Local Public Corruption and Corporate Debt Concentration: Evidence from US firms

Theodora Bermpei, University of Lille

José M. Liñares-Zegarra, University of Essex

Accepted for publication in The European Journal of Finance.

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Theodora Bermpei [1*] and José M. Liñares-Zegarra [2]

October 2023

Abstract

Using debt structure data from a large sample of US non-financial companies during the period 2002-2016 combined with the US Department of Justice (DOJ) data on local public corruption, we examine the effect of public corruption on the degree of debt concentration in a firm's debt structure. The results imply that firms in corrupt areas tend to use several debt types simultaneously, decreasing in that way debt concentration. These findings remain robust to tests that control for endogeneity. In further analysis, we show that these results are stronger for more informationally transparent firms, i.e., investment grade rated and publicly listed firms, that have easier access to capital debt markets. Lastly, in terms of debt choices, we find that firms in corrupt areas issue more commercial paper, senior bonds and capital leases, while they borrow less from banks. The study provides useful policy implications for combating corruption, as informationally opaque firms face increased barriers to debt financing.

Keywords: Public corruption, Debt concentration, Information asymmetry, Financing policy.

JEL Codes: G30, G32, G38, D73.

[1] IESEG School of Management, Univ. Lille, CNRS, UMR 9221 - LEM - Lille Economie Management, F-59000 Lille, France. Email: t.bermpei@ieseg.fr

[2] Essex Business School, University of Essex, Colchester, CO4 3SQ, UK. Email: jmlina@essex.ac.uk

[*] **Corresponding author:** Theodora Bermpei, Email: t.bermpei@ieseg.fr

1. Introduction

Early empirical research highlights the importance of public corruption in macroeconomic outcomes (Mauro 1995; Pagano 2008), while more recent work provides evidence of the significant links between public corruption and firm-level outcomes. Previous studies find that corruption increases unethical corporate behaviour (Alon & Hageman 2013; Parsons *et al.* 2018; Dass *et al.* 2020), deteriorates firm performance and corporate transparency (Van Vu *et al.* 2018; Dass *et al.* 2016; Brown *et al.* 2019), decreases firm efficiency (Hanousek *et al.* 2019) and stifles corporate innovation (Ellis *et al.* 2019; Huang & Yuan 2021). Another strand of the literature looks at the association between public corruption and financing policies, showing that corruption increases leverage (Alves & Ferreira 2011; Smith 2016) and reduces short-term debt (Hassan *et al.* 2022). Motivated by Smith's (2016) study, we focus on a research question that remains unexplored. Do firms increase debt levels from multiple sources or a single source of finance in areas with high level of local public corruption? In this paper, we aim to fill this gap by exploring the effect of local public corruption on debt concentration of public US firms.

Firms display heterogeneity in terms of the mix of debt types that they rely on (Rauh & Sufi 2010; Colla *et al.* 2013, 2020). Despite the high variation in the mix of debt portfolios between firms, empirical research that focuses on the determinants of debt concentration is scarce. Castro *et al.* (2020) show that increases in CEO risk-taking incentives lead to more concentrated debt structures. Li *et al.* (2021) find a significant causal relationship between accounting quality and debt concentration, while John *et al.* (2021) provide evidence of a significant association between country-level creditor protection rights and debt concentration. Therefore, limited evidence on factors that could affect debt concentration encourages us to investigate if and to what extent the local institutional environment as measured by the level of local corruption is an important determinant of debt concentration.

The literature points to two competing hypotheses regarding the association between corruption and debt concentration. The first hypothesis supports a positive relationship between local public corruption and debt concentration. Recent literature suggests that corruption increases corporate misconduct (Parsons *et al.* 2018; Dass *et al.* 2020) and reduces firms' performance and transparency (Dass *et al.* 2016; Brown *et al.* 2019). Consequently, corruption increases information asymmetries between borrowing firms and lenders. Colla *et al.* (2013) suggest that less informationally transparent firms would tend to hold more concentrated debt portfolios to limit monitoring costs. Additionally, recent empirical studies show that banks operating in areas with higher levels of public corruption reduce lending and impose higher borrowing costs (Bermpei *et al.* 2021; Hossain *et al.* 2021). Therefore, banks and investors would be less willing to lend debt capital to firms in corrupt areas, not only through limiting loan credit, but also through limiting the range of available debt instruments. Under this hypothesis, firms in corrupt areas would be expected to have a higher level of debt concentration (***H1A*** hypothesis). On the other hand, since firms in corrupt areas are more informationally opaque and more likely to engage in corporate unethical behaviour, they may rely on multiple sources of funding as the average amount of debt granted from each source reduces. This in turn could also decrease lenders' motives in screening and monitoring firms' operations (Park 2000; Carletti 2004; Carletti *et al.* 2007). Also, recent research suggests that firms in areas of higher local public corruption face increased bank financing constraints (Bermpei *et al.* 2020; Du *et al.* 2020; Hossain *et al.* 2020), which may prompt them to optimise their access to finance by using all possible debt instruments to surmount their financing restrictions, resulting in a decrease in their debt portfolio concentration (Jaffee & Russell 1976; Stiglitz & Weiss 1981). Based on this notion, our competing hypothesis suggests that local public corruption would have a negative relationship with debt concentration (***H1B*** hypothesis). Therefore, in this study, our aim is to find whether ***H1A*** or ***H1B*** holds in relation to the impact, if any, of public corruption on debt concentration.

Most research on the effects of corruption is focused on developing countries. In this study, we focus our analysis on the US, which provides an ideal testing ground to disentangle the impact of local public corruption on debt concentration. First, it is notable that between the period 1990-2010, over 16,000 US government officials were found guilty of conducting political-related corruption crime. There is also high variation across states in corruption levels (Glaeser & Saks 2006). This diminishes concerns that corruption is less important issue in the US because of its developed country status. Figure 1 illustrates significant variation in public corruption levels across US states.

[Insert Figure 1 around here]

Second, the cross-state variation in corruption levels allows us to separate the effect of corruption on debt concentration in the US. As all firms in our sample operate in the same country, they share the same institutional and economic environment. Previous empirical work has focused on the effect of corruption on economic outcomes across countries. However, segregating the effect of corruption on debt concentration using a cross-country study is challenging due to differences in the economic and institutional background that may confound the results. Therefore, our US-focused research provides a suitable setting for this type of study. Figures 1 and 2 offer supporting evidence for the relationship between corruption and debt concentration in the US, where states with higher corruption conviction rates (Figure 1) are linked to firms that exhibit lower levels of debt concentration (Figure 2).

[Insert Figure 2 around here]

Third, we obtain data on corruption for each US district from the Section of Public Integrity of the US Department of Justice (DoJ). As in Smith (2016), we standardise the yearly number of convictions related to crimes conducted by public officials by the population of each state (100,000 residents). Contrary to cross-country-level studies that employ survey-based measures of corruption, we use conviction-based measures of public corruption that reflect the *'real'* level of corruption and hence provide a more objective measure of corruption (Glaeser & Saks 2006). Moreover, as the US federal system has control over all the cases of public corruption, there is a greater homogeneity of enforcement (Glaeser & Saks 2006; Smith 2016) that improves comparability.

In this study, we use annual data on the debt structure of US firms from Capital IQ, with our final sample comprising 19,503 firm-year observations from 2002 to 2016. Our baseline estimations indicate that local public corruption—measured by the number of convictions related to corruption conducted by public officials in each district, normalized by its population—decreases debt concentration, as measured by the Herfindahl-Hirschman Index (Colla *et al.* 2013, 2020). This finding supports our ***H1B*** hypothesis. Upon further analysis, we find that the negative effect of local public corruption on debt concentration is more pronounced for firms with high credit ratings and those that are publicly listed. Additionally, we investigate the specific debt choices of firms in corrupt areas and observe a positive effect on the use of commercial paper, senior bonds and notes, and capital lease debt. Conversely, we find that these firms borrow less in the form of bank loans. These results are important, considering that these types of debt (commercial paper, senior bonds and notes, capital leases, and bank loans) constitute approximately 70% of the debt portfolio of US firms for the studied period (see Table 2).

One of the econometric issues of our identification strategy is endogeneity, which may stem from the omission of variables that could be related with corruption. We remedy this issue by using the two-stage least squares instrumental variable (2SLS-IV) method and employ two instruments for corruption. The first instrument is state-capital isolation, which has been found to be negatively related with citizen scrutiny on public officials' actions (Wilson 1966).

According to previous studies, isolated state capitals exhibit higher levels of corruption. Our estimations also confirm this association. As a second instrument, we use the change in intensity of state laws related to the facilitation about information of public officials' actions. Freedom of Information Act (FOIA) laws and their differences in terms of enforcement across US states enable us to use a time variant state-level instrument for corruption. Previous studies find that states with higher intensity of FOIA laws are associated with lower levels of public corruption (Cordis & Warren 2014; Bermpei *et al.* 2021). Adopting the 2SLS-IV regression method with the two instruments presented above, we continue to observe a negative and significant effect of local public corruption on debt concentration.

In addition, we perform additional empirical exercises to check the validity of our results. Firstly, we use alternative survey-based measures of corruption, to capture the corruption which is beyond the uncovered level of corruption. Second, we perform estimations using alternative measures of debt concentration. We also employ the propensity score matching technique and perform estimations with additional fixed effects to further tackle omitted variable issues.

Our paper makes significant contributions to the existing body of literature on the impact of public corruption on corporate finance, advancing beyond traditional discussions of firm leverage. First, we contribute to the emerging literature on the determinants of debt concentration. While most of this literature focuses on firm-level characteristics, such as Environmental, Social, and Governance (ESG) ratings, the quality of accounting information and CEO compensation that affect debt concentration (Asimakopoulos *et al.* 2023, Castro *et al*. 2020; Li *et al.* 2021), research relating the local institutional environment to debt concentration is scarce. We show that local public corruption has a causal and negative relationship with debt concentration. Second, studies like those by Alves & Ferreira (2011) and Smith (2016) suggest that corruption increases aggregate leverage. However, they do not clarify whether this increase in leverage is driven by one or multiple debt sources. Our research uniquely explores the influence of local corruption on a firm's debt structure—specifically, the choice between concentrated and diversified debt portfolios. Theoretical considerations point in opposing directions regarding the relationship between corruption and debt concentration, making empirical investigation warranted. We develop a dual-hypothesis approach, identifying two possible competing paths firms may take in response to corruption: increasing debt concentration due to informational opacity or diversifying debt to mitigate individual lenders' influence. This framework enriches the existing debates by integrating theories on informational opacity, credit rationing, and lender influence and allows for a more detailed understanding of debt dynamics, particularly in high-corruption environments.

Third, our research also contrasts with corruption studies focused on developing countries. The shift in geographical focus towards a developed country broadens our understanding of how corruption impacts financial decision-making in such contexts and offers an ideal testing ground. Although our study focuses on one country (US), it provides the opportunity to exploit the high variation in corruption across different US states. In this context, within US states that share a similar socioeconomic environment, there is a lower likelihood of confounding factors distorting our findings. Fourth, we go beyond the often-used survey-based measures of corruption and leverage conviction-based data from the U.S. Department of Justice. Coupled with our use of 2SLS-IV and propensity score matching econometric techniques, our methodology not only addresses potential pitfalls of endogeneity but also provides empirical validity to our findings.

The paper proceeds as follows. Section 2 reviews the theoretical background. Section 3 describes our data, the measurement of the key variables, and our econometric method. Section 4 presents the empirical results, Section 5 describes further analysis, and Section 5 concludes the paper.

2. Research Gap and Hypotheses Development

2.1 Research Gap

Firms operating in areas with high level of corruption have lower access to equity capital, which prone them to substitute equity financing with more debt.[1] In support of this argument, Alves & Ferreira (2011) and Fan *et al.* (2012) find cross-country evidence that higher perceived public corruption increases firms' leverage levels. A potential reason for the increase in leverage is that investors are less willing to invest in stocks of firms operating in areas with higher levels of corruption, and thus borrowing firms decide to shift to debt financing (Alves & Ferreira 2011). Also, firms wishing to limit rent-seeking from corrupt officials could increase leverage, and hence reduce financial resources available to pay bribes (i.e., cash). In the US context, Smith (2016) provides support for this argument and finds that firms increase their leverage in US districts with higher levels of local public corruption. Thus, although empirical evidence demonstrates that local public corruption raises firm leverage, the impact of local corruption on a firm's decision to opt for more or less concentrated debt structures remains largely unexplored.

