Political Corruption and Accounting Choices

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Abstract

We examine how political corruption affects firms' accounting choices. We hypothesize and find that firms headquartered in corrupt states manipulate earnings downwards, relative to firms headquartered elsewhere. Our findings are robust to alternative corruption measures, restatement-based earnings management measures, the instrumental variable approach and the difference-in-differences analysis. Consistent with the motive to depress earnings, we find that firms headquartered in more corrupt states are more likely to choose the accelerated depreciation method, report higher LIFO reserve and depreciation reserve, and have a lower depreciable life estimate. Finally, we 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. In sum, our findings suggest that firms respond to corruption by lowering their accounting earnings.

Keywords: Earnings Management, Political Corruption, Rent Seeking

JEL Classification: M41; G38

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1. Introduction

Political corruption is pervasive. In its 2012 Global State of Mind Report, Gallup reports that, for 108 out of 129 countries, the majority of adults being surveyed perceive corruption as a widespread problem in their government.[1] Another survey shows that about one out of five firms worldwide have been asked to pay bribes by public officials.[2] Given the pervasiveness of political corruption, how it affects firms' accounting choices is an important question for practitioners, regulators and academics. However, the current literature offers surprisingly little related evidence, and we intend to address this gap.

Following Butler et al. (2009), we 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. Therefore, we hypothesize that firms facing high corruption are incentivized to manipulate earnings downwards.

Our hypothesis is not without tension. Glaeser et al. (1996) show that social factors have a major impact on individuals' decisions to break rules. Political corruption may influence local social norms so that unethical behaviors become socially acceptable, encouraging corporate executives to more aggressively manipulate earnings upwards. Executives are motivated to manage earnings upwards because higher reported earnings elevate the management's current compensation and reduce its likelihood of being fired (Healy, 1985; Murphy and Zimmerman, 1993; Ball 2001; Watts 2003; Graham et al., 2005; Lafond and Roychowdhury 2008).

We choose to use data from the U.S. to empirically test our hypothesis for the following reasons. First, using data from one single country alleviates the concern that myriad international differences in institutional settings are responsible for our empirical results. Second, as discussed in Section 4.2, there

[1] Please refer to http://www.gallup.com/file/poll/165497/GlobalStateMind_Report_10-13_mh.pdf.
[2] This statistics come from the World Business Environment Survey, based on surveys of more than 131,000 firms from 139 countries. Please refer to http://www.enterprisesurveys.org/data/exploretopics/corruption.

exist substantial variations in the severity of political corruption across the states in the U.S., allowing us to conduct cross-sectional analyses under a homogenous nation-wide environment. Third, the U.S. is typically deemed a low corruption country. If we are able to document a meaningful effect of political corruption in the U.S., our results highlight the profound influence of political corruption on firms' accounting choices.

Our sample consists of 56,096 firm-year observations from 1987 to 2011. Our measure of corruption is based on the U.S. Department of Justice (DOJ) data on the number of corruption convictions of public officials in each of the 94 federal judicial districts. This measure is popular in the literature and is used in the following studies: Fisman and Gatti (2002), Fredricksson et al., (2003), Glaeser and Saks (2006), Butler et al. (2009), Campante and Do (2014), and Smith (2016). These studies typically argue that the DOJ conviction data are objective and verifiable, and therefore they are superior to survey data, which are based on subjective assessment.[3] Specifically, we aggregate the number of cases from the federal judicial district level to the state level. The number of convictions *per capita* in the headquarter state is our main measure of political corruption, with a higher value indicating a more corrupt environment.

Following Kothari et al. (2005), we measure a firm's earnings management through performance-matched discretionary accrual. We regress it on the corruption measure of the firm's headquarter state and control for a battery of headquarter state characteristics and firm characteristics, including those firm characteristics associated with earnings management incentives. We find that a one standard deviation increase in our corruption measure is associated with a reduction of 0.4 percentage points in the performance-matched discretionary accrual. This effect is economically significant, considering that the mean value of discretionary accrual in our sample is -2.4 percentage points.

To check the robustness of our results, we use seven alternative political corruption measures that are suggested by prior literature. The first four measures are based on the actual number of corruption convictions. They include the average value of the number of convictions *per capita* in the headquarter

[3] One plausible concern with the data is that a convicted corruption case depends on not only the existence of corruption, but also the detection of the misdeed. We discuss this concern in Section 3.3.

state in the last five years (a measure that indicates the long-run local corruption level), the number of corruption conviction cases per government employee (a measure that considers the number of civil servants in the state), the number of corruption convictions *per capita* in the headquarter state multiplied by the percentage of the firm's operations in the state (a measure that takes into account the importance of the headquarter state to the firm), and the raw number of corruption convictions (a measure that's irrespective of the population size). The next three measures are perception-based and include the ranking of the headquarter state in the 2013 Better Government Association (BGA) Integrity Index, the ranking of the state in the 2012 State Integrity Investigation conducted by the Centre for Public Integrity, and the perception of the level of corruption by State House reporters. These perception-based measures complement the measures based on actual convictions and they help to address the concern that the number of convictions reflects detection efforts rather than the extent of corruption. We take comfort in that our conclusion is robust to the use of all seven measures.

We also examine whether our conclusion holds when we measure earnings management through accounting restatements. We find that, relative to firms located in non-corrupt states, firms located in corrupt states are more likely to report income-increasing restatements (i.e., the restated earnings is higher than the originally reported), consistent with their deliberate effort to lower reported earnings in the financial statements.

We continue to study how political corruption affects accounting policy choices. Bowen et al. (1995) document that firms incentivized to report higher earnings are likely to choose the straight line depreciation method instead of the accelerated depreciation method, and FIFO instead of LIFO. We find that firms located in corrupt states are more likely to choose the accelerated depreciation method, their depreciation reserve (a measure that reflects the excess amount of accumulated depreciation) is higher, and their estimate of useful life is lower. Although these firms do not differ from firms headquartered elsewhere in the likelihood of choosing LIFO, they do report higher LIFO reserves, indicating that, for those of them that select LIFO, their cumulative earnings would be much higher if they adopted FIFO.[4] Overall, our results are consistent with firms in corrupt areas deliberately choosing accounting policies to depress earnings.

To address the concern that the choice of headquarter state is not a random decision and thus a firm's headquarter state political corruption and the firm's earnings management may be endogenously determined, we use 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. Thus our instrumental variable is positively related to political corruption. In addition, being a geographic measure, it is unlikely correlated with local firms' earnings management except through the channel of corruption. Our finding is robust to the instrumental variable approach.

Furthermore, we conduct a difference-in-differences test by focusing on firms 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. For each treatment firm (i.e., a firm that moves between corrupt and non-corrupt states), we match it to a control firm (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. Our 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.

