Greasing A Hollow Wheel: Political Corruption and Innovation Strategy

Hesham Ali

Business School

University of Nottingham

Xin Deng

Alliance Manchester Business School

University of Manchester

Mohamed Mekhaimer

Business School

St. John Fisher University

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Abstract:

We examine the potential impacts of local political corruption on innovation strategies, using the number of corruption convictions at the federal juridical district level. Consistent with the "greasing the wheel" hypothesis, we show that corruption can drive firms toward exploratory rather than exploitative innovations. Corruption also broadens firms' innovation scope while reducing their focus on depth, leading to a greater reliance on new rather than known patents. Our results identify lobbying efforts and government contracts as key channels through which corruption fosters riskier innovation strategies. However, we also find that political corruption is negatively associated with innovation efficiency, market value, and the development of breakthrough innovations, suggesting that corruption greases a hollow wheel. Our results are robust to alternative model specifications, endogeneity concerns, and different measures of local corruption and innovation strategies.

Keywords: Local political corruption; Innovation strategy; Exploratory innovation; Exploitative innovation.

JEL: D72, G31, G38, O31, O32, O38

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1. Introduction

Political corruption is defined as the abuse of public office for private gain (e.g., Jha et al., 2021). Previous literature suggests that political corruption negatively affects economic growth by interfering with resource allocation and distorting the regulatory frameworks (Shleifer and Vishny, 1993; Jain, 2001; Svensson, 2005; Dal Bo and Rossi, 2007; Stulz, 2005; Smith, 2016; Fisman and Golden, 2017). However, the evidence of corruption's impacts on economic growth is inconclusive. Other studies argue that firms can benefit from political corruption by bypassing bureaucratic obstacles (Leff, 1964; Huntington, 1968).

In this study, we examine the potential impact of political corruption on a firm's innovation strategy. Despite the recent findings on the relationship between political corruption and innovation (e.g., Ellis, Smith, and Roger, 2020; Huang and Yuan, 2021; Ovtchinnikov et al., 2020), little is known about how political corruption may influence a firm's innovation strategy. Earlier literature argues that firms can prioritize one of two distinct innovation strategies: exploratory or exploitative (Gao et al., 2018; McGrath, 2001; Benner and Tushman, 2002; Smith and Tushman, 2005; Manso, 2011). These two strategies offer alternative routes to competitive advantage and market growth but compete for scarce resources (March, 1991). Hence, firms should consider which strategy fits their unique environment, balancing the trade-offs between the potential for groundbreaking innovations and the optimization of existing capabilities.

Exploratory innovation emphasizes developing novel ideas and technologies to enter new and emerging markets. It typically diverges from established knowledge paths, focusing on radical innovations to create new products, services, and market niches. This strategy involves taking risks and learning through exploration, which, despite the inherent uncertainty, can lead to substantial rewards with industry-redefining products or services (Lee et al., 2018). However, a heavy emphasis on exploration can come at the cost of excessive resources and insufficient rewards, resulting in too many underdeveloped ideas and too little distinctive competence (March, 1991; Levinthal and March, 1993; Greve, 2007; Lavie et al., 2010).

Contrarily, exploitative innovation builds on a firm's existing knowledge and expertise, aiming to enhance and optimize current products, processes, or services. This approach aligns with incremental innovation and caters to existing market demands. By delivering improved products and services, firms can enjoy immediate returns, minimized risks, and capitalize on existing technologies (Benner and Tushman, 2003). However, over-reliance on exploiting known knowledge might dampen a firm's motivation to explore new domains and possibly hinder its adaptability to changing circumstances (Greve, 2007).[2]

Building on previous literature, we propose two competing hypotheses for the relationship between political corruption and innovation strategy. Our first hypothesis, the **shielding hypothesis,** suggests that the uncertainty about government regulation, resource allocation, and government officials' ex-post possible rent-seeking reduces the ex-ante incentives to pursue radical innovations and adopt exploratory innovation strategy (Huang and Yuan, 2021; Murphy, Shleifer, and Vishny, 1991; Shleifer and Vishny, 1993). Consistent with this argument, previous studies find that firms operating in a corrupted environment tend to alter their investment strategy (Wei 2000; Rodriguez, Uhlenbruck, and Eden 2005), produce less transparent disclosure (Durnev and Fauver, 2011; Jha et al., 2021; Stulz, 2005), and reduce their cash holding but increase debt-holding (Caprio, Faccio, and McConnell 2013; Smith 2016) to shield their assets and resources from local corruption.[3]

Recent innovation studies support this hypothesis. Ellis et al. (2021) and Huang and Yuan (2021) posit that the frequent interactions between innovators and corrupted government officials

[2] The primary distinguishing factor between exploitative and exploratory innovations lies in their novelty levels (Beck et al., 2016). Nevertheless, both exploitation and exploitation are essential for long-run adaptation (Gupta et al., 2006), where the former refines existing offerings, the latter aims to generate completely novel value propositions. Studies have conceptualized the relationship between exploitation and exploration either as two ends of a continuum or as an orthogonal choice (Gupta et al., 2006; Cho and Kim, 2017). He and Wong (2004) argue that given the fundamentally different logics that create tensions between exploration and exploitation, firms could benefit from maintaining a balance between the two activities as there is a synergistic effect between the two as well.

[3] Related to this argument, a thread of literature (Bronars and Deere, 1991; Matsa, 2010; Perotti and Spier, 1993) argues that firms strategically adjust their financial policies to navigate external pressures, such as labor unions. For example, Matsa, (2010) posits that firms may increase debt financing to pre-commit cash flow, reduce liquidity, and appear financially unstable, thereby sheltering their resources from labor unions.

could elevate the risk of extortion, increase firms' innovation costs, and reduce innovation efficiency. They show empirically that political corruption negatively affects innovation quantity and quality. Consistent with this view, our shielding hypothesis posits that political corruption discourages exploratory innovation while encouraging exploitative strategies. The shielding hypothesis assumes that the heightened uncertainty, risks of extortion, and resource inefficiencies driven by local corruption render high-risk, long-term innovation projects, instead prompting safer, incremental improvements that limit exposure to corruption.

In contrast, our second hypothesis, the **greasing the wheel hypothesis**, argues that political corruption may facilitate risk-taking and encourage more exploratory rather than exploitative innovation. Previous studies (e.g., Leff, 1964; Huntington, 1968; Vial and Hanoteau, 2010; Mironov, 2015) suggest that corruption might expedite processes within stringently bureaucratic systems by enabling firms to circumvent regulatory impediments and access otherwise unattainable resources. Various studies show that developing strong connections with government officials can benefit firms by receiving preferential access to government contracts (Cordis, and Warren 2014; Fisman, 2001; Liu et al., 2014), bailout treatment (e.g., Faccio, Masulis, and McConnell, 2006), favorable funding terms (Claessens, Feijen, and Laeven, 2008; Duchin and Sosyura, 2012; Tahoun, 2014) and increase firm valuation (Goldman, Rocholl, and So, 2009).

With access to otherwise restricted resources, including funding, information, or technologies, local corruption may increase firms' incentives to innovate and explore new areas rather than exploiting current products, processes, or services. This setting may encourage firms to strategically direct their innovation efforts towards exploratory innovation, where firms invest in new ideas, technologies, and markets to adapt to rapidly changing business conditions (Cheung, Rau, and Stouraitis, 2012; Jansen et al., 2006; McGrath, 2001; Sidhu et al., 2004). By mitigating bureaucratic inefficiencies through informal networks, corruption may lower the barriers to entry for radical innovation projects, fostering a strategic shift toward exploratory innovation.

We create a comprehensive sample of 26,086 observations of 3,160 U.S. firms spanning 1990 to 2019 to explore the impact of corruption on different innovation strategies. Following previous literature (Ellis et al., 2020; Glaeser and Saks; 2006; Butler, Fauver, and Mortal, 2009; Smith, 2016), we measure local corruption as the annual number of corruption convictions of public officials in each federal judicial district. Our proxy for local corruption assumes that firms headquartered in districts with higher levels of convictions experience a greater level of local corruption (Dass, Nanda, and Xiao, 2016; Ellis, Smith, and White, 2021).

We start our analysis by validating previous findings on the relationship between political corruption and innovation output. Consistent with earlier literature (Ellis, Smith, and White, 2021; Huang and Yuan, 2021), we find corroborating evidence of the negative relationship between political corruption and overall innovation output measured by the logarithm of one plus the total number of granted patents. These results confirm that local corruption hinders innovation and reduces overall innovation activities within firms. However, it does not offer any new insight into the possible impact of local corruption on innovation strategies.

To test our competing hypotheses, we define exploratory (exploitative) innovation as the ratio of a firm's number of exploratory (exploitative) patents over the total number of patent applications. Our baseline results reveal that corruption is positively associated with exploratory innovation yet negatively related to exploitative innovation. The results are consistent with the "greasing-the-wheel" hypothesis, suggesting that local corruption increases the firm's ex-ante incentives to pursue exploratory innovation rather than optimizing and refining existing products, processes, or services through exploitative innovation. These findings are robust to alternative model specifications, additional controls, different measures of local corruption, and innovation strategies. We further find that local corruption encourages firms to expand (scale down) their innovation scope (depth) and cite (neglect) new (known) patents more.

To consider possible explanations for our findings, we investigate the channel through which local corruption may alter a firm's innovation strategy. One possible channel is that firms in corrupted districts may leverage their political connections to secure additional government contracts, enabling them to engage more in exploratory innovation, which involves long-term investment relative to exploitative innovation. Previous literature shows that firms maintaining strong connections with government officials receive various forms of preferential treatment, including better funding opportunities, loan terms, and the likelihood of federal investment (Cohen and Malloy, 2016; Cordis and Warren, 2014; Faccio, Masulis, and McConnell, 2006; Tahoun, 2014). For example, Duchin and Sosyura (2012) show that politically connected firms that engage in lobbying expenditures and campaign contributions are more likely to access federal investment funds than non-connected firms. If this hypothesis applies to innovation strategies, we should find that connected firms in more corrupt districts are more likely to pursue exploratory innovation and work with the government.

