Rigging the Scores: Corruption through Scoring Rule Manipulation in Public Procurement Auctions

Qianmiao (Michelle) Chen *

November 12, 2024†

Click here for the most recent version ‡

Abstract

Public procurement is highly susceptible to corruption, especially in developing countries. Although open auctions are widely adopted to curb it, I document that corruption remains prevalent even within this procurement format. Procurement officers can collaborate with firms to manipulate scoring rules, ensuring predetermined winners, while corrupt firms submit non-competitive bids to meet minimum bidder requirements. Using extensive data from Chinese public procurement auctions, I introduce model-driven statistical tools to detect such corruption, identifying a corruption rate of 65%. A procurement expert audit survey confirms the tools' reliability, with a 91% probability that experts recognize suspicious scoring rules when flagged. Firm-level analysis reveals that local, state-owned, and less productive firms are favored in corrupt auctions. Lastly, I explore policy implications. Analysis of the anti-corruption campaign suggests that general investigations may be insufficient to address deeply ingrained corrupt practices. Using counterfactuals based on an estimated structural model, I find that implementing anonymous call-for-tender evaluations could improve social welfare by 10% by eliminating suspicious rules and encouraging broader participation.

Keywords **: Public Procurement, Open Scoring Auction, Corruption**

JEL classification: **D44, H57, K21, L44**

---

*Research Economist, World Bank DIME. Email: qianmiao@worldbank.org

†I would like to thank Marco Gonzalez-Navarro, Steve Tadelis, Kei Kawai, and Fred Finan for their advice, guidance, and support. I also thank Betty Sadoulet, Cailin Slattery, Daniel Rogger, Edward Miguel, Ethan Ligon, Francesco Trebbi, Jed Silver, Joel Ferguson, Juan Ortner, Karl Schurter, Kirill Borusyak, Thiago Scot, and Guo Xu, as well as numerous seminar participants at NEUDC, DevPEC, IIOC, Conference on Auctions and Firms, and UC Berkeley. Zan Song, Yuning Xue, and Tiffany Liu provided excellent research assistance. All remaining errors are my own.

‡The previous version was circulated under the title "Corruption in Public Procurement Auctions: Evidence from Collusion between Officers and Firms".

1 Introduction

Corruption is a persistent and widespread challenge that affects governments worldwide, distorting market dynamics, hindering economic development, and undermining public trust. Among various government activities, public procurement is particularly susceptible to corruption, with bribes in this sector accounting for a significant portion of total corruption bribes (OECD, 2016). Corruption in public procurement involves the use of illicit or illegal methods to manipulate the awarding of government contracts for goods, services, and works. It can lead to contracts being awarded to unqualified companies, resulting in the provision of substandard goods and services and the waste of public resources. The consequences extend across both the public and private sectors, driving up costs for goods and services and placing a burden on taxpayers and businesses. The issue is particularly problematic in developing countries, where institutional deficiencies and a lack of effective accountability mechanisms are prevalent.

To improve transparency and combat corruption, many countries worldwide, under the guidance of UNCITRAL Model Law on Public Procurement,[1] have adopted open tendering for public procurement. Within the realm of open tendering, the open scoring auction stands out as one of the most widely adopted.[2] In an open scoring auction, all interested firms are eligible to participate, submitting confidential bids that are assessed based on predetermined criteria encompassing both quality and price components. The contract is ultimately awarded to those achieving the highest combined scores, derived from the sum of quality and price evaluations. To further foster competition, a specified minimum number of bidders is typically mandated, such as three in the case of China.

However, the effectiveness of open scoring auctions in curbing corruption and improving efficiency remains a subject of debate. Personal interviews with Chinese public procurement officials suggest that: corruption remains prevalent even within open scoring auctions. An insidious practice consists of customizing scoring rules to orchestrate a victory for predetermined suppliers. As elucidated by one official, *"Smart' rms often begin to contact government o cials before the bidding process starts. In those cases, only one bidder will meet all the requirements and will get the highest score in the bid evaluation. Other rms participate only to create the appearance of legitimate competition."*

In this paper, I study this issue quantitatively by introducing a reliable screening tool to detect corruption and conduct an in-depth analysis of the distortions caused by corrupt scoring practices. Over 65% scoring auctions in public procurement show evidence of scoring rule manipulation. Additionally, I explore policy instruments that can enhance social welfare

[1] United Nations Commission on International Trade Law (UNCITRAL, 2014)

[2] The majority of countries implementing modern public procurement systems incorporate open scoring auctions as a procurement mechanism.

and mitigate corruption in public procurement. To achieve these goals, I compiled a novel dataset on public procurement auctions in China, including firm profiles and their bidding outcomes. Spanning a timeframe from 2006 to 2021, this dataset encompasses more than three hundred thousand procurement projects. Notably, this constitutes the first comprehensive analysis of detailed public procurement data within the Chinese context. Furthermore, I supplemented this data by acquiring administrative firm data and incorporating information pertaining to corruption investigations.

I begin by documenting two stylized facts in the public procurement data. First, in over two-thirds of procurement cases, there are only three bidders - the minimum required for the auction to be considered valid, indicating a lack of significant competition. Second, there are abnormally large score gaps between winning and losing bids. This discrepancy is most pronounced in auctions featuring only three bidders, where winning bids often stand in isolation with a conspicuous absence of close competitive losing bids.

Next, I propose tools to identify corruption through scoring rule manipulation in the standard scoring auction model. Building on the work of Che (1993), Asker and Cantillon (2008), and Hanazano et al. (2020), I construct a measure called "pseudotype," representing the highest scores bidders can achieve while maintaining nonnegative profits. I then demonstrate how scoring rule customization can create bidding patterns inconsistent with competitive behavior. Under the null hypothesis of a competitive procurement auction, the winning score should closely align with the expected pseudotype of the strongest rivals. If the winning score significantly exceeds the expected strongest rivals' pseudotypes, the winner has left a substantial amount of potential profit untouched. At the auction group level, I use a nonparametric maximum likelihood estimation to estimate the proportion of corruption by comparing the mean of winning scores with the mean pseudotype of the strongest rivals. At the individual auction level, I compare the pseudotypes of losing bidders with the expected rivals' pseudotypes given the winning scores. When scoring rule manipulation occurs, a marked discrepancy emerges, resulting in an unusually low average of losers' pseudotypes and rejection of the null hypothesis. Results from the two detection methods closely align, particularly in cases with three bidders, indicating that the null hypothesis of no corruption in scoring rule manipulation is rejected in over 65% of auctions, revealing evidence of scoring rule customization, favoritism, and coordinated non-competitive bids.

To further validate my test, I conducted a procurement expert audit study. Public procurement officials acknowledged the existence of significant opportunities for manipulation in the bidding process(Gong and Zhou, 2015). However, detecting irregularities can be challenging for the public without the necessary expertise to verify the criteria. To address this issue, I engaged five procurement experts from the Province's bid evaluation expert pool, selected for their active involvement in bid evaluation meetings and deep industry and firm

knowledge. They evaluated a random sample of 500 procurement projects without knowledge of the bidders or outcomes, identifying signs of criteria customization and assessing the level of competition. The survey results were compared to the predictions made by my model, resulting in high degrees of congruence.[3] When my model predicted a potentially corrupt auction, there was a 91% chance that procurement experts highlighted signs of scoring rule customization, demonstrating the model's effectiveness in detecting suspicious patterns.

The corruption test results obtained from the previous step enable a more comprehensive investigation of corruption, extending beyond just relying on personal name connections as indicators of political corruption ties (Brugués, Brugués, and Giambra, 2024). Initially, I scrutinize the disparities between winners in competitive and noncompetitive scenarios, revealing that winners implicated in suspected cases exhibit characteristics such as lower productivity, stronger ties to state-owned entities, and closer proximity to the local procurement government. Subsequently, I utilize the corruption investigation data to analyze the impact of corruption investigations during anti-corruption campaigns on procurement outcomes. I discover that investigations prompt heightened competition and diminish corruption in the short term, yet fail to yield a sustained, long-term reduction in corrupt activities. Notably, this finding is predominantly driven by investigations directed at high-level officials.

Lastly, I enhance the scoring auction model by incorporating semi-parametric estimates of firm cost functions to conduct counterfactual policy analyses. I examine two different counterfactual scenarios to study the impact of various policy changes on procurement outcomes. First, I assess how pre-determined winners would bid if anonymously selected experts were tasked with reviewing call-for-tender files prior to auction commencements. If these experts identify any unnecessary rules, scoring rules will be revised accordingly. The elimination of such unnecessary rules leads to an 18% decrease in the winning price and a 3% increase in quality. Collectively, this translates to an 11% increase in social welfare measured by score change. 70% of these welfare gains arise from competitive bidding and the remaining 30% stem from increased entries. Second, considering that corrupt officials often attempt to assign lower weights to transparent factors like price and higher weights to quality in order to manipulate outcomes, I investigate the consequences of increasing the evaluation weights on the price component.

This paper makes contributions to several distinct strands of literature. First, it adds to the small but growing body of research on detecting corruption in public procurement. Existing studies measure corruption in procurement auctions through direct indicators such as bid leakage (Andreyanov and Korovkin, 2017), exaggerated bids (Huang, 2019), and price signaling (Cai, Henderson, and Zhang, 2013). Indirectly, several studies examine procure-

[3]Defined as the concordance between corruption test outcomes and the identification of suspicious call-for-tender files by experts, the accuracy rate measures the percentage of cases for which both experts and model predictions correctly classify them as corrupt or not corrupt. This accuracy rate stands at 81%.

ment thresholds that require public disclosure (Coviello and Mariniello, 2014), the adoption of open auctions (Palguta and Pertold, 2017; Coviello, Guglielmo, and Spagnolo, 2018; Baltrunaite et al., 2021; Szucs, 2024[4]),and scrutiny through audits (Gerardino, Litschig, and Pomeranz, 2024), showing evidence of bunching to avoid competition. Additionally, several studies focus on favoritism toward politically connected rms in procurement awards, nding that such rms are more likely to win contracts and often at higher prices (Cao, 2022; Baltrunaite, 2020; Baltrunaite et al., 2021; Colonnelli and Prem, 2021; Brugues, Brugues, and Giambra, 2024). This paper contributes to the literature by identifying corruption mechanisms without the need for underlying political connections or the simple binary of open versus non-open auctions. To the best of my knowledge, this study is among the rst to directly investigate manipulation within scoring rules in public procurement auctions. Moreover, the tools I developed here could be applied to other contexts.

Second, this study contributes to the literature on the e ects of anti-corruption investigations and audits in reducing corruption. Existing research suggests that anti-corruption investigations and audits can decrease corruption (Avis, Ferraz, and Finan, 2018), increase government revenue (Chen and Kung, 2019), reduce expenditure (Olken, 2007; Lichand, Lopes, and Medeiros, 2016; Zamboni and Litschig, 2018), improve rm performance (Colonnelli and Prem, 2021), and enhance electoral accountability (Ferraz and Finan, 2011). Conversely, some studies nd that audits are not always e ective in reducing corruption and may even have adverse e ects due to poor targeting (Du o et al., 2018), inadequate design (Gerardino, Litschig, and Pomeranz, 2024), or distorted incentives (Khan, Khwaja, and Olken, 2016; Lichand and Fernandes, 2019). My paper contributes to this literature by rst linking corruption detection with anti-corruption campaigns and demonstrating that, without changes to procurement policies, investigations fail to produce lasting e ects. Second, I design a targeted audit study to show how improved audit designs can help reduce corruption and enhance procurement outcomes.

Third, this research contributes to the existing literature on scoring auctions by incorporating corrupt practices into the auction model and validating the e ectiveness of a model-based testing tool using audit survey data. Foundational work by Che (1993) analyzed various types of scoring auctions and identi ed optimal scoring rules, while subsequent studies like Asker and Cantillon (2008) and Chen-Ritzo et al. (2005) demonstrated that scoring auctions can yield higher payo s for buyers compared to minimum-quality or price-only auctions. More recent works by Hanazono et al. (2013), Takahashi (2018), Andreyanov (2018), and Hanazano et al. (2020) further examine equilibrium and mechanism design in

[4]This strand of literature often posits that a lack of transparency in procurement processes signals potential corruption, while an open and transparent process is presumed to mitigate corrupt practices. Consequently, these studies have shown that corruption is often associated with a higher prevalence of non-open procurement processes.

scoring auctions, adding to the understanding of this auction format. Additionally, studies such as Bajari, Houghton, and Tadelis (2014), Ryan (2020), and Kong, Perrigne, and Vuong (2022) extend the scoring auction model to encompass contract design in public procurement. Building on this literature, my research links theoretical insights with empirical evidence by uncovering patterns of corruption within scoring auctions and o ers policy implications for reducing corruption in public procurement.

Lastly, this study contributes to the literature on collusion detection in auctions and markets, speci cally the detection of non-competitive agreements among two or more bidders.[5] However, corruption originating from the auctioneer or agency side has received comparatively less attention, despite being a signi cant issue in many developing countries where public procurement laws are poorly enforced. My study takes a novel approach by allowing for both corruption and collusion and investigating their relationship within the context of public procurement in a developing country. As a result, this research not only introduces a data-driven method for detecting corruption but also examines the distortions and policy implications arising from such practices.

The remainder of the paper is organized as follows. In Section 2, I o er background information on the scoring auction procedure and China's public procurement system. Section 3 describes the dataset used for the analysis. Moving forward, Section 4 presents key stylized facts that motivate the investigation. In Section 5, a theoretical model is constructed, laying the foundation for the empirical test conducted in Section 6. To further validate the proposed approach, Section 7 presents the design and results of the expert survey. Section 8 delves into a discussion of the implications of corruption in public procurement by exploring the impact of anti-corruption investigation policies, and conducting counterfactual analyses through the structural model to evaluate di erent policy scenarios. Finally, Section 9 provides concluding remarks, summarizing the ndings and their implications.

2 Background

2.1 Public Procurement in China

Public procurement in China is delineated into three phases: pre-procurement, procurement, and post-procurement. Initially, the procuring entity, often a government department or state-owned enterprise, outlines its requirements and drafts a detailed procurement plan. This stage entails evaluating project feasibility and determining the essential product, services, or construction required.

[5] See Porter (2005) for a literature review on collusion in auctions. More recent papers include Conley and Decarolis (2016); Schurter (2017); Chassang et al. (2022); Kawai and Nakabayashi (2022); Kawai et al. (2023); Kawai, Nakabayashi, and Shimamoto (2022).

With requisites established, the procuring entity nalizes a procurement plan that includes crucial details such as project speci cs, chosen procurement method, budget allocation, timeline, and rules for choosing nal suppliers. This plan then undergoes review and approval from pertinent monitoring government branches, usually including the Audit Bureau and the Bureau of Finance.

Figure 1: Public Procurement Procedure

Notes : The standards for procurement choices are guided by the Regulations for the Implementation of the Government Procurement Law of the People's Republic of China. There are non-open auction methods, such as negotiations, rst-price bidding on online platforms, and price solicitations.