Finally, to test whether the results are indeed related to rent seeking by corrupt officials, we conduct two sub-sample 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). We thus expect that the impact of local political corruption on earnings management is more pronounced for geographically concentrated firms. We test this expectation by dividing the sample into two subsamples based on geographic concentration. Consistent with our expectation, the effect of corruption on discretionary accruals is greater for firms with more concentrated operations.

[4] LIFO reserves represent the difference in ending inventory between LIFO and FIFO. Since the total value of goods available for sale is the same across the two inventory methods, higher LIFO reserves indicate that cumulative (since the adoption of the inventory valuation method) COGS will be higher and therefore cumulative earnings will be lower under LIFO.

Firms without political connections are more vulnerable to expropriations by politicians, such as bribe solicitations (Clarke and Xu, 2004). Therefore, we 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), we use the establishment of corporate political action committee (PAC) to identify political connection, and our empirical results lend support to our prediction.

Our paper contributes to the literature in the following ways. First, our paper adds to the understanding of the effect of political costs on firms' accounting practices. One important type of political costs is the rent-seeking of corrupt officials. As discussed in Section 2, while other types of political costs have been studied by prior studies (Liberty and Zimmerman, 1986; Han and Wang, 1998; Johnston and Rock, 2005; Grace and Leverty, 2010; Bova, 2013), the impact of corruption has received scant attention. Given the pervasiveness of political corruption, this paper addresses an important question neglected by prior accounting literature.

Second, 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. Fisman and Gatti (2002), however, point out that within country studies, such as ours, have the advantage that they effectively control for institutional and cultural differences at the national level. Furthermore, while international studies suggest that accounting quality is low in countries with high corruption, the direction of earnings management is unclear. We extend this line of inquiry by corroborating prior international studies and identifying the direction of corruption-induced earnings management.

A growing literature focuses on political connection. Chaney et al. (2011) show, in an international setting, that the presence of political connections is associated with lower quality of earnings. Hope et al. (2017) use the setting in China and show that firm-level transparency increases after politically connected directors are removed as a result of "Rule 18". Political corruption and political connection are two distinct concepts. Political corruption reflects the agency issue of government officials while political connection refers to the relationship between the firm and politicians. While political corruption is clearly against the law, political connection is legal. Politically connected firms may be located in either high or low corruption states while firms in corrupted area can be either politically connected or otherwise. Therefore, results based on political connection do not speak to the research question of this paper.

The rest of the paper proceeds as follows. Section 2 reviews prior literature and develops hypotheses. Section 3 discusses research methodology. Section 4 reports sample formation and descriptive statistics. Section 5 tests the hypothesis. Section 6 conducts robustness checks. Section 7 reports sub-sample analyses. Section 8 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 cost 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 notion that managers deem downward earnings management an effective way to reduce political cost.

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. Thus, firms have incentives to manage earnings downwards to shield their assets from corrupt officials.

The above discussion gives rise to the following hypothesis.

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

Our hypothesis is not without tension. Glaeser et al. (1996) show that social factors have an important influence on individuals' decisions to break or respect the laws. Their findings are consistent with descriptive research and help to explain the substantial variations in crime rates across time and space, e.g., two similar neighborhoods in the same city have vastly different crime rates.[5] Political corruption may influence the local culture so that unethical behaviors become socially acceptable, which encourages executives to engage in upward earnings manipulation. The influence can go through the following two channels. First, since the government's resources to detect and punish wrong-doers are finite, the resources per offender are reduced when the number of offenders increases. Wide-spread corruption may lead corporate executives to the conclusion that the chances of their unethical behaviors being detected and punished are low, as a result of limited resources. Second, as the number of corrupt officials increases, a corrupt official becomes a "normal" member of the society and the stigma of unethical behaviors becomes less visible. The lack of reputation damage resulting from breaking the laws therefore encourages executives to engage in questionable accounting practices, such as earnings management. Managers are motivated to manage earnings upwards because higher reported earnings increase their compensation, establish their reputation in the labor market, and lower their chances of being fired. (Healy, 1985; Murphy and Zimmerman, 1993; Ball 2001; Watts 2003; Graham et al., 2005; Lafond and Roychowdhury 2008).

Our hypothesis is based on some important assumptions. We implicitly assume that the firm's cost of moving its headquarter to another state is higher than its cost of manipulating earnings. If this

[5] Adler (1995) documents that Detroit's largest crack dealership is a result of Billie Joe Chambers being urged by his friend to sell the drug. A young criminal Bopete, was quoted "but when I am with my homeboys, I don't think of dyin' never at all. Only when I am alone." in Bing (1991), which shows that social interactions encourage breaking the law by creating a sense of invulnerability. Jankowski (1991) gives a detailed description of the social interactions in gangs.

assumption does not hold, firms will rationally choose to relocate and we won't be able to see our hypothesis substantiated by empirical results. In Section 7.1, we explore the variation in the firm's moving cost and we find that indeed the effect of corruption is less pronounced when firms' moving cost is low. Furthermore, we assume that the choice of the headquarter state is exogenous. This assumption is based on the notion that many factors unrelated to firms' accounting policies influence the choice of headquarter, for example, the home location of the founder, and the level of innovative activities of the area. However, since the choice of the headquarter state is not a random decision, we can't completely rule out the possibility that the relation between political corruption and earnings management is driven by omitted correlated variables. This represents a limitation of this study and we attempt to address it in Sections 6.4 and 6.5.

3. Research Design

3.1 Baseline Model

We test our hypothesis by running the following OLS regression:

$$DA_{ist} = \alpha_0 + \alpha_1 Corruption_{st} + \alpha_2 Control\ Variables_{(i)st} + Industry\ FE + Year\ FE + \varepsilon_{ist} \quad (1)$$

The dependent variable DA_{ist} is discretionary accrual of firm *i* headquartered in state *s* in year *t*. The independent variable is $Corruption_{st}$, a measure of the local corruption level in state *s* in year *t*. Its computation details are provided in Section 3.3. Our model also controls a set of firm characteristics that affect earnings management, as well as state characteristics that may be correlated with local corruption.

Our 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 economy-wide shocks. Since the independent variable (*Corruption*) is measured at the state-year level, we cluster the standard errors by state-year (Butler et al., 2009).

3.2 Measure of Earnings Management

We follow Kothari et al. (2005) and use the performance-matched discretionary accruals as a proxy for earnings management. Specifically, we first run the modified Jones (1991) model as described in Dechow et al. (1995) for each two-digit SIC-year combination, using all available observations from Compustat U.S. universe:

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

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.

The residual from Equation (2) is the discretionary accrual measure. Following Kothari et al. (2005), we 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.

3.3 Measure of Political Corruption

The U.S. Department of Justice Public Integrity Section (PIN) reports annual public corruption conviction numbers for the 94 US district courts in its yearly *Report to Congress on the Activities and Operations of the Public Integrity Section*. The data are used widely in finance and economics literature to measure corruption in the U.S (Fisman and Gatti, 2002; Fredricksson et al., 2003; Glaeser and Saks, 2006; Butler et al., 2009; Campante and Do, 2014; and Smith, 2016). The researchers suggest that the data are superior to survey data, because they are objective and verifiable.

