.2 Alternative Measures Based on Perception

Although the main measure of corruption is objective, this *ex post* measure may not accurately portrait political corruption. In this subsection, I address this concern by using three alternative measures that are based on perception.

The first two measures are based on the strength of state institutions that safeguard against political corruption. Two non-government organizations, the Better Government Association and the Centre for Public Integrity, separately issued reports that ranked states based on transparency, accountability and anti-corruption mechanisms. I obtain the former ranking data from the 2013 BGA-Alper Integrity Index and the latter ranking data from the 2012 State Integrity survey. I define *Low integrity_BGA* as a dummy variable that equals 1 if the state ranks in the bottom quartile of all the states in the 2013 BGA-Alper Integrity Index, and 0 otherwise. I define *Low integrity_SII* as a dummy variable that equals 1 if the state ranks in the bottom quartile of all the states in the 2012 State Integrity Survey, and 0 otherwise. Both variables are cross-sectional, and are not available for Washington D.C.

The third measure is State House reporters' perception of corruption. I obtain the data from the survey conducted by Boylan and Long (2003) in 1999. I define *Perceived corruption* as the corruption scale from Table 2 of Boylan and Long (2003). This variable is not available for Massachusetts, New Hampshire, New Jersey, and Washington D.C.

I re-estimate Equation (1) by replacing *Corruption* with these three alternative measures and report regression results in Table 6 Panel B. Because the three measures are not available for all the companies, the sample size is smaller in these three columns. Table 4 Panel B shows that the coefficients on the three measures are negative and significant. Which suggests that the baseline regression results are also robust to various subjective measures of corruption.

6.2 Restatement Analysis

I also test whether the results are robust to an alternative measure of earnings management, i.e. earnings restatement. Specifically, I run the following regression.

$$\%\ of\ Restating\ Firms_{st} = \alpha_0 + \alpha_1 Corruption_{st} + \alpha_2 State\ Characteristics_{st} + State\ FE + Year\ FE + \varepsilon_{st}\ (3),$$

Where $\%\ of\ Restating\ Firms_{st}$ is the number of companies with restated earnings divided by the number of companies located in state *s* in year *t*. A company is deemed as understates (overstates) earning if the original net income is lower (higher) than restated net income. I include all the companies in the Compustat U.S. universe. Among the 226,507 observations from 1987 to 2011, 1.81% understates their net income, and 6.94% overstates their net income. Because there is not enough within-firm variation in terms of earnings understatement, I conduct the analysis in state level, rather than firm level. The sample consists of 1,275 state-year observations. The results are reported in Table 7.

Table 7 Column (1) reports the result when the focus is income-increasing restatement (i.e., the restated earnings is higher than the originally reported earnings), which results from downward earnings management. The coefficient on *Corruption* is positive and significant at the 10% level, suggesting that the percentage of firms that understate earnings increases with the level of political corruption. This is consistent with my conclusion that firms manipulate earnings downwards to protect themselves against the expropriation by corrupt officials.

Table 7 Column (2) reports the result when the focus is income-decreasing restatement (i.e., the restate earnings is lower than the originally reported earnings), resulting from upward earnings management. The coefficient on *Corruption* is not significant, indicating that political corruption does not affect firms' likelihood of overstating income.

In sum, this analysis based on restatement suggests that the findings in baseline regression is robust to an alternative measure of earnings management.

6.3 Accounting Policy Analysis

I test the robustness of my baseline regression results by focusing on the choices of inventory valuation methods and depreciation methods. I first test the impact of political corruption on the choice of inventory valuation methods by running the following Logit model.

$$Inv\ method_{ist} = \alpha_0 + \alpha_1 Corruption_{st} + \alpha_2 Firm\ Characteristics_{ist} + \alpha_3 State\ Characteristics_{st} + Industry\ FE + Year\ FE + \varepsilon_{ist}\ (4),$$

Where the dependent variables is *INV method*, a dummy variable that equals 1 if the firm adopts FIFO (first-in, first-out) as the primary inventory valuation method, and 0 if the firm adopts LIFO (last-in, first-out) or average cost method as the primary inventory valuation method. Table 8 Column (1) reports the results. The coefficient on *Corruption* is not significantly different from zero, suggesting no association between political corruption and the choice of inventory valuation method.

Then I examine the relation between *Corruption* and LIFO reserve. LIFO reserve is the difference between LIFO and FIFO carrying values (Penman and Zhang, 2002). All the firms using LIFO are required to disclose this value (Jennings et al., 1996). I re-run Equation (1) where, *LIFO reserve*, the value of LIFO reserve divided by lagged total assets, is the dependent variable. The results are reported in Table 8 Column (2). The coefficient on *Corruption* is positive and significant at 1%, indicating that LIFO-using firms in more corrupt areas would have reported much higher earnings if they switch from LIFO to FIFO.

Next, I test firms' choices of depreciation methods. I re-run Equation (4) by replacing *INV method* with *DEP method*, a dummy variable that equals 1 if the firm adopts accelerated depreciation method, and 0 if the firm adopts straight-line depreciation method, or the mix of accelerated depreciation method and straight-line depreciation method. The results are reported in Table 8 Column (3). The results suggest that companies located in more corrupt states are more likely to choose accelerated depreciation method.

Further, I test how political corruption affects depreciation reserve, the excess amount of accumulated depreciation (Penman and Zhang, 2016). I re-run Equation (1) with *DEP reserve* as the dependent variable. It is estimated by multiplying the gross amount of PPE by the difference of the accumulated-depreciation-to-gross-PPE ratio and the median accumulated-depreciation-to-gross-PPE ratio of all firms within the same industry-year combination, divided by lagged total assets. The regression results are reported in Table 8 Column (4). The coefficient on *Corruption* is significantly positive, suggesting that firms in more corrupt areas record a higher amount of accumulated depreciation.

Overall, above analyses suggest that companies located in more corrupt areas are more likely to choose income-decreasing accounting policies.

6.4 Instrument Variable Approach

I address the endogeneity concerns by using an instrumental variable approach. The instrumental variable is the isolation of state capital from its populace, measured by the size-normalized version of Gravity-based Centered Index for Spatial Concentration (GCISC2) from Campante and Do (2014). The measure ranges from zero to one, with zero indicating minimum isolation where all individuals live close to the state house, and one indicating maximum isolation where all individuals live as far from the state house as possible. Campante and Do (2014) find that states with isolated capital cities are associated with greater political corruption. They attribute it to less oversight and scrutiny.

Following Campante and Do (2014), I compute GCISC2 for each state in each year. The details of the calculation are shown in Appendix C. I obtain the geospatial data and population data from the U.S. Census Bureau. Because the geospatial data are not available for Alaska, Hawaii, and Washington D.C., the sample size is reduced slightly to 55,850 observations. The *F*-statistic for weak instrument test is 105.41 (Kleibergen and Paap, 2006), exceeding the Stock and Yogo (2005) 10% maximal IV size critical value of 16.38. Therefore, I can reject the null hypothesis that the instrument is weak.

Table 9 reports the second stage regression results. The coefficient on the instrumented value of *Corruption* is -0.042, significant at the 5% level. The results suggest that the baseline finding is unlikely to be driven by endogeneity.

6.5 Difference-in-Differences Analysis

To further address the endogeneity concern, I conduct a difference-in-differences test by focusing on companies that move between corrupt and non-corrupt states. This test effectively controls for non-time-varying firm characteristics and time-series trends having similar influences on treatment and control firms. Specifically, a state is deemed as corrupt (non-corrupt), if the mean value of *Corruption* in the state across years is above (below) the median of all the states. For each treatment company that moves between corrupt and non-corrupt states, I match it to a control company (i.e., a firm that does not move) which is in the same 2-digit SIC industry, located in the same state, and with most similar ROA. For each matched pair, I keep the observations from five years before to five years after the move. I then run the following regression.

$$DA_{ist} = \alpha_0 + \alpha_1 Treat_i \times Post_{it} + \alpha_2 Treat_i + \alpha_3 Post_{it} + \alpha_4 Firm\ Chracteristics_{ist} + \alpha_5 State\ Chracteristics_{st} + Pair\ FE + Year\ FE + \varepsilon_{ist} \quad (5),$$

Where $Treat_i$ is a dummy variable that takes the value one if the company is a treatment company, and zero if it is a control firm. $Post_{it}$ is a dummy variable that takes the value one for the years after the move, and zero for the years before the move. I control for pair fixed effects, to avoid the correlated omitted variable problem (Cram et al., 2009).

Table 10 Column (1) reports the result when treatment companies move from non-corrupt states to corrupt states. The coefficient on *Treat*×*Post* is -0.108 and significant at the 5% level. The result suggests that firms tend to manipulate earnings downwards after moving to a more corrupt state.

Table 10 Column (2) reports the result when treatment companies move in the opposite direction, i.e., from corrupt states to non-corrupt states. The coefficients on *Treat*×*Post* is 0.057 and significant at the 5% level. The results show that firms are more likely to manipulate earnings upwards after moving to a less corrupt state.

Taken together, the results from Table 10 show that political corruption causally results in downward earnings management.

6.6 Tax Avoidance Analysis

Political corruption breaches the trust between governments and companies, leading to tax avoidance (Ayyagari et al., 2014). Since companies may evade tax by manipulate earnings downwards (Chen and Daley, 1996), my findings may only reflect the relation between political corruption and tax avoidance.