2.2. Hypotheses Development: The relationship between local public corruption and debt concentration

Public corruption could have a positive effect on firms' debt concentration through the information asymmetry channel. Dass *et al.* (2016) show that US firms exhibit lower information transparency, as proxied by earnings management, in states of higher local public corruption as a mechanism to protect their assets from expropriation. In addition, firms operating in areas of high corruption have been found to engage in unethical corporate behaviour, such as tax evasion and litigation of securities fraud claims (DeBacker *et al.* 2015;

[1] Firms are more likely to react to changes in the environment where they operate (i.e., corruption), by adapting their balance sheet and debt policies rather than moving headquarters, which is costly and not very common.

Parsons *et al.* 2018; Dass *et al.* 2020). This is explained because corruption is closely associated with illegal and unlawful activities (Shleifer & Vishny 1993). The above discussion suggests that firms operating in high corruption areas tend to be more informationally opaque, which increases informational frictions in debt markets between potential borrowers and lenders. Colla *et al.* (2013) suggest that informationally opaque firms present more concentrated debt portfolios to reduce screening and coordination costs among multiple lenders.

In addition, recent literature provides evidence of the negative effect of corruption on credit supply through decreased lending (Bermpei *et al.* 2020) and an increased cost of bank loans (Du *et al.* 2020; Hossain *et al.* 2020). Therefore, we argue that corruption would reduce the supply of debt capital to firms in corrupt areas not only by limiting loan amounts and increasing the cost of borrowing but also through decreasing the available sources of funding. Given that firms that locate in areas with higher levels of local public corruption encounter more barriers in accessing credit, it is thus natural to expect that firms may hold more concentrated debt portfolios. Thus, based on the above discussion, we develop our first ***H1A*** hypothesis:

H1A. Firms facing higher levels of local public corruption are associated with a higher debt concentration.

On the other hand, it can also be argued that increased local corruption could decrease the firms' debt concentration. As previously discussed, literature on the relationship between corruption and firm-level characteristics suggests that firms in corrupt areas are less informationally transparent and could engage in corporate misconduct (Dass *et al.* 2016; 2018; Alon & Hageman 2013; DeBacker *et al.* 2015; Parsons *et al.* 2018). According to Diamond (1991), firms opt for a concentrated debt structure to incentivize lenders to monitor. However, given the decreased transparency of a firm's information induced by local corruption, managers may prefer to increase debt diversification to avoid scrutiny from lenders. This reduction in the average amount granted from each debt source decreases lenders' monitoring efforts regarding firms' operations (Park 2000; Carletti 2004; Carletti *et al.* 2007). By borrowing from various sources, firms can circumvent the intense monitoring associated with larger loans or debt from a single source. This strategy not only offers operational flexibility but also ensures that the firm remains agile in achieving its financial goals.

Additionally, as discussed in the first hypothesis, firms in areas with higher levels of local public corruption face additional financing barriers compared to firms in areas with lower corruption levels due to the contraction of bank lending and rising loan costs (Bermpei *et al.* 2020; Du *et al*. 2020; Hossain *et al.* 2021). As a result, the credit-rationing mechanism induced by higher levels of public corruption could make it more challenging for firms in these areas to raise debt capital if they rely solely on one source. This would prompt firms to borrow from multiple lenders to continue their profitable projects (Jaffee & Russell 1976; Stiglitz & Weiss 1981). Under credit rationing and stringent lending conditions, firms can mitigate the risk of being financially constrained by diversifying their debt sources to meet financial needs. Moreover, as corruption is known to hamper firm performance, borrowing from multiple lenders allows firms in corrupt areas access to a variety of debt instruments (short-term, long-term, secured, unsecured, and other specialized debt products), according to their financial requirements and enabling the improvement of their financial position.

Consequently, we would expect that as corruption increases, firms in areas of higher local corruption may hold more dispersed debt to limit lenders' monitoring efforts and/or overcome the credit rationing issue they face. Based on the above, we develop the competing hypothesis ***H1B*** as follows:

H1B. Firms facing higher levels of local public corruption are associated with a lower debt concentration.

3. Data and Methodology

3.1. Sample Description

We source firm-year data on debt structure for a sample of US firms from Capital IQ for the 2002-2016 period.[2] Capital IQ provides detailed information on firm-level debt composition obtained from the 10K SEC filings. We exclude from our sample firm-year observations that have missing, zero, or negative values for total debt. We further merge the sample with firm-level financial data from the Compustat database using the GVKEY identifier. We then exclude from our sample, firm-year observations that have missing, zero or negative values for total assets and sales. We remove from our sample utility and financial firms (SIC codes 4900–4949 & SIC codes 6000–6999) because they are subject to different regulations and restrictions in raising debt. We further remove firm-years with market or book leverage outside the unit interval and where the difference between total debt, as reported in Compustat, and the sum of the different debt types reported in Capital IQ exceeds 10% of total debt (Colla *et al.* 2013; Castro *et al.* 2020). Our final sample involves 19,503 firm-year observations. Table 1 provides a description and measurement details of the variables used in our empirical analysis. Table 2 presents descriptive statistics. Table 3 includes a correlation matrix for all the variables included in the analysis.

[Insert Tables 1 and 2 around here]

[Insert Table 3 around here]

3.2 Firm-level debt structure and specialization

Following Colla *et al.* (2013), we are able to distinguish seven mutually exclusive debt types: commercial paper (*CP*), revolving credit facilities (*RC*), term loans (*TL*), senior bonds and notes (*SenB&N*) and subordinated bonds and notes (*SubB*), capital leases (CL), and other

[2] The database provides comprehensive information only from 2002 and onwards, and thus in line with previous studies (Colla *et al.* 2013), we start our analysis from this year to enhance the validity of our estimations.

debt (*OtherB*).[3] To measure the debt specialisation of firms, we compute a normalized Herfindahl-Hirschman Index (HHI Index). First, we calculate:

$$SS_{i,t} = \left(\frac{CP_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{RC_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{TL_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{SBN_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{SUBD_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{CL_{i,t}}{TD_{i,t}}\right)^2 + \left(\frac{Other_{i,t}}{TD_{i,t}}\right)^2 \quad (1)$$

where $SS_{i,t}$ denotes the sum of the squared seven debt ratios for firm i in year t. TD refers to total debt. Next, we obtain the HHI index using the following formula:

$$HHI_{i,t} = \left(\frac{SS_{i,t} - \frac{1}{7}}{1 - \frac{1}{7}}\right) \quad (2)$$

When the firm employs only one source of debt, the HHI Index takes the value of 1, while when the firm employs all the seven different types of debt equally, the index takes the value of 0. Firms with high levels of debt specialisation show higher HHI indices. We also use an alternative measure of debt specialisation, which is a binary variable (*HHI DUM*) that takes the value of 1 if a firm holds at least 90% of its debt from one debt source and 0 otherwise. The sample average HHI index reported in Table 2 suggests that firms in our sample tend to specialise in fewer debt types (72.3%). In a similar way, we observe that 40.7% of the firm-year observations in our sample hold at least 90% of its debt from one debt source.

3.3 Measuring local public corruption in the US

Our primary measure of corruption is the yearly convictions data from 2002 to 2016 obtained from the Public Integrity Section (PIN) of the US Department of Justice (DOJ) across the 94 US Federal Judicial districts as in Smith (2016) and Nguyen *et al.* (2020). To match district-level corruption to a firm, we convert the historical headquarter location of the firm

[3] Revolving credit facilities are also known as drawn credit lines. In line with previous studies, operating leases are not included due to not being categorized as debt on the balance sheet. Other debt consists of any other unclassified short-term borrowings.

(ZIP code) into FIPS county codes.[4] Then we match the FIPS county codes to judicial districts using the US Marshals Service, which mirrors the geographical structure of the US district courts.[5] As an alternative measure of corruption, we also compute a state-level measure of public corruption based on historical firm's headquarter location (US states) from the augmented 10-X header dataset.[6]

Using conviction-based measures of corruption has several key advantages. Firstly, compared to perception-based corruption measures, conviction-based measures are more objective as they capture to a certain extent the *'actual'* level of corruption (Glaeser & Saks 2006). Perception-based measures rely on survey data and may lack objectivity given the time frame during which the survey was conducted and the nonresponse bias in survey sampling. Secondly, in contrast to country-level measures, our district-level and state-level conviction measures correspond only to the US reducing any bias arising from cross-country differences in the socioeconomic, cultural and institutional environments (Fisman & Gatti 2002; Smith 2016). Moreover, given that the Federal Justice system handles all the cases of local corruption, this may enhance homogeneity of prosecution (Glaeser & Saks 2006; Smith 2016), which in turn could improve the comparability of public corruption cases across different districts/states. Lastly, the conviction-based measure displays high variability in terms of the cases of corruption, including well-known cases of corrupted public officials that hold very prestigious positions in the government but also less significant cases which involve government employees. Table 4 presents the mean and median values of corruption across US states.

[Insert Table 4 around here]

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[4] We source the relevant data to transfer ZIP codes to county Federal Information Processing Standard (FIPS) codes from the Missouri Data Center: http://mcdc.missouri.edu/applications/geocorr2000.html

[5] https://www.usmarshals.gov/district/county.htm

[6] Compustat only reports the most recent headquarter location. The Augmented 10-X Header data, which captures all the information in the header section in the 10-K for each fiscal year, is available here: https://sraf.nd.edu/data/augmented-10-x-header-data/

4. Main results

4.1 Baseline estimations

Table 5 shows the results from the baseline estimations which aim to test our hypothesis (*H1A and H1B)*, on the relationship between local public corruption and debt concentration. We use OLS estimator with year and industry fixed effects to control for time variation in macroeconomic conditions and industry specific characteristics, respectively.[7] In Models 1-2 of Table 5, we report the findings from using as dependent variable the debt concentration index (*HHI Index*). In Model 1, we include the district-level conviction-based measure of corruption (*DISTRICT COR*) as the only independent variable. We observe that corruption (*DISTRICT COR*) exerts a negative and significant effect at the 5% level on debt concentration index (*HHI Index*). In Model 2, we add the firm-level control variables and the state-level control characteristics to achieve our full specification. The results show that corruption (*DISTRICT COR*) continues to have a negative and significant effect at the 10% level on debt concentration index (*HHI Index*). Next, in Models 3-4 of Table 5, we employ as an alternative measure of debt concentration the binary variable that takes the value of one when the firm holds at least 90% of its debt on one specific type of debt and zero otherwise (*HHI DUM*). Both the simple and full specification models show that corruption (*DISTRICT COR*) exerts a negative and significant effect at the 1% level on debt concentration (*HHI DUM*). Given that our dependent variable is binary, we run a probit estimation in Models 5- 6 of Table 5. The results are in line with our previous findings. These findings show that corruption decreases

[7] In line with several previous studies (Smith 2016; Hossain *et al.* 2020; Huang & Yang, 2021; Hassan *et al.* 2022) that have analysed the effect of public corruption on firm-level characteristics, we include industry and year fixed effects in our baseline model. The use of industry fixed effects—as opposed to firm fixed effects—is critical to our study. Corruption exhibits high variation between firms located in different states and little variation across firms located within the same state. Additionally, firms do not change headquarters during the period of the study. Hence, since corruption is quite persistent and firms do not alter their location, within-firm estimation—i.e., firm fixed effects—would increase the potential bias on the estimation of the coefficients of the explanatory variables in our regression model (Gormley & Matsa, 2014), thereby making it difficult to draw valid conclusions from our results. To this end, we opt for industry and year fixed effects in our baseline estimations.

debt concentration, suggesting that firms in corrupt areas would try to maximise their access to debt capital through multiple sources to overcome financing frictions in the debt market. This, in turn, provides preliminary evidence of a negative association of corruption with debt concentration, in line with the ***H1B*** hypothesis.

[Insert Table 5 around here]

4.2 Main Robustness Analysis

Although in the baseline estimations, presented in the previous section, we control for several firm-level and state-level characteristics, endogeneity might still stem from the omission of other variables that could be correlated with corruption (Wooldridge 2010). To address this issue that may cause bias in our results, in this Section, we present a battery of robustness checks which include Instrumental Variable (IV) Estimations, matching estimators, alternative measures of debt concentration, additional fixed effects and alternative ways of clustering standard errors. In additional estimations, we also use alternative perception-based measures of corruption (perceived and real) the results of which are included in the online Internet Appendix. Our results below confirm the preliminary results in Section 4.1 (baseline estimations) and provide robust evidence in support of H1B.