Our results confirm this channel. Using firm-level corporate lobbying expenditure, we find that the interaction terms between an indicator variable of lobbying efforts and political corruption are positively (or negatively) related to the number of exploratory (exploitative) innovations. We further find that the increase (decrease) in the number of exploratory (exploitative) innovations is exclusive to the firms located in corrupted districts where the government is a major customer. The previous findings confirm that firms in corrupt districts with strong government connections can afford to pursue exploratory innovation strategy.

Our baseline results suggest that political corruption might promote exploratory innovation through access to government funding. However, whether such exploratory innovations contribute to firm value, enhance innovation efficiency, or represent significant breakthroughs remains unclear. Interestingly, our additional results show robust evidence that political corruption is negatively associated with innovation efficiency, market value of innovation, and the development of breakthrough innovations. These results are consistent with the findings of Duchin and Sosyura (2012), who also find that while politically connected firms are more likely to receive government funds, they tend to underperform unconnected recipients on stock-based and accounting-based performance measures. Our findings concur with these findings, showing that firms in corrupt districts are more likely to assume an exploratory innovation strategy even if such a strategy does not enhance shareholder value and innovation efficiency or lead to breakthrough innovation.

Our results may suffer from endogeneity as the decision to locate the firm's headquarter in a specific district might be driven by various factors, including potential support for certain innovation strategies. To address possible endogeneity concerns, we adopt an instrumental variable approach. We follow political corruption literature (Dass et al., 2016; Huang and Yuan, 2021; Jayakody et al., 2023) and use two instrumental variables: the number of days a person needs to be resident in a state to vote and the age of the state's constitution. We assume that the longer the days a citizen needs to reside in a state to vote, the harder it is for citizens to influence incumbent politicians (Huang and Yuan, 2021; Ucar & Staer, 2020). Moreover, the quality of the state's current constitution is highly correlated with its age, and hence, the older the state constitution, the lower the perceived corruption in a given stat (Dass et al., 2016; Johnson et al., 2011). These results confirm our baseline findings, suggesting that endogeneity is unlikely to drive our results. Using the instrumental variable approach, we show that political corruption and exploratory (exploitative) innovation strategy are positively (negatively) related.

This study provides various contributions to extant literature. First, it adds to the growing literature examining the impact of political corruption on firm policies (Butler et al., 2019; Smith, 2016; Ellis et al. 2021; Jha et al., 2021; Tahoun, 2014). Our findings provide novel evidence that political corruption can drive a firm's innovation strategy toward exploratory rather than exploitative innovations. Further results suggest that lobbying efforts and strong business relations with the government drive this tendency toward exploratory innovation. We show that firms that engage in lobbying efforts and contract with the government tend to have a higher possibility of producing more (less) exploratory (exploitative) innovation. These findings are also related to the growing literature that investigates the role of political connections and lobbying in shaping firms' outcomes (Khwaja and Mian, 2005; Faccio, Masulis, and McConnell, 2006; Goldman, Rocholl, and So, 2009; Duchin and Sosyura, 2012).

Our findings also contribute to the literature that examines the impact of political corruption and activism on innovation (Ellis et al., 2020; Huang and Yan, 2021; Ovtchinnikov et al., 2020). Our preliminary analysis confirms previous findings that political corruption negatively affects the quantity and quality of innovation. Further, we show that firms that reside in a corrupted district are more likely to have a lower economic value of innovation, innovation efficiency, or develop breakthrough innovation. However, we present robust evidence that political corruption may encourage firms to explore innovations and expand their scope rather than increasing their innovation depth or pursuing known innovation.

Our works provide important insights for executives and policymakers about the impact of political corruption on firms' innovation strategy. Our findings suggest that policymakers should adopt more effective policies to curb corruption without hindering risk-taking and exploratory innovation. Our results also suggest that firms that plan to engage in exploratory innovation should actively participate in anti-corruption measures while strengthening government relations to mitigate the negative impact of local corruption. Moreover, innovative firms must emphasize the economic outcomes and possible efficiency of exploratory innovation in corrupted districts.

2. Data and variable definitions

We compile several data sources to construct our main sample. We first draw accounting data from the Compustat-CRSP Merged database covering all the listed firms in the U.S. from 1990 to 2019. Following Huang and Yuan (2021), Financial firms (SIC codes 6000-6999), utilities (SIC codes 4900-4999), public sectors (SIC 9000-9999), and firms with headquarters outside the US are excluded from the sample. The data on public corruption convictions are obtained from the report to Congress by the U.S. DOJ's Public Integrity Section (PIN). We merge the corruption data with the Compustat-CRSP Merged database based on each firm's historical headquarters location. Since the database only provides a firm's current headquarters location, we obtain data on historical headquarters locations from Securities and Exchange Commission (SEC) filings.[4] Moreover, to address missing location data from SEC filings and supplement the remaining Compustat current headquarters data, we utilize information from Jennings et al. (2017 & 2020).[5] Patent data is obtained from both Orbis Intellectual Property (Orbis IP hereafter) and Kogan et al. (2017). Following Gao et al. (2018), to include a firm in our sample, we require the firm to have at least one patent over the three-year period from year t-2 to year t. This selection criterion ensures our sample includes patent-intensive firms, making them more relevant to our research on innovation strategy.

2.1. Political corruption

Following previous literature, we use public officials' annual number of corruption convictions as our baseline measure of local corruption in each federal juridical district (Ellis et al., 2020; Jha et al., 2021; Nguyen et al., 2020; Qian et al., 2023; Smith, 2016). This is because variation within the state (i.e., at district-level) elevates the power of our analysis as court districts within a state are exposed to same regulations and similar economic environment but have different corruption magnitude. As mentioned previously, we begin by collecting firms' historical location data (i.e., headquartered state for each firm and its headquarters' ZIP code) from SEC's EDGAR and supplement any missing data from Jennings et al. (2017 & 2020). Firms do not explicitly disclose the federal district in which they are located. Therefore, we then convert each firm headquarters' ZIP code to its respective Federal Information Processing Standard (FIPS) code

[4] The data are obtained from the Notre Dame Software Repository for Accounting and Finance (SRAF). More information can be found: https://sraf.nd.edu/sec-edgar-data/.

[5] The electronic SEC filings began in 1993, while the data from Jennings et al. (2017 & 2020) in 1990. The data is accessible through Joshua A. Lee website. Our analysis extends through 2019 for two primary reasons. First, it typically takes two to three years for a patent to be granted; following Dass et al. (2017), when assigning patents to their application years, it is prudent to exclude the last three to four years of patent data to minimize truncation bias. Second, concluding the sample period before the pandemic helps mitigate potential distortions from COVID-19 on firms' innovation strategies.

using data from the U.S. Department of Housing and Urban Development.[6] Then, we match each firm's FIPS codes to a federal judicial district using Law Enforcement Agency identifiers crosswalk file.[7] Following the well-established literature on political corruption, we assume that areas with a higher number of corruption convictions are associated with a higher prevalence of corrupt practices since the judicial system maintains the same level of vigilance in prosecuting corruption cases across states (Butler et al., 2009; Dass et al., 2016; Ellis et al., 2020; Jha et al., 2021; Smith, 2016). Consistent with Glaeser and Saks (2006) and Xie et al. (2023), we argue that as the majority of corruption cases are prosecuted by the federal judicial system, the prosecutorial standards and enforcement efforts are alike across states.

Following Glaeser and Saks (2006) and Ellis et al. (2020), we standardized the corruption proxy (*CORRUPT*) by dividing the trailing sum of convictions over a specified period, scaled by the 5-year average population (per 100,000 people) of each federal juridical district. We collect population data from the Bureau of Economic Analysis. Since the Bureau of Economic Analysis only compiles population data at the state and county levels (not at the district level), we aggregate the county-level population to the district level. Furthermore, in line with Ellis et al. (2020), we rank each state according to its trailing 5-year conviction rate to generate an alternative corruption proxy (*CORRUPT_RANK*), where 100% represents the most corrupt state.

2.2. Innovation strategy

We evaluate the impact of local political corruption on the innovative strategy by analyzing patent data. Patents are one of the most recognized innovation indicators because they are less influenced by individual or subjective biases (Bronzini and Piselli, 2016). Additionally, patent data offers some insight into the quality of an innovation, as each patented invention undergoes scrutiny by experts assessing its uniqueness and practicality. While only a (random) subset of all inventions

[6] The data is collected at https://www.huduser.gov/portal/datasets/usps_crosswalk.html.

[7] The data could be accessed via https://www.icpsr.umich.edu/web/ICPSR/studies/35158.

gets patented, Griliches (1990) proposes that patenting activity be viewed as a marker of the growth in economically valuable knowledge, and thus, patents can provide a sound method for gauging inventive efforts.

To measure innovation strategy, we examine a firm's existing expertise and determine the extent to which its innovation efforts deviate from or align with its established knowledge base (Benner and Tushman, 2002). According to prior research (e.g., Benner and Tushman, 2002, 2003; Custódio et al., 2019; Levine et al., 2020), a firm's existing knowledge is drawn from two sources: patents filed within the past five years and the patents cited by those filings. Each patent abstract includes citations to earlier patents, known as "prior art," which lay the foundation for the current patent. According to Benner and Tushman (2002), a firm's existing knowledge includes patents that are repeatedly cited or self-cited (i.e., a firm's own patents). A patent is classified as exploratory if at least 60% of its backward citations - references to earlier patents – are unrelate to the firm's previous patents or those cited by the firm's other patents within the last five years (Custódio et al., 2019; Levine et al., 2020; He and Hirshleifer, 2022). Exploratory patents reflect the extent to which a firm engages in innovative efforts that diverge from its previous inventions and existing search trajectories (Levine et al., 2020). Conversely, a patent is defined as exploitative if at least 60% of its backward citations relate to the firm's prior patents or to those cited by its other patents over the past five years. Exploitative patents indicate the degree to which a firm focuses on innovations aligned with its past inventions and existing search trajectories (Levine et al., 2020).