Speci c criteria guide the choice of a procurement method, as shown in Figure 1. When dealing with uniquely quali ed suppliers or unforeseen emergencies, single-source procurement, also known as direct contracting, becomes a viable option. This method is also used when it is crucial to maintain project consistency or align with existing services. In other cases, the choice of procurement method depends on the procurement budget. To ensure transparency, projects exceeding a certain threshold are required to use the standard open-scoring auction method.[6] Projects below this threshold have several options, including invited-only auctions, online rst-price auctions, and direct price inquiries. However, even for smaller-scale procurement, there is a preference for open-scoring auctions due to the increased scrutiny and audit associated with non-open methods. Various studies (Calvo, Cui, and Serpa, 2019; Decarolis et al., 2020) have found that public procurement using non-open methods often leads to higher costs and greater susceptibility to corruption. In this paper,

[6] The thresholds for open scoring auctions in public procurement vary across di erent provinces in China. In the province under study, a signi cant change occurred in 2020, setting the benchmark for public bidding on government procurement of goods or services at 4 million yuan across the province. Similarly, the threshold for public bidding in construction projects adheres to both national and provincial regulations. These thresholds have been revised several times since 2007.

I speci cally focus on the open-scoring auction method highlighted in Figure 1.

Upon approval of the plan, the procuring entity must publicize procurement information on national and local procurement websites. This information includes project details, the chosen procurement method, budget allocation, timeline, and scoring criteria. According to regulations, an open auction requires at least three quali ed bidders to be considered valid. If an open auction ends with only two quali ed bidders, experts must decide whether to adjust the call-for-tender documents and restart the auction or switch to non-open methods. If only one bidder participates in the open auction, the procuring entity may opt for single-source procurement, provided that experts con rm the call-for-tender documents are fair and compliant with competition regulations.

Because of the complexity of public procurement, corruption within the realm of public procurement has remained a longstanding concern. In the context of open-scoring auctions, a complex network of actors is involved, as shown in Figure A1. This network involves various roles, such as city or county leaders, directors, and their subordinates within government departments responsible for procurement requests (e.g., education, transportation, health), the procurement agencies overseeing bid conferences, and the public procurement experts tasked with bid evaluation.

2.2 Scoring Auction Procedure

In addition to the general public procurement procedures, a detailed outline of the open-scoring auction process is presented in Figure 2. Once the procurement request is approved, a procurement agent is chosen. The agent is responsible for drafting the call-for-tender les, which outline the requirements speci ed by the procuring entity. These les are then published on o cial websites and newspapers. A noteworthy characteristic of open auctions, as compared to non-open methods, is that any interested companies enter the competition and have the possibility to win the contract. All bidders are given a one-month period to conduct research on the les and submit their proposals, which typically include quality speci cations and pricing details.

On the day of the auction, a procurement committee composed of at least ve randomly selected experts evaluates the submitted bids according to predetermined scoring rules. The random selection of experts helps minimize the risk of corruption, such as bribery, which could lead to unfairly awarding extra points to certain bidders. Each expert assigns a score to each bid based on the evaluation criteria. These scores are then used to rank the bids and determine the winning bidder. The contract is awarded to the bidder with the highest score.

Figure 2: Open Scoring Auction Procedure

Notes : The detailed procedure of an open scoring auction can be found on this website

Typically, the final total score is the weighted sum of the quality score and price score:

$$\text{score} = w_q \quad \text{Quality Score} + w_p \quad \text{Price Score} \in [0; 100]$$

where w_q is the weight of the quality score, and w_p is the weight of price score. The quality scores are multi-dimensional and include various aspects subject to subjective evaluation, such as product parameters, functions, post-purchase services, detailed implementation plans, and demonstration quality. They also consider evidence of the bidder's productive and financial capabilities, such as various certifications. The price score is based on the bid price. Firms with higher bid prices receive lower price scores. Specifically, the price score is calculated by dividing the minimum bid price among all firms by the individual firm's own bid price.

Given that quality criteria allow for more discretion compared to price, corrupt officials might aim to reduce the weight of the price component to exert greater control over the outcome. To prevent extreme cases where the price weight is entirely disregarded, the Public Procurement Law stipulates that price weights must fall within specific ranges: [30%, 60%] for goods procurement and [10%, 30%] for construction and service procurement. In practice, many open-scoring auctions tend to use the lowest possible price weight, thus providing more leeway for discretion in quality requirements.

In an interview with a local procurement official, I learned that many public projects he managed had preselected winners:

"There was an example when the city leaders and rm owners had a private dinner together. The leader revealed the information about a new construction project. The rm owner expressed the willingness to do the project and then a deal was reached. To pass the check from other authorities, the lower-level o cials chose an open auction and disguised it with fake competition. Only the predetermined bidder can meet all the requirements and get the highest score in the bid evaluation. Other zombie bids only create the appearance of legitimate competition."

Some may be surprised by the seemingly straightforward nature of these corrupt practices. However, this behavior aligns with the audit processes and incentive structures that government o cials face. Audits of government procurement primarily focus on budget adherence, execution methods, procurement standards, contract ful llment, project acceptance, and fund distribution. Given the large sums often involved in procurement projects, those using non-open methods face more frequent audits. Consequently, projects that use open auctions are less scrutinized, making them a more favorable cover for corrupt activities.

3 Data

In this section, I describe the datasets I use for the paper. There are ve datasets, public procurement data, corruption investigation data, rm registration data, rm tax data, and expert evaluation data. I leave the expert evaluation data for Section 7.

3.1 Public Procurement Data

I collect all the publicly available public procurement data of one province of China from 2006 to January 2021. As far as I know, I am the rst to do this, at least at the provincial level. With the improvement of transparency, all procurement procedures except those related to national secrets are required to be able to be tracked down by the public. However, the format of the procurement information is inconsistent and messy. The same issue is common in most developing countries. Non-transparent data fosters corruption and hinders the government's ability to use big data to detect collusion or corruption. The nal public procurement database consists of three primary datasets: procurement plans, procurement announcements, and outcomes. The procurement plan dataset includes procurement objects, purchaser names, reserve prices, and procurement methods. The procurement announcement dataset contains details about the bidding process, while the outcome dataset lists bidder names, bid prices, and scores. Excluding the procurement without bid information, Figure A2 shows the distribution of the number of procurement projects with complete information.

3.2 Firm registration data

The rm registration dataset includes all o cially registered rms in China, no matter whether they are still in operation or not. The data are extracted from the Firm Search Platform belonging to Alibaba Group, whose data are from the State Administration for Market Regulation, the Supreme People's Court, and Ali Map. The multi-dimensional data covers rms' names, open dates, industry, type, current status, capital size, and employment size. The dataset has been used in Bai et al. (2021) and Chen et al. (2022). I cleaned the names of companies in public procurement data and linked them to rm registration data to obtain the basic registration data of all bidders. The overall successful matching rate is over 99%. I further match the bidders with the government departments initiating procurement and use QGIS to calculate the geographical distances between them. I also obtain the headquarters information of all bidders.

In Figure A3, I plot the distribution of both the number of procurement projects in which rms participate and the number of procurement contracts that rms secure. The data reveal that approximately 80% of rms engage in fewer than ve projects, and a mere 5% participate more than 20 times. In terms of victories, 60% of rms never secure a contract, and about 95% win fewer than ve contracts. These distributions indicate that the majority of rms have limited participation and success in procurement projects."

3.3 Firm Tax data

The rm tax data used in this study were sourced from the Chinese State Administration of Tax (SAT) for the years 2007 to 2016. Serving as China's counterpart to the IRS, the SAT is responsible for tax collection and audit procedures. My dataset is derived from administrative records of enterprise income tax, o ering insights into rms' activities over this period. This comprehensive panel data includes critical aspects such as overall production, sales, and input data. Moreover, the inclusion of detailed cost breakdowns provides a nuanced perspective, enabling the assessment of various subcategories within administrative expenses. Using this dataset, I adopt the method employed by Chen et al. (2021) to formulate residualized measures of rm productivity, commonly referred to as Total Factor Productivity (TFP). The mechanics of this TFP measurement process are detailed in Appendix B1. [7]

[7] It's important to note a limitation of this dataset: It doesn't comprehensively include every rm in China for each year. The frequency of the survey varies, with more thorough coverage for larger-scale rms. In contrast, smaller rms undergo random sampling annually. This selective coverage suggests that the TFP-based estimates relate speci cally to a subset of procurement projects.

3.4 Corruption Investigations Data

The investigation data from 2011 to August 2016 are obtained from Wang and Dickson (2022), who collected the data from Tencent.Co|the largest Internet company in China. During the anti-corruption campaign, Tencent launched a searchable online database of all corruption investigations across China in 2011. Based on the information provided by Party disciplinary committees, courts, and procuratorates from the central to local levels, Tencent's database includes each o cial's name, position, locality, rank, and reason for the investigation. As for data after August 2016, since the mainstream aborted the use of the word anti-corruption and Tencent stopped updating the database, I manually collected them from Party disciplinary committees, courts, and the People's Procuratorates from all di erent government levels.[8] The monthly numbers of corruption investigations in the province I study, starting from 2011 are shown in Figure A4.

4 Motivating Stylized Facts

Before discussing how to detect corruption, it's important to note two key stylized facts from the public procurement data. First, approximately 70% of the procurement budget is allocated to contracts with just three bids, the minimum requirement for legal procurement. In contrast, only 7% of projects have fewer than three bidders, and 18% have four bidders. Second, winners in many auctions exhibit signi cant score gaps compared to losers, raising concerns about the motivation behind the costly participation of the latter.

4.1 Three-Bidder Auctions Dominate

On average, competition within procurement auctions in China remains remarkably low. Figure 3 presents the distribution of bidders in these auctions. Figure 3 the darker bars, which encompass all years, including instances where procurement projects failed due to insu cient bidders, show less than 7% of procurement projects initially fail the requirement of having at least three bidders. Approximately 61% of procurement auctions feature only three bidders, with the percentage decreasing to 18% for those with four bidders. Surprisingly, the proportion of procurement auctions with more than six bidders is less than 10%.

Kang and Miller (2022) discusses several reasons why there is so little competition in U.S. public procurement, including seller homogeneity, and agency information rent. These reasons are possible in my study as well. However, when I examine the distribution of the number of bidders in U.S. data, as illustrated in Figure 3 (a) with the lighter bars, a striking

[8] The People's Procuratorates in China are legal bodies responsible for overseeing the enforcement of laws, safeguarding citizens' legal rights, and prosecuting criminal cases within the Chinese legal system.

Figure 3: Distribution of number of bidders

Notes : The gure illustrates the average percentage of the number of bidders across all years, including procurement projects with fewer than three bidders. The darker bars represent data in China and the lighter bars represent data in the U.S.. Data from both countries exclude the procurement by the Department of Defense.

disparity emerges. Unlike the U.S. data[9], where the distribution of number of bidders is notably smooth and boasts over 20% of auctions featuring more than seven bidders, the Chinese dataset I've analyzed paints a di erent picture, with a mere 4% of auctions falling into this category. The predominant presence of three-bidder cases in my dataset contrasts with the general expectation of competition in public procurement.

4.2 Large Winning Margins

In gauging the level of competition within procurement auctions, I adopt the concept of the winning margin, akin to the approach employed by Claudio, Frederico, and Dimitri (2015) and Kawai and Nakabayashi (2022). This variable is computed using the equation:

$$\text{Win Margin}_i = \text{Score}_i - \text{Score}_{-i}$$

where Score_{-i} is the largest score, excluding the bidder herself. Therefore, winners have positive winning margins, while losers have negative ones. The less the absolute winning margin, the ercer the competition is.

A notable case with signi cant winning margins is detailed in Table 1. This case involves an organic fertilizer procurement auction, which was part of a modern agricultural sector promotion project with a budget of approximately 5 million RMB in 2013. In this auction,

[9] Public procurement requested by the Department of Defense (DOD) is excluded from US data to ensure a comparable comparison.

Table 1: Example of A Corrupt Case

Company	Quality Score (70)	Price Score(30)	Final Score	Order
A	68.4	29.9	98.3	1
B	21.2	30	51.2	2
C	17.2	29.5	46.7	3

Notes : This corruption case is revealed by the judicial judgment. The outcomes of the procurement auction are shown on the public procurement website.

exactly three bidders met the minimum requirement for participation. Although the three rms had similar price scores, indicating comparable bid amounts, there was a large gap in their quality scores. The quality score for the winning rm, A, was nearly 100%, while the scores for the losing rms, B and C, were very low. This suggests that Firms B and C did not put in the e ort to maximize their chances of winning, as they did not invest time and resources into preparing competitive proposals.

This case is a real example of corruption, drawn from retrospective ndings on China Judgement Online. The deputy director of a county-level Agriculture and Forestry Department, who managed this auction, was sentenced to seven years in prison for corruption in public procurement. His confession revealed that he had manipulated scoring rules to favor colluding rms. Firm A admitted to promising a 5% kickback to the o cial upon winning the contract, and Firms B and C acknowledged that Firm A had received insider assistance. These revelations highlight the severity of the corrupt practices, which led to a signi cant disparity in the scores.

To systematically examine how common large winning margins are, I plot the distribution of bid winning margins in Figure 4. Figure 4 visualizes this distribution. Speci cally, Figure 4 (a) shows the distribution for procurement auctions with only three bidders. The notable absence of mass around the 0 mark indicates that narrow winning margins are rare in such auctions. This suggests that close victories are uncommon, with most losing bids being signi cantly distant from the winning bid. This pattern re ects a lack of intense competition, even if winning bidders increased their prices. In contrast, Figure 4 (b) presents auctions with four or more bidders, where the previously observed "two-peak" pattern is no longer evident. The addition of more bidders signi cantly alters the distribution of winning margins, suggesting that the lack of competition is particularly pronounced in auctions with only three bidders.[10]

Despite the contrast between three-bidder and four-or-more-bidder scenarios indicating a reduced prevalence of large winning margins in the latter, it is crucial to note that this discrepancy does not necessarily imply the absence of corruption in the latter case. A case in

[10] Figures for di erent numbers of bidders are shown in Figure A5.

Figure 4: Distribution of bid-di erences over (bidder, auction) pairs

(a) Three Bidders

(b) Four and More Bidders

Notes : The X-axis represents the score gap between a bidder's own score and the highest score among all bidders, excluding the bidder's own score.

point, as detailed in Table A1, illustrates another four-bidder procurement auction wherein Company A emerges as the unequivocal victor over Company C. Despite the participation of four bidders, substantial score gaps persist between the winner and the losers, underscoring that the issue of signi cant winning margins can persist even in scenarios with more bidders.

Aside from the presence of minimal bidders and substantial winning margins, there exists evidence indicating notable disparities in the performance of rms across various auctions. This variance often eludes simple attributions to divergences in procurement prerequisites or evaluation methodologies. Firms undertake diverse roles within this spectrum, including that of predetermined winners, zombie bidders, and genuine competitors. Detailed examinations through a case study and additional data analysis are provided in Appendix B2.

Collectively, these motivating stylized facts o er compelling substantiation for the existence of pervasive corruption within scoring auctions. This malpractice is especially conspicuous in auctions featuring only three bidders.

5 Model

This section uses a standard scoring auction model to show how the customized scoring rules result in substantial winning margins inconsistent with the competition null hypothesis.

A government entity seeks to procure a project using a scoring auction. A call-for-tender

le is public for all rms, incorporating essential details like the project's budget,[11] location, project timeline, and transaction plan. Of particular importance, it outlines a detailed scoring rule function $S : (p; \mathbf{q}) \to \mathbb{R}$, which takes into consideration both the price bid p, with $p \in [\underline{p}; \bar{p}]$,[12] and the quality bid $\mathbf{q}$, with $\mathbf{q} \in \mathbb{R}^L$. More speci cally, quality $\mathbf{q} = (\mathbf{q}^R; \mathbf{q}^U)$ consist of both project related quality $\mathbf{q}^R$ and unrelated quality $\mathbf{q}^U$.

