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Nam H. Nguyen
The University of Texas Rio Grande Valley

Hieu V. Phan

Thuy Simpson

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* Nam H. Nguyen, namhoang.nguyen@utrgv.edu, Robert C. Vackar College of Business & Entrepreneurship, University of Texas Rio Grande Valley, 1201 W University Dr, Edinburg, TX 78539, phone: (956) 665-7471; Hieu V. Phan, hieu_phan@uml.edu, Manning School of Business, University of Massachusetts Lowell, 72 University Avenue, MA 01854. Phone: (978) 934-2633; Thuy Simpson, simpsoth@gvsu.edu, Seidman College of Business, Grand Valley State University, 50 Front Ave SW, Grand Rapids, MI 49504. Phone: (616) 331-7408.
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Political Corruption and Mergers and Acquisitions

Abstract

This research examines the relation between political corruption and mergers and acquisitions (M&As). We find that local corruption increases firm acquisitiveness but decreases firm targetiveness. The levels of corruption in acquirer areas relate positively to the bid premiums and negatively to the likelihood of deal completion. Corruption motivates acquiring firms to use excess cash for payment, which mitigates the negative effect of corruption on acquirer shareholder value. The evidence indicates that acquisitions help acquiring firms convert cash into hard-to-extract assets and relocate assets from the high to low corruption areas, thereby shielding their liquid assets from expropriation by local officials.

Keywords: Political Corruption; Mergers and Acquisitions; Liquid Assets Shielding

JEL classifications: G30, G32

"*Corruption is a cancer: a cancer that eats away at a citizen's faith in democracy, diminishes the instinct for innovation and creativity; already-tight national budgets, crowding out important national investments. It wastes the talent of entire generations. It scares away investments and jobs.*" – Joe Biden

I. Introduction

Political corruption is prevalent in the U.S. despite the country being a leading economic power. The total number of public corruption convictions in the U.S. has grown significantly, from 244 cases per year in 1976 to over 1,000 cases per year in the past two decades.[1] The increasing pervasiveness and deteriorating nature of U.S. political corruption prove to be harmful for business operations and the society. Rent seeking due to corruption increases transaction costs, uncertainty, inefficient investments, and misallocation of resources (Shleifer and Vishny (1993), Mauro (1995), Rose-Ackerman (1978)). Corruption also lowers tax revenues, increases public expenditures and debt, heightens financial risks, and weakens productivity, competitiveness, and economic growth (Kauffman (2010)).

Political corruption has important implications for corporate policies, such as firm liquidity, capital structure, and capital expenditures (Campos, Lien, and Pradhan (1999), Fisman and Svensson (2007), Malesky and Samphantharak (2008), Fan, Titman, and Twite (2012), Caprio, Faccio, and McConnell (2013), Dass, Nanda and Xiao (2016), and Smith (2016)). However, no

[1] Authors' own calculation based on the yearly number of corruption convictions of each of the 94 federal judicial districts in the U.S., which is obtained from the Report to Congress on the Activities and Operations of the Public Integrity Section.

prior research has considered the effects of corruption on mergers and acquisitions (M&As), an important form of corporate investment. In this study, we ask whether and how political corruption affects M&As. In particular, we investigate the effects of U.S. political corruption on the key aspects of M&As including firm acquisitiveness, targetiveness, bid premiums, the likelihood of deal completion, payment consideration, and acquirer and target shareholder value.

McChesney (1987) points out that public officials can employ targeted taxation and threats of regulation to extort firms. Extortion is carried out, at both the local and federal levels, via multiple methods such as introducing "milker" bills, which are regulations with narrow focus and typically expire every few years so that they are used as leverage to ask businesses for donation to politicians' election campaigns or extract other personal benefits. In a similar fashion, tax extenders – once used to provide tax breaks and incentives to certain industries for economic growth – are now gaining popularity among politicians as common fund raising tool (Schweiser (2013)).

Shleifer and Vishnyi (1993) and Smith (2016) argue that firms may view bribes as a tax they want to avoid paying. Faced with local corruption, firms may choose to reduce corporate liquidity while increasing debt financing and shortening debt maturity, pursue more opaque disclosure policies to shield themselves from local officials' expropriation, or channel liquid assets to hard-to-extract investments (Myers and Rajan (1998), Stulz (2005), Durnev and Fauver (2011), Fan, Titman, and Twite (2012), Caprio et al. (2013), Smith (2016)).

In the M&A context, to the extent that shielding liquid assets from local officials' expropriation serves the shareholders' interest, we expect firms located in more corrupt areas to be more likely to engage in the acquisition of target firms located in less corrupt areas for at least two possible reasons. First, acquisitions can help the acquiring firms to convert their liquid assets into hard ones, which are more difficult to extract. Second, acquisitions can facilitate the relocation of the acquirers' assets from more corrupt to less corrupt areas, which further shields their assets from local officials' extraction. Also consistent with the assets shielding argument, firms located in more corrupt areas are less likely to be acquisition targets due to a greater threat of expropriation to the acquiring firms.

We begin our analysis by examining the relation between the level of local corruption and firm acquisitiveness and targetiveness. We use the corruption per capita measure as a proxy for corruption (Butler, Fauver, and Mortal (2009), Smith (2016)). This measure is calculated as the yearly number of corruption convictions of each of the 94 federal judicial districts in the U.S., which is obtained from the Report to Congress on the Activities and Operations of the Public Integrity Section, scaled by the respective district population. We then match the judicial districts' corruption data with the Compustat data and the M&A subsample based on firm headquarters location. We use the headquarters location as the identifier since it is where the majority of plants and operations of a firm is presumably based (Bai, Fairhurst, and Serfling (2017)).[2]

Using a sample that includes 77,338 firm-year observations of 8,314 unique firms spanning from 1986 to 2014, we find that the levels of local corruption are positively related to firm acquisitiveness but negatively related to firm targetiveness. Since local corruption and corporate investments, including M&As, might be correlated with local economic conditions, we control for state Gross Domestic Product (GDP) growth and GDP per capita in our analysis but our findings are insensitive to these controls. To alleviate a concern that corruption is correlated with time-invariant factors specific to their location, we control for state or judicial district fixed effects in

[2] However, we relax this assumption by considering the degree of firm operation concentration around the headquarters location in the robustness check section.

our analysis but our results are qualitatively unchanged. To address a possibility that both local corruption and M&As are correlated with other unobservable factors, a cause of endogeneity bias, we further use the instrumental variable (IV) model for estimation but our results continue to hold.

Using the number of corruption convictions in a judicial district as a proxy for local corruption is subject to a possible criticism that a more corrupt district may have a smaller number of convictions. To dispel this concern, we use two other measures of political corruption to verify our results. The first measure is the outcome of the 2012 State Integrity Investigation conducted by the Center of Public Integrity to grade each state's transparency, accountability, and the law systems to deter corruption. The second measure is corruption scores based on the results of a survey of State House reporters conducted by Boylan and Long (2003). We find that our results for firm acquisitiveness and targetiveness persist. We further employ the recent adoption of the anti-corruption laws by Texas and Florida as a plausibly exogenous shock to political corruption to identify the relation between corruption and M&As but our findings are essentially unchanged. Overall, our findings are consistent with the shielding argument.

Next, we investigate the relation between corruption and the method of payment in M&As. To the extent that corruption motivates firms to shield their liquid assets by managing liquidity downward but financial leverage upward (Smith (2016)), acquiring firms located in highly corrupt areas are more likely to use stock for acquisition payment due to their low corporate liquidity and high debt ratios. This shielding argument further implies that acquiring firms will be more likely to use cash for payment if they have excess cash. Consistent with our expectation, we find a negative (positive) relation between the corruption levels in the acquirer areas and the likelihood of all-cash (stock) payment. Moreover, corruption is positively related to the likelihood of all-cash payment conditional on acquiring firms' excess cash.

While firms from highly corrupt areas may choose to pursue acquisitions to shield their liquid assets from local officials' expropriation, target shareholders would be concerned about the corruption practice in the acquirers' areas and view their bids unfavorably. We find that that the level of corruption in an acquiring firm's area relates positively to the bid premium and negatively to the likelihood of the deal completion. This evidence suggests that target shareholders demand higher bid premiums as compensation for a possible expropriation risk following the merger and, to the extent that the premiums are not worth the risk, they may reject the bids, leading to lower probability of deal completion. Furthermore, we find a negative relation between cash payment and bid premiums, which implies that acquiring firms can mitigate the adverse effect of corruption by paying cash for their acquisition deals.

Finally, we investigate the relations between corruption and acquirer and target shareholder values. Using the three-day M&A deal announcement cumulative abnormal stock returns (CAR) as a proxy for shareholder value, we find that corruption is negatively related to acquirer shareholder value but cash payment can mitigate such negative value effect. Moreover, corruption in the target areas reduces target shareholder value, which implies a corruption discount, probably due to the acquirers' concern about the threat of expropriation by local officials in the target areas. In summary, our results demonstrate a positive relation between corruption and cash payment conditional on excess cash, a negative relation between cash payment and bid premiums, and a positive relation between corruption and acquirer shareholder value conditional on cash payment. The evidence suggests M&As as an effective channel through which acquiring firms can shield their liquid assets from expropriation by local officials.

Our research makes three important contributions to the literature. First, to the best of our knowledge, this is the first study that examines the relation between political corruption and

M&As, an important form of corporate investments. Whereas previous research documents that corruption impedes corporate investments, particularly capital expenditures (Campos et al. (1999), Malesky and Samphantharak (2008)), our research indicates that corruption motivates M&As. An advantage of using M&As for empirical research is that they are observable at precisely the points in time when the decisions are made, which allows us to establish a direct link between political corruption and M&As. Although increasing corporate payouts can help firms shield their liquid assets from political expropriation (Smith (2016)), it may undermine firms' growth in the long term. As M&As enable firms to convert cash into hard-to-extract assets and relocate assets from the more corrupt to the less corrupt areas, acquiring firms not only shield their liquid assets but also maintain their growth trajectory. Thus, our evidence suggests M&As as a plausible channel through which firms can shield their liquid assets from local officials' expropriation.