We then construct measures of exploratory (*EXPLORE*) and exploitative innovations (*EXPLOIT*), following established literature (e.g., Balsmeier et al., 2017; Gao et al., 2018), as the ratio of a firm's number of exploratory (exploitative) patents to its total number of patent applications from year *t-2* to *t*. The percentage of exploratory (or exploitative) patents reflects whether a firm's innovation strategy is oriented toward exploring new (or known) technologies (Brav et al., 2018). Considering that the innovation process typically spans multiple years, we address the timing ambiguity in the patenting process relative to a firm's underlying exploratory activities by aggregating patents from years *t*-2 to *t*, following the methodology of Cornaggia et al. (2015) and Ellis et al. (2020). Specifically, our *EXPLORE* (*EXPLOIT*) metric is calculated as follows:

$$EXPLORE\ (EXPLOIT)_{i,t} = \frac{Exploratory\ Patents\ (Exploitative\ Patents)_{i,t-2\ -\ t}}{Total\ Patents_{i,t-2\ -\ t}}. \quad (1)$$

2.3. Empirical model

To investigate this relationship between political corruption and innovation strategy, we construct our baseline estimation model as follows:

$$INNOSTRATEGY_{i,t} = \alpha_0 + \beta CORRUPTION_{i,t-3} + \gamma CONTROLS_{i,t-3} + \varepsilon_{i,t} \quad (2)$$

where $INNOSTRATEGY$ denotes a firm's innovation search strategy (*EXPLORE* and *EXPLOIT*), as defined in in Section 2.2, for firm *i* in year *t*. (*CORRUPT*) is our key variable of interest, as discussed in Section 2.1, measured by the trailing sum of convictions over a rolling 5-year period, scaled by the rolling 5-year average population (per 100,000 people). In line with previous literature (e.g., Cornaggia et al., 2015; Gao et al., 2018; Ellis et al., 2020), *CONTROLS* is a set of variables known to influence a firm's innovation strategy.

Our control variables include, firm size (*SIZE*), R&D intensity (*R&D*), firm age (*AGE*), debts over total assets (*LEVERAGE*), Return on assets (*ROA*), property, plant and equipment (*PPE*), capital expenditures (*CAPEX*), Tobin's Q (*TOBINQ*), Kaplan and Zingales index (*KZINDEX*). We control for the growth opportunities faced by a firm (*SGROWTH*) and market competition using the raw score and squared value of the score of Herfindahl-Hirschman Index (*HHI*) and (*HHISQ*), respectively (Aghion et al., 2005). Finally, following prior literature, we control for total patent stock scaled by the total asset (*PTSTOCKS*). To calculate patent stock, we apply a constant depreciation rate (ρ) of 15% per year when calculating patent stock (e.g., Hall et al., 2005). We also include industry-by-year fixed effects to control for unobserved, time-variant heterogeneity across industries. The detailed definitions of all variables are summarized in Table 1A in the Appendix.

3. Empirical results

3.1. Summary statistics

Our final sample consists of 26,086 observations from 3,160 unique listed US firms spanning from 1990 to 2019. Figure 1 is a choropleth map showing the geographical distribution of political corruption across US federal judicial districts. The measure used is the average annual conviction rate for each juridical district from 1990 to 2019, with higher values (represented by darker colors) indicating higher levels of corruption. Similarly, in Figure 2, we use the average ratio of exploratory innovation (Panel A) and exploitative innovation (Panel B) for firms located in each district, also from 1990 to 2019. The figures suggest a slightly positive relationship between corruption and exploratory innovation but a negative association between corruption and exploitative innovation.

[Insert Figure 1 and Figure 2]

Table 2 presents the summary statistics of the variables used in our baseline analysis. The average value for our *INNO* measure is 2.661, while the mean values for *EXPLORE* and *EXPLOIT* are 0.639 and 0.292, respectively, indicating that, on average, approximately 63.9% of patents filed by firms in our sample are exploratory, and 29.2% are exploitative. The average value for our corruption measure is 1.309 with a median of 1.069. These statistics are consistent with those reported in prior studies (e.g., Ellis et al., 2020). Overall, the descriptive statistics for our sample firms align with those from previous research (e.g., He and Tian, 2013; Gao et al., 2018).

The low magnitudes of all pairwise correlation coefficients of our explanatory variables, as presented in Table 3, indicate that collinearity will not be an issue in our analysis.[8] Furthermore, Table 3 reveals that political corruption is negatively correlated with a firm's overall innovation and exploitative innovation but positively correlated with exploratory innovation.

[Insert Table 2 &Table 3]

[8] Our model's mean Variance Inflation Factor (VIF) is 3.26, suggesting no substantial collinearity issues.

3.2. Univariate analysis

We begin our analysis by reporting the univariate comparison of the innovation output, *INNO,* and our measures of innovation strategies *EXPLORE* and *EXPLOIT* for subsamples of low and high political corruption (based on the median value of *CORRUPT*). The univariate results in Table 4 provide preliminary evidence that, on average, firms in a relatively highly corrupt environment exhibit approximately 7.6% reduction in overall innovation, 4.2% higher exploratory innovation, and 8.2% lower exploitative innovation.[9] The results provide preliminary support for our second hypothesis, greasing the wheel, suggesting that firms in a relatively corrupt district have more incentives to explore new innovations rather than improvising current ones through exploitative innovation. However, univariate analysis may suffer from omitted variable bias and can be driven by other confounding factors.

[Table 4]

3.3. Baseline results

Tables 5 and 6 present our baseline results. In Table 5, we first explore the association between corruption and a firm's overall innovation, measured by the total number of patents eventually granted. Consistent with findings from Ellis et al. (2020) and Huang and Yuan (2021), we observe that local political corruption is negatively associated with a firm's overall innovation. The findings suggest that firms in relatively corrupt districts are more likely to produce fewer patents due to the uncertainty of their business environment; however, whether such environment firms prioritize one innovation strategy over another is still unclear.

[Insert Table 5]

Focusing on the firm's innovation strategy, we regress the firm's innovation strategy on the local political corruption. Table 6 presents the regression results. The dependent variable in columns (1)-(3) is exploratory innovation (*EXPLORE*), measured as the number of exploratory

[9] Calculations for overall innovation (*INNO*): 0.195/2.560 = 0.076; for exploratory innovation: 0.026/0.653 = 0.042; for exploitative innovation: 0.023/0.280= 0.082.

patents filed from year *t*-2 to *t* relative to the total patents filed by a firm during the same period. In columns (4)-(6), the dependent variable is exploitative innovation (*EXPLOIT*), measured similarly but with a focus on exploitative patents. In columns (1) and (4), we estimate our empirical model with industry and year-fixed effects but without controlling for the additional firm and industry-specific factors. In columns (2) and (5), we incorporate firm and industry-level control variables discussed in section 2.3. Consistent with our univariate analysis, the results show clear evidence supporting a positive (negative) and statistically significant relationship between political corruption and exploratory (exploitative) innovation. We further show that our results continue to show similar findings regardless of controlling for firm and industry-level factors. Specifically, a one-standard-deviation increase in corruption corresponds to an approximate 0.65 percentage point increase in exploratory innovation. Relative to the mean value of exploratory innovation, this represents a modest yet economically meaningful rise of approximately 1.02%. In contrast, the same increase in corruption leads to a 0.46 percentage point reduction in the exploitative innovation ratio. When compared to the mean value of exploitative innovation, this decline translates to a reduction of approximately 1.58%. Finally, in columns (3) and (6), we use the Corruption rank, *CORRUPT_RANK*, as our primary independent variable instead of the number of convictions in the previous models. The findings remain unchanged for the alternative measure of corruption.

[Table 6]

In line with the "greasing the wheel" hypothesis, our findings indicate that local political corruption appears to encourage firms headquartered in corrupt districts to adopt exploratory innovation strategies while discoursing exploitative innovation strategies. The results are consistent with the notion that political corruption may facilitate risk-taking, allowing companies to evade regulatory barriers and gain access to resources that would otherwise be out of reach. (e.g., Leff, 1964; Huntington, 1968; Vial and Hanoteau, 2010; Mironov, 2015)

3.4. Underlying Channel

Understanding the underlying channel through which political corruption may facilitate (discourage) exploratory (exploitative) innovation is important. To shed more light on these mechanisms, we borrowed on earlier literature presenting evidence that politically connected firms tend to receive preferential treatment and get access to unattainable resources that are unavailable to firms without such connection (Claessens, Feijen, and Laeven, 2008; Cohen and Malloy 2016; Faccio, Masulis, and McConnell, 2006; Duchin and Sosyura, 2012; Tahoun, 2014). Previous literature refers to lobbying (fee-for-service contract) as form of bribery that cannot be enforced by courts (Tahoun, 2014). By engaging in lobbying effort firms can support certain candidate or advocate certain policies to their positions to receive political favors, especially when government officials are relatively corrupt.

To test this argument, we regress our dependent variables, *EXPLORE* and *EXPLOIT* on the interaction terms between with our measures of political corruption, *CORRUPT* and *CORRUPT_RANK,* and an indicator variable, ***LOBBY,*** that takes the value of one for firms that engage in lobbying effort, and zero otherwise. Table 7 reports the regression results. As shown in columns (1-4), we find the interaction terms between corruption and lobbying effort to be positively related to exploratory innovation, but negatively related to exploitative innovation. These results suggests that lobbying effort encourages firms to pursue a riskier innovation strategy, exploratory, rather than hedging with exploitative innovation strategy. However, these results will only be viable if firms can secure future business that suffice funding requirement needed for exploratory innovative strategy.

We hypothesis that having business relationship with the government, especially in corrupt district, increases the likelihood of securing enough funding to pursue long-term investment risky innovation that but lead to groundbreaking products or services that reshape the industry. We investigate this conjecture by regressing innovation strategy variables on the interaction terms between an indicator variable, *GOV_CUSTOMER*, and our corruption variables. Our findings show that *GOV_CUSTOMER* having the government as client in politically corrupted environment steers firm's innovation strategy toward exploratory innovation rather than exploitative innovation. We find that the interaction terms to be positively (negatively) related to exploratory (exploitative) innovation. The results are aligned with the "greasing the wheel" hypothesis supporting the view that political corruption and government connection may accelerate access to resources and overcome political and regulatory boundaries.