In the context of this paper, the nal scores are the weighted sum of quality scores and price scores:

$$S(p; \mathbf{q}) = \mathbf{w}_{\mathbf{q}} \quad \mathbf{q} + w_p \frac{p}{\bar{p}}; \text{ with } \sum_{l=1}^{L} w_q^l + w_p = 100 \text{ and } q^l \in [0; 1]$$

where $\mathbf{w}_{\mathbf{q}}$ and w_p represent the weights assigned by the government to the quality and price parts, respectively. The nal scores ranges from 0 to 100

The scoring rule re ects the utility function of the government agent.[13] For a competitive auction trying to maximize social welfare, the weights on unrelated quality is $\mathbf{w}_{q^U} = \mathbf{0}$, while for a corrupt auction trying to customize the scoring rules to favor speci c rms, $\mathbf{w}_{q^U} > \mathbf{0}$.

In a competitive procurement auction, only related quality is required $\mathbf{q} = \mathbf{q}^R$. n ex-ante symmetric and risk-neutral rms participate in the auction, denoted by $i = 1; 2; :::; n$.[14] The number of competitors is known. Firm i in the auction a draws its private information, rm type $_i \in \mathbb{R}^M$, independently from a publicly known absolutely continuous distribution function $F( )$.[15] Firm i has a cost function $C(\mathbf{q}; \ _i)$,[16] depending on the quality bid $\mathbf{q}$ and the rm type $_i$, and a pro t function $= P(s; \mathbf{q}) \quad C(\mathbf{q}; \ )$.

Assumption 1. Cost function $C(\mathbf{q}; \ )$ is continuous, and has a quasilinear format:

$$C(\mathbf{q}; \ ) = \ ^0 + C^0(\mathbf{q}; \ ^0)$$

where $^0 = (\ ^1; :::; \ ^M \ ^1)$. For $\forall l$, $C_{q^l}(\mathbf{q}; \ ) > 0$, $C_{q^l q^l}(\mathbf{q}; \ ) > 0$, and $\forall k$, $C_{\ k}(\mathbf{q}; \ ) > 0$.

Assumption 2. The Hessian matrix of $P(s; \mathbf{q}) \quad C(\mathbf{q}; \ )$ is negative de nite given scores, with $\forall l$, $P_{q^l}(s; \mathbf{q}) \quad C_{q^l}(\mathbf{q}; \ ) > 0$ at $q^l = 0$, and $P_{q^l}(s; \mathbf{q}) \quad C_{q^l}(\mathbf{q}); \ ) < 0$ at $q^l = 1$.

[11] The budget is publicly disclosed information, known to all rms prior to the submission of bids. It represents the maximum allowable bid, serving as an upper limit on the prices rms are permitted to propose. Consequently, any bids exceeding this budget are deemed invalid.

[12] $\bar{p}$ is the budget of the project, and $\underline{p}$ is the minimum price bound.

[13] Follow the literature Asker and Cantillon (2008); Takahashi (2018); Huang and Xia (2019); Hanazano et al. (2020).

[14] I also introduce some asymmetry based on rm characteristics z in Appendix C. Then rms with di erent z, (jz) have di erent bidding strategies. The results are not sensitive to the asymmetry.

[15] If rms are ex-ante asymmetric, the distribution of rm type is $F(\ jz)$

[16] The assumption here is the cost only depends on the related quality $\mathbf{q}^R$ but is independent of the unrelated quality $\mathbf{q}^U$.

With the above assumptions, shown in Hanazano et al. (2020), a symmetric pure-monotone equilibrium $s = \quad (\ )$ exists. The score distribution $G(s)$ is monotone and differentiable. Its density is $g(s)$.

Theorem 1. The competitive equilibrium bidding strategy $(p(\ ); q(\ ))$ is given by

$$P(\ (\ ); \mathbf{q}(\ )) = C(\mathbf{q}(\ ); \ ) \quad P_s(\ (\ ); \mathbf{q}(\ )) \frac{G(\ (\ ))}{(n \quad 1)g(\ (\ ))}$$

$$C_{\mathbf{q}}(\mathbf{q}(\ ); \ ) = \quad P_{\mathbf{q}}(\ (\ ); \mathbf{q}(\ ))$$

Proof. See Appendix C

□

Following Asker and Cantillon (2008) and Hanazono et al. (2013), I de ne the pseudotype, the e ective cost measured by score, as

$$k(\ (\ ); \ ) = \quad (\ ) \quad \frac{(\ (\ ); \ )}{{}_s(\ (\ ); \ )} \tag{1}$$

${}_s(\ (\ ); \ )$ represents marginal pro t of score and is negative. Pseudotype k can be interpreted as the highest score the rm can achieve with nonnegative pro t.

The equilibrium strategy $s = \quad (\ )$ can be characterized by the order statistics of pseudotype k in the following corollary.

Corollary 1.1. In the competitive equilibrium, the winning scoring bid is the expectation of the strongest rival's pseudotype k:

$$s^{win} = E[k^{rival\ (1)} | s^{win}] \tag{2}$$

Proof. See Appendix C

□

Corollary 1.1 says that under competition, the scores of the winners represent the expected pseudotype of the strongest rivals. For winners, it's unnecessary to submit scores surpassing the expected pseudotype of their strongest rivals. Going beyond the value would involve excessive e ort and expenditure and ultimately leave potential extra pro ts on the table. This is the key to testing the competition null hypothesis.

In a corrupt auction with customization of scoring rules, unrelated quality $\mathbf{q}^U$ is required

with $\mathbf{w}_{q^U} > \mathbf{0}$. [17] The predetermined winners get $\mathbf{w}_{q^U}\mathbf{q}^U$ advantage over other firms. To make sure the predetermined suppliers win the bids, the corrupt officials usually make the $\mathbf{w}_{q^U}$ large enough. Potential non-corrupt competitors see the signal $\mathbf{w}_{q^U}$ and understand that the contract is locked by another corrupt firm. They will not enter the auction because they cannot obtain $\mathbf{w}_{q^U}\mathbf{q}^U$. Even if they lower the price and enhance other quality aspects, they still cannot win the auction. To meet the minimum number of bidders requirement, fake bidders participate. These fake bidders also cannot obtain $\mathbf{w}_{q^U}\mathbf{q}^U$. Also, fake bidders do not prepare seriously for price and other quality bids and merely submit the minimum standard bid to fulfill the agreement with the predetermined winners. When there are fake bidders and no strong competitors, the predetermined winners will bid as close as possible to the highest allowable price, which is the project budget, to maximize their profits.

Because of the unrelated quality requirement, pseudotype, the highest possible score of bidders, of both potential competitors and fake bidders in corrupt auctions $k^{rival}_{corrupt}$, are downgraded compared to that in competitive auctions k^{rival}.

Corollary 1.2. With corruptly unrelated quality requirement $\mathbf{w}_{q^U} > \mathbf{0}$:

$$E[k^{rival} | s^{win}] > E[k^{rival}_{corrupt} | s^{win}] \tag{3}$$

and the equation in Corollary 1.1 doesn't hold, instead

$$s^{win} > E[k^{rival\ (1)}_{corrupt} | s^{win}] \tag{4}$$

Proof. See Appendix C

□

6 Empirical Test

The two corollaries provide methods for detecting manipulation and corruption in scoring rules. Equations (2) and (4) offer estimates of group-based corruption proportions, while Equation (3) provides a test for corruption at the auction level.

To proceed with the tests, following Hanazano et al. (2020), Andreyanov (2018), and Huang (2019), I first estimate the pseudotype k_i for each bidder i, assuming auctions are competitive. Using equation (1) and the equilibrium conditions,[18] the definition of pseudo-

[17] The corrupt behaviors modeled here are achieved not through a direct increment in the quality score during the bid evaluation process (Burguet and Che, 2004; Huang and Xia, 2019) a stage where the evaluation experts merely add additional points to enable corrupt winners to outperform their competitors. Instead, it is executed through the customization of scoring rules before the initiation of auction competition, impacting both corrupt winners and their competitors.

[18] For more details please see Appendix C

type can be rewritten as:

$$k(\ (\ );\ ) = \quad (\ ) \quad \frac{(\ (\ );\ )}{{}_s(\ (\ );\ )} = \quad (\ ) + \frac{G(\ (\ ))}{(n \quad 1)g(\ (\ ))} \tag{5}$$

Then the pseudotype can be estimated using:

$$\hat{k}_i = s_i + \frac{\hat{G}(s_i)}{(n \quad 1)\hat{g}(s_i)}$$

The estimated score distribution $\hat{G}(s)$ and density $\hat{g}(s)$ can be obtained non-parametrically following Guerre, Perrigne, and Vuong (2000), Athey and Haile (2002), and Li, Perrigne, and Vuong (2002):

$$\hat{G}_s(s; n; \mathbf{x}) = \frac{1}{T h_{g_n} h_{g_x}} \sum_{a=1}^{A} \frac{1}{n_a} \sum_{i=1}^{n_a} 1(s_{ia} \quad s) K_G\left(\frac{n \quad n_a}{h_{g_n}}; \frac{\mathbf{x} \quad \mathbf{x_a}}{h_{g_x}}\right)$$

$$\hat{g}_s(s; n; \mathbf{x}) = \frac{1}{T h_s h_{g_n} h_{g_x}} \sum_{a=1}^{A} \frac{1}{n_a} \sum_{i=1}^{n_a} K_g\left(\frac{s \quad s_{ia}}{h_s}; \frac{n \quad n_a}{h_{g_n}}; \frac{\mathbf{x} \quad \mathbf{x_a}}{h_{g_x}}\right)$$

where n_a is the number of bidders; $\mathbf{x}$ is a vector of auction characteristics; $1(:)$ is the indicator function; A is the number of auctions; K_G and K_g are kernels; and $h_{g_n}; h_{g_x}; h_s$ are bandwidths. The estimated distribution of scores is conditional on the number of bidders and other auction characteristics.[19]

6.1 Corruption Proportion Estimation

Equation (2) provides the null hypothesis of a competitive auction, and Equation (4) serves as the alternative hypothesis. By taking expectations with respect to winning scores on the right and left sides, the test becomes applicable for a group of auctions:

$$H_0 : E[s^{win}] \quad E[k^{rival\ (1)}] = 0 \qquad H_1 : E[s^{win}] \quad E[k^{rival\ (1)}] > 0$$

Theoretically, the null hypothesis can be tested directly. However, when corrupt and competitive auctions are mixed in a group, both the scores and the estimated k^{rival} are biased. Generally, $k^{rival\ (1)}$ is subject to an upward bias in competitive auctions, while it experiences a downward bias in corrupt auctions due to the prevalence of low scores caused by manipulations in the scoring rule and the presence of fake bidders.[20] Also, $E[s^{win}]$

[19] In the estimation, auction characteristics include procurement categories, project budget, and price weights.

[20] Please see Corollary 1.3 in Appendix C for more discussion.

is higher when there are corrupt auctions because the scores of predetermined winners are exaggerated. This results in a separation between competitive and corrupt auctions, with $E[s^{win}] \quad E[k^{rival\ (1)}] < 0$ for competitive auctions and $E[s^{win}] \quad E[k^{rival\ (1)}] > 0$ for corrupt auctions. For instance, the bar graphs for professional service projects in Figure 5 show two peaks in $s^{win} \quad k^{rival\ (1)}$, with one peak clustering on the negative side and the other on the positive side.

Figure 5: Estimation of Mixed Analysis and Fitting with Public Procurement Data

(a) Professional Service I (b) Professional Service II

Notes : The histograms plot the distribution of the winning score minus the pseudotype of the strongest rival, while the smooth densities represent estimations from the mixed analysis. Figure (a) focuses on professional service projects with 4 bidders, a budget greater than 2 million RMB and less than 3 million RMB, and a price weight of 10 points. Figure (b) features professional service projects with 3 bidders, a budget exceeding 3 million RMB but less than 4 million RMB, and also a price weight of 10 points.

The separation facilitates mixture analysis. I use the nonparametric maximum likelihood estimation (NPMLE) approach to recover the distribution F of $s^{win} \quad k^{rival\ (1)}$, following methods outlined in Jiang and Zhang (2009), Koenker and Mizera (2014), Gu, Koenker, and Volgushev (2018), and Gilraine, Gu, and McMillan (2020). These papers establish a general framework for quantifying unobserved heterogeneity without imposing parametric assumptions on it. In the context of corruption within auctions, this framework is applicable as the unrelated quality scores, $\mathbf{w}_{q^U}\mathbf{q}^U$, remain unobservable. Consequently, $s^{win} \quad k^{rival\ (1)}$ can be viewed as a manifestation of unobserved heterogeneity within the auction environments. Although the distribution F of $s^{win} \quad k^{rival\ (1)}$ is unobserved, it can be estimated non-parametrically from the data:

$$\hat{F} \quad \operatorname{argmax}_{F\ 2F} f \sum_{a=1}^{A} \log \int ' {}_d((s_a^{win} \quad k_a^{rival\ (1)}) \quad)dF(\ )g$$

where $'_d$ represents the standard d-dimensional normal density, and $\mathcal{F}$ denotes the set of all probability distributions on $\mathbb{R}$ is the nonparametric maximum likelihood estimator (NPMLE) for $\hat{F}$. Kiefer and Wolfowitz (1956) have demonstrated the consistency of the NPMLE for the mixing distribution F. By integrating the density for > 0, the proportion of corrupt auctions can be obtained.

The estimated mixing distributions in Figure 5, shown in di erent colors, illustrate how well the model ts the data. I analyze two groups of professional service projects: one with three bidders and the other with four bidders. The estimation, which models both corrupt (green) and non-corrupt (red) groups as mixtures, aligns closely with the observed data distribution. To further validate the NPMLE, I conducted Monte Carlo simulations, nding that the estimated proportion of corruption matches closely with the data-generating process (DGP). Additional details are provided in Appendix D1 and D2.

I then apply the method to the entire public procurement dataset. The results are presented in the rst part of Table 2. Aggregating the corruption proportions from all subgroups, it is found that 61% of auctions are corrupt. For auctions with three bidders, the estimated proportion is 71%.

6.2 Auction level test

Equation (3) provides an action-level corruption test. For each auction a:

$$H_0 : E[k_a^{rival} \mid s_a^{win}] = E[k^{rival} \mid s_a^{win}] \quad H_1 : E[k_a^{rival} \mid s_a^{win}] < E[k^{rival} \mid s_a^{win}]$$

where $E[k_a^{rival} \mid s_a^{win}]$ is the mean pseudotype of the actual rivals in auction a, and $E[k^{rival} \mid s_a^{win}]$ is expected pseudotype of rivals in competitive auctions conditional on the winning score s_a^{win}.

Rejecting the null hypothesis H_0 provides evidence in favor of H_1, suggesting that rivals' scores are downgraded compared to the winners. This, in turn, leads to the rejection of the hypothesis that the auction is competitive. However, the presence of corrupt auctions threatens the estimation of the distribution of s and introduces bias into the estimation of k. Unlike the corruption proportion estimation, the auction-level test requires unbiased pseudotype estimates.