To address this concern, I analyze how political corruption affects tax avoidance. Following Frank et al. (2009), I use *BTD* (total book-tax difference) to capture corporate tax avoidance. *BTD* is calculated as $(pre-tax\ book\ income - estimated\ taxable\ income)/lagged\ total\ assets$, where $estimated\ taxable\ income$ is $(federal\ income\ taxes + foreign\ income\ taxes)/U.S.statutory\ tax\ rate$. Following the suggestions of Dyreng and Lindsey (2009), I calculate $estimated\ taxable\ income$ as $(total\ income\ taxes - deferred\ income\ taxes)/U.S.statutory\ tax\ rate$, if either federal income taxes data or foreign income taxes data are missing. I obtain financial data from Compustat, and statutory tax rate data from the Internal Revenue Service.

Then I re-run Equation (1) by using total book-tax difference as the dependent variable. Table 11 reports the regression results. The coefficient on *Corruption* is not significantly different from zero. The regression results suggest that the reduction in discretionary accrual is unlikely to be related with tax avoidance.

6.7 Party Affiliation

One concern for my study is that the number of political corruption convictions may be proxy for state party affiliation. For example, Merier and Holbrook (1992) study the prosecution of political corruption during the Reagan administration and find more intensive prosecution of political corruption in Democratic states. To figure out whether my findings are driven by state party affiliation, I conduct a subsample analysis based on state party affiliation. I identify a state's party affiliation with the party affiliation of the state governor. A firm is in the Republican (Non-Republican) subsample, if the governor of the firm's headquarter state is a Republican (Non-Republican). I obtain state governor party affiliation data from the National Governors Association.

Table 12 report the results. In the Republican subsample, the coefficient on *Corruption* is -0.023, significant at the 5% level. In the Non-Republican subsample, the coefficient on *Corruption* is -0.031, significant at the 1% level. These two coefficients are not significantly different (p=0.581). The results suggest that no matter whether a state is Republican or not, companies manipulate earnings downwards in response to political corruption.

6.8 High-Profile Political Corruption Case and Earnings Management

Another approach to identify the change in corruption is through the prosecution of high profile corruption cases. These cases are likely to elevate local politicians' assessment of the likelihood of corrupt deeds being detected and penalized, and therefore deter their rent-seeking activities. In this sub-section, I provide some evidence by studying how a high-profile corruption case, the Siegelman case, affects firms' discretionary accruals.

I choose this case because it involves the highest local official, the governor, and it has two turning points, offering different implications. One point is in June 2007, when the U.S. District Court for the Middle District of Alabama sentenced Siegelman, the former Alabama governor, to 88 months in prison plus other penalties. The second point is in March 2008, when the 11th U.S. Circuit Court of Appeals released him from prison, effectively cutting his jail time from 88 months to 10 months.

The information from Google Trends suggests that both the sentence and the release of Mr. Siegelman received tremendous public attention from the state Alabama. The implications of the two events are distinct. While the sentencing and the related heavy penalty are likely to lower local corruption, the drastic reduction in penalty indicated by the early release has the opposite effect.

I utilize this event and run the following two regressions. I run Equation (6) with the data from 2006 to 2007, and run Equation (7) with the data from 2007 to 2008.

$$DA_{ist} = \alpha_0 + \alpha_1 Alabama_i \times Post\_sentence_t + \alpha_2 Alabama_i + \alpha_3 Post\_sentence_t + \alpha_4 Firm\ Chracteristics_{ist} + \alpha_5 State\ Chracteristics_{st} + Industry\ FE + \varepsilon_{ist}\ (6),$$

$$DA_{ist} = \alpha_0 + \alpha_1 Alabama_i \times Post\_release_t + \alpha_2 Alabama_i + \alpha_3 Post\_release_t + \alpha_4 Firm\ Chracteristics_{ist} + \alpha_5 State\ Chracteristics_{st} + Industry\ FE + \varepsilon_{ist}\ (7),$$

Where $Alabama_i$ is a dummy variable that equals 1 if the company is located in Alabama, and zero if it is a control firm. $Post\_sentence_t$ is a dummy variable that equals 1 for 2007, and 0 for 2006. $Post\_release_t$ is a dummy variable that equals 1 for 2008, and 0 for 2007. Due to multi-collinearity, I do not include year fixed effects in the model.

I report the results in Appendix D. The table shows that after the public sentencing of Don Siegelman, companies located in Alabama increase their discretionary accruals. While after Siegelman was released, companies located in Alabama reduces their discretionary accruals. These results are consistent with my argument that companies manipulate earnings downwards to shield their assets from political corruption.

7. Conclusion

Political corruption can be regarded as an inefficient form of taxation and firms have incentives to avoid rent-seeking by corrupt officials. Since prior studies document that downward earnings management is helpful in reducing political costs (Watts and Zimmerman, 1986; Han and Wang, 1998; Johnston and Rock, 2005; Grace and Leverty, 2010; Bova 2013), I hypothesize that firms respond to political corruption by manipulating earnings downwards. However, Shleifer and Vishny (1994) argue that corruption can be viewed as an efficient mechanism to help firms cut through bureaucracies. Therefore, it may be optimal for firms to bribe corrupt officials in exchange for political favors. In this case, firms may manage earnings upwards to hide expense items related to illicit dealings with government officials.

Using a sample of 56,096 observations, I empirically investigate the relation between political corruption and earnings management. Consistent with Glaeser and Saks (2006) and Smith (2016), I use the number of corruption convictions *per capita* to measure political corruption.

I find that corruption is negatively related to discretionary accruals, suggesting that corruption leads to downward earnings management. Specifically, the performance-matched discretionary accrual, is reduced by 2.1 percentage points, when *Corruption* increases by one standard deviation. This effect is economically significant, since the mean value of discretionary accrual in the sample is only -2.4 percentage points.

To test whether the results are indeed related to the rent-seeking by corrupt officials, I examine whether the effect of corruption on earnings management is more pronounced for firms whose operations concentrate in their headquarter states. Political corruption has lower impact on geographically dispersed firms, because these firms' cost of relocating to a less corrupt state is lower (Bai et al., 2015). Consistent with the explanation of corruption, the effect of political corruption on earnings management is more significant for firms whose operations concentrate in their headquarter states. I also examine whether the impact of corruption is more pronounced for firms without political connections. These firms are more vulnerable to bribe demands (Clarke and Xu, 2006), and thus having stronger incentives to manipulate earnings downwards. Consistent with my expectation, the impact of political corruption on earnings manipulation is more significant for these firms. Besides, I test whether the effect of corruption is weaker for firms with higher costs of downward earnings management. Consistent with the view that companies are faced with the trade-off between the costs of downward earnings management and the benefits of downward earnings management (Bova, 2013), I find that the impact of political corruption on downward earnings manipulation is not significant for firms faced with higher costs of downward earnings management.

This negative relation between corruption and earnings management is robust to six alternative measures of corruption, the earnings restatement analysis, the accounting policy analysis, the instrumental variable approach, the difference-in-differences test, and an event study. Additional tests also show that my findings are unlikely to be driven by tax avoidance or state party affiliation. While I can't completely rule out the possibility that omitted correlated variables explain the findings, the predominance of my results suggests otherwise.

One limitation of the study is that there could be a time lag between corrupt behaviors and corruption convictions. As a result, the number of corruption convictions in a given year could be unrelated with the underlying political corruption level in that year. Subject to this caveat, this study shows that when faced with high political corruption, firms manipulate earnings downwards to shield their assets from expropriations by public officials. These results contribute to both the literature on earnings management and the literature on political corruption.

Future studies could further explore the interaction between corporate corruption and political corruption. For example, managers in a company with corrupt culture may be happy to use bribes to gain some competitive advantages.

Reference

Aboody, D., Lev, B., 2000. Information asymmetry, R&D, and insider gains. The Journal of Finance 55, 2747-2766.

Ali, A., Zhang, W., 2015. CEO tenure and earnings management. Journal of Accounting and Economics 59, 60-79.

Ayyagari, M., Demirgüç-Kunt, A., Maksimovic, V., 2014. Bribe payments and innovation in developing countries: Are innovating firms disproportionately affected? Journal of Financial and Quantitative Analysis 49, 51-75.

Bai, J., Jayachandran, S., Malesky, E.J., Olken, B.A., 2015. Does economic growth reduce corruption? Theory and evidence from Vietnam. Massachusetts Institute of Technology working paper.

Barton, J., Simko, P.J., 2002. The balance sheet as an earnings management constraint. The Accounting Review 77, 1-27.

Bebchuk, L.A., Cremers, K.M., Peyer, U.C., 2011. The CEO pay slice. Journal of Financial Economics 102, 199-221.

Borisov, A., Goldman, E., Gupta, N., 2016. The corporate value of (corrupt) lobbying. The Review of Financial Studies 29, 1039-1071.

Bova, F., 2013. Labor unions and management's incentive to signal a negative outlook. Contemporary Accounting Research 30, 14-41.

Boylan, R.T., Long, C.X., 2003. Measuring political corruption in the American states: A survey of state house reporters. State Politics & Policy Quarterly 3, 420-438.

Burgstahler, D., Dichev, I., 1997. Earnings management to avoid earnings decreases and losses. Journal of Accounting and Economics 24, 99-126.

Butler, A.W., Fauver, L., Mortal, S., 2009. Corruption, political connections, and municipal finance. Review of Financial Studies 22, 2673-2705.