[Insert Table 7]

3.5. Endogeneity

The relationship between innovation strategy and political risk might be endogenous. The level of corruption in the location where the firm is located and the firm's innovation strategy could be correlated with other unobservable variables due to potential omitted variable bias. To handle this endogeneity problem, we adopt an instrumental variable approach. Following previous literature, we use two instrumental variables for state-level corruption (Dass et al., 2016; Huang and Yuan, 2021; Jayakody et al., 2023).[10] The first instrumental variable is the number of days that a person needs to be resident in a state, as determined in 1970, before becoming eligible to vote. The intuition behind this instrument is that the longer the period a citizen has to wait to become eligible to vote, the more deprived the citizen of holding politicians accountable. In this case, this waiting period will likely positively correlate with political corruption (Ucar & Staer, 2020).

The second instrumental variable is the age of the state's current constitution as determined in 1970. The state's constitution depicts the rules and regulations governing state politics. When the citizens of a state wish to change regulations that preside over state politics, they can either amend the existing constitution or adopt a new one. Arguably, the latter option changes the fundamental governing regulations between the state and its citizens (Johnson et al., 2011). As such, the longevity of a state's constitution can indicate the quality of these rules (Dass et al., 2016). Consequently, an older constitution is more likely to negatively correlate with

[10] As both instruments are measured at state-level, we conduct the 2SLS analysis using state-level political corruption.

corruption. Arguably, both instruments are valid instruments as they are related to state-level corruption but have no direct effect on corporate innovation strategy.

We re-estimate our main model by replacing the dependent variable with state-level corruption in the first-stage analysis. As presented in Table 8, the coefficients of both instruments are significant at the 1% level, affirming that both instruments are related to state-level political corruption. The F-statistics in the first stage analysis is above 10, rejecting the null hypothesis of a weak instrument. Our baseline results in the second-stage regressions for the exploratory and exploitative innovations are also robust. In both columns, the coefficients of the predicted value of corruption are still significant and consistent with our main results. These results corroborate our main findings and suggest that it is unlikely for omitted variable bias to drive our results.

[Insert Table 8]

4. Robustness

4.1. Innovation strategy: Alternative measures

Following prior studies (e.g., Gao et al., 2018), we adopt alternative measures for innovation strategies. As discussed in Section 2.2, a patent is categorized as exploratory (exploitative) if at least 60% of its backward citations are different from (based on) existing knowledge. In table 9 columns (1) and (2), we redefine exploratory (exploitative) patents to require that at least 80% of their citations are based on new (existing) knowledge (e.g., Brav et al., 2018). This measure introduces a more stringent definition of exploration and exploitative innovations. Across these measures, we continue to find consistent evidence that political corruption (*CORRUPT* and *CORRUPT_RANK*) increases a firm's exploratory innovation and decreases its exploitative innovation.[11]

In line with previous literature, we also use alternative measures of innovation strategy that depends on the scope and depth of innovation knowledge (e.g., Katila and Ahuja, 2002; Gao et

[11] Our results remain robust if we use 90% cutoff percentage.

al., 2018). Innovation scope captures the frequency with which a firm acquires new knowledge outside of its existing knowledge. For a given firm *i*, in year *t*, we define *SCOPE* as the number of citations made by the firm's patent applications in the same year that are not included in the list of patents and citations from the previous five years. An increased *SCOPE* value reflects a more substantial level of a firm's investigation into new knowledge. On the other hand, *DEPTH* is calculated as the number of repeated citations made by patents filed in year *t* over the total number of citations made by all patents filed for over the same period. A higher *DEPTH* value indicates a greater degree of exploitation of existing knowledge. Table 8 columns (3) and (4), show consistent finding using *SCOPE* and *DEPTH* as our alternative measures of innovation strategy.

Finally, in columns (5) and (6) of both panels, we revise the method for assessing a firm's engagement with new knowledge and its exploratory activities. Rather than relying on patent backward citations, we identify new and known patents based on the number of patents filed in the International Patent Classification (IPC) class. Following Tzabbar and Kehoe (2013), we classify patent as new (new) if the firm has not filed (filed) patents within the same IPC class in the preceding five years. Our alternative measure, *NEW*, is defined by as the number of new patents filed from year *t*-2 to *t*, divided by the total number of patent applications during the same period. Alternatively, *KNOWN* is computed as the ratio of the total number of known patents from year *t*-2 to *t* to the total number of patent applications in the same timeframe. Consistent with earlier findings, we find that the positive (negative) relationship between political corruption and exploratory (exploitative) remains unchanged across all alternative measures.

[Insert Table 9]

4.2. Additional robustness

Prior literature show that political corruption can be extremely high in certain juridical districts (e.g., Ellis et al, 2020), which may influence our inferences and potentially mislead our results. To forestall this possibility, we recalculate our political corruption measures at the State level to smooth out the effect of certain juridical districts and confirm our inference. In table 10 columns (1-4), we reproduce our baseline results to confirm that our results are not sensitive to a specific juridical district. We find that our results provide comparable results for the state-level corruption measures. We confirm a positive and statistically significant relationship between political corruption and exploratory innovation strategy, but negative relationship with exploitative innovation strategy.

We also investigate if our results are driven by certain group a partition in our sample. To examine the influence extreme values on our interface, we drop the top and bottom quantile based on the 75 and 25 percentiles of our corruption measures. In columns (5-8), we drop observations that scores above the top 25 percentiles of our corruption measure, while columns (9-12) drop the observations below the bottom 25 percentiles. We find that our results hold for all regression models, suggesting that our findings are not sensitive to sample outliers.

[Insert Table 10]

5. Beyond innovation strategy

5.1. Political corruption and patent value

In this section, we turn our attention to whether political corruption creates shareholder value. We argue that political corruption is "greasing a hollow wheel", leading firms to engage in excessive exploration without creating meaningful value for themselves or the market. Corruption may temporarily boost exploratory innovation by enabling firms access restricted resources and avoid tape but tend to be opportunistic rather than transformative. We hypothesis that, in corrupt settings, firms are more likely to exploit system loopholes and engage in rent-seeking behavior rather than investing in high-quality, scalable innovations. Consequently, although more exploratory innovations may be produced, their economic value tends to be lower due to the lack of institutional support and the absence of long-term viability necessary for substantial returns.

Furthermore, exploitative innovation, which focuses on refining and improving existing technologies and processes, may suffer even more under corrupt conditions. Corruption introduces instability, making it difficult for firms to maintain the consistent, predictable environment required for incremental improvements. The uncertainty caused by corruption discourages firms from investing in long-term process enhancements, resulting in a sharp decline in both the quantity and quality of exploitative innovations. Firms are forced to divert resources away from efficiency-driven innovations and toward managing corrupt transactions and mitigating unpredictable costs. This diversion weakens the overall productivity and competitiveness of the innovation ecosystem, further reducing the potential for both exploratory and exploitative innovations to generate meaningful economic value.

To examine this relationship, we employ the market reaction-based construct of patent values from Kogan et al. (2017). Kogan et al. (2017) propose a measure for calculating the private economic value of innovation, noting that a firm's trading activity can indicate private economic value of patents which can differ significantly from technological value. Kogan et al. (2017) also highlight that a patent with little scientific value can be used strategically by firms to restrict competition, thereby generating significant private rents. In column (1) of Table 11, we investigate whether political corruption impacts the overall value of firms' innovations. The results indicate that firms operating in corrupt environments produce fewer valuable patents. In columns (2) and (3) of both panels, we regress political corruption (using either the *CORRUPT* or *CORRUPT_RANK* measure) against the total market value of exploratory and exploitative patents. Our findings reveal that political corruption reduces the market value of both exploratory and exploitative innovations. In the final two columns, we calculate the mean value of each exploratory and exploitative patent, as the total value could be influenced by the number of patents filed. The results show that political corruption not only decreases the overall market value of a firm's patents but also lowers the average value of patents. This effect is pronounced for both exploratory and exploitative innovations. Even though firms in corrupt environments may engage in more exploratory innovation, our findings demonstrate that corruption misdirects this activity, resulting in lower-value patents.

[Insert Table 11]

5.2. Political corruption and innovation efficiency

Next, we investigate the impact of political corruption on overall innovation efficiency. Our findings so far indicate that political corruption creates an environment where both excessive exploration and limited exploitation lead to innovations with lower market value. In a corrupt political system, companies and individuals may prioritize gaining political favors or navigating bureaucratic inefficiencies over genuine technological or market-driven progress. This diverts R&D efforts away from optimal innovation processes. For instance, excessive exploratory innovation, driven by short-term gains from politically influenced opportunities, can lead to projects that are not well-aligned with market demands.

Innovation efficiency defined as the innovation outputs per unit of R&D investment (Cruz-Cázares et al., 2013; Xie et al., 2020), tends to decline in corrupt environments as the corruption-induced inefficiencies in resource allocation inflate costs while undermining the quality and market relevance of innovations. As R&D efforts are increasingly directed by political considerations rather than by competitive forces or genuine market needs, the gap between R&D input and the market value it can potentially create widens, leading to reduced innovation efficiency. To test this, we calculate the patent value for each firm each year as the sum of the market value of all patents applied for (and eventually granted) in the same year. Innovation efficiency (*INNOEFF*) is calculated as the sum of the market value of patents applied for in year *t* over the R&D capital, which is defined as the weighted average of R&D expenses over the last five years with an annual depreciation rate of 20% (Chan et al., 2001). According to earlier literature (e.g., Gao and Chou, 2015; Hirshleifer et al. 2013; Zhong, 2018), we estimate R&D capital for firm *i* in year *t* as follows:[12]

$$R\&D\ Capital_{i,t} = R\&D_{i,t} + 0.8R\&D_{i,t-1} + 0.6R\&D_{i,t-2} + 0.4R\&D_{i,t-3} + 0.2R\&D_{i,t-4} \quad (4)$$

[12] The measurement of R&D capital in this study differs slightly from the approach used by Hirshleifer et al. (2013). While they align innovation with stock returns based on the grant date, we focus on firms' ability to convert R&D into innovation, using the application year instead.