To correct the biased pseudotype, I employ a systematic method similar to the methods such as Iterative Outlier Removal (IOR) (Parrinello et al., 2016) from public health literature, and the Outlier Removal Clustering algorithm (ORC) (Hautamäki et al., 2005), k-means with outlier removal (KMOR) (Gan and Ng, 2017), and mean-shift outlier ltering (Yang, Rahardja, and Fränti, 2021) from the domain of computer science and data mining. The steps are detailed below:

Step 1. Estimate the pseudotypes of all bidders in all auctions using equation (5).

Step 2. Conduct the auction-level test.[21]

Step 3. Filter out the auctions that reject the null hypothesis (H_0) and repeat steps 1 and 2 until the proportion of rejected auctions is within the desired level.[22]

Step 4. Use the estimated distribution of $\hat{k}$s from Step 3 to estimate the pseudotypes of all bidders in all auctions and apply the statistical test to save p-values.

The structured approach ensures the systematic and iterative application of the pseudotype estimation method, accounting for corrupt auctions. For example, in the \for-sure corrupt case" in Section 4, Table 1, the auction involved three bidders with scores of 98.3, 51.2, and 46.7. Given the winning score of 98.3 and the auction characteristics,[23] $\hat{k}^{rival}$ conditional on winning score 98.3 from the iterative method is 90.72. However, in this auction $\hat{k}_a^{rival}$ are 53.91. The p-value of the Wilcoxon test is 0.002, leading to the rejection of the null hypothesis. Therefore, the auction is successfully identi ed as corrupt using my method. The graphical illustration is shown in Figure D7. There are more discussions about the example auctions can be found in Appendix D4.

To demonstrate the e ciency and accuracy of these iterative test steps, I conduct a Monte Carlo Study with simulations in Appendix D3. In the Monte Carlo Study, the approach can achieve an overall 90% accurate prediction rate when mixing 20% to 80% of corrupt auctions. Instead of the test with an iterative way to estimate the corrected pseudotypes, I also propose a method using the biased pseudotypes and the k-means unsupervised learning clustering method (Wu et al., 2008; Hartigan and Wong, 1979; Celebi, Kingravi, and Vela, 2013) to label corrupt and noncorrupt auctions. However, the iterative method overperforms the k-means learning in both simulated data and procurement data in terms of accuracy rate.[24]

Table 2 part 2 summarizes the test results by showing the proportion of procurement auctions that reject the null hypothesis. Overall, approximately 65% of the auctions reject the competitive auction null hypothesis, and even with the conservative approach, this gure is 57%. In three-bidder auctions, the majority reject the null hypothesis. Speci cally, in 70% of the 3-bidder auctions, the test results show evidence of a downgrade of the scores of rivals.[25] For four-bidder auctions, although the proportion is smaller than in three-bidder auctions, it is still signi cant. More conservative results with $= 0.05$ can be found in Table A2.

[21] For statistical test methods and signi cance level choices, please see Appendix D3 for more details.

[22] For main results, I choose $= 0.1$ to ensure the power of the test, but I also show the results for $= 0.05$ in Section 6.3.

[23] Auction characteristics include budget, price/variable quality weight, procurement category, and number of bidders

[24] Please see Appendix D5 for more details.

[25] Using adjusted p-values, the proportion diminishes to 63%. Even employing the most conservative approach, utilizing $= 0.05$ and adjusted p-values, over 50% of auctions consisting of three bidders still reject the null hypothesis.

Table 2: Corruption Proportion Estimation and Auction-level Test Results

	All	3 Bidders	4 Bidders	5 Bidders
	Corruption Proportion Estimation			
Corruption Proportion	60.57%	70.88%	46.49%	26.85%
	[60.19, 60.96]	[70.21, 71.55]	[45.95, 47.03]	[24.77, 28.93]
	Auction Level Test = 0:10			
Unadjusted P-value	64.71%	69.74%	51.18%	47.74%
	[64.64, 64.78]	[69.61, 69.87]	[51.03, 51.33]	[47.44, 48.04]
Adjusted P-value	56.83%	62.36%	43.39%	38.32%
	[56.78, 56.89]	[62.26, 62.47]	[43.27, 43.51]	[38.17, 38.46]

Notes : 95% con dence intervals from bootstrapping are indicated in brackets. The rst two rows of the auction-level test results represent the results using unadjusted p-values, while the following two rows display the adjusted p-values to control the false discovery rate. Unadjusted p-values are more powerful than adjusted p-values but have a higher type I error rate.

The aggregated proportions of corruption derived from auction-level tests closely align with the proportions directly estimated using the nonparametric maximum likelihood estimator (NPMLE). [26] Furthermore, these proportions are similar to those estimated through the k-means clustering method, detailed in Appendix D5.

6.3 Discussion

Although rejecting the null hypothesis indicates evidence of the downgrading of rivals' scores, it cannot be concluded that the downgrading is solely due to the manipulation of scoring rules by corruption. One of the most possible ones is collusive bidding by all participants in a cartel group without corrupt o cials' involvement. However, several factors make this scenario less likely, including the low co-entry frequency, fragmented markets, and high cost of collusion maintenance under the dominant power of the government.

Low co-entry frequency. Cartel members often establish co-entry arrangements to bolster their capacity to manipulate auction outcomes in favor of the cartel (Porter and Zona, 1993; Conley and Decarolis, 2016; Schurter, 2017; Kawai, Nakabayashi, and Ortner, 2021). A pivotal indicator of collusion is the recurrent participation of a group of rms in the same auction. In order to examine how frequently the same pair or trio of rms co-participate in procurement projects, I provide a frequency distribution in Figure 6 that covers all 214,000

[26] As shown in the Table A2, for cases with three and four bidders, the results of the proportion estimation and the auction-level test are very similar. However, as the number of bidders increases, the results gradually diverge. This occurs because the proportion estimation only leverages the scores of the winner and the second-highest bidder, without considering other bidders. If the other bidders' scores are clustered closely but at a distance from the winner, the auction test can detect collusion among them.

procurement instances in my dataset.[27] About 86% of all possible pairs of rms participate in the same procurement equal or less than twice, and only a small minority participate more than twice. For trios of rms, this percentage increases to 96%, indicating that only 4% of three-bidder groups interact more than twice.[28]

Figure 6: Frequency of Bidder Pairs and Trios

(a) The Frequency of Bidder Pairs (b) The Frequency of Bidder Trios

Notes : The X-axis represents the frequency of occurrence where the same pair or trio of rms participate in the same public procurement auctions. The Y-axis indicates the proportion of occurrences for each frequency.

Furthermore, I applied the participation test using the approach proposed by Conley and Decarolis (2016).[29] The null hypothesis is that the entry of groups of rms is competitive. The results of the test are intriguing, as only a small percentage of groups with two or more members - speci cally 7.64% - rejected the null hypothesis. The number was even lower for groups with three or more members, at 2.59%. These gures are signi cantly lower than the 69% of auctions in Conley and Decarolis (2016) that rejected the null hypothesis. These results indicate that repeated participation, which is a crucial red ag of bid rigging, is not a common occurrence in the data.

Fragmented Market. Overall, compared to developed countries, the market in China is notably fragmented and is also characterized by its dynamism, marked by the frequent

[27] It is noteworthy that more auctions can o er more comprehensive insights into the rm network. Therefore this analysis uses both open auctions and non-open auctions.

[28] While my dataset doesn't provide comprehensive procurement information for all provinces, it is worth noting that repeated participation is less common in this setting, as rms are less likely to participate in procurement conducted in other provinces.

[29] More details on the methodology and results of the participation test can be found in Appendix D.

emergence and exit of rms. To assess the level of concentration[30] I utilize rm tax data from 2016 to calculate the Her ndahl{Hirschman Index (HHI) by industry and illustrate the distribution of the HHI in Figure A6. With a mean HHI of 335, the market is substantially below the concentrated market threshold of 2500, indicating prevalent market fragmentation.

High Collusion Maintenance Cost. Maintaining collusion is costly due to two reasons. First, in economies where government authorities have signi cant control, they can manipulate auctions to bene t speci c bidders, making it di cult for other companies to engage and win contracts. Consequently, rms that manage to forge corrupt connections have a higher chance of securing contracts, eliminating the need for other companies to create collusive groups. Second, even the predetermined winner within a cartel faces the need to bid competitively, incurring signi cant expenses. This dynamic is made even more complex by the continuous entry of numerous genuine competitors into the market. In such an environment, the presence of these additional competitors and the necessity for competitive bidding undermine the rationale for forming collusive groups, making the maintenance of such groups logically and economically challenging.

The points mentioned above show that it is less likely for simple cartel groups to control procurement auctions and create big di erences in scores resulting in the rejection of the test. To further con rm this is true, I conduct an expert audit study in the next section.

7 Expert Evaluation Survey

In this section, I utilize data from a dedicated audit study of procurement experts to further show the missing mass screened out by the statistical tests is primarily caused by the manipulation of scoring rules.

In interviews with procurement o cers, they emphasized that ensuring the predetermined winner secures the auction victory involves crafting customized scoring rules for the favored rm. These rules are deliberately designed with a level of opacity that makes them unfamiliar and unidenti able to those outside the local industry network. Even government auditing teams are often unable to address this issue because they lack in-depth knowledge of the speci c project and industry, making it nearly impossible to nd tangible evidence like covert agreements or illicit nancial transfers between the corrupt rm and the involved o cer. Consequently, annual scal auditing reports primarily list procurement cases conducted outside legal procedures, with very few cases addressing the presence of unreasonable scoring rules. Fortunately, government evaluation experts, who are randomly selected to assess bid proposals, possess substantial knowledge about project requirements and the local

[30] Literature (Scherer and Ross, 1990; Motta, 2004) has taken market fragmentation as an important factor undermining the ability of rms to collude

Table 3: Balance Table for the Survey Sample

	Sample	All	P-Value
Obs	500	186,351	
#Bidders	3.68	3.74	0.48
Reserve Price	4.91	4.46	0.5
Winning Ratio	0.97	0.97	0.71
Price Weight	22.76	23.36	0.29
%Construction	0.09	0.09	0.85
%Service	0.39	0.35	0.1
Median Year	2017	2017	

Notes : The last row presents the engineer's estimated markup, which is derived from the project document and is exclusively available in the survey sample.

market structure. They can readily identify any super uous rules in place for the project and determine if these rules have been tailored to favor speci c rms.

Drawing from the insights of these procurement experts, I designed the survey as follows. I randomly selected 500 procurement projects from the comprehensive procurement dataset. Table 3 provides a summary of the survey sample alongside all procurement projects. On average, each auction involved 3.68 bidders, with an average project budget of 0.7 million USD. The winning bidder's revenue constituted 97% of the project budget, and the average quality score for the winner was 0.858 out of 1. Notably, there were no statistically signi cant di erences between the survey sample and all procurement cases.

Second, I categorized the procurement projects in the sample and distributed the corresponding call-for-tender les to ve procurement experts, each based on their area of expertise. In general, two experts focused on procurement for goods, one on construction procurement, and the other two on service procurement. These call-for-tender les included comprehensive project requirements and scoring rules. Without knowledge of the bidders or the outcomes of the procurement sample, the experts were tasked with reading each call-for-tender le and responding to a set of questions. These questions covered various aspects, including the expert's estimation of the general markup,[31] the local market competition, and the design of the RFPs.[32]

The most crucial part of the survey entailed asking the experts whether they detected any redundant requirements within the scoring rules, particularly in the technical and business sections, that might suggest the customization of scoring rules. If any such instances

[31] Experts are requested to provide approximate estimates of the standard markup for similar projects with which they have had prior experience. The average markup rate provided by the experts is 23%, indicating that the projects are appealing to rms.

[32] An English version of the survey can be found in Appendix B.

were identi ed, the experts were instructed to highlight and provide comments. Prior to distributing the survey, I ensured that none of the experts had participated in the evaluation of the procurement projects they were assigned to review.

Figure 7: An Example of Procurement Survey

Notes : The graphs displayed are screenshots taken from the expert evaluation survey responses.

Figure 7 provides a snapshot of a call-for-tender le for county-level government procurement of closed-circuit television (CCTV) equipment in 2021. In the business section, the expert identi ed three signi cant rule sets. The rst set mandated high information security certi cation for all bidders, a requirement that appeared unnecessary for the project. The second set drew attention because it is typical to demand compliance with three basic system certi cations, whereas this speci c le only requested two. The expert suspected that the target rm might possess only two of these certi cations. The third set related to the quali cations of team members, encompassing degrees, majors, and examination certi cates. Meeting all these stipulations would limit the eligible bidders to just one or two local rms. In the technical section, the expert noted that only one manufacturer could provide the speci c test reports requested by the le, and the ultimate winner must be the exclusive local supplier authorized by that manufacturer. Reassuringly, the winning rm and its brand closely aligned with the expert's observations.

Table A3 presents the auction results for the above case. This case rejects the null hy-

pothesis of competitive procurement auctions and is marked as corrupt. The winning bidder achieved a perfect score in the business score section and nearly a full score overall, indicating compliance with all non-essential requirements highlighted by the expert. Consequently, this case falls into the True Positive category.

I collected and digitized responses from the 500 surveys, including the unobserved expert-estimated markup, which is presented in the nal row of Table 3. On average, this markup amounted to approximately 23%. This substantial markup gure makes these procurement auctions attractive to competing entities. If experts highlighted any rules in the call-for-tender documents, the corresponding procurement auction is classi ed as corrupt, as indicated by expert surveys. Conversely, if no such highlights were identi ed, the auction is considered non-corrupt. The consistency rate is calculated by dividing the number of auctions that statistical tests and surveys give the same classi cation by the total number of auctions. The results are outlined in Table 4. Remarkably, the consistency rate reaches 82%, with a test power of 84.5% and a test size of 25.6% when assuming the highlights of scoring rules from the expert are the ground truth of corruption.

While the information obtained from the expert survey closely approximates the ground truth, it is important to acknowledge that the binary corruption indicator based on the scoring rules does not achieve a perfect 100% representation of corruption. Notably, among the false positive instances, there are nine cases where experts did not highlight unnecessary rules, but they indicated that the scoring criteria were excessively subjective. This subjectivity creates an environment conducive to score manipulation. Excluding these 9 les results in a test size of 18.4%.

I also provide the same table using adjusted p-values in Appendix Table A4. The overall consistency rate is 79.4%, which is slightly lower than that achieved using unadjusted p-values, but with a lower type I error rate. This comparison further reinforces the decision to use unadjusted p-values as the primary results.

Table 4: Expert Survey and Model Prediction

Consistency Rate=82%	Total=500	Model Prediction		
		Corrupt H_1	Not Corrupt H_0	
Expert Survey	Corrupt (P)	317	58 False N	Test Power 84.53%
	Not Corrupt (N)	23+(9) False P	93	Test Size 25.6% (18.4%)

Notes : For the expert survey, if any evaluation survey reveals highlighted scoring rules accompanied by expert explanations and concerns, the procurement project is labeled as corrupt. The classi cation of model prediction uses unadjusted p-values with a signi cance level of 0.1.

The comparison between test results with the expert audit study shows that in general, the model-based statistical test yields reliable performance. The majority of substantial score disparities identi ed by the test are attributed to the tailored scoring rules, rather than to other conceivable reasons.