4.2.1 Addressing endogeneity: Instrumental Variable (IV) Estimation

We use an instrumental variable (IV) approach and adopt the two-stage least squares (2SLS) regression method to alleviate concerns related to endogeneity. To this end, our aim is to find appropriate instruments for US local public corruption. Firstly, following Smith (2016) we consider state-capital isolation as a potential instrument. Campante & Do (2014) show that segregated US state-capital cities are positively related to local public corruption. There are two main underlying reasons for the positive association. Campante & Do (2014) show that when the audience of local media coverage is not clustered around the state-capital, the reporting of state politics is low. They also show that individuals who live far from the state-capital are less concerned with state politics. As a result, lower levels of public officials' reporting and low citizens' interest in state politics induce public officials to perform unethical practices for their personal benefit.

We source the data on state-capital isolation from the study of Campante & Do (2014). The variable spans from zero to one, with higher values indicating lower levels of capital isolation. We employ the earliest year in the study, i.e.,1920, and we conjecture that state-level capital isolation will have a predictive capacity on the level of corruption for the 2002-2016 period. In addition, we argue that state-capital isolation in 1920 is unlikely to have a direct effect on firm financing choices except through its impact on local public corruption (hence satisfying the exclusion restriction).

Secondly, we employ a time-variant instrument that is based on the change of intensity of the Freedom Information Act (FOIA) regulations in each state. The purpose of FOIA laws is to refrain public officials from unethical practices due to the increased public exposure and scrutiny. Cordis & Warren (2014) show empirically that states that transitioned from weak FOIA laws status to strong FOIA laws status exhibit a reduction in local public corruption. They measure the strength of FOIA laws in each state using a continuous score from 0 to 10 per year; with states scoring seven or more being strong FOIA states. States that transitioned from weak to strong FOIA laws have shown a reduction in public corruption after seven years after the transition. This seven-year delay in the actual reduction of conviction-based rate by public officials is explained by the higher detection rate of unethical cases in the first years (short-term) and the lower incentive of public officials to engage in unethical practises in the long term (after seven years). Hence, following previous studies (Bermpei *et al.* 2020; Huang & Yuan 2020), we employ as a second instrument a dummy variable that takes the value of 1 for the years after the seventh year that a state has shifted from weak to strong FOIA law state, while it takes the value of zero for the years before the seventh year after the shift. We argue that this binary variable should be negatively related to local corruption, while there is a low probability that this variable would directly affect debt concentration, apart from its indirect effect through corruption (i.e., exclusion restriction). Estimation of these models is based on a relatively smaller number of observations compared to the previous models, given that we only employ firm-year observations of firms operating in states that experience a FOIA law transition. The results of the 2SLS-IV estimations are available in Table 6 which tests our hypothesis ***H1A*** and ***H1B***.

[Insert Tables 6 around here]

In Table 6, we run 2SLS IV specifications to control for endogeneity issues between local public corruption and debt concentration. We report the first stage results in the lower part of the table. In models 1 and 4 of Table 6, where we use as our instrumental variable the state-level capital isolation (*CAPIS1920*), we find that the instrument exerts a negative and statistically significant effect at the 1% level on corruption. Higher values of the instrumental variable denote less state-capital isolation. Therefore, we find that higher values of CAPIS1920 are associated with lower levels of local public corruption. In addition, the appropriateness of the instrument is further supported by the Kleibergen-Paaprk LM test (under-identification test (UIT) and the weak instrument test (Wald F-Test (WIT)). The results from the second stage lend support to the previous baseline estimations and ***H1B*** hypothesis. We find that the instrumented corruption *(Pred COR*) exerts a negative and significant effect at the 5% and 1% level on debt concentration as gauged by the two alternative proxies (*HHI Index* and *HHI DUM*, respectively). In Model 7 of Table 6, we use the probit estimator and find similar results.

Next, in Models 2, 5 and 8 of Table 6, we repeat this exercise by employing *FOIA* as our second instrumental variable. In the lower part of Table 6, we observe that *FOIA* variable exerts a negative and significant effect at the 1% level on public corruption (Models 2, 5 and 8 of Table 6). Thus, we observe that the transition dummy variable FOIA (i.e., which denotes that a state shifts from weak to strong FOIA law state) is negatively related to local public corruption. The first stage results are reported in the upper part of models 2, 5 and 8 of Table 6. In Model 2, we observe that the instrumented corruption variable (*Pred COR*) has a negative and significant effect at the 1% level on debt concentration (*HHI Index*). In Model 5, we find that instrumented corruption (*Pred COR*) exerts a negative and significant effect at the 1% level effect on the debt concentration dummy variable (*HHI DUM*). In Model 8 of Table 6, we use a probit model, as our dependent variable is a binary measure of debt concentration (*HHI DUM*), and we find similar results.

Next, in Models 3, 6 and 9 of Table 6, we run models where we use both instruments simultaneously (*CAPIS1920* and *FOIA*). These estimations allow us to estimate the Hansen over-identification (OIT) test. In the lower part of these models, we report the first stage findings, where we observe that both instruments continue to exert a negative and significant effect at the 1% on local public corruption. The efficacy of the instruments is also reinforced by the OIT test, where we find insignificant p-values. In the second stage results of the upper part of the Models 3,6, and 9 of Table 6, we find that the instrumented corruption *(Pred COR*) exerts a negative and significant effect at the 1% level on the two proxies of debt concentration (*HHI Index* and *HHI DUM*). Altogether, these findings lend support to our baseline estimations and the *H1B* hypothesis, where we posit that higher local public corruption would prompt firms to borrow from a wider variety of debt sources to overcome credit rationing, thus decreasing debt concentration.

4.2.2 Matching estimation

It is possible that firms operating in areas of high local public corruption would be very different in terms of their observable characteristics from firms operating in areas of low local public corruption. Therefore, it is plausible that our results could be driven by these differences rather than the actual level of corruption. To mitigate these concerns, we employ a propensity score matching (PSM) technique (Heckman *et al.* 1998). This approach is used by several previous studies in corporate finance, as it mimics sample randomisation and allows us to identify both a treated and control group of firms which are similar on average based on a set of observable characteristics. In the treated group, we include firms that belong to a district of high local public corruption, while in the control group we include very similar firms in terms of their observable characteristics, but operating in areas of low local public corruption.

We define an area of high local public corruption as a district for which its level of corruption in a year is in the top quartile. To proceed with the matching technique, we create a dummy variable where the district-year observations take the value of one if they are in the top quartile and zero otherwise. We run a probit model with this binary variable as a dependent variable along with firm-level and state-level control variables included in our previous analysis as the explanatory factors (Smith 2016). This estimation produces propensity scores, which are the probabilities that a firm would belong to the district of high local public corruption based on the set of observable characteristics. This process would enable us to match treated firms with similar propensity scores from the control group (i.e., operating in low corruption areas). We follow a one-to-one nearest neighbour matching process, with no replacement and a 10% calliper. Therefore, we perform the baseline estimations employing only the matched samples. The results of these estimations are reported in Table 7. We find that local public corruption exerts a negative and significant effect at the 1% level on our binary debt concentration variable (*HHI DUM*) (models 2-3 of Table 7). Overall, these findings lend further support to the ***H1B*** hypothesis.

[Insert Table 7 around here]

4.3 Alternative debt concentration measures

In this section, as a robustness test, we employ alternative measures of debt concentration to reinforce the validity of our baseline results. In these Models, we use an OLS estimator with year and industry fixed effects as in the baseline estimations. The first measure of debt concentration is the number of different types of debt that a firm uses in each year. We multiply this number by minus one so that higher values of this variable denote lower levels of debt concentration (*Inverse Debt Number*). We proxy for public corruption using the district-level measure of corruption (*DISTRICT COR*). We find that corruption (*DISTRICT COR)* exerts a negative and significant effect at the 1% level on debt concentration (*Inverse Debt Number*). As a second alternative measure of debt concentration, we employ the ratio of number of the different debt types employed by a firm in a year over the total number of debt types (seven types of debt). We again multiply this ratio of debt concentration by minus one, indicating that higher values of this ratio correspond to lower levels of debt concentration. The results are shown in Model 2 of Table 8, where we see that the district-level corruption measure (*DISTRICT COR*) has a negative and significant effect at the 1% level on debt concentration (*Inverse Debt Ratio*). As a third alternative measure of debt concentration, we construct a dummy variable that takes the value of one if a firm has a ratio of the number of debt types in a year over the total types of debt (seven types of debt) below the median and zero otherwise. The results are shown in Model 3 of Table 8, where we find that corruption has a negative and significant effect at the 1% level on debt concentration (*Debt Conc Dummy*). Given that this variable is dichotomous, we also run probit regression and find similar results (Model 4 of

Table 8). Altogether, these findings are in line with our baseline findings and further support the hypothesis ***H1B***.

[Insert Table 8 around here]

4.4 Alternative conviction-based corruption measure

In Models 1-3 of Table 9, we repeat the above exercise using the state-level corruption measure (*STATE COR*). The state-level measure of corruption is the ratio of the number of public corruption-related convictions over the population in a US state (100,000 inhabitants). First, in Model 1 of Table 9, we find that the state-level corruption (*STATE COR*) has a negative effect on debt concentration index (*HHI Index*), but the effect is not statistically significant. Next, we employ as a dependent variable the debt concentration binary variable (*HHI DUM*). In this model, we find that corruption (*STATE COR*) exerts a negative and statistically significant effect at the 1% level on debt concentration dummy (*HHI DUM*). In Model 3 of Table 9, we also run a probit model and we obtain similar results. All in all, the above findings lend support to hypothesis ***H1B***, which suggests that firms operating in areas with higher levels of local public corruption are associated with lower levels of debt concentration. The reason being that local public corruption reduces lending (Bermpei *et al.* 2020) and increases the cost of borrowing (Du *et al.* 2020; Hossain *et al.* 2020), which in turn creates credit rationing issues for firms. As a response, firms would try to borrow from multiple sources to overcome the credit tightening issue, decreasing debt concentration in that way.

[Insert Table 9 around here]

4.5 Estimations with additional fixed effects

In our main set of results, we control for various firm-level and state-level characteristics and employ both industry and year fixed effects, in line with many previous studies. However, there might be omitted observables and unobservable factors that could affect the relationship between public corruption and debt concentration. In this section, to further ease the omitted variable bias, we add a battery of additional fixed effects.

[Insert Table 10 around here]

In Model 1 of Table 10, we saturate the model by adding firm and state-level fixed effects. In this way, we control for all time-invariant firm and state characteristics in our baseline model. We find that public corruption, as gauged by the district measure *(DISTRICT COR)*, exerts a negative and significant effect at the 5% level on debt concentration (*HHI Index*). In Model 2 of Table 10, we also find that corruption has a negative and significant effect at the 5% level on debt concentration (*HHI DUM)*. Next, in Models 3 and 4 of Table 10, we add industry-year fixed effects and state-year fixed effects to control for all the time-variant characteristics that vary for firms that belong to different industries and states and that could have a potential effect on the relationship between corruption and debt concentration. We run estimations where we employ *HHI Index* and *HHI DUM* as proxies of debt concentration, respectively. The effect of public corruption on debt concentration remains negative and statistically significant at least at the 5% level. Taken together, these results further support our previous findings.

4.6 Alternative clustering of standard errors

In all our previous estimations, we cluster standard errors at the state-year level, as our main variable of interest varies across time and state (Smith 2006). In this section, considering that our data are at the firm level, we perform estimations in which we cluster standard errors at both the firm and firm-year levels. Hence, in Models 1-3 of Table 11, we cluster by firm-year level, and in Models 4-6 of Table 11, we cluster standard errors by firm level. We also conduct estimations where we cluster standard errors at the state-level, as showed in Models 7-9 of Table 11. The results are similar to those of our main analysis.

[Insert Table 11 around here]

5. Further analysis

5.1 Accounting for demand-side considerations

Our baseline estimations reveal a negative relationship between corruption and debt concentration, a finding which could be also driven by shifts in the demand and/or supply of debt. Corruption can impact the supply of debt in several ways; for instance, local corruption can influence lenders' perception of risk associated with lending to firms in such regions, leading to reluctance in extending credit (Bermpei *et al*. 2021). Simultaneously, firms in corrupt areas might increase the demand for debt from multiple sources to decrease in that way intensive monitoring stemming from one lender. Also, they might aim to increase leverage through several sources to limit expropriation risk from public officials (Smith 2016). Hence, increasing leverage could affect the debt concentration of firms as it this increase could come from an increase in borrowing from one source or by considering multiple debt sources.