We replace missing R&D expenses reported in Compustat with zero following prior studies (e.g., Gao and Chou, 2015). The innovation efficiency represents a firm's ability to generate one dollar of market value per dollar of R&D investment, examining the quality of R&D investment decisions as gauged by firms' efficiency gains in terms of innovation. The results are presented in Table 11 and indicate a significant and negative relationship between political corruption and innovation efficiency.

[Insert Table 12]

5.3. Political corruption and breakthrough innovation

Our results have shown that firms under corrupt environment are more inclined to undertake exploration. This exploration process is argued as the cornerstone for ground-breaking inventions and transformative advancements. Existing literature suggests that exploratory activities tend to foster breakthrough innovation by enriching the knowledge repository within a firm and augmenting combinatory possibilities (March, 1991; Ahuja and Lampert, 2001; Fleming and Sorenson, 2001). In this section, we investigate the impact of political corruption on the exploration of new knowledge through breakthrough innovation. Breakthrough innovation is a distinct category of innovation that has the potential to transform competitive dynamics and create new market opportunities (Gatignon et al., 2002), playing a critical role in creating the "next big thing".

In the light of prior findings which associate the volume of forward citations with the technological significance of a patent (Trajtenberg, 1990; Ahuja and Lampert, 2001; Srivastava and Gnyawali, 2011; Cho and Kim, 2017), in columns (1) and (2) of Table 12, we identify breakthrough innovations as those patents which, over the course of five years following the granting year, rank within the top five percent based on the number of forward citations. We calculate breakthrough innovation as the natural logarithm of one plus the number of breakthrough patents identified for each firm aggregated from year t-2 to t. To address the truncation bias that arises when older patents accrue citations more frequently than their newer counterparts (Hall et al., 2001), following

Cho and Kim (2017), we normalize each patent's count of forward citations by the mean number of forward citations for all patents in the same technological subcategory each year.

Alternatively, in columns (3) and (4), apart from using the patent forward citations, we utilize the data constructed by Arts et al. (2021) to identify breakthrough innovation characterized by highly novel and significantly impactful technologies. By analyzing patent document content, Arts et al. (2021) develop natural language processing techniques to identify the creation and impact of new technologies within the U.S. patent population. We utilize their measure (*new_word_comb_reuse*) as an alternative to forward citation counts to identify a firm's breakthrough patents following a similar process. This measure, based on the number of new pairwise keyword combinations introduced by a patent and weighted by their future reuse, captures how all possible keyword pairs within a patent are employed and influence subsequent patents. Arts et al. (2021) demonstrate that this measure outperforms traditional ones, such as forward citations, in locating highly novel technologies with substantial impact. Hence, we adopt this measure as a robustness check.

Our results across columns in Table 13 consistently demonstrate that, across two different measures of breakthrough innovation, firms under highly corrupt environment produce less breakthrough innovations. This finding indicates the detrimental impact of local political corruption on firms' exploration of new knowledge. Firms in corrupt environments tend to over explore and adapt to immediate uncertainties rather than focusing on intrinsically impactful innovation. This over-exploration, aimed at navigating the corrupt system, consumes significant resources, diverting focus and investment away from deep, radical innovation that could lead to market and technology breakthroughs. Moreover, pervasive uncertainty and the frequent redirection of resources towards maintaining operational viability in a corrupt context also diminish the potential returns on the substantial R&D investments required for breakthrough innovations.

[Insert Table 13]

6. Conclusion

We investigate the relationship between local political corruption and innovation strategies. March (1991) underlines the crucial role of exploring new knowledge and exploiting existing knowledge in firms' success. These two exploratory and exploitative innovation strategies offer differing routes to competitive advantage and market expansion. Exploitative innovation leverages a firm's existing knowledge base and technical know-how (Benner and Tushman, 2003; March 1991). The strategy focuses on optimizing and refining existing products, processes, or services, aligning with the trajectories of incremental innovation. In contrast, an exploratory innovation strategy pursues novel ideas and technologies, targeting new and emerging markets. It significantly deviates from existing knowledge trajectories and associates itself with radical innovations, aiming to create new products, services, and market spaces. This type of innovation implies risk-taking, discovery, and learning through exploration (Lavie et al., 2010).

We develop two competing hypotheses on the relationship between political corruption and innovation strategy. The **shielding hypothesis** posits that political corruption may induce the risk of extortion and increase uncertainty about the business environment and regulation, thus reducing the ex-ante incentive for firms to adopt exploratory innovation that requires risky long-term investment (Huang and Yuan, 2021; Murphy, Shleifer, and Vishny, 1991; Murphy et al., 1993; Shleifer and Vishny, 1993). In contrast, the "**greasing-the-wheel hypothesis**" suggests that political corruption may promote risk-taking, shifting the firm's orientation toward exploratory rather than exploitative innovations. The intuition behind this hypothesis is that political corruption avoids bureaucratic inefficiencies and provides access to resources that could have been unattainable in a non-corrupt environment (e.g., Leff, 1964; Huntington, 1968; Vial and Hanoteau, 2010; Mironov, 2015).

Following previous literature, we use the annual number of corruption convictions as our primary measure of local corruption at the federal juridical district level (Chen et al., 2021; Ellis et al., 2020; Jha et al., 2021; Smith, 2016). Our results suggest that political corruption provides an aiding environment for firms to pursue exploratory innovation strategies. We find a positive (negative) and statistically significant relationship between political corruption and exploratory (exploitative) innovation strategy. We further find that local corruption enables firms to expand their innovation scope and rely more on new patents. Corruption also broadens firms' innovation scope while reducing their focus on depth, leading to a greater reliance on new rather than known patents. Our channel analysis shows that government contracts and lobbying efforts are important variables in the relationship between corruption and innovation strategy. Although the results are consistent with the "greasing-the-wheel" hypothesis, we find strong evidence that political corruption reduces innovation efficiency, the market value of innovation, and the development of breakthrough innovations. Our findings are robust to alternative model specifications, endogeneity concerns, and different measures of local corruption and innovation strategies.

This study contributes to the existing literature in various ways. It provides novel evidence of the impact of local political corruption on innovation strategy. The study highlights that political corruption promotes exploratory innovation but discourages exploitative innovation. Although the results point out a positive externality of political corruption, they also show that such a positive externality greases a hollow wheel that reduces economic-based measures of innovation, including innovation efficiency and innovation market value.

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Figure 1 The geography of political corruption across states

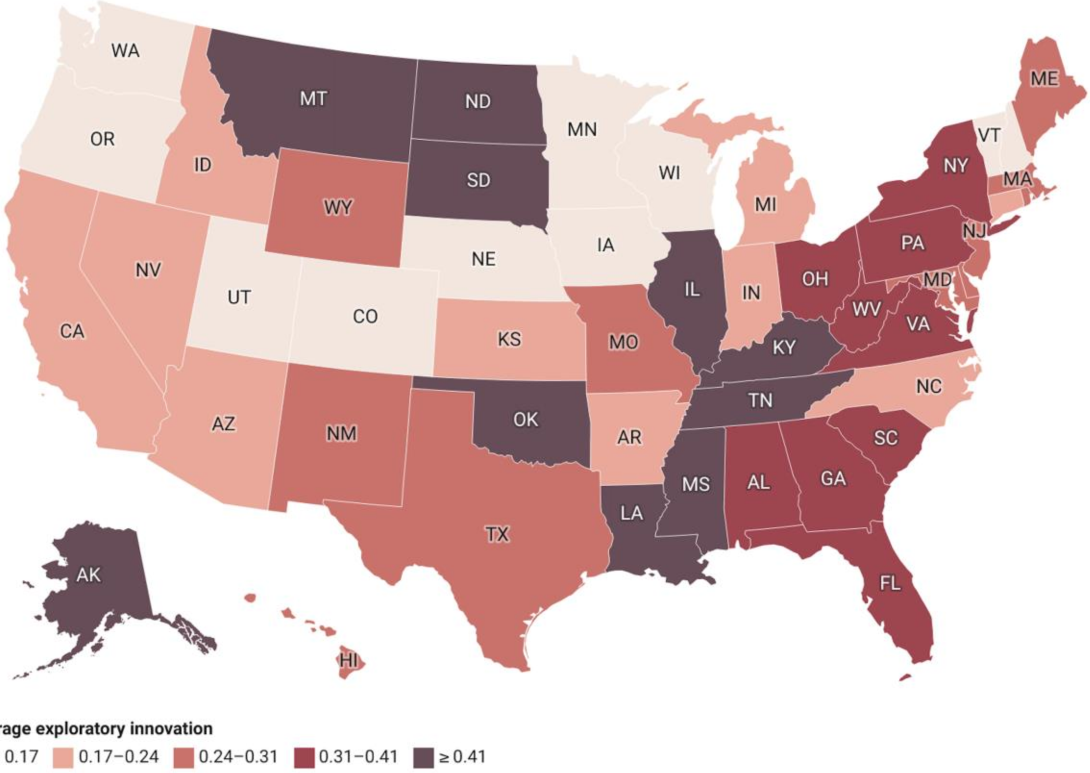
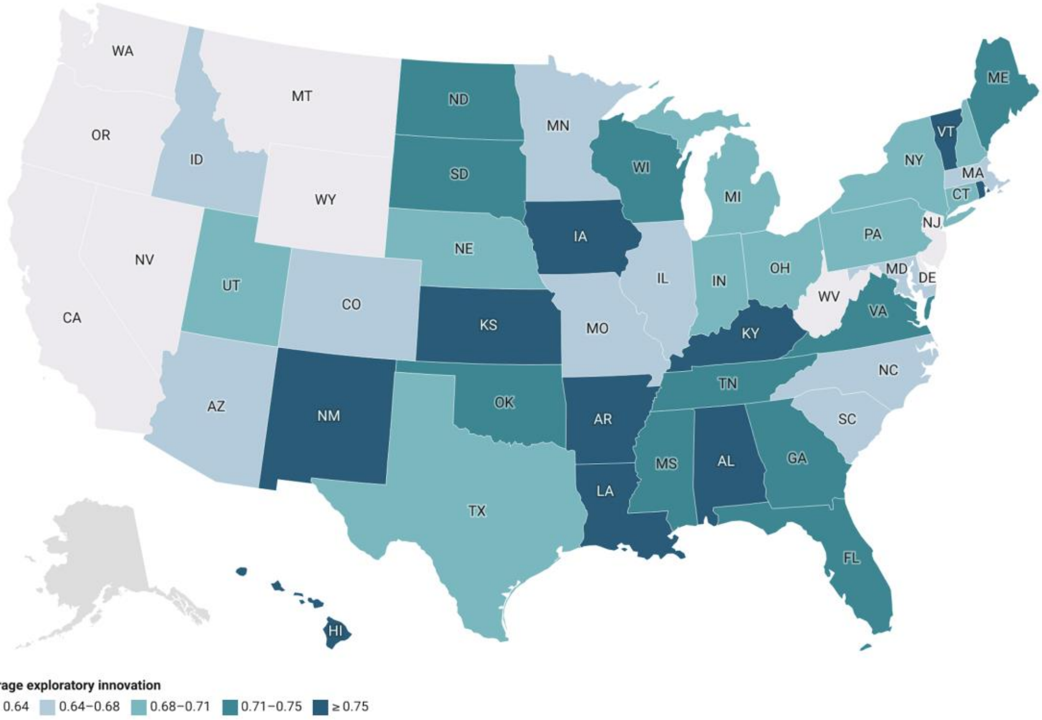