8 Policy Implications

In this section, I will rst present evidence of the selection of less e cient rms due to corruption in procurement auctions. Then, I will discuss three policies aimed at reducing corruption in scoring auction procurement. The rst policy is anti-corruption investigations. I use the recent anti-corruption campaign in China and an event-study design to analyze its e ects on corruption. The other two policies are counterfactuals: anonymous evaluation of Requests for Proposals (RFPs) and increasing the weight given to price in procurement decisions. I will use an estimated structural model to evaluate these counterfactual scenarios.

8.1 Anti-corruption Investigations

Anti-corruption investigations have been widely recognized as e ective tools for reducing corruption (Avis, Ferraz, and Finan, 2018; Chen and Kung, 2019; Colonnelli and Prem, 2021). I examine whether a recent anti-corruption campaign in China has led to changes in the procedures and outcomes of public procurement, potentially reducing corruption. After President Xi came to power in 2014, the Chinese Communist Party launched an anti-corruption campaign aimed at eliminating corruption among o cials at all levels. Although the campaign targets general corruption issues beyond just public procurement, recent evidence (Manion, 2016; Wang and Dickson, 2022; Fang, 2023) indicates that it has altered the government's incentive structure and e ectively reduced opportunities for bureaucratic corruption.

Unlike much of the prior research, which often relies on indirect measures of corruption, my study uses a direct approach to assess corruption in public procurement. To investigate systematic di erences in procurement methods, outcomes, collusion among bidders, and corruption involving both bidders and o cials, I analyze variations in exogenous corruption investigations conducted on o cials across di erent government departments. The event study reduced form is presented below:

$$y_{idt} = {}_{t} + {}_{d} + {}_{0}\text{Procurement}_{idt} + {}_{1T} \sum_{T=\ 4}^{r5} \text{Time to Investigation}_{idT} + {}_{idt}$$

where the dependent variables y_{idt} for procurement contract i purchased by department d at time t include procurement methods, number of bidders, corruption prediction from

the test, and an indicator for whether the winner is a new supplier to the department. $Time\ to\ Investigation_{idT}$ equals 1 if, at time t, T quarters have passed before/since a government official in department d was under corruption investigations.[33] I control $_t$ time year-month fixed effects, and $_d$ buyer department fixed effects. I also control $Procurement_{idt}$, other procurement characteristics, such as procurement of product categories and reserve prices. The analysis uses samples from all departments, regardless of whether corruption investigations occurred or not. Results derived exclusively from departments that underwent investigations are detailed in Appendix A Figure A7.

The analysis focuses on two sets of dependent variables related to the impact of corruption investigations. The first dependent variable examines the selection of auction methods. Specifically, a value of 1 is assigned to y_{idt} if the auction is an open auction, and 0 otherwise. To capture the gradual decline of the shock resulting from the investigation over time, the event study window is limited to one year prior to and one and a half years subsequent to the investigation. The outcomes are illustrated in Figure 8 (a). The results indicate that after the corruption investigations, the departments immediately had 5 percentage points more likely to choose open auctions instead of non-open auction methods. However, the coefficient is only statistically significant in the first following quarter. After the second quarter, this positive effect faded away.

The second set of dependent variables focuses on the outcomes of auctions. Figure 8 (b) examines the number of bidders as the dependent variable. It shows an increase of 0.3 bidders in the first and third quarters following the investigations. Beyond the second quarter, while the coefficients retain their positive values, there's a slight decline. However, they sustain statistical significance at the 0.1 level. The effect indicates a sustained increase in firm entries as a supply-side effect, likely spurred by the corruption investigations. Figure 8 (c) uses the labels of corruption from the statistical test as the dependent variable. The investigation decreases the probability of corruption in a procurement auction of an investigated department, the effect is particularly statistically significant in the post-third quarter, representing a 6 percentage point drop. The delay aligns with the timeline of open scoring auctions, given that the procurement plan is often published several months prior to the actual bid evaluation meeting. Finally, Figure 8 (d) examines the probability of the winning firm being a first-time supplier for the particular local procurement government. The exploration is to see whether there is a new supplier-government network built after the corruption investigation. The results indicate that there is an increase in the probability of new firms winning procurement auctions during the post-investigation period.

The findings from the event study indicate that corruption investigations bolster com-

[33] The event study specification is similar to the one in Beraja et al. (2023) and consolidates the treatment time period to a quarterly level.

Figure 8: The E ect of Corruption Investigations

(a) Open Auction

(b) Number of Bidders

(c) Corruption Indicator

(d) New Winning Firm=1

Notes : The regression model incorporates time- xed e ects and procurement government department xed e ects. Standard errors are clustered at the department level.

petition in open auctions by prompting more rms to join the bidding process. Also, these investigations reduce manipulative practices in the design of scoring rules. By referencing the estimated coe cients from the third quarter as depicted in Figure 8 (b) and (c), I can gauge the in uence of corruption on the number of entrants using a back-of-the-envelope calculation of corruption's marginal e ects:

$$\text{Entry E ect of Corruption} = \frac{\text{Number of Bidders}}{\text{Corruption Probability}} = \frac{0:169}{0:058} = 2:914$$

The calculation exercise can be further used in the counterfactual analysis in Section 8.3 to decompose the e ects of reducing unnecessary scoring rules on social welfare.

The impacts of \Flies or Tigers" crackdowns exhibit variance across o cials at di erent

hierarchical levels. To comprehend which investigations, especially those involving o cials at divergent levels, contribute to the observed e ects, I categorize the sample into two cohorts: investigations engaging o cials who are at least the principal leader of a county-level department, and those involving o cials positioned below this level.[34] The impacts of corruption investigations reveal disparities among o cials at varied levels.[35] The comparisons are presented in Figure 9. The positive e ects on promoting competition from Figure 8 come from the investigations on high-level o cials. Investigations on higher-level leaders reduced the likelihood of corruption in open auctions by 10 percentage points, whereas scrutiny of lower-level leaders did not impact corruption within such settings. Correspondingly, the in uence on the preference for open auctions is also predominantly traced back to investigations focused on high-ranking o cials. Additional illustrative material is provided in Figure A8.

The comparison between high-level and low-level o cials aligns with empirical realities. As o cials rise in the hierarchy, their in uence and power increase. In contrast, lower-level o cials, who hold less authority, often nd themselves held accountable and sometimes act as scapegoats for the wrongdoings of their superiors.

Additionally, a more detailed discussion of corrupt rms and variations in city-level corruption is provided in Appendix H.

8.2 Counterfactuals: Estimation

Since anti-corruption investigations have failed to generate a sustainable reduction in corruption in public procurement, an alternative approach could be to reform some of the auction procedures. To explore this idea, I rst estimate rm type using a scoring auction model applied to public procurement data, followed by a counterfactual analysis. The rm type is estimated separately for competitive and corrupt auctions.

For competitive auctions, I use the equilibrium conditions provided in Theory 1 to infer rm type . With the estimated CDF G(s) and PDF g(s) of the scores from Section 6, the only remaining component that is not yet structured is the cost function. I propose a restricted polynomial form for the cost function with two unknown parameters, $_0$ and $_1$,

[34] O cials who are principal leaders of a county-level department, such as the primary director of the education department in M County or the director of the transportation department in B district, G City, are designated as level nine based on China's bureaucratic hierarchy, while o cials ranked below are at level ten or lower.

[35] In certain instances, lower-ranking o cials are targeted as scapegoats for their higher-ranking counterparts.

Figure 9: The E ect of Corruption Investigation by O cials with Di erent Levels

(a) Number of Bidders: High-level O cials

(b) Number of Bidders: Low-level O cials

(c) Corruption Indicator: High-level O cials

(d) Corruption Indicator: Low-level O cials

Notes : The regression model incorporates time- xed e ects and procurement government department xed e ects. Standard errors are clustered at the department level.

representing rm type . [36]

$$C(q; {}_0; {}_1) = {}_0 + {}_1({}_1 + q)^2$$

I set ${}_1 = (4\frac{w_q}{w_p})^2$ to account for the scale di erences caused by the weight of price and quality in P_s for di erent auctions, ensuring that Assumption 2 holds. Additionally, I choose ${}_2 = 4$, making the cost function a fourth-order polynomial. This ensures the cost function satis es Assumption 2, guaranteeing the existence of an optimal choice. With this setup ${}_0$ and ${}_1$ are identi ed. The 3D estimated joint distribution of ${}_0$ and ${}_1$ is shown in Figure A9 (a),

[36] I follow existing literature in using a polynomial cost function. Since I only have two equilibrium conditions, I cannot introduce more exible parameters as coe cients.

while Figure A9 (b) presents the two-dimensional at density.

However, in the case of corrupt auctions, I am unable to use the rst-order competitive equilibrium to estimate the rm type. [37] This is because all bidders achieve systematically di erent scores in corrupt auctions. Moreover, I do not have direct observations of the manipulation of the scoring rules $\mathbf{w}_{q^U}$. As a result, I estimate the rm types in corrupt auctions by regressing estimated rm type parameters $_0$ and $_1$ on auction and rm characteristics in non-corrupt cases using the following regression speci cation for winners and losers respectively[38]:

$$_{ia} = \ _0 + \ _1 \text{Firm Characteristics}_i + \ _2 \text{Auction Characteristics}_a + \ _{ia}$$

where the dependent variable $_{ia}$ is $_0$ or $_1$ of the bidder i in the auction a. Firm characteristics include rm capital size, and formal employee size, the exitsing years, and stateowned connection. Auction Characteristics $_a$ are procurement auction-level characteristics, including budget size, price weights, category xed e ects, and region xed e ects. The regression outcomes are presented in Table A5 for winners and Table A6 for losers. Then I obtain the predicted for rms in corrupt auctions.[39]

With the estimated rm types , I am now equipped to conduct the two counterfactual analyses in the following two subsections.

8.3 Counterfactual: Implementing Anonymous Evaluation on RFP

The expert audit survey in Section 7 shows an e ective way to identify the unnecessary quality requirements in the RFP. Governments could employ a strategy of randomly selecting anonymous experts to assess the RFP prior to the commencement of the auction competition, akin to the expert audit study. Should these anonymous experts identify any super uous scoring rules, the respective government department would be instructed to revise the RFP. This approach strikes a balance by retaining some discretion in scoring rule design, yet diminishes the chances of tailored scoring rules. Such a policy mirrors the practice of randomly selecting bid evaluation experts.

In the majority of procurement auctions, it's unclear which elements are tailored to favor

[37] I present a comparison of the estimated parameters between corrupt auctions and noncorrupt auctions, assuming they are all estimated from the competitive rst-order conditions. I group the values into quintiles for each procurement category. Lower quintile rankings represent higher e ciency. The comparison is shown in Figure A10 and Figure A11.

[38] As depicted in Figure A10 and Figure A11, there are signi cant di erences between winners and losers, even in some non-corrupt scenarios.

[39] The predicted values of winners in corrupt cases were then added to the quintile bar plots depicted in Figure A12 and Figure A13, showing that the predicted losing rm types are more e cient the original values suggesting.

predetermined winners. However, within the expert survey sample, I've requested experts to identify the rules deemed unnecessary. In a counterfactual scenario where no rules are deliberately designed to bene t winners, other requirements would take the place of the current customization. I conduct a counterfactual analysis, eliminating all preferential rules in the quality requirement $\mathbf{w}_{q^U} = 0$.

The e ects of removing unnecessary scoring rules come from two components. First, as there are no customized rules granted to the predetermined winners, they have to participate in the bidding process competitively. Second, because of the removal of restrictive rules as a signal of corruption (Cai, Henderson, and Zhang, 2013), more rms would enter into the auctions. I set the extra number of bidders as two, as shown in the back-of-envelope calculation in Figure 8 (b). Therefore, I can decompose these two e ects. For the two more bidders, they are drawn randomly from the other competitive auctions with the same auction characteristics, such as project type, budget range, and number of bidders. By applying the competitive equilibrium conditions, and the adjusted rm type, I conducted re-simulations of the auctions to estimate the changes in price and quality bids when the predetermined winners engaged in competitive bidding. The results are presented in Table 5.

Table 5: Implementing Anonymous Evaluation on RFP

Counterfactual	Price	Quality	Score(Welfare)
Competitive Bid	-12.19%	4.25%	6.76%
	[-13.63%, -10.74%]	[2.27%, 6.23%]	[5.27%, 8.25%]
Competitive Bid+Entry	-14.51%	3.86%	9.58%
	[-16.36%, -12.65%]	[1.84%, 5.88%]	[8.07%, 11.1%]

Notes : In this exercise, the adjusted estimated values are used in the competition model to estimate how predetermined winners bid in a real competitive environment. In the entry exercise, there are two more bidders, the number is estimated from Figure 8. 95% con dence intervals are included in the brackets.

In a counterfactual competitive scenario without entry e ects, the predetermined winner tends to submit a price bid that is 12.19% lower than the initial bid, along with a 4.25% increase in quality. This translates to a 6.76% increase in the real nal score compared to the original. When accounting for both competitive bidding and entry e ects, the price decreases by 14.51% with a 3.86% increase in quality. Increased entries intensify competition over prices, leading to a rise of 9.58% in the nal scores. Compared to the scenario without entry e ects, 70% of the welfare gains from the introduction of anonymous RFP evaluations stem from removing the unnecessary rules, while the remaining 30% is attributable to more entries, as shown in the rst group of bars in Figure 10.

As shown in Table A7 and Figure 10, when segmented by procurement categories, product procurement demonstrates a greater price reduction compared to construction or service

Figure 10: Decomposition of Welfare Changes by Procurement Categories

Notes : The rst bar in each group represents the score changes when there is an increase in the number of bidders coupled with competitive bidding. The second bar indicates the score changes when the number of bidders remains constant but the bidding becomes competitive and noncorrupt. The last bar in each group shows the di erence between the rst two bars. All bars are with 95% con dence intervals.

procurement. This trend is primarily driven by the higher price weights assigned to product procurement. Additionally, entry e ects contribute more to the welfare gains in product procurement than in service or construction procurement. Overall, product procurement bene ts more from the combined e ects of increased entry and competitive bidding.

Implementing an anonymous evaluation of RFPs o ers the dual bene t of retaining a level of discretion while eradicating super uous scoring rules. In practical application, the selection of experts becomes important. These experts should not only possess the requisite knowledge but also be motivated to provide truthful insights.

8.4 Counterfactual: Increasing Price Weights

As highlighted in the background about scoring auctions, public procurement law establishes guidelines on choosing price weights across various procurement categories. This is intended to curb corruption by not emphasizing the quality elements of the auctions too much. Nonetheless, o cers frequently choose the lowest available option. Moreover, choosing a price weight above the lowest bound serves as a robust indicator of non-corruption. In this subsection, I explore the counterfactual scenario of elevating price weights. Here, the number of bidders and other variables, are retained as constants, with adjustments being made exclusively to the price weights.

Table 6 reports the results of increasing price weights by 10 percent points. The rst column presents the average change in the price bid of the winner. The second column shows the average change in the quality bid of the winner. In the nal column, I report the mean

Table 6: Increasing Price Weights by 10pp

Counterfactual	Price	Quality	Score(Welfare)
Noncorrupt	-2.88%	-6.51%	-3.88%
	[-4.79%, -0.96%]	[-6.79%, -6.24%]	[-4.24%, -3.51%]
Corrupt	-8.17%	-1.53%	0.92%
	[-9.68%, -6.67%]	[-3.52%, 0.46%]	[-0.56%, 2.4%]
Overall	-6.59%	-3.24%	-0.67%
	[-7.82%, -5.37%]	[-4.58%, -1.9%]	[-1.69%, 0.35%]

Notes : In this exercise, I examine the change in bid behaviors by increasing the price weights while holding other conditions constant. For predetermined winners in corrupt cases, I utilize the adjusted and conditions from the corruption model, assuming all previous bidders were non-fake bidders. The results are presented with 95% con dence intervals in brackets.

change in the nal score, representing social welfare as per Asker and Cantillon (2008) and Hanazano et al. (2020). These values are computed using the original scoring rules.