One plausible concern with the data is that a convicted corruption case depends on not only the existence of corruption, but also the detection of the misdeed. In fact, a lower number of conviction cases could reflect weak oversight and law enforcement, rather than a less corrupt environment. This concern is alleviated in the following ways. First, because all conviction cases in our sample are handled by a federal government department, we expect the enforcement to be homogenous across states. Glaeser and Saks (2006) argue that the federal judicial system, which is responsible for the cases, should be above the influence of local corruption and therefore, the enforcement effort is about the same across the country. Second, Smith (2016) shows that the number of conviction is aligned with intuition and anecdotal evidence in identifying the most and least corrupt areas in the U.S. Third, we test the robustness of our results, using three survey-based measures of corruption, and our results survive the robustness check.

Since a state may have more than one districts, we aggregate the number of convicted cases to the state level. We then standardize the number by the state population data obtained from the U.S. Census Bureau, and a higher *per capita* number of conviction cases suggests a more corrupt environment.

3.4 Control variables

We control for *Ln(total assets)*, as larger firms are more politically visible (Watts and Zimmerman, 1986). We 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). We control for *R&D* (research and development expenses divided by lagged total assets), because firms with high R&D expenditure may experience high information asymmetry and they may 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), we 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.

We control for *Acquisition*, an indicator for M&A involvement, because acquisitive activities have a significant influence on financial accounting (Ali and Zhang, 2015). We 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).

We control for *Institution* (the percentage of shares held by institutional investors) and *Ln(Analyst)* (the logged value of the 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 influence earnings management (Francis and Krishnan, 1999; Matsumoto, 2002; Yu, 2008; Khan and Watts, 2009).

We 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).

We 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. We therefore control for *NOA* (net operating assets divided by lagged sales), a measure of bloatedness of the balance sheet. We 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.

We additionally control for state characteristics. Specifically, we 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), because 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

We start with all U.S. public firms in the Compustat database. We only include companies that are incorporated and headquartered in the U.S. We exclude firms in financial industries (SIC codes 6000-6999) or utility industries (SIC codes 4900-4999), as they are under extensive regulatory oversights. We require at least 10 observations in each industry-year combination (industry is based on the two-digit SIC code). Following Heider and Ljungqvist (2015), we obtain historical location and incorporation data from the SEC's EDGAR service for the period after May 1996, and from Compact Disclosure for the period before May 1996. The SEC's EDGAR data are provided by Prof. Bill McDonald[6].

We obtain debt covenant data from the Dealscan database and institutional shareholding data from Thomson Reuters Institutional (13f) Holdings. We collect data related to financial analysts from the I/B/E/S.

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

We 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. Following Hribar and Collins (2002)'s suggestion, we use earnings minus operating cash flows reported on the cash flow statement to measure total accrual. Our sample starts in 1987, because the cash flow statement became available in that year. Our sample period ends in 2011, because *Tight covenant* is based on the Dealscan-Compustat linking, which is only available before 2011 (Chava and Roberts, 2008). Our final sample consists of 56,096 firm-year observations from 1987 to 2011.

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

4.2 Descriptive Statistics

Panel A of Table 1 reports summary statistics for *Corruption*, the number of corruption convictions per 100,000 by state. As indicated by the median value of *Corruption*, Washing D.C., Louisiana, and North Dakota are the most corrupt states, while Oregon, New Hampshire, Colorado and Nebraska are the least corrupt. Consistent with Smith (2016), the value for Washington D.C. is exceptionally high, reflecting the fact that D.C. is a political centre with few residents. To prevent outliers from unduly influencing our results, in our later analyses, we winsorize *Corruption* at its 1th and 99th percentiles. Our results however continue to hold if we trim the data, remove D.C. from our sample, or do not winsorize.

As indicated by the standard deviation and the difference between minimum and maximum values, there exists substantial time-series variation in the number of corruption conviction across the states. The extent of corruption can be influenced by many factors, such as changing political landscapes, the appointment of new staff of the federal judicial system, and major conviction cases. For example, after the former Alabama governor Don Siegelman was convicted on several counts of corruption charges in 2007, the number of conviction cases per 100,000 in Alabama drops from 1.10 in 2006 to 0.42 in 2008, probably as a result of the deterrence effect of the high-level conviction case.

Figure 1 provides a visual illustration of the median value of the number of corruption conviction cases per 100,000. This figure demonstrates substantial cross-state differences in corruption and it also indicates no obvious geographic cluster in political corruption.

Panel B 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. The mean value of *Corruption* is 0.31, indicating that there are 0.31 corruption convictions every 100,000 people in an average state. The average firm in our sample has total assets of $1.80 billion, its *ROA* is 0.61%, and its cash flow from operations and R&D expenses are about 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 our 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, the mean annual sales growth is about 24%, 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.

Panel C provides descriptive statistics by the level of corruption. The corrupt (non-corrupt) group consists of observations whose value of *Corruption* is in the top (bottom) quartile of all the observations. The mean value of *DA* is -1.52% in the non-corrupt group, and -2.12% in the corrupt group, the latter being 39% higher than the former and the difference being significant at the 10% level. On average, firms in the corrupt group are located in states where there are 0.61 corruption convictions every 100,000 people while firms in the non-corrupt group are located in states where there are only 0.11 corruption convictions every 100,000 people, the former being about 6 times the latter and the difference being significant at the 1% level.

Many variables are significantly different between the two groups. Specifically, firms in the corrupt group exhibit higher cash flow from operations, better firm performance, lower R&D expenditure, higher market-to-book ratio, higher leverage, a higher likelihood to be involved in M&A activities, financing activities and tight debt covenants, lower net operating assets, higher operating cycle, and higher leverage. The state-level statistics show that corrupt states have lower per capita income, lower proportion of high-tech firms, and higher proportion of college-educated labor-force participants. These differences give rise to the need to control for these variables in our regression analyses.

5. Baseline Regression

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

The results in these three columns are similar. Since the model specification in Column (3) is the most comprehensive, we 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 -0.4% decrease in discretionary accrual. The economic magnitude is sizeable, because the mean value of discretionary accrual is only -2.4%. The coefficients are significantly negative for *CFO*, *R&D*, *Acquisition*, *Ln(Analyst)*, and *Big N*, suggesting that firms with higher cash flow from operations, firms with higher R&D expenses, firms involved in M&A deals, firms followed by many analysts and firms whose auditors are one of the Big N, are less likely to manipulate earnings upwards. This finding is consistent with prior literatures, e.g., DuCharme et al. (2004), Ali and Zhang (2005), and Chen et al. (2015).

In sum, our results suggest that, relative to firms located in less corrupt states, firms located in more corrupt states engage in downward earnings management, which supports H1.