To address concerns of simultaneity in our identification strategy, we adopt a two-fold approach. Initially, we incorporate three macroeconomic state-level variables—education, unemployment, and personal income growth—as controls (Delis *et al.* 2017; Bermpei *et al*. 2021). We also explore interactions between corruption and firm-level variables to observe the role of demand-side considerations.[8]One such characteristic is the credit rating of the firm. Credit ratings provide invaluable information to investors about the creditworthiness of the firm (Reiter & Zeibart 1991). Credit ratings also offer an additional governance mechanism that aims to increase the transparency of a bond issue. Thus, credit-rated firms are expected to

[8] In this study, we do not have lender-level data to empirically control for supply-side considerations regarding the effect of corruption on debt concentration. However, the use of year fixed effects along with macroeconomic factors in our estimations capture, to a certain extent, the business cycle and therefore the supply of private and public funding at the US level.

be more transparent and exhibit lower information asymmetry compared to their non-rated counterparts. Another firm-level characteristic is if the firm is listed in the stock market exchange. Listed firms have easier access to multiple sources of funding as they continuously report useful information to the public. Hence, credit ratings and stock market listing status are crucial firm-level characteristics, influencing transparency and access to diverse funding sources. We anticipate the negative effect of corruption on debt concentration to be more pronounced for highly credit-rated and publicly listed firms, given their credibility and adaptability in their use and mix of debt instruments. Interactions between our corruption proxy and these characteristics help identify the firms capable of overcoming financial frictions in corrupt areas. The results of these estimations are detailed in Table 12.

[Insert Table 12 around here]

Models 1-3 of Table 12 incorporate the interaction between district-level corruption and the investment-grade variable *(DISTRICT COR* INV GRADE RATED)*, where the latter is a dummy variable indicating firms with long-term credit rating by S&P of "BBB-" or higher. In all the specifications, the interaction term is negative and statistically significant, suggesting a stronger negative effect of corruption on debt concentration for high-rated firms. Subsequently, models 4-6 include the interaction between the local public corruption variable and the listing status *(DISTRICT COR*LISTED)*, revealing a negative and significant effect, particularly in Model 4. Although the statistical significance is weaker in Models 5-6, where we employ the debt concentration dummy variable as a dependent variable *(HHI DUM)*, the overall findings corroborate our hypothesis that the negative association between local public corruption and debt concentration is stronger for high-rated and listed firms compared to low-rated and unlisted counterparts. Altogether the above findings, support the conjecture that demand-side considerations are instrumental in the relationship between corruption and debt concentration.

5.2 US firms and debt choices in corrupt areas

In Section 5.1, we find that the negative association between corruption and debt concentration is more pronounced for informationally transparent firms, i.e., investment-graded firms and listed firms. In this section, we aim to delve deeper to understand a firm's choice of debt type in corrupt regions. This analysis is motivated by the varying accessibility of different debt sources for different types of borrowers.

Literature suggests that high-credit-quality firms tend to borrow from public capital markets (Denis & Mihov 2003), allowing them to overcome the credit tightening imposed by banks in corrupt areas. Consequently, low-rated, unrated, or private companies may face increased financing problems in such environments as they are more likely to borrow from banks and private lenders. The results of this analysis are presented in Table 13.

[Insert Table 13 around here]

In Panel A of Table 13, we test the effect of corruption on individual debt components of the HHI Index. In Model 1 of Panel A, we examine the influence of corruption *(DISTRICT COR)* on the ratio of commercial paper to total debt *(CP)*, finding a positive and significant effect at the 1% level. Model 2 of Panel A shows the effect of corruption *(DISTRICT COR)* on the ratio of revolving credit to total debt *(RC)*, showing a negative relationship, though not statistically significant. Model 3 employs the ratio of term loans over total debt *(TL)* as a dependent variable, revealing that corruption *(DISTRICT COR)* has a negative and significant effect at the 1% level. Model 4 tests the effect of corruption *(DISTRICT COR)* on the ratio of senior bonds and notes over total debt *(SeniorB&N)*, showing a positive and significant effect at the 5% level. In Model 5, we examine the influence of corruption *(DISTRICT COR)* on the ratio of subordinate bonds and notes over total debt *(SubB&N)*, with results indicating a negative and significant effect at the 1% level. Model 6 reveals that corruption *(DISTRICT COR)* has a positive and significant impact at the 1% level on the ratio of capital leases over total debt *(CL)*. Finally, Model 7 shows that corruption (DISTRICT COR) has a positive, but not statistically significant, effect on the ratio of other borrowing over total debt *(OtherB)*.

In Panel B of Table 13, we report interactions between corruption *(DISTRICT COR)* and the investment-grade variable *(INV GRADE RATED)* and their impact across different debt types. Model 1 of Panel B shows that this interaction has a positive and significant effect at the 1% level on commercial paper *(CP)*. Model 4 of the same panel reveals a positive and significant relationship at the 10% level with senior bonds and notes *(SeniorB&N)*. In Model 6, this interaction has a positive and significant effect at the 1% level on capital leases *(CL)*. Panel C introduces results from interacting corruption with the listed variable *(DISTRICT COR * Listed)* and their impact across different debt types. Model 1 shows the interaction to be positive and significant at the 5% level, indicating that listed firms in corrupt areas increase their borrowing in commercial paper *(CP)*. Model 2 reveals a negative and significant effect at the 10% level on revolving credit *(RC)*, while Model 6 indicates a positive and significant impact at the 1% level on capital leases *(CL)*.

Altogether, the results from Panels B and C of Table 13 demonstrate that in corrupt areas, firms with higher informational transparency, i.e., those with high investment grades and listed firms, increase market-based debt (commercial paper debt, senior bonds, and notes securities, and capital leases) while showing some evidence of borrowing less from banks (revolving credit).

6. Conclusions

In this paper, we examine the effect of local political corruption on debt concentration. We develop two competing hypotheses that point in different directions regarding the association between political corruption and debt concentration. On the one hand, the first hypothesis suggests that firms in corrupt areas would be granted fewer options of debt financing because of their increased information asymmetry induced by the local environment, resulting in an increase in debt concentration. On the other hand, firms in areas of higher local corruption would try to minimise the scrutiny from lenders by borrowing smaller amounts of debt from multiple lenders. This, in turn, will decrease lenders' incentive of lenders to monitor firm operations. Hence, this channel predicts a negative relationship between local public corruption and debt concentration.

Our results suggest a negative association between local public corruption and debt concentration. Furthermore, our evidence shows that the effect is strong for firms with lower financing concerns. In summary, we find that in corrupt areas, firms that have a high investment grade and are publicly listed have a less concentrated debt portfolio. A decomposition of debt portfolio shows that firms in corrupt areas increase public-based debt (i.e., commercial paper, senior bonds and notes, and capital leases) and reduce bank-based debt (i.e., term loans). Our main results remain largely unchanged compared to our baseline models across several tests that address endogeneity issues. We use an instrumental variable approach with the state-level capital isolation and implementation of FOIA laws as instruments for local public corruption. Furthermore, we employ alternative perception-based measures of corruption and matching analysis. Finally, we perform estimations using alternative measures of debt concentration and additional fixed effects.

Our findings have practical implications for firms, investors, stakeholders (e.g., credit rating agencies), and policymakers. Firms could use these insights to make informed decisions about debt concentration, especially if they operate in or are considering entering regions with high levels of corruption. Investors can be more mindful of the underlying factors, such as corruption, that influence a firm's capital structure decisions. Credit rating agencies might factor in the regional corruption index when analysing a firm's risk profile based on its debt structure. Furthermore, from a policymaker and regulatory perspective, our results call for the implementation of policy measures. Both preventive (e.g., enhanced financial audits for companies, especially those operating in corruption-prone regions; strengthened regulatory oversight) and punitive measures (e.g., fines, disqualification from participating in public procurement processes for a stipulated period, and in extreme cases, revocation of licenses, thus depriving them of significant revenue opportunities) could be implemented to mitigate the unwanted effects of corruption on corporate debt structures.

This study has limitations that could be addressed in future research. First, we measure local corruption using actual conviction data and survey-based perception indicators. Although these proxies have been employed in previous studies, measuring corruption is challenging due to its covert nature and the variety of forms it can take. In this regard, future research could utilize additional measures such as audit reports and whistleblower information to capture the full extent of corruption, which is not fully captured by publicly available sources. Second, while we employ an instrumental variable approach and propensity score matching techniques to address endogeneity concerns, future studies could leverage exogenous shocks, such as local changes in anti-corruption laws or enforcement actions targeting specific firms and sectors, within a difference-in-differences empirical framework. Third, the period we studied (2002-2016) may limit the generalizability of our findings to periods of increased economic uncertainty, such as the recent COVID-19 pandemic. Research into this particular period of uncertainty would be beneficial. Finally, our sample is limited to U.S. non-financial firms. The theoretical arguments we present may not hold in other institutional contexts where corruption operates differently. Therefore, future studies should compare our results with those from other regions in Europe or globally.

Declarations

Funding and/or Conflicts of interests/Competing interests

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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List of Tables

Table 1. Definitions and measurement details of all variables

Variable Name	Definition	Source
Variables used in the main analysis		
HHI Index	It is an index that ranges from 0 to 1 and measures the level of debt concentration using the method followed by Colla et al. (2013). Higher values of this index denote higher levels of debt concentration.	CAPITAL IQ
HHI DUM	It is a binary variable that takes the value of 1 if a firm holds at least 90% of its debt from one debt source, and 0 otherwise.	idem
DISTRICT COR	Yearly district-level measure of public corruption convictions normalised by 100,000 residents.	Department of Justice (DOJ) PIN reports to Congress
STATE COR	Yearly state-level measure of public corruption conviction normalised by 100,000 residents	Department of Justice (DOJ) PIN reports to Congress
Market-to-book	Book assets minus common equity plus common shares outstanding*share price at fiscal year-end divided by book assets	Compustat
EBITDA	Earnings before interest depreciation and amortisation divided by total assets	idem
PP&E	Property, plant, and equipment divided by total assets	idem
Modified Altman-Zscore	The modified Altman Z-score is calculated using the following formula=3*3(Earnings before interest and tax/Total assets) +1*(Sales/Total assets) +1.2*(Current assets/Total assets) +1.4*(Retained earnings/Total assets)	idem
INV GRADE RATED	Investment grade rated a dummy variable that takes the value of 1 when the firm has an equal to or above “BBB-” long-term credit rating by S&P, and takes the value of zero if the firm has a rating below “BBB-”	idem
Listed	It is a binary variable that takes the value of 1 if a firm is listed in the stock exchange and 0 otherwise.	idem
Ln(sales)	The natural logarithm of sales	idem
Ln(size)	The natural logarithm of total assets	idem
Leverage	Total debt (long and short-term) divided by total assets	idem
Education	The state-level percentage of residents that have obtained a four-year university degree	US Census Current Population Survey
Unemployment	The state-level unemployment rate	Bureau of Labor Statistics
Personal income	The state-level personal income growth	Bureau of Economic Analysis (BEA)
Variables used in the robustness analysis		
CAPIS1920	This is the state-capital isolation that ranges from 0 to 1 with higher values denoting lower capital isolation. This measure is adjusted for state size and shape and for the earliest year available, i.e., 1920.	Campante's and Do (2014) study
FOIA	This is a dummy variable that takes the value of 1 following seven years after the transition of a state from weak to strong freedom of information act (FOIA) laws and 0 the years before the transition.	Cordis's and Warren (2014) study
Inverse Debt Number	The number of debt types that a firm uses in each year multiplied by minus one.	CAPITAL IQ
Inverse Debt Ratio	The ratio of the number of different types a firm uses in each year divided over all the different types of debt (seven types of debt) multiplied by minus one.	idem
Debt Conc Dummy	This is a dummy variable that takes the value of 1 when the firm has a ratio of the number of debt types in each year over the seven types of debt which is below the median, and 0 otherwise.	idem

Table 2 Summary statistics

	N	Mean	Std. Dev.	p25	Median	p75
HHI index	19503	.722	.262	.463	.78	1
HHI DUM	19503	.406	.491	0	0	1
Commercial paper	19503	.67	4.729	.004	.001	.001
Revolving credit	19503	21.316	33.339	.001	.001	32.60
Term loans	19503	24.396	35.24	.001	.001	44.70
Senior Bonds and Notes	19503	35.828	39.974	.001	12.52	77.71
Subordinate Bonds and Notes	19503	6.09	19.903	.001	.001	.001
Capital Leases	19503	8.628	24.511	.001	.001	1.64
Other borrowing	19503	3.063	13.892	.001	.001	.001
DISTRICT COR	19503	.181	.299	.062	.117	.235
STATE COR	19503	.31	.3	.187	.267	.387
Market-to-book	19503	1.991	2.745	1.147	1.499	2.145
EBITDA	19503	.055	.286	.047	.109	.159
PP&E	19503	.262	.229	.083	.186	.377
Modified Altman-Z	19503	1.15	7.014	1.086	2.295	3.389
Ln(sales)	19503	6.021	2.282	4.533	6.221	7.603
Ln(size)	19503	5.230	2.102	3.703	4.228	5.708
Leverage	19503	.475	.264	.311	.475	.593
INV GRADE RATED	19503	.351	.477	0	0	1
Listed	19503	.752	.432	1	1	1
Education	19503	.289	.045	.256	.283	.317
Unemployment	19503	6.488	1.972	5	6.1	7.567
Personal income	19503	3.432	2.815	2.2	3.432	5.3

Notes: This table presents summary statistics for the variables used in this study over the sample period (2002-2016).

