UC Berkeley
UC Berkeley Electronic Theses and Dissertations

Title

Essays on Public Procurement and Firms in China

Permalink

https://escholarship.org/uc/item/46c4b0jq

Author

Chen, Qianmiao

Publication Date

2024

Peer reviewed|Thesis/dissertation

eScholarship.org Powered by the California Digital Library
University of California

Essays on Public Procurement and Firms in China

by

Qianmiao Chen

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Agricultural and Resource Economics

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Marco Gonzalez-navarro, Chair
Professor Steve Tadelis
Professor Frederico Finan

Spring 2024

Essays on Public Procurement and Firms in China

Copyright 2024
by
Qianmiao Chen

Abstract

Essays on Public Procurement and Firms in China

by

Qianmiao Chen

Doctor of Philosophy in Agricultural and Resource Economics

University of California, Berkeley

Professor Marco Gonzalez-navarro, Chair

Public procurement, contributing to total GDP, not only impacts economic growth and development by shaping market dynamics and competition but also plays a key role in promoting fairness and mitigating corruption within public sector transactions. This dissertation dives into public procurement, focusing on the challenges of corruption, its detection, and its impact on businesses and the economy. In Chapter 1, I reveal the prevalence of corruption in scoring auctions in public procurement in China, design a model-based tool to detect this corruption, and discuss policies to reduce it. In Chapter 2, inspired by complaint data, I propose another method to detect corruption in close games, which complements the first chapter, and I also discuss how to better design a complaint system to curb corruption. In Chapter 3, I link public procurement data to universal firm-to-firm transaction data to study the direct and indirect effects of participating in the public procurement supply chain through the propagation of production networks. Together, these chapters provide a comprehensive understanding of public procurement's role in shaping economic outcomes and propose targeted strategies for reform.

My first chapter proposes a method to screen out scoring rule manipulation corruption in scoring auctions in public procurement and discusses the policies to reduce corruption and increase transparency. I start the chapter by documenting that corruption is widespread in scoring auctions. Procurement officers can collaborate with firms to manipulate scoring rules, favoring predetermined winners, while corrupt firms orchestrate non-competitive bids from others to meet minimum bidder requirements. Drawing from extensive data on public procurement auctions in China, I introduce a model-driven statistical tool to detect this specific form of corruption. The findings indicate a corruption rate of approximately 65%. A procurement expert evaluation audit study confirms the test's validity, revealing a 91% probability that experts identify suspicious scoring rules when the test signals potential corruption. I also link procurement data to comprehensive firm data to examine the distortions caused by corruption. I find that local and state-owned firms, as well as less productive

ones, are more favored in corrupt auctions. Lastly, I explore policy implications from the anti-corruption campaign, as well as the counterfactuals by estimating a structural model, concluding that general corruption investigations may be insufficient to address deeply ingrained corrupt practices in the long run whereas implementing anonymous call-for-tender file evaluation could significantly improve social welfare.

My second chapter complements the first, which focuses on the unreasonably large score gaps between winners and losers. It examines the ex-post complaint dataset, proposes a method to detect corruption in close-game cases in scoring auctions, and discusses how to better design the complaint system. The complaint system enables reporting of potential corruption and collusion in public procurement auctions, offering insights not visible to outsiders and facilitating corruption detection. In this chapter, I have gathered a dataset of complaints from China's public procurement system. Based on the patterns observed in the ex-post complaints, where the price bids of winners are much higher than those of the complainants, I applied the Regression Discontinuity Design (RDD) to detect corruption. My findings indicate that, contrary to competitive cases where winners and losers are chosen at random, in complaints, winners tended to submit prices that were, on average, 5% higher than those of the losing complainants. This suggests that at least 20% of the auctions in the complaint dataset were corrupt. When extending this methodology to the entire public procurement auction dataset, it appeared that 13% of the auctions in close-game scenarios were corrupt. To explore the low rate of complaints, I developed a model to investigate the decision-making process behind the lodging of complaints, with a specific focus on those bidders who lost by a narrow margin, and conducted a counterfactual analysis. I found that protecting whistleblowers by concealing their names can increase the reporting rate, and that random auditing by the financial team does not crowd out the functionality of the complaint system.

In my third chapter, coauthored with Ming Li and Wei Lin, we study the direct and indirect effects of participating in the public procurement supply chain through the propagation of production networks, utilizing tax data that tracks firm-to-firm transactions in China. To quantify the effects of directly winning public procurement contracts on firms, we employ an event study design. Our estimates reveal that firms winning public procurement contracts experience increased purchasing activities and gain additional non-public procurement contracts in the following months without crowding out effects. Moreover, these spillover effects in the non-public sectors originate from competitive procurement projects, rather than potentially corrupt ones. We then use a model-based method to measure the total ratio of public procurement contracts to sales through both direct and indirect channels, using the complete firm production network. We find that although only 0.5% of firms directly participate in the public procurement supply chain, a greater number are involved indirectly. Using these total ratios, we explore the effect of public procurement on firm revenue through network propagation. Without considering the indirect channels through the production network, we would underestimate the role of public procurement demand.

Contents

List of Figures

List of Tables

Acknowledgments

First and foremost, I am deeply indebted to my dissertation committee—Professors Marco Gonzalez-Navarro, Steve Tadelis, Frederico Finan, and Kei Kawai—for their unconditional support, regular availability, and insightful feedback throughout my entire PhD study.

I completed my second-year paper under the guidance of Professor Marco Gonzalez-Navarro. Since then, Marco has provided me with valuable research assistant opportunities and spent countless hours discussing my research progress. He meticulously reviewed every word of my working papers and every page of my presentation slides, always sharing his experience and advice without reservation.

Professor Steve Tadelis is one of the pioneers in the study of public procurement and contracts. During our first discussion about my research topic, he quickly helped me identify a novel angle and the appropriate methods to address my questions. Throughout the challenging job market season, Steve provided tremendous support, including multiple mock interviews, slide refinement, and continuous emotional encouragement. I cannot imagine completing my PhD without Steve's support.

I took political economy in development economics with Professor Frederico Finan. His course sparked my interest in political economy, and he continuously provided constructive suggestions during both in-person office hours and BPERLab meetings. He helped me refine the logic of the introduction in my job market paper, sentence by sentence. I have learned immensely about how to motivate and write an economics paper from him.

In my second year, I took a course on industrial organization with Professor Kei Kawai. In the class, Kei shared his own research on detecting collusion in procurement auctions. His impressive research inspired me to start paying attention to public procurement policies. Kei's insightful advice helped me select the topic for my job market paper. I will never forget the conversations with him outside Evans Hall under the sunshine.

In addition to my advisors mentioned above, many other professors at Berkeley were extremely generous to me with their time. I am really thankful to Professor Francis Annan, Kirill Borusyak, Samuel Kapon, Ethan Ligon, Jeremy Magruder, Aprajit Mahajan, Ted Miguel, Sarah Moshary, Elisabeth Sadoulet, Cilin Slattery, Carolyn Stein, Francesco Trebbi, Sofia Villas-Boas, and Guo Xu, who provided me with great suggestions during my presentations and our private conversations.

I am deeply grateful to my coauthors, Qingyang Huang, Chang Liu, Peng Wang, Wei Lin, Shaoda Wang, Ming Li, Yang Song Caimei Guo, Gang Wang, and Shi Zheng. I look forward to more fruitful collaborations with them in the future. I also thank my supervisors Huan Wang and Scott Rozelle in Stanford, and Ling Jin and Anna Spurlock at the Berkeley Lawrence Lab for providing me with research assistant opportunities. I also thank my 2018 cohort at Berkeley ARE, Daniel Agness, Pierre Biscaye, Joel Ferguson, Wei Guo, Qingyang Huang, Leila Safavi, and Jed Silver for their friendship and support. I also thank my other Berkeley peers, including but not limited to Chi Man Cheung, Luna Huang, Sherry He, Runjiu Liu, Yunbo Liu, Bobing Qiu, Jie Song, Zehan Song, David Wu, Shuo Yu, and Fan

Zhang; my friends outside Berkeley, including but not limited to Tony (Zirui) Yang and his parents for the valuable consultant, and Jun Shi.

Of course, none of this would have been possible without the unconditional love and unwavering encouragement of my parents, Jiansu Xia and Songchang Chen. They respect and support every decision I make. They are proud of any progress I make. They are always there to listen, help, and support me, no matter what I experience, be it ups or downs. They never complained about the limited time I could spend with them since I studied abroad. I owe so much to them.

Finally, to my dearest partner, Guihong Li. We have been pursuing our doctoral degrees in different cities, but our hearts have always been together. You are always sweet and warm, especially when I am disappointed by unwanted results or negative feedback. Without your support and understanding, there is no way I could have completed this challenging journey.

Chapter 1

Corruption in Public Procurement Auctions: Evidence from Collusion between Officers and Firms

1.1 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

[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.

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' firms often begin to contact government officials 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 firms 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 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 an approach to identifying corruption in scoring auctions achieved by integrating the possibility of scoring rule customization into the standard scoring auction model. Drawing on the works of Che (1993), Asker and Cantillon (2008), and Hanazano et al. (2020), I transform the scoring auction problem into a one-dimensional competition on pseudotype, representing the highest scores bidders can bid with nonnegative profits. Then I demonstrate how scoring rule customization can manifest in bidding patterns that are inconsistent with those under competition. Under the null hypothesis of a competitively conducted procurement auction, the mean of losers' pseudotypes closely aligns with the expected rivals' pseudotypes held by the winners. If the average of losers' pseudotypes significantly deviates downward from the expected rivals' pseudotypes, it suggests that the winner has left a substantial amount of potential profit untouched. To detect potential score manipulation corruption, I compare the losers' pseudotypes with the expected rivals' pseudotypes given the winning scores that the winners target. When the manipulation of scoring rules occurs, a marked discrepancy emerges, leading to an unusually low average of losers' pseudotypes and the rejection of the null hypothesis. My analysis reveals that the null hypothesis of no corruption in scoring rule manipulation is rejected in over 65% auctions, indicating scoring rule customization, favoritism, or zombie competing 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, 2022). 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. The results show the welfare change is statistically and economically

[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%.

insignificant.

This paper makes contributions to three distinct strands of literature. First, the paper contributes to the literature on corruption in procurement, which can be classified into two groups. The first group of papers explores the discretion involved in selecting different procurement methods. Studies within this realm (Coviello and Mariniello, 2014; Palguta and Pertold, 2017; Calvo, Cui, and Serpa, 2019; Decarolis et al., 2020) often posit that a lack of transparency in the procurement process indicates corruption, while an open and transparent process is presumed to be free of such malpractices. As a result, these studies have found that corruption tends to be associated with a higher prevalence of non-open procurement processes. The second group of papers studies the relationship between political connections and procurement awards. Research in this domain (Cao, 2022; Baltrunaite, 2020; Baltrunaite et al., 2021; Colonnelli and Prem, 2021; Brugués, Brugués, and Giambra, 2022) has consistently shown that politically connected firms are more likely to succeed in winning procurement awards. This paper contributes to the existing literature by identifying corruption without having any markers of political connection and estimating the fraction of corruption that takes place among all firms, both connected firms and non-connected firms. Furthermore, my approach enables the exploration of counterfactual policies, such as adjusting price weights, increasing the minimum bidder requirement, and standardizing scoring rules. This study also contributes to the broader literature on corruption within developing countries (Olken, 2007; Ferraz and Finan, 2011; Bobonis, Cámara Fuertes, and Schwabe, 2016; Colonnelli and Prem, 2021).

Second, this study contributes to the existing literature in the field of industrial organization concerning the detection of collusion in auctions and markets. An increasing body of research has focused on identifying non-competitive behavior among cartels or bidding rings, with notable works by Porter and Zona (1993), Conley and Decarolis (2016), Schurter (2017), Chassang et al. (2022), and Kawai and Nakabayashi (2022*a*). The possibility of corruption originating from the auctioneer or agency side has received comparatively less attention, with an exception being the work by Andreyanov, Davidson, and Korovkin (2017), which examines collusion between auctioneers and bidders in sealed first-price auctions by exploring abnormal bid timing patterns. Some studies have proposed models that incorporate increasing scores for corrupt firms during the evaluation stage (Burguet and Che, 2004; Huang and Xia, 2019; Huang, 2019), but this type of corruption is prevented in the context I study. Moreover, these models often assume no collusion among suppliers and no manipulation in the design of scoring rules. My study takes a novel approach by allowing the existence of both corruption and collusion and investigating their relationship in the context of public procurement within a developing country. As a result, my research not only introduces a data-driven method for detecting corruption but also explores the distortions and policy implications that arise from such practices.

My research also contributes to the existing literature on scoring auctions by not only developing a model that characterizes corrupt practices but also validating the effectiveness of the model-based testing tool using auditing survey data. Che (1993) laid the groundwork by extensively analyzing various forms of scoring auctions and determining optimal scoring rules, and subsequent studies like Asker and Cantillon (2008) and Chen-Ritzo et al. (2005) highlighted the higher payoff for buyers in scoring auctions compared to minimum-quality auctions and price-only auctions. More recent works by Hanazono et al. (2013), Takahashi (2018), Andreyanov (2018), and Hanazano et al. (2020) have delved into the equilibrium and mechanism design in scoring auctions, further enriching the understanding of the auction format. Furthermore, studies like Bajari, Houghton, and Tadelis (2014), Ryan (2020), and Kong, Perrigne, and Vuong (2022) have extended the scoring auction model to encompass contract design in public procurement. Based on the above literature, this research paper links theoretical insights with empirical data by uncovering corruption patterns within scoring auctions. It offers valuable empirical implications that illuminate how corruption erodes market competition. It also provides policy implications for combating corruption in public procurement. The dedicated auditing survey, employed to validate predictions from the model-based test, provides an insightful means of confirmation.

The remainder of the paper is organized as follows. In Section 2, I offer 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 and explores the potential impact of anti-corruption investigation policies. Subsequently, in Section 9, I illustrate how I estimate the parameters in the scoring auction model and conduct counterfactual analyses to evaluate different policy scenarios. Finally, Section 10 provides concluding remarks, summarizing the findings and their implications.

1.2 Background

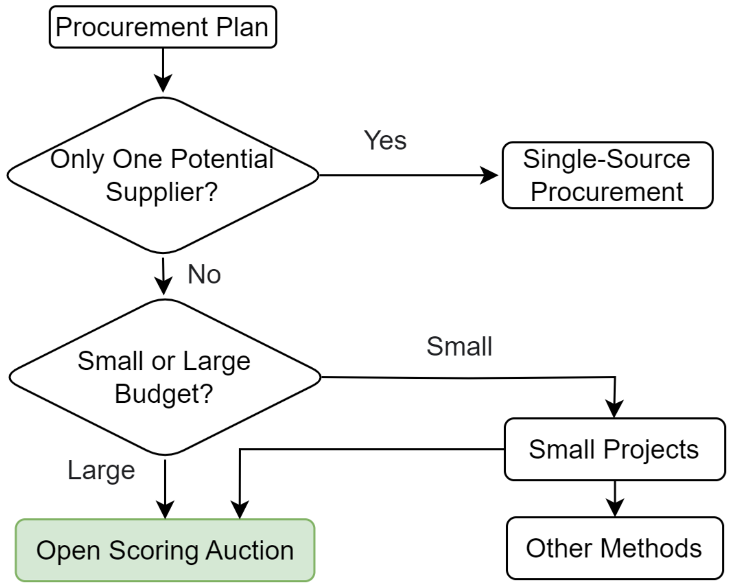
1.2.1 Public Procurement in China

Public procurement in China is shaped by the guidelines established in the Public Procurement Law and its accompanying regulations. Each procurement process 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.

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

The choice of an appropriate procurement method is governed by specific criteria, shown

Figure 1.1: 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, first-price bidding on online platforms, and price solicitations.

in Figure 1.1. In instances involving solitary qualified suppliers or unforeseen emergencies, the option of single-source procurement becomes viable. This approach is also adopted when preserving project consistency or aligning with existing services is paramount. In other scenarios, the selection of the procurement method hinges upon the allocated procurement budget. To fortify transparency, projects surpassing a certain threshold mandate the use of the standard open-scoring auction method.[4] Projects falling below this threshold offer an array of options, including invited-only auctions, online first-price auctions, and direct price inquiries. It's noteworthy that even for smaller-scale procurement, the preference leans towards open-scoring auctions due to heightened scrutiny and audit associated with non-open methods. Notably, various studies (Calvo, Cui, and Serpa, 2019; Decarolis et al., 2020) conclude that public procurement through non-open methods results in elevated costs and heightened vulnerability to corruption. In this paper, I specifically concentrate on the highlighted method, the open scoring auction detailed in Figure 1.1.

Upon plan approval, the procuring entity is obligated to publicize procurement information on national and local procurement websites. This information includes project particu-

[4]The thresholds for open scoring auctions in public procurement vary across different provinces in China. Notably, in the province under study, a significant change occurred in 2020. The benchmark for public bidding concerning government procurement of goods or services was uniformly set at 4 million yuan province-wide. Similarly, the standard for public bidding in construction projects adheres uniformly to pertinent national and provincial regulations. These thresholds have undergone several revisions since 2007.

lars, chosen method, budget allocation, timeline, as well as scoring rules. As per regulations, an open auction requires a minimum of three qualified bidders to validate its legitimacy. In cases where an open auction concludes with just two qualified bidders, experts decide between adjusting call-for-tender files and reinitiating the auction or shifting to non-open methods. If an open auction attracts just one bidder, the procuring entity can opt for single-source procurement if randomly selected experts endorse that the call-for-tender files are devoid of unreasonable rules and in line with relevant competition regulations.

1.2.2 Scoring Auction Procedure

In addition to the general public procurement procedures, a detailed outline of the open-scoring auction process is presented in Figure 1.2. Once the procurement request is approved, a procurement agent is chosen. The agent is responsible for drafting the call-for-tender files, which outline the requirements specified by the procuring entity. These files are then published on official 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 files and submit their proposals, which typically include quality specifications and pricing details.

Figure 1.2: Open Scoring Auction Procedure

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

On the auction day, a procurement committee consisting of at least five randomly selected procurement experts evaluates the submitted bids based on predetermined scoring rules. The committee assigns each bid a score according to the evaluation scoring rules. The scores are then used to rank the bids and determine the winning bidder. The contract is awarded to the bidder with the highest score.

Typically, the final total score comprises three components: business score, technical score, and price score. This can be expressed as:

$$score = w_B \times BusiScore + w_T \times TechScore + w_p \times \frac{min\ Price}{Price} * 100\%$$

The price score is calculated by dividing the minimum price among firms by a firm's own price. The business score is based on quality requirements that are subject to objective evaluation. This consists of factors such as production certificates, the financial health of the firm, and the professional qualifications of the proposed team. The technical score differs depending on the type of procurement. For product procurement, it relates to product parameters, functions, and post-purchase services. For construction and service projects, it typically pertains to detailed implementation plans. w_B is the weight of the business score, w_T is the weight of the technical score, and w_p is the weight of price score. Therefore, the business and technical scores can be represented using a general quality $Quality\ Score \in \mathbb{R}^L$ with multi L dimensions, as indicated in the second line of the equation:

$$score = w_q \times Quality\ Score + w_p \times Price\ Score \in [0, 100]$$

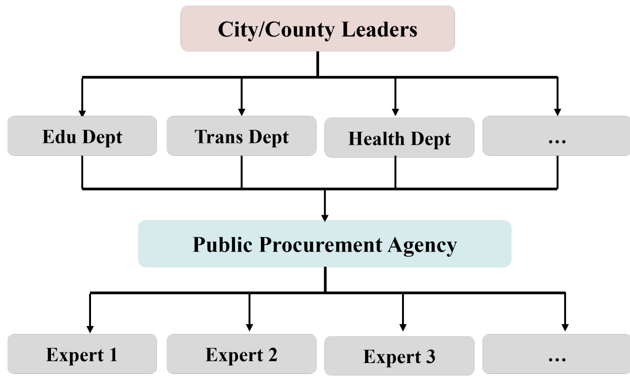
One can imagine that quality rules involve more discretion room compared to the price part, corrupt officials want to reduce the weight of price to increase their control on winning results. To avoid the extreme cases with no weights on prices, the Public Procurement Law mandates that the price weights fall within the range of [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.

1.2.3 Sources of Corruption in 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 1.3. 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. Consequently, corruption can potentially infiltrate from any layer of this multifaceted system.

Notably, the role of procurement experts in manipulating bidder scores has diminished significantly since the introduction of a random expert selection system in 2004, initially at the provincial level. Before this reform, experts were appointed by government procurement departments, and their identities were somewhat public. In many instances of corruption, rather than tampering with scoring rules, malfeasance primarily revolved around altering bidder scores during evaluations. Post-2004, the randomization process became progressively

Figure 1.3: Different 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.

more stringent, centralizing the pool of experts and implementing encryption measures for expert selection. Consequently, attempting to sway scores through bribery has become increasingly difficult, as corrupt firms lack advanced knowledge of the experts, and bribing one or two experts no longer significantly impacts the final score, which is an average of all experts' assessments.

Public procurement agencies themselves are less likely to be the primary source of corruption. Typically, these agencies are chosen by the government department responsible for the procurement project. They collaborate closely with the department to comprehend project requirements and draft call-for-tender files. These files must be approved by the responsible government department before being released publicly to all firms. If a government department already favors a particular bidder, the procurement agency is usually informed but doesn't possess the authority to countermand this choice. They simply adhere to the department's guidelines. In some instances, these agencies might be unjustly blamed for corrupt activities that are actually masterminded by the government departments.

Corruption in open scoring auctions is often attributed to officials from government departments or those in leadership roles. In a political regime like China's, where lower-level governments are accountable to higher-level authorities rather than to the voters, officials with higher ranks exert greater influence over the allocation of public procurement contracts. My interview with a local procurement official revealed that most of the public projects he managed had preselected winners:

> *"There was an example when the city leaders and firm owners had a private dinner together. The leader revealed the information about a new construction project. The firm owner expressed the willingness to do the project and then a deal was reached. To pass the check from other authorities, the lower-level officials 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 raise eyebrows at the seemingly straightforward nature of these corrupt practices. Yet, this strategic behavior is consistent with the audit processes and the incentive structures that government officials operate under. Audits for government procurement primarily focus on areas like budget adherence, execution methods, procurement standards, contract fulfillment, project acceptance, and fund distribution. Given the significant amounts often tied to procurement projects, those using non-open procurement methods face more frequent audits. As a result, procurement projects that employ open auctions are less scrutinized, making them a more favorable cover for corrupt undertakings.

1.3 Data

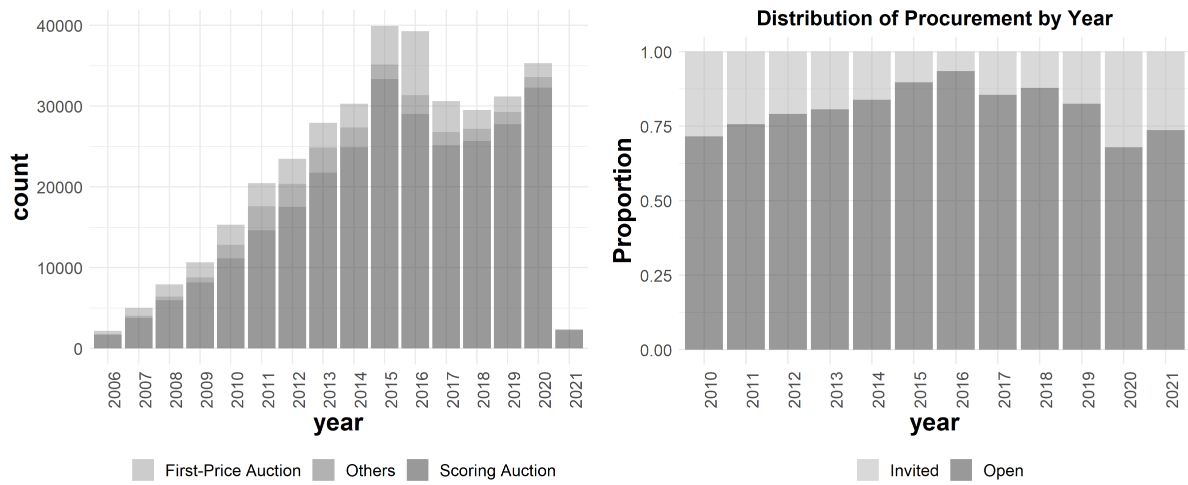
In this section, I describe the datasets I use for the paper. There are five datasets, public procurement data, corruption investigation data, firm registration data, firm tax data, and expert evaluation data. I leave the expert evaluation data for Section 1.7.

1.3.1 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 first 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 final 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 1.4 shows the distribution of the number of procurement projects with complete information. Recent trends indicate an upswing in procurement amounts, with a concurrent rise in the share of invited auctions from 2016 onward. A particularly significant development occurred in 2020 during the COVID-19 outbreak, wherein over 30% procurement projects employed non-open procurement methods to expedite responses to emergent pandemics.

Figure 1.4: 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 first-price auction, scoring auction, and other methods. (b) illustrates the proportion of procurement projects utilizing an open auction format.

1.3.2 Firm registration data

The firm registration dataset includes all officially registered firms 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 firms' 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 firm 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 A1, I plot the distribution of both the number of procurement projects in which firms participate and the number of procurement contracts that firms secure. The data reveal that approximately 80% of firms engage in fewer than five projects, and a mere 5% participate more than 20 times. In terms of victories, 60% of firms never secure a contract, and about 95% win fewer than five contracts. These distributions indicate that the majority of firms have limited participation and success in procurement projects."

1.3.3 Firm Tax data

The firm 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, offering insights into firms' 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 firm productivity, commonly referred to as Total Factor Productivity (TFP). The mechanics of this TFP measurement process are detailed in Appendix B. I merge the derived TFP estimates with the public procurement dataset. This integration is achieved through a careful matching process involving company names and the respective year of procurement.

However, it's important to note a limitation of my dataset: It doesn't comprehensively include every firm in China for each year. The frequency of the survey varies, with more thorough coverage for larger-scale firms. In contrast, smaller firms undergo random sampling annually. This selective coverage suggests that my TFP-based estimates relate specifically to a subset of procurement projects.

1.3.4 Corruption Investigations Data

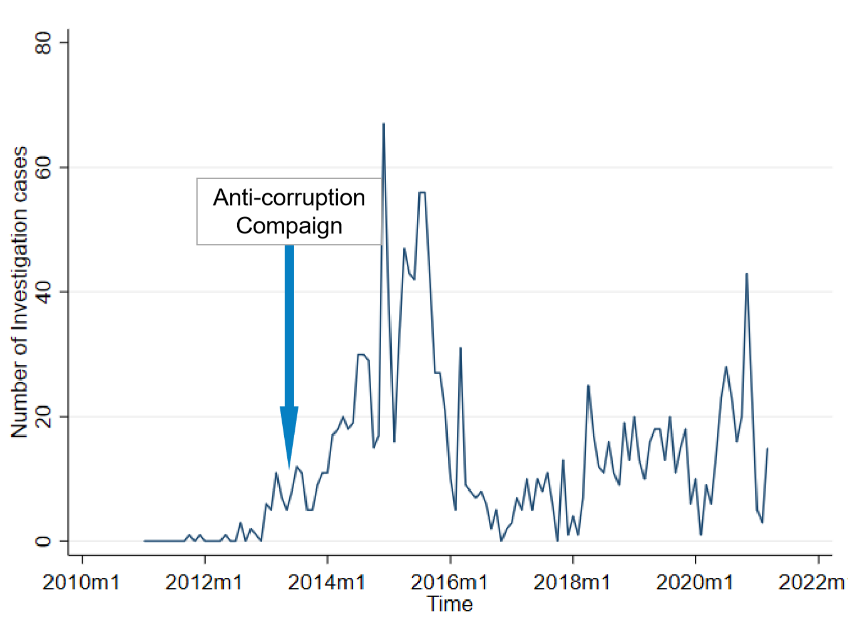
The investigation data from 2011 to August 2016 are obtained from Wang and Dickson (2022), who collected the data from Tencent.Co—the largest Internet company in China. During the anti-corruption campaign, Tencent launched a searchable online database of all corruption investigations across China in 2011. Based on the information provided by Party disciplinary committees, courts, and procuratorates from the central to local levels, Tencent's database includes each official'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 different government levels.[5] To verify the database and ensure that every investigation was made public, I ran an internet search on every name to find its original source and record the announcement date. So far, the updated database is the most comprehensive public database on China's corruption investigations. It synthesizes information from official statistics at all levels of government and all branches.

The monthly numbers of corruption investigations in the province I study, starting from 2011 are shown in Figure 2.2. The number increased dramatically from 2014, which was the start year of the anti-corruption campaign, and then gradually decreased before the 19th

[5] 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.

National Congress of the Communist Party of China in 2017. After the Congress, the level increases again. The trend in the number of investigation cases aligns with the ebb and flow of the anti-corruption campaign.

Figure 1.5: Number of Corruption Investigation Cases



Notes: The y-axis of the figure 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.

I document the department names where incumbent officials are under investigation. This information becomes crucial in Section 1.8, where I merge corruption investigations and public procurement data through the names of government departments responsible for local procurement projects. The corruption investigations act as a shock to the local government departments. The impacts of corruption investigations on public procurement are studied in Section 1.9.

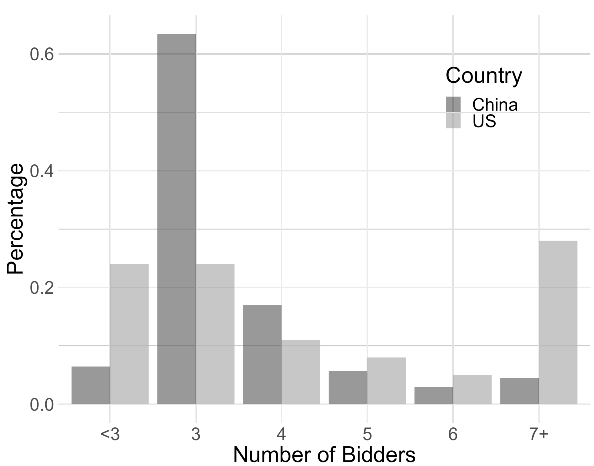
1.4 Motivating Stylized Facts

Analyzing the public procurement data, I find two motivating stylized facts defying the expectations of standard competitive models. 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 significant score gaps compared to losers, raising concerns about the motivation behind the costly participation of the latter.

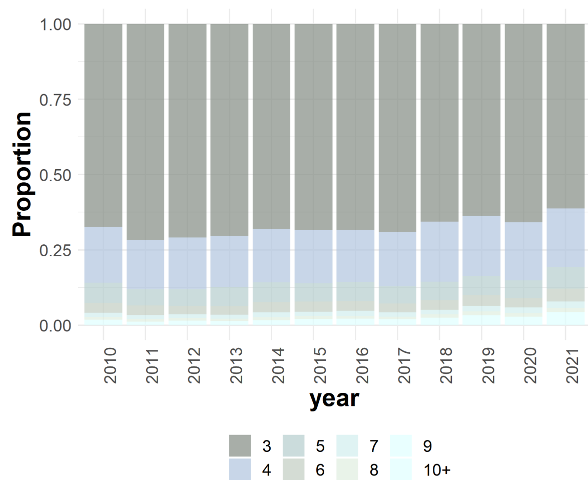
1.4.1 Few Bidders

On average, competition within procurement auctions in China remains remarkably low. Figure 1.6 presents the distribution of bidders in these auctions. Figure 1.6 (a) the darker bars, which encompass all years, including instances where procurement projects failed due to insufficient bidders, show less than 7% of procurement projects initially fail the requirement of having at least three bidders. Approximately 67% 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%. In Figure 1.6 (b), I focus exclusively on valid procurement projects while observing the year-to-year trend. While the percentage of procurement projects with three bidders decreased slightly from 70% to 65%, the dominance of auctions with precisely three bidders remains conspicuous. Experts suggest that this concentrated distribution is a common occurrence, often stemming from government procurement departments already having specific suppliers in mind and tailoring scoring rules to ensure these predetermined suppliers emerge as winners.

Figure 1.6: Number of Bidders



(a) Distribution of number of bidders



(b) Number of bidders by year

Notes: (a) 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. (b) depicts the proportions of valid procurement auctions categorized by the number of bidders, focusing on the years 2010 to 2021.

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 1.6 (a) with the lighter bars, a striking disparity emerges. Unlike the U.S. data,[6] 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 different 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.

1.4.2 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*a*). This variable is computed using the equation:

$$Win\ Margin_i = Score_i - \Delta Score_{-i}$$

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

Upon scrutinizing the public procurement data, a conspicuous trend emerges – a prevalence of auctions marked by substantial winning margins, especially in scenarios involving only three bidders. This phenomenon could be attributed to tailored scoring rules that prelude predetermined outcomes, effectively discouraging potential entrants. The favored candidates, already designated as winners, invite two additional zombie bidders to submit noncompetitive bids, thereby satisfying the requisite three-bid condition. To diminish the prospects of success for the other zombie bidders, these fictitious participants submit subpar proposals, creating a secure margin for the victor to accommodate stochastic evaluation randomness.

A pertinent case exemplifies this dynamic. Notably, Table 1.1 showcases a significant score gap between the winner and the second-best bidder. Note the low business and tech scores of firms B and C, indicating their lack of competitive bidding intent since they did not submit their bids to maximize their winning probability at the cost of time and labor preparing the proposals. Interestingly, if not for the subsequent investigation uncovering misconduct by the officials after their five-year tenure, the corrupt practices within this procurement event would have gone undetected, as all procedures adhered to regulatory norms.