Campante, F.R., Do, Q.-A., 2014. Isolated Capital Cities, Accountability, and Corruption: Evidence from US States. The American Economic Review 104, 2456-2481.

Carter, M.E., Lynch, L.J., Tuna, I., 2007. The role of accounting in the design of CEO equity compensation. The Accounting Review 82, 327-357.

Chava, S., Roberts, M.R., 2008. How does financing impact investment? The role of debt covenants. The Journal of Finance 63, 2085-2121.

Chen, X., Cheng, Q., Wang, X., 2015. Does increased board independence reduce earnings management? Evidence from recent regulatory reforms. Review of Accounting Studies 20, 899-933.

Chen, P., Daley, L., 1996. Regulatory capital, tax, and earnings management effects on loan loss accruals in the Canadian banking industry. Contemporary Accounting Research 13, 91-128.

Claessens, S., Feijen, E., Laeven, L., 2008. Political connections and preferential access to finance: The role of campaign contributions. Journal of Financial Economics 88, 554-580.

Clarke, G., Xu, L.C., 2004. Privatization, competition, and corruption: How characteristics of bribe takers and payers affect bribes to utilities. Journal of Public Economics 88, 2067-2097.

Chow, G.C., 1960. Tests of equality between sets of coefficients in two linear regressions. Econometrica: Journal of the Econometric Society 28, 591-605.

Cohen, D.A., Dey, A., Lys, T.Z., 2008. Real and accrual-based earnings management in the pre-and post-Sarbanes-Oxley periods. The Accounting Review 83, 757-787.

Cooper, M.J., Gulen, H., Ovtchinnikov, A.V., 2010. Corporate political contributions and stock returns. The Journal of Finance 65, 687-724.

Cordis, A.S., Warren, P.L., 2014. Sunshine as disinfectant: The effect of state Freedom of Information Act laws on public corruption. Journal of Public Economics 115, 18-36.

Correia, M.M., 2014. Political connections and SEC enforcement. Journal of Accounting and Economics 57, 241-262.

Cram, D.P., Karan, V., Stuart, I., 2009. Three threats to validity of choice- based and matched- sample studies in accounting research. Contemporary Accounting Research 26, 477-516.

Dass, N., Nanda, V., Xiao, S.C., 2016. Public Corruption in the United States: Implications for Local Firms. The Review of Corporate Finance Studies 5, 102-138.

Dechow, P.M., Sloan, R.G., Sweeney, A.P., 1995. Detecting earnings management. The Accounting Review 70, 193-225.

DeFond, M.L., Jiambalvo, J., 1994. Debt covenant violation and manipulation of accruals. Journal of Accounting and Economics 17, 145-176.

Dou, Y., Khan, M., Zou, Y., 2016. Labor unemployment insurance and earnings management. Journal of Accounting and Economics 61, 166-184.

DuCharme, L.L., Malatesta, P.H., Sefcik, S.E., 2004. Earnings management, stock issues, and shareholder lawsuits. Journal of Financial Economics 71, 27-49.

Duchin, R., Sosyura, D., 2012. The politics of government investment. Journal of Financial Economics 106, 24-48.

Dyreng, S. D., Lindsey, B.P., 2009. Using financial accounting data to examine the effect of foreign operations located in tax havens and other countries on US multinational firms' tax rates. Journal of Accounting Research, 47, 1283-1316.

Ellis, J.A., Smith, J.D., White, R.M., 2016. Corruption and corporate innovation. Arizona State University working paper.

Faccio, M., Masulis, R.W., McConnell, J., 2006. Political connections and corporate bailouts. The Journal of Finance 61, 2597-2635.

Fisman, R., 2001. Estimating the value of political connections. The American Economic Review 91, 1095-1102.

Flood, S., King, M., Ruggles, S., Warren, J., 2015. Integrated public use microdata series, Current population survey: Version 4.0 [dataset]. Minneapolis, MN: University of Minnesota, http://doi.org/10.18128/D030.V4.0.

Francis, J.R., Krishnan, J., 1999. Accounting accruals and auditor reporting conservatism. Contemporary Accounting Research 16, 135-165.

Frank, M.M., Lynch, L. J., Rego, S.O., 2009. Tax reporting aggressiveness and its relation to aggressive financial reporting. The Accounting Review 84, 467-496.

Fredriksson, P.G., List, J.A., Millimet, D.L., 2003. Bureaucratic corruption, environmental policy and inbound US FDI: theory and evidence. Journal of Public Economics 87, 1407-1430.

Garcia, D., Norli, Ø., 2012. Geographic dispersion and stock returns. Journal of Financial Economics 106, 547-565.

Glaeser, E.L., Saks, R.E., 2006. Corruption in America. Journal of Public Economics 90, 1053-1072.

Godfrey, J.M., Hamilton, J., 2005. The impact of R&D intensity on demand for specialist auditor services. Contemporary Accounting Research 22, 55-93.

Goldman, E., Rocholl, J., So, J., 2009. Do politically connected boards affect firm value? The Review of Financial Studies 22, 2331-2360.

Grace, M.F., Leverty, J.T., 2010. Political cost incentives for managing the property- liability insurer loss reserve. Journal of Accounting Research 48, 21-49.

Graham, J.R., Harvey, C.R., Rajgopal, S., 2005. The economic implications of corporate financial reporting. Journal of Accounting and Economics 40, 3-73.

Gul, F.A., 2006. Auditors' response to political connections and cronyism in Malaysia. Journal of Accounting Research 44, 931-963.

Gupta, M., Khurana, I.K., Pereira, R., 2008. Legal inforcement, short maturity debt, and the incentive to manage earnings. The Journal of Law and Economics 51, 619-639.

Han, J.C., Wang, S.-W., 1998. Political costs and earnings management of oil companies during the 1990 Persian Gulf crisis. The Accounting Review 73, 103-117.

Heider, F., Ljungqvist, A., 2015. As certain as debt and taxes: Estimating the tax sensitivity of leverage from state tax changes. Journal of Financial Economics 118, 684-712.

Hribar, P., Collins, D.W., 2002. Errors in estimating accruals: Implications for empirical research. Journal of Accounting Research 40, 105-134.

Jennings, R., Simko, P.J., Thompson, R.B., 1996. Does LIFO inventory accounting improve the income statement at the expense of the balance sheet? Journal of Accounting Research 34, 85-109.

Johnston, D., Rock, S., 2005. Earnings management to minimize superfund clean- up and transaction costs. Contemporary Accounting Research 22, 617-642.

Jones, J.J., 1991. Earnings management during import relief investigations. Journal of Accounting Research 29, 193-228.

Khan, M., Watts, R.L., 2009. Estimation and empirical properties of a firm-year measure of accounting conservatism. Journal of Accounting and Economics 48, 132-150.

Kim, C.F., Zhang, L., 2016. Corporate political connections and tax aggressiveness. Contemporary Accounting Research 33, 78-114.

Kleibergen, F., Paap, R., 2006. Generalized reduced rank tests using the singular value decomposition. Journal of Econometrics 133, 97-126.

Koh, P.-S., Reeb, D.M., 2015. Missing R&D. Journal of Accounting and Economics 60, 73-94.

Kothari, S.P., Leone, A.J., Wasley, C.E., 2005. Performance matched discretionary accrual measures. Journal of Accounting and Economics 39, 163-197.

Leuz, C., Nanda, D., Wysocki, P.D., 2003. Earnings management and investor protection: An international comparison. Journal of Financial Economics 69, 505-527.

Liberty, S.E., Zimmerman, J.L., 1986. Labor union contract negotiations and accounting choices. The Accounting Review 61, 692-712.

Ljungqvist, A., Wilhelm, W. J., 2003. IPO pricing in the dot-com bubble. The Journal of Finance 58, 723-752.

Matsumoto, D.A., 2002. Management's incentives to avoid negative earnings surprises. The Accounting Review 77, 483-514.

McChesney, F.S., 1987. Rent extraction and rent creation in the economic theory of regulation. The Journal of Legal Studies 16, 101-118.

Meier, K.J., Holbrook, T.M., 1992. "I Seen My Opportunities and I Took'Em:" Political Corruption in the American States. The Journal of Politics 54, 135-155.

Murphy, K.M., Shleifer, A., Vishny, R.W., 1993. Why is rent-seeking so costly to growth? The American Economic Review 83, 409-414.

Penman, S.H., Zhang, X.J., 2002. Accounting conservatism, the quality of earnings, and stock returns. The Accounting Review 77, 237-264.

Penman, S.H., Zhang, X.J., 2016. Connecting book rate of return to risk and return: The information conveyed by conservative accounting. Columbia University working paper.

Reichelt, K. J., Wang, D., 2010. National and office- specific measures of auditor industry expertise and effects on audit quality. Journal of Accounting Research 48, 647-686.

Shleifer, A., Vishny, R.W., 1994. Politicians and firms. The Quarterly Journal of Economics 109, 995-1025.

Skinner, D.J., Sloan, R.G., 2002. Earnings surprises, growth expectations, and stock returns or don't let an earnings torpedo sink your portfolio. Review of Accounting Studies 7, 289-312.

Smith, J.D., 2016. US political corruption and firm financial policies. Journal of Financial Economics 121, 350-367.

Stock, J.H., Yogo, M., 2005. Testing for weak instruments in linear IV regression. In: Stock, J.H., Andrews, D.W.K. (Eds.), Identification and Inference for Econometric Models: A Festschrift in Honor of Thomas Rothenberg. Cambridge University Press, Cambridge, UK, 80–108.