Figure 2 The geography of exploratory and exploitative innovation across states

Panel A: exploratory innovation across states



Panel B: exploitative innovation across states

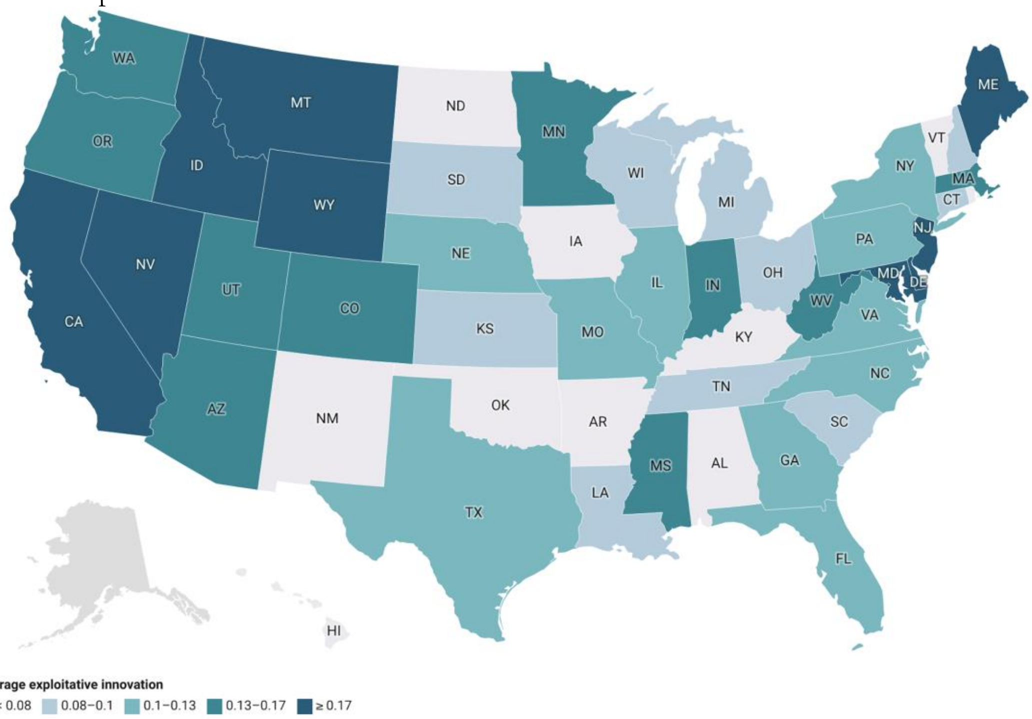


Table 2 Summary statistics

	N	Mean	Std.V	Min	25%	50%	75%	Max
INNO	26,086	2.661	1.687	0.693	1.386	2.303	3.689	7.631
EXPLORE	26,086	0.639	0.316	0.000	0.429	0.667	1.000	1.000
EXPLOIT	26,086	0.292	0.293	0.000	0.000	0.231	0.486	1.000
CORRUPT	26,086	1.309	0.927	0.113	0.638	1.069	1.736	4.609
CORRUPT_RANK	26,086	0.447	0.276	0.011	0.211	0.422	0.678	1.000
PTSTOCKS	26,086	0.139	0.276	0.000	0.006	0.044	0.136	1.887
SIZE	26,086	6.035	2.140	1.325	4.430	5.871	7.515	11.308
R&D	26,086	0.098	0.146	0.000	0.009	0.045	0.123	0.858
ROA	26,086	0.043	0.250	-1.160	0.022	0.114	0.172	0.382
PPE	26,086	0.212	0.170	0.006	0.082	0.168	0.296	0.766
LEVERAGE	26,086	0.180	0.185	0.000	0.007	0.141	0.289	0.859
CAPEX	26,086	0.048	0.043	0.001	0.019	0.036	0.063	0.242
TOBINQ	26,086	2.493	2.097	0.663	1.259	1.774	2.876	13.384
KZINDEX	26,086	0.415	1.243	-4.914	-0.123	0.404	1.018	4.647
AGE	26,086	2.586	0.947	0.693	1.946	2.639	3.296	4.407
HHI	26,086	0.269	0.204	0.054	0.128	0.198	0.356	0.969
HHISQ	26,086	0.114	0.181	0.003	0.016	0.039	0.126	0.938

Table 3 Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) INNO	1																
(2) EXPLORE	-0.228*	1															
(3) EXPLOIT	0.182*	-0.922*	1														
(4) CORRUPT	-0.047*	0.018*	-0.014*	1													
(5) CORRUPT_RANK	-0.077*	0.061*	-0.060*	0.900*	1												
(6) PTSTOCKS	0.151*	-0.240*	0.229*	-0.010*	-0.096*	1											
(7) SIZE	0.559*	0.032*	-0.047*	0.116*	0.065*	-0.345*	1										
(8) R&D	-0.018*	-0.256*	0.268*	-0.094*	-0.111*	0.400*	-0.422*	1									
(9) ROA	0.169*	0.233*	-0.246*	0.036*	0.048*	-0.393*	0.456*	-0.750*	1								
(10) PPE	-0.019*	0.132*	-0.145*	0.089*	0.144*	-0.150*	0.252*	-0.276*	0.233*	1							
(11) LEVERAGE	0.042*	0.055*	-0.056*	0.124*	0.136*	-0.145*	0.294*	-0.162*	0.071*	0.298*	1						
(12) CAPEX	0.010	0.081*	-0.088*	0.005	0.046*	-0.036*	0.045*	-0.088*	0.145*	0.605*	0.066*	1					
(13) TOBINQ	0.031*	-0.178*	0.175*	-0.022*	-0.029*	0.211*	-0.242*	0.416*	-0.311*	-0.215*	-0.146*	0.011+	1				
(14) KZINDEX	-0.067*	-0.016*	0.019*	0.025*	0.033*	0.059*	-0.087*	0.179*	-0.248*	0.070*	0.480*	0.058*	0.264*	1			
(15) AGE	0.231*	0.038*	-0.060*	0.116*	0.112*	-0.158*	0.469*	-0.299*	0.291*	0.201*	0.166*	-0.045*	-0.213*	-0.147*	1		
(16) HHI	0.008	0.079*	-0.078*	0.028*	0.037*	-0.077*	0.100*	-0.203*	0.137*	0.038*	0.074*	-0.035*	-0.128*	-0.016*	0.187*	1	
(17) HHISQ	0.030*	0.065*	-0.064*	0.026*	0.027*	-0.069*	0.111*	-0.167*	0.119*	0.032*	0.070*	-0.030*	-0.108*	-0.010	0.165*	0.954*	1

+ p<0.10, * p<0.05

Table 4 Univariate test

	High corruption			Low corruption			Differences (H-L)	
	Mean	Median	N	Mean	Median	N	Mean	Median
INNO	2.560	2.197	12,604	2.755	2.398	13,482	-0.195***	-0.201***
EXPLORE	0.653	0.692	12,604	0.627	0.667	13,482	0.026***	0.025***
EXPLOIT	0.280	0.204	12,604	0.303	0.250	13,482	-0.023***	-0.046***

* p<0.1 ** p<0.05 *** p<0.01.

Table 5 Local political corruption and innovation

	(1)	(2)
CORRUPT	-0.083***	
	(-8.357)	
CORRUPT_RANK		-0.282***
		(-8.653)
SIZE	0.682***	0.681***
	(97.086)	(98.009)
PTSTOCKS	1.901***	1.899***
	(48.465)	(48.561)
R&D	1.952***	1.945***
	(24.788)	(24.821)
ROA	0.582***	0.579***
	(12.247)	(12.209)
PPE	-0.828***	-0.824***
	(-9.965)	(-9.882)
LEVERAGE	-0.414***	-0.415***
	(-8.196)	(-8.237)
CAPEX	2.530***	2.513***
	(11.505)	(11.414)
TOBINQ	0.081***	0.081***
	(17.754)	(17.757)
KZINDEX	-0.026***	-0.026***
	(-3.384)	(-3.345)
AGE	-0.003	-0.001
	(-0.255)	(-0.065)
HHI	-0.759***	-0.755***
	(-5.930)	(-5.914)
HHISQ	0.953***	0.947***
	(6.879)	(6.855)
Constant	-0.948***	-0.971***
	(-4.981)	(-4.917)
Observations	26,086	26,086
R-squared	0.624	0.624
Industry-Year FE	*YES*	*YES*