6. Robustness checks

6.1 Alternative Measures of Corruption

6.1.1 Alternative Measures Based on Corruption Convictions

In this section, we test whether our baseline results are robust to alternative measures of corruption conviction.

The first alternative measure is *Average Corruption*, which is computed as the five-year average number of conviction cases from year t-5 to year t-1, scaled by the five-year average population. This measure addresses the concern that the corruption statistics in the current year may not be reflective of long-term corruption level.

The number of political corruption convictions may be proportional to the number of civil servants, rather than the number of population. Following Cordis and Warren (2014), we 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[7]. We obtain the government employment data from the U.S. Census Bureau.

The third alternative measure of corruption is *Weighted Corruption*, which is the number of corruption conviction cases *per capita* in the headquarter state multiplied by the percentage of the firm's operation in the state. This measure considers the economic importance of the headquarter state. Following Garcia and Norli (2012) and Smith (2016), we 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 are obtained from Diego Garcia.[8]

The fourth 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. This measure addresses the concern that it is the absolute level of corruption rather than the per capita level of corruption that influences firms' earnings management.

We re-estimate Equation (1) by replacing *Corruption* with these four alternative measures and report regression results in Table 3 Panel A. Because the operation distribution data are not available for all firms, the sample size is smaller in Column (3). Across all four columns, the coefficients on corruption measures are negative and significant at least at the 5% level, suggesting that the baseline regression results are robust to various alternative measures based on corruption convictions.

6.1.2 Alternative Subjective Measures of Corruption

In this section, we test the robustness of our finding by using three alternative corruption measures that are based on subjective assessment.

[7] 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.

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

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 (BGA) and the Centre for Public Integrity (CPI), separately issued reports that ranked states based on transparency, accountability and anti-corruption mechanisms[9]. We obtain the 2013 BGA Integrity Index and the 2012 State Integrity survey issued by CPI. We define *Low Integrity_BGA* as a dummy variable that takes the value of one if the state ranks in the bottom quartile of all the states in the 2013 BGA Integrity Index, and zero otherwise. We define *Low Integrity_SII* similarly. It is a dummy variable that takes the value of one if the state ranks in the bottom quartile of all the states in the 2012 State Integrity Survey, and zero otherwise.

The third measure, *Perceived Corruption,* is State House reporters' perception of corruption. We obtain the data from Boylan and Long (2003), who report the results of their survey of state house reporters. *Perceived Corruption* is the corruption scale from Table 2 of Boylan and Long (2003). This variable ranges from -1.897 to 1.611 and is not available for Massachusetts, New Hampshire, New Jersey, and Washington D.C.

We re-estimate Equation (1) by replacing *Corruption* with these three alternative measures and report regression results in Table 3 Panel B. Because the three measures are not available for all firms, 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 robust to these subjective measures of corruption.

6.2 Restatement Analysis

In this section, we test whether the results are robust to an alternative measure of earnings management based on earnings restatements. Specifically, we estimate the effect of political corruption on the proportion of firms with income decreasing/increasing restatements in a state, controlling for various state characteristics, state fixed effects, and year fixed effects. The proportion is computed by

[9] Both rankings do not include the state of Washington DC.

dividing the number of firms with the restatements by the total number of firms in the state in the year. Income decreasing/increasing restatements are restatements where the restated net income is lower/higher than the originally reported number, which indicates upward/downward earnings manipulation. We use state-level regression instead of firm-level regression because there is lack of sufficient within-firm variation in the restatement likelihood. Our sample consists of 1,275 state-year observations, and we report our results in Table 4.

Column (1) reports for income increasing restatements, which reflect 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 our conclusion that firms manipulate earnings downwards to protect their assets from the expropriation by corrupt officials.

Column (2) reports for income decreasing restatements. 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 finding in baseline regression is robust to the alternative measure of earnings management based on earnings restatements.

6.3 Accounting Policy Analysis

In this section, we consider how political corruption affects firms' choices of accounting policies. We first test the impact of political corruption on the choice of inventory valuation method. Our model specification is the same as Equation (1), except that the dependent variable 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. Since the dependent variable is binary, we run a logistic regression, and report our results in Table 5 Column (1). The coefficient on *Corruption* is not significantly different from zero, suggesting no association between political corruption and the choice of inventory valuation method.

We then examine the relation between *Corruption* and LIFO reserve. LIFO reserve is the difference between LIFO and FIFO carrying values, and all firms using LIFO are required to disclose LIFO reserve. Since the total value of goods available for sale is the same across the two inventory methods, higher LIFO reserves indicate that cumulative COGS will be higher and therefore cumulative earnings will be lower under LIFO. We re-run Equation (1), with *LIFO reserve*, the value of LIFO reserve divided by lagged total assets, being the dependent variable. Our results are reported in Table 5 Column (2). We find that the coefficient on *Corruption* is positive and significant at the 1% level, indicating that LIFO firms in more corrupt states would report much higher cumulative earnings than LIFO firms in less corrupt states if firms switch from LIFO to FIFO.

Next, we examine firms' choices of depreciation methods. Our dependent variable is *DEP method*, a dummy variable that equals 1 if the firm adopts the accelerated depreciation method, and 0 if the firm adopts the straight-line depreciation method, or the mix of accelerated and straight-line depreciation method. We report the results in Table 5 Column (3). Our results suggest that firms located in more corrupt states are more likely to choose the accelerated depreciation method.

Further, we test how political corruption affects depreciation reserve, the excess amount of accumulated depreciation (Penman and Zhang, 2016). Our measure of depreciation reserve, *DEP reserve*, is estimated by subtracting industry-level accumulated depreciation from the firm's accumulated depreciation, divided by lagged total assets. The industry-level accumulated depreciation is computed by multiplying the firm's gross amount of PPE with the median accumulated-depreciation-to-gross-PPE ratio of all firms within the same industry-year combination. We report our results in Table 5 Column (4). The coefficient on *Corruption* is significantly positive, suggesting that firms in more corrupt areas recognize a higher excess amount of accumulated depreciation.

Lastly, we study the useful life estimate of depreciable assets, an important factor affecting the amount of depreciation (Dichev and Li, 2003). We re-run Equation (1), and replace the dependent variable with *DEP life*, the natural logarithm of the useful life estimate, which is computed as gross PPE divided by annual depreciation expense. We report the results in Table 5 Column (5). The coefficient on *Corruption* is significantly negative, implying that firms located in more corrupt states are more likely to choose a lower useful life estimate.

In sum, we find that firms located in corrupt states are more likely to choose the accelerated depreciation method, report higher LIFO reserve and depreciation reserve, and have a lower depreciable life estimate. Taken together, these results indicate that firms located in more corrupt states are more likely to choose income-decreasing accounting policies.

6.4 Instrumental Variable Approach

We are concerned that corruption and firms' earnings management are endogenously determined. To address this concern, we resort to an instrumental variable approach. The instrumental variable is the isolation of state capitol from its populace, measured by the size-normalized version of Gravity-based Centered Index for Spatial Concentration (GCISC2) from Campante and Do (2014). This measure ranges from zero to one, and a higher value indicates greater isolation of state capitol from its populace.