It is not surprising that when procurement o cers place more emphasis on price, bidders attempt to lower their bid prices. With a 10-point increase in the weight assigned to price, corrupt winners reduce their bids by approximately 8% to gain an advantage in the price score. Competitive winners also lower their bids, but the reduction is much smaller than in corrupt cases. Regarding quality bids, predetermined winners in corrupt auctions do not make signi cant adjustments to their actual quality o ers, likely due to their advantage under manipulated scoring rules. Their quality tends to be considerably lower than that of genuine bidders, allowing them to reduce prices without compromising much on quality. Meanwhile, in competitive cases, with a lower weight on quality, bidders invest less in quality, leading to a 6% decrease in their quality scores.

From a social welfare perspective, increasing the weight on price does not necessarily result in statistically or economically signi cant improvements. The outcome largely depends on the level of corruption and the extent of the increase in price weight. In non-corrupt auctions, any welfare gains from lower prices are often o set by a corresponding drop in quality, potentially resulting in a net decrease in overall welfare. The scenario with a 20-point increase in the price weight is shown in Table A8.

9 Conclusion

In this paper, I focus on one of the most prevalent forms of corruption observed in scoring auctions, where corrupt procurement o cers manipulate scoring rules to favor predetermined winning rms. To quantify and identify this corruption, I developed a statistical test based on the standard scoring auction model. The results from the model-based test show that

approximately 65% of the procurement auctions reject the null of no corruption. To further validate my model's predictions, I conducted an expert survey to evaluate the call-for-tender les and identify instances of scoring rule manipulation. By comparing the survey results with my model's predictions, I found that the model achieves a high accuracy rate of 81%.

To study the distortions introduced by corruption, I merged rm administrative data with public procurement data. The results indicate that rms with lower e ciency, smaller sizes, and stronger connections to state-owned entities are more likely to be corrupt winners. Which policies can help mitigate corruption in public procurement? I explored the exogenous shocks resulting from corruption investigations during China's most extensive Anti-corruption campaign. I found that these corruption investigations only had a temporary impact on enhancing competition and reducing corruption, lacking a lasting impact. Moreover, most of these e ects can be attributed to the involvement of o cials from higher bureaucratic levels in the investigations.

In subsequent analyses, I parametrically estimated rm types from the scoring auction model and conducted a counterfactual analysis. In a counterfactual scenario with anonymous evaluations of RFPs, social welfare increases by 11%. Of this increase, 70% arises from compelling rms to bid competitively, while 30% stems from increased participation. However, increasing price weights doesn't lead to a signi cant improvement in social welfare.

Looking forward, there are several paths for future research. Firstly, I plan to supplement the test by including cases where additional exogenous competitive bidders join the auctions. Moreover, I intend to evaluate the e ectiveness of several related public procurement policies, such as set-aside programs and green-energy innovation promotion initiatives. Furthermore, more rigorous and experimental studies are needed to study bidder responses to the policy experiments mentioned in this paper and to uncover potential adaptive strategies that bidders might employ to evade detection.

References

Andreyanov, Pasha. 2018. \Mechanism choice in scoring auctions."Working Paper.

Andreyanov, Pasha, Alec Davidson, and Vasily Korovkin. 2017. \Detecting auctioneer corruption: Evidence from Russian procurement auctions."Working Paper.

Asker, John, and Estelle Cantillon. 2008. \Properties of scoring auctions."The RAND Journal of Economics, 39(1): 69{85.

Athey, Susan, and Philip A Haile. 2002. \Identi cation of standard auction models." Econometrica, 70(6): 2107{2140.

Avis, Eric, Claudio Ferraz, and Frederico Finan. 2018. \Do government audits reduce corruption? Estimating the impacts of exposing corrupt politicians." Journal of Political Economy, 126(5): 1912{1964.

Bai, Chong-En, Ruixue Jia, Hongbin Li, and Xin Wang. 2021. \Entrepreneurial Reluctance: Talent and Firm Creation in China." National Bureau of Economic Research.

Bajari, Patrick, Stephanie Houghton, and Steven Tadelis. 2014. \Bidding for incomplete contracts: An empirical analysis of adaptation costs."American Economic Review, 104(4): 1288{1319.

Baltrunaite, Audinga. 2020. \Political contributions and public procurement: evidence from Lithuania." Journal of the European Economic Association, 18(2): 541{582.

Baltrunaite, Audinga, Cristina Giorgiantonio, Sauro Mocetti, and Tommaso Orlando. 2021. \Discretion and supplier selection in public procurement."The Journal of Law, Economics, and Organization, 37(1): 134{166.

Brugués, Felipe, Javier Brugués, and Samuele Giambra. 2024. \Political connections and misallocation of procurement contracts: evidence from Ecuador."Journal of Development Economics, 170: 103296.

Burguet, Roberto, and Yeon-Koo Che. 2004. \Competitive procurement with corruption." RAND Journal of Economics, 50{68.

Cai, Hongbin, J Vernon Henderson, and Qinghua Zhang. 2013. \China's land market auctions: evidence of corruption?" The Rand journal of economics, 44(3): 488{521.

Calvo, Eduard, Ruomeng Cui, and Juan Camilo Serpa. 2019. \Oversight and e ciency in public projects: A regression discontinuity analysis." Management Science, 65(12): 5651{5675.

Cao, Yiming. 2022. \Institutional Weakness and Societal Vulnerability: Evidence from the Sichuan Earthquake."

Celebi, M Emre, Hassan A Kingravi, and Patricio A Vela. 2013. \A comparative study of e cient initialization methods for the k-means clustering algorithm." Expert systems with applications, 40(1): 200{210.

Chassang, Sylvain, Kei Kawai, Jun Nakabayashi, and Juan Ortner. 2022. \Robust screens for noncompetitive bidding in procurement auctions." Econometrica, 90(1): 315{346.

Chen, Qianmiao, Qingyang Huang, Chang Liu, and Peng Wang. 2022. \Career Incentives of Local Leaders and Crisis Response: A Case Study of COVID-19 Lockdowns in China." European Journal of Political Economy, 75: 102180.

Chen-Ritzo, Ching-Hua, Terry P Harrison, Anthony M Kwasnica, and Douglas J Thomas. 2005. \Better, faster, cheaper: An experimental analysis of a multi-attribute reverse auction mechanism with restricted information feedback." Management science, 51(12): 1753{1762.

Chen, Ting, and James Kai-sing Kung. 2019. \Busting the \Princelings": The campaign against corruption in China's primary land market." The Quarterly Journal of Economics, 134(1): 185{226.

Chen, Zhao, Zhikuo Liu, Juan Carlos Suarez Serrato, and Daniel Yi Xu. 2021. \Notching R&D investment with corporate income tax cuts in China." American Economic Review, 111(7): 2065{2100.

Che, Yeon-Koo. 1993. \Design competition through multidimensional auctions." The RAND Journal of Economics, 668{680.

Claudio, Ferraz, Finan Frederico, and Szerman Dimitri. 2015. \Procuring Firm Growth: The E ects of Government Purchases on Firm Dynamics."

Colonnelli, Emanuele, and Mounu Prem. 2021. \Corruption and Firms." The Review of Economic Studies, 89(2): 695{732.

Conley, Timothy G, and Francesco Decarolis. 2016. \Detecting bidders groups in collusive auctions." American Economic Journal: Microeconomics, 8(2): 1{38.

Coviello, Decio, and Mario Mariniello. 2014. \Publicity requirements in public procurement: Evidence from a regression discontinuity design."Journal of Public Economics, 109: 76{100.

Coviello, Decio, Andrea Guglielmo, and Giancarlo Spagnolo. 2018. \The e ect of discretion on procurement performance."Management Science, 64(2): 715{738.

Decarolis, Francesco, Raymond Fisman, Paolo Pinotti, and Silvia Vannutelli. 2020. \Rules, discretion, and corruption in procurement: Evidence from Italian government contracting." National Bureau of Economic Research.

De Winter, Joost CF. 2019. \Using the Student's t-test with extremely small sample sizes." Practical Assessment, Research, and Evaluation, 18(1): 10.

Du o, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan. 2018. \The value of regulatory discretion: Estimates from environmental inspections in India." Econometrica, 86(6): 2123{2160.

Fang, Hanming. 2023. \Measurements, Determinants and Causes of Corruption: Lessons from China's Anti-Corruption Campaign."

Fay, Michael P, and Michael A Proschan. 2010. \Wilcoxon-Mann-Whitney or t-test? On assumptions for hypothesis tests and multiple interpretations of decision rules." Statistics surveys, 4: 1.

Ferraz, Claudio, and Frederico Finan. 2011. \Electoral accountability and corruption: Evidence from the audits of local governments." American Economic Review, 101(4): 1274{1311.

Gan, Guojun, and Michael Kwok-Po Ng. 2017. \K-means clustering with outlier removal." Pattern Recognition Letters, 90: 8{14.

Gerardino, Maria Paula, Stephan Litschig, and Dina Pomeranz. 2024. \Distortion by audit: Evidence from public procurement." American Economic Journal: Applied Economics, 16(4): 71{108.

Gilraine, Michael, Jiaying Gu, and Robert McMillan. 2020. \A new method for estimating teacher value-added." National Bureau of Economic Research.

Gong, Ting, and Na Zhou. 2015. \Corruption and marketization: Formal and informal rules in Chinese public procurement." Regulation & Governance, 9(1): 63{76.

Gordon, A.D. 1999. Classi cation, 2nd Edition. Chapman & Hall/CRC Monographs on Statistics & Applied Probability, CRC Press.

Guerre, Emmanuel, Isabelle Perrigne, and Quang Vuong. 2000. \Optimal nonparametric estimation of rst-price auctions." Econometrica, 68(3): 525{574.

Gu, Jiaying, Roger Koenker, and Stanislav Volgushev. 2018. \Testing for homogeneity in mixture models." Econometric Theory, 34(4): 850{895.

Hanazano, Makoto, Yohsuke Hiroze, Jun Nakabayashi, and Masanori Tsuruoka. 2020. \Theory, Identi cation, and Estimation for Scoring Auctions." Working Paper.

Hanazono, Makoto, Jun Nakabayashi, Masanori Tsuruoka, et al. 2013. \Procurement auctions with general price-quality evaluation." Working Paper.

Hartigan, John A, and Manchek A Wong. 1979. \Algorithm AS 136: A k-means clustering algorithm." Journal of the royal statistical society. series c (applied statistics), 28(1): 100{108.

Hautamäki, Ville, Svetlana Cherednichenko, Ismo Kärkkäinen, Tomi Kinnunen, and Pasi Fränti. 2005. \Improving k-means by outlier removal." 978{987, Springer.

Hodges Jr, Joseph L, and Erich L Lehmann. 1956. \The e ciency of some nonparametric competitors of the t-test." The Annals of Mathematical Statistics, 324{335.

Hsieh, Chang-Tai, and Peter J. Klenow. 2009. \Misallocation and Manufacturing TFP in China and India." The Quarterly Journal of Economics, 124(4): 1403{1448.

Huang, Yangguang. 2019. \An empirical study of scoring auctions and quality manipulation corruption." European Economic Review, 120: 103322.

Huang, Yangguang, and Jijun Xia. 2019. \Procurement auctions under quality manipulation corruption." European Economic Review, 111: 380{399.

Jiang, Wenhua, and Cun-Hui Zhang. 2009. \General maximum likelihood empirical Bayes estimation of normal means."

Kang, Karam, and Robert A Miller. 2022. \Winning by Default: Why is There So Little Competition in Government Procurement?" The Review of Economic Studies, 89(3): 1495{1556.

Kawai, Kei, and Jun Nakabayashi. 2022. \Detecting large-scale collusion in procurement auctions." Journal of Political Economy, 130(5): 1364{1411.

Kawai, Kei, Jun Nakabayashi, and Daichi Shimamoto. 2022. \A Study of Bid-rigging in Procurement Auctions: Evidence from Indonesia, Georgia, Mongolia, Malta, and State of California." National Bureau of Economic Research Working Paper 30271.

Kawai, Kei, Jun Nakabayashi, and Juan M Ortner. 2021. \The value of privacy in cartels: an analysis of the inner workings of a bidding ring." National Bureau of Economic Research.

Kawai, Kei, Jun Nakabayashi, Juan Ortner, and Sylvain Chassang. 2023. \Using bid rotation and incumbency to detect collusion: A regression discontinuity approach." The Review of Economic Studies, 90(1): 376{403.

Khan, Adnan Q, Asim I Khwaja, and Benjamin A Olken. 2016. \Tax farming redux: Experimental evidence on performance pay for tax collectors." The Quarterly Journal of Economics, 131(1): 219{271.

Kiefer, Jack, and Jacob Wolfowitz. 1956. \Consistency of the maximum likelihood estimator in the presence of in nitely many incidental parameters." The Annals of Mathematical Statistics, 887{906.

Koenker, Roger, and Ivan Mizera. 2014. \Convex optimization, shape constraints, compound decisions, and empirical Bayes rules." Journal of the American Statistical Association, 109(506): 674{685.

Kong, Yunmi, Isabelle Perrigne, and Quang Vuong. 2022. \Multidimensional auctions of contracts: An empirical analysis." American Economic Review, 112(5): 1703{1736.

Lichand, Guilherme, and Gustavo Fernandes. 2019. \The dark side of the contract: do government audits reduce corruption in the presence of displacement by vendors?" University of Zurich, Switzerland, mimeo.

Lichand, Guilherme, Marcos FM Lopes, and Marcelo C Medeiros. 2016. \Is corruption good for your health." Job Market Paper.

Li, Tong, Isabelle Perrigne, and Quang Vuong. 2002. \Structural estimation of the a liated private value auction model." RAND Journal of Economics, 171{193.

Manion, Melanie. 2016. \Taking China's anticorruption campaign seriously." Economic and Political Studies, 4(1): 3{18.

Motta, Massimo. 2004. Competition policy: theory and practice. Cambridge university press.

OECD. 2016. \Preventing Corruption in Public Procurement." https://www.oecd.org/gov/ethics/Corruption-Public-Procurement-Brochure.pdf .

Olken, Benjamin A. 2007. \Monitoring corruption: evidence from a eld experiment in Indonesia." Journal of Political Economy, 115(2): 200{249.

Palguta, Jan, and Filip Pertold. 2017. \Manipulation of procurement contracts: Evidence from the introduction of discretionary thresholds." American Economic Journal: Economic Policy, 9(2): 293{315.

Parrinello, Christina M, Morgan E Grams, Yingying Sang, David Couper, Lisa M Wruck, Danni Li, John H Eckfeldt, Elizabeth Selvin, and Josef Coresh. 2016. \Iterative outlier removal: a method for identifying outliers in laboratory recalibration studies." Clinical chemistry, 62(7): 966{972.

Porter, Robert H. 2005. \Detecting collusion." Review of Industrial Organization, 26: 147{167.