The elucidation of this case draws from retrospective findings on the China Judgement Online. The deputy director of a county-level Agriculture and Forestry Department, responsible for this auction, was sentenced to a seven-year prison term for corruption in public

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

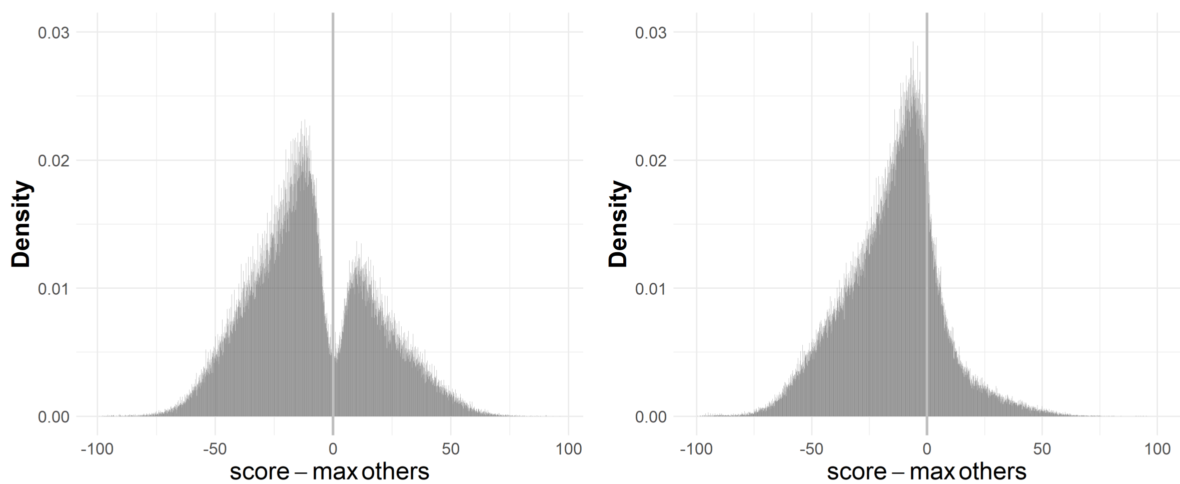
procurement. His confession unveiled instances where he orchestrated customized scoring rules for colluding firms. Firm A's acknowledgment of promising a 5% kickback to the officer upon winning the procurement, along with Firms B and C's admission that Firm A had secured insider assistance, reinforces the gravity of these corrupt practices, resulting in large spreads of scores.

Table 1.1: Example of A Corrupt Case

Company	BusiTech 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.

Figure 1.7: Distribution of bid-differences 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.

To systematically see how common the large winning margin is, I plot the distribution of the bid winning margin in Figure 1.7. Visualized in Figure 1.7, the distribution of winning margins is rendered. Specifically, Figure 1.7 (a) captures the distribution within procurement auctions that feature merely three bidders. The conspicuous absence of mass around the 0 mark is noteworthy, implying infrequent instances of narrow winning margins in such auctions. The rarity of close victories becomes evident, as most losing bids are distant from the winning threshold. This phenomenon signifies a dearth of intense competition, even if winning bidders were to escalate their price bids. Conversely, Figure 1.7 (b) showcases auctions involving four or more bidders, wherein the distinctive "two-peak" pattern dissipates. Adding one or more bidders significantly changes the distribution of winning margins suggesting a significant lack of competition in three-bidder cases.

Table 1.2: 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.

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 point, as detailed in Table 1.2, 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 significant 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 firms 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 B.

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

1.5 Model

To theoretically demonstrate that the substantial winning margins are inconsistent with the competition null hypothesis, this section uses a standard scoring auction model, examining both a competitive scenario and a corruption scenario involving customized scoring rules.

In the scoring auction model, a government entity seeks to procure a project using an open scoring auction. The government entity initiates the procurement process by releasing a comprehensive procurement announcement designed to attract potential suppliers. This public notice provides an exhaustive account of the project, incorporating essential details like the project's budget,[7] location, project timeline, and transaction plan. Of particular significance, it outlines a detailed scoring rule function S, $\mathbb{R} : (p, \boldsymbol{q}) \to S(p, \boldsymbol{q})$, which represents a continuous preference relation over contract characteristics. The scoring rule takes into consideration both the price bid p, with $p \in [\underline{p}, \overline{p}]$,[8] and the quality bid $\boldsymbol{q}$, with $\boldsymbol{q} \in \mathbb{R}^L$. The scoring rule is defined as that the final scores are the weighted sum of quality scores and price scores:

$$S(p, \boldsymbol{q}) = \boldsymbol{w_q} \cdot \boldsymbol{q} + w_p \frac{\underline{p}}{p}, \text{ with } \sum_{l=1}^{L} w_q^l + w_p = 100$$

where $\boldsymbol{w_q}$ and w_p represent the weights assigned by the government to the quality and price parts, respectively. The sum of the weights is equal to 100. Government set the optimal $\boldsymbol{w_q}$ and w_p to maximize social welfare.

The quality scores $\boldsymbol{q}$ range from 0^L to 1^L. The minimum price that a firm can bid denoted as $\underline{p}$, serves as a reference for the calculation of price scores. Both price bids p and $\underline{p}$ are standardized by the project budget (reserve price), $\overline{p}$, which is the maximum price firms can offer. Thus, p and $\underline{p}$ both fall in the range of (0,1] and the ratio $\frac{\underline{p}}{p}$ also lies in (0,1]. Then the total score s ranges from 0 to 100. The function s increases as any dimension of quality bid $\boldsymbol{q}$ increases, but decreases as the price bid p increases. The partial derivative of s with respect to p is negative, i.e., $S_p(p, \boldsymbol{q}) < 0$, while the partial derivative of s with respect to q^l, for any l =1...L, is positive, i.e., $S_{q^l}(p, \boldsymbol{q}) > 0$.

Following the literature (Asker and Cantillon, 2008; Takahashi, 2018; Huang and Xia, 2019; Hanazano et al., 2020), I assume the scoring rule reflects the true utility function of the government entity.[9] The optimal design of the scoring rule is beyond my discussion in this paper, but in Section 1.9, I discuss the scenarios with different price weights.

1.5.1 Competitive Model

In a competitive procurement project a with characteristics $\boldsymbol{x_a}$, n ex-ante symmetric and risk-neutral firms participate in the auction, denoted by $i = 1, 2, ..., n$.[10] The number of competitors is known. Firm i in the project a draws its firm type $\boldsymbol{\theta_i} \in \mathbb{R}^T$, with T dimensions, independently from a publicly known absolutely continuous distribution function $F(\boldsymbol{\theta})$.[11]

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

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

[9] In reality, the scoring rule does not necessarily reflect the true social preference given the fixed equation format of score calculation. What's more, the corruption from procurement officials might bias upward or downward the weights on some attributes.

[10] I also introduce some asymmetry based on firm characteristics z in Appendix C. Then firms with different z, $(\theta|z)$ have different bidding strategies. The results are not sensitive to the asymmetry.

[11] If firms are ex-ante asymmetric, the distribution of firm type is $F(\theta|z)$

The distribution is also conditional on project characteristics $\boldsymbol{x_a}$. The type $\boldsymbol{\theta_i}$ is private information of firm i. For the sake of notational simplicity, the reference to t will be omitted for the remainder of this model section.

Firm i has a cost function $C(\boldsymbol{q_i}, \boldsymbol{\theta_i})$,[12] in which cost depends on the submitted variable quality bid $\boldsymbol{q_i}$ and the firm type combination $\boldsymbol{\theta_i}$. I assume that the cost function satisfies the following conditions.

Assumption 1. *Cost function $C(\boldsymbol{q}, \boldsymbol{\theta})$ is continuous, $C_{q^l}(\boldsymbol{q}, \boldsymbol{\theta}) > 0$, $C_{q^l q^l}(\boldsymbol{q}, \boldsymbol{\theta}) > 0$, for any l =1...L, and $C_{\theta^k}(\boldsymbol{q}, \boldsymbol{\theta}) > 0$, for any k =0...$K-1$. The cost is increasing and convex in each dimension of quality $\boldsymbol{q}$ and increasing in each dimension of type $\boldsymbol{\theta}$.*

Without loss of generality, I can rewrite the firm's choice of the bid combination $(p, \boldsymbol{q})$ as choosing a score s and quality $\boldsymbol{q}$. Therefore the price bid is $p(s, \boldsymbol{q})$. 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 firm selects a profit-maximizing price p and quality $\boldsymbol{q}$ combination. Then the firm selects the optimal score s.

In the first step, if the firm i wins the auction at score s_i, its profit is given by $\pi(s_i|s_i > s_{-i}) = P(s_i, \boldsymbol{q_i}) - C(\boldsymbol{q_i}, \boldsymbol{\theta_i})$. The firm chooses the optimal $\boldsymbol{q_i}$ to solve the profit maximization problem:

$$q(s_i, \boldsymbol{\theta_i}) = arg \max_{\boldsymbol{q}} \pi(s_i|s_i > s_{-i}) = arg \max_{\boldsymbol{q}} P(s_i, \boldsymbol{q_i}) - C(\boldsymbol{q_i}, \boldsymbol{\theta_i})$$

Plug in the optimal $\boldsymbol{q}$ back to the profit function:

$$\pi(s_i, \boldsymbol{\theta_i}) = P(s_i, q(s_i, \boldsymbol{\theta_i})) - C(q(s_i, \boldsymbol{\theta_i}), \boldsymbol{\theta_i}) \tag{1.1}$$

$\pi(s_i, \boldsymbol{\theta_i})$ is analogue to the profit-maximizing quantity in the general production decision problem. Applying the envelope theorem, the profit function $\pi(s_i, \boldsymbol{\theta_i})$ satisfies two first-order conditions with respect to $\boldsymbol{q}$ and s:

$$P_{q^l}(s_i, q(s_i, \boldsymbol{\theta_i})) = C_{q^l}(q(s_i, \boldsymbol{\theta_i}), \boldsymbol{\theta_i}) \tag{1.2}$$

$$\pi_s(s_i, \boldsymbol{\theta_i}) = P_s(s_i, q(s_i, \boldsymbol{\theta_i})) \tag{1.3}$$

The two equations stipulate that, conditional upon winning, the marginal cost is equal to the marginal revenue, and the marginal profit corresponds to the marginal price with respect to the price bid. π_s is strictly negative by Assumption 1. The quality is chosen endogenously, and the target score s is a sufficient statistic for the optimal bid in the profit-maximizing problem (1.1).

Next, in the second step, the firm chooses the target score s to maximize expected profit:

$$s(\boldsymbol{\theta_i}) = arg\ max_s [P(s_i, q(s_i, \boldsymbol{\theta_i})) - C(q(s_i, \boldsymbol{\theta_i}), \boldsymbol{\theta_i})] Pr\{s_i > s_{-i}\} \tag{1.4}$$

[12] As mentioned before, the cost is also conditional on project characteristics $\boldsymbol{x_t}$

Assumption 2. *The Hessian matrix of $P(s,\boldsymbol{q}) - C(\boldsymbol{q},\boldsymbol{\theta})$, $P_{q^l q^l} - C_{q^l q^l}$ is negative definite given score s, with $P_{q^l}(s,\boldsymbol{q}) - C_{q^l}(\boldsymbol{q},\boldsymbol{\theta}) > 0$ at $q^l = 0$, and $P_{q^l}(s,\boldsymbol{q}) - C_{q^l}(\boldsymbol{q},\boldsymbol{\theta}) < 0$ at $q^l = 1$, for any l =1...L*

The assumption simply ensures an interior solution. For the existence of a pure-monotone strategy equilibrium, another assumption is shown below.

Assumption 3. *Bidder's profit function satisfies the Log-submodularity condition:*

$$\frac{\partial^2 log\ \pi(s,\boldsymbol{\theta})}{\partial s \partial \theta^k} < 0$$

for any k =1...K.

As demonstrated in Andreyanov (2018) and Hanazano et al. (2020), under Assumptions 1-3, in a symmetric scenario, a symmetric monotone equilibrium denoted as $S(\boldsymbol{\theta})$ exists in the scoring auction model, with the property that $S_{\theta^k}(\boldsymbol{\theta}) < 0$. The regularity, existence, and uniqueness of equilibrium are discussed in Andreyanov (2018) and Hanazano et al. (2020).

I use the distribution function (CDF) and density function (PDF) of score s as $G(s)$ and $g(s)$ respectively. Theorem 1 shows the competitive equilibrium bidding strategy.

Theorem 1. *The competitive equilibrium bidding strategy is given by*

$$P(s, q(s,\boldsymbol{\theta})) = \underbrace{C(q(s,\boldsymbol{\theta}),\boldsymbol{\theta})}_{cost} - \underbrace{P_s(s, q(s,\boldsymbol{\theta})\frac{G(s)}{(n-1)g(s)}}_{Markup:\ relative\ advantage\ of\ MC} \tag{1.5}$$

$$C_{q^l}(q(s,\boldsymbol{\theta}),\boldsymbol{\theta}) = P_{q^l}(s, q(s,\boldsymbol{\theta}))\ for\ any\ l = 1...L \tag{1.6}$$

with the condition that $P_{q^l q^l} - C_{q^l q^l} < 0$ to ensure the profit maximizing.

Proof. See Appendix D

□

Following Asker and Cantillon (2008), I define the pseudotype, the effective cost measured by score, as

$$k(S(\boldsymbol{\theta}),\boldsymbol{\theta}) = S(\boldsymbol{\theta}) - \frac{\pi(S(\boldsymbol{\theta}),\boldsymbol{\theta})}{\pi_s(S(\boldsymbol{\theta}),\boldsymbol{\theta})} \tag{1.7}$$

$\pi_s(S(\boldsymbol{\theta}),\boldsymbol{\theta})$ represents marginal profit of score and is negative. Pseudotype k can be interpreted as the highest score the firm can achieve with nonnegative profit.

Corollary 1.1. *The pseudotype k is monotone in $\boldsymbol{\theta}$ based on Assumption 3 and is a sufficient statistic for firm type $\boldsymbol{\theta}$.*

Proof. See Appendix D

□

Since s is monotone equilibrium and the pseudotype k is monotone in firm types, pseudotype k is monotone in score s. The competition is transformed to a one-dimensional competition on pseudotype.

Theorem 2. *In the competitive equilibrium, the winning scoring bid is the expectation of the strongest rival's pseudotype k:*

$$s^{win} = E[k^{rival(1)} | s^{win}] \tag{1.8}$$

Proof. See Appendix D

□

Theorem 2 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 effort and expenditure and ultimately leave potential extra profits on the table.

1.5.2 Corruption Model

In the scenario involving corruption, I model a situation where public officials show favoritism to corrupt firms by artificially elevating their quality scores. This augmentation is 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 prior to the initiation of auction competition, impacting both corrupt winners and their competitors. [13] Rules customization includes the imposition of stringent qualifications that other firms can not satisfy, and giving corrupt firms privileged information about the project.[14] Corrupt officials skew the scoring rule weights from the optimal $\boldsymbol{w_q}$ to corrupt $\boldsymbol{\tilde{w}_q}$, then the corrupt scoring rules are:

$$S(p, \boldsymbol{q}) = \boldsymbol{\tilde{w}_q} \cdot \boldsymbol{q} + w_p \frac{\underline{p}}{p}, \text{ with } \sum_{l=1}^{L} w_q^l + w_p = 100$$

The quality $\boldsymbol{q}$ comes with two parts $(\boldsymbol{q}^N, \boldsymbol{q}^U)$, necessary quality, and unnecessary quality for the project. For noncorrupt auctions, officials put zero weights on unnecessary quality parts, $\boldsymbol{w_q} = (\boldsymbol{w_q}^N, \boldsymbol{0})$, while for corrupt officials, they set $\boldsymbol{\tilde{w}_q} = (\boldsymbol{\tilde{w}_q}^N, \boldsymbol{\tilde{w}_q}^U)$ with $\boldsymbol{\tilde{w}_q}^U > \boldsymbol{0}$

[13]This is consistent with the context of my research. Interviews with officials have disclosed that lobbying activities typically unfold before the release of call-for-tender documents and designs to the public.

[14]Based on interviews, this is primarily because the quality aspect is more subject to control by officials. By crafting unique requirements, officials can signal to potential competitors (Cai, Henderson, and Zhang, 2013) and discourage their participation in the procurement competition. Since quality score is determined by averaging the evaluation scores of five randomly selected experts. Attempting to manipulate all five experts is considerably more challenging, so making bribery in this regard is less feasible.

Different firms playing different roles behave differently in the auction. **Non-corrupt competitors** who are potential contenders typically recognize bias $\tilde{w}_q$ in the call-for-tender documents. Consequently, they may choose to abstain from participating in the auction, anticipating an unfair competition. Alternatively, if they mistakenly enter the auction competitively, they are highly likely to lose because their quality is $\boldsymbol{q} = (\boldsymbol{q}^N, \mathbf{0})$ and the total score is downgraded by $\tilde{\boldsymbol{w}}_{\boldsymbol{q}}{}^U$.

With entry deterred for genuine competitors due to customized scoring rules, predetermined winners must still enlist two **fake bidders** as accomplices to meet the minimum three-bidder requirement, creating an illusion of competition. These fake bids typically feature exceptionally low quality scores, mainly for two reasons. Firstly, the evaluation process for q_2 incorporates subjective elements that introduce unpredictability into quality scores. Consequently, the quality component of fake bids is deliberately kept low to avoid unexpected positive evaluations. Secondly, fake bidders lack any incentive to bid competitively, as they are ineligible for m and often submit minimal-effort bids. Even if these fake bidders were to submit genuinely competitive bids in violation of their agreement, they would still stand little chance of winning due to the bias favoring predetermined winners. Thus, they have no reason to deviate from the agreed-upon strategy, resulting in a negligible winning probability for fake bids, $Pr\{s_i > s_{-i}\} = 0$.

For **predetermined winners**, upon winning, they must pay the officers a fixed proportion α of the project budget as a kickback, which is also unobserved. The winner cannot submit a really low $\boldsymbol{q}$, since there is an auditing risk $r(\boldsymbol{q})$, which is conditional upon engagement in corrupt practices. Given that $r_{q^l}(\boldsymbol{q}) < 0$, should the winning firm deliver a project of unacceptable quality, it might invoke an audit on the firm. The predetermined winner maximizes the profit if there are real competitors:

$$\max_{s_i} \pi_i = [(1-\alpha)P(s_i, q(s_i, \boldsymbol{\theta_i})) - C(q(s_i, \boldsymbol{\theta_i}), \boldsymbol{\theta_i}) - r(q(s_i, \boldsymbol{\theta_i}))]Pr\{s_i + 2w_q m > s_{-i}\}$$

where s_i is the true score, while the observed score is $s_i + w_q m$. The trade-off is between the profit and winning probability. In the other scenario where all other bidders are zombie bidders:

$$\max_{s_i} \pi_i = (1-\alpha)P(s_i, q(s_i, \boldsymbol{\theta_i})) - C(q(s_i, \boldsymbol{\theta_i}), \boldsymbol{\theta_i}) - r(q(s_i, \boldsymbol{\theta_i}))$$

The expected profit is constrained by the trade-off between the profit and auditing risks.

Because of the scoring rule customization and zombie bids, Corollary 2.1 follows.

Corollary 2.1. *With corruptly screwed $\tilde{\mathbf{w}}_q$:*

$$E[\tilde{k}^{rival}|s^{win}] < E[k^{rival}|s^{win}] \tag{1.9}$$

and the equation in Theorem 2 doesn't hold, instead

$$E[\tilde{k}^{rival(1)}|s^{win}] < s^{win} = E[k^{rival(1)}|s^{win}] \tag{1.10}$$

Proof. Based on Corollary 1.1, k exhibits a monotonic decrease with respect to $\boldsymbol{\theta}$. Similarly, s also demonstrates a monotonic decrease with respect to $\boldsymbol{\theta}$. Consequently, this implies that k will have a strictly monotonic increase in s. In instances of corruption, the customized scoring rules downgrade the scores of the competitors, $\tilde{k}^{rival} < k^{rival}$.

□

Equation (1.10) in Corollary 2.1 provides a test for detecting corruption involving scoring rules manipulations. However, only one draw of a group of rivals and one $k_t^{rival(1)}$ is observed for each auction t, this test isn't suitable at the auction level. Instead, by taking expectations on both sides, the test becomes applicable for a group of auctions:

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

A challenge arises when there are undetected corrupted auctions, as it biases the estimated k, resulting in the statistical test being unreliable. On the bright side, this bias creates a separation of $E[s^{win}] - E[k^{rival(1)}]$ between noncorrupt auctions and corrupt auctions. The separation can be leveraged to estimate a consistent nonparametric maximum likelihood estimator (NPMLE) representing the ratio of corrupt auctions within a group of auctions. Please refer to Appendix I for a detailed explanation of the NPMLE estimation. I show in the next section that the auction-level test results are similar to the NPMLE results.

For auction-level test, instead of using Equation (1.10), I use Equation (1.9), the necessary condition based on Corollary 2.1, to do the test for each project a:

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

where $E[k^{rival}|s^{win}]$ is the expected pseudotype of potential rivals conditional on the winning score s^{win}, and $E[k_a^{rival}|s^{win}]$ is expected pseudotype of the actual rivals in auction a.

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. In the next section, I propose a method to reduce the concern.

1.6 Empirical Test

In this section, I outline the method for estimating the pseudotype k based on observed data and detail the steps involved in performing the statistical test to identify auctions that reject the null hypothesis.

1.6.1 Test Steps

First, I estimate the pseudotype, k, from the dataset consisting of A independent scoring auctions. Within each auction a, the number of participating firms is represented as n_t.

The public procurement dataset provides bids (p_{ia}, q_{ia}), the corresponding scores s_{it} for each participating bidder, and auction-specific covariates denoted as $\boldsymbol{x_a}$, including project budgets, procurement categories, price weights, and variable quality weights. To estimate the cumulative distribution function (CDF) and probability density function (PDF) of scores, a non-parametric approach is employed. This involves utilizing the standard kernel estimator used in Guerre, Perrigne, and Vuong (2000), Athey and Haile (2002), and Li, Perrigne, and Vuong (2002).

$$\hat{G}_s(s,n,\boldsymbol{x}) = \frac{1}{Th_{g_n}h_{g_x}}\sum_{a=1}^{A}\frac{1}{n_a}\sum_{i=1}^{n_a}\mathbb{1}(s_{ia} \leq s)K_G(\frac{n-n_a}{h_{g_n}}, \frac{\boldsymbol{x}-\boldsymbol{x_a}}{h_{g_x}})$$

$$\hat{g}_s(s,n,\boldsymbol{x}) = \frac{1}{Th_s h_{g_n}h_{g_x}}\sum_{a=1}^{A}\frac{1}{n_a}\sum_{i=1}^{n_a}K_g(\frac{s-s_{ia}}{h_s}, \frac{n-n_a}{h_{g_n}}, \frac{\boldsymbol{x}-\boldsymbol{x_a}}{h_{g_x}})$$

where $\mathbb{1}(.)$ is the indicator function; K_G and K_g are kernels; and h_{g_n}, h_{g_x}, h_s are bandwidths.

I can rewrite the definition of pseudotype k equation (1.7) with equation (A.1):

$$k(S(\boldsymbol{\theta}),\boldsymbol{\theta}) = S(\boldsymbol{\theta}) - \frac{\pi(S(\boldsymbol{\theta}),\boldsymbol{\theta})}{\pi_s(S(\boldsymbol{\theta}),\boldsymbol{\theta})} = S(\boldsymbol{\theta}) + \frac{G(s)}{(n-1)g(s)} \tag{1.11}$$

Therefore the pseudotype defined above can be estimated using:

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

Then for each auction t I conduct the following hypothesis test:

$$H_0\text{: } E[k_a^{rival}|s^{win}] = E[k^{rival}|s^{win}] \text{ and } H_1\text{: } E[k_a^{rival}|s^{win}] < E[k^{rival}|s^{win}]$$

Rejecting the null hypothesis H_0 provides evidence in favor of H_1, which suggests that in auction a rivals' scores are indeed downgraded in comparison to the winner.

Directly applying the pseudotype estimation method to the entire dataset is unsuitable due to the contamination of the presence of corrupt public procurement on the estimation. The auction outcomes comprise a mixture of competitive and corrupt auctions, leading to biased pseudotype estimates and a reduction in test power. For example, when a mass of zombie bids are present and the distribution of k pseudotype presents a heavy left tail, the pseudotypes of competitive bids with high scores are biased upward.[15] Without correcting the pseudotype estimates, I take advantage of the separation of the gap between winning scores and the pseudotype of the strongest rivals distinguishing between corrupt auctions due to the bias introduced by corruption. I propose a method using a nonparametric maximum

[15]Mathematically illustrating the bias, consider the zombie bids where $k = s + \frac{G(s)}{(n-1)g(s)}$. Due to the corruption signal deterring entry, n is smaller than its competitive counterfactual. Consequently, $G(s)$ is biased upward, while $g(s)$ is downward biased. Taken together, k exhibits an upward bias.

likelihood estimator (NPMLE) to estimate the proportion of corrupt auctions within a group, conditional on the characteristics, detailed in Appendix I.

For auction-level test, to obtain unbiased pseudotype estimates, 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 filtering (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 (1.11).

Step 2. Conduct a statistical test to determine if the pseudotypes of realized rivals in auction a, denoted as $\hat{k}_a^{rival}|s^{win}$, are equal to or exceed the pseudotypes of potential rivals, represented as $\hat{k}^{rival}|s^{win}$, when conditioned on the winning score, in terms of either their mean values or rankings.

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.[16] Save the estimated distribution of s.

Step 4. Use the estimated distribution of s to estimate the pseudotypes of all bidders in all auctions and apply the statistical test to save p-values.

This structured approach ensures the systematic and iterative application of the pseudotype estimation method, accounting for corrupt auctions. Ultimately, it yields unbiased pseudotype estimates, thus enabling effective statistical testing. To demonstrate the efficiency and accuracy of these iterative test steps, I conduct a Monte Carlo Study with simulations in the next subsection.

Regarding the choice of statistical test types for evaluating systematic one-directional bias in the sample, researchers commonly employ two categories of methods: parametric approaches like the t-test, and non-parametric methods exemplified by the Wilcoxon-Mann-Whitney test. Numerous studies (Hodges Jr and Lehmann, 1956; Fay and Proschan, 2010; De Winter, 2019) have extensively examined the test power and type I error comparisons between these two approaches. Given that most auctions involve only three bidders and the underlying distribution of score is unknown, I employ a strategy of conducting multiple tests using both the t-test and Wilcoxon-test for each auction, thus enhancing test power. The resulting outcomes encompass both unadjusted p-values and adjusted p-values, which account for multiple testing concerns. The selection between unadjusted and adjusted p-values is also discussed in the Monte Carlo study of the following subsection.

Instead of the test with an iterative way to estimate the unbiased pseudotypes, I also propose a method using the biased pseudotypes and the k-means unsupervised learning

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

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. Please see Appendix J for more details.

1.6.2 A Monte Carlo Study

Before applying the proposed test steps 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,[17] 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 1.8 (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.[18]. 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 1.8 (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 1.8 (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 1.7 (a).

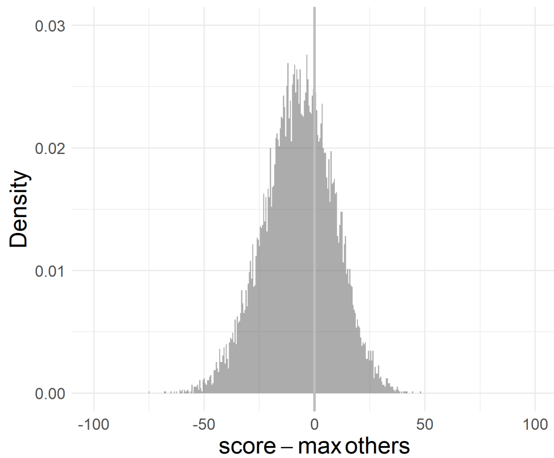
For each corruption ratio, I implemented the test steps, separately employing both the Wilcoxon test and the t-test. To enhance test power, I set the significance level at 0.1, considering that each auction involved three bidders.[19] One way to classify auctions is to reject the null hypothesis of competitiveness if either a p-value from the Wilcoxon test or the t-test was smaller than 0.1. However, to control the overall false positive rate arising from multiple tests, I also calculated adjusted p-values. Therefore, the second and more conservative

[17]The choice of three bidders aligns with the prevalent scenario in real auction data; further discussion on cases with more bidders can be found in Appendix E.

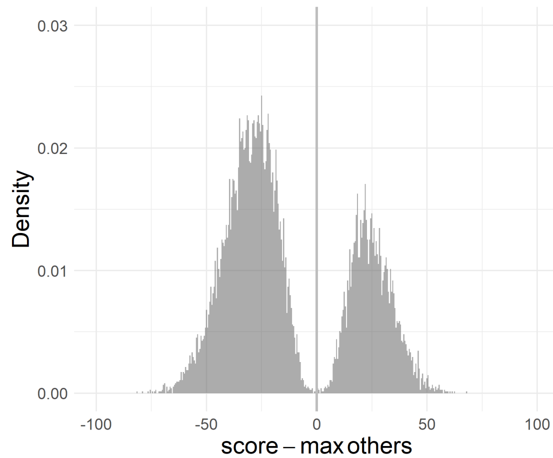
[18]Predetermined winners typically attain higher scores compared to competitive winners and are closer to a perfect score of 100.

[19]For auctions with more bidders, such as six or more, a significance level of 0.05 could be considered.

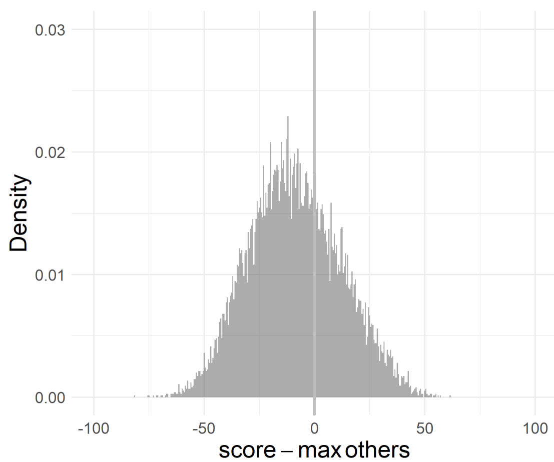
Figure 1.8: Distribution of Winning Margins



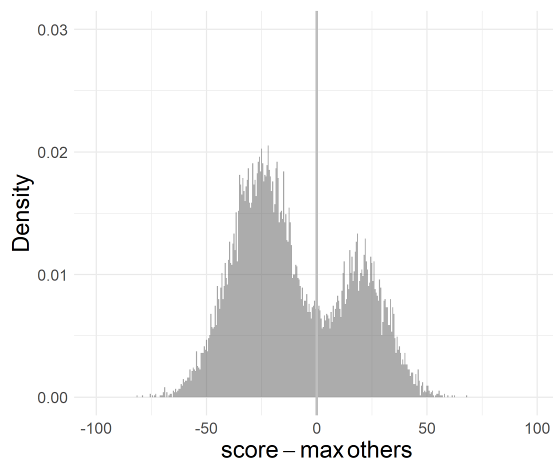
(a) Simulated Competitive Auctions



(b) Simulated Manipulated Auctions



(c) Corruption Ratio 30%



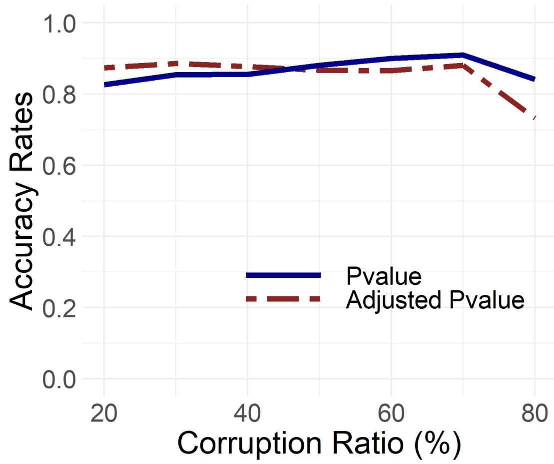
(d) Corruption Ratio 70%

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.

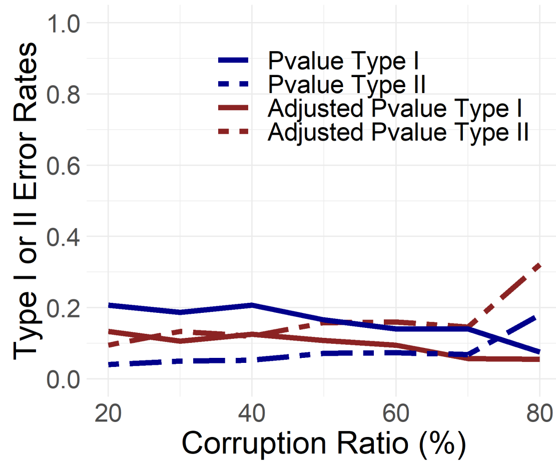
classification method considered auctions as non-competitive if either an adjusted p-value from the Wilcoxon test or the t-test was smaller than 0.1. Utilizing the known underlying data-generating process, I calculated accuracy rates, type I error rates, and type II error rates for both classification methods under varying corruption ratio scenarios.

The summary of results is presented in Figure 1.9 (a) and (b). As the corruption ratio increases, the accuracy rate of using unadjusted p-values rises from 81% to 87%, surpassing that of using adjusted p-values when the corruption rate is around 45%. Conversely, the accuracy rate of using adjusted p-values declines from 86% to 77% as they tend to be overly

Figure 1.9: Comparison between Unadjusted and adjusted P-value



(a) Test Accuracy Rate



(b) Type I and II Error Rate

Notes: (1) The accuracy rate is computed by adding the number of auctions from a competitive DGP failing to reject the null and the number of auctions from a corrupt DGP rejecting the null. The sum is then divided by 1000, the total number of auctions. (2) The Type I error rate is calculated by dividing the number of auctions from a competitive DGP but still rejecting the null hypothesis by the total number of competitive auctions. (3) The Type II error rate is calculated by dividing the number of auctions from a corrupt DGP but failing to reject the null hypothesis by the total number of corrupt auctions.

conservative in cases of dominant corruption. Figure 1.9 (b) illustrates a trade-off between type I error and type II error, with a decrease in type I error leading to an increase in type II error and a reduction in test power. By setting the significance level at 0.1, the type I error using unadjusted p-values remains restrained below 0.1 when the corruption ratio exceeds 0.5, whereas, in all scenarios deploying adjusted p-values, it is maintained below 0.1 and even converges to 0.05 when corruption is pervasive.