We choose this instrumental variable for the following reasons. First, Campante and Do (2014) find that states with isolated capital cities are associated with greater political corruption, as a result of lack of oversight and monitoring. The relationship between the isolation of state capitol and political corruption is strong and robust. Second, conceptually, it is hard to see why the isolation, a geographic measure, is affected by firms' accounting choices, except through its association with political corruption.

Following Campante and Do (2014), we compute GCISC2 for each state in each year. The details of the calculation are shown in Appendix B. We 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 the 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, we can reject the null hypothesis that the instrument is weak.

Table 6 reports the second stage regression results. The coefficient on the instrumented value of *Corruption* is -0.042, significant at the 5% level. This result suggests that the baseline finding is unlikely driven by endogeneity.

6.5 Difference-in-Differences Analysis

To further address the endogeneity concern, we conduct a difference-in-differences test by focusing on firms that move between corrupt and non-corrupt states. This test effectively controls for non-time-varying firm characteristics and time-series trends that have 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 firm that moves between corrupt and non-corrupt states, we match it to a control firm (i.e., a firm that does not move) which is in the same 2-digit SIC industry, located in the same state, and with the most similar ROA. For each matched pair, we keep the observations from five years before to five years after the move. We then run the following regression.

$$DA_{ist} = \alpha_0 + \alpha_1 Treat_i \times Post_{ist} + \alpha_2 Treat_i + \alpha_3 Post_{ist} + \alpha_4 Control\ variables_{(i)st} + Pair\ FE + Year\ FE + \varepsilon_{ist} \quad (3)$$

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. $Post_{ist}$ is a dummy variable that takes the value one for the years after the move, and zero for the years before the move. We control for pair fixed effects, to avoid the correlated omitted variable problem (Cram et al., 2009).

Table 7 Column (1) reports the result when treatment firms 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 7 Column (2) reports the result when treatment firms 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 result shows that firms manipulate earnings upwards after moving to a less corrupt state.

Taken together, the results from Table 7 show that political corruption causally results in downward earnings management.

7 Sub-Sample Analyses

7.1 Geographic Concentration

We 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 moving costs increase firms' bargaining power when they encounter 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. The measure of the proportion is discussed in Section 6.1.1, and based on Garcia and Norli (2012). We re-estimate Equation (1) for the two subsamples that are formed based on geographic concentration.

Table 8 Panel A report the results. In the subsample of geographically concentrated firms, the coefficient on *Corruption* is -0.035, significant at the 1% level. In contrast, in the subsample of geographically dispersed firms, the coefficient on *Corruption* is -0.007, much smaller in magnitude and not significant. A Chow test rejects the null hypothesis of no difference between the two coefficients at the 10% level (Chow 1960).

In sum, our results suggest that the impact of political corruption on earnings management is more pronounced for concentrated firms.

7.2 Political Connections

We hypothesize 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), we use the establishment of corporate political action committee (PAC) to measure political connection.

A firm is deemed as politically connected if it registers a PAC in November of the year. We 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. We then match company names from FEC to company names from Compustat by using the fuzzy merge method developed by Wasi and Flaaen (2015). We use the historical company name data provided by Prof. Bill McDonald to adjust for name change[10]. Then we re-estimate Equation (1) for the two subsamples that are formed based on whether the firm has a PAC. Our sample consists of 56, 096 observations.

Table 8 Panel B report 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 connection, the coefficient on *Corruption* is -0.024, significant at the 1% level. The difference between the two coefficients is significant at the 10% level.

In sum, Panel B of Table 8 lends support to the prediction that the impact of corruption on earnings management is more pronounced for firms without political connection.

8. Conclusion

Political corruption is pervasive, rendering it an important question how political corruption affects firms' accounting choices. 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), we hypothesize that firms manipulate earnings downwards when they face high political corruption, in order to shield firms' assets from rent-seeking corrupt officials. This hypothesis is not without tension, because political corruption may also influence the local culture and encourage executives to manipulate earnings upwards (Glaeser et al., 1996).

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

Using a sample of 56,096 firm-year observations from 1987 to 2011 from the U.S., we empirically investigate the relation between political corruption and earnings management. Consistent with Glaeser and Saks (2006) and Smith (2016), we use the actual number of corruption convictions to measure political corruption.

We find that high corruption is associated with low discretionary accruals. Specifically, the performance-matched discretionary accrual, is reduced by 0.4 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. This negative relation between corruption and earnings management is robust to alternative measures of corruption, restatement-based earnings management measure, the instrumental variable approach, and the difference-in-differences test.

We also find that firms in more corrupt states are more likely to choose the accelerated depreciation method, report higher LIFO reserve and depreciation reserve, and have a lower depreciable life estimate, than firms in less corrupt states. This finding is consistent with the notion that firms choose income-decreasing accounting policies to shield their assets from corrupt officials.

To test whether the results are indeed related to the rent-seeking by corrupt officials, we examine whether the effect of corruption on earnings management is more pronounced for firms whose operations concentrate in their headquarter states. Political corruption has a 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 greater for firms whose operations concentrate in their headquarter states. We also predict that the impact of corruption is less pronounced for firms with political connections. Since political connection offers protection against expropriations by government officials, politically connected firms are less motivated to depress earnings to shield their assets. Our results support this prediction.

In sum, this study demonstrates 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.

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Appendix A Variable Definition

Variable	Definition
DA	Discretionary accruals computed according to Kothari et al. (2005).
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 method.
LIFO reserve	LIFO reserve (the difference between LIFO and FIFO carrying value) divided by lagged total assets.
DEP method	A dummy variable that equals 1 if the firm adopts the accelerated depreciation method, and 0 if the firm adopts the straight-line depreciation method, or the mix of accelerated and straight-line depreciation method.
DEP reserve	Excess amount of accumulated depreciation. It is estimated by subtracting industry-level accumulated depreciation from the firm's accumulated depreciation, divided by lagged total assets. The industry-level accumulated depreciation is computed by multiplying the firm's gross amount of PPE with the median accumulated-depreciation-to-gross-PPE ratio of all firms within the same industry-year combination.
DEP life	Natural logarithm of depreciable life, which is calculated as gross PPE divided by annual depreciation expense.
Corruption	Number of corruption convictions divided by the population (in 100,000s) in the state.
Corruption per Government Employee	Number of corruption convictions divided by the number of full-time equivalent state and local government employees (in 100,000s) in state.
Weighted Corruption	The number of corruption conviction cases *per capita* in the headquarter state, multiplied by the percentage of the firm's operation in the state.
Number of convictions	Raw number of corruption convictions divided by 1,000.
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 Integrity Index, and 0 otherwise.
Low Integrity_SII	A dummy variable that equals 1 if the state ranks in the bottom quartile of all the states in the 2012 State Integrity Investigation, and 0 otherwise.
Perceived Corruption	Corruption scale from Table 2 of Boylan and Long (2003).
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, we 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 firm 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. We 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 Gravity-based Centered Index for Spatial Concentration (GCISC2)

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

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 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.