Second, we add to the M&A literature by suggesting local corruption as a determinant of firm acquisitiveness and targetiveness. To the extent that M&As represent the market discipline that helps reallocate assets to a better use (Andrade and Stafford (2004), Martynova and Renneboog (2008), and Jovanovic and Rousseau (2008)), the negative effect of local corruption on firm targetiveness indicates that corruption impedes market discipline and hampers efficient asset reallocation.

Finally, our research has important implications for policy makers, corporate managers, and investors. Our evidence indicates that local corruption discourages businesses from investing in their local areas while encouraging them to relocate their assets to less corrupt areas. Corruption, thus, distorts corporate investments and raises business costs, which adversely affect investors' benefits and local economies.

The remainder of the paper is organized as follows. We present a description of the data and variables construction in Section II. Section III develops empirical predictions and discusses the research methods and results. Section IV presents robustness checks and Section V concludes the paper.

II. Samples, Variables Construction, and Descriptive Statistics

We obtain firm accounting data from Compustat, stock price and return data from the Center for Research in Security Prices (CRSP) databases, and M&A data from the Securities Data Company's (SDC) Platinum Database. We merge the M&A and Compustat data to form the full sample to investigate the effect of political corruption on firm acquisitiveness and targetiveness. Following the literature, we exclude firms from the utility (Standard Industrial Classification (SIC) codes from 4900-4999) and financial industries (SIC codes 6000-6999) since these industries are subject to more stringent regulations.[3] We retain firm-year observations with at least one M&A deal to form the M&A subsample for cross-sectional analysis. Moreover, to focus on M&A deals that can have significant effects on the acquiring firms, we exclude small M&A deals with values below one million U.S. dollars from the M&A subsample. The sample period spans from 1986 to 2014.

Similar to Butler et al. (2009) and Smith (2016), we use the number of yearly corruption convictions of each of the 94 U.S. federal judicial districts obtained from the Report to Congress on the Activities and Operations of the Public Integrity Section as a measure of political corruption. This number of corruption convictions is scaled by the annual population estimate from the U.S. Census for each judicial district to ensure that a high corruption level is not merely due to a large

[3] However, more regulations may induce more political corruption. Thus, we include these industries in the analysis and discuss the results in the robustness check section.

population of the district. By construction, a higher level of corruption per capita of a judicial district indicates a more corrupt environment in that district. We manually identify the ZIP codes associated with each federal judicial district and merge the corruption data with the full sample and the M&A subsample using the historical ZIP codes of firm headquarters locations.[4]

Table 1 presents the number of M&A deals over the sample period, distributed by year in Panel A and by industry using the 2-digit SIC code in Panel B. The annual number of M&As deals increased over the period 1986-2000, peaking in 1998 before decreasing during the recession in 2001-2002 and in 2009. Industries that experience high frequency of M&As include business services, electronic and other electrical equipment, chemicals and allied products, instruments and related products, industrial and commercial machinery, and computer equipment.

[Insert Table 1 about here]

We report the summary statistics of the full sample and the M&A subsample in Panels A and B, respectively, of Table 2. The full sample includes 77,338 firm-year observations of 8,314 unique firms while the M&A subsample consists of 7,325 firm-year observations of 2,906 unique firms. *District corruption* is the yearly number of convictions per 100,000 of the judicial district in which a firm is headquartered. *ACOR* is the corruption per 100,000 of the judicial district in which an acquirer is headquartered. *Firm size* is measured as the natural logarithm of the book value of assets. *Market-to-book* is the ratio of the market value of assets to the book value of assets. *Book leverage* is the ratio of the book value of debt divided by the book value of assets. *Past 12-month returns* is the acquirer 12-month buy-and-hold stock return in the year prior to the M&A announcement. *Average sales growth* is the average annual sales growth rate over the last three

[4] Since the Compustat database reports only the most recent ZIP codes of firm headquarters, we use a web crawler program to collect the ZIP codes of firm headquarters over the time from their 10-K reports.

years. Other variables are defined in Appendix A. The average corruption per 100,000 of the full sample and M&A subsample are 0.335 and 0.333, respectively, which are close to the figure (0.327) reported by Smith (2016). The average firm size, market-to-book ratio, past 12-month returns, and firm age of the M&A subsample appear to be larger than those of the full sample.

[Insert Table 2 about here]

III. Empirical Predictions, Research Methods, Results, and Discussions

A. Political Corruptions, Firm Acquisitiveness, and Firm Targetiveness

Anecdotal evidence indicates that expropriation by public officials presents a real threat to firms. For instance, former Arkansas state senator, Jeremy Hutchinson, pleaded guilty to multiple bribes in connection with several investigations, spanning the Western District of Missouri and Eastern and Western Districts of Arkansas. Hutchinson admitted that he was hired as outside counsel to perform official acts on behalf of Preferred Family Healthcare, Inc., including holding up agency budgets and drafting and voting on legislation in exchange for payments. In a separate scheme, Hutchinson also pleaded guilty on June 25, 2019 to bribery in which the former Arkansas state senator took official action in exchange for bribes from an owner of orthodontic clinics throughout the state of Arkansas.[5]

Early theoretical work by Myers and Rajan (1998) suggests that firms are more likely to channel its liquid assets to hard-to-extract investments to reduce rent-seeking that arises from corruption. Fan, Titman, and Twite (2012) examine the impact of corruption, among other institutional differences, on the capital structure and debt maturity choices of firms from 39

[5] Source: Press Release from the U.S. Department of Justice, available at https://www.justice.gov/usao-wdmo/pr/former-arkansas-state-senator-pleads-guilty-bribery (last accessed on September 9, 2019)

developed and developing countries. These authors find that firms located in more corrupt countries use more debt financing with shorter maturity to shelter their assets from political expropriation. Similarly, Caprio et al. (2013) report that firms respond to political corruption and threats of rent extraction by holding significantly lower liquid assets while channeling their cash to harder to extract assets, including property, plant, equipment, and inventory, and paying more dividends. However, it is worth noting that investing in fixed assets alone might not fully insulate firms from expropriation risk since firms will have less flexibility and become more vulnerable to future extortion by local officials. Smith (2016) examines the impact of U.S. corruption on firm behavior and finds that firms manage their cash level downward while managing their debt ratio upward to shelter their liquid assets from political expropriation. These arguments suggest that political corruption increases not only direct costs due to politicians' rent-seeking but also indirect costs associated with asset reallocation that deviates from an otherwise optimal structure

Bai et al. (2014) develops a model in which local officials set a bribe rate and firms either pay the bribe or move elsewhere. Although M&As involve significant costs, to the extent that the benefits of engaging in M&As to shelter firm liquid assets from local officials' expropriation outweigh their costs, we predict that firms located in more corrupt areas are more likely to pursue acquisitions to convert their liquid assets into hard ones, which are more difficult to extract. In addition, acquisitions also allow acquiring firms to relocate liquid assets to less corrupt areas, further shielding their assets from potential expropriation by local officials. Conversely, firms in highly corrupt areas will be less likely to become acquisition targets due to a greater threat of political extraction.

We examine the effect of political corruption on firm acquisitiveness using the following linear probability model:[6]

$$\text{M\&A dummy}_{i,t} = \alpha + \beta * \text{District corruption}_{i,t-1} + \boldsymbol{\lambda} * \mathbf{C}_{i,t-1} + \delta \text{Year dummies} + \gamma \text{Industry dummies} + \varepsilon_{i,t}, \quad (1)$$

where *M&A dummy* is an indicator variable that takes a value of 1 if firm *i* makes at least one acquisition announcement in year *t*, and 0 otherwise. *District corruption* measures the level of political corruption of the judicial district in which firm *i*'s headquarters is located in a given year.[7] Following the M&A literature, we control for several firm characteristics documented to have power in explaining firm acquisitiveness including *size*, *market-to-book ratio*, *book leverage*, *past 12-month returns*, *firm age*, *non-cash working capital*, and *average sales growth*. The control variables are lagged by one period to alleviate possible endogeneity concern. We additionally control for industry and year fixed effects in our M&A linear probability model. We cluster the standard errors by firms.[8] The definitions of the variables are provided in Appendix A.

Columns 1-2 of Table 3 reports the M&A linear probability model results. The coefficients of *District corruption* are positive (0.009 and 0.012) and highly significant. These results indicate that firms headquartered in more corrupt areas are more likely to pursue M&As.[9] Since both the corruption level and M&A activities could be correlated with the economic conditions of the firms' headquarters states, we further control for the natural logarithm of the state GDP per capita and

[6] We use the linear probability model to alleviate concern about the incidental parameter problem since the model controls for several dummy variables. However, our findings are qualitatively unchanged if we use the probit model.

[7] Our results are qualitatively similar if we use the contemporaneous level of political corruption in the regressions.

[8] For robustness, we also cluster the standard errors by judicial districts and years but find qualitatively similar results.

[9] In an unreported univariate analysis, we find that acquirers, on average, choose targets located in relatively less corrupt areas.

state GDP growth rate in the M&A linear probability model and report the results in Column 3 of Table 3. We find that the coefficient of *District corruption* remains positive (0.018) and statistically significant at the 1% level. To illustrate the economic effect of corruption, we use the coefficient estimate in Column 3 for calculation and find that, holding other variables unchanged at their sample means, a 1-standard-deviation increase in *District corruption* above its sample mean is associated with 75 basis points (0.75%) increase in acquisition probability, which is equivalent to 3% of the sample mean. Since political corruption can be correlated with other unobserved time-invariant factors, we control for either state, judicial district, or firm fixed effects in alternative model specifications but our results are qualitatively unchanged (to save space, the estimation results are not reported but are available from the authors).