In conclusion, in terms of accuracy rates, the test steps perform reasonably well in this Monte Carlo study. In cases with more bidders, as detailed in Appendix E, the overall accuracy rate can exceed 90%. The choice between using the unadjusted p-value or adjusted p-value depends on the specific objectives and the underlying situation. If the goal is to maximize the overall accuracy rate, especially when corruption is prevalent, as in this setting, the unadjusted p-value proves more powerful. Therefore, the unadjusted p-value is chosen as the primary result, while the adjusted p-value results are also presented as a conservative measure. However, if the agency prioritizes minimizing type I errors, if the estimated corruption level is low, or if there is a high average number of bidders, then the adjusted p-value may be a more suitable choice.

1.6.3 Test Results

I apply the test steps used in the Monte Carlo Study to the real public procurement auction data.[20] To provide a concrete example of how the statistical tests work, I used an auction described as the "for-sure corrupt case" in Section 1.4, Table 1.1, as an illustration.

This 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, including budget, price/variable quality weight, procurement category, and number of bidders, there is a distribution of $\hat{k}$ for bidders with scores lower than 98.3, as shown in Figure 1.10 (a). The expected $\hat{k}$ of rivals is 90.72, inferred from the winning score of 98.3 and represented by the red dashed vertical line. However, the realized rivals' $\hat{k}$ are 54.79 and 53.03, drawn by the solid blue lines and located in the low tail of the distribution. The p-value of the Wilcoxon test is 0.002, leading to the rejection of the null hypothesis. Therefore, the auction is successfully identified as corrupt using my method.

The same is true for the four-bidder procurement auction described in Section 1.4, Table 1.2. Given the winning score of 98.25 and the auction characteristics, the distribution of $\hat{k}$ is shown in Figure 1.10 (b). The expected $\hat{k}$ is 84.89, while the realized rivals' $\hat{k}$ are 66, 64, and 60, drawn by the solid blue lines and located in the low tail of the distribution. The p-value of the Wilcoxon test is 0.008, resulting in the rejection of the null hypothesis and labeling the auction as corrupt.

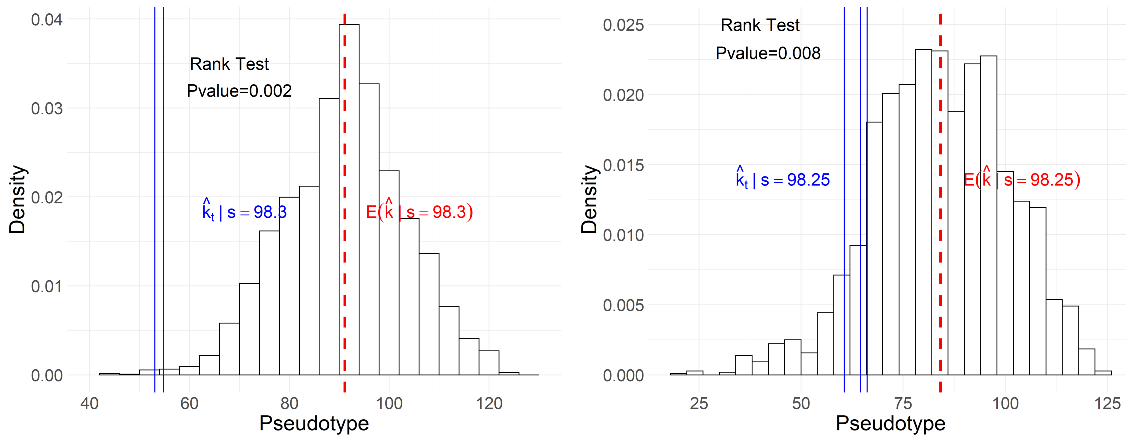
Table 1.3: Test Results

	Proportion of Procurement Auctions Reject the Null				
	All	3 Bidders	4 Bidders	5 Bidders	6 Bidders
	$\alpha = 0.10$				
Unadjusted P-value	65.06%	70.03%	51.52%	48.13%	57.76%
	[63.9, 66.22]	[68.92, 71.13]	[51.04, 52.01]	[46.34, 49.92]	[56.8, 58.71]
Adjusted P-value	57.23%	62.72%	43.76%	38.62%	44.18%
	[55.99, 58.48]	[61.49, 63.95]	[43.19, 44.34]	[37.35, 39.89]	[43.47, 44.9]
	$\alpha = 0.05$				
Unadjusted P-value	54.83%	60.31%	41.06%	34.76%	43.19%
	[53.61, 56.05]	[59.13, 61.5]	[40.46, 41.66]	[33.5, 36.03]	[42.51, 43.86]
Adjusted P-value	45.58%	50.38%	33.98%	27.45%	33.3%
	[44.4, 46.75]	[49.26, 51.5]	[33.25, 34.71]	[26.24, 28.67]	[32.7, 33.89]

Notes: 95% confidence intervals from bootstrapping are indicated in brackets. The first two rows 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.

[20] The desired significance level $\alpha = 0.1$ is achieved after five iterations for the t-test and six iterations for the Wilcoxon test. In Appendix A, Figure A3 illustrates the CDF of scores and the estimated ps $\hat{k}$ for different iterations. To analyze the characteristics of the remaining auctions after each iteration, a summary is provided in Table A1.

Figure 1.10: Test Examples



(a) Test for Table 1.1 (b) Test for Table 1.2

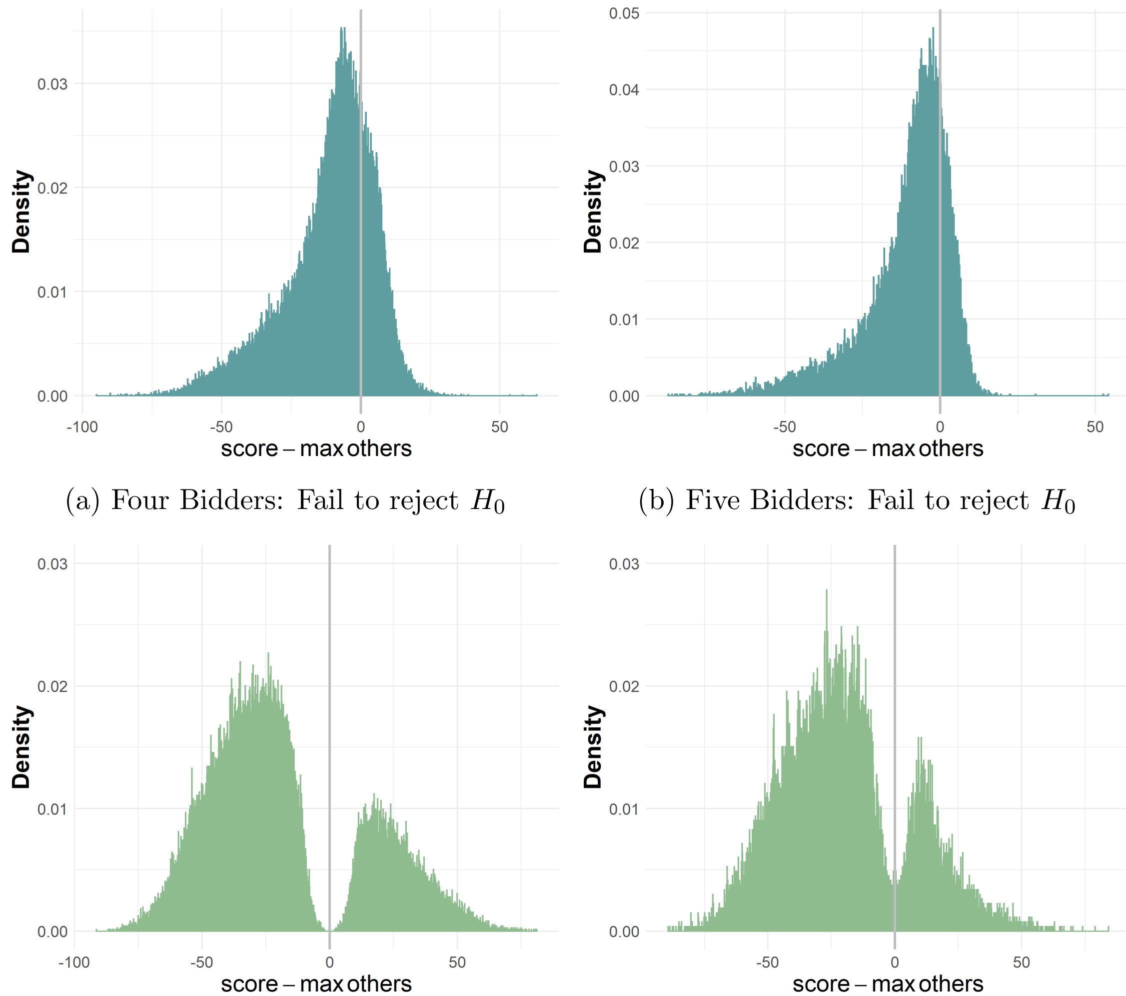
Notes: The distributions of pseudotype are conditional on the winning scores and take procurement project characteristics into consideration.

Table 1.3 summarizes the test results by showing the proportion of procurement auctions that reject the null hypothesis. As discussed in the Monte Carlo study, to maximize the overall accuracy rate and gain test power, unadjusted p-values are used as the primary results in the first two rows with a significance level of 0.1. Results under adjusted p-values are also presented as a conservative measurement in the next two rows. For the second part of the table, I show the results under the significance level of 0.05, which provides an even more conservative measurement by reducing the false positive rate. Overall, approximately 65% of the auctions reject the competitive auction null hypothesis, and even with the conservative approach, this figure is 57%. In three-bidder auctions, the majority reject the null hypothesis. Specifically, in 70% of the 3-bidder auctions, the test results show evidence of a downgrade of the scores of rivals.[21] For four-bidder auctions, although the proportion is smaller than in three-bidder auctions, it is still significant. The estimated confidence intervals, obtained through bootstrapping, are shown below each proportion number.

Furthermore, I plot the distributions of the density of winning margins separately for the procurement auctions that reject and do not reject the null hypothesis in Figure 1.11, grouped by 4-bidders and 5-bidders. Figure 1.11 (a) and (b) show the distributions of winning margins for auctions that fail to reject the null. The distributions are concentrated around the threshold 0, with a thin tail of low scores. Figure 1.11 (c) and (d) show the distributions of winning margins for auctions that reject the null. There are missing mass areas around 0, and the low-score tail is heavy, indicating a significant number of exceptionally low-quality

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

Figure 1.11: Distribution of Winning Margins



(a) Four Bidders: Fail to reject H_0

(b) Five Bidders: Fail to reject H_0

(c) Four Bidders: Reject H_0

(d) Five Bidders: Reject H_0

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.

bids. The missing gap is more pronounced when there are fewer bidders. The comparison of graphs shows that the screening process works as expected.

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

1.6.4 Discussion

Although rejecting the null hypothesis indicates evidence of the downgrading of rivals' scores, it cannot be concluded that 100% of 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 officials' 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 firms in the same auction. In order to examine how frequently the same pair or trio of firms co-participate in procurement projects, I provide a frequency distribution in Figure 1.12 that covers all 214,000 procurement instances in my dataset. [22] About 86% of all possible pairs of firms participate in the same procurement at least once, and only a small minority participate more than twice. For trios of firms, this percentage increases to 96%, indicating that only 4% of three-bidder groups interact more than twice.[23]

Furthermore, I applied the participation test using the approach proposed by Conley and Decarolis (2016).[24] The null hypothesis is that the entry of groups of firms is competitive. The results of the test are intriguing, as only a small percentage of groups with two or more members - specifically 7.64% - rejected the null hypothesis. The number was even lower for groups with three or more members, at 2.59%. These figures are significantly 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 flag 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 emergence and exit of firms. To assess the level of concentration [25]. I utilize firm tax data from 2016 to calculate the Herfindahl–Hirschman Index (HHI) by industry and illustrate the distribution of the HHI in Figure A4. 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 significant control, they can manipulate auctions to benefit specific bidders, making it difficult for other companies to

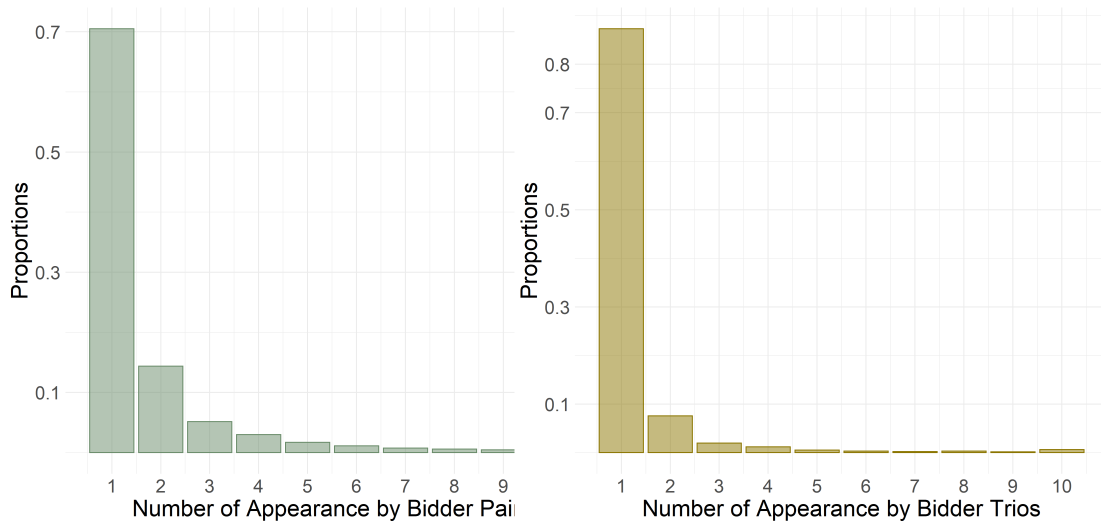
[22] It is noteworthy that more auctions can offer more comprehensive insights into the firm network. Therefore this analysis uses both open auctions and non-open auctions.

[23] 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 firms are less likely to participate in procurement conducted in other provinces.

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

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

Figure 1.12: 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 firms participate in the same public procurement auctions. The Y-axis indicates the proportion of occurrences for each frequency.

engage and win contracts. Consequently, firms 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 significant 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 differences in scores resulting in the rejection of the test. To further confirm this is true, I conduct an expert audit study in the next section.

1.7 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 officers, they emphasized that ensuring the predetermined winner secures the auction victory involves crafting customized scoring rules for the favored firm. These rules are deliberately designed with a level of opacity that makes them

Table 1.4: Balance Table for the Survey Sample

	Sample	All	P.Value
Obs	500	185,120	
bidders	3.732	3.74	0.932
Reserve Price	0.86million	0.69million	0.214
Winning Ratio	0.953	0.957	0.275
Quality Score	0.858	0.862	0.374
Price Weight	0.307	0.306	0.844
%Good	52.56%	55.53%	0.145
%Construction	9.26%	9.16%	0.938
%Service	38.18%	35.31%	0.147
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.

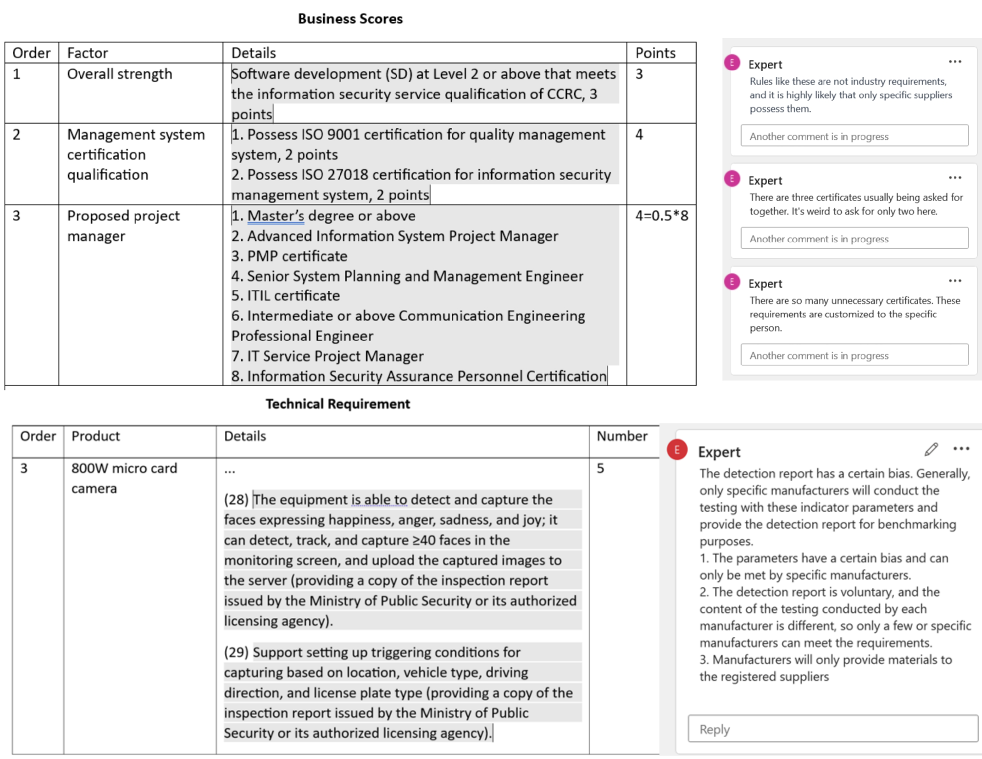
unfamiliar and unidentifiable to those outside the local industry network. Even government auditing teams are often unable to address this issue because they lack in-depth knowledge of the specific project and industry, making it nearly impossible to find tangible evidence like covert agreements or illicit financial transfers between the corrupt firm and the involved officer. Consequently, annual fiscal 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 market structure. They can readily identify any superfluous rules in place for the project and determine if these rules have been tailored to favor specific firms.

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 2.3 provides a summary of the survey sample alongside all procurement projects. On average, each auction involved 3.73 bidders, with an average project budget of 0.86 million USD. The winning bidder's revenue constituted 95.3% of the project budget, and the average quality score for the winner was 0.858 out of 1. Notably, there were no statistically significant differences between the survey sample and all procurement cases.

Second, I categorized the procurement projects in the sample and distributed the corresponding call-for-tender files to five 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 files 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 file and responding to a set of questions. These questions covered various aspects, including the expert's estimation of the general markup,[26] the local market competition, and the design of the RFPs.[27]

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 were identified, 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 1.13: An Example of Procurement Survey



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

Figure 1.13 provides a snapshot of a call-for-tender file for county-level government procurement of closed-circuit television (CCTV) equipment in 2021. In the business section, the expert identified three significant rule sets. The first set mandated high information security certification 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

[26]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 firms.

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

system certifications, whereas this specific file only requested two. The expert suspected that the target firm might possess only two of these certifications. The third set related to the qualifications of team members, encompassing degrees, majors, and examination certificates. Meeting all these stipulations would limit the eligible bidders to just one or two local firms. In the technical section, the expert noted that only one manufacturer could provide the specific test reports requested by the file, and the ultimate winner must be the exclusive local supplier authorized by that manufacturer. Reassuringly, the winning firm and its brand closely aligned with the expert's observations.

Table 1.5 presents the auction results for the above case. This case rejects the null hypothesis 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.

Table 1.5: 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.

I collected and digitized responses from the 500 surveys, including the unobserved expert-estimated markup, which is presented in the final row of Table 2.3. On average, this markup amounted to approximately 23%. This substantial markup figure makes these procurement auctions attractive to competing entities. If experts highlighted any rules in the call-for-tender documents, the corresponding procurement auction is classified as corrupt, as indicated by expert surveys. Conversely, if no such highlights were identified, 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 classification by the total number of auctions. The results are outlined in Table 1.6. Remarkably, the consistency rate reaches 81.4%, with a test power of 83% and a test size of 23.3% (17%) 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 files results in a test size of 17% and a test power of 83.3%.

I also provide the same table using adjusted p-values in Appendix Table A2. The overall consistency rate is 78.2%, 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 1.6: Expert Survey and Model Prediction

<table>
<tr><td rowspan="2">Consistency Rate=81.4%</td><td rowspan="2">Total=500</td><td colspan="2">Model Prediction</td><td rowspan="2"></td></tr>
<tr><td>Corrupt H_1</td><td>Not Corrupt H_0</td></tr>
<tr><td rowspan="2">Expert Survey</td><td>Corrupt (P)</td><td>311</td><td>64
False N</td><td>Test Power
82.9%</td></tr>
<tr><td>Not Corrupt (N)</td><td>20+(9)
False P</td><td>96</td><td>Test Size
23.2% (17%)</td></tr>
</table>

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 classification of model prediction uses unadjusted p-values with a significance 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 identified by the test are attributed to the tailored scoring rules, rather than to other conceivable reasons.

1.8 Corruption and Firms

In the previous sections, I discussed corruption in scoring auctions and developed a test specifically designed to identify this type of corruption. In this section, I utilize the corruption test results at the procurement auction level with firm-level data and anti-corruption information to analyze the economic consequences of corruption in public procurement.

1.8.1 Which Firms Participate in Corruption

The impact of corruption on economic growth remains a topic of ongoing debate. One perspective posits that corruption hampers economic progress by hindering various processes and causing resource misallocation among companies (Hsieh and Klenow, 2009; Colonnelli and Prem, 2021; Brugués, Brugués, and Giambra, 2022). Conversely, an opposing viewpoint suggests that, in the presence of bureaucratic red tape, corruption might actually function as a form of "grease in the wheel," smoothing business processes and enhancing overall performance. In this subsection, I delve into what characteristics explain firms' participation in corrupt auctions aiming to provide evidence of resource misallocation due to the selection into corruption relationship.

To investigate this question, I use a Lasso probit model to identify firm and auction characteristics that have explanatory power on rejecting the null hypothesis in the previous test section. Specifically, I collect firm factors such as the location of firms, state ownership of firms, registered capital size, formal employee size, and firm productivity, as measured by Total Factor Productivity (TFP)[28]. Predetermined winners often tend to be located within the same region as the procurement department, and state-owned firms frequently have close relationships with local governments. The relationship between TFP and selection is not yet clear. Some studies suggest that highly efficient firms are more likely to seek corrupt relationships due to their profitability, while others find that connected firms may be less efficient, motivating them to engage in bribery as a means of compensating for their lack of competitiveness.

I also include auction characteristics including price weights, budget, year, and procurement categories. Corrupt auction design usually puts lower price weights since higher price weights lead to more competition on price and reduce the markup. Project with large budget size is more vulnerable to corruption since the profit is higher.

I fit a Lasso-regularized probit model for predicting corrupt auctions as follows:

$$\min_{(\beta_0,\beta)\in\mathbb{R}^{p+1}} -[\frac{1}{N}\sum_{i=1}^{N} Corrupt_i \cdot (\beta_0 + x_i^T\beta) - \Phi(1+e^{\beta_0+x_i^T\beta})] + \lambda[(1-\alpha)||\beta||_2^2/2 + \alpha||\beta||_1]$$

where $Corrupt_i$ is from the test results in Section 1.6 and has value 1 if the test rejects the null hypothesis, and x_i^T include auction characteristics and firm characteristics, consisting of both winners and losers.[29] The Lasso regularization helps identify words with the strongest predictive power while avoiding over-fitting. The results of this analysis are presented in Table 1.7.

The second and third columns display the penalized coefficients for the characteristics of winning and losing firms respectively. The characteristics of the firms are arranged in descending order of coefficients in the column denoting winners. Winners in instances of corruption tend to have smaller capital sizes, lower Total Factor Productivity (TFP), and connections to state-owned entities. This suggests that firms that are less competitive are more likely to resort to corruption as a means to secure contracts. Additionally, winners in corrupt scenarios typically exhibit closer ties to local government procurement departments, indicative of local protectionism. Regarding the losers, firms that fail to win contracts in corrupt auctions generally exhibit significantly lower TFP and have smaller capital and workforce sizes. This underscores the presence of numerous non-competitive, or zombie firms in corrupt auctions, seemingly invited solely to satisfy the requirement for a minimum of three bidders. These findings collectively show the various dynamics and implications of corruption within procurement processes.

The final column presents the penalized coefficients corresponding to the characteristics of the auction. The outcomes align consistently with my hypothesis, indicating that projects with substantial budgets are more susceptible to corrupt practices, and the chosen price

[28]The calculation of firm productivity TFP follows the method outlined in Chen et al. (2021) Additional details can be found in Appendix B, Section B2.

[29]I use 75% random sample to train the model and select an optimal λ^*.

Table 1.7: Characteristics Predictive of Corruption in Auctions

	Winner	Loser	Auction Characteristics	
Variables	Coefs	Coefs	Variables	Coefs
Log(Capital Size)	-0.1471	-0.0556	Log(Budget Size)	0.0466
TFP	-0.0513	-0.1346	w_p >Lowest bound	-0.0595
Stateowned	0.0381	0.0097		
Public Listed	0.0201	-0.0154		
Foreign Funded	0.0140	-0.0043		
Distance to Gov Dept	-0.0110	-0.0050		
log(#Group Members)	0.0102	-0.0372		
log(Formal Employee)	0.0055	-0.0372		

Notes: The model was trained on a 75 percent sample. The firm characteristics are sorted in descending order of coefficients in the winner column.

weight can, to a certain degree, serve as an indicator of corruption. Notably, auctions where the selected price weights exceed the lowest permissible bounds tend to exhibit lower likelihoods of corruption. This consistency reinforces the potential link between budget size, price weight selection, and the propensity for corrupt practices in auctions.

This analysis substantiates that authentic competition is integral in prioritizing efficient firms, whereas corruption induces secondary efficiency losses by disproportionately benefiting less proficient entities.

1.8.2 Anti-corruption Campaign

Next, I delve into an examination of whether a recent anti-corruption campaign has the potential to induce changes in the procedures and outcomes of public procurement, thereby leading to a reduction in corruption within this domain. Following the transition of central power to President Xi in 2014, the Chinese Communist Party initiated an anti-corruption campaign with the explicit objective of eradicating corruption among officials at both low and high ranks. It is important to note that this campaign aims to address general corruption concerns beyond the scope of public procurement. Recent empirical evidence (Manion, 2016; Wang and Dickson, 2022; Fang, 2023) suggests that the campaign has reshaped the government's incentive structure and effectively curbed opportunities for bureaucratic corruption.

In contrast to the majority of prior research that relies on proxies to measure corruption, my study employs a direct approach to assessing corruption in public procurement. To examine the presence of systematic disparities in the choice of procurement methods, procurement outcomes, collusion among bidders, and corruption involving bidders and officials, I use the variances in relative exogenous corruption investigations conducted on officials across diverse government departments. The event study reduced form is presented below:

$$\begin{aligned} y_{idt} = \alpha_t + \alpha_d + \alpha_0 Procurement\ Characteristics_{idt} \\ + \beta_{1T} \sum_{T=-4}^{+5} Time\ to\ Investigation_{idT} + \epsilon_{idt} \end{aligned}$$

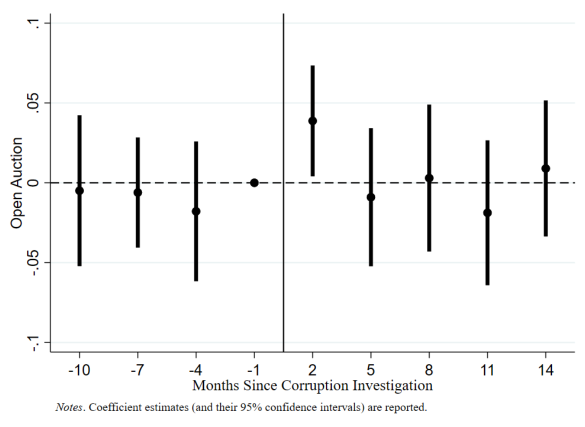
where the dependent variables y_{idt} for procurement i purchased by department d at time t include procurement methods, number of bidders, corruption prediction from the test, and an indicator for whether the winner is a new supplier to the department. $Time\ to\ Investigation_{idT}$ equals 1 if, at time t, T quarters have passed before/since a government official in department d was under corruption investigations.[30] I control α_t time year-month fixed effects, and α_d procurement department fixed effects. I also control the 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 A5.

The analysis in this section 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 1.14 (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.

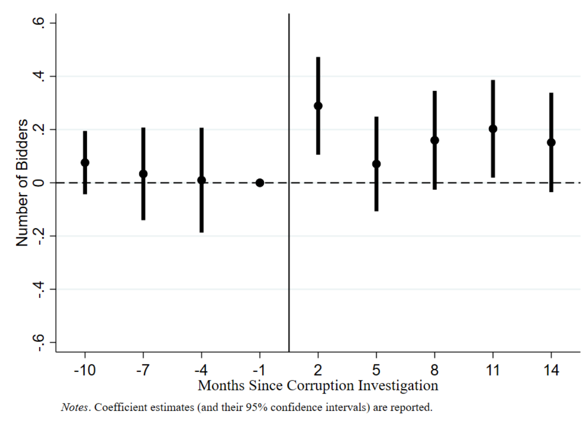
The second set of dependent variables focuses on the outcomes of auctions. Figure 1.14 (b) examines the number of bidders as the dependent variable. It shows an increase of 0.3 bidders in the first and third quarters following the investigations. Beyond the second quarter, while the coefficients retain 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 1.14 (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

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

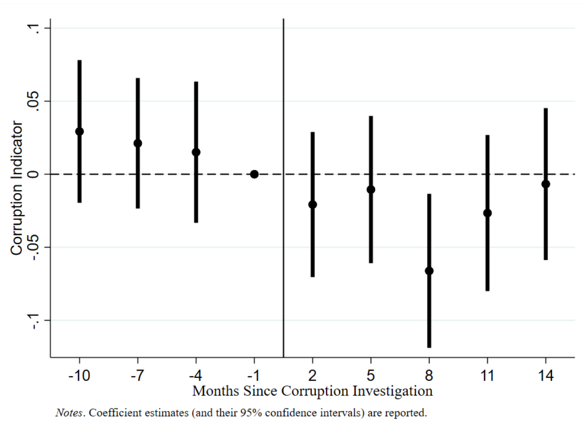
Figure 1.14: The Effect of Corruption Investigations



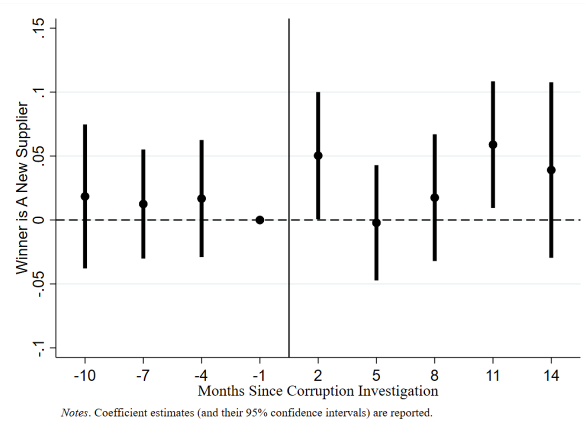
(a) Open Auction



(b) Number of Bidders



(c) Corruption Indicator



(d) New Winning Firm=1

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

quarter, representing a 7 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 1.14 (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 competition in open auctions by prompting more firms to join the bidding process. Also, these investigations reduce manipulative practices in the design of scoring rules. By referencing the estimated coefficients from the third quarter as depicted in Figure 1.14 (b) and (c), I can gauge the influence of corruption on the number of entrants using a back-of-the-envelope calculation of corruption's marginal effects:

$$\text{Entry Effect of Corruption} = \frac{\Delta Number\ of\ Bidders}{\Delta Corruption\ Probability} = \frac{0.160}{-0.066} = -2.424$$

The calculation exercise can be further used in the counterfactual analysis in Section 1.9 to decompose the effects of reducing unnecessary scoring rules on social welfare.

The impacts of "Flies or Tigers" crackdowns exhibit variance across officials at different hierarchical levels. To comprehend which investigations, especially those involving officials at divergent levels, contribute to the observed effects, I categorize the sample into two cohorts: investigations engaging officials who are at least the principal leader of a county-level department, and those involving officials positioned below this level. [31] The impacts of corruption investigations reveal disparities among officials at varied levels.[32] The comparisons are presented in Figure 1.15. The positive effects on promoting competition from Figure 1.14 come from the investigations on high-level officials. 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 influence on the preference for open auctions is also predominantly traced back to investigations focused on high-ranking officials. Additional illustrative material is provided in Figure A6.

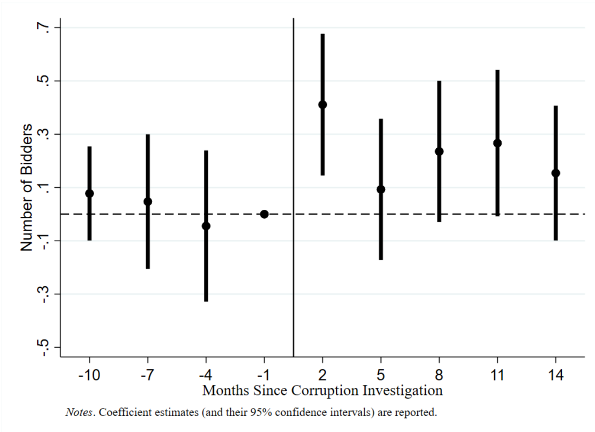
The outcomes of the comparison between high-level and low-level officials resonate with empirical realities. The ascendancy and influence of an officer augment with their hierarchical level; deputy roles, wielding lesser authority, often find themselves accountable, sometimes serving as scapegoats for the transgressions of their superior counterparts.