Table 3 Matrix of correlation for the variables included in the main analysis

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) HHI index	1.000													
(2) DISTRICT COR	-0.004	1.000												
(3) Market-to-book	0.117	-0.003	1.000											
(4) EBITDA	-0.075	0.022	-0.252	1.000										
(5) PP&E	-0.139	-0.027	-0.120	0.132	1.000									
(6) Modified Altman-Z	-0.026	0.015	-0.376	0.624	0.066	1.000								
(7) Ln(sales)	-0.158	0.018	-0.129	0.476	0.105	0.357	1.000							
(8) Ln(size)	-0.134	0.016	-0.108	0.385	0.163	0.305	0.527	1.000						
(9) Leverage	-0.238	0.001	0.100	-0.188	0.030	-0.363	0.034	-0.029	1.000					
(10) INV GRADE RATED	-0.002	0.043	0.091	0.112	-0.007	0.058	0.349	0.355	-0.029	1.000				
(11) Listed	-0.026	-0.005	-0.006	0.077	0.038	0.063	0.166	0.164	-0.007	0.067	1.000			
(12) Education	0.056	0.262	0.058	-0.083	-0.195	-0.050	-0.044	-0.020	-0.015	0.028	0.020	1.000		
(13) Unemployment	0.038	-0.034	0.006	-0.039	-0.051	-0.050	-0.005	-0.011	0.004	0.003	0.011	0.038	1.000	
(14) Personal income	0.006	-0.052	0.014	0.014	-0.030	0.019	0.000	-0.007	-0.009	-0.006	-0.010	-0.093	-0.229	1.000

Notes: This table presents Pearson correlation coefficients for the variables used in the main regressions. Table 1 includes definitions and measurement details for all variables.

Table 4 Corruption by state

State	Mean	Median	State	Mean	Median
Alaska	0.581	0.407	Montana	0.663	0.732
Alabama	0.535	0.457	North Carolina	0.181	0.183
Arkansas	0.342	0.281	Nebraska	0.161	0.161
Arizona	0.358	0.3	New Hampshire	0.120	0.076
California	0.195	0.21	New Jersey	0.450	0.477
Colorado	0.130	0.117	New Mexico	0.232	0.192
District of Columbia	4.652	4.105	Nevada	0.131	0.148
Delaware	0.377	0.328	New York	0.282	0.267
Florida	0.339	0.322	Ohio	0.342	0.324
Georgia	0.305	0.271	Oklahoma	0.446	0.512
Hawaii	0.182	0.15	Oregon	0.101	0.085
Iowa	0.161	0.131	Pennsylvania	0.401	0.368
Idaho	0.141	0.07	Rhode Island	0.332	0.284
Illinois	0.366	0.334	South Carolina	0.108	0.105
Indiana	0.254	0.258	South Dakota	0.833	0.971
Kansas	0.127	0.109	Tennessee	0.44	0.428
Kentucky	0.632	0.653	Texas	0.342	0.322
Louisiana	0.881	0.96	Utah	0.121	0.071
Maine	0.309	0.294	Virginia	0.569	0.501
Maryland	0.494	0.505	Vermont	0.245	0.16
Maine	0.257	0.264	Washington	0.119	0.102
Michigan	0.223	0.239	Wisconsin	0.197	0.201
Minnesota	0.109	0.111	West Virginia	0.448	0.441
Missouri	0.304	0.340	Wyoming	0.398	0.377

Notes: The table shows the mean and median of corruption at state level measured by the number of convictions per thousand population for the period covered in the study (2002-2016). All variables are defined in Table 1.

Table 5 The effect of corruption on debt specialization (OLS with fixed effects estimations)

	(1) HHI Index	(2) HHI Index	(3) HHI DUM	(4) HHI DUM	(5) HHI DUM	(6) HHI DUM
DISTRICT COR	-.013**	-.015*	-.041***	-.049***	-.115***	-.154***
	(-2.087)	(-1.95)	(-3.401)	(-3.514)	(-3.053)	(-3.132)
Market-to-book (t-1)		.013***		.025***		.085***
		(4.744)		(5.231)		(8.606)
EBITDA (t-1)		-.027*		-.04		-.113
		(-1.83)		(-1.339)		(-1.288)
PP&E (t-1)		-.105***		-.207***		-.594***
		(-7.505)		(-8.08)		(-7.808)
Modified Altman-Z (t-1)		-.001		.001		-.002
		(-.813)		(.087)		(-.642)
Ln(sales) (t-1)		.01		-.01		-.016
		(.055)		(-1.466)		(-.832)
Ln(size) (t-1)		-.013***		-.023***		-.074***
		(-3.938)		(-3.338)		(-3.642)
Leverage (t-1)		-.276***		-.468***		-1.369***
		(-20.232)		(-17.604)		(-15.427)
INV GRADE RATED (t-1)		.032***		.016		.043
		(2.95)		(.743)		(.688)
Listed (t-1)		.002		.004		.017
		(.339)		(.365)		(.537)
Education		.107**		.275***		.794***
		(1.969)		(2.728)		(2.705)
Unemployment		.008***		.01**		.023**
		(3.538)		(2.389)		(2.058)
Personal income		.001		.001		.004
		(.188)		(.65)		(.682)
Constant	.725***	.881***	.414***	.697***	-.43***	.473**
	(248.476)	(29.554)	(77.315)	(11.647)	(-3.535)	(2.129)
Observations	23603	14387	23603	14387	23603	14387
R-squared	0.042	0.121	0.042	0.121	-	-
R-pseudo	-	-	-	-	.034	.094
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Model	OLS	OLS	OLS	OLS	Probit	Probit

Notes: This table shows results from regressing HHI (debt concentration) on district-level public corruption after controlling for firm- and state-level characteristics. Table 1 presents full definition and measurement details of all variables. Standard errors clustered at the state-year level. Significance at the 10%, 5% and 1% levels is represented by *, **, and ***, respectively.

Table 6 The effect of corruption on debt concentration (2SLS IV estimations)

	(1) HHI Index	(2) HHI Index	(3) HHI Index	(4) HHI DUM	(5) HHI DUM	(6) HHI DUM	(7) HHI DUM	(8) HHI DUM	(9) HHI DUM
Pred COR	-.15**	-.209***	-.255***	-.418***	-.444***	-.574***	-1.115***	-1.314***	-1.709***
	(-2.465)	(-3.419)	(-4.516)	(-3.492)	(-3.671)	(-5.591)	(-3.602)	(-3.778)	(-5.127)
Market-to-book (t-1)	.013***	.007***	.007***	.025***	.013***	.013***	.082***	.05**	.049**
	(4.824)	(2.897)	(2.912)	(5.355)	(3.232)	(3.261)	(8.46)	(2.38)	(2.37)
EBITDA (t-1)	-.025*	.007	.009	-.036	-.038	-.033	-.098	-.078	-.064
	(-1.693)	(.203)	(.254)	(-1.17)	(-.553)	(-.474)	(-1.138)	(-.398)	(-.325)
PP&E (t-1)	-.107***	-.086***	-.085***	-.211***	-.21***	-.209***	-.583***	-.661***	-.656***
	(-7.536)	(-3.7)	(-3.669)	(-8.069)	(-4.517)	(-4.473)	(-7.753)	(-4.804)	(-4.743)
Modified Altman-Z (t-1)	-.001	-.001	-.001	.001	.001	.001	-.002	-.003	-.003
	(-.797)	(-.629)	(-.641)	(.112)	(-.147)	(-.161)	(-.614)	(-.407)	(-.439)
Ln(sales) (t-1)	.002	.002	.001	-.006	.002	.002	-.006	.017	.016
	(.475)	(.263)	(.24)	(-.896)	(.188)	(.157)	(-.306)	(.499)	(.461)
Ln(size) (t-1)	-.014***	-.02***	-.02***	-.025***	-.038***	-.037***	-.077***	-.117***	-.114***
	(-4.164)	(-3.308)	(-3.232)	(-3.586)	(-3.263)	(-3.162)	(-3.914)	(-3.352)	(-3.238)
Leverage (t-1)	-.277***	-.303***	-.303***	-.471***	-.555***	-.555***	-1.333***	-1.669***	-1.658***
	(-20.182)	(-12.671)	(-12.699)	(-17.486)	(-11.626)	(-11.625)	(-15.077)	(-10.826)	(-10.773)
INV GRADE RATED (t-1)	.033***	.097***	.099***	.015	.086*	.09**	.039	.24*	.25*
	(2.977)	(5.439)	(5.609)	(.702)	(1.883)	(1.992)	(.658)	(1.818)	(1.921)
Listed (t-1)	.002	.011	.01	.002	.014	.013	.012	.044	.042
	(.249)	(.843)	(.818)	(.211)	(.624)	(.588)	(.367)	(.671)	(.64)
Education	.088	.29*	.307*	.201	.797***	.846**	.554	2.367***	2.522***
	(1.212)	(1.85)	(1.838)	(1.263)	(2.682)	(2.512)	(1.29)	(2.738)	(2.58)
Unemployment	.005	.009	.009	.001	-.007	-.007	.001	-.014	-.015
	(1.549)	(1.378)	(1.292)	(.196)	(-.538)	(-.504)	(.048)	(-.404)	(-.385)
Personal income	.001	.007	.007	.002	.013	.014*	.006	.037*	.042*
	(.43)	(1.293)	(1.348)	(.834)	(1.638)	(1.693)	(.849)	(1.657)	(1.717)
First stage									
CAPIS1920	-.333***		-.432***	-.333***		-.432***	-.333***		-.432***
	(-6.103)		(-5.005)	(-6.103)		(-5.005)	(-6.103)		(-5.005)
FOIA		-.201***	-.133***		-.201***	-.133***		-.201***	-.133***
		(-4.752)	(-2.954)		(-4.752)	(-2.954)		(-4.752)	(-2.954)
Observations	14314	3594	3594	14314	3594	3594	14314	3594	3594
R-squared	.018	.021	.019	.15	.035	.028	-	-	-
UIT p-value	.000	.000	.000	.000	.000	.000	-	-	-
WIT	37.015	22.157	28.952	37.015	22.157	28.952	-	-	-
With critical value	16.38	16.38	19.93	16.38	16.38	19.93	-	-	-
Hansen j p-value	-	-	.1977	-	-	.100	-	-	-
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Model	2sls	2sls	2sls	2sls	2sls	2sls	2sls	2sls	2sls

Notes: This table shows the results from regressing HHI (debt concentration) on the predicted state level public corruption after controlling for firm- and state-level characteristics. The instruments of these 2SLS-IV estimations are the state-capital isolation in 1920 (CAPIS1920) and the transition to strong Freedom of Information Act (FOIA) laws in each state. The CAPIS1920 variable ranges from zero to one with lower values representing a more isolated state-capital. FOIA is a dummy variable that takes the value of one for the years beyond the seventh year after a state has transitioned from weak to strong freedom of information act (FOIA) laws while it takes the value of zero up to the seventh year after the transition. The instrument is constructed only for those states that experienced a weak to strong transition in terms of FOIA laws and thus, in these estimations, our sample is restricted to these states only. UIT is the under-identification LM test by Kleibergen and Paap, WIT is the Wald F-statistic of the weak identification test, which must be higher than its critical value to reject the null. Table 1 presents full definition and measurement details of all variables. Standard errors clustered at the state-year level. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***, respectively.