[Insert Table 3 about here]

We investigate the effects of political corruption on firm targetiveness by estimating the following linear probability model:

$$\text{Target dummy}_{i,t} = \alpha + \beta^{*}\text{District corruption}_{i,t-1} + \boldsymbol{\lambda}^{*}\mathbf{C}_{i,t-1} + \delta\text{Year dummies} + \gamma\text{Industry dummies} + \varepsilon_{i,t}, \quad (2)$$

where *Target dummy* takes a value of 1 if a firm is an acquisition target in a given year, and 0 otherwise. $\boldsymbol{C}_{i,t-1}$ is a set of control variables similar to that in Equation 1. The estimation results of the targetiveness linear probability models reported in Columns 4-6 of Table 3, indicate that the coefficient estimates of *District corruption* are negative (-0.008 and -0.01) and highly significant, suggesting that firms located in more corrupt areas are less likely to be acquisition targets.

In summary, our evidence in this section is consistent with the argument that the threat of expropriation by local officials leads to an increase (decrease) in firm acquisitiveness (targetiveness).

B. Corruption and Payment Consideration

In response to the rent-seeking behavior of local officials, firms tend to hold lower cash reserves and maintain higher debt ratios (Caprio et al. (2011), Smith (2016)). This finding suggests that acquirers in highly corrupt areas are more (less) likely to use stock (cash) as a medium of payment for acquisition deals. However, if these firms have excess cash, they will be more likely to use cash for acquisition payment to reduce their exposure to expropriation risk.

We use the following linear probability model to examine the relation between political corruption and payment consideration:

$$\text{Cash dummy}_{ij} = \alpha + \beta^{*}\text{ACOR}_{i,t-1} + \Upsilon^{*}\text{TCOR}_{i,t-1} + \boldsymbol{\lambda^{*}C}_{i,t-1} + \delta\text{Year dummies} + \gamma\text{Industry dummies} + \varepsilon_{i,t}, \quad (3)$$

where *cash dummy* is an indicator variable that takes a value of 1 if the payment for M&A deal *j* of firm *i* is fully in stock, and 0 otherwise. *ACOR* (*TCOR*) is the level of corruption in the acquirer (target) judicial district. Following previous studies (e.g., Dong, Hirshleifer, Richardson, and Teoh (2006), Faccio and Masulis (2005), and Phan (2014)), we control for firm and deal characteristics such as *size*, *market-to-book*, *past 12-month returns*, *average sales growth*, *book leverage*, *noncash working capital*, *firm age*, *excess cash*, *deal ratio*, *diversifying dummy*, *hostile dummy*, *public dummy*, and *challenge dummy*. Appendix A provides the description of the variables.

The results of the payment consideration regression reported in Table 4 indicate that, on average, the level of corruption in an acquirer area is negatively related to the likelihood of cash payment. We further estimate the payment consideration model augmented with an interaction between *ACOR* and corporate excess cash. We follow Harford (1999) in calculating excess cash as the residuals from the regression of a firm's level of cash holdings on firm size, financial leverage, market-to-book ratio, cash flows, standard deviation of cash flows over the last 10 years, net working capital, capital expenditures, research and development expenses, acquisition spending, dividend expense, S&P credit ratings, and industry and year fixed effects. The results reported in Columns 5-8 of Table 4 indicate that the coefficients of the interaction between *ACOR* and excess cash are positive and statistically significant at the 1% level in all models, suggesting that acquiring firms with larger excess cash and located in more corrupt areas are more (less) likely to use cash (stock) as the medium of payment for M&A deals. These results are consistent with our predictions. On the other hand, the effect of the target judicial district's corruption level on the payment consideration is inconclusive.

[Insert Table 4 about here]

C. Political Corruption, Bid Premiums, and Likelihood of Deal Completion

To the extent that political corruption increases operating costs and impedes business operations, we predict a positive (negative) relation between acquirer district corruption and the bid premium (deal completion likelihood). Moreover, we expect these relations to be more pronounced when the level of corruption in the acquirer judicial district is higher than that in the target one.

We examine the relation between political corruption and bid premiums by estimating the following regression model:

$$\text{Bid premium}_{ij} = \alpha + \beta * \text{ACOR}_{i,t-1} + \Upsilon * \text{TCOR}_{i,t-1} + \boldsymbol{\lambda} * \mathbf{C}_{i,t-1} + \delta \text{Year dummies} + \gamma \text{Industry dummies} + \varepsilon_{i,t}, \quad (4)$$

where *Bid premium* is measured as the percentage difference between the bid price and the target's stock price one week before the deal announcement. ***C*** is a vector of control variables that include firm and deal characteristics similar to those in Equation 3 (Officer (2003), Dimopoulos and Sacchetto (2014)). Table 5 reports the results of the bid premium regressions. The regression sample for this analysis is small since the bid premiums can be calculated for only public targets. The coefficients of *ACOR* are positive, ranging from 0.035 to 0.056, and statistically significant in all models. However, cash payment is negatively related to the bid premiums. These results suggest that acquiring firms located in highly corrupt areas have to pay higher bid premiums but using cash for acquisition payment decreases the bid premiums. On the other hand, the coefficients of *TCOR* are statistically insignificant.

[Insert Table 5 about here]

Next, we investigate the relation between political corruptions and the likelihood of deal completion. The dependent variable is *completion dummy* that takes a value of 1 for a deal completion, and 0 for a deal abandonment. The deal completion linear probability model includes either both *ACOR* and *TCOR* or the difference between these two variables (labeled *Delta corruption*). The results of the linear probability regression reported in Columns 1-4 of Table 6, which include both *ACOR* and *TCOR*, are consistent with the view that corruption impedes business operations. In particular, the coefficient estimates of *ACOR* are negative and statistically significant, indicating that acquisition deals of acquirers headquartered in more corrupt areas have lower likelihood of completion. Similarly, the negative and highly significant coefficients of *Delta corruption* reported in Columns 5-8 of Table 6 suggest that acquirers located in relatively more corrupt areas have lower likelihood of completing the acquisition deals with targets located in less corrupt areas. One possible explanation is that target shareholders reject the bids of acquirers from highly corrupt areas due to their concerns about the expropriation risk in the latter' areas.

[Insert Table 6 about here]

C. Political Corruption and Shareholder Value

In this section, we examine the effects of corruption on acquirer and target shareholder values. The level of corruption in an acquirer district should be negatively related to its shareholder value due to the direct and indirect costs associated with corruption discussed above. However, acquirers from highly corrupt areas may create shareholder value through acquisitions if they help shelter the acquiring firms' liquid assets from expropriation by local officials. Therefore, we expect a positive effect of the interaction between corruption and cash payment on acquirer shareholder value or, put in a different way, cash payment will mitigate the adverse effect of corruption on acquirer shareholder value. Furthermore, following the shielding argument, we predict a negative relation between the corruption level in the target district and acquirer shareholder value.

Columns 1-4 of Table 7 reports the results of the cross-sectional regressions of acquirer three-day abnormal stock returns (CAR(-1, 1)) on *ACOR*, *ACOR*cash dummy*, *ACOR*stock dummy*, and other firm and deal characteristics.[10] We use the market model and value-weighted CRSP index returns to estimate acquirer three-day CARs. Following a long line of M&A research (e.g., Harford (1999), Moeller, Schlingemann, and Stulz (2005), and Masulis, Wang, and Xie (2007)), we control for the following firm and deal characteristics in the CAR regressions: *size*, *market-to-book ratio*, *financial leverage*, *past 12-month returns*, *high-tech dummy*, *cash dummy*, *stock dummy*, *deal attitude dummy*, *target public status*, *challenge dummy*, and *industry M&A intensity*. All variables are defined in Appendix A.

Firms may self-select to pursue M&As and, all else being equal, they are more likely to pursue deals that create greater shareholder value. This observation indicates that our cross-sectional regression is subject to a possible self-selection problem that biases the coefficient

[10] Mixed payment consideration is left out to avoid perfect collinearity.

estimates. We address the self-selection bias problem by using the Heckman's (1976, 1979) two-step self-selection correction model. Specifically, we use the estimates from the M&A probit model to calculate the inverse Mill's ratio (IMR), then we include the IMR in the cross-sectional regressions as an additional control variable (however, our results are insensitive to the correction for self-selection bias).

The acquirer CAR regression results reported in Columns 1-4 of Table 7 indicate that the coefficients of the stand-alone *ACOR* are negative and statistically significant while the coefficients of the interaction between *ACOR* and *cash dummy* are positive and statistically significant. This result indicates that firms' sheltering of their liquid assets from potential expropriation by using cash for acquisition payment is viewed favorably by their shareholders. Using the coefficient estimates to calculate the economic effect of corruption on acquirer shareholder value, we find that, holding other variables fixed at their sample means, a 1-standard-deviation increase in *ACOR* above its sample mean is associated with 35 basis points (i.e., 0.35%) or $17.2 million decrease in acquirer shareholder value. However, the result of a Wald test indicates that the sum of the coefficient of ACOR and that of its interaction with cash payment is statistically indifferent from zero, implying that cash payment neutralizes the negative effect of corruption on acquirer shareholder value. On the other hand, the coefficients of *TCOR* are statistically insignificant, indicating little effect of the corruption level of the target's judicial district on acquirer shareholder value.

[Insert Table 7 about here]

We examine the effects of political corruption on target CARs and report the results in Columns 5-8 of Table 7. The coefficients of *ACOR* are positive and statistically significant at the 1% and 5% levels in all specifications. This result is consistent with our earlier finding that acquirers located in more corrupt areas tend to pay higher bid premiums, which appear to benefit target shareholders. In contrast, the coefficients of *TCOR* are negative and statistically significant in Columns 1 and 2, indicating that target firms located in more corrupt areas suffer from a larger corruption discount that decreases target shareholder value. The estimation results indicate that, holding other variables unchanged at their sample means, a 1-standard-deviation increase in *TCOR* above its sample mean is associated with a decrease of 48 basis points (i.e., 0.48%) or a loss of $16.1 million in target shareholder value.

In summary, our evidence in this section indicates that corruption in the acquirer and target districts is negatively related to their respective shareholder value. However, cash payment attenuates the negative effect of corruption on acquirer shareholder value.