Svensson, J., 2003. Who must pay bribes and how much? Evidence from a cross section of firms. The Quarterly Journal of Economics 118, 207-230.

Sweeney, A. P., 1994. Debt-covenant violations and managers' accounting responses. Journal of Accounting and Economics 17, 281-308.

Tahoun, A., 2014. The role of stock ownership by US members of Congress on the market for political favors. Journal of Financial Economics 111, 86-110.

Teoh, S.H., Welch, I., Wong, T.J., 1998. Earnings management and the underperformance of seasoned equity offerings. Journal of Financial Economics 50, 63-99.

Wasi, N., Flaaen, A., 2015. Record linkage using STATA: Pre-processing, linking and reviewing utilities. The STATA Journal 15, 672-697.

Watts, R.L., Zimmerman, J.L., 1986. Positive accounting theory: Prentice-Hall.

Yu, F., 2008. Analyst coverage and earnings management. Journal of Financial Economics 88, 245-271.

Appendix A Variable Definition

Variable	Definition
DA	Discretionary accruals from the modified Jones model (Jones, 1991; Dechow et al., 1995) and matched according to Kothari et al. (2005).
Corruption	Number of corruption convictions divided by the population (in 100,000s) in a state.
Total assets	Book value of total assets.
CFO	Cash flow from operations divided by lagged total assets.
ROA	Income before extraordinary items divided by lagged total assets.
R&D	Research and development expenses divided by lagged total assets. If R&D value is missing, I set it to zero.
R&D missing	A dummy variable that equals 1 if R&D value is missing, and zero otherwise.
Acquisition	A dummy variable that equals 1 if the company is involved in a merger or acquisition, and 0 otherwise.
Issuance	A dummy variable that equals 1 if the value of *Acquisition* is 0, and the number of outstanding shares increases by at least 10 percent, or long-term debt increases by at least 20 percent during the year, or the firm first appears on the CRSP monthly returns database in the year, and 0 otherwise.
Institution	The percentage of shares held by institutional investors at the quarter end preceding the fiscal year end.
Analyst	Total number of analysts that make at least one one-year-ahead earnings forecast for the company from the beginning of the fiscal year to the date when the actual earning is released.
Tight covenant	A dummy variable that equals 1 if the tightest slack of a company is smaller than the sample median in the year, and equals 0 if the tightest slack of a company is larger than the sample median in the year, or if the company is not limited by debt covenant in the year, or if the company's tightest slack is negative. I measure slack as [(maximum threshold-actual) / maximum threshold] for maximum threshold covenants, and [(actual-minimum threshold)/ absolute value of minimum threshold] for minimum threshold covenants (Dou et al., 2016).
Meet/Beat	A dummy variable that equals 1 if the net income before extraordinary items scaled by total assets lies in $[0,0.005)$ or the change in net income before extraordinary items scaled by total assets lies in $[0,0.005)$, or EPS beats analyst forecasts by one cent per share or less, and 0 otherwise (Cohen et al., 2008).
Sales growth	Annual sales growth rate from year t-1 to year t.
MB	Market value of equity divided by book value of equity.
Net operating assets	Shareholder's equity minus cash and short-term investments plus total debt at the beginning of the year, divided by lagged sales.
Sales volatility	Standard deviation of the ratio of total sales divided by total assets in the prior five years.
Operating cycle	[Average Inventory/(Cost of Sales/365)] +[Average Accounts Receivable/(Sales/365)].
Big N	A dummy variable that equals 1 if the annual report is audited by a Big N audit firm, and 0 otherwise.
Leverage	Long-term debt plus debt in current liabilities, divided by lagged total assets.
Per capita income	Personal Income (in $10,000) *per capita* in a given state.
Hightech	The percentage of high tech companies in a state, measured as the number of high-tech companies divided by the total number of companies in the state, as recorded by Compustat. Following Ljungqvist and Wilhelm (2003), a firm is considered a high-tech company, if its SIC code is 3571, 3572, 3575, 3577,

	3578, 3661, 3663, 3669, 3674, 3812, 3823, 3825, 3826, 3827, 3829, 4899, 7370, 7371, 7372, 7373, 7374, 7375, 7378, or 7379.
Education	The percentage of labor force who have finished four years' college education.

Appendix B Summary Statistics for Corruption by State

This table reports summary statistics for *Corruption* (number of corruption convictions per 100,000 population in a state) for each state during the 1987-2011 period.

State	Number of Years	Mean	Std. Dev	P25	Median	P75
Alabama	25	0.43	0.27	0.27	0.42	0.57
Alaska	25	0.59	0.68	0.14	0.33	0.95
Arizona	25	0.25	0.19	0.15	0.21	0.30
Arkansas	25	0.24	0.18	0.13	0.20	0.30
California	25	0.25	0.09	0.19	0.23	0.28
Colorado	25	0.16	0.15	0.02	0.12	0.28
Connecticut	25	0.26	0.16	0.12	0.24	0.34
Delaware	25	0.35	0.35	0.11	0.22	0.57
District of Columbia	25	6.76	3.36	4.01	6.29	8.04
Florida	25	0.44	0.16	0.32	0.37	0.52
Georgia	25	0.36	0.20	0.23	0.37	0.46
Hawaii	25	0.35	0.27	0.16	0.32	0.51
Idaho	25	0.23	0.18	0.07	0.20	0.34
Illinois	25	0.51	0.23	0.33	0.47	0.68
Indiana	25	0.23	0.12	0.14	0.22	0.29
Iowa	25	0.17	0.11	0.07	0.14	0.30
Kansas	25	0.16	0.12	0.07	0.17	0.23
Kentucky	25	0.52	0.23	0.36	0.49	0.65
Louisiana	25	0.76	0.31	0.55	0.71	0.96
Maine	25	0.29	0.21	0.15	0.30	0.38
Maryland	25	0.35	0.25	0.15	0.31	0.56
Massachusetts	25	0.30	0.17	0.20	0.27	0.43
Michigan	25	0.21	0.08	0.15	0.21	0.26
Minnesota	25	0.15	0.10	0.08	0.13	0.18
Mississippi	25	0.71	0.41	0.48	0.58	0.85
Missouri	25	0.33	0.11	0.23	0.34	0.42
Montana	25	0.56	0.56	0.11	0.50	0.75
Nebraska	25	0.14	0.15	0.06	0.11	0.22
Nevada	25	0.18	0.15	0.00	0.18	0.28
New Hampshire	25	0.09	0.10	0.00	0.08	0.09
New Jersey	25	0.39	0.17	0.27	0.44	0.51
New Mexico	25	0.22	0.13	0.13	0.20	0.34
New York	25	0.43	0.16	0.33	0.43	0.55
North Carolina	25	0.19	0.08	0.13	0.18	0.25
North Dakota	25	0.71	0.56	0.31	0.63	0.92
Ohio	25	0.44	0.13	0.34	0.44	0.49
Oklahoma	25	0.30	0.18	0.20	0.26	0.37
Oregon	25	0.09	0.08	0.03	0.08	0.16
Pennsylvania	25	0.39	0.11	0.30	0.40	0.45
Rhode Island	25	0.29	0.22	0.10	0.20	0.48
South Carolina	25	0.26	0.22	0.12	0.19	0.32
South Dakota	25	0.63	0.45	0.26	0.51	0.96
Tennessee	25	0.45	0.29	0.27	0.38	0.52
Texas	25	0.26	0.09	0.23	0.27	0.32
Utah	25	0.13	0.12	0.00	0.09	0.23
Vermont	25	0.22	0.24	0.00	0.17	0.33
Virginia	25	0.50	0.25	0.33	0.49	0.67
Washington	25	0.13	0.10	0.05	0.12	0.18

West Virginia	25	0.36	0.22	0.22	0.28	0.49
Wisconsin	25	0.18	0.08	0.14	0.18	0.21
Wyoming	25	0.37	0.39	0.18	0.21	0.62

Appendix C Gravity-based Centered Index for Spatial Concentration (GCISC2)

$$GCISC2_{st} = 1 - \sum_{i} p_{ist} \times \left[\frac{-1}{Ln(\overline{d_s})} \times Ln(d_{is}) + 1 \right]$$

Where p_{ist} is the number of people living in county i divided by the number of people living in the state s in year t. d_{is} is the distance between county i's centroid and the state house or assembly of state s. $\overline{d_s}$ is the maximum distance between the state house or assembly of state s's and any point in the state.

This measure is not available in Washington DC, Hawaii, and Alaska. The geospatial data and population data are both provided by the U.S. Census Bureau.