Porter, Robert H, and J Douglas Zona. 1993. \Detection of bid rigging in procurement auctions." Journal of Political economy, 101(3): 518{538.

Ryan, Nicholas. 2020. \Contract enforcement and productive e ciency: Evidence from the bidding and renegotiation of power contracts in India." Econometrica, 88(2): 383{424.

Scherer, Frederic M, and David Ross. 1990. \Industrial market structure and economic performance." Working Paper.

Schurter, Karl. 2017. \Identi cation and inference in rst-price auctions with collusion." Working Paper.

Szucs, Ferenc. 2024. \Discretion and favoritism in public procurement." Journal of the European Economic Association, 22(1): 117{160.

Takahashi, Hidenori. 2018. \Strategic design under uncertain evaluations: structural analysis of design-build auctions." The RAND Journal of Economics, 49(3): 594{618.

UNCITRAL. 2014. \UNCITRAL model law on public procurement."

Wang, Yuhua, and Bruce J Dickson. 2022. \How corruption investigations undermine regime support: evidence from China." Political Science Research and Methods, 10(1): 33{48.

Wu, Xindong, Vipin Kumar, J Ross Quinlan, Joydeep Ghosh, Qiang Yang, Hiroshi Motoda, Geo rey J McLachlan, Angus Ng, Bing Liu, Philip S Yu, et al. 2008. \Top 10 algorithms in data mining." Knowledge and information systems, 14: 1{37.

Yang, Jiawei, Susanto Rahardja, and Pasi Fränti. 2021. \Mean-shift outlier detection and ltering." Pattern Recognition, 115: 107874.

Zamboni, Yves, and Stephan Litschig. 2018. \Audit risk and rent extraction: Evidence from a randomized evaluation in Brazil." Journal of Development Economics, 134: 133{149.

Appendix A: Supplementary Tables and Figures

Figure A1: Di erent Roles Involved Public Procurement

Notes : Government departments primarily initiate public procurement for public projects. In autocratic regimes, lower-level government agencies are accountable to higher-level authorities rather than to the voters.

Figure A2: The Distribution of Public Procurement by Year

(a) All Procurement (b) Open V.S. Invited Auctions

Notes : (a) presents the number of procurement projects in the dataset spanning from 2006 to 2021, categorized by various procurement auction methods such as rst-price auction, scoring auction, and other methods. (b) illustrates the proportion of procurement projects utilizing an open auction format.

Figure A3: How frequently do rms participate in public procurement

(a) Distribution of Participation Times (b) Distribution of Winning Times

Notes : (1) displays the distribution of the number of rms participating in procurement project competitions. (2) illustrates the distribution of the number of procurement contracts rms secure. These graphs encompass all procurement projects, extending beyond open-scoring auctions to incorporate those from non-open procurement competitions.

Figure A4: Number of Corruption Investigation Cases

Notes : The y-axis of the gure represents the total number of anti-corruption investigations per month in the Province from which the public procurement data was collected. The investigation data prior to August 2016 are sourced from Wang and Dickson (2022), while the data from August 2016 onwards have been collected manually by me, encompassing all levels of Commissions for Discipline Inspection.

Figure A5: Distribution of bid-di erences over (bidder, auction) pairs

(a) Three Bidders

(b) Four Bidders

(c) Five Bidders

(d) Six and More Bidders

Notes : The X-axis represents the score gap between a bidder's own score and the highest score among all bidders, excluding the bidder's own score.

Table A1: A Four-Bidder Case

Company	BusiTech Score (65)	Price Score(35)	Final Score	Order
A	63.6	34.65	98.25	1
D	26.2	35	61.2	3
E	28.2	34.53	62.73	2
C	22.6	34.56	57.16	4

Notes : The outcomes of this procurement auction are shown on the public procurement website.

Table A2: Corruption Proportion Estimation and Auction-level Test Results

	All	3 Bidders	4 Bidders	5 Bidders
	Corruption Proportion Estimation			
Corruption Proportion	60.57%	70.88%	46.49%	26.85%
	[60.19, 60.96]	[70.21, 71.55]	[45.95, 47.03]	[24.77, 28.93]
	Auction Level Test = 0:05			
Unadjusted P-value = 0:05	54.43%	59.95%	40.7%	34.45%
	[54.37, 54.49]	[59.84, 60.05]	[40.58, 40.82]	[34.29, 34.61]
Adjusted P-value = 0:05	45.23%	50.06%	33.71%	27.18%
	[45.19, 45.27]	[49.99, 50.13]	[33.61, 33.82]	[27.03, 27.33]

Notes : 95% con dence intervals from bootstrapping are indicated in brackets. The rst two rows of the auction-level test results represent the results using unadjusted p-values, while the following two rows display the adjusted p-values to control the false discovery rate. Unadjusted p-values are more powerful than adjusted p-values but have a higher type I error rate.

Figure A6: Distribution of HHI for Industries

Notes : HHIs are derived from the 2016 Firm Tax data. Typically, an HHI exceeding 2500 signi es a highly concentrated market.

Table A3: Bidding Results

Company	Tech Score (50)	Busi Score (20)	Price Score(30)	Final Score	Order
M	49.86	20	27.13	96.99	1
N	21.57	15.5	30	67.07	2
O	11.43	9	27.06	47.49	3

Notes : The outcomes of this procurement auction are shown on the public procurement website.

Table A4: Expert Survey and Model Prediction

Accuracy Rate=79.4%	Total=500	Model Prediction		
		Corrupt (PP)	Not Corrupt (PN)	
Expert Survey	Corrupt (P)	300	75 False N	Test Power 80%
	Not Corrupt (N)	28 False P	97	Test Size 22.4%

Notes : For the expert survey, if any evaluation survey reveals highlighted scoring rules accompanied by expert explanations and concerns, the procurement project is labeled as corrupt. The classi cation of model prediction uses adjusted p-values with a signi cance level of 0.1.

Table A5: Firm Characteristics and of Bidders

	Winners: Noncorrupt		Winners: Corrupt	
	$_0$	$_1$	$_0$	$_1$
Log(capital)	0.0012	0.0004	-0.0074***	-0.0014
	(0.0025)	(0.0009)	(0.0023)	(0.0008)
Log(formal employee)	-0.0132***	-0.0052***	-0.0124***	-0.0047***
	(0.0019)	(0.0006)	(0.0013)	(0.0004)
Log(#members)	-0.0023	-0.0008	0.0014	-0.0003
	(0.0018)	(0.0006)	(0.0017)	(0.0004)
State-owned	0.0095	0.0131	-0.0104	0.0015
	(0.0252)	(0.0090)	(0.0210)	(0.0109)
Log(budget)	0.0093**	-0.0045***	0.0082**	-0.0056***
	(0.0040)	(0.0013)	(0.0037)	(0.0007)
Auction Characteristics	Y	Y	Y	Y
N	30651	30651	67533	67533

Notes : The rst two columns present the estimated $_0$ and $_1$ for winners in non-corrupt auctions, while the third and fourth columns display the estimated $_0$ and $_1$ for winners in corrupt auctions. All regressions control for category xed e ects, number of bidders xed e ects, price weights xed e ects, xed quality weights xed e ects, procurement year, and rm entry year. Standard errors are clustered at the procurement category level. *p < 0:10, ** p < 0:05, *** p < 0:01

Figure A7: The E ect of Corruption Investigation

(a) Open Auction

(b) Number of Bidders

(c) Corruption Indicator

(d) New Winning Firm

(e) Score Gaps

(f) Final Price/Budget

Notes : The regression model incorporates time- xed e ects and procurement government department- xed e ects. Standard errors are clustered at the department level.

Figure A8: The E ect of Corruption Investigation by O cials with Di erent Levels

(a) Open Auction: High-level O cials (b) Open Auction: Low-level O cials

Notes : The regression model incorporates time- xed e ects and procurement government department xed e ects. Standard errors are clustered at the department level.

Figure A9: Distribution

(a) 3D Density distribution of $_0$ and $_1$ (b) 2D Density distribution of $_0$ and $_1$

Notes : (a) shows the 3D density distribution of ($_0$; $_1$). (b) shows the 2D density distribution. Lighter colors are associated with larger density.

Figure A10: $_0$ Quintile Distribution

(a) All Bidders (b) Winners

Notes : I rank the estimated $_0$ within di erent groups based on procurement categories, number of bidders, price weights, and xed quality weights. Lower ranking numbers indicate higher e ciency. (a) shows the ranking distribution of all bidders, categorized by corrupt and non-corrupt cases. (b) displays the ranking distribution of winners in procurement auctions.

Figure A11: $_1$ Quintile Distribution

(a) All Bidders (b) Winners

Notes : I rank the estimated $_1$ within di erent groups based on procurement categories, number of bidders, price weights, and xed quality weights. Lower ranking numbers indicate higher e ciency. (a) shows the ranking distribution of all bidders, categorized by corrupt and non-corrupt cases. (b) displays the ranking distribution of winners in procurement auctions.

Figure A12: Quintile Distribution for Winners after the Adjustment

(a) $_0$ (b) $_1$

Notes : I rank the estimated $_0$ and $_1$ within di erent groups based on procurement categories, number of bidders, price weights, and xed quality weights. Lower ranking numbers indicate higher e ciency. (a) shows the ranking of $_0$. (b) shows the ranking of $_1$.

Table A6: Firm Characteristics and of Bidders

	Losers: Noncorrupt		Losers: Corrupt	
	$_0$	$_1$	$_0$	$_1$
Log(capital)	-0.0053***	-0.0082***	-0.0027**	-0.0033*
	(0.0017)	(0.0016)	(0.0010)	(0.0017)
Log(formal employee)	-0.0074***	-0.0070***	-0.0023***	-0.0053***
	(0.0017)	(0.0014)	(0.0008)	(0.0014)
Log(#members)	-0.0040***	-0.0039***	-0.0032***	-0.0048***
	(0.0013)	(0.0013)	(0.0009)	(0.0011)
State-owned	-0.0217	0.0178*	-0.0130	-0.0083
	(0.0230)	(0.0100)	(0.0112)	(0.0086)
Log(budget)	0.0075***	0.0020	0.0037*	0.0039
	(0.0020)	(0.0021)	(0.0022)	(0.0031)
Auction Characteristics	Y	Y	Y	Y
N	88736	88736	195349	195349

Notes : The rst two columns present the estimated $_0$ and $_1$ for losers in non-corrupt auctions, while the third and fourth columns display the estimated $_0$ and $_1$ for losers in corrupt auctions. All regressions control for category xed e ects, number of bidders xed e ects, price weights xed e ects, xed quality weights xed e ects, procurement year, and rm entry year. Standard errors are clustered at the procurement category level. *p < 0:10, ** p < 0:05, *** p < 0:01

Figure A13: Quintile Distribution for Losers

(a) $_0$ (b) $_1$

Table A7: Implementing Anonymous Evaluation on RFP

Counterfactual	Price	Quality	Score(Welfare)
	Product Procurement		
Competitive Bid	-10.3%	3.81%	6.4%
	[-11.94%, -8.67%]	[1.01%, 6.62%]	[4.47%, 8.34%]
Competitive Bid+Entry	-15.31%	6.35%	11.23%
	[-17.66%, -12.96%]	[1.1%, 11.59%]	[7.24%, 15.22%]
	Construction and Service Procurement		
Competitive Bid	-14.11%	4.7%	7.14%
	[-16.5%, -11.73%]	[1.86%, 7.54%]	[4.84%, 9.45%]
Competitive Bid+Entry	-4.25%	7.39%	8.6%
	[-6.91%, -1.58%]	[2.17%, 12.61%]	[3.98%, 13.23%]

Notes : In this exercise, the adjusted estimated values are used in the competition model to estimate how predetermined winners bid in a real competitive environment. In the entry exercise, there are two more bidders, the number is estimated from Figure 8. 95% con dence intervals are included in the brackets.

Table A8: Increasing Price Weights by 20pp

Counterfactual	Price	Quality	Score(Welfare)
Noncorrupt	-4.63%	-12.33%	-7.29%
	[-6.58%, -2.68%]	[-12.71%, -11.96%]	[-7.69%, -6.89%]
Corrupt	-9.79%	-7.38%	-2.61%
	[-11.17%, -8.41%]	[-9.35%, -5.42%]	[-4.05%, -1.16%]
Overall	-8.28%	-9.11%	-4.14%
	[-9.45%, -7.12%]	[-10.44%, -7.78%]	[-5.14%, -3.14%]

Notes : In this exercise, I examine the change in bid behaviors by increasing the price weights while holding other conditions constant. For predetermined winners in corrupt cases, I utilize the adjusted and conditions from the corruption model, assuming all previous bidders were non-fake bidders. The results are presented with 95% con dence intervals in brackets.

Appendix B: Data

B1 Estimation of TFP

The estimation of total factor productivity (TFP) for rms is based on administrative enterprise income tax records obtained from the Chinese State Administration of Tax (SAT), which is responsible for tax collection and auditing in China. The SAT maintains rm-level records of tax payments and other nancial statement information used in tax-related calculations. In this study, I followed the codes and methodology provided by Chen et al. (2021), with the time period extended to 2007-2016 instead of 2008-2011.

They use the structure in the model of constant elasticity demand to write rm value-added r_{it} as:

$$\ln r_{it} = \frac{1}{\quad}[\ \ln k_{it} + (1 \qquad)\ln l_{it} + \quad_{it}]$$

where k_{it} is the capital input, l_{it} is labor input, and $_{it}$ is rm residual productivity. To get the $_{it}$, I need to know the parameters and . Set the = 5 as the benchmark, I have to estimate the . The rst-order condition of cost minimization gives the relation as follows:

$$\ln \frac{wl_{it}}{r_{it}} = \ln[(1 \qquad)\frac{\quad}{1}] + v_{it}$$

where w is the price of labor, and v_{it} iid and $E[v_{it}] = 0$ is the measurement error in factor prices. $\frac{wl_{it}}{r_{it}}$ is the ratio of labor input to revenue. Then I can get the industry average from the above equation. Finally, I can calculate the rm TFP:

$$\hat{\ }_{it} = \frac{\quad}{1}\ln r_{it} \qquad \ln k_{it} \quad (1 \qquad)\ln l_{it}$$

I present the distribution of estimated Total Factor Productivity (TFP) for two sets of rms: the entire dataset from the State Administration of Tax (SAT) and rms that participated in public procurement. Figure B1 displays the distributions, with the blue distribution representing all rms in all available years, and the red distribution representing rms that have engaged in the procurement competition. The comparison of these distributions reveals that rms involved in public procurement tend to exhibit higher levels of TFP, indicating a general superiority in terms of productivity.

B2 Large Performance Variance in Public Procurement Data

In the public procurement data, many rms perform substantially di erently across di erent procurement auctions. This variability often de es straightforward explanation through differences in procurement requirements or scoring methodologies. While I assess the requisites

Figure B1: The Estimated TFP Distribution

Notes : The blue distribution represents the estimated total factor productivity (TFP) using all available data from the SAT dataset across multiple years. On the other hand, the red distribution represents the estimated TFP using only the rms that have matched records in the public procurement data.

stipulated in call-for-tender documents, these divergences don't manifest to the extent seen in bid outcomes.

For instance, consider the case of Wonders Information Corporation, a public sector IT software and service provider with a registered capital of 0.2 billion USD and over 1,300 copyrighted software products. Its expertise in medical information procurement stands out. Foresight Industry Research Institute's study on the medical information system market underscores its low concentration and vibrant competition dynamics, characterized by a "big industry, small enterprises" pattern. In 2020, Wonders Information Corporation held a 2.39% market share, ranking third in the medical information industry.