IV. Robustness Checks and Other Analyses

A. Political Connections and Political Balance

Both political corruption and M&A activities could be correlated with firms' political connections so failing to control for political connections may bias the results. Moreover, political corruption and M&As decisions can also be correlated with the political balance in a state. In particular, states with Republican dominance tend to favor businesses, whereas states with Democrat dominance tend to favor labor. To alleviate these concerns, we rerun firm acquisitiveness and targetiveness regressions that further control for political connections and state political balance. Following Faccio and Hsu (2017), we first obtain the background information such as employment positions, education, political positions and affiliations for all firm executives from the Capital IQ database. We identify politically connected individuals by matching each executive position and affiliation with 42 political keywords provided by Faccio and Hsu such as

"Governor of the State", "Senator", "Congress", and "White House", etc. We consider a firm as politically connected if they employ at least one politically connected executive anytime during the sample period. We construct the political connection variable as an indicator that equals 1 for politically connected firms and 0 otherwise. State political balance is proxied by the state-level fraction of the Democratic Party members in the House of Representatives in a given year (Serfling (2016); Bai, Fairhurst, and Serfling (2017)).

The results reported in Panel A of Table A1 in the Internet Appendix indicate that our findings are qualitatively unchanged. Furthermore, we find a negative relation between political connections and firm acquisitiveness, implying that politically connected firms are less likely to engage in M&As deals. One possible explanation for this result is that acquiring firms typically pursue out-of-state targets, whereas politically connected firms may prefer to stay local to take advantage of their connections with local officials. In another robustness check, we rerun the acquirer CAR regressions while additionally controlling for political connections and political balance. The reported results in Panel B of Table A1 in the Internet Appendix indicate that our findings are qualitatively similar.

B. Product Market Competition

Political corruption and M&As decisions can also be correlated with product market competition. Specifically, Hoberg and Phillips (2010) argue that firms in competitive industries can use restructuring, possibly through M&As, to reduce competition. Alexeev and Song (2013) document that product market competition is positively associated with corruption while Ades and Di Tella (1999) and Emerson (2006) find a negative relation between the degree of product market competition and the level of corruption. In the next robustness check, we rerun firm acquisitiveness regressions that control for industry competition proxied by the text-based Herfindahl-Hirschman

Index (HHI). Using over 50,000 business descriptions in 10-K annual filings on the SEC from 1996-2017, Hoberg and Phillips (2016) develop a new industry classification (referred to as the Text-based Network Industry Classification (TNIC)) and construct the text-based Herfindahl-Hirschman Index (HHI) based on the this industry classification. Since the HHI data is available from 1996, our M&A subsample consists of 48,411 firm-year observations. Results of the firm acquisitiveness regressions reported in Columns 1 and 2 of Panel A of Table A2 in the Internet Appendix indicate that the coefficients of *District corruption* remain positive (ranging from 0.013 to 0.020) and statistically significant at the 1% level in all models. We also rerun firm targetiveness regressions augmented with text-based product market competition and report the results in Columns 3 and 4 of Panel A of Table A2 in the Internet Appendix. The results indicate that our finding is essentially unchanged. We rerun acquirer CARs regressions while additionally controlling product market competition and report the results in Panel B of Table A2 in the Internet Appendix. Our findings are qualitatively similar.

C. IV Regressions

Although our regressions control for state economic conditions, political connections, political balance, and product market competition, political corruption and M&As could be jointly correlated with other unobservable variables, raising an endogeneity concern due to possible omitted variables. Endogeneity could bias the coefficient estimates of the M&As linear probability models and invalidate the statistical inferences. We use the instrumental variable (IV) approach to address endogeneity concern. Brunetti and Weder (2003) and Gentzkow et al. (2006) argue that media and press coverage can constrain corruption. Campante and Do (2014) suggest that politicians are more corrupt in isolated capital cities due to lower media coverage of politics and less oversight from voters. Following these arguments, we use the isolation of state capital city measured by the Gravity-based Centered Index for Spatial Concentration (GCISC) developed by Campante and Do as an instrument for state corruption (Smith (2016)).[11] This variable measures the concentration of a state's population and its distance to a state's capital city. As such, a measure of 0 indicates a state's population concentrates around its capital while a measure of 1 suggests that a majority of the state's residents live as far away from the capital city as possible.

We use the state-level shocks to newspaper reporter employment as the second instrument for political corruption. Intuitively, a larger decrease in the journalist employment may result in lower media and press coverage, leading to more political corruption. Using the news journalist employment data from Bureau of Labor Statistics, we construct the *journalist employment shock* variable as an indicator that equals 1 if the state news journalist employment decreases by more than 40% in a given year, and 0 otherwise.[12] Our selected instruments should be valid since they relate directly to state corruption but there is no obvious reason that they have direct ties to M&A activities except through political corruption.

[Insert Table 8 about here]

We report the results of M&A IV linear probability model in Table 8. The first-stage results of the IV model reported in Column 1 indicate that the coefficients of the *isolated capital city* and *journalist employment shock* are positive (0.589 and 0.246, respectively) and significant at the 1% level, confirming the relevance of the instruments. The over-identification and weak identification test statistics indicate that the selected instruments are valid and strong. The results of the second-

[11] We thank Campante and Do for making the isolation of capital city data available.

[12] The results are qualitatively similar if we use the continuous version of the journalist employment change as an instrument.

stage of the IV model reported in Column 2 indicate that the coefficient of *instrumented district corruption* is positive (0.194) and statistically significant at the 1% level, suggesting that our findings are robust to endogeneity correction.

We estimate the targetiveness IV linear probability model and report the results in Columns 3-4 of Table 8. The first-stage results and identification test statistics reported in Column 3 confirm the relevance and validity of the selected instruments. The results of the second-stage IV model reported in Column 4 indicate that the coefficient of *instrumented district corruption* is negative (-0.043) and statistically significant at the 5% level, suggesting that the results of the targetiveness linear probability model are insensitive to endogeneity correction.

D. Alternative Measures of Corruption

Using the number of corruption convictions in a judicial district to measure local corruption is prone to a possible criticism that the most corrupt districts may have the lowest number of convictions (Smith (2016)). Moreover, the data reflects federal corruption convictions but do not include cases tried by state and local prosecutors (Dincer and Johnston (2014)). Boylan and Long (2003) point out that there is usually a time lag between crimes and conviction. These observations suggest that our political corruption measure may underestimate the true nature of political corruption in the judicial district. To dispel this concern, we employ two other alternative measures of political corruption for robustness check. The first measure is the outcome of the 2012 State Integrity Investigation conducted by the Center of Public Integrity to grade each state's transparency, accountability, and the law systems to deter corruption. A score of 100 indicates a state without corruption while a score of 0 means the state has the highest level of corruption. To ease interpretation, we invert the state integrity scores: A higher (lower) score indicates a higher (lower) level of corruption. The second measure is the corruption score based on the results of a survey of State House reporters conducted by Boylan and Long. Specifically, State House reporters were asked to rank their states' corruption on a scale from 1 to 7. A state's score of 1 (7) is perceived as not corrupt (highly corrupt). Boylan and Long construct the state corruption score as the average of the responses for each state.

We rerun firm acquisitiveness linear probability regressions using either the inverted 2012 State Integrity Investigation score or the corruption score provided by Boylan and Long as proxies for political corruption in a firm's location and report the results in Columns 1-4 of Table 9. Since the State Integrity Investigation was conducted in 2012, we use the subsample period 2010–2014 for analysis. We find that the coefficients of the corruption measure based on the State Integrity Investigation are positive and statistically significant in all four columns.

Column 5 of Table 9 report results of the regression that use the corruption scores based on the survey of State House reporters. Since Boylan and Long (2003) conduct the survey in 1999, we estimate the firm acquisitiveness linear probability model for the 5-year period centered on 1999. The results indicate that the coefficients of the corruption measure are positive and highly significant, suggesting that our firm acquisitiveness results are robust to alternative measures of political corruption.[13]

[Insert Table 9 about here]

E. Adoption of Anti-Corruption Laws as Exogenous Shock to Corruption

[13] In an unreported analysis, we rerun the acquirer CAR regressions with these two alternative corruption measures and find consistent, albeit weaker, results.

To further address endogeneity concern associated with possible corruption mismeasurement, we exploit the state adoption of anti-corruption laws as a plausibly exogenous shock to identify the causal relations between political corruption and firm acquisitiveness and targetiveness. In particular, Texas adopted anti-corruption law (HB1690) in September 2015 and Florida adopted anti-corruption Act in October 2016. These two anti-corruption laws expand the applicability of offenses to any "state officers" and "state employees" and create new procedures for investigating and prosecuting corrupted officers, which potentially reduces the level of political corruption. We rerun firm acquisitiveness regressions on the anti-corruption law adoption and other control variables and report the results in Table A3 in the Internet Appendix. *Anti-corruption law* is an indicator that takes a value of 1 for firms located in states that adopted anti-corruption laws in a given year, and 0 otherwise. To the extent that anti-corruption laws reduce political corruption, we expect firms headquartered in these states to be less likely to engage in M&A activities as a way to shield their liquid assets. It is worth noting that firms affected by anti-corruption laws could be systematically different from those not affected by these laws. Thus, the analysis results might reflect their systematic differences rather than the effects of the anti-corruption measures. To alleviate this concern, we estimate the firm acquisitiveness model with a firms headquartered in Texas and Florida as treatment firms and those in their bordering states as control firms. Since these anti-corruption laws were adopted recently, we extend the regression sample to 2018.

The results reported in Columns 1-2 of Table A3 in the Internet Appendix indicate that the coefficients of *Anti-corruption law* are negative and statistically significant, suggesting that firms are less likely to engage in acquisitions following the state anti-corruption law adoption. To mitigate a concern that the results could be driven by time trends of M&A and the adoption of anti-corruption laws, we estimate dynamic models that include indicators for years *t*-2, *t*-1, *t*, *t*+1 and after, where *t* is the year in which a state adopted the anti-corruption law. The results reported in Columns 3-4 of Table A3 indicate that the effect is only statistically significant in the year the law was adopted and after. We re-estimate the firm targetiveness regressions on the anti-corruption law adoption and report the results in Columns 5-8 of Table A3. We find that the coefficients of anti-corruption law are positive and highly significant in all models, indicating that firms are more likely to become acquisition targets after their headquarters state adopt the anti-corruption laws. We also examine the effect of anti-corruption laws on acquirer CARs but the results are inconclusive, possibly due to a small number of observations of acquisitions for firms headquartered in these states following the anti-corruption law adoption.