Figure 1 Map of the State Median Corruption

A map of the district median conviction data from Panel A of Table 1.

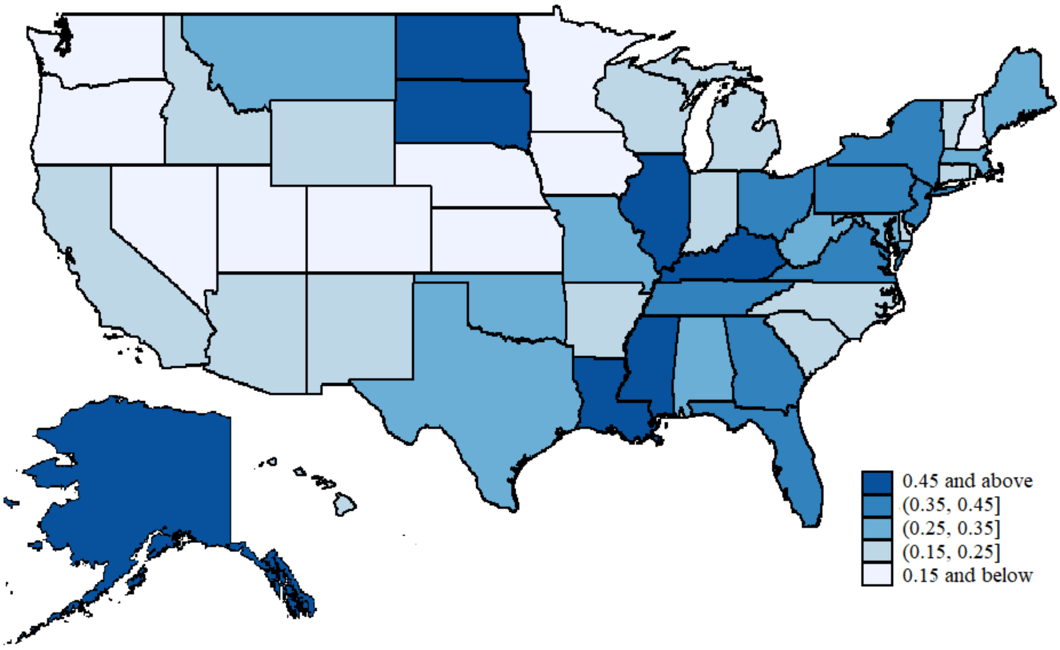

Table 1 Descriptive Statistics

This table reports summary statistics. Panel A provides the summary statistics for *Corruption* (number of corruption convictions per 100,000 for each state) during the 1987-2011 period. All the 50 states and Washington D.C. are included. Conviction data come from the U.S. Department of Justice Public Integrity Section. Data are ordered by median value of *Corruption*. Panel B reports the descriptive statistics of the full sample consisting of 56,096 observations. Panel C reports the average values of 27,836 observations in corrupt and non-corrupt groups. A firm-year observation is in the corrupt (non-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 Summary statistics for convictions per 100,000 by state

State	Firm-year in state	Median	Mean	Std. Dev	Min	Max
District of Columbia	166	6.29	6.92	3.19	2.04	14.16
Louisiana	412	0.81	0.79	0.28	0.12	1.37
North Dakota	12	0.69	0.54	0.39	0.00	0.94
Kentucky	309	0.63	0.56	0.21	0.03	0.95
Mississippi	146	0.56	0.68	0.43	0.17	2.13
South Dakota	61	0.53	0.66	0.44	0.00	1.66
Alaska	33	0.49	0.76	0.80	0.00	2.55
Illinois	2,658	0.48	0.53	0.21	0.16	1.08
Ohio	2,256	0.44	0.44	0.14	0.27	0.89
New Jersey	2,061	0.44	0.41	0.16	0.09	0.72
New York	3,870	0.43	0.43	0.15	0.19	0.82
Florida	2,043	0.42	0.46	0.17	0.21	0.89
Virginia	1,296	0.41	0.46	0.24	0.12	0.94
Pennsylvania	2,488	0.39	0.38	0.11	0.17	0.60
Tennessee	897	0.37	0.42	0.24	0.10	1.57
Georgia	1,518	0.36	0.34	0.19	0.09	0.80
Missouri	990	0.34	0.34	0.11	0.13	0.52
West Virginia	71	0.33	0.36	0.22	0.00	0.93
Alabama	355	0.31	0.39	0.25	0.05	1.11
Maryland	848	0.30	0.33	0.24	0.00	0.99
Maine	58	0.30	0.28	0.21	0.00	0.81
Massachusetts	3,345	0.29	0.30	0.16	0.02	0.82
Oklahoma	412	0.28	0.32	0.17	0.03	0.63
Texas	4,988	0.27	0.27	0.09	0.05	0.46
Montana	60	0.27	0.41	0.44	0.00	1.77
Hawaii	47	0.25	0.31	0.25	0.00	1.10
Delaware	171	0.24	0.37	0.36	0.00	1.14
Connecticut	1,380	0.24	0.26	0.16	0.00	0.68
Indiana	665	0.22	0.22	0.10	0.07	0.54
California	10,593	0.22	0.25	0.08	0.12	0.46
Rhode Island	169	0.20	0.29	0.22	0.00	0.76
New Mexico	56	0.20	0.21	0.15	0.00	0.44
Idaho	168	0.20	0.22	0.18	0.00	0.60
Arkansas	337	0.20	0.23	0.18	0.00	0.70
Wyoming	10	0.19	0.39	0.47	0.00	1.56
South Carolina	255	0.19	0.26	0.20	0.00	0.82
North Carolina	895	0.18	0.19	0.08	0.06	0.34
Michigan	1,122	0.18	0.21	0.07	0.11	0.42
Arizona	676	0.18	0.24	0.19	0.02	0.82
Wisconsin	962	0.17	0.17	0.07	0.02	0.40
Vermont	63	0.17	0.21	0.20	0.00	0.80

Nevada	365	0.15	0.17	0.16	0.00	0.50
Washington	1,166	0.14	0.15	0.09	0.00	0.35
Kansas	306	0.14	0.15	0.11	0.00	0.43
Iowa	331	0.13	0.16	0.11	0.00	0.36
Minnesota	2,123	0.12	0.14	0.09	0.02	0.48
Utah	471	0.09	0.12	0.12	0.00	0.35
Oregon	741	0.08	0.09	0.08	0.00	0.30
New Hampshire	214	0.08	0.09	0.10	0.00	0.39
Colorado	1,204	0.08	0.13	0.14	0.00	0.50
Nebraska	253	0.06	0.12	0.13	0.00	0.57