Appendix D High-Profile Political Corruption Case and Earnings Management

This table reports the OLS regression results that examine the impact of a high-profile corruption case on discretionary accruals. In Column (1), I study how Alabama companies change their discretionary accruals after the sentence of Don Siegelman. In Column (2), I study how Alabama companies change their discretionary accruals after the release of Don Siegelman. The sample period is 2006 to 2007 in Column (1), and 2007 to 2008 in Column (2). The dependent variable is *DA*. The indicator variable *Alabama* equals 1 for Alabama firms, and 0 otherwise. The indicator variable *Post_sentence* equals 1 for 2007, and 0 for 2006. The indicator variable *Post_release* equals 1 for 2008, and 0 for 2007. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. *T* statistics based on robust standard errors clustered by state-year are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *DA*	(2) *DA*
*Alabama * Post_sentence*	0.285***	
	(3.007)	
Post_sentence	0.010	
	(0.567)	
*Alabama * Post_release*		-0.461***
		(-8.149)
Post_release		-0.010
		(-0.736)
Alabama	-0.047	0.411***
	(-1.422)	(13.888)
Ln (total assets)	-0.001	-0.003
	(-0.127)	(-0.456)
CFO	-1.038***	-0.803***
	(-10.467)	(-7.148)
ROA	0.627***	0.566***
	(7.163)	(6.849)
R&D	-0.289***	-0.161
	(-3.321)	(-1.080)
R&D missing	0.017	0.036
	(0.862)	(1.625)
Acquisition	-0.024	-0.061***
	(-1.140)	(-2.937)
Issuance	-0.020	-0.005
	(-0.916)	(-0.216)
Institution	-0.022	-0.072**
	(-0.619)	(-2.517)
Ln(Analyst)	0.013	0.003
	(0.926)	(0.203)
Tight covenant	0.015	0.006
	(0.626)	(0.235)
Meet/Beat	-0.034	0.003
	(-1.549)	(0.124)
Sales growth	-0.008	-0.041
	(-0.348)	(-1.301)
MB	-0.003	-0.003
	(-1.218)	(-1.289)
Net operating assets	-0.004	0.017

	(-0.448)	(1.237)
Sales volatility	-0.075	-0.124*
	(-1.390)	(-1.939)
Ln (operating cycle)	-0.029**	-0.036**
	(-2.004)	(-2.607)
Big N	-0.039*	-0.022
	(-1.868)	(-0.890)
Leverage	0.012	-0.003
	(0.243)	(-0.055)
Per capita income	-0.013	-0.013
	(-0.381)	(-0.699)
Hightech	-0.058	-0.113
	(-0.538)	(-1.255)
Education	-0.051	0.129
	(-0.187)	(0.708)
Industry Fixed Effects	Yes	Yes
N	4,622	4,445
Adj_R2	0.052	0.042

Figure 1 Map of the State Average Corruption

A map of the state average corruption data from Appendix B, where states are split into groups by the level of political corruption.

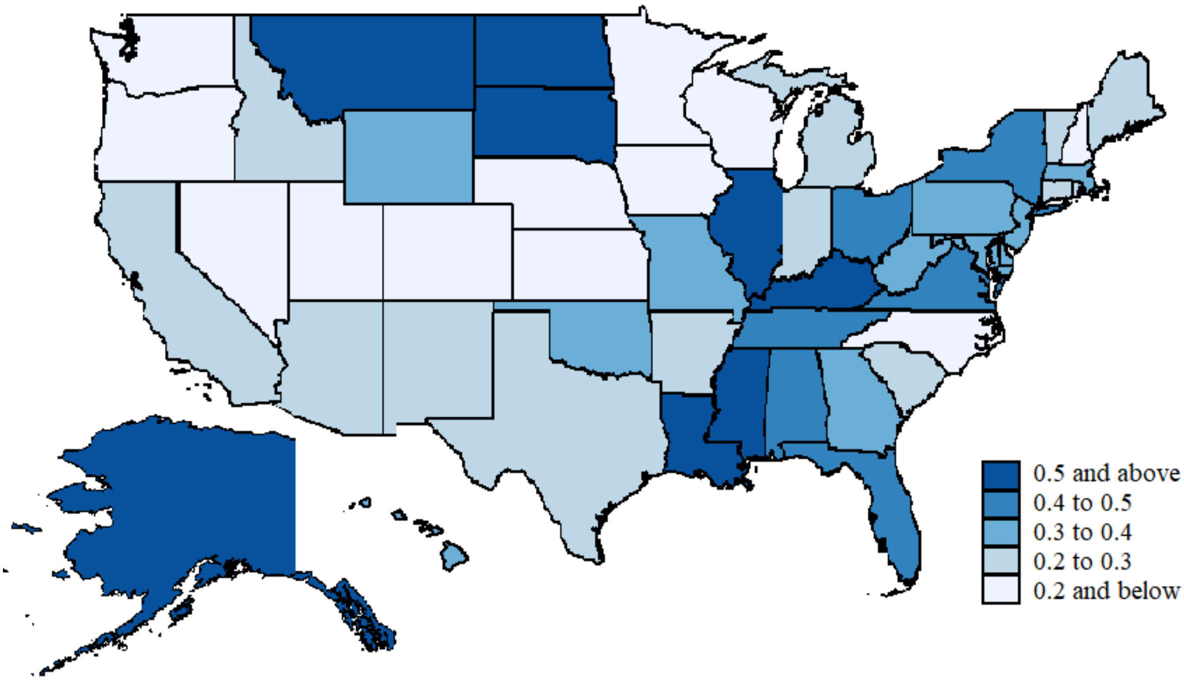

Table 1 Descriptive Statistics

This table reports summary statistics during the 1987-2011 period. Panel A reports the descriptive statistics of the full sample consisting of 56,096 observations. Panel B reports the average values of 27,836 observations in corrupt and non-corrupt groups. A firm-year observation is in the most corrupt (least corrupt) group, if its corruption is in the top (bottom) quartile of all the observations. All sample firms are U.S. public firms, excluding financial and utility firms. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles.

Panel A Descriptive statistics for the full sample

Variable	N	Mean	Std. Dev	P25	Median	P75
DA	56,096	-2.39%	30.80%	-10.65%	-0.92%	7.92%
Corruption	56,096	0.31	0.19	0.19	0.27	0.43
Total assets ($ million)	56,096	1796.17	5007.69	87.42	277.44	1027.02
Ln(total assets)	56,096	5.79	1.78	4.47	5.63	6.93
CFO	56,096	6.75%	18.50%	2.22%	9.07%	15.63%
ROA	56,096	0.61%	21.56%	-1.16%	4.81%	9.94%
R&D	56,096	6.41%	12.12%	0.00%	0.58%	7.98%
R&D missing	56,096	0.36	0.48	0	0	1
Acquisition	56,096	0.20	0.40	0	0	0
Issuance	56,096	0.28	0.45	0	0	1
Institution	56,096	49.73%	27.49%	26.64%	49.39%	71.75%
Analyst	56,096	8.63	8.29	3	6	12
Ln(Analyst)	56,096	1.70	1.00	1.10	1.79	2.48
Tight covenant	56,096	0.11	0.32	0	0	0
Meet/Beat	56,096	0.16	0.37	0	0	0
Sales growth	56,096	24.05%	57.10%	0.77%	11.26%	28.43%
MB	56,096	3.25	3.57	1.36	2.17	3.65
Net operating assets	56,096	0.75	0.95	0.30	0.50	0.81
Sales volatility	56,096	21.90%	22.21%	8.12%	14.78%	26.96%
Operating cycle (days)	56,096	130.76	89.46	71.12	112.09	166.24
Ln(operating cycle)	56,096	4.64	0.74	4.26	4.72	5.11
Big N	56,096	0.90	0.30	1	1	1
Leverage	56,096	23.30%	24.62%	2.02%	17.88%	35.37%
Per capita Income ($10,000)	56,096	3.08	0.87	2.36	2.97	3.69
Hightech	56,096	15.31%	8.54%	8.61%	13.15%	22.08%
Education	56,096	27.14%	5.29%	23.35%	26.46%	30.45%

Panel B Descriptive statistics by non-corrupt and corrupt group

	Least Corrupt Group	Most Corrupt Group	T-statistic difference in means
DA	-1.52%	-2.12%	0.594%*
Corruption	0.11	0.61	-0.500***
Ln(total assets)	5.63	5.89	-0.251***
CFO	6.61%	7.82%	-1.208%***
ROA	0.16%	3.07%	-2.909%***
R&D	6.75%	4.75%	2.000%***
R&D missing	0.33	0.40	-0.071***
Acquisition	0.19	0.20	-0.018***
Issuance	0.28	0.29	-0.010*
Institution	48.83%	49.23%	-0.401%
Ln(Analyst)	1.69	1.67	0.013
Tight covenant	0.10	0.12	-0.019***
Meet/Beat	0.16	0.16	-0.001
Sales growth	22.43%	21.46%	0.967%

MB	3.12	3.19	-0.074*
Net operating assets	0.76	0.69	0.065***
Sales volatility	21.57%	21.30%	0.272%
Ln(operating cycle)	4.63	4.65	-0.019**
Big N	0.90	0.90	-0.004
Leverage	21.80%	26.12%	-4.316%***
Per capita Income ($10,000)	3.06	3.01	0.047***
Hightech	16.47%	11.98%	4.488%***
Education	27.19%	27.96%	-0.779%***