F. Business Operation Concentration

In our analysis, we assume that most firms' business operation is concentrated in their headquarters locations. However, it is possible that firms' major operation could be located in areas other than their headquarters locations. As such, the level of corruption in a firm's headquarters location is unlikely to affect its business operation in a significant way. To explore this possibility, we follow Garcia and Norli (2012) in estimating the degree of a firm's operation concentration in its headquarters state as the number of times the firm's headquarters state was mentioned in the form 10-K each year during the period 1993-2008.[14] We then re-examine the firm acquisitiveness linear probability model augmented with the degree of geographical concentration of a given firm's operation and its interaction with the political corruption measure. The results of firm acquisitiveness model reported in Table 10 indicate that the coefficients of the

[14] We thank Drs. Garcia and Norli for generously sharing data on firms' geographical concentration of operation.

interaction between *ACOR* and the degree of operation concentration in the firm headquarters state are positive and statistically significant, suggesting that, conditional on the degree of operation concentration, firms headquartered in more corrupt areas are more likely to pursue M&As. This evidence is consistent with our earlier findings. On the other hand, the coefficient of the stand-alone *ACOR* is statistically insignificant, implying that firms headquartered in highly corrupt areas do not necessarily pursue M&As to shield their liquid assets if their business operation is dispersed to other areas.

[Insert Table 10 about here]

G. Additional Analyses

Since the SDC database focuses on M&A deals but may omit firms' asset purchases, we further examine the relation between total assets acquisitions and political corruption using the ratio of a firm's acquisition costs reported in the balance sheet (variable "*aqc*" in Compustat) to its book value of assets. The results reported in Table A4 in the Internet Appendix confirm our finding of a positive relation between political corruption and acquisitions.

Both political corruption and M&A activities could be correlated with the crime rates of the firms' headquartered states and failing to control for the crime rates may bias our findings. Thus, we rerun firm acquisitiveness and targetiveness regressions that further control for the state-level crime rates.[15] The results reported in Panel A of Table A5 in the Internet Appendix indicate that our findings are qualitatively unchanged. In another robustness check, we rerun the acquirer CAR regressions while additionally controlling the crime rates of firm headquarters states. The

[15] State-level crime rates are retrieved from the U.S. Department of Justice via the Uniform Crime Reporting Statistics, available at https://www.ucrdatatool.gov/. Last accessed on May 15, 2019.

reported results in Panel B of Table A5 in the Internet Appendix indicate that our findings are qualitatively similar.

In our analyses, we follow the literature to exclude firms from the utility and financial industries since these industries are subject to more stringent regulations. However, it is possible that stringent regulations breed even more corruption. Thus, we rerun firm acquisitiveness and targetiveness regressions with a larger sample that does not exclude firms from the utility and financial industries. The results reported in Panel A of Table A6 in the Internet Appendix indicate that our findings are qualitatively similar. We further rerun acquirer CAR regressions and the results reported in Panel B of Table A6 in the Internet Appendix indicate that our findings are robust.

Firms may engage in acquisitions to simply redeploy assets to other areas that offer better investment opportunities rather than shield their assets from potential expropriation by local officials. To investigate this alternative explanation for our findings, we run a univariate test to compare the GDP growth rates, which proxies for investment opportunities, of the acquirer and target states. The results indicate that the difference in GDP growth between acquirer and target states is small (-0.012%) and statistically insignificant. We further examine the difference in Tobin's Q, another proxy for investment opportunities, of the acquirer and target of each acquisition deal along the corruption dimension but the difference is statistically insignificant. This evidence indicates that political corruption can better explain the acquisition decisions of the acquirers.

Another possible alternative explanation for the positive relation between political corruption and firm acquisitiveness is that acquiring firms located in highly corrupt areas strategically engage in acquisitions and relocate assets from the targets' less corrupt areas to their home states to benefit from the corrupt environment and loose oversight by the local officials. If this argument is valid, we should observe a positive relation between acquirer shareholder value and the difference between *ACOR* and *TCOR* (i.e., *Delta corruption*). However, the negative relation between *Delta corruption* and acquirer CAR reported in Table 6 does not support this argument.

Finally, we investigate the effects of political corruption on M&As at the judicial district level. Specifically, we estimate the district-level OLS regressions with either the natural logarithm of the number of M&A deals or the natural logarithm of the aggregate deal value for each judicial district in a given year as the dependent variable and report the estimation results in Table A7 in the Internet Appendix. The control variables include the judicial district-level averages of the firm characteristics similar to those in Equation 1. We find that district corruption is negatively related to both the number and aggregate deal values, which further corroborates the negative relation between corruption and firm acquisitiveness.

V. Conclusions

Previous research argues that faced with political corruption, firms pursue corporate policies that shield their assets from local officials' expropriation. Using different measures of political corruption for analysis, we find robust evidence that local corruption is positively related to firm acquisitiveness but negatively related to firm targetiveness. When pursuing acquisition deals, acquiring firms located in highly corrupt areas are more likely to use stock payment, possibly because these firms typically maintain low cash reserves and high debt ratios to avoid local officials' expropriation. However, when these firms have excess cash, they are more likely to use cash for acquisition payment, which help them shield liquid assets from expropriation by converting liquid assets into hard-to-extract assets and relocate assets away from a corrupt environment. We further find that target shareholders are concerned about the threat of expropriation associated with corruption in the acquiring firms' areas, leading to their demand for higher bid premiums as compensation for bearing the expropriation risk or even rejection of the bids if additional compensation is not worth the risk.

We examine the relations between corruption and acquirer and target shareholder value and find that the level of corruption in the acquirer area is negatively related to acquirer shareholder value; however, cash payment can mitigate the negative value effect of corruption, which suggests the benefits of using M&As as a way to shield acquirers' liquid assets. On the other hand, target shareholders suffer from corruption discounts. Overall, our findings suggest M&As as a plausible channel through which firms can shield their liquid assets from local officials' expropriation.

Appendix A: Variables Definition

Variable name	Construction	Data source
ACOR	The number of corruption convictions per 100,000 of the judicial district where the acquirer is headquartered.	Report to Congress on the Activities and Operations of the Public Integrity Section and Census data
Acquisition cost	The ratio of acquisition costs reported in the balance sheet to the book value of assets.	Compustat
Average sale growth	The average annual sale growth over the last 3 years.	Compustat
Book leverage	The ratio of book value of short-term and long-term debts to the book value of assets.	Compustat
CAR	Cumulative abnormal stock returns over the window (-1, +1) centered on the M&A announcement day.	CRSP and SDC Platinum
Cash dummy	An indicator equals 1 if an M&A deal is fully funded by cash, and 0 otherwise.	SDC Platinum
Challenge dummy	An indicator equals 1 if the acquirer's offer is challenged by a competing offer, and 0 otherwise.	SDC Platinum
Delta corruption	The difference between the levels of corruption in the acquirer's and target's judicial districts	Report to Congress on the Activities and Operations of the Public Integrity Section
Deal ratio	The ratio of the M&A deal value to the acquirer's market value of equity measured four weeks before the deal announcement.	SDC Platinum

District corruption	The number of corruption convictions per 100,000 of the judicial district where the acquirer is headquartered.	Report to Congress on the Activities and Operations of the Public Integrity Section
Diversifying dummy	An indicator equals 1 if the acquirer and target belong to different 2-digit SIC code industries, and 0 otherwise.	Compustat
Excess Cash	The difference between the expected and realized cash holdings.	Compustat
Firm age	Number of years that a firm appeared in Compustat.	Compustat
High tech dummy	An indicator that takes a value of 1 if an acquirer's 4-digit SIC code is equal to 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3671, 3672, 3674, 3675, 3677, 3678, 3679, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7371-7375, 7378, 7379, and 0 otherwise.	Compustat
Hostile dummy	An indicator that equals 1 if the M&A deal is a hostile takeover, and 0 otherwise.	SDC Platinum
IMR	The inverse Mill's ratio calculated using the M&A probit model estimates.	Compustat and SDC Platinum
Industry M&A intensity	The ratio of target book value of assets to the aggregate book value of assets of all firms in the same 2-digit SIC code industry and year.	Compustat and SDC Platinum
M&A dummy	An indicator equals 1 if a firm makes at least one M&A announcement in a given year, and 0 otherwise.	SDC Platinum
Market-to-book ratio	The ratio of the market value of assets to the book value of assets.	Compustat

Noncash working capital ratio	The ratio of (working capital – cash) to the book value of assets.	Compustat
Past 12-month returns	The buy-and-hold 12-month stock return of the year preceding an M&A announcement.	CRSP
Public dummy	An indicator that equals 1 for a publicly listed target, and 0 otherwise.	SDC Platinum
Size	The natural logarithm of the book value of assets.	Compustat
Stock dummy	An indicator that equals 1 if the payment is fully in stock, and 0 otherwise.	SDC Platinum
TCOR	The number of corruption convictions per 100,000 in the judicial district where the target is headquartered.	Report to Congress on the Activities and Operations of the Public Integrity Section
Tobin's Q	(Book value of assets – book value of equity + market value of equity – deferred taxes)/book value of assets.	Compustat

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Table 1: Distribution of M&As by Year and Industry

Table 1 reports the annual and 2-digit SIC code industry distribution of M&A subsample for the period 1986-2014.