Table 7 Matched sample estimations

	(1) HHI Index	(2) HHI DUM	(3) HHI DUM
DISTRICT COR	-.01	-.052***	-.168***
	(-1.53)	(-3.462)	(-3.122)
Market-to-book (t-1)	.01***	.021***	.085***
	(3.066)	(3.588)	(4.712)
EBITDA (t-1)	-.029	-.058	-.103
	(-1.442)	(-1.286)	(-.848)
PP&E (t-1)	-.083***	-.165***	-.452***
	(-3.922)	(-4.467)	(-4.09)
Modified Altman-Z (t-1)	.001	.002	-.003
	(.425)	(.637)	(-.442)
Ln(sales) (t-1)	-.007	-.014	-.022
	(-1.509)	(-1.254)	(-.706)
Ln(size) (t-1)	-.009*	-.023**	-.074**
	(-1.813)	(-2.036)	(-2.345)
Leverage (t-1)	-.49***	-.49***	-1.478***
	(-12.267)	(-12.267)	(-11.386)
INV GRADE RATED (t-1)	.023	-.016	-.067
	(1.384)	(-.475)	(-.658)
Listed (t-1)	-.014	-.015	-.031
	(-1.615)	(-.885)	(-.645)
Education	.088	.342**	1.031**
	(1.081)	(2.171)	(2.222)
Unemployment	.006*	.008	.019
	(1.815)	(1.291)	(1.067)
Personal income	-.001	-.002	-.005
	(-.49)	(-.623)	(-.539)
Constant	.945***	.712***	.139
	(22.27)	(7.941)	(.388)
Observations	5580	5580	5556
R-squared	.155	.131	-
Pseudo R_2	-	-	.104
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Model	OLS	OLS	Probit

Notes: This table presents the estimation results for the effect of district-level corruption on debt concentration in matched samples based on propensity score methods after controlling for a set of firm-level and state-level characteristics. Table 1 presents full definition and measurement details of all variables. Standard errors clustered at the state-year level. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***, respectively.

Table 8 Alternative debt concentration measures

	(1) Inverse Debt Number	(2) Inverse Debt Ratio	(3) Inverse Debt Dummy	(4) Inverse Debt Dummy
DISTRICT COR	- .081***	-.012***	-.034***	-.11***
	(-3.284)	(-3.284)	(-3.822)	(-3.593)
Market-to-book (t-1)	.072***	.01***	.015***	.165***
	(4.958)	(4.958)	(5.368)	(4.979)
EBITDA (t-1)	-.053	-.008	.014	-.264*
	(-.822)	(-.822)	(.882)	(-1.957)
PP&E (t-1)	-.339***	-.048***	-.053**	-.189**
	(-5.645)	(-5.645)	(-2.569)	(-2.109)
Modified Altman-Z (t-1)	.006**	.001**	.002**	.01**
	(1.988)	(1.988)	(2.102)	(2.527)
Ln(sales) (t-1)	-.05***	-.007***	-.014***	-.084***
	(-3.727)	(-3.727)	(-3.551)	(-3.558)
Ln(size) (t-1)	-.126***	-.018***	-.031***	-.107***
	(-9.669)	(-9.669)	(-8.008)	(-4.781)
Leverage (t-1)	-1.357***	-.194***	-.272***	-1.216***
	(-23.065)	(-23.065)	(-15.563)	(-15.972)
INV GRADE RATED (t-1)	-.097**	-.014**	-.053***	-.183***
	(-2.235)	(-2.235)	(-3.05)	(-3.189)
Listed (t-1)	.004	.001	.006	.024
	(.177)	(.177)	(.73)	(.683)
Education	.828***	.118***	.199**	.626*
	(3.419)	(3.419)	(2.23)	(1.677)
Unemployment	.025***	.004***	.005*	.022*
	(2.751)	(2.751)	(1.892)	(1.838)
Personal income	.006	.001	.001	.005
	(1.396)	(1.396)	(.751)	(.649)
Constant	-1.277***	-.182***	1.054***	1.807***
	(-10.451)	(-10.451)	(25.14)	(7.891)
Observations	14336	14336	14336	14292
R-squared	0.258	0.258	0.134	-
Pseudo-R^2	-	-	-	0.148
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Model	OLS	OLS	OLS	Probit

Notes: This table shows results from regressing alternative measures of debt concentration (Inverse number debt, Inverse debt ratio, Inverse debt dummy) on district-level public corruption after controlling for firm- and state-level characteristics. Table 1 presents full definition and measurement details of all variables. Standard errors clustered at the state-year level. Significance at the 10%, 5% and 1% levels is represented by *, **, and ***, respectively.

Table 9 Alternative conviction-based corruption measure

	(1) HHI Index	(2) HHI DUM	(3) HHI DUM
STATE COR	-.005	-.035***	-.099***
	(-.798)	(-2.963)	(-2.586)
Market-to-book (t-1)	.013***	.025***	.085***
	(4.743)	(5.236)	(8.615)
EBITDA (t-1)	-.027*	-.041	-.115
	(-1.847)	(-1.355)	(-1.302)
PP&E (t-1)	-.106***	-.208***	-.596***
	(-7.514)	(-8.089)	(-7.817)
Modified Altman-Z (t-1)	-.001	.001	-.002
	(-.811)	(.086)	(-.644)
Ln(sales) (t-1)	.001	-.01	-.017
	(.029)	(-1.481)	(-.852)
Ln(size) (t-1)	-.013***	-.023***	-.073***
	(-3.914)	(-3.311)	(-3.609)
Leverage (t-1)	-.276***	-.469***	-1.371***
	(-20.242)	(-17.635)	(-15.455)
INV GRADE RATED (t-1)	.032***	.015	.04
	(2.899)	(.703)	(.651)
Listed (t-1)	.002	.004	.017
	(.35)	(.376)	(.545)
Education	.08	.199**	.562**
	(1.556)	(2.049)	(2.004)
Unemployment	.008***	.01**	.024**
	(3.561)	(2.383)	(2.094)
Per capita income	.001	.002	.005
	(.257)	(.764)	(.786)
Constant	.887***	.72***	.524**
	(30.089)	(12.049)	(2.376)
Observations	14336	14336	14328
R-squared	0.120	0.117	-
Pseudo-R_2	-	-	.094
Year FE	YES	YES	YES
Industry FE	YES	YES	YES
Model	OLS	OLS	Probit

Notes: This table shows results from regressing HHI (debt concentration) on state-level public corruption after controlling for firm- and state-level characteristics. Table 1 presents full definition and measurement details of all variables. Standard errors clustered at the state-year level. Significance at the 10%, 5% and 1% levels is represented by *, **, and ***, respectively.

Table 10 Estimations with additional fixed effects

	(1) HHI Index	(2) HHI DUM	(3) HHI Index	(4) HHI DUM
DISTRICT COR	-.11**	-.193**	-.123***	-.187**
	(-2.363)	(-2.393)	(-2.61)	(-2.312)
Market-to-book (t-1)	.002*	.004	.002*	.003
	(1.682)	(1.185)	(1.718)	(.965)
EBITDA (t-1)	.039	.065	.035	.051
	(1.595)	(1.263)	(1.288)	(.928)
PP&E (t-1)	-.207***	-.349***	-.199***	-.328***
	(-5.875)	(-5.022)	(-5.468)	(-4.459)
Modified Altman-Z (t-1)	.001	-.002	.001	-.002
	(-.165)	(-.958)	(-.042)	(-1.008)
Ln(sales) (t-1)	.02	.011	.002	.018
	(-.054)	(.731)	(.296)	(1.184)
Ln(size) (t-1)	-.056***	-.111***	-.06***	-.115***
	(-7.679)	(-7.041)	(-7.388)	(-6.926)
Leverage (t-1)	-.136***	-.321***	-.135***	-.324***
	(-7.303)	(-8.866)	(-6.959)	(-8.478)
INV GRADE RATED (t-1)	.009	-.016	.008	-.021
	(.557)	(-.438)	(.426)	(-.514)
Listed (t-1)	.019*	.034	.013	.012
	(1.776)	(1.553)	(1.052)	(.485)
Constant	1.201***	1.248***	1.212***	1.238***
	(23.868)	(13.217)	(22.716)	(12.5)
Observations	13620	13620	13521	13521
R-squared	.621	.567	.648	.597
Year FE	YES	YES	NO	NO
Industry FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
State FE	YES	YES	NO	NO
State-Year FE	NO	NO	YES	YES
Industry-Year FE	NO	NO	YES	YES
Model	OLS	OLS	OLS	OLS

Notes: This table shows results from regressing debt concentration measures (HHI) on district-level public corruption after controlling for firm- and state-level characteristics and additional fixed effects (industry, state, state-year and industry-year). Table 1 presents full definition and measurement details of all variables. Standard errors clustered at the state-year level. Significance at the 10%, 5% and 1% levels is represented by *, **, and ***, respectively.

Table 11 Estimations with alternative clustering

	(1) HHI Index	(2) HHI DUM	(3) HHI DUM	(4) HHI Index	(5) HHI DUM	(6) HHI DUM	(7) HHI Index	(8) HHI DUM	(9) HHI DUM
DISTRICT COR	-.015**	-.049***	-.154***	-.015	-.049***	-.154**	-.015	-.049***	-.154***
	(-2.272)	(-4.078)	(-3.095)	(-1.559)	(-2.84)	(-2.118)	(-1.49)	(-3.318)	(-2.815)
Market-to-book (t-1)	.013***	.025***	.085***	.013***	.025***	.085***	.013***	.025***	.085***
	(4.712)	(5.167)	(8.398)	(4.281)	(4.63)	(6.319)	(4.795)	(5.05)	(7.832)
EBITDA (t-1)	-.027*	-.04	-.113	-.027	-.04	-.113	-.027	-.04	-.113
	(-1.711)	(-1.276)	(-1.213)	(-1.394)	(-1.089)	(-1.043)	(-1.245)	(-1.061)	(-1.043)
PP&E (t-1)	-.105***	-.207***	-.594***	-.105***	-.207***	-.594***	-.105***	-.207***	-.594***
	(-7.319)	(-8.102)	(-7.762)	(-4.087)	(-4.875)	(-4.691)	(-3.97)	(-4.393)	(-4.307)
Modified Altman-Z (t-1)	-.001	.001	-.002	-.001	.001	-.002	-.001	0	-.002
	(-.81)	(.087)	(-.62)	(-.687)	(.073)	(-.497)	(-.541)	(.062)	(-.478)
Ln(sales) (t-1)	.001	-.01	-.016	.001	-.01	-.016	0	-.01	-.016
	(.056)	(-1.551)	(-.885)	(.035)	(-1.066)	(-.608)	(.033)	(-.87)	(-.487)
Ln(size) (t-1)	-.013***	-.023***	-.074***	-.013***	-.023**	-.074***	-.013*	-.023	-.074*
	(-4.31)	(-3.828)	(-4.212)	(-2.635)	(-2.537)	(-2.802)	(-1.885)	(-1.614)	(-1.719)
Leverage (t-1)	-.276***	-.468***	-1.369***	-.276***	-.468***	-1.369***	-.276***	-.468***	-1.369***
	(-22.009)	(-20.338)	(-17.86)	(-14.973)	(-14.623)	(-13.16)	(-18.828)	(-12.743)	(-12.182)
INV GRADE RATED (t-1)	.032***	.016	.043	.032*	.016	.043	.032	.016	.043
	(3.243)	(.827)	(.771)	(1.666)	(.453)	(.419)	(1.416)	(.363)	(.341)
Listed (t-1)	.002	.004	.017	.002	.004	.017	.002	.004	.017
	(.371)	(.401)	(.592)	(.225)	(.253)	(.375)	(.187)	(.202)	(.297)
Education	.107**	.275***	.794***	.107	.275*	.794*	.107	.275	.794
	(1.973)	(2.755)	(2.722)	(1.092)	(1.655)	(1.648)	(.87)	(1.395)	(1.41)
Unemployment	.008***	.01**	.023**	.008**	.01	.023	.008**	.01	.023
	(3.838)	(2.529)	(2.154)	(2.248)	(1.508)	(1.287)	(2.144)	(1.357)	(1.208)
Per capita income	.001	.001	.004	.001	.001	.004	.001	.001	.004
	(.171)	(.624)	(.646)	(.167)	(.59)	(.613)	(.172)	(.69)	(.749)
Constant	.881***	.697***	.473**	.881***	.697***	.473	.881***	.697***	.473
	(31.493)	(13.13)	(2.355)	(17.937)	(7.873)	(1.422)	(13.675)	(5.697)	(1.202)
Observations	14336	14336	14328	14336	14336	14328	14336	14336	14328
R-squared	.119	.118		.119	.118		.119	.118	
Pseudo- R_2			.094			.094			.094
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clustering of SE	Firm-year level	Firm-year level	Firm-year level	Firm-level	Firm-level	Firm-level	State-level	State-level	State-level
Model	OLS	OLS	Probit	OLS	OLS	Probit	OLS	OLS	Probit

Notes: This table shows results from regressing HHI (debt concentration) on district-level public corruption after controlling for firm- and state-level characteristics. Models 1-3 shows results whereby we cluster standard errors at the firm-year level. Models 4-6 show results from regressions whereby we cluster standard errors at the firm level, while Models 7-8 present findings from clustering standard errors at the state level. Table 1 presents full definition and measurement details of all variables. Significance at the 10%, 5% and 1% levels is represented by *, **, and ***, respectively.