Table 2 Baseline Regression

This table reports the OLS regression results that examine the impacts of political corruption on discretionary accrual. The sample consists of 56,096 observations. The dependent variable is *DA*. The independent variable is *Corruption*. Column (1) reports the results where I control for all the firm-level and state-level characteristics. Column (2) shows the results after I further control for year fixed effects. Column (3) reports the results after I further include industry fixed effects. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. *T* statistics based on robust standard errors clustered by state-year are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *DA*	(2) *DA*	(3) *DA*
Corruption	-0.023***	-0.021***	-0.021***
	(-3.341)	(-3.055)	(-3.027)
Ln (total assets)	-0.001	-0.001	0.001
	(-0.919)	(-0.973)	(0.400)
CFO	-0.805***	-0.810***	-0.840***
	(-40.221)	(-40.660)	(-40.687)
ROA	0.558***	0.564***	0.581***
	(31.597)	(32.184)	(32.740)
R&D	-0.097***	-0.096***	-0.096***
	(-4.814)	(-4.736)	(-4.314)
R&D missing	0.012***	0.012***	0.011***
	(4.124)	(4.020)	(3.139)
Acquisition	-0.011***	-0.010***	-0.011***
	(-2.777)	(-2.618)	(-2.746)
Issuance	-0.001	-0.001	-0.001
	(-0.447)	(-0.223)	(-0.274)
Institution	-0.004	-0.006	-0.003
	(-0.570)	(-0.844)	(-0.469)
Ln(Analyst)	-0.003	-0.003	-0.006***
	(-1.323)	(-1.319)	(-2.743)
Tight covenant	0.004	0.003	0.004
	(0.947)	(0.584)	(0.922)
Meet/Beat	0.000	0.001	0.001
	(0.137)	(0.243)	(0.179)
Sales growth	-0.006	-0.005	-0.004
	(-1.429)	(-1.137)	(-0.896)
MB	-0.001	-0.001	-0.001
	(-1.417)	(-1.255)	(-1.421)
Net operating assets	0.004	0.003	0.001
	(1.593)	(1.467)	(0.476)
Sales volatility	-0.015*	-0.017**	-0.012
	(-1.796)	(-2.071)	(-1.491)
Ln (operating cycle)	-0.017***	-0.017***	-0.011***
	(-7.897)	(-7.856)	(-3.628)
Big N	-0.012**	-0.012**	-0.013**
	(-2.542)	(-2.311)	(-2.557)
Leverage	0.041***	0.041***	0.047***
	(4.539)	(4.552)	(5.064)
Per capita income	0.000	-0.016**	-0.014**
	(0.056)	(-2.563)	(-2.262)

Hightech	-0.052**	-0.043**	-0.048**
	(-2.309)	(-2.027)	(-2.253)
Education	-0.013	0.074	0.076
	(-0.289)	(1.481)	(1.517)
Year Fixed Effects	No	Yes	Yes
Industry Fixed Effects	No	No	Yes
N	56,096	56,096	56,096
Adj_R^2	0.100	0.101	0.104

Table 3 Geographic Concentration

This table reports the subsample analysis based on firms' geographic concentration. A firm is deemed as concentrated (dispersed) if the percentage of operation in its headquarter state is above (below) sample median in the year. The dependent variable is *DA*. The independent variable is *Corruption*. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. *T* statistics based on robust standard errors clustered by state-year are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *DA*	(2) *DA*
	Concentrated	Dispersed
Corruption	-0.037***	-0.009
	(-3.181)	(-1.014)
Ln (total assets)	0.002	-0.000
	(1.188)	(-0.128)
CFO	-0.868***	-0.822***
	(-30.150)	(-30.512)
ROA	0.591***	0.595***
	(22.457)	(22.793)
R&D	-0.039	-0.165***
	(-1.368)	(-3.945)
R&D missing	0.018***	0.006
	(3.209)	(1.366)
Acquisition	-0.011*	-0.013**
	(-1.741)	(-2.330)
Issuance	-0.001	-0.001
	(-0.139)	(-0.337)
Institution	-0.007	-0.002
	(-0.636)	(-0.205)
Ln(Analyst)	-0.012***	-0.002
	(-3.678)	(-0.658)
Tight covenant	0.014*	-0.004
	(1.915)	(-0.703)
Meet/Beat	0.003	0.001
	(0.623)	(0.329)
Sales growth	-0.002	-0.001
	(-0.412)	(-0.079)
MB	-0.002**	-0.000
	(-2.070)	(-0.193)
Net operating assets	0.003	-0.002
	(0.984)	(-0.518)
Sales volatility	-0.005	-0.025*
	(-0.396)	(-1.802)
Ln (operating cycle)	0.003	-0.027***
	(0.724)	(-6.132)
Big N	-0.023***	-0.007
	(-3.030)	(-0.826)
Leverage	0.035**	0.055***
	(2.496)	(4.616)
Per capita income	-0.023**	-0.009
	(-2.021)	(-1.166)

Hightech	-0.075**	-0.012
	(-2.489)	(-0.429)
Education	0.091	0.068
	(1.134)	(1.037)
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
P value of test of equal coefficients on *Corruption* between (1) and (2)	0.067*	
N	25,354	25,801
Adj_R^2	0.125	0.077

Table 4 Political Connection

This table reports the subsample analysis based on firms' political connection. A firm is deemed as politically connected if it registered a PAC in November of the year. The dependent variable is *DA*. The independent variable is *Corruption*. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. *T* statistics based on robust standard errors clustered by state-year are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *DA*	(2) *DA*
	With Political Connection	Without Political Connection
Corruption	0.005	-0.024***
	(0.320)	(-3.127)
Ln (total assets)	0.003	-0.000
	(1.127)	(-0.146)
CFO	-0.834***	-0.840***
	(-15.713)	(-38.582)
ROA	0.523***	0.587***
	(9.207)	(32.562)
R&D	-0.076	-0.093***
	(-0.895)	(-4.019)
R&D missing	0.030***	0.009**
	(3.615)	(2.354)
Acquisition	-0.012	-0.011***
	(-1.378)	(-2.696)
Issuance	-0.003	-0.001
	(-0.430)	(-0.267)
Institution	-0.020	-0.001
	(-1.017)	(-0.156)
Ln(Analyst)	0.001	-0.006***
	(0.140)	(-2.859)
Tight covenant	0.003	0.004
	(0.252)	(0.896)
Meet/Beat	-0.002	0.001
	(-0.303)	(0.416)
Sales growth	0.016	-0.005
	(0.918)	(-1.069)
MB	-0.002	-0.001
	(-1.369)	(-1.060)
Net operating assets	-0.034***	0.004
	(-3.441)	(1.372)
Sales volatility	-0.014	-0.014*
	(-0.512)	(-1.708)
Ln (operating cycle)	-0.011	-0.010***
	(-1.359)	(-3.224)
Big N	-0.014	-0.012**
	(-0.681)	(-2.299)
Leverage	0.048**	0.049***
	(2.573)	(4.972)
Per capita income	-0.027	-0.013*
	(-1.643)	(-1.849)
Hightech	-0.068	-0.044**

	(-1.294)	(-2.039)
Education	0.020	0.081
	(0.155)	(1.489)
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
P value of test of equal coefficients on *Corruption* between (1) and (2)	0.098*	
N	6,812	49,284
Adj_R^2	0.075	0.108

Table 5 Costs of Downward Earnings Management

This table reports the supsample analysis based on firms' costs of manipulating earnings downwards. A firm is deemed with high costs of downward earnings management, if meets or beats earnings benchmarks at a small margin, of if it is faced with tight debt covenant, and is deemed with low costs otherwise. The dependent variable is *DA*. The independent variable is *Corruption*. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. *T* statistics based on robust standard errors clustered by state-year are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *DA*	(2) *DA*
	High Costs	Low Costs
Corruption	-0.010	-0.024***
	(-0.713)	(-3.097)
Ln (total assets)	-0.001	0.001
	(-0.303)	(0.673)
CFO	-0.829***	-0.845***
	(-23.973)	(-37.772)
ROA	0.656***	0.571***
	(14.358)	(30.877)
R&D	-0.016	-0.104***
	(-0.304)	(-4.308)
R&D missing	0.025***	0.006
	(3.575)	(1.552)
Acquisition	-0.009	-0.012**
	(-1.428)	(-2.535)
Issuance	-0.006	0.000
	(-1.041)	(0.037)
Institution	-0.001	-0.003
	(-0.099)	(-0.300)
Ln(Analyst)	-0.009**	-0.005**
	(-1.984)	(-2.054)
Sales growth	-0.011	-0.002
	(-0.914)	(-0.498)
MB	-0.001	-0.001
	(-1.519)	(-1.296)
Net operating assets	-0.005	0.002
	(-0.916)	(0.905)
Sales volatility	-0.035**	-0.006
	(-2.117)	(-0.640)
Ln (operating cycle)	-0.017***	-0.009***
	(-2.855)	(-2.743)
Big N	-0.012	-0.013**
	(-1.183)	(-2.285)
Leverage	0.072***	0.041***
	(5.125)	(3.819)
Per capita income	-0.006	-0.018**
	(-0.552)	(-2.412)
Hightech	-0.087**	-0.037
	(-2.304)	(-1.590)
Education	-0.006	0.107**
	(-0.060)	(1.964)

Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
P value of test of equal coefficients on *Corruption* between (1) and (2)	0.400	
N	14,305	41,791
Adj_R^2	0.069	0.118

Table 6 Alternative Measures of Corruption

This table reports the OLS regression results that examine the impacts of political corruption on discretionary accrual by using alternative measures of corruption. In Panel A, I use the alternative measures based on corruption convictions. In Column (1), the independent variable is *Corruption per government employee*, the number of corruption convictions divided by the number of full-time equivalent state and local government employees (in 100,000s). In Column (2), the independent variable is *Weighted corruption, per capita* corruption convictions weighted by a firm's operation in each state. In Column (3), the independent variable is *Number of convictions*, the raw number of corruption convictions divided by 1,000. In Panel B, I use the alternative measures based on perception. In Column (1), the independent variable is *Low integrity_BGA*, a dummy variable that equals 1 if the state ranks in the bottom quartile of all the states in the 2013 BGA-Alper Integrity Index, and 0 otherwise. In Column (2), the independent variable is *Low integrity_SII*, a dummy variable equals 1 if the state ranks in the bottom quartile of all the states in the 2012 State Integrity Investigation, and 0 otherwise. In Column (3), the independent variable is *Perceived corruption*, the corruption scale from Table 2 of Boylan and Long (2003). The dependent variable is *DA*. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. T statistics based on robust standard errors clustered by state-year are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A Alternative Measures Based on Corruption Convictions