The findings from this section reveal discernible patterns in the formation of corrupt relationships. Firms exhibiting smaller scales, diminished efficiency, and state-owned affiliations tend to be more inclined to forge corrupt bonds with officers, resulting in the misallocation of resources in public procurement. While corruption investigations do curtail corrupt practices and foster competition, their efficacy is short-lived and lacks enduring impact. Additionally, a discussion is conducted regarding procurement at the city level by aggregating data from various procurement auctions. For additional details, please refer to Appendix H.

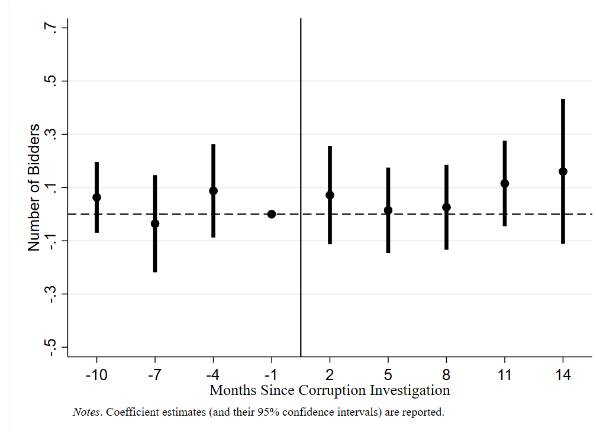
[31] Officials who are principal leaders of a county-level department, such as the primary director of the education department in M County or the director of the transportation department in B district, G City, are designated as level nine based on China's bureaucratic hierarchy, while officials ranked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

[32] In certain instances, lower-ranking officials are targeted as scapegoats for their higher-ranking counterparts.

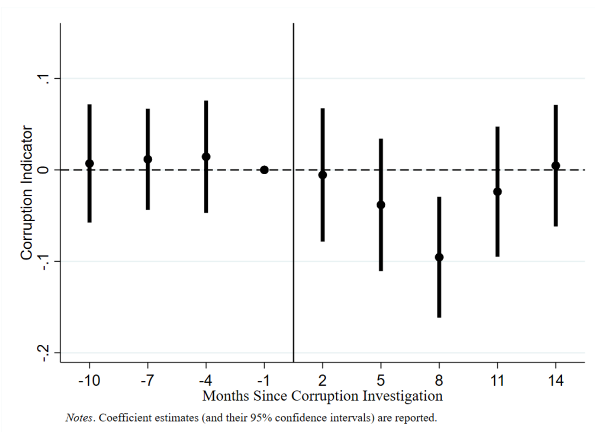
Figure 1.15: The Effect of Corruption Investigation by Officials with Different Levels



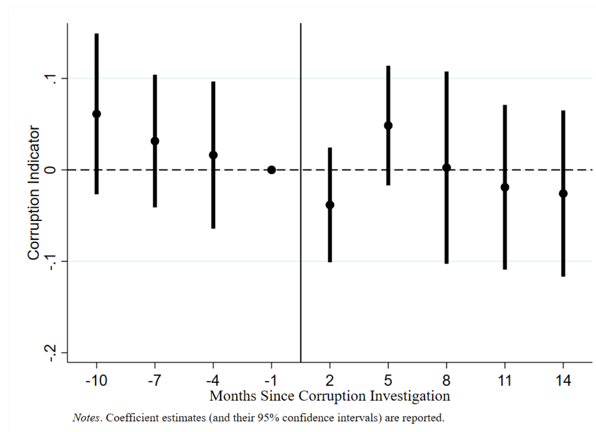
(a) Number of Bidders: High-level Officials



(b) Number of Bidders: Low-level Officials



(c) Corruption Indicator: High-level Officials



(d) Corruption Indicator: Low-level Officials

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

1.9 Counterfactuals

Up to this point, I have established that corruption is a widespread issue in public procurement auctions, and it results in the selection of less efficient firms. The question now becomes: how to design policies for scoring auctions to mitigate corruption effectively? In this section, I introduce a parametric approach to estimate firm types $\boldsymbol{\theta}$ and cost functions. This estimation method incorporates specific structures into the cost function. I then use the estimated parameters to assess the relative efficiency of two potential policies: emphasizing price bids with additional weights and employing anonymous evaluators to assess the scoring rules, thereby preventing superfluous scoring criteria.

While regulations already exist concerning price weights, the majority of auctions opt for the lowest possible price weights. One potential strategy to reduce corruption—by raising its associated costs—is to elevate these price weights. Additionally, to prevent manipulation within scoring rules, it might be beneficial to randomly draw anonymous evaluators to read through the RFP. They could then eliminate superfluous scoring criteria, while still affording officers a certain level of discretion.

1.9.1 Identification and Estimation of θ

In general, for competitive auctions, I can use equilibrium equations (1.5) and (1.6) from Theorem 1 to back out the firm type $\boldsymbol{\theta}$. Theorem 1 summarizes the equilibrium conditions,

$$\begin{cases} P(s, q_2(s, \boldsymbol{\theta})) = C(q(s, \boldsymbol{\theta}), \boldsymbol{\theta}) - P_s(s, q(s, \boldsymbol{\theta})\frac{G(s)}{(n-1)g(s)} \\ C_{q^l}(q(s, \boldsymbol{\theta}), \boldsymbol{\theta}) = P_{q^l}(s, q(s, \boldsymbol{\theta})) \end{cases}$$

Two conditions can solve for two unknown parameters. Since I estimate the CDF function $G(s)$ and PDF $g(s)$ of score s in Section 1.6, the only part that remains unstructured is the cost function. I propose a restricted polynomial structure on the cost function with two unknown parameters θ_0 and θ_1 as firm type $\boldsymbol{\theta}$, [33]

$$C(q, \theta_0, \theta_1) = \theta_0 + \beta_1(\theta_1 + q)^{\beta_2}$$

I further assign $\beta_1 = (4\frac{w_q}{w_p})^2$ to account for the scale differences introduced by the weight of price and quality in P_s for different auctions and make sure the Assumption 2 is satisfied. I assign the cost function as a fourth-order polynomial $\beta_2 = 4$, hence the fixed cost is $\theta_0 + \beta_1\theta_1^4$ and θ_1 is the quality-related efficiency. The cost function satisfies Assumption 2, $C_q > 0$, $C_{qq} > 0$, $C_{\theta_0} > 0$, and $C_{\theta_1} > 0$. The cost function also satisfies $p_{qq} - C_{qq} < 0$ to make sure the bids are profit maximized. Then θ_0 and θ_1 are identified.

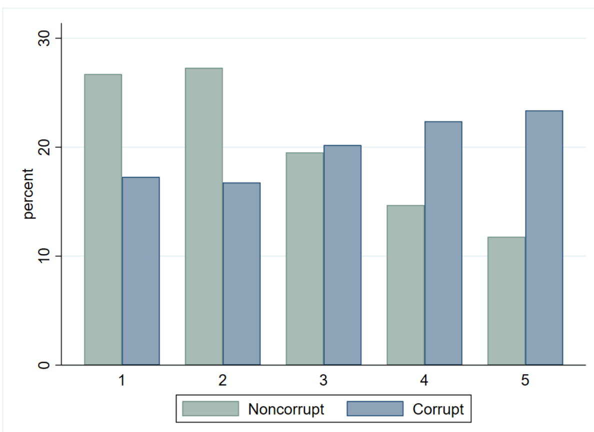
By solving the nonlinear equilibrium conditions, I plot the 3D estimated joint distribution of θ_0 and θ_1 in Figure A7 (a). Axes x and y represent θ_0 and θ_1 respectively. The range of θ is concentrated, and for each parameter, the marginal distribution is approximately a normal distribution. Figure A7 (b) shows the two-dimension flat density. θ_0 concentrated in $(0, 1)$ and θ_1 spans $(-1, 0.3)$.

However, in the case of corrupt auctions, I am unable to use the first-order equilibrium to estimate the firm type of the winners. This is because when all other bids are fake, then there are no real competitors and the first-order condition becomes degenerate. Moreover, I do not have direct observations of the manipulation variable m and the bribe variable α. Therefore, estimating the real firm types using the corrupt model becomes challenging. As a result, I adjust the firm types θ in corrupt auctions using noncorrupt auctions.

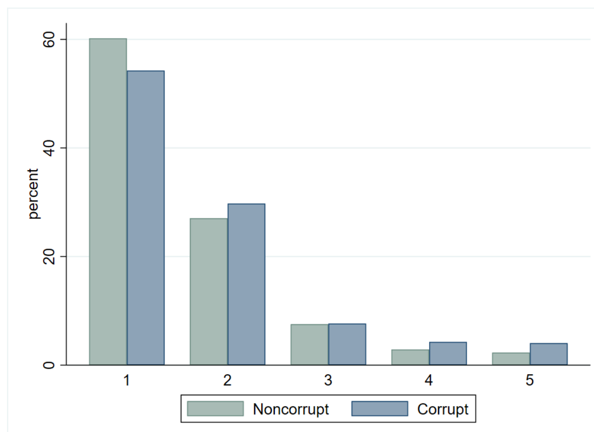
[33] I follow the literature in using a polynomial cost function. Since I only have two equilibrium conditions, I can't put more flexible parameters as coefficients.

Before delving into the inference process, I present a comparison of the estimated parameters between corrupt auctions and noncorrupt auctions, assuming they are all estimated from the competitive first-order conditions. I group the θ_0 values into quintiles for each procurement category. Lower θ_0 values indicate lower rankings and higher efficiency. I then plot the distribution of θ_0 quintiles for all bidders and winners in Figure 1.16. In noncorrupt auctions, the bidders tend to concentrate more on the high-efficiency groups. Conversely, in corrupt cases, a larger proportion of bidders fall into the low-efficiency groups. However, when considering only the winners from both types of cases, the majority of winners originate from the high-efficiency ranks. On average, the winners in noncorrupt auctions exhibit slightly higher efficiency. This comparison highlights that the efficiency of rivals in corrupt cases is significantly low due to the presence of zombie bids. The estimation results are consistent with the previous reduced form results shown in Table 1.7. The similar quintile barplots for θ_1 are shown in Figure A8.

Figure 1.16: θ_0 Quintile Distribution



(a) All Bidders



(b) Winners

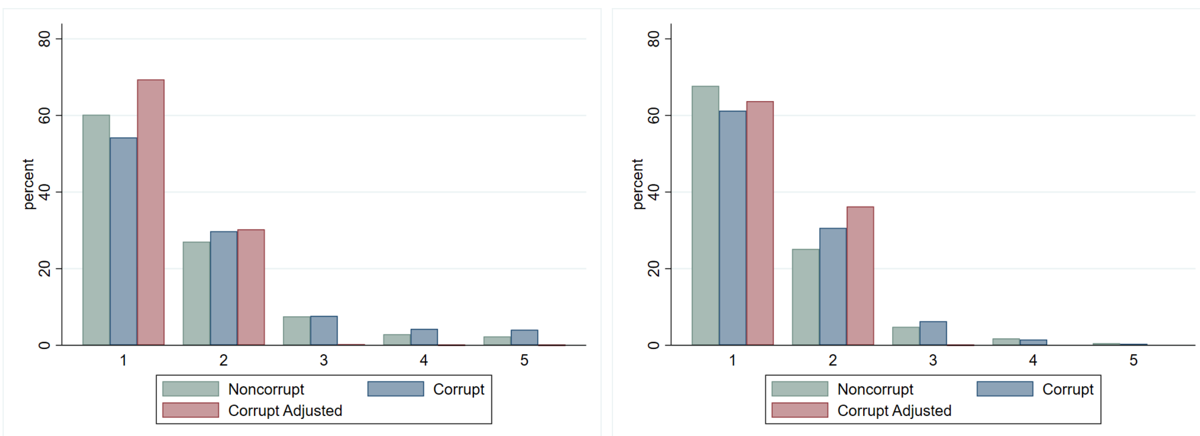
Notes: I rank the estimated θ_0 within different groups based on procurement categories, number of bidders, price weights, and fixed quality weights. Lower ranking numbers indicate higher efficiency. (a) shows the ranking distribution of all bidders, categorized by corrupt and non-corrupt cases. (b) displays the ranking distribution of winners in procurement auctions.

With the existence of zombie bids, I cannot rely on the estimation from the competitive first-order conditions. To estimate the true firm types θ for corrupt auctions, I regress firm type parameters θ_0 and θ_1 on auction and firm characteristics in non-corrupt cases using the following regression specification for winners and losers respectively:

$$\theta_{it} = \alpha_0 + \alpha_1 Firm\ Characteristics_i + \alpha_2 Auction\ Characteristics_t + \epsilon_{it}$$

where the dependent variable θ_{it} is θ_0 or θ_1 of the bidder i in the auction t. Firm characteristics, including firm capital size, and formal employee size are data from the general firm registration data. *Auction Characteristics*$_t$ include procurement auction-level characteristics, such as budget size, price weights, category fixed effects, and region fixed effects. As depicted in Figure 1.16, there are differences between winners and losers, even in some non-corrupt scenarios. My primary interest lies in understanding the real types of preordained winners. Therefore, I execute the specification for both winners and losers across both non-corrupt and corrupt auctions. However, only estimations from the regression on winners in non-corrupt auctions will be utilized to deduce the firm type of predetermined winners in corrupt auctions. The outcomes are presented in Table A3 for winners and A4 for losers.

Figure 1.17: θ Quintile Distribution for Winners after the Adjustment



(a) θ_0 (b) θ_1

Notes: I rank the estimated θ_0 and θ_1 within different groups based on procurement categories, number of bidders, price weights, and fixed quality weights. Lower ranking numbers indicate higher efficiency. (a) shows the ranking of θ_0. (b) shows the ranking of θ_1.

After conducting the regressions, I use the estimated models for winners and losers to predict the firm types θ_0 and θ_1 for bidders in corrupt cases. The predicted θ values of winners in corrupt cases were then added to the quintile bar plots depicted in Figure 1.17. In the plot, the green bars represent θ values of winners in competitive auctions, the blue bars indicate θ values of winners in corrupt auctions estimated using competitive equilibrium conditions, and the red bars denote the adjusted θ values for winners in corrupt auctions, obtained through regressions based on competitive auctions and real firm characteristics. It is evident from the plot that the adjusted firm types θ are smaller than the original values, suggesting higher efficiency. When the scoring rules are manipulated, the predetermined winners lack incentives to provide low price p. Consequently, the estimated θ values obtained using the competitive equilibrium conditions are smaller compared to those observed in cases of genuine competition. Therefore, after adjusting the firm types θ based on firm characteristics, higher efficiency types are obtained. The adjusted firm types for losers are shown in Figure A9

With the estimated firm types θ, I am now equipped to conduct the two counterfactual analyses in the following subsections. These analyses will delve into the effects of implementing anonymous evaluations on RFP and increasing price weights.

1.9.2 Counterfactual: Implementing Anonymous Evaluation on RFP

To minimize the likelihood of scoring rule manipulation, the government 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 described in Section 1.7. Should these anonymous experts identify any superfluous 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 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 benefit winners, other requirements would take the place of the current customization. I conduct a counterfactual analysis, eliminating all preferential rules in the quality requirement q.

The effects 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 firms would enter into the auctions. I set the extra number of bidders as two, as shown in the estimation from Figure 1.14 (b) in Section 1.8. Therefore, I can decompose these two effects. However, there's an underlying assumption that the original winner retains their winning position, given the absence of a suitable counterfactual firm, making these effects a lower bound. By applying the competitive equilibrium conditions, and the adjusted firm 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 1.8.

In a counterfactual competitive scenario without entry effects, the predetermined winner tends to submit a price bid that is 11.79% lower than the initial bid, along with a 4.26% increase in quality. This translates to a 7.58% increase in the real final score compared to the original. When accounting for both competitive bidding and entry effects, the price decreases by 18.3% with a 3.21% increase in quality. Increased entries intensify competition over prices, leading to a rise of 10.84% in the final scores. Compared to the scenario without entry effects, 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 first group of bars in Figure 1.18.

When segmented by procurement categories, product procurement exhibits a price de-

Table 1.8: Implementing Anonymous Evaluation on RFP

Counterfactual	ΔPrice	ΔQuality	ΔScore(Welfare)
	All Cases		
Competitive Bid	-11.79%	4.26%	7.58%
	[-13.28%, -10.3%]	[2.28%, 6.25%]	[6.02%, 9.14%]
Competitive Bid+Entry	-18.3%	3.21%	10.84%
	[-20.15%, -16.46%]	[1.19%, 5.23%]	[9.27%, 12.42%]
	Product Procurement		
Competitive Bid	-13.23%	3.06%	7.69%
	[-15.01%, -11.44%]	[0.31%, 5.82%]	[5.66%, 9.72%]
Competitive Bid+Entry	-23.62%	1.58%	11.95%
	[-25.23%, -22.02%]	[-1.2%, 4.36%]	[9.99%, 13.92%]
	Construction and Service Procurement		
Competitive Bid	-10.29%	5.55%	7.46%
	[-12.7%, -7.87%]	[2.66%, 8.43%]	[5.03%, 9.88%]
Competitive Bid+Entry	-12.72%	4.92%	9.63%
	[-15.85%, -9.59%]	[1.98%, 7.87%]	[7.13%, 12.13%]

Notes: In this exercise, the adjusted estimated θ 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 1.14. 95% confidence intervals are included in the brackets.

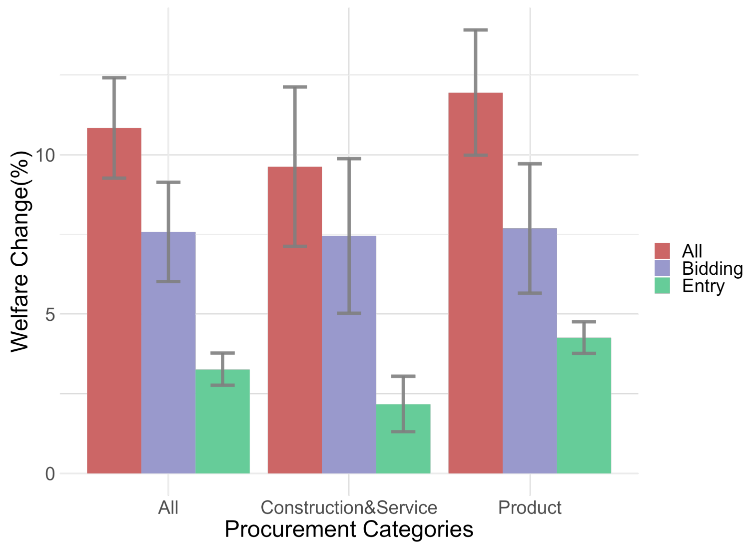
duction of 13%. This trend is largely due to the larger price weights associated with product procurement, which amplify price-based competition. The welfare gains in this category are divided between two main contributors: 65% from competitive bidding and 35% from entry effects as illustrated in the second set of bars in Figure 1.18. For construction and service projects, the price bids decrease by 10.29% accompanied by a 5% increase in quality. For these projects, 80% of the welfare gains are attributed to competitive bidding, with the remaining 20% stemming from more entries, as displayed in the final set of bars in Figure 1.18. Overall, product procurement benefits more from the combination of increased entry and competitive bidding.

Implementing an anonymous evaluation of RFPs offers the dual benefit of retaining a level of discretion while eradicating superfluous 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.

1.9.3 Counterfactual: Increasing Price Weights

As highlighted in the discussion on scoring auctions, public procurement law establishes guidelines on the distribution of price weights across various procurement categories. This is

Figure 1.18: Decomposition of Welfare Changes by Procurement Categories



Notes: The first 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 difference between the first two bars. All bars are with 95% confidence intervals.

intended to curb corruption by emphasizing the quality elements of the auctions. Nonetheless, within the legally permissible range of price weights, officers frequently choose the lowest available option. Moreover, the findings in Table 1.7 Section 1.8 illustrate that opting for a price weight above the lowest bound serves as a robust indicator of non-corruption. In this counterfactual analysis, 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 1.9 reports the results. The first 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 final column, I report the mean change in the final score, representing social welfare as per Asker and Cantillon (2008) and Hanazano et al. (2020). These values are computed using the original scoring rule, without accounting for any changes in price weights.

It is not surprising that when procurement officers assign more weight to the price score, bidders will attempt to lower their price bids. When an addition of 10 weight points to prices, corrupt winners reduce their prices by approximately 10% to gain an advantage in the price score, competitive winners also reduce the price bid but the change is not statistically significant. When it comes to quality bids, predetermined winners in corrupt cases don't make substantial shifts in their real quality bids. This trend may be traced back to these winners benefiting from the tailored scoring rules. Their actual quality considerably lags behind that of other genuine bidders, allowing them to reduce prices without making major

Table 1.9: Increasing Price Weights

Counterfactual	ΔPrice	ΔQuality	ΔScore(Welfare)
Add 10 on Price Weights			
Noncorrupt	-0.2%	-3.11%	-2.05%
	[-1.38%, 0.97%]	[-3.51%, -2.71%]	[-2.29%, -1.81%]
Corrupt	-9.99%	0.68%	3.7%
	[-11.5%, -8.48%]	[-1.19%, 2.55%]	[2.21%, 5.19%]
Overall	-7.05%	-0.66%	1.77%
	[-8.25%, -5.85%]	[-1.92%, 0.6%]	[0.75%, 2.8%]
Add 20 on Price Weights			
Noncorrupt	-3.42%	-7.9%	-4.24%
	[-4.85%, -2%]	[-8.89%, -6.92%]	[-4.62%, -3.85%]
Corrupt	-10.15%	-2.72%	1.09%
	[-11.37%, -8.93%]	[-4.75%, -0.7%]	[-0.38%, 2.56%]
Overall	-8.15%	-4.49%	-0.66%
	[-9.16%, -7.14%]	[-5.9%, -3.08%]	[-1.68%, 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 θ and conditions from the corruption model, assuming all previous bidders were non-fake bidders. The results are presented with 95% confidence intervals in brackets.

sacrifices in quality.

When prices are endowed with an extra 20 weight points, winners are more aggressive in curtailing their price bids than they are with just 10 weight points. This is particularly pronounced for predetermined winners in corrupt instances. They feel forced to decrease their prices even more, given their initially elevated prices and the emphasis on prices, which undermines their contrived advantages.

From a social welfare perspective, amplifying the weight on price doesn't yield statistically or economically meaningful enhancements. In even the noncorrupt auctions, any welfare gains stemming from the dip in price are offset by the dip in quality, leading to a net decrease in welfare.

1.10 Conclusion

In this paper, I focus on one of the most prevalent forms of corruption observed in scoring auctions, where corrupt procurement officers manipulate scoring rules to favor predetermined winning firms. 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 files 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 firm administrative data with public procurement data. The results indicate that firms with lower efficiency, 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 effects can be attributed to the involvement of officials from higher bureaucratic levels in the investigations.

In subsequent analyses, I parametrically estimated firm 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 firms to bid competitively, while 30% stems from increased participation. However, increasing price weights doesn't lead to a significant 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 effectiveness 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.

Chapter 2

Heard and Unheard Whistleblowers: Complaint Systems for Corruption Detection in Procurement Auctions

2.1 Introduction

Public procurement represents approximately 13-20 percent of the global GDP. The substantial scale of procurement expenditures often attracts corruption. For instance, corrupt officials may manipulate scoring rules to unfairly benefit specific firms in scoring auction procurement projects (Chen, 2023). Establishing a comprehensive complaint reporting system is crucial to ensuring the fairness of procurement processes. Complainants often possess more information than regulators, and the data derived from their reports are valuable resources for developing methods to detect corruption. This paper aims to address two specific research questions: Can we detect corruption in procurement auctions based on patterns found in complaint datasets, and how can we increase the efficiency of the complaint system?

An increasing number of countries are implementing complaint systems to enhance procurement regulation and provide firms with mechanisms to address grievances and submit evidence of potential misconduct within the public procurement system.[1] These systems enable bidders to file ex-post complaints regarding suspected manipulative or corrupt practices observed during open auctions. Often, genuine competitors, after participating in the auction, discover evidence of collusion among bidders or corruption favoring pre-selected winners and consequently feel compelled to file a complaint. Analyzing bidding behaviors and characteristics, especially contrasting those of the challengers with the so-called predetermined winners, presents a viable method for detecting corruption.

Particularly, in scoring auctions, predetermined winners, benefiting from favoritism in the scoring rule design, tend to submit higher price bids compared to their real competitors.

[1]Both developed countries and low middle-income countries have set similar complaint systems, including but not limited to the United States, EU, India, Mexico, and Kenya

This strategy not only maximizes their profits but also helps cover any costs associated with bribery. Furthermore, these predetermined winners often exhibit distinct firm characteristics, such as closer geographical proximity to the procurement agency—a factor that may stem from local protectionism and relationship-building—or a stronger affiliation with state-owned enterprises. However, it is important to note that non-corruption, cost-based explanations may also account for these bidding behaviors.

Speaking to the first research question, I begin by applying a specific analysis to datasets comprised of complaints from a province in China. Complaints filed by participants typically contest the outcomes of the auction after the results have been announced, citing unfair treatment. The majority of these complainants are challengers who were defeated by groups engaged in collusion or corruption, thereby suggesting they are likely not involved in any corrupt networks themselves. This makes them a credible benchmark for evaluating the integrity of non-corrupt competitors. My analysis aims to determine whether winners with narrow victory margins submit price bids that are significantly higher than those of the nearest losers and whether they are geographically closer to local procurement agencies.

In the datasets where the complainants are the losing bidders, referred to as ex-post complaints,[2] I observe that most auctions are close games, where the complainants are close losers who received several score points below the winners. Also, in these close games, when applying the Regression Discontinuity Design, the price bids from the winners are approximately 5% higher than those from the close losers, who are usually the complainants, and these winners are situated 43% closer to the procurement agencies. The findings diverge from the null hypothesis, which posits that in a competitive environment, conditional on close games, winners and losers would be selected randomly Kawai et al. (2023). The findings also differ from the pure collusive pattern described in their paper Kawai et al. (2023), where the price bids from the winners are lower than those from the close losers. Interestingly, in the ex-ante complaint dataset, there are few close games and no patterns similar to those observed in the ex-post complaint dataset. The differences provide evidence of noncompetitive behaviors and further suggest corruption rather than pure collusion in the ex-post complaints

I further apply the same close game Regression Discontinuity Design to detect corruption in general noncomplaint scoring auctions. The analysis uses public procurement data from the same province in China, covering the period from 2017 to 2021, which also supports the investigation into scoring rule manipulation reported in Chen (2023). Similar to the results in ex-post complaints, the findings reveal that auctions with close competitions—where the winning and losing bids are narrowly separated—frequently result in close winners submitting bids that are statistically significantly higher than those of their closest competitors. This discrepancy in bid prices, particularly notable at around 4% in auctions with four bidders, often involves a collusion group of three bidders plus an additional, externally arising competitor in scenarios where the scoring rules are not entirely exclusive. In terms of other

[2]Generally, there are two types of complaints. One type includes complaints submitted after the auction has concluded, where complainants have seen the results and believe they have been treated unfairly; these are called ex-post complaints. The other type, known as ex-ante complaints in this paper, is filed before the auction by potential bidders.

firm characteristics, close winners tend to be smaller in size, as measured by registered capital and the number of insured employees. Additionally, consistent with observations from the initial complaint dataset, close winners are typically geographically closer to the procurement agency. These findings indicate the presence of corrupt practices that favor local firms over more efficient competitors, consequently leading to increased expenditures on products or services of marginally equivalent quality.

The methodology for detecting corruption is validated by examining public procurement projects requested by departments two years before and two years after corruption investigations. Prior research Chen (2023) has indicated that corruption investigations during anti-corruption campaigns have a short-term effect in diminishing corruption and facilitating market entry. By applying this test to periods before and after the investigations, I noted a significant discontinuity in the bids' prices and the quality scores in the public procurement data preceding the investigations. However, this disparity lessens in the data gathered after the investigations. Regarding other firm characteristics, close winners before the investigations were statistically smaller in capital and labor size, more frequently affiliated with state-owned enterprises, and geographically nearer to local government procurement agencies. In stark contrast, the data post-investigation revealed no significant differences in these characteristics of firms.

Addressing the second research question, I develop a discrete choice model to analyze the decision-making process behind submitting a complaint, following the framework outlined in Boudreau et al. (2023). This model incorporates various factors: the expected revenue from winning the current project after filing a complaint, influenced by the corruption signal from the price bid gaps; the potential revenue loss due to damaging the relationship with local procurement agencies; and the costs associated with possible retaliatory actions. All these factors significantly influence the decision to submit a complaint. Subsequently, I explore two hypothetical policies: anonymizing the names of complainants to protect their identities and introducing random government audits. The protection of complainants' identities is likely to encourage more reports, and the implementation of government audits is predicted not to significantly crowd out complaint submissions from firms.

This paper contributes to an emerging, yet still relatively underexplored, area of research that focuses on detecting corruption in public procurement auctions. It builds upon the studies, including Huang (2019), Andreyanov, Davidson, and Korovkin (2017), and Chen (2023). The paper introduces a novel, easily implemented, and theory-consistent method for detecting corruption. It also offers a methodology to quantify the fiscal waste attributable to corruption. Moreover, this paper intersects significantly with literature on the detection of cartels in auction settings, contributing to a key domain with works such as Hendricks and Porter (1988), Porter and Zona (1993), Conley and Decarolis (2016), Schurter (2017), Chassang et al. (2022), Kawai et al. (2023), and Kawai and Nakabayashi (2022*a*).

This paper also speaks to the whistleblowing literature in report system design. There is a strand of theory papers studying misbehavior and crime reporting in the finance sector and public service (Aubert, Rey, and Kovacic, 2006; Heyes and Kapur, 2009; Felli and Hortala-Vallve, 2015; Chassang and Miquel, 2019). However, due to the fundamental measurement and identification challenge, since only illegal behaviors have been discovered, some empirical work relies heavily on scenario-based surveys and management models to predict whistleblowing behaviors (Liu et al., 2018). More recently, an increase in experiment studies explores the factors of whistleblowing decisions (Reuben and Stephenson, 2013; Carpenter, Robbett, and Akbar, 2018; Mechtenberg, Muehlheusser, and Roider, 2020; Boudreau et al., 2023). For example, Boudreau et al. (2023) theoretically and experimentally show that garbling the information of sexual harassment reports can encourage truth misconduct reports and protect workers. This paper links the results from identifying corruption to the complaint decision to deal with the measurement issue. With a specific focus on public procurement auctions, which attract many wrongdoers, the paper shows an efficient complaint system can largely increase transparency.

The remainder of the paper is organized as follows. In Section 2, I offer background information and datasets on the scoring auction procedure and China's public procurement system. Section 3 describes the complaint data and the stylized facts. In Section 4, a theoretical model is constructed, laying the foundation for the empirical test. Section 5 presents the main results by applying the test tool to the public procurement dataset. Section 6 shows the validation by comparing the data before and after corruption investigations. Section 7 constructs and estimates a complaint submission decision model and then conducts counterfactual policy analysis Finally, Section 8 provides concluding remarks, summarizing the findings and their implications.

2.2 Background and Data

2.2.1 Background

2.2.1.1 Open Scoring Auction of Public Procurement in China

In the public procurement auctions in China, operations are rigorously governed by the Public Procurement Law and its associated regulations. This structured process spans pre-procurement, procurement, and post-procurement stages. During the pre-procurement phase, the procuring entity—whether it is a government agency or a state-owned enterprise—identifies its requirements and develops a detailed procurement plan. This stage involves a thorough evaluation of project feasibility and the precise specification of the necessary goods, services, or works. The selection of the procurement method is based on specific criteria.[3] This paper focuses on the most common method for large-budget public procurements: scoring auctions.

Scoring auctions follow a sequence of steps. First, audited requests designate agents who then release the requirements. Interested bidders, who meet the specified criteria, submit their proposals after a month of preparation that encompasses both price and quality aspects.

[3]For a more detailed discussion on the selection of procurement methods, please see the related work (Chen, 2023).

On the day of the auction, a committee, randomly composed of five experts, meticulously evaluates the bids according to predefined criteria. This committee assigns scores to each bid to determine the winner. The contract is awarded to the bidder with the highest score, where the score integrates elements of business ability, technicality, and price, as expressed by the formula:

$$score = \underbrace{w_B \times BusiScore + w_T \times TechScore}_{w_Q \times Quality\ Score} + w_P \times \frac{min\ P}{Price} 100\%$$

Here, w_B, w_T, w_P denote the weights allocated to each component of the proposal submitted by bidders in procurement auctions. The business score $BusiScore$ remains relatively stable, encompassing factors such as certificates and past performance. The technical component $TechScore$ varies across different procurement types: for product procurement, it focuses on product specifications, while for services and construction, it assesses the quality of proposals. The combined business and technical scores constitute the quality score. Ensuring the trade-off between price and quality parts, the Public Procurement Law stipulates that price weights w_P lie within the range [30%, 60%] for goods and [10%, 30%] for construction or services. In practice, many open-scoring auctions gravitate toward the lowest feasible price weight.