Table 12 The role of rated and publicly listed firms in the association between corruption and debt concentration

	(1) HHI Index	(2) HHI DUM	(3) HHI DUM	(4) HHI Index	(5) HHI DUM	(6) HHI DUM
DISTRICT COR	-.027***	-.077***	-.839***	.013	-.038**	-.125*
	(-3.991)	(-4.441)	(-3.321)	(1.385)	(-2.14)	(-1.728)
DISTRICT COR INV GRADE RATED (t-1)*	-.022**	-.041**	-.735***			
	(-2.298)	(-2.493)	(-2.861)			
DISTRICT COR Listed (t-1)*				-.036***	-.015	-.036
				(-3.015)	(-.595)	(-.378)
Market-to-book (t-1)	.013***	.024***	.082***	.013***	.025***	.085***
	(4.565)	(4.98)	(7.964)	(4.736)	(5.227)	(8.595)
EBITDA (t-1)	-.014	-.015	-.026	-.027*	-.04	-.113
	(-.976)	(-.512)	(-.326)	(-1.819)	(-1.337)	(-1.286)
PP&E (t-1)	-.112***	-.22***	-.631***	-.105***	-.207***	-.594***
	(-7.634)	(-8.156)	(-7.922)	(-7.496)	(-8.079)	(-7.804)
Modified Altman-Z (t-1)	-.001	-.001	-.004	-.001	.001	-.002
	(-1.179)	(-.394)	(-1.141)	(-.841)	(.081)	(-.648)
Ln(sales) (t-1)	-.001	-.012*	-.024	.001	-.01	-.016
	(-.247)	(-1.794)	(-1.19)	(.021)	(-1.472)	(-.836)
Ln(size) (t-1)	-.012***	-.021***	-.067***	-.013***	-.023***	-.074***
	(-3.574)	(-2.966)	(-3.248)	(-3.917)	(-3.333)	(-3.638)
Leverage (t-1)	-.283***	-.48***	-1.415***	-.276***	-.468***	-1.369***
	(-21.617)	(-18.998)	(-17.273)	(-20.25)	(-17.606)	(-15.432)
INV GRADE RATED (t-1)	.033***	.026	.174**	.033***	.016	.043
	(2.808)	(1.11)	(2.215)	(3.031)	(.758)	(.696)
Listed (t-1)	.001	.002	.013	.009	.007	.023
	(.124)	(.218)	(.419)	(1.334)	(.547)	(.637)
Education	.078	.264**	.817***	.106*	.275***	.792***
	(1.414)	(2.504)	(2.683)	(1.96)	(2.728)	(2.703)
Unemployment	.008***	.01**	.024**	.008***	.01**	.023**
	(3.58)	(2.435)	(2.084)	(3.593)	(2.403)	(2.077)
Per capita income	.001	.001	.003	.001	.001	.004
	(-.03)	(.362)	(.434)	(.203)	(.653)	(.682)
Constant	.895***	.72***	.605***	.877***	.695***	.468**
	(28.308)	(11.384)	(2.584)	(29.411)	(11.619)	(2.103)
Observations	14336	14336	14328	14336	14336	14328
R-squared	0.121	0.1193	-	0.120	0.118	-
Pseudo R^2	-	-	0.096	-	-	0.0944
Year FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Model	OLS	OLS	Probit	OLS	OLS	Probit

Notes: Models 1-3 of this table show results from regressing debt concentration (HHI) on the interaction between the district-level measure of corruption and the credit rated variable (INV GRADE RATED). Models 4-6 show results from regressing debt concentration (HHI) on the interaction between the district level measure of corruption and the listed variable (Listed). Table 1 presents full definition and measurement details of all variables. Standard errors clustered at the state-year level. Significance at the 10%, 5% and 1% levels is represented by *, **, and ***, respectively.

Table 13 The effect of corruption on individual debt instruments

Panel A

	(1) CP	(2) RC	(3) TL	(4) SeniorB&N	(5) SubB&N	(6) CL	(7) OtherB
DISTRICT COR	.489***	-.011	-2.063***	1.605**	-1.438***	1.731***	-.266
	(3.101)	(-.015)	(-3.039)	(2.348)	(-3.718)	(3.729)	(-1.247)
INV GRADE RATED (t-1)	7.328***	-8.081***	-10.18***	18.451***	-6.628***	-2.237***	.94*
	(14.165)	(-10.075)	(-11.643)	(13.663)	(-9.896)	(-4.017)	(1.802)
Listed (t-1)	.272***	-.257	.112	.059	.884**	-1.222**	-.003
	(4.46)	(-.385)	(.151)	(.074)	(2.162)	(-2.49)	(-.008)
Constant	7.358***	48.777***	34.634***	8.486**	-14.403***	11.681***	2.759**
	(9.182)	(15.078)	(9.554)	(2.107)	(-6.341)	(5.256)	(2.023)
Observations	14336	14336	14336	14336	14336	14336	14336
R-squared	.158	.154	.104	.241	.109	.134	.025
Control Variables	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

Panel B

	(1) CP	(2) RC	(3) TL	(4) SeniorB&N	(5) SubB&N	(6) CL	(7) OtherB
DISTRICT COR	1.604***	.473	-1.374***	1.286*	-1.272***	.687**	-.025
	(3.08)	(1.099)	(-2.778)	(1.775)	(-3.817)	(2.362)	(-.128)
INV GRADE RATED (t-1)	7.069***	-7.9***	-10.148***	18.389***	-7.157***	-1.713***	1.03*
	(12.489)	(-8.821)	(-11.094)	(12.663)	(-9.885)	(-2.944)	(1.833)
*DISTRICT COR * INV GRADE RATED (t-1)*	1.594***	.428	1.2	1.178*	.344	3.472***	.331
	(3.045)	(.431)	(1.334)	(1.653)	(.833)	(4.892)	(.944)
Constant	7.191***	49.774***	34.156***	8.667**	-15.88***	12.151***	3.1**
	(8.3)	(14.638)	(9.18)	(2.05)	(-6.601)	(5.266)	(2.154)
Observations	13386	13386	13386	13386	13386	13386	13386
R-squared	.163	.156	.102	.239	.11	.139	.026
Control Variables	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

Panel C

	(1) CP	(2) RC	(3) TL	(4) SeniorB&N	(5) SubB&N	(6) CL	(7) OtherB
DISTRICT COR	.119	3.935	-1.332	.23	-1.21*	-1.586*	-.318
	(1.054)	(1.433)	(-.976)	(.086)	(-1.881)	(-1.684)	(-.677)
Listed (t-1)	.483**	.692	.288	-.272	.939**	-2.02***	-.015
	(2.575)	(.834)	(.352)	(-.272)	(2.133)	(-3.686)	(-.045)
*DISTRICT COR *Listed (t-1)*	.185**	-5.171*	-.959	1.802	-.298	4.347***	.068
	(2.179)	(-1.955)	(-.597)	(.553)	(-.374)	(4.149)	(.134)
Constant	7.415***	48.166***	34.52***	8.699**	-14.438***	12.194***	2.767**
	(9.309)	(14.817)	(9.491)	(2.152)	(-6.345)	(5.494)	(2.022)
Observations	14336	14336	14336	14336	14336	14336	14336
R-squared	.158	.154	.104	.241	.109	.135	.025
Control Variables	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES

Notes: Panel A of Table 13 shows results from regressing debt instruments on district-level public corruption. As dependent variables we use the following debt instruments: Commercial paper over total debt (Model 1), revolving credit over total debt (Model 2), term loans over total debt (Model 3), senior bonds and notes over total debt (Model 4), subordinate bonds and notes over total debt (Model 5), capital leases over total debt (Model 6), and other borrowing over total debt (Model 7). In Panel B we repeat this exercise by interacting our local public corruption variable (DISTRICT COR) with the investment grade rated variable (INV GRADE RATED), while in Panel C we interact corruption (DISTRICT COR) with listed variable (Listed). Table 1 presents full definition and measurement details of all variables. Standard errors clustered at the state-year level. Significance at the 10%, 5% and 1% levels is represented by *, **, and ***, respectively.

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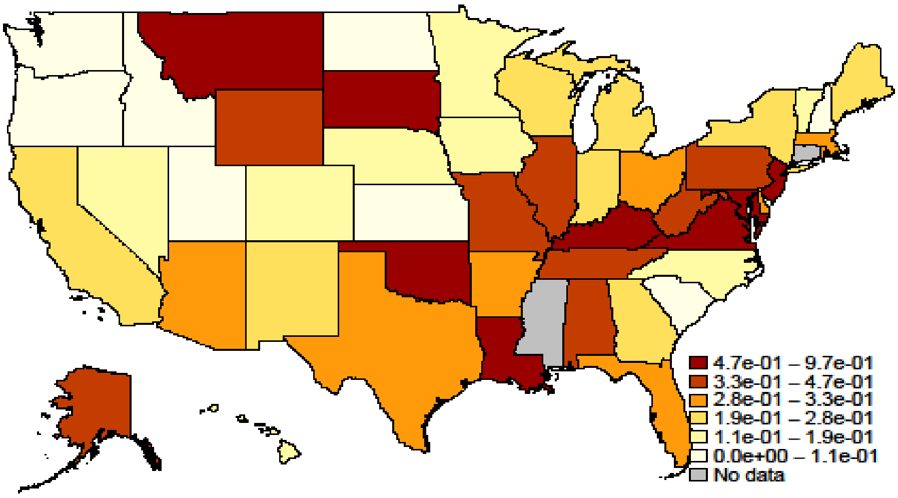

Fig 1. *A map of the median corruption conviction rate by state from 2002-2016.*

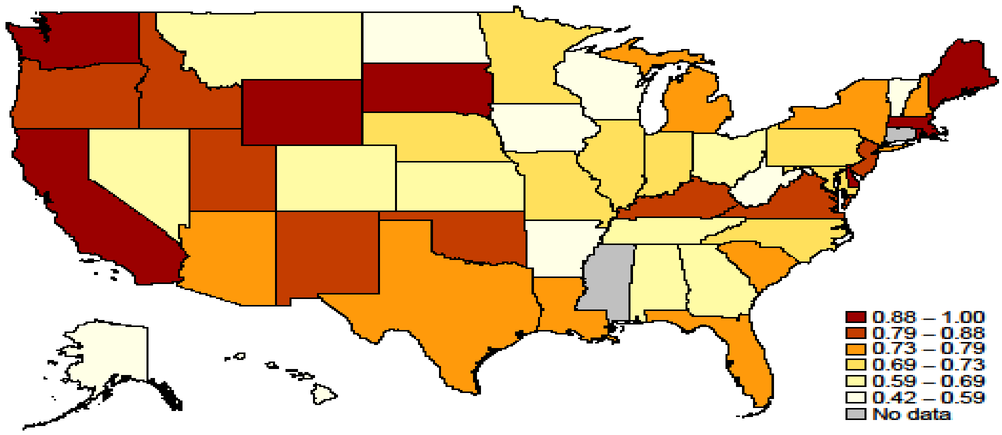

Fig 2. *A map of the median debt concentration index (HHI Index) by state from 2002-2016.*

Internet Appendix for "Local Public Corruption and Corporate Debt Concentration: Evidence from US firms."

This Internet Appendix provides and discusses the results of some robustness tests that we briefly discuss but do not tabulate in our paper titled "Local Public Corruption and Corporate Debt Concentration: Evidence from US firms."

IA.1 Alternative perception-based conviction measures

Although the conviction-based measures that we employ in our main analysis display several advantages, there is criticism that these measures gauge only the level of unearthed corruption (Goel & Nelson 2011). For example, corruption-related convictions are contemporaneous as there is an inherent delay from the actual time that the corruption-related crime takes place (Smith 2016). Consequently, as a robustness check, we employ two perception-based measures that capture aspects of public corruption that the conviction-based measures may not reflect. We employ *i)* the illegal corruption perception proxy developed by Dincer & Johnston (2015) from a survey conducted in 2014 on reporters covering corruption-related crimes, and *ii)* the corruption perception index by Boylan & Long (2003), which is based on the feedback from a survey of state house reporters about the level of public corruption in each state.

We estimate a 2SLS IV model to address endogeneity concerns in the use of the two alternative measures of corruption as our main independent variables. We employ two instrumental variables to perform the analysis: i) state-level capital isolation *(CAPIS1920)*, and ii) an *FOIA* dummy variable *(FOIA)*. The findings from the 2SLS models are reported in Tables IA.1 and IA.2, respectively.