	(1) *DA*	(2) *DA*	(3) *DA*
Corruption per government employee	-0.001***		
	(-2.848)		
Weighted corruption		-0.024**	
		(-2.020)	
Number of convictions			-0.116***
			(-2.924)
Ln (total assets)	0.001	0.001	0.001
	(0.389)	(0.633)	(0.486)
CFO	-0.840***	-0.843***	-0.840***
	(-40.683)	(-37.500)	(-40.672)
ROA	0.580***	0.588***	0.581***
	(32.736)	(30.942)	(32.704)
R&D	-0.096***	-0.090***	-0.095***
	(-4.314)	(-3.771)	(-4.268)
R&D missing	0.011***	0.011***	0.011***
	(3.118)	(2.986)	(3.202)
Acquisition	-0.011***	-0.011***	-0.011***
	(-2.752)	(-2.785)	(-2.739)
Issuance	-0.001	-0.000	-0.001
	(-0.280)	(-0.145)	(-0.294)
Institution	-0.003	-0.005	-0.003
	(-0.462)	(-0.701)	(-0.473)
Ln(Analyst)	-0.006***	-0.007***	-0.006***
	(-2.736)	(-3.092)	(-2.815)
Tight covenant	0.004	0.004	0.004
	(0.927)	(0.944)	(0.940)
Meet/Beat	0.001	0.003	0.001
	(0.182)	(0.785)	(0.195)

Sales growth	-0.004	-0.002	-0.004
	(-0.899)	(-0.490)	(-0.887)
MB	-0.001	-0.001	-0.001
	(-1.426)	(-1.321)	(-1.434)
Net operating assets	0.001	0.001	0.001
	(0.479)	(0.496)	(0.484)
Sales volatility	-0.012	-0.013	-0.012
	(-1.494)	(-1.385)	(-1.478)
Ln (operating cycle)	-0.011***	-0.011***	-0.010***
	(-3.644)	(-3.450)	(-3.603)
Big N	-0.013**	-0.014***	-0.013***
	(-2.542)	(-2.610)	(-2.617)
Leverage	0.047***	0.044***	0.046***
	(5.064)	(4.592)	(5.016)
Per capita income	-0.015**	-0.019***	-0.011
	(-2.295)	(-2.752)	(-1.643)
Hightech	-0.044**	-0.032	-0.021
	(-2.088)	(-1.444)	(-0.958)
Education	0.075	0.097*	0.023
	(1.500)	(1.800)	(0.440)
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
N	56,096	51,155	56,096
Adj_R^2	0.104	0.099	0.104

Panel B Alternative Measured Based on Perception

	(1) *DA*	(2) *DA*	(3) *DA*
Low integrity_BGA	-0.014***		
	(-2.861)		
Low integrity_SII		-0.008*	
		(-1.664)	
Perceived corruption			-0.007**
			(-2.482)
Ln (total assets)	0.000	0.000	-0.000
	(0.313)	(0.299)	(-0.325)
CFO	-0.840***	-0.840***	-0.834***
	(-40.571)	(-40.569)	(-36.910)
ROA	0.580***	0.580***	0.582***
	(32.668)	(32.642)	(31.031)
R&D	-0.097***	-0.098***	-0.104***
	(-4.336)	(-4.383)	(-4.136)
R&D missing	0.010***	0.011***	0.011***
	(3.040)	(3.072)	(3.053)
Acquisition	-0.011***	-0.010***	-0.010**
	(-2.697)	(-2.687)	(-2.477)
Issuance	-0.001	-0.001	-0.001
	(-0.193)	(-0.172)	(-0.397)
Institution	-0.003	-0.004	-0.009
	(-0.480)	(-0.519)	(-1.248)
Ln(Analyst)	-0.005***	-0.005***	-0.004*
	(-2.634)	(-2.602)	(-1.775)
Tight covenant	0.004	0.004	0.005

	(0.898)	(0.889)	(1.042)
Meet/Beat	0.001	0.001	0.000
	(0.278)	(0.250)	(0.012)
Sales growth	-0.004	-0.004	-0.005
	(-0.864)	(-0.851)	(-1.134)
MB	-0.001	-0.001	-0.001*
	(-1.544)	(-1.512)	(-1.773)
Net operating assets	0.001	0.001	0.002
	(0.430)	(0.450)	(0.656)
Sales volatility	-0.012	-0.012	-0.012
	(-1.444)	(-1.433)	(-1.374)
Ln (operating cycle)	-0.011***	-0.011***	-0.011***
	(-3.650)	(-3.633)	(-3.750)
Big N	-0.013***	-0.013***	-0.012**
	(-2.585)	(-2.652)	(-2.212)
Leverage	0.046***	0.047***	0.050***
	(5.010)	(5.039)	(5.051)
Per capita income	-0.018***	-0.018***	-0.014*
	(-2.816)	(-2.797)	(-1.946)
Hightech	-0.048**	-0.031	-0.036
	(-2.202)	(-1.477)	(-1.611)
Education	0.069	0.089*	0.049
	(1.330)	(1.705)	(0.827)
Year Fixed Effects	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes
N	55,930	55,930	50,310
Adj_R2	0.104	0.104	0.099

Table 7 Restatement Likelihood

This table reports the OLS regression results that examine the impacts of political corruption on earnings restatement. In column (1), the dependent variable is the proportion of firms understating income in a state in a year. In column (2), the dependent variable is the proportion of firms overstating income in a state in a year. A firm understates (overstates) net income if the original net income is lower (higher) than restated net income. The independent variable is *Corruption*. The sample consists of 1,275 state-year observations. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. *T* statistics based on robust standard errors clustered by state-year are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) % of Firms Understating Income	(2) % of Firms Overstating Income
Corruption	0.003*	0.006
	(1.766)	(1.292)
Per capita income	-0.006*	-0.002
	(-1.863)	(-0.198)
Hightech	0.018	0.117**
	(0.956)	(2.483)
Education	-0.041	0.038
	(-1.526)	(0.531)
Year Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
N	1,275	1,275
Adj_R^2	0.175	0.309

Table 8 Accounting Policy Analysis

This table examines the impacts of political corruption on alternative measures of earnings management. I run Logit regressions in Column (1) and Column (3), and run OLS regressions in Column (2) and Column (4). In Column (1), the dependent variables is *INV method*, a dummy variable that equals 1 if the firm adopts FIFO as the primary inventory valuation method, and 0 if the firm adopts LIFO or average cost method as the primary inventory valuation mehod. In Column (2), the dependent variable is *LIFO reserve*, calculated as LIFO reserve divided by lagged total assets. In Column (3), the dependent variable is *DEP method*, a dummy variable that equals 1 if the firm adopts accelerated depreciation method, and 0 if the firm adopts straight-line depreciation method, or the mix of accelerated depreciation method and straight-line depreciation method. In Column (4), the dependent variable is *DEP reserve*, calculated as the excess amount of accumulated depreciation divided by lagged total assets. The independent variable is *Corruption*. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. T statistics based on robust standard errors clustered by state-year are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *INV method*	(2) *LIFO reserve*	(3) *DEP method*	(4) *DEP reserve*
Corruption	0.100	0.009***	0.423*	0.005*
	(0.964)	(4.123)	(1.712)	(1.937)
Ln (total assets)	-0.378***	-0.000	0.362***	0.004***
	(-32.286)	(-0.345)	(9.202)	(8.363)
CFO	-0.113	-0.002	0.944**	0.007
	(-0.825)	(-0.225)	(2.343)	(1.551)
ROA	0.378***	0.010	-0.131	-0.025***
	(2.733)	(0.953)	(-0.364)	(-5.083)
R&D	2.906***	-0.092***	1.595***	0.032***
	(9.291)	(-3.938)	(3.143)	(4.909)
R&D missing	0.117***	-0.003***	-0.445***	-0.010***
	(3.658)	(-2.700)	(-4.416)	(-9.362)
Acquisition	0.157***	-0.003***	-0.178	-0.016***
	(4.628)	(-2.648)	(-1.494)	(-13.615)
Issuance	0.013	-0.000	-0.126	-0.020***
	(0.449)	(-0.026)	(-1.290)	(-18.642)
Institution	0.320***	-0.001	-1.103***	0.011***
	(4.491)	(-0.448)	(-5.901)	(5.016)
Ln(Analyst)	0.160***	-0.004***	-0.074	-0.015***
	(8.558)	(-5.923)	(-1.040)	(-22.473)
Tight covenant	0.013	-0.005***	-0.021	-0.002
	(0.354)	(-4.657)	(-0.134)	(-1.168)
Meet/Beat	-0.011	0.000	-0.131	-0.002*
	(-0.359)	(0.051)	(-1.193)	(-1.664)
Sales growth	0.237***	0.013***	-0.087	-0.027***
	(5.381)	(4.497)	(-0.951)	(-19.314)
MB	-0.003	-0.001***	0.015	0.001***
	(-0.627)	(-3.304)	(1.037)	(6.994)
Net operating assets	0.023	-0.025***	0.181***	-0.018***
	(0.838)	(-15.548)	(4.177)	(-17.837)
Sales volatility	0.492***	-0.001	0.654***	-0.029***
	(7.006)	(-0.332)	(3.078)	(-15.625)
Ln (operating cycle)	0.193***	0.002*	-0.190**	0.004***
	(6.711)	(1.780)	(-2.259)	(4.968)
Big N	-0.198***	0.002	-0.663***	0.003**