Panel A: M&A Subsample Distribution by Year

Year	Frequency	Percent
1986	104	1.42%
1987	271	3.70%
1988	142	1.94%
1989	209	2.85%
1990	257	3.51%
1991	138	1.88%
1992	155	2.12%
1993	181	2.47%
1994	223	3.04%
1995	245	3.34%
1996	312	4.26%
1997	339	4.63%
1998	462	6.31%
1999	366	5.00%
2000	239	3.26%
2001	209	2.85%
2002	160	2.18%
2003	190	2.59%
2004	234	3.19%
2005	278	3.80%
2006	269	3.67%
2007	362	4.94%
2008	429	5.86%
2009	204	2.78%
2010	268	3.66%
2011	342	4.67%
2012	272	3.71%
2013	253	3.45%
2014	212	2.89%
Total	7,325	100%

Panel B: M&A Distribution by Industries

2-digit SIC Percent	Industry Description	Frequency	Percent
73	Business services	838	11.44%
36	Electronic and other electrical equipment	753	10.28%
28	Chemicals and allied products	618	8.44%
38	Instruments and related products	614	8.38%
35	Industrial and commercial machinery and computer equipment	600	8.19%
13	Oil and gas extraction	236	3.22%
37	Transportation equipment	220	3.00%
48	Communications	205	2.80%
58	Eating & Drinking Places	204	2.78%
20	Food and kindred products	200	2.73%
50	Wholesale trade - durable goods	194	2.65%
59	Miscellaneous Retail	170	2.32%
	Industries with < 2% representation	2,473	33.76%
	Total	7,325	100%

Table 2: Summary Statistics

Table 2 reports the descriptive statistics of the full sample and the M&A subsample in Panels A and B, respectively. *District corruption* is the yearly number of convictions per 100,000 of the judicial district in which a firm is headquartered. *ACOR* is the yearly number of convictions per 100,000 of the judicial district in which an acquirer firm is headquartered. *Market-to-book ratio* is the ratio of the market value of assets to the book value of assets. *Book leverage* is the ratio of the book value of short-term and long-term debts to book value of assets. *Past 12-month returns* is the acquirer 12-month buy-and-hold stock return in the year preceding an M&A announcement. *Average sales growth* is the average annual sales growth rate over a 3-year period. *Noncash working capital* is the working capital minus cash, scaled by the book value of assets. *Firm age* is the number of years a firm has been included in Compustat.

Panel A: Full Sample

Variable	N	Mean	Q1	Median	Q3	Std. Dev.
District corruption	77,338	0.335	0.129	0.249	0.433	0.411
Book assets (in million $)	77,338	5.338	3.755	5.241	6.793	2.111
Market-to-book ratio	77,338	1.568	0.773	1.117	1.792	1.379
Past 12-month returns	77,338	0.164	-0.229	0.059	0.382	0.656
Average sale growth	77,338	0.196	0.014	0.098	0.225	0.444
Book leverage	77,338	0.215	0.029	0.182	0.336	0.199
Non-cash working capital	77,338	0.322	0.163	0.307	0.461	0.194
Firm age	77,338	19.318	9.000	15.000	26.000	12.819

Panel B: M&A Subsample

Variable	N	Mean	Q1	Median	Q3	Std. Dev.
ACOR	7,325	0.333	0.125	0.248	0.433	0.417
Book assets (in million $)	7,325	6.323	4.911	6.247	7.624	1.890
Market-to-book ratio	7,325	1.644	0.888	1.276	1.931	1.238
Past 12-month returns	7,325	0.206	-0.109	0.122	0.392	0.544
Average sale growth	7,325	0.163	0.031	0.100	0.205	0.305
Book leverage	7,325	0.184	0.020	0.157	0.286	0.175
Non-cash working capital	7,325	0.318	0.174	0.305	0.445	0.180
Firm age	7,325	22.214	11.000	18.000	31.000	14.005

Table 3: Political Corruption and Firm Acquisitiveness and Targetiveness

Table 3 reports the results of firm acquisitiveness and targetiveness linear probability models in Panels A and B, respectively. The dependent variable in Columns 1-3 is *M&A dummy* that takes a value of 1 if a firm makes at least one M&A announcement in a given year, and 0 otherwise. The dependent variable in Columns 4-6 is *Target dummy* that takes value of 1 if a firm is an acquisition target in a given year, and 0 otherwise. *District corruption* is the yearly number of convictions per 100,000 of the judicial district in which the firm is headquartered. Other variables are defined in Appendix A. *t*-statistics based on heteroscedasticity-robust standard errors clustered by firms are reported in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Firm Acquisitiveness			Firm Targetiveness		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
District corruption	0.009**	0.012***	0.018***	-0.008***	-0.010***	-0.010***
	(2.53)	(3.25)	(4.51)	(2.74)	(2.92)	(2.66)
State GDP per capita			-0.057***			-0.002
			(4.97)			(0.22)
State GDP growth rate			0.380***			0.013
			(6.71)			(0.19)
Size	0.060***	0.059***	0.064***	0.025***	0.026***	0.030***
	(70.45)	(68.34)	(70.55)	(33.87)	(33.84)	(36.85)
Market-to-book ratio	0.014***	0.014***	0.013***	-0.001	-0.002**	-0.004***
	(11.32)	(11.55)	(9.90)	(1.13)	(2.09)	(3.11)
Past 12-month returns	0.028***	0.027***	0.028***	-0.004*	-0.004	-0.001
	(10.78)	(10.95)	(11.29)	(1.78)	(1.55)	(0.13)
Average sale growth	0.001	0.007*	0.012	-0.007**	-0.005	-0.005
	(0.55)	(1.95)	(1.46)	(2.22)	(1.41)	(1.47)
Book leverage	-0.160***	-0.160***	-0.182***	-0.087***	-0.082***	-0.093***
	(19.92)	(19.77)	(21.64)	(12.28)	(11.17)	(12.26)
Non-cash working capital	0.038***	0.027***	0.011	0.011	0.016*	0.01
	(4.50)	(2.95)	(1.18)	(1.48)	(1.81)	(1.12)
Firm age	-0.004*	-0.005**	-0.014***	-0.006***	-0.003	-0.011***
	(1.67)	(1.99)	(4.90)	(2.77)	(1.09)	(4.19)
Intercept	-0.111***	-0.047***	0.538	0.004	-0.106	-0.032
	(3.05)	(5.28)	(1.32)	(0.13)	(0.69)	(0.26)

Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	Yes	Yes	No	Yes	Yes
Number of observations	77,338	77,338	77,338	77,338	77,338	77,338
Adjusted R^2	0.09	0.08	0.09	0.03	0.04	0.04

Table 4: Political Corruption and Payment Consideration

Table 4 reports the results of the payment consideration linear probability models. The dependent variable is *Cash dummy* that equals 1 if the payment for an M&A deal is fully in cash, and 0 otherwise. *ACOR* (*TCOR*) is the yearly number of convictions per 100,000 of the judicial district in which the acquirer (target) is headquartered. *Excess cash* is the difference between expected cash holdings and actual cash holdings. Other variables are defined in Appendix A. *t*-statistics based on heteroscedasticity-robust standard errors clustered by firms are reported in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ACOR	-0.028***	-0.027***	-0.033***	-0.031***	-0.028***	-0.027***	-0.033***	-0.032***
	(2.76)	(2.67)	(2.99)	(2.77)	(2.65)	(2.61)	(2.96)	(2.68)
ACOR* Excess cash					0.162***	0.163***	0.100**	0.142***
					(3.05)	(3.06)	(2.17)	(3.06)
Excess cash	-0.001	-0.001	-0.001	-0.001	-0.001**	-0.001**	-0.001	-0.001**
	(1.17)	(1.30)	(0.99)	(1.22)	(2.40)	(2.36)	(1.55)	(2.06)
TCOR	0.034*	0.027	0.030	0.024	0.031	0.031*	0.033*	0.028
	(1.80)	(1.44)	(1.63)	(1.31)	(1.64)	(1.65)	(1.76)	(1.50)
Size	0.009***	0.008**	0.020***	0.020***	0.008**	0.008**	0.020***	0.019***
	(2.81)	(2.47)	(5.83)	(5.84)	(2.43)	(2.40)	(5.79)	(5.80)
Market-to-book ratio	-0.008*	-0.005	-0.002	0.001	-0.005	-0.005	-0.002	0.001
	(1.85)	(1.19)	(0.54)	(0.17)	(1.17)	(1.16)	(0.51)	(0.21)
Past 12-month returns	0.009	0.006	0.015*	0.012	0.005	0.005	0.015*	0.012
	(1.10)	(0.72)	(1.84)	(1.55)	(0.67)	(0.64)	(1.81)	(1.51)
Average sale growth	-0.010	-0.029*	-0.018	-0.040**	-0.028*	-0.029*	-0.018	-0.040**
	(0.58)	(1.72)	(1.03)	(2.30)	(1.69)	(1.77)	(1.07)	(2.34)
Book leverage	-0.255***	-0.258***	-0.320***	-0.332***	-0.260***	-0.259***	-0.321***	-0.334***
	(7.71)	(8.20)	(9.40)	(10.23)	(8.28)	(8.26)	(9.44)	(10.29)
Non-cash working capital	-0.011	0.074***	-0.055	0.042	0.068**	0.073***	-0.054	0.042
	(0.32)	(2.76)	(1.57)	(1.48)	(2.57)	(2.75)	(1.55)	(1.46)
Firm age	0.006	0.009	0.003	0.001	0.008	0.008	0.003	0.000

	(0.75)	(1.07)	(0.31)	(0.03)	(1.03)	(1.05)	(0.29)	(0.01)
Deal ratio	-0.319***	-0.325***	-0.289***	-0.293***	-0.324***	-0.324***	-0.289***	-0.293***
	(6.34)	(6.29)	(6.51)	(6.45)	(6.30)	(6.29)	(6.51)	(6.45)
High tech dummy	-0.037***	-0.017	-0.036**	-0.013	-0.019*	-0.017*	-0.036**	-0.013
	(2.59)	(1.61)	(2.38)	(1.12)	(1.79)	(1.66)	(2.38)	(1.16)
Diversifying dummy	-0.357***	-0.357***	-0.369***	-0.371***	-0.356***	-0.355***	-0.368***	-0.369***
	(14.00)	(13.62)	(14.85)	(14.56)	(13.59)	(13.56)	(14.81)	(14.52)
Hostile dummy	-0.010	-0.012	-0.018	-0.022	-0.009	-0.012	-0.019	-0.023
	(0.10)	(0.12)	(0.20)	(0.24)	(0.09)	(0.13)	(0.20)	(0.24)
Target public dummy	0.113*	0.118*	0.171**	0.183**	0.116*	0.119*	0.171**	0.184**
	(1.79)	(1.92)	(2.36)	(2.55)	(1.89)	(1.93)	(2.37)	(2.56)
Challenge dummy	0.021	0.023	0.011	0.011	0.023	0.023	0.011	0.012
	(1.03)	(1.09)	(0.53)	(0.52)	(1.09)	(1.10)	(0.53)	(0.54)
Intercept	-0.129*	0.743***	-0.186**	0.598***	-0.129*	0.743***	-0.186**	0.598***
	(1.92)	(11.06)	(2.44)	(7.82)	(1.92)	(11.06)	(2.44)	(7.82)
Year fixed effects	Yes	Yes	No	No	Yes	Yes	No	No
Industry fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Number of observations	7,325	7,325	7,325	7,325	7,325	7,325	7,325	7,325
Adjusted R^2	0.23	0.22	0.16	0.14	0.22	0.22	0.16	0.14