Given the evaluation of proposal quality, there exists inherent randomness in the score introduced by subjective assessments from experts. For example, $Quality\ Score$, q_{ia}, consisting of $BusiScore$ and $TechScore$, assigned by each expert e, q_{iae}, for bidder i in the procurement auction a encapsulates not only the genuine underlying unobservable quality q^r_{ia} but also incorporates an error term ϵ_{iae} linked to individual expert preferences.

$$q_{ia} = \frac{\sum_{e=1}^{5} q_{iae}}{5} = \frac{\sum_{e=1}^{5} (q^r_{ia} + \epsilon_{iae})}{5} = q^r_{ia} + \epsilon_{ia}$$

As highlighted in the related paper by Chen (2023), corruption in open scoring auctions in China often appears as customized scoring rules designed to favor certain predetermined winners. This widespread issue involves procurement officers setting up scoring rules to benefit these chosen winners, usually in collaboration with bidders who support these favored parties. Since the price score is determined by the bids submitted, most of the manipulation occurs in the quality assessment area. In other words, corrupt officials manipulate reasonable w_Q to $\tilde{w}_Q$.[4] This abuse takes advantage of the broad powers that government departments have in defining the rules of the process.

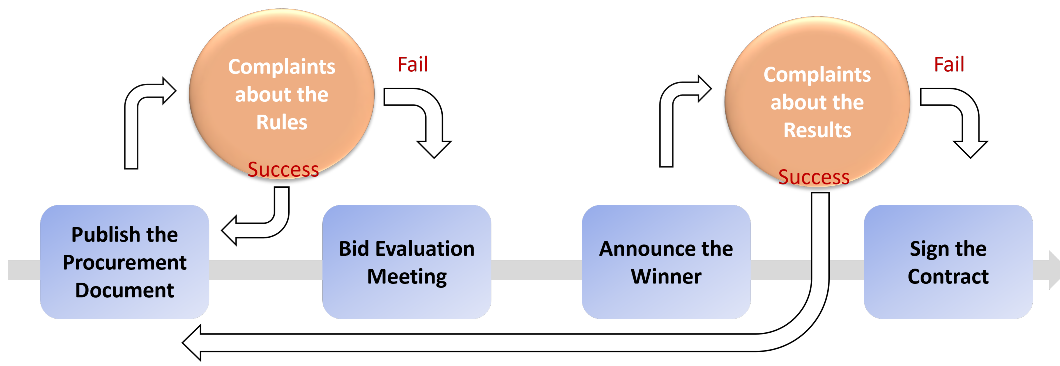
2.2.1.2 Complaints in Public Procurement

Public procurement complaint mechanisms are essential for ensuring transparency, accountability, and fairness in government procurement processes. These mechanisms provide suppliers with a platform to express concerns and objections regarding decisions, practices, and

[4]For instance, there are several corruption cases, the scoring rules ask for uncommon certificates or product characteristics that unnecessary at all for the procurement project at all and only the predetermined winners can satisfy the requirements.

biases, thereby promoting a competitive environment, bolstering legal protections, and preventing corruption. In China's public procurement system, complaints typically occur at two stages: upon the release of call-for-tender documents, referred to as ex-ante complaints, and after the completion of auctions, referred to as ex-post complaints, as shown in Figure 2.1.

Figure 2.1: Procedure of the Public Procurement Complaint



Notes: The detailed procedure of submitting and processing a complaint can be found on this website

For ex-ante complaints, at the stage when call-for-tender documents are released, all potential bidders can access the publicly available scoring rules. If a firm finds these rules overly restrictive and contrary to the principles of fair and open auction design, it can file a complaint, providing evidence to demonstrate how the rules appear designed to exclude other competitors. Upon validation by the overseeing authority, a substantiated complaint necessitates the reorganization of the procurement auction and the redrafting of the tender documents. If the investigation confirms the presence of exclusionary requirements, the procurement agency will be instructed to revise the call-for-tender documents and reorganize the auction.

Table 2.1: A Complaint Case: Submission at Call-for-tender Stage

Company	Busi Score (10)	Tech Score (60)	Price Score(30)	Final Score	Order
A	0.75	48.2	29.72	80.47	2
B	2.55	49.4	29.55	79.7	3
C	5.62	59.2	30	94.82	1

Notes: This procurement project was initiated by a county-level public hospital in 2015. The outcomes of the procurement auction are shown on the public procurement website.

Table 2.1 presents an example of an ex-ante complaint in a medical machine procurement project that successfully led to a rebidding. Firm D identified an exclusive certificate requirement and submitted evidence to the regulatory department. Following the investigation, the regulatory department confirmed a violation of competition law and instructed the procurement agency to organize a rebidding. However, as indicated in the table, Firm D, the original complainant, did not participate in the rebidding process. This outcome is common, regardless of the complaint's success [5] Additionally, the final auction results exhibit a pattern similar to those described in Chen (2023), characterized by the participation of only three bidders, significant quality disparities between the winner and the losers, and comparable price bids. To sum up, auction results from ex-ante complaints are either screened by the authority or reorganized following a successful investigation. When looking into the ex-ante complaints, no salient patterns, especially conditional on close games, would be expected.

For ex-post complaints, after the auction concludes, all participants have the right to submit a complaint if they perceive unfairness at any point during the auction process. If the investigation uncovers a violation of competition law, the contract will be revoked, and the firm that ranked second will be declared the winner. Conversely, if the complaint is not upheld, the auction results will remain unchanged.

Table 2.2: A Complaint Case: Submission at Auction Complete Stage

Company	Busi Score (30)	Tech Score (30)	Price Score(40)	Final Score	Order
E	10	12	33.19	55.19	3
F	25.2	30	34.42	89.62	1
G	6.4	12	36.73	55.13	4
H (Complainant)	26.2	17	40	83.2	2

Notes: This procurement project was initiated by a county-level urban planning and water supply department in 2014. The outcomes of the procurement auction are shown on the public procurement website.

Table 2.2 presents an example of an ex-post complaint submitted by a participant after the completion of a firefighting equipment procurement auction. The complainant, who finished second, challenged the exclusive scoring rule applied in the technology assessment. Following the investigation, the financial team concluded that there was no breach of law. Despite the complaint not being upheld, an analysis of the auction's outcome—excluding the complainant—reveals patterns similar to those described in Table 2.1. Firm F emerged as the definitive winner, possessing a significant advantage in the quality score over the other bidders, Firms E and G. While the exact nature of the relationships among these firms remains unclear, it is evident that the complainant was not part of Firm F's bidding consortium.

Based on the timing of submissions, I categorize complaints as either ex-ante or ex-post and use these terms throughout the paper. I am particularly interested in ex-post

[5]Based on interviews, the primary reason complainants often do not participate in subsequent auctions is their recognition of corruption and manipulative scoring rules, perceiving their chances of winning as slim. Successful complaints can sour relationships with the local procurement department, making future cooperation challenging. Failed complaints suggest that even if the potential bidders find unfair rules, the authority doesn't want to change them. Therefore, no matter whether the complaint is successful or not, the complainant won't participate in the following auction.

complaints since they are submitted by firms that participated in the auctions and provide more information on auction implementation. In contrast, auctions from ex-ante complaint projects are pre-screened and are relatively cleaner in terms of corruption. Regardless of the type of complaint, the identities of the complainants are known to everyone within the overseeing organization and the procurement department. Therefore, there is a risk of retaliation; if a firm submits a complaint, it challenges not only the other competitors but also the government department responsible for oversight and procurement.

2.2.2 Data

2.2.2.1 Public Procurement Complaint Data

Spanning the timeframe of 2014 to 2022, I have systematically gathered an array of complaint cases. Notably, despite the substantial magnitude of over three hundred thousand procurement projects, the repository comprises a mere 1192 cases. This stark contrast underscores the infrequent utilization of the complaint channel, presumably attributed to apprehensions among firms regarding potential ramifications on their relationships with local government bodies. The complaint dataset encompasses crucial variables, including the outcomes of the complaints, the categorization of the grievances, and the presence of complainants within the final bidder list. Moreover, the dataset meticulously compiles comprehensive bidding results, encompassing both the price bids and the corresponding quality scores secured by each participating bidder.

2.2.2.2 Public Procurement Data

Gathering a comprehensive repository of publicly available public procurement data from a single province spanning 2006 to January 2021 represents a pioneering endeavor. This provincial-level dataset, also employed in the study by Chen (2023), capitalizes on the enhanced transparency regulations, stipulating that all procurement procedures, save those concerning classified information, are subject to public scrutiny. However, the structure of procurement information exhibits inconsistencies and disorderliness. A standardized approach to preserving the usability of procurement data on a large scale has not yet crystallized within governmental practices, impeding the effective utilization of big data analytics for detecting collusion or corruption. The extraction process was notably time-intensive, culminating in a meticulously refined database encompassing three fundamental datasets: procurement plan data, announcement data, and outcome data. Procurement plans encompass particulars regarding procurement objects, procurer names, reserve prices, and the chosen procurement method. The announcement data offers insights into intricate bidding details, while the outcome data divulges bidder names, bid prices, and corresponding scores.

The comparison summary between different complaint datasets and the full procurement data is presented in Table 2.3. The complaint dataset has an average of 5.48 bidders, which is higher than the full dataset's average of 3.74. For ex-ante complaints, this number is lower

Table 2.3: Summary Statistics for Complaint and Full Datasets

	Complaint	Ex-ante	Ex-post	Full
Obs	1,075	410	665	186,360
#Bidders	5.48	4.82	5.88	3.74
Reserve Price (million)	17.77	27.62	11.69	6.9
Price Weight (%)	22.87	22.55	23.08	23.36
Median Year	2018	2018	2018	2017
Winning Margin	11.44	17.19	7.89	18.55
Dist winner to gov (km)	261.39	269.35	256.5	247.83
Complaint Success Rate	0.29	0.26	0.31	

Notes: The last row represents the complaint success rate, a statistic exclusive to the complaint dataset. Ex-ante complaints correspond to complaints filed during the call-for-tender release stage or 'complainant-out', whereas ex-post complaints pertain to complaints submitted by participants after the completion of the auctions or 'complainant-in'.

at 4.82, while for ex-post complaints, it is even higher at 5.88. The reserve price, i.e. project budget, in the complaint datasets, is notably higher than the 6.9 million RMB in the full dataset. The winning margin, indicating the difference in bid prices between the winner and the closest competitor, is comparable between ex-ante complaints and the full dataset. It is the smallest in ex-post complaints, where the losing bidders submitted the complaints post-auction.[6] The overall success rate for complaints is approximately 29%.

2.2.2.3 Firm registration data

The corpus of firm registration data enshrines information pertaining to all officially registered entities in China, irrespective of their operational status. Sourced from the Firm Search Platform under Alibaba Group, this multi-faceted dataset draws from the State Administration for Market Regulation, the Supreme People's Court, and Ali Map. This rich dataset presents a mosaic of dimensions encompassing firm names, inception dates, industry affiliations, typologies, current status, capital magnitude, and workforce dimensions. Rigorous data cleansing endeavors encompassed refining company names in the public procurement dataset, linking them with firm registration data to garner foundational registration insights for all bidders. Moreover, bidders and procurement department pairs were established and subsequently utilized to calculate geographical distances via QGIS. The headquarters' particulars of all bidders were also procured.

[6] In ex-ante complaints, the complainants are not the final participants, and the actual participants might include many non-competitive or 'zombie' bidders, resulting in a larger winning margin. In ex-post complaints, the complainants are participants who are definitively outside the winner's collusion group, hence they submitted more competitive bids.

2.2.2.4 Corruption Investigations Data

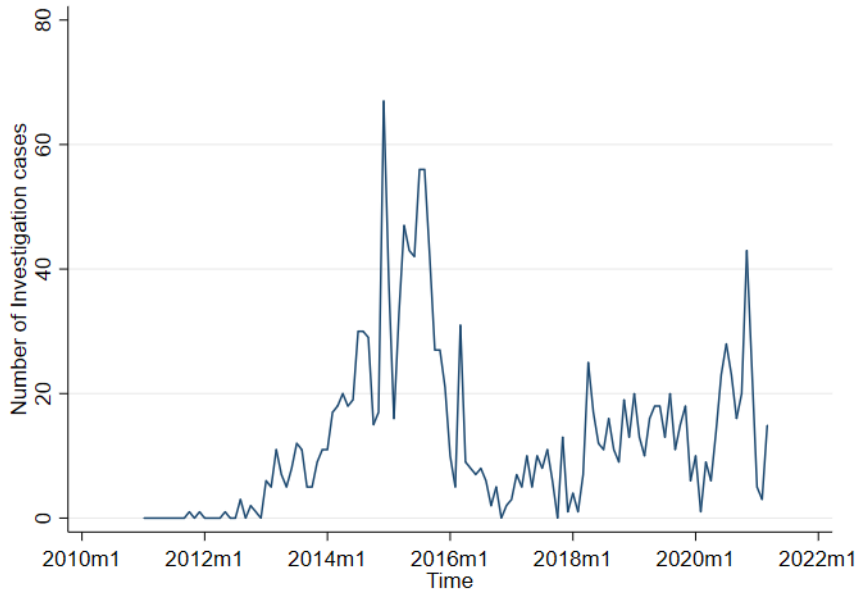
The dataset concerning corruption investigations spanning 2011 to August 2016 emanates from Wang and Dickson (2022), sourced via Tencent—the preeminent internet entity in China. Notably, Tencent launched an accessible online repository chronicling all corruption investigations across China in 2011 during the anti-corruption campaign. Synthesizing data from Party disciplinary committees, courts, and procuratorates across diverse administrative tiers, Tencent's database encapsulates a comprehensive array of data points, including officials' names, designations, localities, ranks, and the rationale behind the investigations. For post-August 2016 data, subsequent to the mainstream discontinuation of the term "anti-corruption" and Tencent's cessation of database updates, the endeavor necessitated a manual compilation from Party disciplinary committees, courts, and procuratorates across varying government echelons. Rigorous validation was upheld through extensive internet searches on each name to ascertain the primary source and announcement date. Presently, this updated database stands as the most extensive publicly available compendium on corruption investigations in China. This repository inherently mirrors the evolving landscape of corruption investigations, as delineated in the province of study. The illustrated trajectory, depicted in Figure 2.2, illustrates a marked upsurge from 2014, coinciding with the initiation of the anti-corruption campaign, followed by a gradual decline before the 19th National Congress of the Communist Party of China in 2017. Post the Congress, a resurgence in the number of investigations is evident, aligning seamlessly with the database's contextual framework.

2.3 Whistleblowers: Complaints in Public Procurement

The complaint dataset involving insights from the complainants about the unobserved misconduct in procurement projects, which are unknown to outside people, provides a valuable angle to study the corruption and scoring rule manipulation in public procurement. This section starts by looking closely into the complaint dataset.

As indicated in Table 2.3, auctions within the complaint datasets feature a higher number of bidders. To further detail the comparison, I have illustrated the distribution of the number of bidders and winning margins for the ex-ante complaint dataset, the ex-post complaint dataset, and the full dataset in Figure 2.3. In part (a), the distribution of the number of bidders is similar between the ex-ante complaint dataset and the full dataset, with three bidders often being the prevalent scenario. Although the ex-ante complaint dataset averages more bidders, this may be due to successful complaint-driven rule modifications, or in instances where complaints failed, the procurement agency may have added non-competitive 'zombie' bidders to mimic the competitive environment. In contrast, the ex-post complaint dataset predominantly features auctions with more than six bidders, suggesting a different pattern where auctions with three bidders—a configuration more susceptible to corruption—are less common. This aligns with the expectation that a three-bidder scenario often involves collu-

Figure 2.2: Number of Corruption Investigation Cases



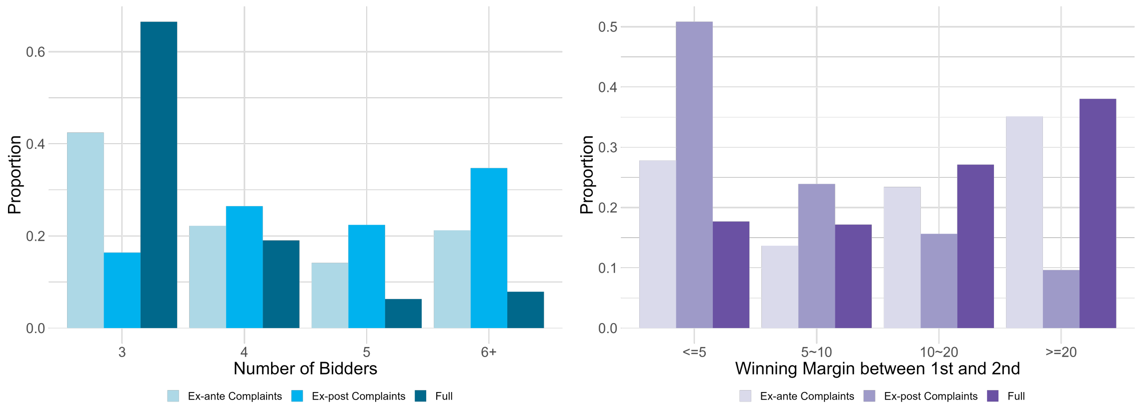
Notes: The y-axis of the figure represents the total number of anti-corruption investigations per month in the Province from which the public procurement data was collected. The investigation data prior to August 2016 are sourced from Wang and Dickson (2022), while the data from August 2016 onwards have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

sion. If a genuine complainant is present, it indicates they are not part of the collusion, and the auction typically has more bidders than three.

The ex-post complaint dataset also exhibits narrower winning margins. As depicted in part (b) of the figure, the distribution of winning margins for ex-ante complaints and the full dataset is again similar, with approximately 40% of auctions showing a winning margin greater than 20. Conversely, in the ex-post complaint dataset, over half of the auctions are tightly contested, with winning margins under 5 points, and less than 10% have a winning margin exceeding 20. This pattern suggests that auctions where non-collusive competitors narrowly lose to the winner are more likely to lead to a complaint.

Beyond the number of bidders and winning margins, the ex-post complaint dataset also exhibits larger bid price gaps between the winner and the complainant when their final scores are close. For instance, in the scenario depicted in Table 2.2, the complainant firm H submitted the lowest bid, while the bids from the other firms, E, F, and G, were similar. The winning price was 16% higher than that of the complainant, marking a significant price gap when compared to other procurement auction data. Such a pattern is not isolated; in fact, it is quite prevalent in the ex-post complaint dataset. Another illustration of this can be found in Table B1, where the complainant and the firm ranked third have bids that are 8% and 19% lower in price, respectively, than that of the winning firm.

Figure 2.3: The Comparison between Complaint Datasets and the Full Dataset



(a) Number of Bidders (b) Winning Margin

Notes: Ex-ante complaints correspond to complaints filed during the call-for-tender release stage or ‘complainant-out’, whereas ex-post complaints pertain to complaints submitted by participants after the completion of the auctions or ‘complainant-in’.

A notable feature of these cases is the substantial price gap: the winner’s bid is markedly higher in price. This phenomenon frequently appears in the complaint dataset. However, winning or losing should be virtually random when bids are very close. Consequently, even if quality and price scores contribute to the total score and the proximity between bidders and purchasers may influence quality scores, the differences in these factors between close winners and close losers should diminish as the bid difference narrows. It is often the price or quality scores that become the decisive factor in winning. If, on the other hand, scoring rules are manipulated to favor predetermined winners, these winners can consistently outperform their competitors on quality scores, and thus given the advantages of the quality scores, the predetermined winners can bid higher prices to increase the profits.

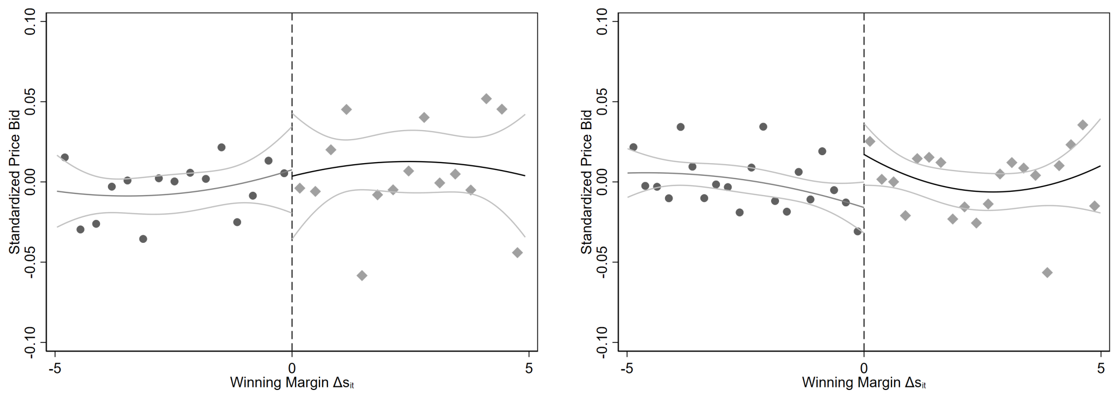
We assess the randomness of bids and firm characteristics within the complaint dataset by employing a regression discontinuity design as follows:

$$\beta = \lim_{\epsilon \to 0+} E[x_{i,a} | \Delta_{i,a} = \epsilon] - \lim_{\epsilon \to 0-} E[x_{i,a} | \Delta_{i,a} = \epsilon]$$

Where the running variable $\Delta_{i,a}$ is the winning margin. The null is $\beta = 0$. If there are no non-competitive behaviors, the null is not rejected. $x_{i,a}$ includes the price bid relative to the budget, the quality score, and the distance of the firm location to the procurement government department.

The test for randomness in the price bids is detailed in Table 2.4 and visually depicted in Figure 2.5. The first column shows the winning margin for price bids within the entire complaint dataset. It reveals that as the winning margin decreases to zero, the bidders who narrowly win tend to submit price bids that are, on average, 3.7% higher than those of the bidders who just miss winning. The second and third columns present a comparison between

Figure 2.4: Binned Scatter Plot for Price Bids



(a) Ex-ante Complaints (b) Ex-post Complaints

Notes: (1) Ex-ante complaints correspond to complaints filed during the call-for-tender release stage or 'complainant-out', whereas ex-post complaints pertain to complaints submitted by participants after the completion of the auctions or 'complainant-in'.(2) Project fixed effects are included so that the dependent variables in the y-axis are standardized values instead of the original values.

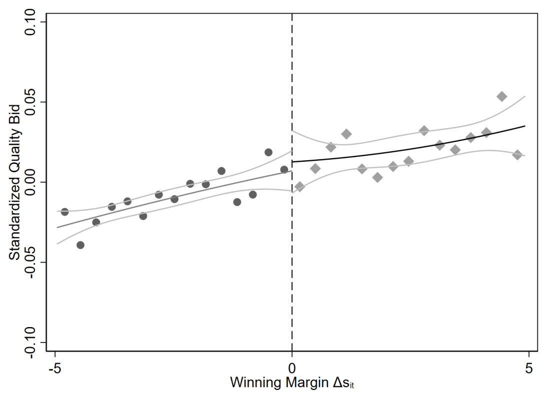
Table 2.4: Complaints Randomness Test for Price Bids

Groups	(1) All	(2) Ex-ante Complaints	(3) Ex-post Complaints
RD Estimate β	0.037***	0.015	0.044***
	(0.009)	(0.014)	(0.010)
Observations	6027	1800	4227
Effective Obs	1247	257	990
Project FE	Yes	Yes	Yes
Bandwidth	5	5	5
Order polyn.	2	2	2

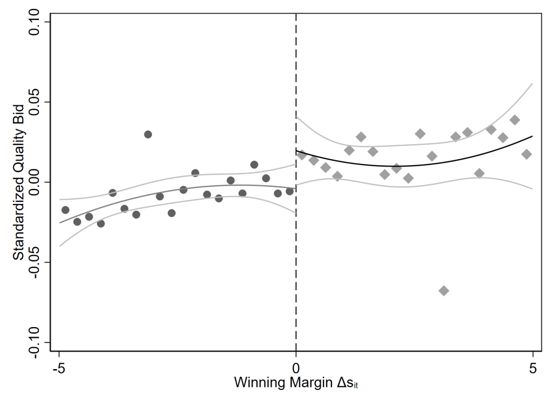
Notes: Ex-ante complaints correspond to complaints filed during the call-for-tender release stage or 'complainant-out', whereas ex-post complaints pertain to complaints submitted by participants after the completion of the auctions or 'complainant-in'. Standard errors in brackets are clustered at the procurement project level.

ex-ante complaints and ex-post complaints. For ex-ante complaints, the estimated β is a statistically insignificant 1.5% above the budgeted price. Conversely, for ex-post complaints, close winners submit price bids that are a statistically significant 4.4% higher than those of their nearly-winning counterparts. Another point worth noting is that when applying the RDD, in ex-ante complaints, only 14% of bids are used, while in ex-post complaints, 23% of bids are used. The estimation results are reflected in Figure 2.5(a), where the price difference remains relatively steady as the winning margin approaches zero. In contrast, Figure 2.5(b) displays a noticeable price gap at the winning threshold, with close winners bidding higher prices.

Figure 2.5: Binned Scatter Plot for Quality Bids



(a) Ex-ante Complaints



(b) Ex-post Complaints

Notes: (1) Ex-ante complaints correspond to complaints filed during the call-for-tender release stage or 'complainant-out', whereas ex-post complaints pertain to complaints submitted by participants after the completion of the auctions or 'complainant-in'. (2) Project fixed effects are included so that the dependent variables in the y-axis are standardized values instead of the original values.

Table 2.5: Complaints Randomness Test for Quality Bids

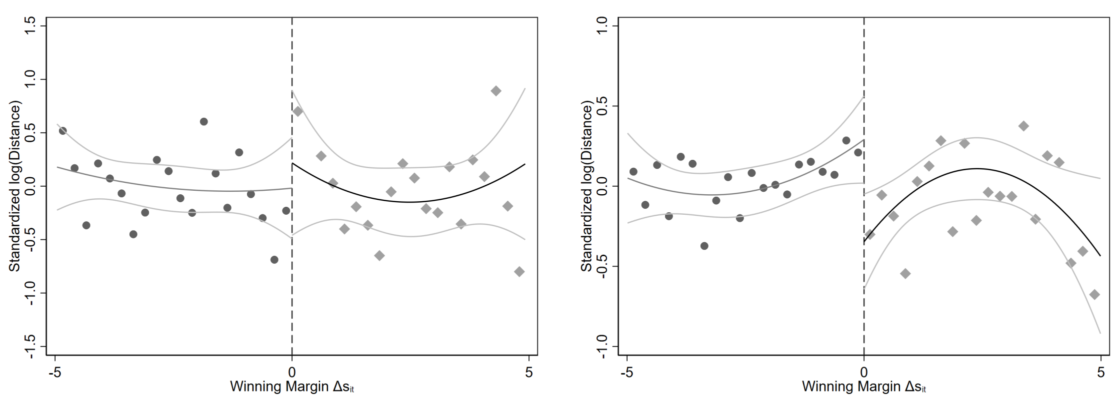
Groups	(1) All	(2) Ex-ante Complaints	(3) Ex-post Complaints
RD Estimate	0.020***	0.005	0.023***
	(0.005)	(0.007)	(0.006)
Observations	6007	1790	4217
Effective Obs	1241	255	986
Project FE	Yes	Yes	Yes
Bandwidth	5	5	5
Order polyn.	2	2	2

Notes: Ex-ante complaints correspond to complaints filed during the call-for-tender release stage or 'complainant-out', whereas ex-post complaints pertain to complaints submitted by participants after the completion of the auctions or 'complainant-in'. Standard errors in brackets are clustered at the procurement project level.

The randomness test for quality bids is outlined in Table 2.5. The first column, which considers both types of complaints, shows that the bidders who narrowly win have quality scores that are on average 2% higher than those who narrowly lose. This trend is consistent when comparing ex-ante and ex-post complaints, paralleling the findings from the price bid randomness test. For ex-ante complaints, detailed in the second column, the estimated difference in quality scores is negligible, indicating no significant statistical or economic discrepancies. However, for ex-post, as reported in the third column, the estimated β is statistically significant at 2.3%. This result indicates that the quality gap identified in the pooled test of the first column predominantly stems from ex-post complaints.

When synthesizing the outcomes of the price and quality randomness tests, it appears that in the ex-ante complaints, both quality and price equally influence the auction's outcome in close games. Conversely, in the ex-post complaint dataset, quality is the decisive factor for winning, with a notable price gap existing between winners and near-winners. These differences can be attributed to two main factors. Firstly, the ex-ante dataset has a considerably smaller proportion of close games—as shown in Table 2.4, only 14% of data points are included in the regression discontinuity (RD) regressions, compared to 23% for ex-post complaints, indicating fewer genuine near-winner competitors in ex-ante complaints. Secondly, ex-ante complaints encompass both re-auctions following successful complaints and auctions conducted post-investigation of unsuccessful complaints. As a result, the ex-ante complaint dataset likely contains fewer corrupt close games.

Figure 2.6: Binned Scatter Plot for the Distances to Procurement Departments



(a) Ex-ante Complaints

(b) Ex-post Complaints

Notes: (1) Ex-ante complaints correspond to complaints filed during the call-for-tender release stage or 'complainant-out', whereas ex-post complaints pertain to complaints submitted by participants after the completion of the auctions or 'complainant-in'.(2) Project fixed effects are included so that the dependent variables in the y-axis are standardized values instead of the original values.

Lastly, I analyze other firm characteristics, such as the distances between firms and their respective procurement government departments, as shown in both Table 2.6 and Figure 2.6.

In the first column, which pools both complaint datasets together, winners who narrowly outperform the losers are, on average, 30% closer to the relevant procurement government department compared to their counterparts who experience a narrow loss, although this finding is not statistically significant. This discrepancy increases to 65% when focusing specifically on ex-post complaints. For ex-ante complaints, the difference in distances is positive but statistically insignificant. Figure 2.5 visually illustrates this pattern. In the ex-ante complaint dataset, there is no statistically significant difference in distance to the government procurement departments between close winners and losers. However, in the ex-post complaint dataset, close winners are significantly closer to the procurement departments than the close losers. This evidence suggests that local governments may be unfairly favoring local firms, engaging in protectionist practices that contravene procurement laws.

Table 2.6: Complaints Randomness Test for Distance

Groups	(1) All	(2) Ex-ante Complaints	(3) Ex-post Complaints
RD Estimate	-0.302	0.205	-0.649***
	(0.205)	(0.291)	(0.223)
Observations	6251	2203	4048
Effective Obs	1265	335	930
Project FE	Yes	Yes	Yes
Bandwidth	5	5	5
Order polyn.	2	1	2

Notes: Ex-ante complaints correspond to complaints filed during the call-for-tender release stage or 'complainant-out', whereas ex-post complaints pertain to complaints submitted by participants after the completion of the auctions or 'complainant-in'. Standard errors in brackets are clustered at the procurement project level.

Using the value range of the price bid, the proportion of corrupt auctions among close games can be estimated from a lower bound, as the estimated β represents the expected gap encompassing both corrupt and non-corrupt auctions. Given that standardized price bids p are bounded between $[0.6, 1]$ by policy regulation,[7] I can express β as the expected sum of the price gap around the winning threshold. Let $Pr_{corrupt}$ and $Pr_{noncorrupt}$ denote the

[7] According to competition law and practice regulations, $p = 1$ signifies a price bid exactly equal to the publicly known budget, while $p = 0.6$ is the lowest price a firm can bid.

proportion of auctions that are corrupt and non-corrupt, respectively:

$$\begin{aligned}\beta &= \lim_{\epsilon\to 0+} E[p_{i,t}|\Delta_{i,t}=\epsilon] - \lim_{\epsilon\to 0-} E[p_{i,t}|\Delta_{i,t}=\epsilon] \\ &= Pr_{corrupt} \times (\lim_{\epsilon\to 0+} E[p_{i,t}|\Delta_{i,t}=\epsilon, corrupt] - \lim_{\epsilon\to 0-} E[p_{i,t}|\Delta_{i,t}=\epsilon, corrupt]) \\ &> Pr_{corrupt} \times 0.4\end{aligned}$$

Utilizing the estimated β Table 2.4 Column (2), 0.044, the lower bound of the proportion of corrupt auctions is 11%. The actual proportion of corruption is higher than 11%, as $(\lim_{\epsilon\to 0+} E[p_{i,t}|\Delta_{i,t}=\epsilon, corrupt] - \lim_{\epsilon\to 0-} E[p_{i,t}|\Delta_{i,t}=\epsilon, corrupt])$ is significantly less than 0.4. If we use the 95% upper bound of $p_{(1)} - p_{(2)}$, [8] 0.25, the lower bound of the proportion of corruption in auctions is 20%, and yet, 20% is still a conservative estimate. Also, the estimate is very close to the complaint success rate of 21%.

The comparison between ex-ante and ex-post complaints provides informative evidence. Auction results from ex-ante complaints are pre-screened and are either less affected by corruption or cleverly manipulated to conceal corrupt behaviors, compared to ex-post complaints. Therefore, in the RDD test, the price bids and firm characteristics between close winners and losers appear random. On the other hand, ex-post complaints submitted by participating firms, who possess more information than outsiders, serve as a good benchmark for investigating corruption.

2.4 Model and Test

In the previous section, I tested the randomness of price bids within the complaint dataset and demonstrated that regression discontinuity acts as a significant indicator of corruption in auctions. In this section, I expand the first-price auction framework, as detailed by Kawai et al. (2023), to encompass scoring auctions. Here, I will show that conditional on close biddings, winning outcomes appear as-if-random, suggesting that competition functions effectively in scoring auctions.

In a scoring auction, the government entity assigns a scoring rule with weights $(\boldsymbol{w_q}, w_p)$ associated with the quality part $\boldsymbol{q}$ and the price part p. The final scores are calculated as

$$S(p, \boldsymbol{q}) = \boldsymbol{w_q} \cdot \boldsymbol{q} + w_p \frac{\underline{p}}{p}, \text{ with } \sum_{l=1}^{L} w_q^l + w_p = 100$$

The sum of the weights is equal to 100. Government set the optimal $\boldsymbol{w_q}$ and w_p to maximize social welfare. The quality scores $\boldsymbol{q}$ range from 0^L to 1^L. The minimum price that a firm can bid denoted as $\underline{p}$, serves as a reference for the calculation of price scores. Both price bids p and $\underline{p}$ are standardized by the project budget (reserve price), $\overline{p}$, which is the maximum price

[8] $p_{(1)}$ is the price of the winner, and $p_{(2)}$ is the price of the runner-up.

firms can offer. Thus, p and $\underline{p}$ both fall in the range of (0,1] and the ratio $\frac{\underline{p}}{p}$ also lies in (0,1]. Then the total score s ranges from 0 to 100.