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). Standard errors are clustered at district and year level. The dependent variable across two columns is the natural logarithm of one plus the total number of granted patents from year t-2 to year t. In column (1), the key variable of interest is the corruption proxy, CORRUPT, which is measured as the trailing sum of convictions over a specified period, scaled by the state's 5-year average population (per 100,000 people). Column (2) introduces CORRUPT_RANK, calculated by ranking each state according to its trailing 5-year conviction rate. SIZE represents firm size measured as the natural logarithm of total book asset. PTSTOCKS is the natural logarithm of one plus the patent stock with a 15% of annual depreciation rate. R&D intensity (R&D) calculated as a firm's R&D expenses over total book asset; Return on assets (ROA) is defined as operating income before depreciation over total assets. PPE denotes property, plant and equipment, scaled by total assets. LEVERAGE is the ratio of debts over the total assets, while CAPEX represents capital expenditures scaled by the total assets. Tobin's Q (TOBINQ) is calculated as the market value plus book value of assets, minus book value of equity, minus balance sheet deferred taxes (replace missing with zero), divided by book value of assets. The Kaplan and Zingales index (KZINDEX) is included to account for Financial constraints. Firm age (AGE) is measured as the natural logarithm of one plus the number of years from the first year of stocks in CRSP. Finally, market competition is controlled for using the Herfindahl-Hirschman Index (HHI) and is square (HHISQ). All independent variables are measured at time t-3. Specifications across columns year-industry fixed effects. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 6 Local political corruption and innovation strategies

	EXPLORE			EXPLOIT		
	(1)	(2)	(3)	(4)	(5)	(6)
CORRUPT	0.016***	0.007***		-0.014***	-0.005***	
	(6.188)	(3.388)		(-6.355)	(-2.663)	
CORRUPT_RANK			0.029***			-0.022***
			(3.983)			(-3.379)
Constant	0.263**	0.406***	0.403***	0.608***	0.511***	0.514***
	(2.437)	(3.925)	(3.929)	(4.859)	(4.130)	(4.160)
Controls	*NO*	*YES*	*YES*	*NO*	*YES*	*YES*
Observations	26,086	26,086	26,086	26,086	26,086	26,086
R-squared	0.190	0.249	0.250	0.192	0.249	0.249
Industry-Year FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). Standard errors are clustered at district and year level. The dependent variable in columns (1)-(3) is exploratory innovation (EXPLORE), measured as the ratio of a firm's number of exploratory patents from year t-2 to t over the total number of patent applications during the same period, while in columns (4)-(6), the dependent variable is exploitative innovation (EXPLOIT), calculated as a firm's number of exploitative patents from year t-2 to t over the total number of patent applications during the same period. In columns (1), (2), (4) and (5), the key variable of interest is the corruption proxy, CORRUPT, which is measured as the trailing sum of convictions over a specified period, scaled by the district's 5-year average population (per 100,000 people). Columns (3) and (6) introduces CORRUPT_RANK, calculated by ranking each district according to its trailing 5-year conviction rate. Control variables are defined in Table 5. All independent variables are measured at time t-3. Specifications across columns year-industry fixed effects. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 7 Underlying channels

	Lobbying				Major government customers			
	EXPLORE		EXPLOIT		EXPLORE		EXPLOIT	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CORRUPT	0.003		0.000		0.006**		-0.002	
	(0.870)		(0.080)		(1.968)		(-0.780)	
CORRUPT_RANK		0.014		-0.003		0.026**		-0.012
		(1.305)		(-0.342)		(2.564)		(-1.345)
LOBBY	-0.030***	-0.029***	0.020***	0.020***				
	(-3.664)	(-3.486)	(2.890)	(2.805)				
CORRUPT # LOBBY	**0.013*** **		**-0.011*** **					
	(2.670)		**(-2.625)**					
CORRUPT_RANK # LOBBY		**0.039** **		**-0.037** **				
		(2.407)		**(-2.489)**				
GOV_CUSTOMER					-0.025**	-0.030**	0.031***	0.038***
					(-2.322)	(-2.394)	(3.030)	(3.237)
CORRUPT # CUSTOMER					**0.024*** **		**-0.023*** **	
					(3.569)		**(-3.638)**	
CORRUPT_RANK # CUSTOMER						**0.080*** **		**-0.083*** **
						(3.380)		**(-3.768)**
Constant	0.974***	0.973***	0.048***	0.049***	0.390***	0.387***	0.517***	0.519***
	(64.637)	(64.409)	(3.615)	(3.628)	(3.664)	(3.678)	(4.087)	(4.113)
Controls	*NO*	*YES*	*YES*	*NO*	*YES*	*YES*	*YES*	*YES*
Observations	17,609	17,609	17,609	17,609	18,144	18,144	18,144	18,144
R-squared	0.235	0.235	0.238	0.238	0.255	0.255	0.257	0.257
Industry-Year FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). Standard errors are clustered at district and year level. The dependent variable in columns (1)-(3) is exploratory innovation (EXPLORE), measured as the ratio of a firm's number of exploratory patents from year t-2 to t over the total number of patent applications during the same period, while in columns (4)-(6), the dependent variable is exploitative innovation (EXPLOIT), calculated as a firm's number of exploitative patents from year t-2 to t over the total number of patent applications during the same period. In columns (1), (2), (4) and (5), the key variable of interest is the corruption proxy, CORRUPT, which is measured as the trailing sum of convictions over a specified period, scaled by the district's 5-year average population (per 100,000 people). Columns (3) and (6) introduces CORRUPT_RANK, calculated by ranking each district according to its trailing 5-year conviction rate. LOBBY is an indicator variable that takes the value of one if a firm has non-zero lobbying expenditure, and zero otherwise. GOV_CUSTOMER is an indicator variable that takes the value of one if a firm has at least one major customer that is government, and zero otherwise. Control variables are included and defined in Table 5. All independent variables are measured at time t-3. Specifications across columns year-industry fixed effects. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 9

VARIABLES	(1) CORRUPT_STATE	(2) EXPLORE	(3) EXPLOIT
Residencybeforevoting1970	0.003***		
	(49.126)		
Constitutionage1970	-0.003***		
	(-39.895)		
CORRUPT_STATE		0.030***	-0.032***
		(3.644)	(-4.168)
Constant	1.058***	0.423***	0.485***
	(4.993)	(4.321)	(5.331)
Controls	YES	YES	YES
Observations	26,002	26,002	26,002
R-squared	0.238	0.248	0.247
Industry-Year FE	YES	YES	YES

Table 9 Alternative measures of innovation strategies

Panel A	Explore vs. Exploit (80%)		Scope vs. Depth		New vs. Known patents	
	(1)	(2)	(3)	(4)	(5)	(6)
	EXPLORE	*EXPLOIT*	*SCOPE*	*DEPTH*	*NEW*	*KNOWN*
CORRUPT	0.008***	-0.004**	0.009***	-0.008***	0.008***	-0.007***
	(3.267)	(-2.296)	(4.201)	(-4.231)	(3.610)	(-3.088)
Constant	0.453***	0.514***	0.434***	0.566***	0.523***	0.483***
	(4.168)	(4.340)	(4.613)	(5.945)	(4.952)	(4.593)
Controls	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Observations	26,086	26,086	26,086	26,086	26,086	26,086
R-squared	0.251	0.246	0.278	0.281	0.280	0.287
Industry-Year FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
	EXPLORE	*EXPLOIT*	*SCOPE*	*DEPTH*	*NEW*	*KNOWN*
CORRUPT_RANK	0.032***	-0.012**	0.032***	-0.031***	0.032***	-0.029***
	(4.138)	(-2.177)	(4.892)	(-4.834)	(4.119)	(-3.702)
Constant	0.450***	0.514***	0.431***	0.568***	0.519***	0.486***
	(4.272)	(4.261)	(4.429)	(5.806)	(4.961)	(4.647)
Controls	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Observations	26,086	26,086	26,086	26,086	26,086	26,086
R-squared	0.252	0.246	0.278	0.281	0.280	0.287
Industry-Year FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). Standard errors are clustered at district and year level. The dependent variable in columns (1) and (2) in both panels is exploratory innovation (EXPLORE), measured as the ratio of a firm's number of exploratory patents from year t-2 to t over the total number of patent applications during the same period, while in columns (4)-(6), the dependent variable is exploitative innovation (EXPLOIT), calculated as a firm's number of exploitative patents from year t-2 to t over the total number of patent applications during the same period. The exploratory and exploitative patents are identified as the one with at least 80% of its citations are based on new (known) knowledge, respectively. In columns (3) and (4) in both panels, the dependent variables are SCOPE and DEPTH. SCOPE is measured as the number of new citations made by patents filed for in year t–5 to year t divided by the total number of citations made by all patents filed for over the same period. New citations are citations that have never been made by the firm in the past 5 years. DEPTH is calculated as the number of repeated citations made by patents filed for in year t–5 to year t divided by the total number of citations made by all patents filed for over the same period. Repeated citations are citations that have been made by the firm in the past 5 years. Finally, in columns (5) and (6) in both panels, NEW is the number of new patents filed from year t-2 to t, divided by the total number of patent applications during the same period. New patents are based on the number of patents filed in an IPC class where the firm has not filed any patents within the preceding five years. KNOWN is the number of known patents filed from year t-2 to t, divided by the total number of patent applications during the same period. Known patents are based on the number of patents filed in an IPC class where the firm has filed any patents within the preceding five years. CORRUPT is measured as the trailing sum of convictions over a specified period, scaled by the district's 5-year average population (per 100,000 people). Columns (3) and (6) introduces CORRUPT_RANK, calculated by ranking each district according to its trailing 5-year conviction rate. Control variables are defined in Table 5. All independent variables are measured at time t-3. Specifications across columns year-industry fixed effects. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 10 Additional robustness tests

	State-level analysis				Drop top quantile				Drop bottom quantile			
	EXPLORE		*EXPLOIT*		*EXPLORE*		*EXPLOIT*		*EXPLORE*		*EXPLOIT*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CORRUPT	0.010***		-0.009***		0.013**		-0.010**		0.006**		-0.004*	
	(3.422)		(-3.399)		(2.543)		(-2.108)		(2.536)		(-1.812)	
CORRUPT_RANK		0.033***		-0.028***		0.034***		-0.027**		0.028***		-0.020**
		(4.037)		(-3.812)		(2.987)		(-2.579)		(3.205)		(-2.504)
Constant	0.725***	0.726***	0.249***	0.248***	0.365***	0.365***	0.481***	0.481***	0.426***	0.422***	0.474***	0.478***
	(12.199)	(12.125)	(5.484)	(5.402)	(5.347)	(5.362)	(4.134)	(4.129)	(3.635)	(3.618)	(3.520)	(3.549)
Controls	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Observations	30,377	30,377	30,377	30,377	19,578	19,578	19,578	19,578	19,437	19,437	19,437	19,437
R-squared	0.242	0.242	0.240	0.240	0.261	0.261	0.262	0.262	0.263	0.263	0.263	0.263
Industry-Year FE	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*