	(-3.944)	(0.817)	(-5.046)	(2.109)
Leverage	0.249***	-0.024***	-1.197***	-0.094***
	(3.691)	(-8.546)	(-4.648)	(-36.311)
Per capita income	-0.100	-0.006***	-0.342*	-0.000
	(-1.378)	(-3.254)	(-1.876)	(-0.131)
Hightech	2.163***	0.001	-4.558***	0.001
	(8.160)	(0.137)	(-5.737)	(0.176)
Education	2.388***	0.002	4.946***	0.030*
	(3.636)	(0.118)	(3.412)	(1.943)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
N	40,707	9,633	47,033	56,096
Adjusted_R^2		0.242		0.174
Pseudo_R^2	0.198		0.157	

Table 9 Instrument Variable Approach Based on Population Concentration

This table reports the second stage of a two-stage OLS regression. The dependent variable is *DA*. The independent variable is *Corruption*. The instrument variable is the size-normalized version of Gravity-based Centered Index for Spatial Concentration from Campante and Do (2014). The weak instrumental variable test is a Kleibergen and Paap (2006) Wald test. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. *T* statistics based on robust standard errors clustered by state-year are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *DA*
Corruption (instrumented)	-0.042**
	(-2.049)
Ln (total assets)	0.001
	(0.568)
CFO	-0.841***
	(-40.639)
ROA	0.581***
	(32.750)
R&D	-0.096***
	(-4.283)
R&D missing	0.011***
	(3.280)
Acquisition	-0.011***
	(-2.721)
Issuance	-0.001
	(-0.191)
Institution	-0.003
	(-0.433)
Ln(Analyst)	-0.006***
	(-2.747)
Tight covenant	0.004
	(0.856)
Meet/Beat	0.001
	(0.230)
Sales growth	-0.004
	(-0.850)
MB	-0.001
	(-1.512)
Net operating assets	0.001
	(0.412)
Sales volatility	-0.011
	(-1.304)
Ln (operating cycle)	-0.010***
	(-3.557)
Big N	-0.013***
	(-2.661)
Leverage	0.047***
	(5.028)
Per capita income	-0.014**
	(-2.151)
Hightech	-0.062**

	(-2.276)
Education	0.082
	(1.602)
Year Fixed Effects	Yes
Industry Fixed Effects	Yes
Weak IV test F value	105.41
N	55,850
Adj_R^2	0.105

Table 10 Difference-in-Differences Analyses Based on Re-Location

This table reports the OLS regression results that examine the impacts of political corruption on discretionary accrual using a difference-in-differences specification. For each treatment company that moves, I match it to a control company that is in the same 2-digit SIC industry, located in the same states, with most similar ROA, and does not move. In Column (1), treatment companies are those move from non-corrupt states to corrupt states. In Column (2), treatment companies are those move from corrupt states to non-corrupt states. A state is deemed as corrupt (non-corrupt), if the mean value of *Corruption* in the state across years is above (below) the median of all the states. For each matched pair, I keep the observations within five years of the move. The dependent variable is *DA*. The indicator variable *Treat* takes the value of one for treatment firms, and zero otherwise. The indicator variable *Post* takes the value of one for the period after move, and zero otherwise. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. *T* statistics based on robust standard errors clustered by state-year are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *DA*	(2) *DA*
	Treatment Companies Move from Non-Corrupt to Corrupt States	Treatment Companies Move from Corrupt to Non-Corrupt States
*Treat * Post*	-0.108**	0.057**
	(-2.136)	(1.996)
Treat	0.014	0.010
	(0.477)	(0.569)
Post	0.057*	-0.048*
	(1.757)	(-1.699)
Ln (total assets)	0.012	0.014
	(0.760)	(1.484)
CFO	-0.982***	-0.885***
	(-7.660)	(-10.038)
ROA	0.619***	0.648***
	(5.913)	(7.592)
R&D	-0.195	-0.283
	(-1.073)	(-1.525)
R&D missing	0.020	-0.004
	(0.499)	(-0.161)
Acquisition	-0.020	-0.040*
	(-0.652)	(-1.960)
Issuance	-0.021	-0.000
	(-0.662)	(-0.023)
Institution	0.096	0.026
	(1.209)	(0.506)
Ln(Analyst)	-0.021	-0.018
	(-1.057)	(-1.362)
Tight covenant	0.007	0.028
	(0.127)	(0.883)
Meet/Beat	0.010	0.004
	(0.367)	(0.204)
Sales growth	-0.030	0.008
	(-0.847)	(0.264)
MB	-0.003	-0.003
	(-0.562)	(-0.593)

Net operating assets	0.025**	0.008
	(2.147)	(0.448)
Sales volatility	-0.029	0.030
	(-0.464)	(0.485)
Ln (operating cycle)	-0.033	-0.001
	(-1.347)	(-0.051)
Big N	-0.082	0.057
	(-1.239)	(1.040)
Leverage	-0.080	0.046
	(-1.227)	(0.803)
Per capita income	0.044	-0.024
	(0.589)	(-0.504)
Hightech	0.141	0.018
	(0.614)	(0.115)
Education	0.251	0.429
	(0.471)	(1.122)
Year Fixed Effects	Yes	Yes
Pair Fixed Effects	Yes	Yes
N	1,600	1,780
Adj_R^2	0.072	0.136

Table 11 Tax Avoidance

This table reports the OLS regression results that examine the impacts of political corruption on book-tax difference. The sample consists of 56,096 observations. The dependent variable is *BTD*, total book-tax difference. The independent variable is *Corruption*. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. *T* statistics based on robust standard errors clustered by state-year are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *BTD*
Corruption	-0.002
	(-1.011)
Ln (total assets)	0.002***
	(5.765)
CFO	-0.032***
	(-7.540)
ROA	0.830***
	(121.954)
R&D	-0.089***
	(-11.752)
R&D missing	-0.007***
	(-7.569)
Acquisition	-0.012***
	(-14.429)
Issuance	-0.012***
	(-15.359)
Institution	-0.006***
	(-3.397)
Ln(Analyst)	-0.006***
	(-11.880)
Tight covenant	0.005***
	(6.300)
Meet/Beat	0.004***
	(5.943)
Sales growth	-0.021***
	(-19.654)
MB	-0.004***
	(-23.027)
Net operating assets	0.004***
	(7.866)
Sales volatility	-0.014***
	(-7.413)
Ln (operating cycle)	-0.000
	(-0.655)
Big N	0.002*
	(1.680)
Leverage	0.041***
	(23.121)
Per capita income	0.002
	(1.523)
Hightech	0.005
	(1.119)

Education	0.032**
	(2.527)
Year Fixed Effects	Yes
Industry Fixed Effects	Yes
N	56,096
Adj_R^2	0.891

Table 12 State Party Affiliation

This table reports the subsample analysis based on state party affiliation. A firm is in the Republican (Non-Republican) subsample, if the governor of the firm's headquarter state is an Republican (not an Republican). The dependent variable is *DA*. The independent variable is *Corruption*. Variable definitions are provided in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. *T* statistics based on robust standard errors clustered by state-year are in parentheses. The superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) *DA*	(2) *DA*
	Republican	Non-Republican
Corruption	-0.023**	-0.031***
	(-2.503)	(-2.898)
Ln (total assets)	0.000	0.001
	(0.022)	(0.673)
CFO	-0.837***	-0.844***
	(-33.902)	(-23.340)
ROA	0.561***	0.611***
	(24.067)	(24.043)
R&D	-0.136***	-0.025
	(-4.760)	(-0.747)
R&D missing	0.010**	0.012**
	(2.158)	(2.257)
Acquisition	-0.010**	-0.009
	(-2.241)	(-1.373)
Issuance	0.001	-0.002
	(0.304)	(-0.407)
Institution	0.011	-0.024**
	(1.213)	(-2.081)
Ln(Analyst)	-0.005*	-0.007**
	(-1.698)	(-2.317)
Tight covenant	0.001	0.009
	(0.184)	(1.156)
Meet/Beat	0.005	-0.005
	(1.189)	(-1.066)
Sales growth	0.002	-0.011
	(0.321)	(-1.382)
MB	-0.001	-0.001
	(-0.940)	(-1.390)
Net operating assets	0.000	0.002
	(0.147)	(0.472)
Sales volatility	-0.005	-0.024**
	(-0.434)	(-2.019)
Ln (operating cycle)	-0.009**	-0.013***
	(-2.496)	(-2.740)
Big N	-0.015**	-0.013
	(-2.422)	(-1.485)
Leverage	0.041***	0.053***
	(3.690)	(3.350)
Per capita income	0.003	-0.032***
	(0.322)	(-3.527)
Hightech	-0.044*	-0.035

	(-1.706)	(-0.999)
Education	-0.041	0.191***
	(-0.607)	(2.840)
Year Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
P value of test of equal coefficients on *Corruption* between (1) and (2)	0.581	
N	33,409	22,521
Adj_R^2	0.113	0.0952