[Insert Tables IA.1 and IA.2 around here]

Table IA.1 presents the findings from employing the Boylan and Long (2003) corruption perception index (BL) as our key variable of interest. In the lower part of Table IA.1, first stage results are reported, where the instrumental variables (*CAPIS1920* and *FOIA*) exert a negative and significant effect at the 1% level on the perception-based measure *(BL)*. The upper part of Table IA.1 presents the second stage results. We find that the instrumented perception-based variable (Pred BL) has a negative and significant effect at the 1% level on debt concentration in most of the models of Table IA.1. Next, we perform a similar exercise by employing the Dincer & Johnston (2015) corruption perception index (DJ). The results are reported in Table IA.2. In the first stage estimations (lower part of Table IA.2), we find that both instruments have a negative and significant effect at the 1% level on the corruption perception index (DJ). The second stage results suggest that the instrumented illegal corruption perception index (Pred DJ) exert a negative and significant effect at the 1% level on the two proxies of debt concentration. Overall, we find strong support for our ***H1B*** hypothesis on the negative association between local public corruption and debt concentration.

References (that are not cited in the manuscript)

Goel, R.K., Nelson, M.A., 2011. Measures of corruption and determinants of US corruption. Economics of Governance 12, 155-176

Dincer, O., Johnston, M., 2015. Measuring Illegal and Legal Corruption in American States: Some Results from the Edmond J. Safra Center for Ethics Corruption in America Survey. Edmond J. Safra Working Papers 58

Table IA.1 Alternative perception-based measure of corruption (Boylan and Long (BL) index)

	(1) HHI Index	(2) HHI Index	(3) HHI Index	(4) HHI DUM	(5) HHI DUM	(6) HHI DUM	(7) HHI DUM	(8) HHI DUM	(9) HHI DUM
Pred BL	-.127***	-.417***	-.507***	-.344***	-.886***	-1.144***	-.943***	-2.596***	-3.352***
	(-2.584)	(-3.579)	(-4.766)	(-3.778)	(-3.769)	(-5.642)	(-3.704)	(-3.879)	(-5.687)
Market-to-book (t-1)	.013***	.006***	.006***	.025***	.012***	.012***	.084***	.049**	.048**
	(4.777)	(2.798)	(2.79)	(5.268)	(3.108)	(3.09)	(8.573)	(2.315)	(2.268)
EBITDA (t-1)	-.028*	.012	.015	-.043	-.027	-.018	-.12	-.045	-.023
	(-1.921)	(.353)	(.432)	(-1.446)	(-.381)	(-.258)	(-1.386)	(-.224)	(-.116)
PP&E (t-1)	-.111***	-.096***	-.098***	-.22***	-.231***	-.237***	-.624***	-.716***	-.726***
	(-7.499)	(-4.189)	(-4.27)	(-8.024)	(-4.873)	(-5.017)	(-7.85)	(-5.173)	(-5.31)
Modified Altman-Z (t-1)	-.001	-.001	-.001	0	-.001	-.001	-.002	-.003	-.003
	(-.775)	(-.678)	(-.701)	(.151)	(-.198)	(-.227)	(-.581)	(-.466)	(-.514)
Ln(sales) (t-1)	0	.003	.004	-.009	.006	.007	-.015	.028	.03
	(.136)	(.53)	(.563)	(-1.345)	(.488)	(.535)	(-.729)	(.792)	(.84)
Ln(size) (t-1)	-.014***	-.022***	-.022***	-.024***	-.041***	-.042***	-.076***	-.126***	-.126***
	(-4)	(-3.485)	(-3.449)	(-3.364)	(-3.486)	(-3.426)	(-3.65)	(-3.565)	(-3.493)
Leverage (t-1)	-.275***	-.299***	-.299***	-.465***	-.547***	-.545***	-1.354***	-1.629***	-1.604***
	(-20.177)	(-12.355)	(-12.269)	(-17.555)	(-11.434)	(-11.369)	(-15.473)	(-10.718)	(-10.694)
Rated (t-1)	.036***	.099***	.1***	.025	.088*	.093**	.068	.246*	.258**
	(3.28)	(5.411)	(5.573)	(1.136)	(1.914)	(2.032)	(1.078)	(1.857)	(1.971)
Listed (t-1)	.001	.007	.005	.001	.006	.002	.007	.018	.008
	(.201)	(.511)	(.419)	(.047)	(.243)	(.099)	(.212)	(.273)	(.126)
Education	.035	.247	.254	.074	.705**	.726**	.225	2.066**	2.133**
	(.556)	(1.521)	(1.482)	(.603)	(2.358)	(2.184)	(.645)	(2.384)	(2.219)
Unemployment	.014***	.021***	.023***	.026***	.019	.026**	.069***	.06	.081**
	(4.028)	(3.39)	(3.654)	(4.26)	(1.492)	(1.982)	(4.116)	(1.625)	(2.145)
First stage									
CAPIS1920	-.397***		-.239***	-.397***		-.239***	-.397***		-.239***
	(-9.977)		(-4.487)	(-9.977)		(-4.487)	(-9.977)		(-4.487)
FOIA		-.101***	-.064***		-.101***	-.064***		-.101***	-.064***
		(-6.755)	(-3.949)		(-6.755)	(-3.949)		(-6.755)	(-3.949)
Observations	14254	3594	3594	14254	3594	3594	14246	3488	3488
R-squared	.033	.017	.010	.042	.029	.019	-	-	-
UIT p-value	.000	.000	.000	.000	.000	.000	-	-	-
WIT	94.172	44.102	32.020	94.172	44.102	32.020	-	-	-
With critical value	16.38	16.38	19.93	16.38	16.38	19.93	-	-	-
Hansen j p-value	-	-	.243	-	-	.100	-	-	-
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Model	2sls	2sls	2sls	2sls	2sls	2sls	Probit 2sls	Probit 2sls	Probit 2sls

Notes: This table shows the results from regressing HHI (debt concentration) on the predicted alternative corruption (BL) after controlling for firm- and state-level characteristics. The instruments of these 2SLS-IV estimations are the state-capital isolation in 1920 (CAPIS1920) and the transition to strong Freedom of Information Act (FOIA) laws in each state. The CAPIS1920 variable ranges from zero to one with lower values representing a more isolated state-capital. FOIA is a dummy variable that takes the value of one for the years beyond the seventh year after a state has transitioned from weak to strong freedom of information act (FOIA) laws while it takes the value of zero up to the seventh year after the transition. The instrument is constructed only for those states that experienced a weak to strong transition in terms of FOIA laws and thus, in these estimations, our sample is restricted to these states only. UIT is the under-identification LM test by Kleibergen and Paap, WIT is the Wald F-statistic of the weak identification test, which must be higher than its critical value to reject the null. Table 1 presents full definition and measurement details of all variables. Standard errors clustered at the state-year level. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***, respectively.

Table IA.2 Alternative perception-based measure of corruption (Dincer and Johnston (DJ) index)

	(1) HHI Index	(2) HHI Index	(3) HHI Index	(4) HHI DUM	(5) HHI DUM	(6) HHI DUM	(7) HHI DUM	(8) HHI DUM	(9) HHI DUM
Pred DJ	-.008***	-.028***	-.034***	-.023***	-.059***	-.076***	-.063***	-.173***	-.223***
	(-2.584)	(-3.579)	(-4.766)	(-3.778)	(-3.769)	(-5.642)	(-3.704)	(-3.879)	(-5.687)
Market-to-book (t-1)	.013***	.006***	.006***	.025***	.012***	.012***	.084***	.049**	.048**
	(4.777)	(2.798)	(2.79)	(5.268)	(3.108)	(3.09)	(8.573)	(2.315)	(2.268)
EBITDA (t-1)	-.028*	.012	.015	-.043	-.027	-.018	-.12	-.045	-.023
	(-1.921)	(.353)	(.432)	(-1.446)	(-.381)	(-.258)	(-1.386)	(-.224)	(-.116)
PP&E (t-1)	-.111***	-.096***	-.098***	-.22***	-.231***	-.237***	-.624***	-.716***	-.726***
	(-7.499)	(-4.189)	(-4.27)	(-8.024)	(-4.873)	(-5.017)	(-7.85)	(-5.173)	(-5.31)
Modified Altman-Z (t-1)	-.001	-.001	-.001	0	-.001	-.001	-.002	-.003	-.003
	(-.775)	(-.678)	(-.701)	(.151)	(-.198)	(-.227)	(-.581)	(-.466)	(-.514)
Ln(sales) (t-1)	0	.003	.004	-.009	.006	.007	-.015	.028	.03
	(.136)	(.53)	(.563)	(-1.345)	(.488)	(.535)	(-.729)	(.792)	(.84)
Ln(size) (t-1)	-.014***	-.022***	-.022***	-.024***	-.041***	-.042***	-.076***	-.126***	-.126***
	(-4)	(-3.485)	(-3.449)	(-3.364)	(-3.486)	(-3.426)	(-3.65)	(-3.565)	(-3.493)
Leverage (t-1)	-.275***	-.299***	-.299***	-.465***	-.547***	-.545***	-1.354***	-1.629***	-1.604***
	(-20.177)	(-12.355)	(-12.269)	(-17.555)	(-11.434)	(-11.369)	(-15.473)	(-10.718)	(-10.694)
Rated (t-1)	.036***	.099***	.1***	.025	.088*	.093**	.068	.246*	.258**
	(3.28)	(5.411)	(5.573)	(1.136)	(1.914)	(2.032)	(1.078)	(1.857)	(1.971)
Listed (t-1)	.001	.007	.005	.001	.006	.002	.007	.018	.008
	(.201)	(.511)	(.419)	(.047)	(.243)	(.099)	(.212)	(.273)	(.126)
Education	.035	.247	.254	.074	.705**	.726**	.225	2.066**	2.133**
	(.556)	(1.521)	(1.482)	(.603)	(2.358)	(2.184)	(.645)	(2.384)	(2.219)
Unemployment	.014***	.021***	.023***	.026***	.019	.026**	.069***	.06	.081**
	(4.028)	(3.39)	(3.654)	(4.26)	(1.492)	(1.982)	(4.116)	(1.625)	(2.145)
Per capita income	.001	.004	.003	.001	.006	.006	.004	.018	.017
	(.204)	(.685)	(.629)	(.511)	(.719)	(.618)	(.541)	(.721)	(.614)
First stage									
CAPIS1920	-5.96***		-3.582***	-5.96***		-3.582***	-5.96***		-3.582***
	(-9.977)		(-4.487)	(-9.977)		(-4.487)	(-9.977)		(-4.487)
FOIA		-1.52***	-.957***		-1.52***	-.957***		-1.52***	-.957***
		(-6.755)	(-3.949)		(-6.755)	(-3.949)		(-6.755)	(-3.949)
							(17.865)	(.801)	(.443)
Observations	14254	3594	3594	14254	3594	3594	14246	3488	3488
R-squared	.032	0.017	.011	.042	.029	.019	-	-	-
UIT p-value	.000	.000	.000	.000	.000	.000	-	-	-
WIT	99.272	43.961	31.987	99.272	43.961	31.987	-	-	-
With critical value	16.38	16.38	19.93	16.38	16.38	19.93	-	-	-
Hansen j p-value	-	-	.234	-	-	.100	-	-	-
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Model	2sls	2sls	2sls	2sls	2sls	2sls	Probit 2sls	Probit 2sls	Probit 2sls

Notes: This table shows the results from regressing HHI (debt concentration) on the predicted alternative corruption (DJ) after controlling for firm- and state-level characteristics. The instruments of these 2SLS-IV estimations are the state-capital isolation in 1920 (CAPIS1920) and the transition to strong Freedom of Information Act (FOIA) laws in each state. The CAPIS1920 variable ranges from zero to one with lower values representing a more isolated state-capital. FOIA is a dummy variable that takes the value of one for the years beyond the seventh year after a state has transitioned from weak to strong freedom of information act (FOIA) laws while it takes the value of zero up to the seventh year after the transition. The instrument is constructed only for those states that experienced a weak to strong transition in terms of FOIA laws and thus, in these estimations, our sample is restricted to these states only. UIT is the under-identification LM test by Kleibergen and Paap, WIT is the Wald F-statistic of the weak identification test, which must be higher than its critical value to reject the null. Table 1 presents full definition and measurement details of all variables. Standard errors clustered at the state-year level. Significance at the 10%, 5%, and 1% levels is represented by *, **, and ***, respectively.