Panel B Descriptive statistics for the full sample

	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 C Descriptive statistics by non-corrupt and corrupt group

	Corrupt Group (1)	Non-Corrupt Group (2)	Difference (Column 1-Column 2)
DA	-2.12%	-1.52%	-0.599%*
Corruption	0.61	0.11	0.500***
Ln(total assets)	5.89	5.63	0.251***
CFO	7.82%	6.61%	1.208%***
ROA	3.07%	0.16%	2.909%***
R&D	4.75%	6.75%	-2.000%***
R&D Missing	0.40	0.33	0.071***
Acquisition	0.20	0.19	0.018***
Issuance	0.29	0.28	0.010*
Institution	49.23%	48.83%	0.401%
Ln(Analyst)	1.67	1.69	-0.013
Tight covenant	0.12	0.10	0.019***

Meet/Beat	0.16	0.16	0.001
Sales growth	21.46%	22.43%	-0.967%
MB	3.19	3.12	0.074*
Net operating assets	0.69	0.76	-0.065***
Sales volatility	21.30%	21.57%	-0.272%
Ln(operating cycle)	4.65	4.63	0.019**
Big N	0.90	0.90	0.004
Leverage	26.12%	21.80%	4.316%***
Per capita Income ($10,000)	3.01	3.06	-0.047***
Hightech	11.98%	16.47%	-4.488%***
Education	27.96%	27.19%	0.779%***

Table 2 Baseline Regression

This table reports the OLS regression results. The sample consists of 56,096 observations. The dependent variable is *DA*. The independent variable is *Corruption*. Column (1) reports the results where we control for all the firm-level and state-level characteristics. Column (2) shows the results after we further control for year fixed effects. Column (3) reports the results after industry fixed effects are added. 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 Alternative Measures of Corruption

This table reports the OLS regression results. The dependent variable is *DA*. In Panel A, we use the alternative measures based on corruption convictions. *Average Corruption* is the five-year average of convictions from year t-5 to year t-1, scaled by the five-year average population. *Corruption per Government Employee* is the number of corruption convictions divided by the number of full-time equivalent state and local government employees (in 100,000s). *Weighted Corruption* is the *per capita* corruption convictions multiplied by the percentage of the firm's operation in the headquarter state. *Number of Convictions* is the raw number of corruption convictions divided by 1,000. *Low Integrity_BGA* is a dummy variable that equals 1 if the state ranks in the bottom quartile of all the states in the 2013 BGA Integrity Index, and 0 otherwise. *Low Integrity_SII* is a dummy variable that equals 1 if the state ranks in the bottom quartile of all the states in the 2012 State Integrity Investigation, and 0 otherwise. *Perceived Corruption* is the corruption scale from Table 2 of Boylan and Long (2003). 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)	(2)	(3)	(4)
	DA	*DA*	*DA*	*DA*
Average Corruption	-0.024***			
	(-2.704)			
Corruption per Government Employee		-0.001***		
		(-2.848)		
Weighted Corruption			-0.029**	
			(-2.560)	
Number of Conviction				-0.116***
				(-2.924)
Ln (total assets)	0.001	0.001	0.001	0.001
	(0.452)	(0.389)	(0.665)	(0.486)
CFO	-0.840***	-0.840***	-0.844***	-0.840***
	(-40.652)	(-40.683)	(-37.479)	(-40.672)
ROA	0.580***	0.580***	0.588***	0.581***
	(32.725)	(32.736)	(30.969)	(32.704)
R&D	-0.096***	-0.096***	-0.090***	-0.095***
	(-4.313)	(-4.314)	(-3.760)	(-4.268)
R&D Missing	0.011***	0.011***	0.011***	0.011***
	(3.122)	(3.118)	(2.950)	(3.202)
Acquisition	-0.011***	-0.011***	-0.012***	-0.011***
	(-2.731)	(-2.752)	(-2.803)	(-2.739)
Issuance	-0.001	-0.001	-0.000	-0.001
	(-0.274)	(-0.280)	(-0.142)	(-0.294)
Institution	-0.003	-0.003	-0.006	-0.003
	(-0.493)	(-0.462)	(-0.751)	(-0.473)
Ln(Analyst)	-0.006***	-0.006***	-0.007***	-0.006***
	(-2.787)	(-2.736)	(-3.157)	(-2.815)
Tight covenant	0.004	0.004	0.004	0.004
	(0.952)	(0.927)	(0.965)	(0.940)
Meet/Beat	0.001	0.001	0.002	0.001
	(0.181)	(0.182)	(0.753)	(0.195)

Sales growth	-0.004	-0.004	-0.002	-0.004
	(-0.899)	(-0.899)	(-0.486)	(-0.887)
MB	-0.001	-0.001	-0.001	-0.001
	(-1.381)	(-1.426)	(-1.280)	(-1.434)
Net operating assets	0.001	0.001	0.001	0.001
	(0.478)	(0.479)	(0.476)	(0.484)
Sales volatility	-0.012	-0.012	-0.013	-0.012
	(-1.490)	(-1.494)	(-1.396)	(-1.478)
Ln (operating cycle)	-0.010***	-0.011***	-0.011***	-0.010***
	(-3.607)	(-3.644)	(-3.407)	(-3.603)
Big N	-0.013**	-0.013**	-0.014***	-0.013***
	(-2.577)	(-2.542)	(-2.641)	(-2.617)
Leverage	0.047***	0.047***	0.044***	0.046***
	(5.055)	(5.064)	(4.569)	(5.016)
Per capita income	-0.014**	-0.015**	-0.017**	-0.011
	(-2.109)	(-2.295)	(-2.536)	(-1.643)
Hightech	-0.049**	-0.044**	-0.038*	-0.021
	(-2.294)	(-2.088)	(-1.701)	(-0.958)
Education	0.068	0.075	0.094*	0.023
	(1.347)	(1.500)	(1.750)	(0.440)
Year Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
N	56,096	56,096	51,155	56,096
Adj_R^2	0.104	0.104	0.099	0.104

Panel B Alternative Subjective Measures of Corruption

	(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 4 Restatement Analysis

This table reports the OLS regression results. In column (1), the dependent variable is the proportion of firms with income increasing restatements in a state in a year. In column (2), the dependent variable is the proportion of firms with income decreasing restatement in a state in a year. A firm commits income increasing (decreasing) restatement if the restated net income is higher (lower) than the originally reported number. 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 5 Accounting Policy Analysis