Table 5: Political Corruption and Bid Premiums

Table 5 reports the bid premiums OLS regressions. The dependent variable is *Bid premiums*, which is measured as the percentage difference between the bidding price and the target stock price one week prior to an M&A announcement. *ACOR* (*TCOR*) is the yearly number of convictions per 100,000 of the judicial district in which the acquirer (target) is headquartered. Other variables are defined in Appendix A. *t*-statistics based on heteroscedasticity-robust standard errors clustered by firms are reported in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1)	(2)	(3)	(4)
ACOR	0.046**	0.035*	0.056***	0.041**
	(1.97)	(1.75)	(3.28)	(2.36)
TCOR	0.159	0.158	0.144	0.144
	(1.23)	(1.14)	(1.20)	(1.11)
Size	0.052	0.072**	0.038	0.052*
	(1.63)	(2.23)	(1.28)	(1.74)
Market-to-book ratio	0.001	0.026	0.012	0.041
	(0.01)	(0.64)	(0.34)	(1.15)
Past 12-month returns	0.088	0.017	0.071	-0.015
	(1.22)	(0.22)	(1.04)	(0.23)
Average sale growth	0.040	0.061	0.045	0.081
	(0.23)	(0.36)	(0.27)	(0.50)
Book leverage	0.237	0.464	0.042	0.250
	(0.80)	(1.58)	(0.15)	(0.86)
Non-cash working capital	0.257	0.551	-0.215	0.029
	(0.65)	(1.38)	(0.68)	(0.09)
Firm age	-0.127	-0.230***	-0.105	-0.203**
	(1.49)	(2.71)	(1.32)	(2.52)
Deal ratio	0.149***	0.169***	0.140***	0.158***
	(2.79)	(3.18)	(2.81)	(3.25)
Stock dummy	-0.012	0.007	0.038	0.061
	(0.10)	(0.06)	(0.32)	(0.50)
Cash dummy	-0.242*	-0.412***	-0.268**	-0.478***
	(1.95)	(3.27)	(2.36)	(4.11)
Diversifying dummy	0.387***	0.503***	0.333***	0.455***
	(3.86)	(4.96)	(3.53)	(4.86)
Hostile dummy	0.335*	0.377**	0.443**	0.525***

	(1.86)	(2.03)	(2.58)	(2.97)
Target public dummy	-0.524	-0.509	-0.369	-0.335
	(1.30)	(1.15)	(1.11)	(1.09)
Challenge dummy	0.512***	0.612***	0.492***	0.611***
	(4.72)	(5.37)	(4.84)	(5.70)
Intercept	-2.622***	-0.133	-1.180***	-1.313***
	(5.12)	(0.23)	(2.66)	(3.03)
Year fixed effects	Yes	No	Yes	No
Industry fixed effects	Yes	Yes	No	No
Number of observations	944	944	944	944
Adjusted R^2	0.20	0.14	0.19	0.12

Table 6: Political Corruption and Propensity of Deal Completion

Table 6 reports results of the deal completion linear probability models. The dependent variable is the completion indicator that takes a value of 1 if the deal is completed and 0 if the deal is withdrawn in a given year. *ACOR* (*TCOR*) is the yearly number of convictions per 100,000 of the judicial district in which the acquirer (target) is headquartered. *Delta corruption* is the difference between *ACOR* and *TCOR*. Other variables are defined in Appendix A. *t*-statistics based on heteroscedasticity-robust standard errors clustered by firms are reported in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ACOR	-0.035***	-0.035***	-0.032***	-0.032***				
	(2.81)	(2.79)	(2.88)	(2.87)				
TCOR	-0.008	-0.009	0.004	0.003				
	(0.33)	(0.39)	(0.18)	(0.14)				
Delta corruption					-0.029***	-0.029***	-0.028***	-0.028***
					(3.20)	(3.19)	(3.14)	(3.15)
Size	0.014***	0.015***	0.014***	0.015***	0.014***	0.014***	0.014***	0.015***
	(3.08)	(3.12)	(2.93)	(2.95)	(3.08)	(3.10)	(2.94)	(2.96)
Market-to-book ratio	-0.005	-0.005	-0.006	-0.006	-0.005	-0.005	-0.005	-0.006
	(0.79)	(0.81)	(0.82)	(0.83)	(0.74)	(0.76)	(0.77)	(0.78)
Past 12-month returns	0.031**	0.032**	0.029**	0.030**	0.029**	0.031**	0.028**	0.029**
	(2.50)	(2.55)	(2.29)	(2.31)	(2.36)	(2.42)	(2.19)	(2.21)
Average sale growth	-0.005	-0.005	-0.014	-0.014	-0.006	-0.005	-0.015	-0.014
	(0.22)	(0.20)	(0.61)	(0.59)	(0.25)	(0.22)	(0.63)	(0.61)
Book leverage	-0.101**	-0.103**	-0.080	-0.079	-0.106**	-0.107**	-0.082	-0.080
	(2.09)	(2.11)	(1.60)	(1.56)	(2.20)	(2.21)	(1.64)	(1.60)
Non-cash working capital	0.052	0.048	0.051	0.047	0.052	0.049	0.050	0.045
	(1.15)	(1.05)	(0.92)	(0.82)	(1.15)	(1.07)	(0.89)	(0.80)
Firm age	-0.009	-0.009	-0.015	-0.015	-0.011	-0.011	-0.017	-0.017

	(0.64)	(0.65)	(1.05)	(1.05)	(0.76)	(0.77)	(1.14)	(1.15)
Excess cash	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.37)	(0.36)	(0.31)	(0.32)	(0.34)	(0.33)	(0.28)	(0.30)
Deal ratio	-0.050**	-0.049**	-0.049**	-0.048**	-0.049**	-0.048**	-0.048**	-0.047**
	(2.40)	(2.38)	(2.41)	(2.38)	(2.34)	(2.31)	(2.36)	(2.33)
Stock dummy	-0.016	-0.017	-0.023	-0.024	-0.015	-0.016	-0.023	-0.024
	(0.61)	(0.64)	(0.87)	(0.90)	(0.58)	(0.61)	(0.86)	(0.88)
Cash dummy	-0.027	-0.025	-0.031*	-0.029	-0.026	-0.024	-0.031*	-0.028
	(1.56)	(1.42)	(1.76)	(1.62)	(1.49)	(1.37)	(1.73)	(1.59)
High tech dummy	-0.01	-0.009	0.018	0.02	-0.008	-0.007	0.019	0.021
	(0.55)	(0.50)	(0.71)	(0.79)	(0.46)	(0.41)	(0.74)	(0.81)
Diversifying dummy	-0.039*	-0.039*	-0.042**	-0.043**	-0.039*	-0.040*	-0.042**	-0.043**
	(1.83)	(1.86)	(1.98)	(2.03)	(1.87)	(1.90)	(2.01)	(2.07)
Attitude dummy	-0.386***	-0.389***	-0.389***	-0.392***	-0.388***	-0.390***	-0.390***	-0.393***
	(5.18)	(5.20)	(5.19)	(5.21)	(5.20)	(5.21)	(5.21)	(5.23)
Target public dummy	-0.051	-0.049	-0.055	-0.052	-0.053	-0.051	-0.056	-0.054
	(0.92)	(0.89)	(0.97)	(0.92)	(0.94)	(0.92)	(0.99)	(0.94)
Challenge dummy	0.119***	0.119***	0.121***	0.121***	0.117***	0.117***	0.120***	0.120***
	(7.91)	(7.83)	(7.83)	(7.74)	(7.86)	(7.78)	(7.81)	(7.72)
Target industry intensity	-0.011***	-0.011***	-0.012***	-0.012***	-0.011***	-0.011***	-0.012***	-0.012***
	(39.39)	(38.42)	(21.02)	(20.79)	(39.72)	(38.48)	(21.01)	(20.73)
Intercept	0.891***	0.890***	0.945***	0.945***	0.883***	0.882***	0.941***	0.941***
	(12.59)	(12.58)	(11.28)	(11.25)	(12.50)	(12.49)	(11.23)	(11.20)
Year fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Number of observations	2,261	2,261	2,261	2,261	2,261	2,261	2,261	2,261
Adjusted R^2	0.05	0.05	0.06	0.06	0.05	0.05	0.06	0.06