This table presents the fixed effects estimated coefficients, with t-statistics in parentheses. Standard errors are clustered at the district and year levels. The dependent variable in columns (1), (2), (5), (6), (9), and (10) is exploratory innovation (EXPLORE), defined as the ratio of a firm's exploratory patents (filed from year t-2 to t) to its total patent applications during the same period. In columns (3), (4), (7), (8), (11), and (12), the dependent variable is exploitative innovation (EXPLOIT), measured as the ratio of a firm's exploitative patents (filed from year t-2 to t) to its total patent applications during the same period. Columns (1)–(4) analyze state-level data, where CORRUPT and CORRUPT_RANK are measured at the state level. CORRUPT represents the trailing sum of corruption-related convictions over a specified period, scaled by the state's 5-year average population (per 100,000 people). CORRUPT_RANK ranks states based on their trailing 5-year conviction rates. In the remaining columns, the two corruption proxies are measured at the district level. Control variables used in all columns are defined in Table 5, and all independent variables are lagged by three years (measured at time t-3). Year-industry fixed effects are included across all specifications. Statistical significance levels are denoted as *p < 0.1; **p < 0.05; ***p < 0.01.

Table 11 Local political corruption and patent value

Panel A	(1) Tot_value	(2) Tot_explore	(3) Tot_exploit	(4) Ave_explore	(5) Ave_ exploit
CORRUPT	-0.090***	-0.173***	-0.190***	-0.018**	-0.031***
	(-5.939)	(-7.471)	(-7.260)	(-2.201)	(-3.767)
Constant	-5.547***	-9.534***	-8.537***	-2.288***	-2.327***
	(-5.102)	(-6.248)	(-5.351)	(-3.419)	(-3.409)
Controls	*YES*	*YES*	*YES*	*YES*	*YES*
Observations	26,086	26,086	26,086	26,086	26,086
R-squared	0.632	0.635	0.603	0.545	0.521
Industry-Year FE	*YES*	*YES*	*YES*	*YES*	*YES*

Panel B	(1) Tot_value	(2) Tot_explore	(3) Tot_exploit	(4) Ave_explore	(5) Ave_ exploit
CORRUPT_RANK	-0.319***	-0.583***	-0.639***	-0.063**	-0.114***
	(-6.263)	(-7.415)	(-7.588)	(-2.377)	(-4.147)
Constant	-5.528***	-9.509***	-8.510***	-2.284***	-2.319***
	(-5.048)	(-6.168)	(-5.275)	(-3.406)	(-3.385)
Controls	*YES*	*YES*	*YES*	*YES*	*YES*
Observations	26,086	26,086	26,086	26,086	26,086
R-squared	0.632	0.635	0.603	0.545	0.521
Industry-Year FE	*YES*	*YES*	*YES*	*YES*	*YES*

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). Standard errors are clustered at district and year level. The dependent variable in column (1) in both panels is the total value of firms' innovations. The value is constructed by Kogan et al. (2017) and based on stock market reactions to patent grants. In columns (2) and (3) of both panels, the dependent variables are the total market value of exploratory and exploitative patents. Finally, in columns (4) and (5), the dependent variables are the mean values of exploratory and exploitative patents. CORRUPT is measured as the trailing sum of convictions over a specified period, scaled by the district's 5-year average population (per 100,000 people), while CORRUPT_RANK is calculated by ranking each district according to its trailing 5-year conviction rate. Control variables are defined in Table 5. All independent variables are measured at time t-3. Specifications across columns year-industry fixed effects. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 12 Local political corruption and innovation efficiency

	(1)	(2)
CORRUPT	-0.050**	
	(-2.136)	
CORRUPT_RANK		-0.221***
		(-3.202)
Constant	-3.799***	-3.769***
	(-8.690)	(-8.641)
Controls	*YES*	*YES*
Observations	26,086	26,086
R-squared	0.244	0.244
Industry-Year FE	*YES*	*YES*

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). Standard errors are clustered at district and year level. The dependent variable across two columns is innovation efficiency, which is calculated as the sum of the market value of patents applied for in year t over the R&D capital, which is defined as the weighted average of R&D expenses over the last five years with an annual depreciation rate of 20% (Chan et al., 2001). CORRUPT is measured as the trailing sum of convictions over a specified period, scaled by the district's 5-year average population (per 100,000 people), while CORRUPT_RANK is calculated by ranking each district according to its trailing 5-year conviction rate. Control variables are defined in Table 5. All independent variables are measured at time t-3. Specifications across columns year-industry fixed effects. *p < 0.1; **p < 0.05; ***p < 0.01.

Table 13 Local political corruption and breakthrough innovation

	Top 5-year citations		Arts et al. (2022)	
	(1)	(2)	(3)	(4)
CORRUPT	-0.039***		-0.026***	
	(-9.364)		(-6.111)	
CORRUPT_RANK		-0.138***		-0.086***
		(-10.393)		(-6.229)
Constant	-1.358***	-1.350***	-1.327***	-1.323***
	(-12.981)	(-13.107)	(-13.641)	(-13.737)
Controls	*YES*	*YES*	*YES*	*YES*
Observations	26,086	26,086	26,086	26,086
R-squared	0.329	0.330	0.329	0.329
Industry-Year FE	*YES*	*YES*	*YES*	*YES*

This table presents the fixed effects estimated coefficients (t-statistics in parentheses). Standard errors are clustered at district and year level. The dependent variable in columns (1) and (2) is the breakthrough innovation measured as the natural logarithm of one plus the number of breakthrough patents identified for each firm aggregated from year t-2 to t. Patents whose value exceeds the 95th percentile are considered breakthrough innovations. In column (3) and (4), we utilize "new_word_comb_reuse" constructed by Arts et al. (2021) as an alternative measure of forward citation counts to identify breakthrough innovation. CORRUPT is measured as the trailing sum of convictions over a specified period, scaled by the district's 5-year average population (per 100,000 people), while CORRUPT_RANK is calculated by ranking each district according to its trailing 5-year conviction rate. Control variables are defined in Table 5. All independent variables are measured at time t-3. Specifications across columns year-industry fixed effects. *p < 0.1; **p < 0.05; ***p < 0.01.

Appendix

Table 1A Variable definition

Variables	Definition	Database
Political corruption		
CORRUPT	The 5-year trailing sum of convictions scaled by the 5-year average population of the state (per 100.000 capita).	PIN
CORRUPT_RANK	The percent conviction rank after ranking each state according to *CORRUPT*. 100% corresponds to the most corrupt state.	PIN
Innovation strategy		
EXPLORE	The ratio of the number of exploratory patents filed in year t over the number of all patents filed by the firm in the same year. An exploratory patent is identified as the one with at least 60% of its citations are based on new knowledge	Orbis IP
EXPLOIT	The ratio of the number of exploitative patents filed in year t over the number of all patents filed by the firm in the same year. An exploitative patent is identified as the one with at least 60% of its citations are based on existing knowledge	Orbis IP
EXPLORE	The ratio of the number of exploratory patents filed in year t over the number of all patents filed by the firm in the same year. An exploratory patent is identified as the one with at least 80% of its citations are based on new knowledge	Orbis IP
EXPLOIT	The ratio of the number of exploitative patents filed in year t over the number of all patents filed by the firm in the same year. An exploitative patent is identified as the one with at least 80% of its citations are based on existing knowledge	Orbis IP
SCOPE	The number of new citations made by patents filed for in year *t–5* to year *t* divided by the total number of citations made by all patents filed for over the same period. New citations are citations that have never been made by the firm in the past 5 years	Orbis IP
DEPTH	The number of repeated citations made by patents filed for in year *t–5* to year *t* divided by the total number of citations made by all patents filed for over the same period. Repeated citations are citations that have been made by the firm in the past 5 years	Orbis IP
NEW	The number of new patents filed from year t-2 to t, divided by the total number of patent applications during the same period. New patents are based on the number of patents filed in an IPC class where the firm has not filed any patents within the preceding five years.	Orbis IP
KNOWN	The number of known patents filed from year t-2 to t, divided by the total number of patent applications during the same period. Known patents are based on the number of patents filed in an IPC class where the firm has filed any patents within the preceding five years.	
Firm- and industry-specific variables		
PATENTSTOCK	The patent stock with an annual depreciation rate of 15% (Hall et al., 2005) over total book asset. $PatentStock_{i,t} = Patent\_applications_{i,t} + (1-\rho)PatentStock_{i,t-1}$	Orbis IP
SIZE	The natural logarithm of total book asset	Compustat
R&D	R&D expenses over total book asset	Compustat
AGE	The natural logarithm of the number of years from the beginning year of stocks in CRSP	CRSP
ROA	Return on assets ratio defined as operating income before depreciation divided by book value of total assets	Compustat
LEVERAGE	Book value of debt divided by book value of total assets	Compustat
PPE	Property, plant and equipment divided by total assets	
CAPEX	Capital expenditure divided by book value of total assets	Compustat
SGROWTH	Sales in year t minus sales in year *t-1* divided by sales in year *t*	Compustat

TOBINQ	Market value plus book value of assets minus book value of equity minus balance sheet deferred taxes (replace missing with zero), divided by book value of assets	Compustat
KZINDEX	Kaplan and Zingales index calculated as -1.002*cash flow + 0.283*Tobin's Q + 3.139*leverage - 39.368*dividends - 1.315*cash holdings	Compustat
HHI	Herfindahl index of 4-digit SIC industry j where firm i belongs	Compustat
HHISQ	Squared term of HHI	Compustat