The quality scores are subjectively evaluated based on the average of scores given by five randomly selected experts. Different experts may have varying opinions on the same quality proposal, introducing uncertainty. This uncertainty can lead to discrepancies between the target quality $\boldsymbol{q}^t$ that bidders aim for to maximize their expected profit and the final quality score calculated from expert grading. Although averaging the quality evaluations from experts can mitigate the impact of this uncertainty, there still remains an element of randomness in the quality score.

I introduce the i.i.d.[9] error $\boldsymbol{\epsilon}_{iea}$ into the quality evaluation of each expert e for bidder i in auction a. Therefore, the quality score given by each expert is the sum of the target quality and the error, $\boldsymbol{q}_{iea} = \boldsymbol{q}^t_{ia} + \boldsymbol{\epsilon}_{iea}$. The final quality score for the bidder i in auction a is

$$\boldsymbol{q}_{ia} = \frac{\sum_{e=1}^{5} \boldsymbol{q}_{iea}}{5} = \frac{\sum_{e=1}^{5} (\boldsymbol{q}^t_{ia} + \boldsymbol{\epsilon}_{iea})}{5} = \boldsymbol{q}^t_{ia} + \boldsymbol{\epsilon}_{ia}$$

The relationship between the final quality score and the target quality score is $\boldsymbol{q}_{ia} = \boldsymbol{q}^t_{ia} + \boldsymbol{\epsilon}_{ia}$. The final score is the sum of the target score and the weighted error $s_{ia} = s^t_{ia} + \boldsymbol{w_q \epsilon}_{ia}$.

To examine the equilibrium of the scoring auction, Che (1993), Asker and Cantillon (2008), and Hanazano et al. (2020) decompose the multidimensional bidding process into two sequential steps. Initially, upon winning the auction with a certain total score s, the bidder selects a profit-maximizing combination of price p and quality $\boldsymbol{p}$. Hanazano et al. (2020) demonstrates that under reasonable assumptions, there exists a symmetric, pure-strategy, monotone equilibrium, $s(\theta)$, in the first scoring auction, where $s'(\theta) < 0$. Subsequently, the bidder chooses the target score s, akin to selecting an optimal price bid b in a first-price auction, where the primary challenge is to solve the maximization problem.[10] Then I show how Proposition 1 in Kawai et al. (2023) can be extended to the scoring auctions.

Proposition 1. *(equilibrium beliefs conditional on close bids). Consider an environment $\mathcal{E}$ and an MPE σ that is competitively enforced. For all $\eta > 0$ there exists $\epsilon > 0$ small enough such that, for two close bidders m and n,*

$$prob_\sigma(s^t_m > s^t_n \mid |s_m - s_n| < \epsilon) \rightarrow 1/2, \text{ when } \epsilon \rightarrow 0$$

Proof.

$$\begin{aligned} & prob_\sigma(s^t_m > s^t_n \mid |s_m - s_n| < \epsilon) \\ = \; & prob_\sigma(\boldsymbol{w_q \epsilon_m} - \boldsymbol{w_q \epsilon_n} \; < \; s_m - s_n \mid |s_m - s_n| < \epsilon) \end{aligned}$$

Given the symmetric distribution of evaluation error ϵ, when $s^t_m > s^t_n$, $prob_\sigma(\boldsymbol{w_q \epsilon_m} - \boldsymbol{w_q \epsilon_n} \; < \; 0 \mid |s_m - s_n| < \epsilon) = \frac{1}{2}$. Same as $s^t_m < s^t_n$. □

[9]The i.i.d. assumption is based on the random selection of experts for each auction and the independent evaluation process.

[10]There are more details about the equilibrium bidding strategies in Chen (2023).

Combined with the bid equilibrium, winning is as-if random conditional on close bids. Therefore, the following corollary holds:

Corollary 2.2. *For all $\eta > 0$, there exists $\epsilon > 0$ small enough such that for all observable $x \in X$,*

$$|prob(x_{ia} = x \mid \Delta_{ia} \in (0, \epsilon)) - prob(x_{ia} = x \mid \Delta_{ia} \in (-\epsilon, 0))| < \eta$$

The analysis above demonstrates that the distribution of observable covariates x_{ia} must be identical for marginal winners and marginal losers in competitive auctions. Kawai and Nakabayashi (2022*b*) also illustrates, in the context of various formats of scoring auctions, that under competitive conditions, the observables of close winners are similar to those of close losers, without accounting for the randomness in quality evaluation.

2.5 Unheard Whistleblowers: Full Procurement Auctions

The model section demonstrates how the randomness test can effectively identify non-competitive and corrupt behaviors in auctions. I applied the framework outlined in Section 2.5 to assess the randomness across the entire public procurement dataset, extending beyond just the complaint dataset.

The initial set of dependent variables includes both price bids and quality bids. The outcomes of the Regression Discontinuity Design (RDD) analysis for price bids are illustrated in Table 2.7 and Figure 2.7(a). In the first column of Table 2.7, which covers the entirety of the public procurement data, the findings indicate that winning bidders placed bids approximately 2.7% higher than the budget compared to their narrowly defeated counterparts. Notably, this tested subset accounts for 14.3% of the total procurement projects, suggesting that a significant majority of procurement auctions exhibit score gaps exceeding 5 points.[11] Moving to the second column, which exclusively analyzes auctions with at least three bidders, a smaller proportion of 6.21% is tested. In my work Chen (2023), I show that the score gaps between winners and the closest losers are substantial, with 72% of them being manipulated in favor of predetermined winners. Consequently, the estimated RD coefficient in this scenario is 1%, reflecting the relatively limited instances of whistleblower participation. Transitioning to the third column, the analysis shifts to procurement auctions involving four bidders. Here, marginal winners placed bids 4.8% higher than their narrowly defeated counterparts. This coefficient is consistent with the results from testing the complaint dataset. Finally, the fourth column examines auctions with five bidders. The more participants there are, the larger the pool of procurement auctions eligible for inclusion in the RD test.

Figure 2.7 (a) corresponds to the binned scatter plot aligned with the findings from the first column of Table 2.7. The horizontal axis reflects the margin of winning, while the x-axis

[11] In a companion work, I use these significant score gaps to investigate corruption in customized scoring rules.

Table 2.7: Randomness Test for Price Bids

Groups	(1) All	(2) 3 Bidders	(3) 4 Bidders	(5) 5 Bidders
RD Estimate	0.027***	0.010***	0.048***	0.037***
	(0.002)	(0.004)	(0.005)	(0.006)
Observations	400137	228095	84120	31156
Effective Obs	39476	10485	9118	6011
Project FE	Yes	Yes	Yes	Yes
Bandwidth	5	5	5	5
Order polyn.	2	2	2	2

Notes: Project fixed effects are included to tease out project heterogeneity. Standard errors in brackets are clustered at the procurement project level.

is positive for winning bidders and negative for losing bidders. The vertical axis represents the price bids. The visual depiction resonates with the analysis outcomes, revealing a discernible price gap as the winning margin approaches zero. Specifically, for marginal losers, the average price bid hovers around 89% of the budget, while for marginal winners, the average price bid escalates to 92% of the budget.

Similar to the application of tests in the complaint dataset, I also apply the lower bound of the proportion of corrupt auctions in the full dataset. The lowest bound of corruption proportion is 6.75%, which is half of the 11% in the complaint dataset.

$$\begin{aligned}\beta &= \lim_{\epsilon\to 0+} E[p_{i,t}|\Delta_{i,t}=\epsilon] - \lim_{\epsilon\to 0-} E[p_{i,t}|\Delta_{i,t}=\epsilon] \\ &= Pr_{corrupt} \times (\lim_{\epsilon\to 0+} E[p_{i,t}|\Delta_{i,t}=\epsilon, corrupt] - \lim_{\epsilon\to 0-} E[p_{i,t}|\Delta_{i,t}=\epsilon, corrupt]) \\ &> Pr_{corrupt} \times 0.4\end{aligned}$$

A reasonable lower bound of corruption proportion calculated by using 95% upper bound of $\lim_{\epsilon\to 0+} E[p_{i,t}|\Delta_{i,t}=\epsilon, corrupt] - \lim_{\epsilon\to 0-} E[p_{i,t}|\Delta_{i,t}=\epsilon, corrupt]$ 0.21 is 13%. All the lower bounds are half smaller than the lower bounds in complaints datasets, which also shows evidence that complainers based on the signal they received from the auction results make decisions about whether they would like to submit a complaint.

Next, I test the randomness in quality scores with the results presented in Table 2.8. Similar to the previous analysis on price bids, I use all available procurement auctions in the first column. This analysis indicates that marginal winners exhibit quality scores approximately 1% higher than their narrowly defeated counterparts. Moving to the second column, which is limited to auctions with just three bidders, the RD estimate remains statistically significant at 0.4%. In the third column, focusing on auctions involving four bidders, the RD

Table 2.8: Randomness Test for Quality Bids

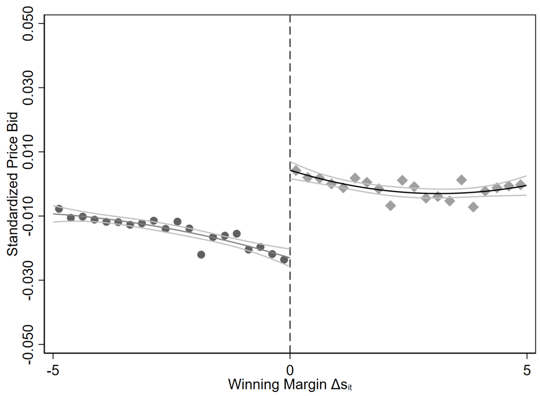
	(1)	(2)	(3)	(5)
Groups	All	3 Bidders	4 Bidders	5 Bidders
RD Estimate	0.012***	0.004**	0.020***	0.015***
	(0.001)	(0.002)	(0.003)	(0.003)
Observations	400137	228095	84120	31156
Effective Obs	39476	10485	9118	6011
Project FE	Yes	Yes	Yes	Yes
Bandwidth	5	5	5	5
Order polyn.	2	2	2	2

Notes: Project fixed effects are included to tease out project heterogeneity. Standard errors in brackets are clustered at the procurement project level.

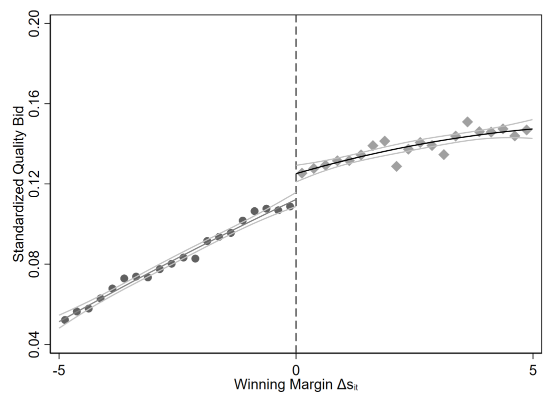
estimate becomes more pronounced and statistically significant at 1.6%. Lastly, the fourth column extends the analysis to auctions featuring five bidders.

Figure 2.7 (b) presents the results from the first column of Table 2.8. This binned scatter plot visually demonstrates a modest yet discernible shift from a negative to a positive winning margin, indicating a slight but statistically significant increase in quality scores.

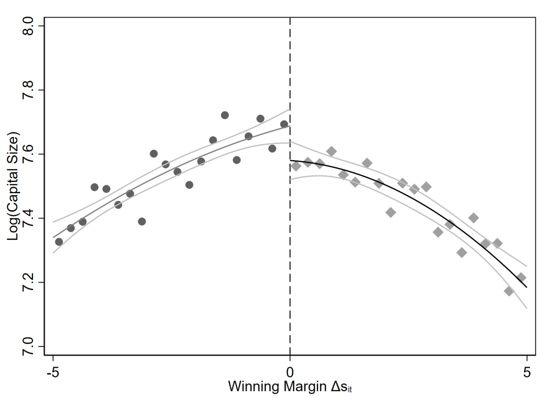
Figure 2.7: Binned Scatter Plot for the Main Dataset



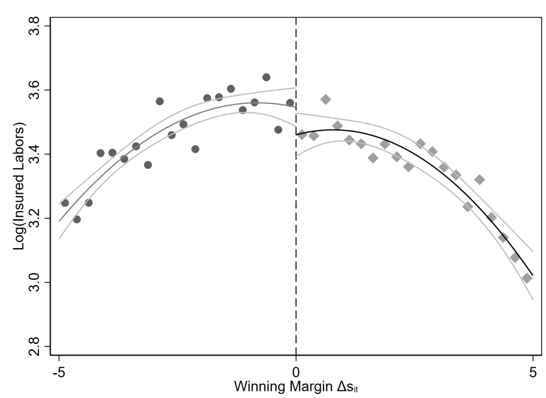
(a) Price Bids



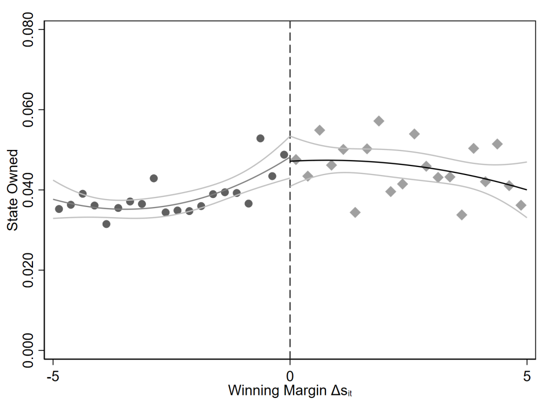
(b) Quality Bids



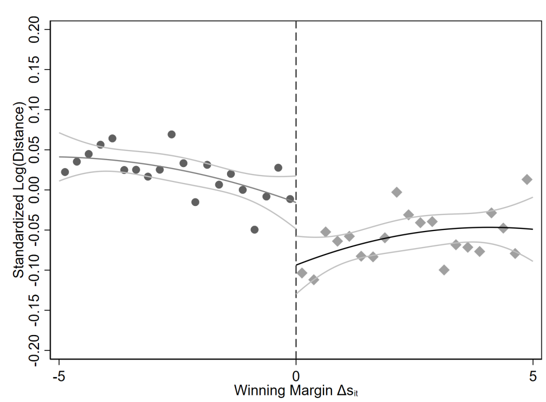
(c) Log(Registered Capital)



(d) Log(Insured Labor)



(e) State Owned



(f) Log(Distance to Govern.)

Notes: Project fixed effects are included so that the dependent variables in the y-axis are standardized values instead of the original values.

Next, I examine a second set of dependent variables: the characteristics of firms. These characteristics include variables such as registered capital size, insured labor size as recorded, state-owned affiliations, and the distance between firms and government procurement departments. The results are presented in Table 2.9. In the absence of biases in manipulated scoring rules, noticeable differences between marginal winners and losers should not exist.

The first column focuses on the log of registered capital. Here, marginal winners, on average, have a registered capital approximately 12.1% lower than that of their narrowly defeated counterparts, a finding that is statistically significant at the 1 % level. The second column shifts the focus to the log of insured labor size. The third column examines whether a firm is state-owned. While marginal winners tend to have smaller insured labor sizes and are more likely to have state-owned affiliations, these coefficients do not reach statistical significance. Moving to the last column, the analysis involves the log of the distance between firms and local government procurement departments. The results suggest that marginal winners are situated approximately 9.8% closer to the procurement departments compared to their narrowly defeated counterparts.

Figures 2.7 (c) to (f) correspond to the results presented in columns 1 to 4 of Table 2.9. Notably, for insured labor size and the state-owned indicator, no pronounced deviation is observed between positive and negative winning margins. However, in the cases of registered capital and distance, distinct downward jumps are noted upon crossing the winning margin threshold. Collectively, these findings provide compelling evidence that firms favored in corrupt practices are more likely to be smaller-scale and locally based.

Table 2.9: Randomness Test for Firm Characteristics

Groups	(1) log(Reg Capital)	(2) log(Insured Labor)	(3) State Owned	(5) log(Distance)
RD Estimate	-0.121***	-0.061	0.000	-0.098***
	(0.030)	(0.038)	(0.004)	(0.028)
Observations	679028	696140	696140	695850
Effective Obs	79198	82443	82443	82383
Project FE	Yes	Yes	Yes	Yes
Bandwidth	5	5	5	5
Order polyn.	2	2	2	2

Notes: Project fixed effects are included to tease out project heterogeneity. Standard errors in brackets are clustered at the procurement project level.

The third set of dependent variables includes changes in firm performance before and after procurement activities, measured through changes in total revenue, main business revenue, net revenue, profits, assets, liabilities, and ratios. These variables are constructed using the following transformation:$asinh(y_{it}) - asinh(y_{it-1})$, which approximates the percentage change in annual performance from pre-procurement to post-procurement periods.

Table 2.10: Public Procurement on Firm Growth

Groups	(1) Total Rev	(2) Main Rev	(3) Net Rev	(4) Profit	(5) Asset	(6) Liability	(7) Ratio
RD Estimate	0.116*	-0.084	-0.012	0.004	0.074*	0.014	0.034
	(0.068)	(0.091)	(0.081)	(0.078)	(0.044)	(0.058)	(0.042)
Observations	279,930	234,321	342,427	336,991	340,252	337,728	342,968
Effective Obs	28,146	21,429	33,813	33,069	33,419	33,146	33,856
Project FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	5	5	5	5	5	5	5
Order polyn.	1	1	1	1	1	1	1

Notes: (1) The dependent variables are constructed by taking the differences between the value $log(Oneyearbefore) - log(Oneyearafter)$. (2) Project fixed effects are included to tease out project heterogeneity. (3) Standard errors in brackets are clustered at the procurement project level.

The outcomes of the analysis are presented in Table 2.10. The first column examines the change in total revenue. After winning a procurement contract, marginal winners see a significant 11.6% increase in total revenue growth compared to their narrowly defeated counterparts, achieving statistical significance at the 10% level. The next three columns evaluate main business revenue, net revenue, and profits as dependent variables. Although the estimates indicate that marginal winners experience lower growth in main business revenue but higher growth in net revenues and profits, these coefficients do not reach statistical significance. In the fifth column, the analysis shifts to changes in total assets as the dependent variable, revealing that marginal winners undergo a 7.4% increase in asset growth. Nevertheless, regarding liabilities and ratios, the results do not achieve statistical significance.

It is crucial to exercise caution when interpreting these results. The previous assessment of randomness in the allocation of public procurement underscores that the process is not random; an unfair and illegal preference towards small and local firms is evident. The foundational assumption of quasi-randomness around a zero winning margin, fundamental to this analysis, is thus violated. Consequently, the observed outcomes cannot be treated as causal effects in reality.

2.6 Validation: Corruption Investigation

To validate the corruption testing method, I leverage corruption investigations conducted during the anti-corruption campaign, following the literature (Chassang et al., 2022; Kawai and Nakabayashi, 2022*b*). This validation approach divides the auctions into two periods:

one covering a two-year span before the investigations and another spanning two years after the investigations. The goal was to determine whether statistically significant shifts could be observed around the winning threshold, particularly in variables such as price bids and specific firm characteristics, including distance proximity to government procurement departments. Given that corruption investigations act as shocks to local governance, if the randomness test is effective, we should observe distinct patterns immediately before and after the corruption investigations.

Following President Xi's ascension to central power in 2014, the Chinese Communist Party initiated a sweeping anti-corruption campaign. This campaign, aimed at eradicating corruption at diverse hierarchical levels, extends beyond the scope of public procurement. It is important to note that this campaign aims to address general corruption concerns beyond the scope of public procurement. Recent empirical evidence (Manion, 2016; Wang and Dickson, 2022; Fang, 2023) suggests that the campaign has reshaped the government's incentive structure and effectively curbed opportunities for bureaucratic corruption.

Table 2.11: Randomness Test for Price and Quality Bids

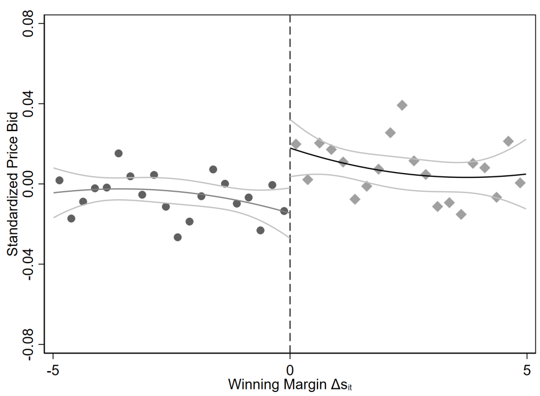
Groups	(1) P before	(2) P after	(3) Q before	(4) Q after
RD Estimate	0.0317***	0.0087	0.0217***	0.0099
	(0.0115)	(0.0102)	(0.0071)	(0.0055)
Observations	1259	1141	1259	1141
Project FE	Yes	Yes	Yes	Yes
Mean dep. var.	0.944	0.941	0.619	0.633
Bandwidth	5	5	5	5
Order polyn.	2	2	2	2

Notes: (1) The before-investigation sample includes auctions conducted two years before the investigations and the after-investigation sample includes auctions conducted two years after the investigations. (2) Project fixed effects are included to tease out project heterogeneity. (3) Standard errors in brackets are clustered at the procurement project level.

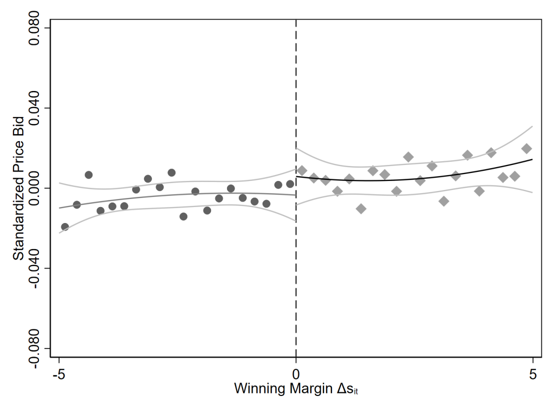
I conducted a regression discontinuity design analysis, separately examining both price and quality variables across two distinct samples. The outcomes are presented in Table 2.11. The first pair of columns in the table displays the results for price bids before and after the investigation. Before the investigation, the analysis revealed that the price bids of marginal winners exhibited a statistically significant increase of 3.17% relative to the budget price compared to their narrowly defeated counterparts. Conversely, after the investigation, the price bids of marginal winners converged with those of the marginal losers. This pattern is further illustrated through the corresponding binned scatter plots, presented in Figure 2.8 (a) and (b).

In Figure 2.8 (a), using the pre-investigation sample, a conspicuous pattern emerges: as the winning threshold is approached, marginal losers, on the left-hand side, submit lower bids than the marginal winners positioned on the right-hand side. However, as depicted in graph (b), associated with the post-investigation sample, there is no significant leap around the winning threshold.

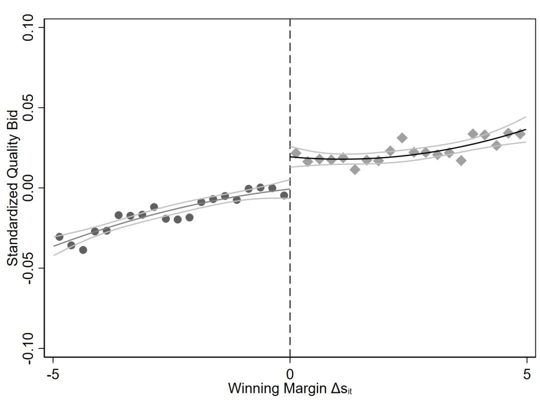
Figure 2.8: Binned Scatter Plot for the before and after Dataset



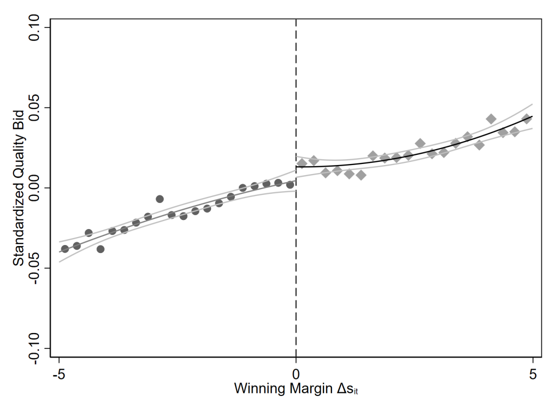
(a) Price Bids: before Investigation



(b) Price Bids: after Investigation



(c) Quality Bids: before Investigation



(d) Quality Bids: after Investigation

Notes: The before-investigation sample includes auctions conducted two years before the investigations and the after-investigation sample includes auctions conducted two years after the investigations. Project fixed effects are included to tease out project heterogeneity. Standard errors in brackets are clustered at the procurement project level.

The next pair of columns in Table 2.11 presents the quality bid estimates. In the period preceding the investigation, marginal winners exhibited a statistically significant increase of 2.17% in quality scores compared to narrowly defeated counterparts. Conversely, following the investigation, the quality scores of marginal winners aligned more closely with those of marginal losers. This pattern is visually presented through the corresponding binned scatter plots presented in Figure 2.8 (c) and (d). Figure 2.8 (c), using the pre-investigation sample, showcases a clear trend: as the winning threshold approaches, quality scores assigned to marginal losers consistently lag behind those evaluated for marginal winners on the right-hand side. However, in Figure (d), using the post-investigation sample, no substantial leap around the winning threshold is apparent.

Table 2.12: Randomness Test for Firm Characteristics

	(1)	(2)	(3)	(4)
Groups	log(Reg Capital)	log(Insured Labor)	State Owned	log(Distance)
Panel A: Before the Investigation				
RD Estimate	-0.179**	-0.232*	0.0216**	-0.188**
	(0.0892)	(0.122)	(0.0104)	(0.0846)
Observations	2392	2523	2523	2523
Mean dep. var.	7.269	3.264	0.0322	3.989
Panel B: After the Investigation				
RD Estimate	-0.136	-0.152	0.0169	-0.0647
	(0.0893)	(0.134)	(0.0142)	(0.101)
Observations	1856	1940	1940	1940
Mean dep. var.	7.274	3.230	0.0414	4.026
Project FE	Yes	Yes	Yes	Yes
Bandwidth	5	5	5	5
Order polyn.	2	2	2	2

Notes: (1) The before-investigation sample includes auctions conducted two years before the investigations and the after-investigation sample includes auctions conducted two years after the investigations. (2) Project fixed effects are included to tease out project heterogeneity. (3) Standard errors in brackets are clustered at the procurement project level.

Then I focus on firm characteristics, including registered capital size, insured labor size, state ownership, and proximity to procurement departments, outcomes are presented in Table 2.12. Panel A presents the period preceding the investigation, while Panel B corresponds to the post-investigation phase. By comparing these panels, a distinct pattern emerges within the pre-investigation sample: marginal winners exhibit unique characteristics. Specifically, they are 17.9% smaller in terms of registered capital size, 23.2% smaller in insured labor size, and 18.8% closer to local government procurement departments. The RD estimates show statistical significance within the pre-investigation sample, though they appear smaller in magnitude and statistically insignificant within the post-investigation sample.

Interestingly, the coefficient associated with state ownership status, initially insignificant in the primary dataset, changes within the smaller pre-investigation sample. Here, the analysis reveals that marginal winners are 2.16% more likely to be state-owned firms than their narrowly defeated counterparts.

Table 2.13: Public Procurement on Firm Performance Change

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Groups	Total Rev	Main Rev	Net Rev	Profit	Asset	Liability	Ratio
Panel A: Before the Investigation							
RD Estimate	-0.178	0.908*	-0.111	0.140	0.432	0.368	-0.298
	(0.411)	(0.493)	(0.543)	(0.516)	(0.277)	(0.302)	(0.216)
Observations	8,382	8,305	11,140	10,704	10,788	10,721	11,160
Effective Obs	766	651	968	915	918	917	965
Project FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	5	5	5	5	5	5	5
Order polyn.	1	1	1	1	1	1	1
Panel B: After the Investigation							
RD Estimate	0.097	-1.097*	0.402	0.337	-0.229	-0.118	-0.104
	(0.480)	(0.613)	(0.485)	(0.457)	(0.246)	(0.354)	(0.278)
Observations	7,523	6,261	8,613	8,392	8,519	8,409	8,638
Effective Obs	738	554	834	786	799	788	834
Project FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	5	5	5	5	5	5	5
Order polyn.	1	1	1	1	1	1	1

Notes: Project fixed effects are included to tease out project heterogeneity. Standard errors in brackets are clustered at the procurement project level.

Lastly, I estimate performance changes for the two different samples. In the pre-investigation sample, marginal winners show a significant 90% increase in growth in main revenue. However, estimates concerning other variables failed to reach statistical significance. The analysis of these results must be approached cautiously, considering the outcomes of the randomness test that indicated manipulation within scoring rules before the investigation. This suggests that these estimates likely reflect the influence of establishing connections with local government entities. Such connections might provide firms with easier access to financial markets and accelerated growth opportunities, facilitated by ensuring victory in public procurement projects.

Conversely, when focusing on the post-investigation sample, winning firms demonstrated higher growth rates in net revenue and profits. Nonetheless, these estimates did not achieve statistical significance, consistent with the insignificance observed in the remaining variables.

2.7 Why is There so Few Complaints

Results from Sections 2.3 and 2.5 demonstrate that, based on the close games from at least 2,088 corrupt auctions,[12] there are 341 complaints. This amounts to less than a 17% complaint rate, conditional on corrupt cases and close games. Furthermore, without conditioning on close games, across all auctions, there are only 1,075 complaint cases out of more than 120 thousand procurement auctions. Compared to the prevalent corruption rate of 65% found in Chen (2023), the complaint rate is only 1%, which is significantly lower than what might be expected by the design of the complaint system.

In this section, I estimate a discrete choice model to understand the decision-making process behind complaints from the close losers and explore why there are so few complaints. Then, I evaluate two counterfactual policies, such as protecting complainants by concealing their names, as discussed in the finance and theory literature, and introducing random audits by the government regulation team.

2.7.1 Setup

I use a similar model framework as Boudreau et al. (2023), which examines the decision to report harassment in the workplace, but I incorporate additional elements of uncertainty regarding the actual status of underlying corruption and the outcomes of investigations since complainants are not 100% sure about their judgment. Figure 2.9 illustrates the complaint decision-making process. In step 1, genuine competitors enter the competition, resulting in a close game where $|\epsilon| < d$.[13] An honest competitor, i, loses the game at the time t and observes a price gap, $\Delta x_t = x_t^{winner} - x_t^i$ with the winner. Based on the gap Δx_t, there is a commonly known function $p : \Delta x_t \to p \in [0, 1]$ that translates the price gap into the probability of actual, unobserved underlying corruption.

Then, in step 2, given $p(\Delta x_t)$, the close loser decides whether to submit a complaint $r = 0$ *or* 1. In step 3, if the close loser submits a complaint $r = 1$, the auditing team initiates an investigation. Everyone can observe the action r. Following the investigation, the auditing team determines whether the complaint is successful or not.

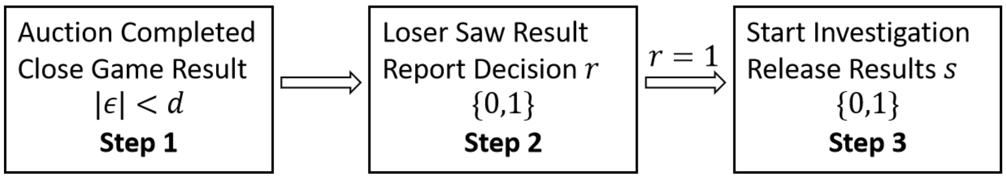
The utility of the close loser, U_{idt}, depends on the intent to complain r and consists of benefits from a successful investigation as well as retaliation costs:

$$U_{idt}(r) = \alpha \mathrm{CP}_{it} \times \mathrm{Pr}_{id}\{s = 1|r, \Delta x_{it}\} + \beta \mathrm{FP}_{id}(r) + \gamma \mathrm{OR}_{id}(r) + \epsilon_{idtr}$$

[12] In the full dataset, there are 16,059 close auction games. The lowest bound of the corruption proportion is 13%, indicating at least 1,445 corrupt auctions.

[13] Here, I do not model the entry decision. All decisions to submit a complaint are conditional on participating in close games.

Figure 2.9: Complaint Decision from The Close Losers



where CP_{it} represents the current profit from the project t that the close loser complains about. The realization of the current profit also hinges on the success status of the complaint, $\text{Pr}_{id}\{s = 1|r, p(\Delta x_{it})\}$, which reflects the district-specific complainer's belief in a successful investigation given the probability of corruption $p(\Delta x_{it})$ signaled by Δx_{it}.[14] $\text{Pr}_{id}\{s = 1|r = 1, \Delta x_{it}\} > 0$ and $\text{Pr}_{id}\{s = 1|r = 0, \Delta x_{it}\} = 0$. If the investigation confirms that the competition was unfair, then the close loser in second place becomes the winner.

FP_{id} represents the potential profit from similar projects procured by the same district d over the next three years. It considers the likelihood of corruptly manipulated auctions and the probability of winning future auctions. This factor is integral to the retaliation phase. If the close loser lodges a complaint about the procurement auction, she will not have the opportunity to win any upcoming auctions within three years, as the government district d retaliates against the complainer. Therefore, $\text{FP}_{id}(r = 1) = 0$ and $\text{FP}_{id}(r = 0) > 0$.

OR_{id} represents other retaliation costs not accounted for by future profits. $\text{OR}_{id}(r = 1) < 0$ and $\text{OR}_{id}(r = 0) = 0$.