Table 7: Political Corruption and Acquirer and Target CARs

Table 7 reports results of the acquirer and target CAR cross-sectional regressions. The dependent variable in Columns 1-4 (5-8) is acquirer (target) three-day CARs centered on the M&A announcement days. *ACOR* (*TCOR*) is the yearly number of convictions per 100,000 of the judicial district in which the acquirer (target) is headquartered. *IMR* is the inverse Mills ratio. Other variables are defined in Appendix A. *t*-statistics based on heteroscedasticity-robust standard errors clustered by firms are reported in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Acquirer CARs				Target CARs			
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ACOR	-0.008**	-0.007**	-0.008**	-0.008**	0.014***	0.012**	0.014***	0.011**
	(2.13)	(2.03)	(2.13)	(2.13)	(2.89)	(2.45)	(2.86)	(2.29)
ACOR * Cash dummy	0.009**	0.010**	0.010**	0.010**				
	(2.11)	(2.17)	(2.20)	(2.32)				
ACOR * Stock dummy	0.032	0.031	0.031	0.032				
	(1.25)	(1.18)	(1.21)	(1.13)				
TCOR	0.002	0.002	0.003	0.002	-0.014**	-0.012*	-0.011*	-0.008
	(0.65)	(0.48)	(0.80)	(0.67)	(2.30)	(1.92)	(1.88)	(1.29)
Size	-0.006***	-0.006***	-0.005***	0.019***	-0.018***	-0.024***	-0.024***	-0.034***
	(7.17)	(5.58)	(5.14)	(2.75)	(14.98)	(17.24)	(18.31)	(21.61)
Market-to-book ratio	-0.003***	-0.003***	-0.002***	0.003*	-0.009***	-0.011***	-0.011***	-0.014***
	(3.44)	(3.40)	(3.34)	(1.83)	(8.19)	(9.82)	(9.80)	(12.26)
Past 12-month returns	-0.007***	-0.007***	-0.006***	0.008*	-0.014***	-0.016***	-0.015***	-0.018***
	(4.56)	(4.64)	(3.73)	(1.87)	(6.77)	(7.56)	(6.94)	(8.30)
Average sale growth	-0.003	-0.004	-0.003	0.002	-0.001	-0.001	-0.001	-0.001
	(1.20)	(1.40)	(1.09)	(0.58)	(0.82)	(1.02)	(0.79)	(1.04)
Book leverage	0.013**	0.014**	0.011**	-0.047***	0.019**	0.023***	0.037***	0.046***
	(2.56)	(2.51)	(2.07)	(2.69)	(2.24)	(2.59)	(4.28)	(5.18)

Non-cash working capital	0.011**	0.005	0.013**	0.026***	-0.032***	-0.048***	-0.024***	-0.041***
	(2.27)	(0.82)	(2.50)	(3.22)	(3.91)	(4.80)	(2.87)	(4.11)
Firm age	-0.002	-0.002	-0.002	0.006**	-0.011***	-0.013***	-0.011***	-0.014***
	(1.43)	(1.41)	(1.34)	(2.25)	(4.48)	(5.02)	(4.66)	(5.66)
Deal ratio	0.030***	0.030***	0.029***	0.029***	0.031***	0.032***	0.028***	0.029***
	(14.81)	(14.85)	(14.52)	(14.47)	(5.92)	(6.13)	(5.21)	(5.53)
Stock dummy	-0.025***	-0.024***	-0.024***	-0.023***	0.038***	0.033***	0.032***	0.029***
	(2.90)	(2.77)	(2.75)	(2.66)	(4.62)	(3.92)	(3.90)	(3.52)
Cash dummy	0.005	0.005*	0.005	0.006*	0.01	0.008*	0.00	0.00
	(1.61)	(1.66)	(1.63)	(1.70)	(1.43)	(1.95)	(0.15)	(0.73)
High tech dummy	0.001	0.001	0.001	0.001	0.004	0.005	-0.001	0.003
	(0.25)	(0.35)	(0.19)	(0.20)	(1.19)	(1.01)	(0.26)	(0.75)
Diversifying dummy	-0.009***	-0.009***	-0.008***	-0.009***	0.118***	0.112***	0.108***	0.095***
	(3.82)	(3.93)	(3.56)	(3.82)	(17.91)	(16.63)	(16.25)	(14.00)
Hostile dummy	-0.060***	-0.060***	-0.059***	-0.060***	0.120***	0.119***	0.132***	0.137***
	(4.74)	(4.71)	(4.66)	(4.70)	(6.42)	(6.38)	(7.05)	(7.41)
Target public dummy	0.001	0.001	0.001	0.001	0.031*	0.032*	0.028*	0.028*
	(0.41)	(0.21)	(0.49)	(0.32)	(1.89)	(1.95)	(1.67)	(1.70)
Challenge dummy	0.032***	0.032***	0.034***	0.033***	0.105***	0.104***	0.099***	0.097***
	(8.43)	(8.36)	(8.75)	(8.56)	(18.46)	(18.32)	(17.46)	(17.09)
Target industry intensity	-0.001	-0.001	-0.001	-0.001	-0.001	0.001	-0.001	0.001
	(0.26)	(0.36)	(0.21)	(0.30)	(0.01)	(0.02)	(0.22)	(0.22)
IMR	0.006	0.001	0.013**	0.190***	-0.105***	-0.146***	-0.144***	-0.211***
	(1.09)	(0.04)	(2.00)	(3.73)	(13.65)	(16.28)	(16.56)	(20.33)
Intercept	0.046***	0.002	0.038**	-0.399***	0.279***	0.344***	0.401***	0.546***
	(3.77)	(0.02)	(2.36)	(3.01)	(11.93)	(13.60)	(14.04)	(17.49)
Year fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Industry fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Number of observations	7,325	7,325	7,325	7,325	7,325	7,325	7,325	7,325
Adjusted R^2	0.06	0.06	0.06	0.06	0.21	0.22	0.23	0.24

Table 8: Political Corruption and Firm Acquisitiveness and Targetiveness – IV Linear Probability Model

Table 8 reports the results of the 2-stage firm acquisitiveness and targetiveness IV linear probability models in Columns 1-2 and 3-4, respectively. The dependent variable in the firm acquisitiveness model is *M&A dummy* that takes a value of 1 if a firm makes at least one M&A announcement in a given year, and 0 otherwise. The dependent variable in the firm targetiveness model is *Target dummy* that takes value of 1 if a firm is acquired in a given year, and 0 otherwise. *Isolation state capital* is the state population concentration around its capital city, adjusted for state size. *Journalist employment shock* is an indicator variable that equals to 1 if the state news journalist employment decreases more than 40% in a given year, and 0 otherwise. Other variables are defined in Appendix A. *t*-statistics based on heteroscedasticity-robust standard errors clustered by firms are reported in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Acquisitiveness IV Regression		Targetiveness IV Regression	
	First-stage	Second-stage	First-stage	Second-stage
Variable	(1)	(2)	(3)	(4)
Instrumented district corruption		0.194***		-0.043**
		(6.35)		(2.03)
Isolation state capital	0.589***		0.800***	
	(31.81)		(57.74)	
Journalist employment shock	0.246***		0.263***	
	(11.12)		(16.16)	
Size	0.004***	0.059***	0.002***	0.030***
	(5.35)	(66.23)	(2.88)	(38.44)
Market-to-book ratio	-0.002*	0.014***	-0.002*	-0.003***
	(1.69)	(10.94)	(1.92)	(3.34)
Past 12-month returns	0.002	0.028***	0.001	-0.003
	(0.63)	(11.37)	(0.63)	(1.44)
Average sale growth	0.021***	0.004	0.011***	-0.006*
	(6.11)	(1.04)	(4.34)	(1.92)
Book leverage	0.022***	-0.149***	0.031***	-0.089***
	(2.73)	(17.49)	(5.23)	(12.32)
Non-cash working capital	0.031***	0.044***	0.068***	0.013

	(3.18)	(4.26)	(9.58)	(1.49)
Firm age	0.023***	-0.010***	0.027***	-0.009***
	(8.71)	(3.62)	(14.02)	(3.56)
Intercept	-0.226***	-0.078***	-0.252***	-0.170***
	(13.83)	(6.65)	(3.48)	(11.77)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Number of observations	77,338	77,338	77,338	77,338
Over-identification test				
Sargan χ^2		0.081		0.343
Weak identification test				
Cragg-Donald Wald F statistic		599.18***		1817.13***
Weak instrument robust inference				
Anderson-Rubin Wald test		41.61***		4.96*

Table 9: Alternative Measures of Political Corruption and Firm Acquisitiveness

Table 9 reports the results of firm acquisitiveness linear probability models. The dependent variable is *M&A dummy* that takes a value of 1 if a firm makes at least one M&A announcement in a given year, and 0 otherwise. *Alternative corruption measure* is the corruption score based on the survey of State House reporters in Columns 1-4 or the inverted integrity investigation scores or corruption survey scores from Boylan and Long (2003) for each state in which the acquirer is headquartered in Column 5. Other variables are defined in Appendix A. *t*-statistics based on heteroscedasticity-robust standard errors clustered by firms are reported in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Corruption Measure Based on State Integrity Investigation				Corruption Measure Based on Boylan and Long (2003) Survey
Variable	(1)	(2)	(3)	(4)	(5)
Alternative corruption measure	3.238*	2.755*	4.818*	4.313*	0.011**
	(1.77)	(1.74)	(1.94)	(1.84)	(2.46)
Other controls	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	No	Yes	Yes
Industry fixed effects	No	No	Yes	Yes	Yes
Number of observations	8,353	8,353	8,353	8,353	13,648
Adjusted R^2	0.06	0.15	0.08	0.17	0.11

Table 10: Political Corruption, Geographic Concentration of Firm Operation, and Firm Acquisitiveness

Table 10 reports the results of the firm acquisitiveness linear probability model. The dependent variable is *M&A dummy* that takes a value of 1 if a firm makes at least one M&A announcement in a given year, and 0 otherwise. *District corruption* is the yearly number of convictions per 100,000 of the judicial district in which the acquirer is headquartered. *Geographic concentration* is the degree of a firm's operation concentrated in the headquarters state. Other variables are defined in Appendix A. *t*-statistics based on heteroscedasticity-robust standard errors clustered by firms are reported in parentheses. The symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variable	(1)	(2)	(3)	(4)
District corruption	-0.018	-0.019	-0.023	-0.022
	(1.23)	(1.33)	(1.56)	(1.54)
District corruption *Geographic concentration	0.057**	0.052*	0.066**	0.065**
	(2.06)	(1.89)	(2.42)	(2.40)
Geographic concentration	-0.072***	-0.071***	-0.078***	-0.078***
	(5.20)	(5.10)	(5.56)	(5.57)
Other controls	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	No	Yes
Industry fixed effects	No	No	Yes	Yes
Number of observations	35,928	35,928	35,928	35,928
Adjusted. R^2	0.09	0.10	0.10	0.10