To illustrate, I present three procurement cases involving medical information systems in which Wonders Information Co. participated in Figure B2 (a), revealing its divergent performances. In the rst case, Wonders emerges as a dominant winner, notably sharing an identical price bid with Company F. In the second case, Wonders experiences a dramatic loss, with Company I securing a resounding win; both losing entities have similar scores. It's important to note that both these cases align with the large winning margin pattern mentioned earlier. In the nal case, Wonders seemingly regains its customary form, placing a reasonable bid despite sti er competition from Company J, which boasts a higher quality score. Intriguingly, the winner J is a state-owned company, while Company L, the dominant

market player, got a very low score.

Figure B2: Performance Variance of the Same Firm

(a) A Case Study: Wonders Co. (b) Distribution of CV

Notes : (a) shows a case study of the rm Wonders Co. participates in di erent procurement projects. (b) calculates the score standard deviation for each rm that participates in more than one procurement auction.

To quantitatively assess the varying bidding scores of rms across multiple auctions, I calculate the coe cient of variation of scores for each rm. The resulting distributions are presented in Figure B2 (b), di erentiating between auctions featuring three bidders and those with four bidders. As depicted, the average coe cient of variation is substantial. A signi cant number of rms have a coe cient of variation exceeding 0.5, implying that their standard deviation is half the size of the mean score. When comparing the coe cient of variation between three-bidder and four-bidder auctions, it becomes evident that the former tends to exhibit a larger coe cient of variation, signifying greater variability in bidding scores within the auctions featuring three bidders.

The substantial variation in performance cannot be fully explained by the characteristics of the procurement projects. This stylized fact provides compelling evidence that rms may not consistently act as competitors across di erent auctions. Instead, they appear to assume varying roles, which encompass predetermined corrupt winners, genuine competitors, and even zombie bidders.

B3 Expert Survey

Here I list the translated survey question design.

1. Based on your experience, what is the normal markup compared to the budget: (please put an estimated number)

2. Are there any unreasonable requirements on the entry threshold?
   A. Yes (please highlight them) B. No

3. Is the price weight reasonable?
   A. Yes B. No, too high C. No, too low

4. Are there any brand preferences you can tell from the technology score part?
   A. Yes (please highlight them) B. No

5. Are there any other unnecessary score points set for the technology section?
   A. Yes (please highlight them) B. No

6. Are there any unnecessary requirements for certi cates in the business section?
   A. Yes (please highlight them) B. No

7. Are there any unnecessary requirements for workers in the business section?
   A. Yes (please highlight them) B. No

8. Are there any unnecessary requirements for previous experiences in the business section?
   A. Yes (please highlight them) B. No

9. Are there any other unnecessary requirements in the business section?
   A. Yes (please highlight them) B. No

10. Are there any other unnecessary subjective scoring rules?
    A. Yes (please highlight them) B. No

11. What is the level of requirement compared to the scoring rules? (5 is just right, 0 is the lowest, 10 is the highest) 0-10

12. How many companies are competitive under the scoring rules?
    A. Less than 5 rms B. 5-10 rms C. 10-20 rms D. 20-50 rms E. 50+ rms

13. What is the possibility that there is a predetermined winner? (0 is the lowest, 10 is the highest) 0-10

Appendix C: Model and Proof

To show how to obtain the equilibrium bidding strategy, without loss of generality, I can rewrite the rm's choice of the bid combination $(p; \mathbf{q})$ as choosing a score s and quality $\mathbf{q}$. Therefore the price bid is $p(s; \mathbf{q})$. To examine the competitive equilibrium of the scoring auction, I follows Asker and Cantillon (2008), Hanazono et al. (2013), and Hanazano et al. (2020) to decompose the multidimensional bidding process into two backward steps. First, upon winning at a score s, the rm selects a pro t-maximizing price p and quality $\mathbf{q}$ combination. Then the rm selects the optimal score s.

In the rst step, if the rm i wins the auction at score s_i, its pro t is given by $(s_i | s_i > s_{\ i}) = P(s_i; \mathbf{q}_i) \quad C(\mathbf{q}_i; \ _i)$. The rm chooses the optimal $\mathbf{q}_i$ to solve the pro t maximization problem:

$$q(s_i; \ _i) = \arg\max_{\mathbf{q}} \ (s_i | s_i > s_{\ i}) = \arg\max_{\mathbf{q}} P(s_i; \mathbf{q}_i) \quad C(\mathbf{q}_i; \ _i)$$

Plug in the optimal $\mathbf{q}$ back to the pro t function:

$$(s_i; \ _i) = P(s_i; q(s_i; \ _i)) \quad C(q(s_i; \ _i); \ _i) \tag{C1}$$

$(s_i; \ _i)$ is analogue to the pro t-maximizing quantity in the general production decision problem. Applying the envelope theorem, the pro t function $(s_i; \ _i)$ satis es two rst-order conditions with respect to $\mathbf{q}$ and s:

$$P_{q'}(s_i; q(s_i; \ _i)) = C_{q'}(q(s_i; \ _i); \ _i) \tag{C2}$$

$$_s(s_i; \ _i) = P_s(s_i; q(s_i; \ _i)) \tag{C3}$$

The two equations stipulate that, conditional upon winning, the marginal cost is equal to the marginal revenue, and the marginal pro t corresponds to the marginal price with respect to the price bid. $_s$ is strictly negative by Assumption 1. The quality is chosen endogenously, and the target score s is a su cient statistic for the optimal bid in the pro t-maximizing problem (C1).

Next, in the second step, the rm chooses the target score $s = \ (\ )$ to maximize expected pro t:

$$(\ ) = \arg\max_s [P(s_i; q(s_i; \ _i)) \quad C(q(s_i; \ _i); \ _i)] \Pr\{s_i > s_{\ i}\} \tag{C4}$$

Theorem 1. The competitive equilibrium bidding strategy $(p(\ ); q(\ ))$ is given by

$$P(\ (\ ); \mathbf{q}(\ )) = C(\mathbf{q}(\ ); \ ) \quad P_s(\ (\ ); \mathbf{q}(\ )) \frac{G(\ (\ ))}{(n \quad 1) g(\ (\ ))}$$

$$C_{\mathbf{q}}(\mathbf{q}(\ ); \ ) = \quad P_{\mathbf{q}}(\ (\ ); \mathbf{q}(\ ))$$

Proof. If a bidder i with $_i$ bids $(p_i; q_i)$ and wins at $s_i = w_p \frac{p}{p_i} + w_q q_i$. The winning probability is $\text{Prob}\{s > s_i\}$. Rewrite the decision problem (C4) as

$$\max_s \ (s; \ )G(s)^{n \ 1} \tag{C5}$$

Di erentiating the above equation with respect to s, I have the rst-order condition:

$$_s(s; \ )G(s)^{n \ 1} + \ (s; \ )(n \ 1)G(s)^{n \ 2}g(s) = 0$$

Rearrange the above equation,

$$(s; \ ) = \ _s(s; \ )\frac{G(s)}{(n \ 1)g(s)} \tag{C6}$$

Replace the $_g(s; \ )$ with equation (C3) and $(s; \ )$ with equation (C1) and $s = \ (\ )$, the rst-order condition can also be written as

$$P(\ (\ ); q(\ )) = C(q(\ ); \ ) \ P_s(\ (\ ); q(\ ))\frac{G(\ (\ ))}{(n \ 1)g(\ (\ ))}$$

At the equilibrium, the bid satis es the pro t-maximizing condition, marginal revenue equals to the marginal cost $C_q = \ P_q$. □

Corollary C.1. The pseudotype k is monotone in $$ and monotone in s.

Proof. From equation (5), I take derivatives of $k(:)$ in respective to $_m$:

$$\frac{dk(\ (\ ); \ )}{d \ _m} = \ _m(\ ) \ \frac{[\ _s \ _m(\ ) + \ _m]\ _s \ [\ _{ss} \ _m(\ ) + \ _s \ _m]}{\ _s^2}$$

$$= \frac{\ _s \ _m \ [\ _{ss} \ _m(\ ) + \ _s \ _m]}{\ _s^2}$$

$$= \frac{\ _s \ _m \ \ _s \ _m}{\ _s^2} + \frac{\ _{ss} \ _m(\ )}{\ _s^2}$$

Assumption 1 gives the rst part as negative.[40] $_m$ is negative. The nal sign depends on $_{ss}$.

$$_{ss}(s; \ ) = P_{ss}(s; q(s; \ )) + \sum_{l=1}^{L} P_{sq^l}(s; q(s; \ ))q^l_s(s; \ )$$

Given the form of the scoring rule, P_{ss} is positive, and P_{sq^l} is negative. The equation (??)

[40] Assumption 1 makes bidder's pro t function satisfy the log-submodularity condition $\frac{\partial^2 \log \ (s; \ )}{\partial s \partial \ _m} < 0$. The log-submodularity condition gives $_s \ _m \ \ _s \ _m < 0$. Please see the proof in Hanazano et al. (2020).

in Theorem 1 gives

$$C_{q'}(q(s;\ );\ ) = P_{q'}(s; q(s;\ ))$$

Taking the derivative with respect to s:

$$P_{q's}(s; q(s;\ )) = [\,C_{q'q'}(q(s;\ );\ ) \quad P_{q'q'}(s; q(s;\ ))]\,q'_s(s;\ )$$

Since Assumption 2 gives $P_{q'q'}$ $C_{q'q'}$ < 0, therefore I have $q_s(s;\ ) < 0$ and then $_{ss} > 0$. Combined all together, k in monotone in . Since s = ( ) is monotone equilibrium and the pseudotype k is monotone in rm types, pseudotype k is monotone in score s. □

Corollary 1.1 In the competitive equilibrium, the winning scoring bid is the expectation of the strongest rival's pseudotype k:

$$s^{win} = E[k^{rival\ (1)} | s^{win}]$$

Proof. As k is monotone in s, I rewrite the decision problem (C5) with respect to pseudotype k:

$$\max_s\ (s(k);\ )G(s(k))^{n\ \ 1} = \max_s\ (s(k);\ )F_k(s^{\ 1}(s(k)))^{n\ \ 1}$$

The rst-order condition is

$$_s(s;\ )F_k(k)^{n\ \ 1} + \ (s;\ )(n \quad 1)F_k(k)^{n\ \ 2}f_k(k)\frac{1}{s'(k)} = 0$$

Since $_s = P_s < 0$, I divide both sides by $_1$ gives

$$F_k(k)^{n\ \ 1} + (s \quad k)(n \quad 1)F_k(k)^{n\ \ 2}f_k(k)\frac{1}{s'(k)} = 0$$

Solving the di erential equation, I get

$$s(k) = \int_{\underline{k}}^{k} \frac{(n \quad 1)f_k(\ )F_k(\ )^{n\ \ 2}}{[F_k(k)]^{n\ \ 1}}\,d \tag{C7}$$

Meanwhile, the expectation of the strongest rival's pseudotype k can be written as:

$$E[k^{rival\ (1)} | s^{win}] = E[k^{rival\ (1)} | k^{rival\ (1)} < k^{win}] = \int_{\underline{k}}^{k^{win}} \frac{(n \quad 1)f_k(\ )F_k(\ )^{n\ \ 2}}{[F_k(k^{win})]^{n\ \ 1}}\,d \tag{C8}$$

Equation (C7) and (C8) give:

$$s^{win} = E[k^{rival\ (1)} | s^{win}]$$

□

Corollary 1.2 With corruptly unrelated quality requirement $\mathbf{w}_{q^U} > \mathbf{0}$:

$$E[k^{rival} \mid s^{win}] > E[k^{rival}_{corrupt} \mid s^{win}]$$

and the equation in Corollary 1.1 doesn't hold, instead

$$s^{win} > E[k^{rival\ (1)}_{corrupt} \mid s^{win}]$$

Proof. Based on Corollary C.1 and Corollary 1.1, k is monotone with respect to . Similarly, s is also monotone with respect to . Consequently, this implies that k will be monotone in s. In instances of corruption, the customized scoring rules downgrade the scores of the competitors, such that $k^{rival} < k^{rival}$.

□

Corollary 1.3 When there are many corrupt bids involving weak zombie bidders, the estimated k for genuinely strong bidders in competitive auctions is upwardly biased, while the estimate for zombie bidders is downwardly biased.

Proof. The pseudotype is estimated from:

$$\hat{k}_i = s_i + \frac{\hat{G}(s_i)}{(n \quad 1)\hat{g}(s_i)}$$

For strong competitors in competitive auctions, their estimated $\hat{G}(s_i)$ for mixing of corrupt and competitive auctions is larger than the $\hat{G}(s_i)$ estimated from all competitive auctions due to the presence of many weak "zombie" bids. Additionally, $\hat{g}(s_i)$ is smaller because these weak zombie bids tend to cluster in the lower tail. Therefore, $\hat{k}_i$ is upwardly biased.

For weak zombie bids, representing less e cient rms with worse, based on the monotonicity of k, they experience a downward bias. □

Appendix D: Empirical Test

D1 Monte Carlo Simulation

Before applying the proposed estimation and test to real scoring auction data, I conduct experiments on simulated datasets with known underlying data-generating processes (DGP). The objective is twofold: to demonstrate the effectiveness and accuracy of the proposed iterative estimation method and to explore the trade-off between type I and type II errors, ultimately identifying the most suitable approach, i.e. unadjusted p-values or adjusted p-values, for identifying corruptly manipulated auctions.

I begin by generating 1,000 competitive scoring auctions. Each auction involves three draws,[41] representing three bidders, with scores sampled from a truncated normal distribution characterized by a mean of 80, a standard deviation of 15, and a range spanning from 0 to 100. This setup closely mimics the score distribution observed in real data. Figure D1 (a) illustrates the distribution of winning margins, revealing no missing mass around 0. Subsequently, I generate an additional 1,000 scoring auctions. In these auctions, the scores are drawn from the same distribution as in the competitive scenario, but with a modification: one extra point is added for predetermined winners.[42] Furthermore, the scores of losers are downgraded by a random value m drawn from a uniform distribution within the range $m \in [10, 20]$. Figure D1 (b) displays the distribution of the winning margin, with no observations approaching 0.

Next, I introduce different corruption ratios to create datasets comprising 1,000 auctions, blending both corrupt and competitive scenarios. Figure D1 (c) and (d) depict the distribution of winning margins for corruption ratios of 30% and 70%, respectively. These visual representations reveal that when the proportion of corrupted cases is relatively small, there is no discernible missing mass pattern around 0. However, when the corrupt cases dominate, the observed pattern aligns with that observed in three-bidder auctions in real auction data, as illustrated in Figure 4 (a).

D2 Corruption Proportion Estimation: Monte Carlo Results

With the simulated auctions, I estimate the NPMLE and the proportion of corrupt auctions under varied corruption ratios and contrast the estimation with the DGP. Figure D2 shows an example where the corruption ratio is 50%. The NPMLE yields two distributions: one with a negative mean and another with a positive mean. The estimated proportions are 51.2% and 48.8%, respectively, which closely align with the actual corruption ratio of 50%.

[41] The choice of three bidders aligns with the prevalent scenario in real auction data

[42] Predetermined winners typically attain higher scores compared to competitive winners and are closer to a perfect score of 100.