Given the observed price gap Δx_t, the close loser is inclined to submit a complaint $r = 1$ if and only if

$$U_{idt}(r = 1) - U_{idt}(r = 0) > 0$$
$$\epsilon_{idt1} - \epsilon_{idt0} > -[\alpha \text{CP}_{it} \times \text{Pr}_{id}\{s = 1|r = 1, p(\Delta x_{it})\} - \beta \text{FP}_{id}(r) + \gamma \text{OR}_{id}(r)] = f(\boldsymbol{\theta}_{id}, x_{idt})$$

Here, it is evident that the greater the close loser's belief in the local audit team's ability to uncover unfair practices during the investigation, given the signal Δx_{it}, the higher the likelihood of the close loser submitting a complaint.

2.7.2 Estimation

To estimate the complaint decision model, I impose parameterization assumptions on each part of the utility function to connect the model with the observed data.

Since the close losers' projection that links the probability of corruption based on the signal to the complaint's success rate is unobservable,

$$\alpha \text{Pr}_{id}\{s = 1|r = 1, p(\Delta x_{it})\} = \alpha_0 + \alpha_1 p(\Delta x_{it}) + D_d + \varepsilon_{id}$$

[14] The success of the investigation depends on the stringency and professionalism of the local auditing government team, and whether there is an intent to protect a procurement agency of the same level from being discovered for corruption.

where $p(\Delta x_{it})$ is the probability of actual corruption based on the price gap signal Δx_{it}, which can be estimated from the previous regression discontinuity design. The coefficients α_d represent the district-specific projection from the probability of corruption to the investigation's success rate, modeled using a polynomial regression. D_d denotes the district-level success rate fixed effect. ε_{id} captures the random error in the investigation, with $\varepsilon_{id} \sim i.i.d.\ N(0, \Sigma)$.

CP_{it} is the *log* of the bidding price that close loser i bid for the project t. FP_{id} is the *log* of the sum budget of similar projects in the following five years in district d. OR_{id} capture firm and district characteristics that other than monetary gains or loss:

$$\gamma \mathrm{OR}_{id}(r) = \gamma_0 + \gamma_1 \mathrm{Firm}_{id} + \mathrm{District}_d$$

where Firm_{id} includes all firm and firm-district characteristics, such as log firm registered capital size, state-owned relation indicator, log distance to the procurement office, and past winning in the district indicator; $\mathrm{District}_d$ are district fixed effects.

With the assumption $\epsilon_{idt1}, \epsilon_{idt0} \sim$ Type I extreme value, the probability of choosing to complain is:

$$P_{idt} = \int_{\varepsilon_{id}} \frac{1}{1 + exp(f(\boldsymbol{\theta}_{id}, x_{idt}))}\, d\Phi(\varepsilon_{id})$$

I can estimate the parameters in the complaint submission decision using the simulated maximum likelihood method, which is linked to mixed logit.

2.7.3 Results

The estimated results are displayed in Table 2.14. Additionally, I explore two counterfactual policies: protecting the names of complainers and implementing random audits.

The first column examines how the budget size of the current project influences the likelihood of submitting a complaint. A larger project provides a stronger incentive for potential complainers to submit a complaint. Furthermore, a positive α_1 indicates that a larger price gap between close winners and losers correlates with a higher probability of corruption, thereby increasing the likelihood of a successful complaint.

The second column highlights the role of the total budget size for future projects over the next three years, representing the potential loss of future revenue due to submitting complaints. The statistically significant β_0 suggests that potential complainers take into account future projects when deciding whether to submit a complaint.

The third column assesses the impact of other retaliation costs, proxied by firm characteristics, on complaint decisions. Firms with larger registered capital are less inclined to submit complaints, all else being equal. The larger the firm, the greater the retaliation cost. Firms with a longer history and foreign funding are more inclined to submit a complaint, possibly because such firms are more experienced and less susceptible to pressure from local governments.

The existing literature discusses two policies to reduce corruption: complainer protection (Chassang and Miquel, 2019; Mechtenberg, Muehlheusser, and Roider, 2020; Boudreau

Table 2.14: Decision of Complaint Submission

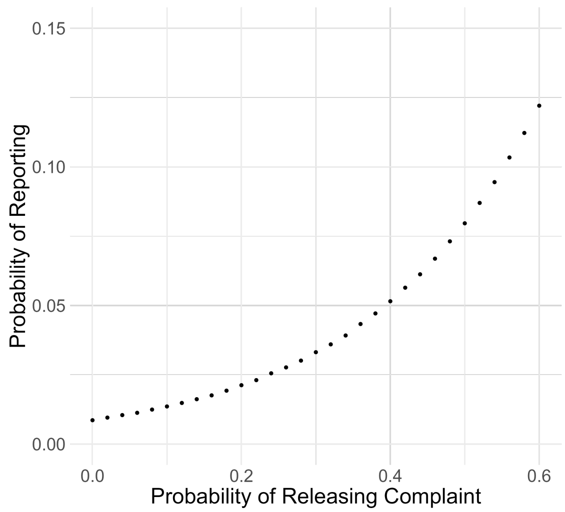
Current Rev (CR)		Future Rev (FR)		Retaliation Cost (ORC)	
α_0	0.730***	β_0	-0.115**	$\gamma_{Longevity}$	0.205*
	(0.245)		(0.044)		(0.124)
α_1	0.158***	$\sigma_{\varepsilon_{FR}}$	0.047*	$\gamma_{capital}$	-0.181***
	(0.060)		(0.025)		(0.054)
$\sigma_{\varepsilon_{CR}}$	0.133***			$\gamma_{foreign}$	0.730*
	(0.035)				(0.433)
				$\gamma_{stateowned}$	-0.816
					(1.052)
				$\gamma_{distance}$	0.034
					(0.055)
		Year FE	Yes	District FE	Yes

et al., 2023) and random auditing (Ferraz and Finan, 2011; Avis, Ferraz, and Finan, 2018; Colonnelli and Prem, 2021). Following this literature, I conduct analyses on two counterfactual policies. First, I introduce the probability of concealing the names of complainers as a protection policy.[15] Since there is a probability that the procurement agency will not know who the complainer is, the future revenue loss and other retaliation costs are proportionally reduced. Figure 2.10a illustrates the impact of complainer protection on the probability of case reporting. With a higher probability of concealing the name of the complainer, competitors are more incentivized to submit a complaint. Concealing the name of the complainer in 50% of cases results in approximately 10% of complaints across all procurement projects.

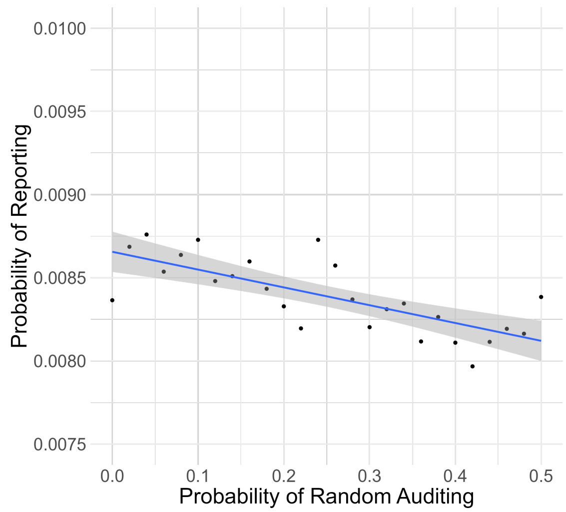
Second, I investigate the impact of random audit frequency on the proportion of reporting cases. Random auditing influences the probability of winning current projects for competitors. The higher the frequency of audits conducted by the regulator, the greater the utility for those who do not complain, thereby reducing the probability of reporting cases by competitors. The results are presented in Figure 2.10b. Random auditing discourages some self-initiated complaints from competitors. With a 50% auditing frequency, the complaint rate decreases by 6%. However, the deterrent effect is modest since, in practice, the frequency of random audits is very low—less than 1%—due to budget constraints and the vast volume of procurement projects.

[15] 100% whistleblower protection is not typically favored due to concerns of moral hazard, where full protection or monetary rewards might encourage individuals to report false cases.

Figure 2.10: Counterfactual Policies



(a) Protect the Names of Complainants



(b) Introducing Random Auditing

2.8 Conclusion

This paper originates from the observation within the complaint dataset that investigations and the reassignment of contracts are most frequently triggered by complaints from close losers who have significantly lower price bids than the winners. I applied the regression discontinuity design (RDD) to the complaint dataset and identified statistically significant gaps in price bids between the close-losing complainers and the winners. Furthermore, I demonstrated that in highly competitive auctions, assuming closely contested bids, the characteristics of losers and winners are alike, with no statistically significant differences.

Simultaneously, I applied RDD to the comprehensive public procurement scoring auction data and discovered similar, albeit smaller, gaps in price bids and other firm characteristics, such as state-owned connections and geographical distance to the procurement department. These results indicate violations of competitive auction principles, and the observed positive price gaps between winners and losers further suggest the presence of corruption. The RDD findings are corroborated by results from corruption investigations, revealing that the gaps identified in prior tests vanish in projects conducted immediately after such investigations.

Employing the price bid as an indicator of potential corruption, I explore the decision-making process behind complaint submissions and analyze the scarcity of complaint cases. The likelihood of winning current projects based on corruption signals, the risk of losing future projects as retaliation, and other retaliatory costs are all significant considerations. A complainer protection policy could enhance the effectiveness of the complaint system.

Investigating how to refine the complaint system to promote honesty while also mitigating moral hazard issues presents important avenues for future research.

Chapter 3

Beyond Direct Impact: Tracing the Total Effects of Public Procurement Through Production Networks

[1]

3.1 Introduction

Public procurement, as one of the largest components of government spending, is regarded as a powerful tool for stimulating aggregate economic activity and employment. This is because public procurement contracts help firms grow, implement industrial policies, and generate economic multipliers through the complex input-output network. This aspect is especially crucial for developing countries, where many firms are small and underperforming (Tybout, 2000). While the macroeconomics literature has studied the economic multipliers using macro data (Ramey, 2011), little has been explored regarding the role of input-output linkages as a channel for the propagation of public procurement from a micro perspective.

In this paper, we investigate the direct and indirect effects of winning public procurement contracts on firms and provide a quantification of public procurement propagation through input-output linkages. Providing a complete answer to these questions is challenging due to two constraints. First, although public procurement data has recently become available, it has been challenging to link this data to firm network data, especially to the entire economy's production network. Without network data, tracing the effect of public procurement at the firm level throughout the economy is impossible. Second, procurement contracts are usually not awarded exogenously. Without identifying close competitors, it is difficult to construct control groups to derive causal interpretations.

[1]This chapter is coauthored with Wei Lin (CUHK-Shenzhen, linwei@cuhk.edu.cn) and Ming Li (CUHK-Shenzhen, liming2020@cuhk.edu.cn).

To overcome these challenges, we use the rich value-added tax data that captures firm-to-firm level universe transactions from China, along with public procurement bidding and contract data. These large-scale datasets allow us to trace the input-output linkages among firms. Based on the data, we use an event study design to estimate the direct effects of winning public procurement contracts by comparing winners and losers in the same contract competition. We study the effects on both the firm annual performance and the first layer of upstream input purchases and downstream output sales, uncovering changes in total sales or purchases, the number of sellers or purchasers, and their characteristics. Then, we derive a model-based measurement of the total ratio of public procurement contracts to sales by considering both direct and indirect sales to governments. Finally, we explore the effects of the propagation of public procurements on firm revenues.

The paper consists of three parts. First, we introduce a new database of public procurement contract data from one province in China and the universal firm-to-firm VAT transaction data from the National Tax Bureau. We have matched these datasets with firm registration data and firm annual performance data from the Administration for Industry and Commerce. We explore the effects of directly winning public procurement contracts at both the firm-year and project levels. At the firm-year level, we aggregate the total size of public procurement contracts by year and regress this on firm performance measurements, such as total revenue, net income, and asset growth. We find that the size of public procurement contracts is positively related to larger growth in income and assets.

For the project-level analysis, we focus on the timing when a firm outcompetes others to win a contract. We concentrate on projects between 2017 and 2018 and plan to expand this as more data becomes available. We compare firms that won a contract to those that lost in the same project competition, using the assumption that those who lost provide a credible counterfactual for those who won. After controlling for firm fixed effects and common shocks to the same city-industry-project over time, we estimate the coefficients for the six months before and after the procurement project as the entire event window. We find that firms winning a public procurement contract experience a strong and persistent increase in purchasing activities over the following six months. Specifically, in the first two months, winning firms make 5% more purchases from 7% more buyers.

Regarding selling activities, there may be concerns that public procurement contracts crowd out other private contracts by reducing the bandwidth of firms. However, we find that winning public procurement contracts helps firms attract more buyers from the private sector, leading to higher sales, not including the public procurement contracts themselves. We also explore the heterogeneous effects between potentially corrupt public procurement contracts and competitive ones, finding that more selling effects come from competitive cases.

In the second part of the paper, using firm network data from firm-to-firm transactions, we propose a method to measure the total ratio of public procurement-driven contracts to firms' sales, considering both direct and indirect contracts through input-output linkages. Using the firm sale ratio matrix, we can calculate the total ratio of public procurement for every firm. Focusing on direct contracts, in the year 2018, only 0.5% of firms participated in the public procurement supply chain, and for most of these firms, public procurement contracts accounted for less than 10% of their total sales. By measuring indirect procurement contracts, we find more firms involved in the public procurement supply chain, and the ratio of public procurement contracts to total sales is also higher. We then explore the differences in the characteristics of firms that directly and indirectly participate in the public procurement supply chain. Firms with direct contracts are more likely to be downstream in the production network.

In the last part of the paper, we leverage relatively exogenous demand shocks from the public procurement plan to study the propagation effect of public procurement contracts on firms' revenues. We regress the percentage change in total sales on the percentage change in exogenous public procurement demand. The exogenous change in public procurement demand is constructed using the public procurement plans from different cities and product categories and is weighted using the previous firm production network. The results will be shown once we gain access to data for additional years.

Our paper is related to three strands of literature. First, this paper contributes to the expanding literature studying policies aimed at increasing demand to help firms grow in developing countries. Most papers (Atkin, Khandelwal, and Osman, 2014; Alfaro-Urena, Manelici, and Vasquez, 2022) focus on the effects of joining exporting and multinational supply chains on firm growth. Government expenditure, as one of the most powerful policy tools to stimulate domestic demand, is less studied, with an exception Ferraz, Finan, and Szerman (2015). It examines the effects of government purchases by comparing firms that won procurement contracts to those that did not and finds significant positive effects. The event study on directly winning public procurement contracts is similar to that in Ferraz, Finan, and Szerman (2015), but with more exploration into possible corruption in the public procurement competition. Additionally, we not only focus on the direct winning but also look into the total public procurement ratio by using production network data to provide a comprehensive analysis of government demand on firm and economic growth.

This paper also relates to the literature on the propagation of shocks through the production network originating from Acemoglu et al. (2012). A group of papers (Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2017; Huneeus, 2018; Baqaee and Farhi, 2019; Bouakez, Rachedi, and Santoro, 2023) builds on the multisector model to study how the propagation of micro-level shocks over the production network translates into large aggregate economic impacts. However, with the restriction of data availability, the role of the economic production network as a propagation mechanism is unexplored. Recently, some empirical studies (Foerster, Sarte, and Watson, 2011; Di Giovanni, Levchenko, and Mejean, 2014; Atalay, 2017) rely on strong assumptions to back out the shock effect from macro data. With more firm production network data, studies (Boehm, Flaaen, and Pandalai-Nayar, 2019; Carvalho et al., 2021; Dhyne et al., 2021; Demir et al., 2024) look into shocks, such as earthquakes and international trade, to provide evidence on the propagation of shocks through production networks. This paper is the first to explore the public procurement angle.

Third, we also add to the literature on corruption in public procurement. Research (Baltrunaite, 2020; Baltrunaite et al., 2021; Colonnelli and Prem, 2021; Brugués, Brugués, and Giambra, 2022; Cao, 2022; Chen, 2023) has consistently shown that politically connected firms are more likely to succeed in winning procurement awards. This paper explores the heterogeneous effects of winning corrupt and non-corrupt contracts and discusses how corruption in public procurement affects the economy through direct and indirect channels.

The paper proceeds as follows. Section 3.2 describes the data and background of public procurement policy in China. Section 3.3 presents the results of directly winning public procurement contracts on firm annual performances, upstream purchasing activities, and downstream selling activities. Section 3.4 provides the method and measurements of the total ratio of public procurement contracts to sales. Section 3.5 provides evidence of the impact of public procurement contracts through network propagation on firm revenues. Section 3.6 concludes.

3.2 Data and Background

3.2.1 Data

3.2.1.1 Public Procurement Data

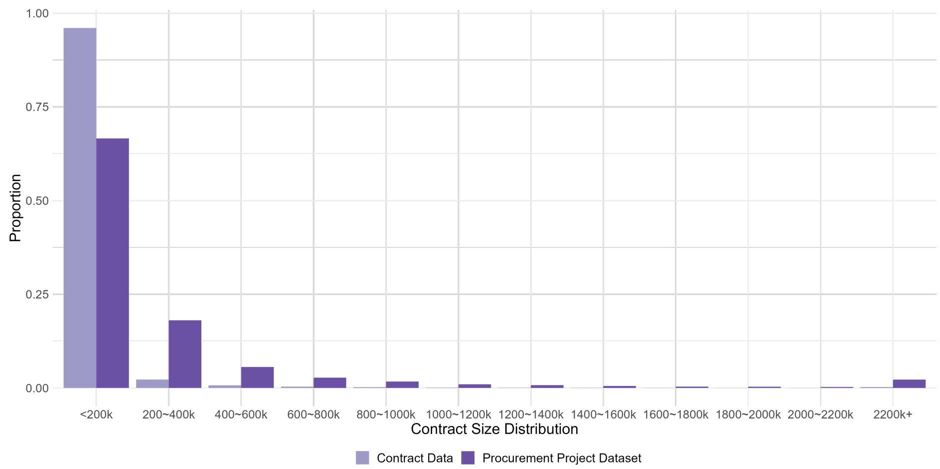
The public procurement database of Guangdong comprises two major datasets: one includes all contracts, regardless of the project's size or the procurement methods used from 2016-2020, and the other consists of procurement projects with large budget sizes purchased through negotiation or open auctions from 2010-2020.

The contract dataset contains information on the procurement government department, the name of suppliers, the contract name, the total contract size, and the contract's effective date. Unlike the other nationwide data used in Liu et al. (2023), which only displays large procurement projects with publication requirements, this dataset is comprehensive, covering contracts of all sizes with detailed information on suppliers and contract sizes.

The procurement project dataset, focusing on large budget sizes acquired through negotiation or open auctions, offers rich information. To my knowledge, I am the first to compile such a dataset at the provincial level. With improvements in transparency, all large procurement procedures, except those related to national secrets, are required to be publicly traceable. This dataset includes three primary subsets: procurement plans, procurement announcements, and outcomes. The procurement plan dataset details procurement objects, purchaser names, reserve prices, and procurement methods. The procurement announcement dataset provides specifics about the bidding process, while the outcome dataset lists bidder names, bid prices, and scores. Compared to the contract dataset, the procurement project dataset offers insights beyond the final supplier, detailing the competition among bidders.

To compare the coverage differences between the two datasets, I plotted the distribution of budget sizes in Figure 3.1. The darker bars represent the contract data, and the lighter bars represent the procurement project dataset. As shown in the graph, the contract data are more complete and include a larger number of small-sized contracts, while the procurement project dataset is skewed towards large projects.

Figure 3.1: Distribution of Budget Size Cross Different Datasets



3.2.1.2 Firm Administration Data

The Industrial and Commercial Enterprises Registration Database encompasses the administrative details of all Chinese companies, including over 80 million registered entities since 1949, even those that have been deregistered or revoked. This dataset offers invaluable, detailed information such as company names, addresses, registration dates, types, industry categories, registered capital, and dates of deregistration or revocation, among other company registration-related variables. The State Administration for Industry and Commerce (SAIC) provides this database, representing the most thorough and comprehensive information source on commercial activities throughout all regions and industries in China. The basic information of firms is frequently updated.

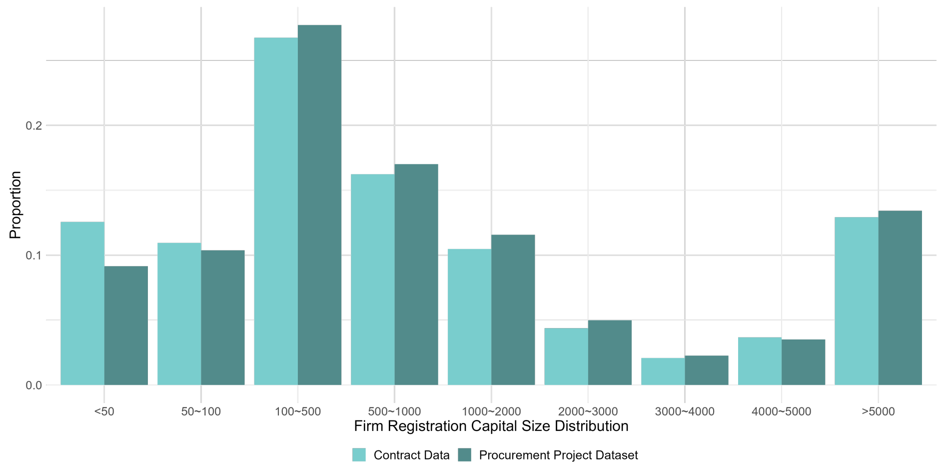
Beyond firm registration data, the State Administration for Industry and Commerce (SAIC) also works collaboratively with the Tax Bureau to monitor the annual performance reports of each active firm entity. These reports contain data on main business revenue, total revenue, profits, liabilities, fixed investments, and loans, offering a reliable method to track the changing performance of firms over time.

We have cleaned company names in the public procurement dataset, linking them to firm registration data to trace all participants in the public procurement supply chain. Furthermore, we established pairs of bidders and procurement departments, which were then used to calculate geographical distances using QGIS.

Although the contract size in the dataset is considerably smaller, after linking the suppliers to the firm's administrative database, the distribution of capital sizes among suppliers in the contract dataset closely resembles that in the procurement project dataset, as illustrated in Figure 3.2. In this figure, the lighter bars represent the contract data, and the darker bars represent the procurement project data.

When examining the procurement project dataset in detail, I compare the characteristics of the winning firms with those of the firms that finished second. There are numerous

Figure 3.2: Distribution of Registration Capital Size



(a) Cross Different Datasets

(b) Between Winners and the 2nd in the Procurement Project Data

differences. For example, as illustrated in Figure 3.2(b), the registered capital size of the winning firms is systematically larger than that of the second-place firms. A more detailed comparison of summary statistics is shown in Table C1 in the Appendix.

3.2.1.3 Firm-to-Firm Transaction Data

The firm-to-firm dataset tracks the near universe of formal firm-to-firm relationships in China between 2015 and 2019. This information is collected by the National Tax Bureau through the Tax Information and Invoice Information from each transaction invoice. The invoice represents extremely detailed information on the daily operations of a company, and at a micro level, it can truly reflect the tax-related business activities of a company. Figure C1 shows a sample of input and output invoices, from which one can intuitively see that the invoice reflects a wealth of value information, including the names of the buyer and seller, bank information, invoice issuance time, invoice amount, type of invoice, name of goods, the unit of goods, the tax rate of goods, and the status of the invoice (red-inked/canceled), among others. This data plays a crucial role in the enforcement of the general sales tax and corporate income tax.

The super-rich dataset not only can help us measure the performance of firms but also track the complicated linkages in the supply chain network. We are the first to use this multi-year firm-to-firm transaction dataset.

3.2.2 Public Procurement Background

3.2.2.1 Procurement Procedure

In China, the way the government buys goods and services follows rules set out in the Public Procurement Law and other detailed regulations. This buying process is split into three parts: before buying, the actual buying, and after buying. At the start, the buyer, usually a government office or a company owned by the state, figures out what it needs and makes a plan. This step involves checking if the project is possible and listing the specific goods, services, or construction work needed.

Once the needs are clear, the buyer completes a plan that spells out the project details, how they'll choose what to buy, the budget when things need to happen, and how they'll pick the suppliers. This plan is then checked and needs to be okayed by relevant government watchdogs, often including the people who check finances and the people who audit.

Picking how to buy depends on certain rules. Sometimes, if there's only one company that can supply what's needed, or in emergencies, they might go directly to one supplier. This method is also used when it's important to keep things consistent or stick with services already in use. For bigger projects, they have to use a process where everyone knows what's being bought, and companies compete openly. For smaller buys, there are different options like inviting only certain companies, online bidding, or just asking directly for prices. However, for big projects, open competitions are preferred because they're watched more closely, which helps prevent overspending and corruption. Studies have shown that when buys aren't open, it often costs more and there's a higher chance for dodgy deals. This paper pays special attention to the open bidding process.

After the buying plan is approved, the buyer has to share information about what they're buying, how, and for how much on websites for everyone to see. This includes what's being bought, the budget, and the timeline. Rules say an open auction needs at least three companies competing to be considered valid. If only two companies are interested, experts might have to review the plans and decide whether to try the auction again or choose a different method. If there's only one bidder, experts might allow buying from that single source if they agree the plans were fair and followed competition laws.

3.2.2.2 Policy Levers

Like many other countries, China takes public procurement as a very important policy lever. The functions of government procurement policy primarily include the following: First, support for special entities. This includes support for small and medium-sized enterprises (SMEs), enterprises benefiting people with disabilities, and areas emerging from poverty, as well as encouraging the industrial development of innovative products and environmentally friendly products. Second, promotion of employment, environmental protection, and innovation incentives. Government procurement focuses not only on the purchasing function but also on policy functions such as promoting employment, protecting the environment, and encouraging innovation. Third, ensuring national security, governing administrative corruption, and the reasonable allocation of rights and interests. This has significant functional effects in the political domain.

Fourth, saving on public spending and improving the efficiency of procurement funds. By implementing a government procurement system, policies that protect domestic industries, support underdeveloped areas, and SMEs can be promoted. Fifth, Encouraging the purchase of domestic goods and supporting SMEs and private enterprises. This helps to promote the development of the national industry, encourage enterprise innovation, and alleviate domestic employment pressure. Sixth, supporting the development of underdeveloped areas and ethnic minority regions. By reserving government procurement quotas and other means, enterprises in these areas can have a stable market and reasonable profits. Lately, strengthening institutional construction. Following principles of openness, transparency, fair competition, justice, and honesty, to avoid issues such as "exorbitantly priced procurement" and ensure the effective execution of system norms.

Given the ambitious goals of public procurement, evaluating its effects on firms and the economy is crucial.

3.3 Direct Effects of Public Procurement Contracts

In this section, we examine the direct effects of winning procurement contracts on firms from three perspectives: annual firm performance,[2] upstream purchasing, and downstream selling.[3]

3.3.1 Firm Performance

First, we are interested in the direct effect of procurement projects on firm performance. Since the firm performance data are derived from annual firm tax reports, we aggregate

[2]Annual firm performance data consist of annual panel data, which include firm vendor revenue, main business revenue, net income, total asset change, liability change, and profit change.

[3]Upstream purchasing and downstream selling data are derived from transaction data related to the supply chain.

each firm's total winnings from public contracts throughout the year. We then estimate a reduced-form equation as follows:

$$Firm_{it} = \beta_0 + \beta_1 Government\ Contract_{it} + \beta_2 X_{it} + \alpha_i + \alpha_t + \epsilon_{it}$$

where $Firm_{it}$ represents the performance variables of firm i in period t, including main business revenue, total revenue, profit, and liability. $Government\ Contract_{it}$ measures the total winning government contracts. X_{it} represents other firm characteristics. α_i is a fixed firm-level effect, and α_t is a fixed time period-level effect. Given that we have two procurement datasets—the complete contract dataset and the large procurement project dataset—we can calculate the total amount won by each firm each year using both datasets.

Table 3.1: Public Procurement Contracts and Firm Performance

	Vendor	Main	Net	Ass Gro	Lia Gro	Pro Gro	Rat Gro
Total PP Contracts	0.037***	0.031***	0.050***	0.022***	0.029***	0.053***	0.031***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Noncorrupt Contracts	0.022***	0.016***	0.034***	0.016***	0.021***	0.035***	0.021***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Corrupt Contracts	0.035***	0.030***	0.048***	0.019***	0.026***	0.049***	0.029***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Obs	462868	382738	523270	518899	517326	516828	524257
Firm FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y

Notes: (1) The dependent variables for each column are taking the inverse hyperbolic of the absolute values of vendor income, main business income, net income, asset change, liability change, profit change, and rationality change. (2) We take the inverse hyperbolic of the total public procurement contracts (3) Each regression includes the firm fixed effects, year fixed effects, and the industry×city×year fixed effects. (4) Standard errors in brackets are clustered at the firm level.

Table 3.1 presents the results using the large procurement project dataset, which includes both winners and losers. For losers in the projects, the contract size is zero, while for winners, the contract size equals the winning bid. In the first panel, we pool all contracts. A 1% increase in the winning contract amount can increase vendor income by 0.04%, main income by 0.03%, and net income by 0.05%. Since vendor income is part of the main income, it is natural that the effect of winning contract amounts on vendor income is smaller than on main income. The impact on net income is larger than on both vendor and main income, considering that on average vendor income is 76 times the net income. This suggests that public procurement contracts are more profitable than private contracts. Furthermore, a 1%

increase in public procurement contracts is associated with a 0.02% increase in total asset change and a 0.03% increase in liability change.[4] Additionally, the dependent variable in the sixth column is the change in profits, consistent with the results in net income, indicating that public procurement contracts are profitable.

In the second panel, we break down the procurement projects by whether the project is predicted to be corrupt or not in Chen (2023). The first two rows are the coefficients estimated associated with noncorrupt contracts and the next two rows are for the corrupt contract. Overall, a 1% increase in corrupt contract amounts leads to higher increases in all the performance measures. The comparison makes sense that the corrupt contract size is 2.5 times the noncorrupt contract size. However, we can see the effects of corrupt contracts are not 2.5 times as the noncorrupt, which might show that corrupt contracts are not as powerful as noncorrupt contracts to transfer to firm performance.

In the second panel, we break down the procurement projects by whether the project is predicted to be corrupt or not, as outlined in Chen (2023). The first two rows present the coefficients estimated for non-corrupt contracts, and the next two rows are dedicated to corrupt contracts. Overall, a 1% increase in the amount of corrupt contracts leads to higher increases in all performance measures. This comparison is logical given that the size of corrupt contracts is 2.5 times that of non-corrupt contracts. However, the effects of corrupt contracts are not 2.5 times those of non-corrupt ones, suggesting that corrupt contracts may not be as effective as non-corrupt contracts in contributing to firm performance, especially regarding firm asset investment growth.

For the complete contract dataset, we have all the suppliers and contracts regardless of the contract size; however, there is no information about the competitors. Therefore, we link the contract dataset with all firms in the province and calculate the contract amount for each firm in each year. The difference between this specification using the contract dataset and the previous one using the procurement project dataset is significant. The earlier exercise includes firms that participate in the public procurement competition, while the current exercise includes all firms in the province, regardless of whether they have ever directly participated in the public procurement competition.

Though the results are consistent, we need to interpret them with caution due to two potential sources of bias affecting causal relationships. First, even if we cover all public procurement contracts within the province, it's possible that firms winning public procurement contracts from other provinces are not accounted for, potentially leading to an underestimation of the coefficients. On the other hand, public procurement contracts can crowd out private contracts, which might cause overestimation. Second, especially in the contract dataset where competitors are unobserved, using all firms from the province introduces a selection problem.

[4] Asset and liability changes are calculated by subtracting the value from the previous year from the value in the current year.