This table examines the impact of political corruption on firms' accounting policies. We report logistic regression results in Column (1) and Column (3), and OLS regression results in the rest of the columns. 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 method. 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 the accelerated depreciation method, and 0 if the firm adopts the straight-line depreciation method, or the mix of accelerated 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. In Column (5), the dependent variable is *DEP life*, the natural logarithm of depreciable life, which is calculated as gross PPE divided by annual depreciation expense. 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*	(5) *DEP life*
Corruption	0.100	0.009***	0.423*	0.005*	-0.035***
	(0.964)	(4.123)	(1.712)	(1.937)	(-2.845)
Ln (total assets)	-0.378***	-0.000	0.362***	0.004***	0.064***
	(-32.286)	(-0.345)	(9.202)	(8.363)	(31.499)
CFO	-0.113	-0.002	0.944**	0.007	-0.164***
	(-0.825)	(-0.225)	(2.343)	(1.551)	(-6.747)
ROA	0.378***	0.010	-0.131	-0.025***	0.380***
	(2.733)	(0.953)	(-0.364)	(-5.083)	(13.942)
R&D	2.906***	-0.092***	1.595***	0.032***	-0.261***
	(9.291)	(-3.938)	(3.143)	(4.909)	(-7.342)
R&D Missing	0.117***	-0.003***	-0.445***	-0.010***	0.016***
	(3.658)	(-2.700)	(-4.416)	(-9.362)	(3.156)
Acquisition	0.157***	-0.003***	-0.178	-0.016***	-0.025***
	(4.628)	(-2.648)	(-1.494)	(-13.615)	(-4.162)
Issuance	0.013	-0.000	-0.126	-0.020***	0.014***
	(0.449)	(-0.026)	(-1.290)	(-18.642)	(3.339)
Institution	0.320***	-0.001	-1.103***	0.011***	0.033***
	(4.491)	(-0.448)	(-5.901)	(5.016)	(2.743)
Ln(Analyst)	0.160***	-0.004***	-0.074	-0.015***	-0.077***
	(8.558)	(-5.923)	(-1.040)	(-22.473)	(-20.940)
Tight covenant	0.013	-0.005***	-0.021	-0.002	-0.015**
	(0.354)	(-4.657)	(-0.134)	(-1.168)	(-2.532)
Meet/Beat	-0.011	0.000	-0.131	-0.002*	0.011**
	(-0.359)	(0.051)	(-1.193)	(-1.664)	(2.349)
Sales growth	0.237***	0.013***	-0.087	-0.027***	-0.044***
	(5.381)	(4.497)	(-0.951)	(-19.314)	(-7.286)
MB	-0.003	-0.001***	0.015	0.001***	0.001
	(-0.627)	(-3.304)	(1.037)	(6.994)	(0.891)
Net operating assets	0.023	-0.025***	0.181***	-0.018***	0.014***
	(0.838)	(-15.548)	(4.177)	(-17.837)	(3.443)
Sales volatility	0.492***	-0.001	0.654***	-0.029***	-0.277***
	(7.006)	(-0.332)	(3.078)	(-15.625)	(-21.916)
Ln (operating cycle)	0.193***	0.002*	-0.190**	0.004***	-0.027***
	(6.711)	(1.780)	(-2.259)	(4.968)	(-5.374)

Big N	-0.198***	0.002	-0.663***	0.003**	-0.030***
	(-3.944)	(0.817)	(-5.046)	(2.109)	(-4.234)
Leverage	0.249***	-0.024***	-1.197***	-0.094***	0.157***
	(3.691)	(-8.546)	(-4.648)	(-36.311)	(15.040)
Per capita income	-0.100	-0.006***	-0.342*	-0.000	-0.014
	(-1.378)	(-3.254)	(-1.876)	(-0.131)	(-1.543)
Hightech	2.163***	0.001	-4.558***	0.001	-0.699***
	(8.160)	(0.137)	(-5.737)	(0.176)	(-21.595)
Education	2.388***	0.002	4.946***	0.030*	0.142*
	(3.636)	(0.118)	(3.412)	(1.943)	(1.834)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes
N	40,707	9,633	47,033	56,096	56,000
Adjusted/Pseudo R^2	0.198	0.242	0.157	0.174	0.417

Table 6 Instrumental Variable Approach Based on Isolation of State Capitol

This table reports the second stage of a two-stage OLS regression. The dependent variable is *DA*. The independent variable is *Corruption*. The instrumental variable is a measure of the isolation of the state capitol, i.e., the size-normalized version of Gravity-based Centered Index for Spatial Concentration from Campante and Do (2014). *F* statistic is based on the weak instrumental variable test in Kleibergen and Paap (2006). 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
F-statistic	105.41
N	55,850
Adj_R^2	0.105

Table 7 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 firm, we match it to a control company that is in the same 2-digit SIC industry, located in the same states, and with most similar ROA. In Column (1), treatment firms are those that move from non-corrupt states to corrupt states. In Column (2), treatment firms are those that 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, we 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 the 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 Moves from Non-Corrupt to Corrupt States	Treatment Companies Moves 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 8 Sub-Sample Analyses

This table reports the subsample analyses. In Panel A, we form subsamples based on the geographic spread of the firm. A firm is deemed as concentrated (dispersed) if the percentage of operation in its headquarter state is above (below) sample median in the year. In Panel B, we form subsamples based on whether the company has a PAC. A firm is deemed as politically connected if it registers 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.

Panel A Geographic Concentration

	(1) *DA*	(2) *DA*
	Concentrated	Dispersed
Corruption	-0.035***	-0.007
	(-3.023)	(-0.778)
Ln (total assets)	0.003	-0.000
	(1.389)	(-0.244)
CFO	-0.871***	-0.812***
	(-36.314)	(-25.981)
ROA	0.587***	0.607***
	(24.560)	(22.538)
R&D	-0.053*	-0.142***
	(-1.876)	(-3.225)
R&D Missing	0.013**	0.009*
	(2.333)	(1.896)
Acquisition	-0.012**	-0.012**
	(-2.060)	(-2.142)
Issuance	-0.002	-0.001
	(-0.406)	(-0.234)
Institution	0.002	-0.012
	(0.229)	(-1.081)
Ln(Analyst)	-0.013***	-0.001
	(-3.998)	(-0.437)
Tight covenant	0.014**	-0.004
	(2.020)	(-0.664)
Meet/Beat	0.004	0.001
	(0.824)	(0.249)
Sales growth	-0.004	0.000
	(-0.621)	(0.067)
MB	-0.001	-0.001
	(-0.998)	(-1.252)
Net operating assets	0.005	-0.004
	(1.439)	(-0.934)
Sales volatility	0.006	-0.036***
	(0.473)	(-2.919)
Ln (operating cycle)	0.000	-0.025***
	(0.096)	(-5.481)
Big N	-0.022***	-0.006
	(-3.148)	(-0.712)
Leverage	0.040***	0.052***

	(2.706)	(4.551)
Per capita income	-0.031***	-0.005
	(-3.322)	(-0.552)
Hightech	-0.053*	-0.028
	(-1.871)	(-1.007)
Education	0.154*	0.047
	(1.958)	(0.727)
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	25,535	25,620
Adj_R^2	0.126	0.076

Panel B Political connection

	(1) *DA*	(2) *DA*
	With a PAC	Without a PAC
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