3.3.2 Purchase Transactions: Upstream

To find causal evidence of the impact of winning public procurement contracts on firms, as well as to examine the supply chain, we utilize firm-to-firm transaction data linked to the public procurement project dataset. We first focus on purchase transactions, which are upstream in the supply chain. To measure the dynamic effect of winning a public contract on firms' purchasing activities, we use the difference-in-difference event study framework as below:

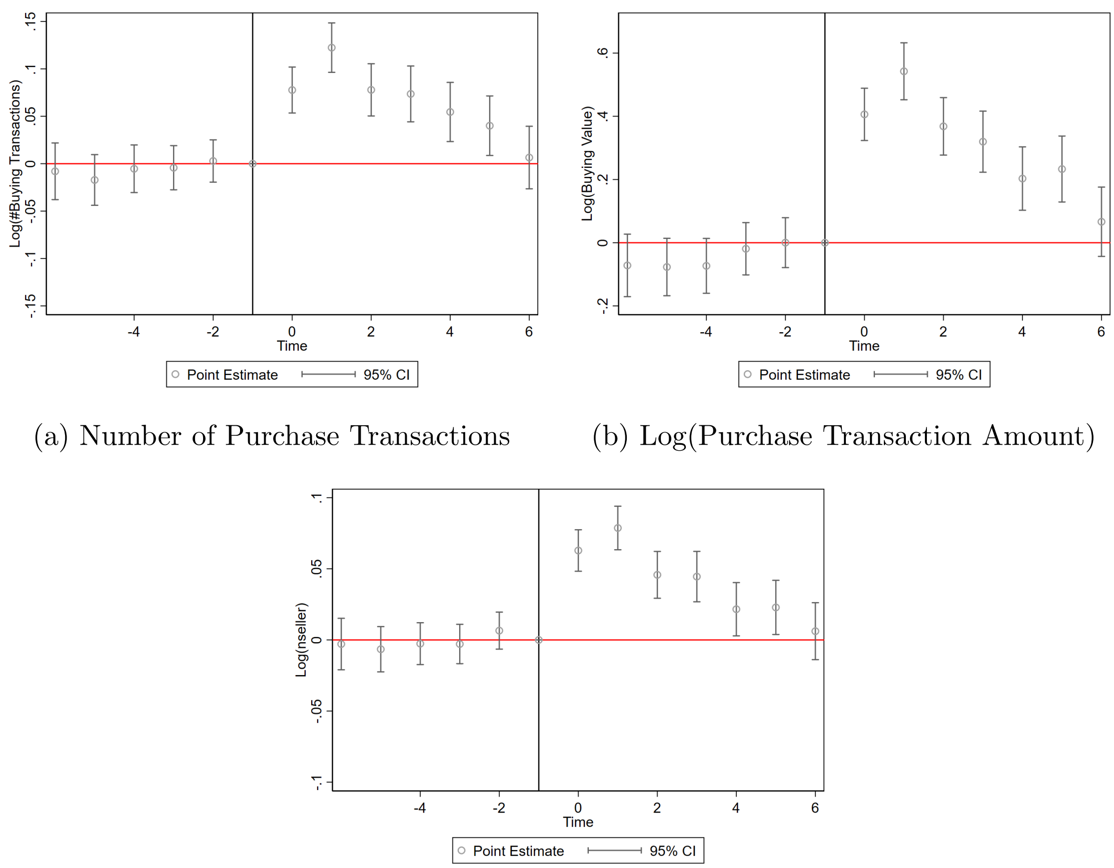
$$Purchase_{ipt} = \sum_{j=-6, j\neq -1}^{6} \gamma_j \mathbb{1}\{Month\ to\ Winning_{ip} = j\} + \alpha_i + \alpha_p + \alpha_t + \epsilon_{ipt}$$

where $Purchase_{ipt}$ represents measures of purchasing activities for firm i in month t related to procurement project p. These measures include the total purchase amount, the number of purchase transactions, and the number of different upstream purchase suppliers. γ_j captures the lags and leads around the winning contracts window up to six months. The first lead $\gamma_{j=-1}$ is excluded as a normalization, and the other leads are to measure pre-trend, assuming $\gamma_{j<-1} = 0$ for the event study. Lags $\gamma_{j>0}$ capture the dynamic treatment effects of winning a public procurement contract. α_i, α_p, and α_t represent the firm, procurement project, and time fixed effects, respectively. For winners in the public procurement competitions, they have time indicators relative to the winning time points, while for losers, they are in the control group, and the coefficients for both lags and leads are set to 0. To avoid the same firm winning multiple contracts within the event window, I selected procurement projects whose winners only won once in the -6 to 6 event window.

Results are shown in Figure 3.3. The dependent variable in (a) is the log of the total purchase amount. In the month of winning the public procurement contract, the total purchase transaction amount jumped by 8%, and in the following month, it was even higher at around 12%. Then, the increase decreases over time. The peak at +1 month can be attributed to the contract signing timeline and preparation for input purchases. The graph indicates that upon winning the contract, the firm started purchasing more inputs for the new contract, and the increased purchase activities continued until the sixth month. The dependent variable in (b) is the log of the total number of purchase transactions, which increased by 50% in the first month. Similarly, in (c), where the dependent variable is the log of the total number of different sellers the firm purchased from, there was an 8% increase in the first month. The comparison of the change between the total number of purchases and the number of sellers indicates that winning a public procurement contract leads firms to make more purchases from a concentrated group of suppliers, rather than a more diverse group of suppliers.

Different industries have different supply chains, and the effects of winning public procurement contracts vary widely. For instance, in product procurement, factories regularly purchase input materials based on the contracts they secure and store these inputs for later production; therefore, we expect to see a clear jump pattern. Additionally, because the cycle of product production is very short—usually requiring delivery within several months—there

Figure 3.3: Direct Effects of Winning Public Contract on Upstream Purchase



(a) Number of Purchase Transactions (b) Log(Purchase Transaction Amount)

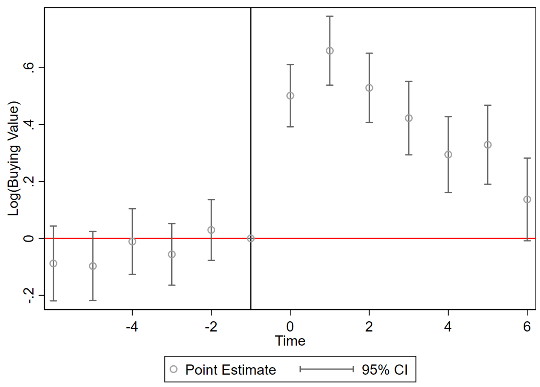
(c) Number of Sellers

Notes: In the event study, we control for public procurement project fixed effects, firm fixed effects, month fixed effects, and city-industry-project time fixed effects. We only use public procurement projects whose winners won only once during the event window to rule out the possible overlap of multiple projects. Standard errors are clustered at the firm level.

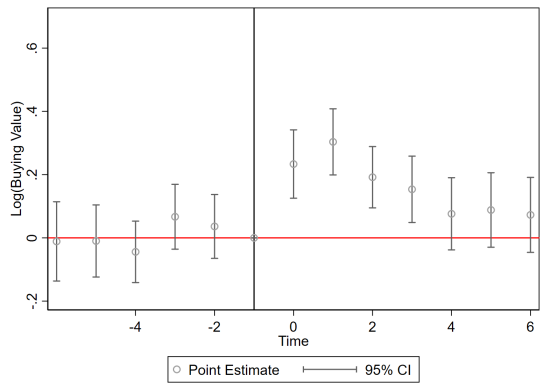
are no long-lasting effects in this short window. In contrast, construction and service procurement projects involve substantial labor costs and salaries. Since salary payments are not included in the tax transaction data records, we expect to see a smaller increase pattern compared to product procurement. Also, construction and service projects span a longer period, resulting in relatively longer-lasting effects. We compare the total purchase values and the number of sellers from which firms purchase in Figure 3.4. The results are consistent with the different characteristics of the procurement projects.

We link the corruption predictions for each procurement project presented in Chen (2023) to firm purchase transaction data and explore the differences between corrupt and non-corrupt projects as shown in Figure 3.5. When comparing the graphs in the left column

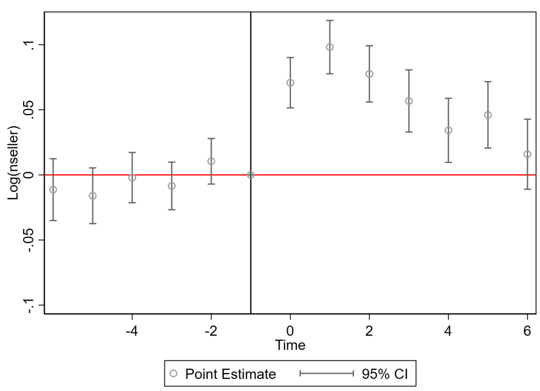
Figure 3.4: Direct Effects of Winning Contract on Purchase: by Categories



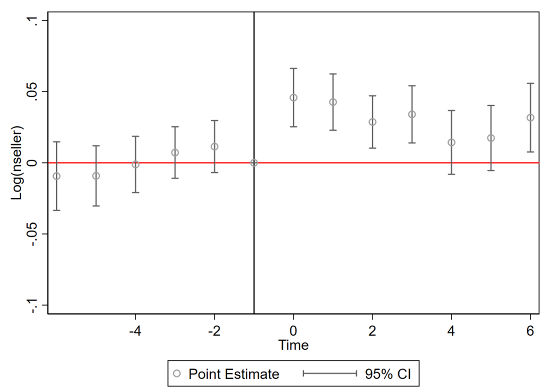
(a) Log(Purchase): Product



(b) Log(Purchase): Construction/Service



(c) Number of Sellers: Product

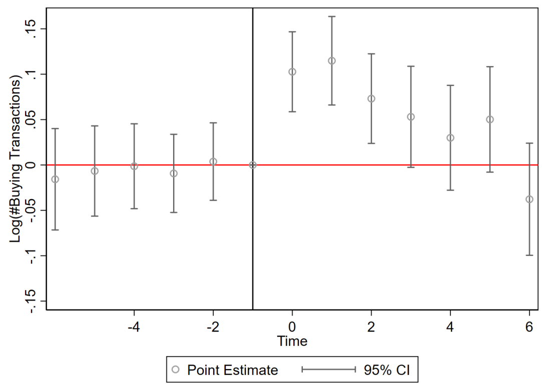


(d) Number of Sellers: Construction/Service

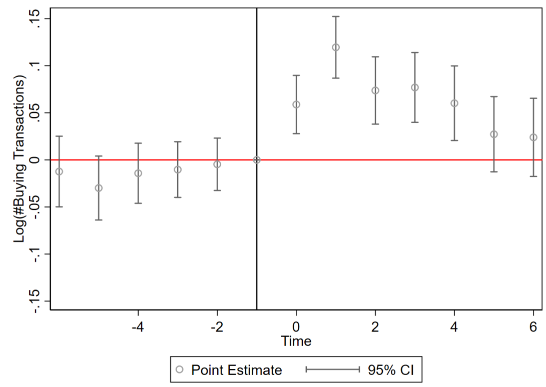
Notes: In the event study, we control for public procurement project fixed effects, firm fixed effects, month fixed effects, and city-industry-project time fixed effects. We only use public procurement projects whose winners won only once during the event window to rule out the possible overlap of multiple projects. We separate the projects into product projects and construction or service projects. Standard errors are clustered at the firm level.

to those in the right column, the magnitudes of the increases in purchase transactions are similar; total purchase amounts and the number of transactions increase by approximately 12% and 50%, respectively, and the number of sellers increases by 8%. However, differences emerge in the post-trend period. For non-corrupt procurement projects, purchase transactions increase immediately in the first month, whereas for corrupt projects, transactions peak in the second month. Additionally, the increase in transactions phases out more quickly for non-corrupt projects compared to corrupt projects.

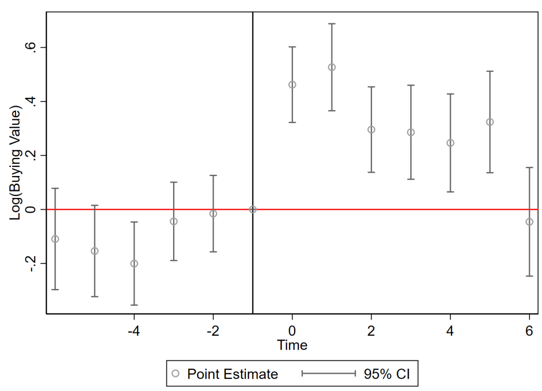
Figure 3.5: Direct Effects of Winning Contract on Purchase: Corrupt V.S. Noncorrupt



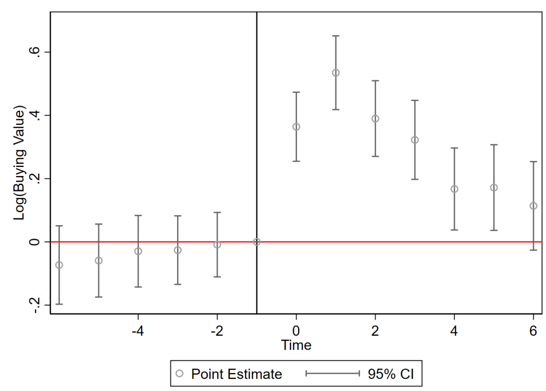
(a) Number of Purchases: Noncorrupt



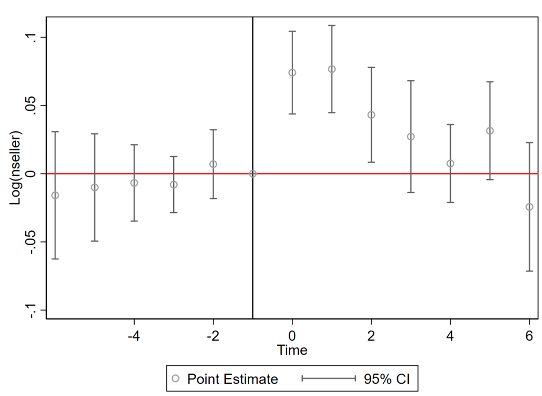
(b) Number of Purchases: Corrupt



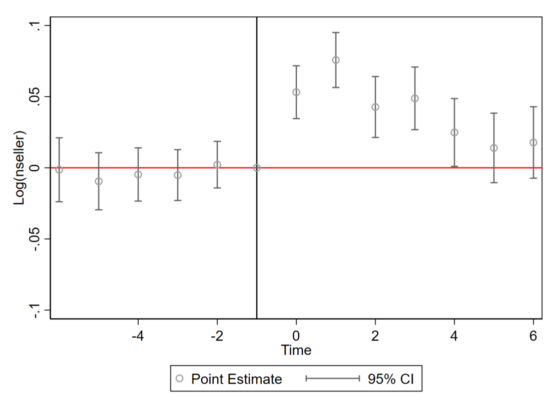
(c) Log(Purchase Amount): Noncorrupt



(d) Log(Purchase Amount): Corrupt



(e) Number of Sellers: Noncorrupt



(f) Number of Sellers: Corrupt

Notes: In the event study, we control for public procurement project fixed effects, firm fixed effects, month fixed effects, and city-industry-project time fixed effects. We only use public procurement projects whose winners won only once during the event window to rule out the possible overlap of multiple projects. Standard errors are clustered at the firm level.

3.3.3 Sell Transactions: Downstream

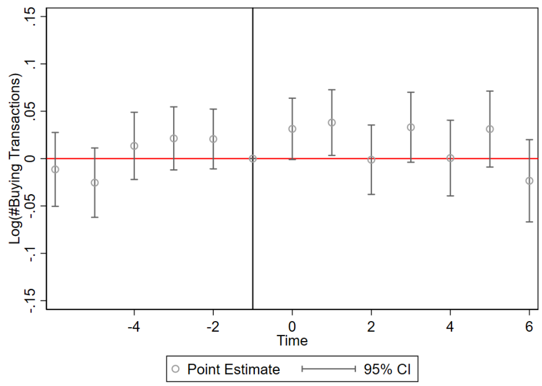
Shifting our focus from purchase to sell transactions downstream in the supply chain, we study the effects of winning public procurement contracts on the number of sell transactions, total sell amount, and the number of purchasers. Similar to purchasing behaviors, which are highly contract-based, the effects on selling transactions are ambiguous in terms of directional change. On one hand, winning a public procurement contract represents a significant transaction that increases sales. On the other hand, there could be a crowd-out effect; firms that win public contracts might face backlogs, limiting their capacity to fulfill private contracts, thus the overall effects remain unclear.

The general results are depicted in Figure 3.6. Figure (a) shows the pattern in the number of sell transactions. Following the win of a public procurement contract, sell transactions increase by 3% in the month of and the first month after the win, predominantly due to the direct impact of the public procurement contract. However, positive effects persist into the third and fifth months, providing evidence of a multiplier effect from winning public procurement contracts that enhances efficiency and attracts other private contracts. Figure (b), with the dependent variable being the log of the total selling amount, shows a consistent increase in selling activities by 15% following public procurement wins, further demonstrating how such wins can help firms secure additional contracts. Lastly, in Figure (c), where the dependent variable is the number of buyers, there is a statistically significant increase of about 2%. This smaller magnitude, compared to the total sell amount, is justified since a large public procurement contract is counted as only one buyer. The modest increase in the number of buyers indicates that a small proportion of the increase in sell amount comes from new buyers, while the majority is from existing buyers.

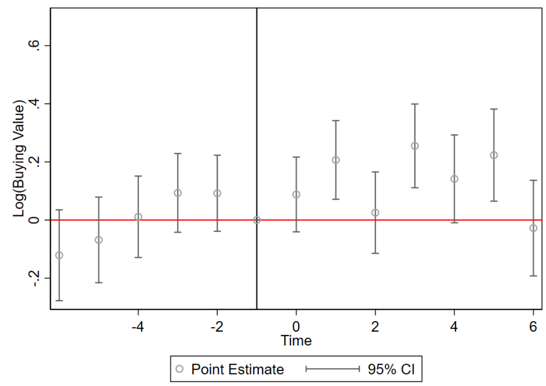
To further rule out concerns that public procurement contracts might crowd out other private contracts, we exclude sales to government agencies from the dependent variables and include only non-public procurement sale transactions. The results are shown in Figure 3.7. Compared to Figure 3.6, we find that the increase pattern in sales transactions remains, and the magnitude of the coefficients on lags is very similar. Overall, the results indicate that winning public procurement contracts does not crowd out other contracts and has a spillover effect that aids in securing additional contracts.

We also distinguish between corrupt and non-corrupt procurement projects in Figure 3.8. The left column presents the results from winning non-corrupt public procurement contracts, and the right column those from winning corrupt contracts. Comparing these, we observe clear and significant positive effects on subsequent selling activities from winning non-corrupt contracts—sell transactions increase by 7%, total selling value by 30%, and the number of buyers by 4%. In contrast, winning corrupt contracts yields muddled effects. For instance, there is no immediate reflection in sell transactions in the month of winning corrupt contracts. This could be due to two reasons: the large scale of corrupt contracts might crowd out regular private contracts, leading to no overall increase, or it might involve illegal qualification affiliations. In such cases, corrupt firms may borrow certificates and names from other companies and manipulate scoring rules through corrupt officials to eliminate

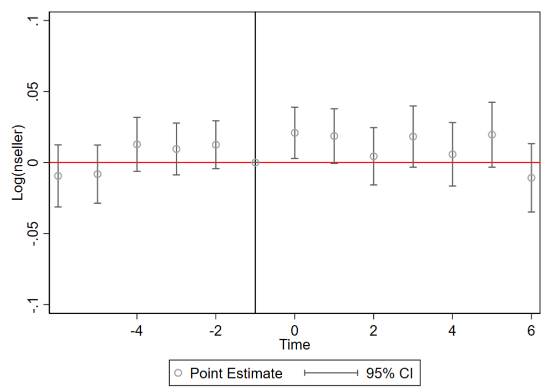
Figure 3.6: Direct Effects of Winning Public Contract on Downstream Sell



(a) Number of Sell Transactions



(b) Log(Sell Transaction Amount)



(c) Number of Buyers

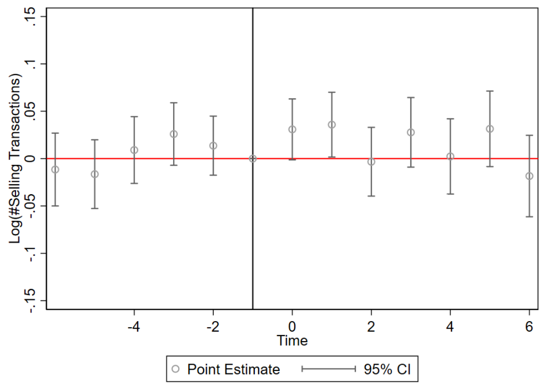
Notes: In the event study, we control for public procurement project fixed effects, firm fixed effects, month fixed effects, and city-industry-project time fixed effects. We only use public procurement projects whose winners won only once during the event window to rule out the possible overlap of multiple projects. Standard errors are clustered at the firm level.

competition. Once they win, the corrupt firms, rather than the legitimate certificate holders, end up implementing the contracts. Further investigation into the identity of buyers could help determine the predominant reason behind these observations.

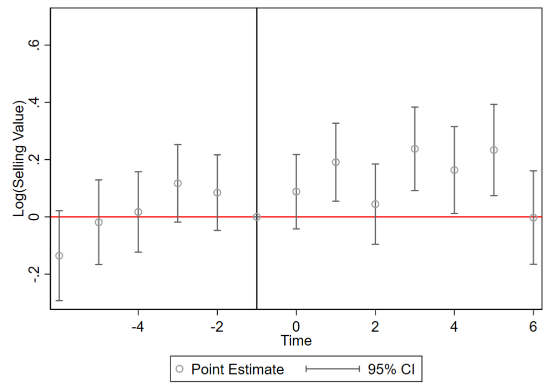
People might be concerned about comparing winners and losers in corrupt cases since winners are better connected with the government, and winners and losers might exhibit different trends. To test the robustness of the results, we restrict our sample to bidders in close-game auctions, where the absolute value of the winning margin is less than 5 points.[5]

[5]The winning margin is calculated by subtracting the highest score of the other bidders from the score of each bidder. Winners have positive winning margins, while losers have negative winning margins.

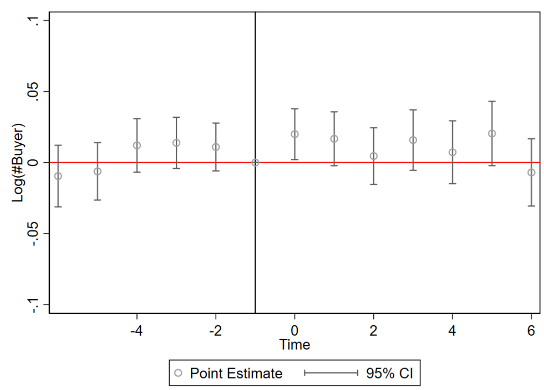
Figure 3.7: Direct Effects on Downstream Non-public Procurement Sell



(a) Number of Sell Transactions



(b) Log(Sell Transaction Amount)

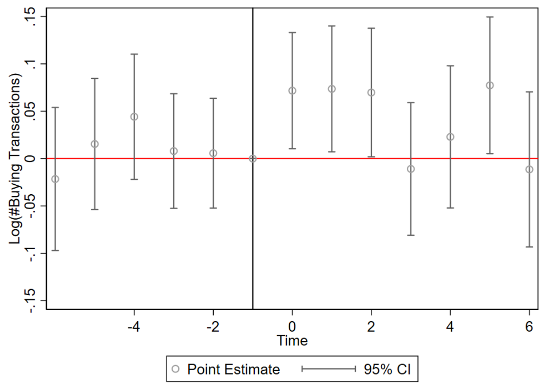


(c) Number of Buyers

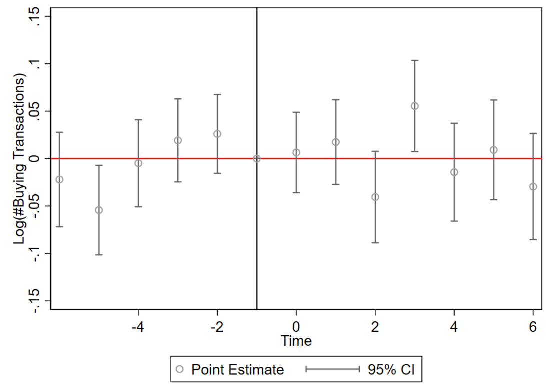
Notes: In the event study, we control for public procurement project fixed effects, firm fixed effects, month fixed effects, and city-industry-project time fixed effects. We only use public procurement projects whose winners won only once during the event window to rule out the possible overlap of multiple projects. We exclude the sales transactions where firms sell to organizations without a firm registration ID, most of which are government agencies. Standard errors are clustered at the firm level.

The results are shown in the Appendix. Figure C2 presents the direct effects of winning public contracts on purchases. The jump-up patterns and magnitudes are very similar to those in Figure 3.3, but with larger standard errors due to a much smaller sample size. Figure C3 presents the direct effects of winning government contracts on sales. Winning government contracts leads to more selling activities for firms compared to their close competitors who lost the competition, and the magnitude of the increase is larger than that observed in the full sample.

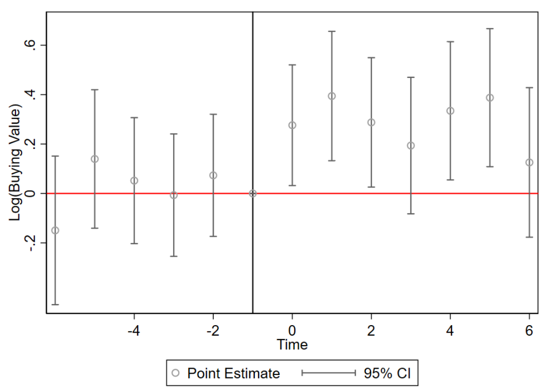
Figure 3.8: Direct Effects on Downstream Sell: Corrupt V.S. Noncorrupt



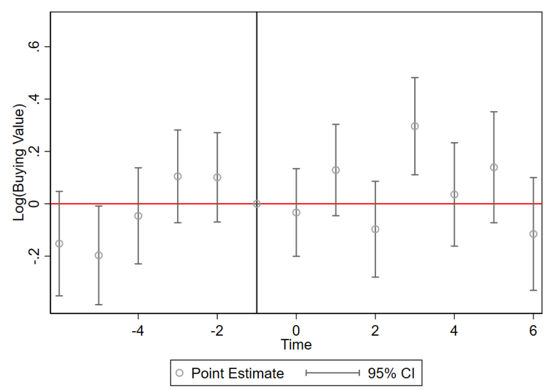
(a) Number of Sells: Noncorrupt



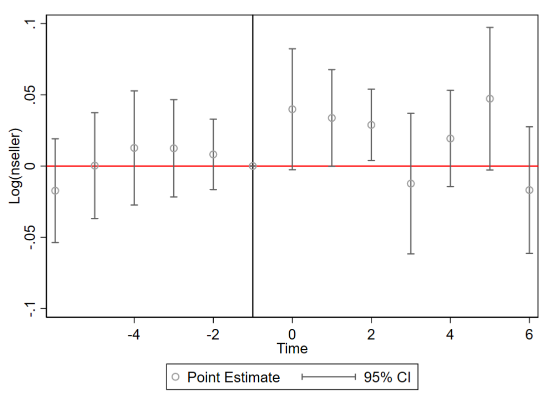
(b) Number of Sells: Corrupt



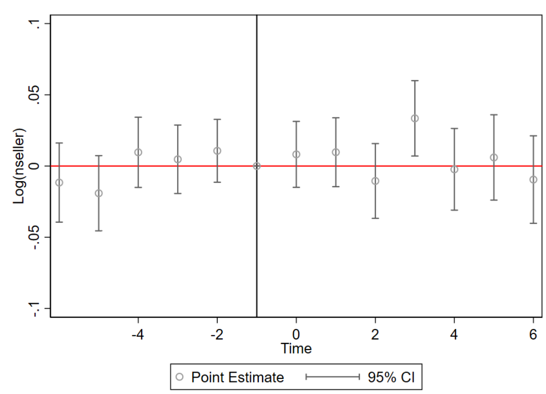
(c) Log(Sell Amount): Noncorrupt



(d) Log(Sell Amount): Corrupt



(e) Number of Buyers: Noncorrupt



(f) Number of Buyers: Corrupt

Notes: In the event study, we control for public procurement project fixed effects, firm fixed effects, month fixed effects, and city-industry-project time fixed effects. We only use public procurement projects whose winners won only once during the event window to rule out the possible overlap of multiple projects. Standard errors are clustered at the firm level.

3.3.4 Alternative Strategy

From the comparison between corrupt and non-corrupt procurement projects, it is evident that selections in corrupt cases often involve predetermined winners who invite two or more 'zombie bidders' to participate in the competition. To mitigate the issues introduced by these zombie bidders, we employ the propensity score matching method to select firms closely related to the winners from across the province.

For the winners of the procurement projects, we selected the closest firms using propensity score matching, based on factors such as industry, business scope, registered capital size, employee size, year of establishment, and location. We then repeated the above event study. Instead of using the actual losers in the procurement projects as a control group, we used the matched firms.

3.4 Indirect and Total Public Procurement Share

In the previous section, we studied how directly winning public procurement contracts affects firm performance and their direct upstream and downstream supply chains. Given that most public procurement contracts target very downstream products that directly reach the final consumer market, such as office products or cleaning services, the influence of public contracts is not just limited to the final market but also extends to the upstream supply chains. Many firms, especially those that produce raw materials and general inputs for downstream operations, are not directly involved in the public procurement supply chain but participate indirectly by supplying inputs. To study the role of public procurement on the entire economy, it's important to measure the indirect effects and the transmission of government demand through the supply chain.

3.4.1 Measurement

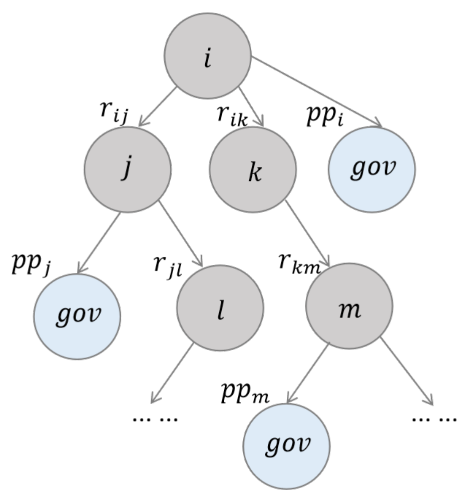
We measure the total public procurement production in a manner similar to the measurement of direct and indirect exports, as described by Dhyne et al. (2021) in their study on trade. A key assumption is that the firms' composition of inputs in production does not vary across different buyers, especially between the public and private sectors. The total public procurement production share of firm i, pp_i^{Total}, is defined as the sum of the share of revenue from direct public procurement contracts, pp_i, and the share of revenue from sales to other firms, which is then multiplied by the total direct public procurement contracts of those firms:

$$pp_i^{Total} = pp_i + \underbrace{\sum_{j \in W_i} r_{ij}[pp_j + \sum_{k \in W_j} r_{jk}(pp_k + ...)]}_{pp_j^{Total}} \tag{3.1}$$

where W_i presents the set of buyers from firm i and r_{ij} is the share of firm i's revenue derived from sales to firm j. After aggregating all direct and indirect revenue stemming from public procurement contracts, we divide by the total revenue of the firm i, which includes all transactions involving i, to obtain the public procurement shares. This measurement equation is recursive: firm i's total public procurement share is the sum of its direct public procurement share and the share of its output purchased by other firms, multiplied by the total public procurement shares of those firms. The public procurement share is high if the firm directly has numerous public procurement contracts or indirectly has substantial sales to buyers with many public procurement contracts.

Figure 3.9 graphically illustrates how pp_i^{Total} is calculated. For each firm i that has direct public procurement contracts, it sells pp_i of its total sales to governments, and r_{ij}, r_{ik} respectively to firms j and k. At the second layer, firm j directly sells pp_j to the government; therefore, through firm j, firm i indirectly sells $r_{ij}pp_j$ to the government. At the third layer, firm m sells pp_m directly to the government, and firm i through firm k and m, indirectly sells $r_{ik}r_{km}pp_m$ to the government. By summing both direct and indirect channels, firm i sells a total of pp_i^{Total} in contracts to the government.

Figure 3.9: Graph Illustration for pp_i^{Total}



The measurement can be motivated by theory. We assume that the production function is Cobb-Douglas in inputs, including labor and intermediate goods, and that the utility functions of private consumers and public agencies are Cobb-Douglas in goods produced by firms. We also assume fixed linkages between firms and fixed markups in firm-to-firm trade. Let us denote firm i's total sales by S_i. Firm i sells to final private market consumers (S_{iPC}), government agencies through public procurement projects (S_{iPP}), and its downstream firms (S_{ij}):

$$S_i = \sum_{j \in W_i} S_{ij} + S_{iPC} + S_{iPP}$$

Taking the first difference and dividing both sides by S_i:

$$\frac{\Delta S_i}{S_i} = \sum_{j \in W_i} r_{ij} \frac{\Delta S_{ij}}{S_{ij}} + r_{iPC} \frac{\Delta S_{iPC}}{S_{iPC}} + pp_i \frac{\Delta S_{iPP}}{S_{iPP}} \tag{3.2}$$

Here, r_{ij}, r_{iPC}, and pp_i are respectively the shares of sales to firm j, to final private market consumers, and to public procurement projects.

Given the Cobb-Douglas assumption for the production and utility functions, we have $S_{ij} = \alpha_{ij} C_j$, where C_j is the total cost of firm j and α_{ij} is the exponential term in the CD production function. Further, we know that $\frac{dC_j}{C_j} = \frac{dS_j}{S_j}$ given the constant markups across buyers. Also, $S_{iPC} = \alpha_{iPC} E_{PC}$ and $S_{iPP} = \alpha_{iPP} E_{PP}$, where E_{PC} is the total expenditure of final private market and E_{PP} is the total expenditure of the public procurement contracts. The terms α_{iPC} and α_{iPP} are the exponential coefficients in the utility functions of the final private market consumers and the government, respectively. The above equation can be written as:

$$\frac{\Delta S_i}{S_i} = \sum_{j \in W_i} r_{ij} \frac{\Delta S_j}{S_j} + r_{iPC} \frac{\Delta E_{PC}}{E_{PC}} + pp_i \frac{\Delta E_{PP}}{E_{PP}} = (1 - pp_i^{Total}) \frac{\Delta E_{PC}}{E_{PC}} + pp_i^{Total} \frac{\Delta E_{PP}}{E_{PP}}$$

This second part is derived through recursive steps. The equation demonstrates that the change in firm i's sales is the weighted average of the changes in aggregate private and public expenditures. The weight associated with the change in public demand is the firm's total public procurement share, pp_i^{Total}.

To calculate the pp_i^{Total} for each firm i using transaction data, we can rewrite the equation (3.1) to incorporate the production network matrix of all firms R:

$$pp_i^{Total} = \sum_j (I - R)_{ij}^{-1} pp_j \tag{3.3}$$

where the production network matrix R is a $n \times n$ matrix, and the i,j element is the proportion of revenue of firm i coming from the sales to firm j, i.e. r_{ij}. The diagonal of R is $r_{ii} = 0$, which represents the ratio firm i sell to i. I is an identity matrix. Different from the equation (3.1) wherein the first layer, we only sum the firms in the direct purchasing network with i that $j \in W_i$, here we incorporate all firms no matter whether there are direct transactions. The two equations are equivalent. $(I - R)^{-1}$ captures both direct and indirect transactions among firms, and the i,j element is the sum of direct and indirect transactions j purchases from i. pp_j is the share of direct public procurement contract size firm j won to the total sale revenue. Therefore, pp_i^{Total} captures both the direct and indirect public procurement contract ratio compared to total revenue for firm i.

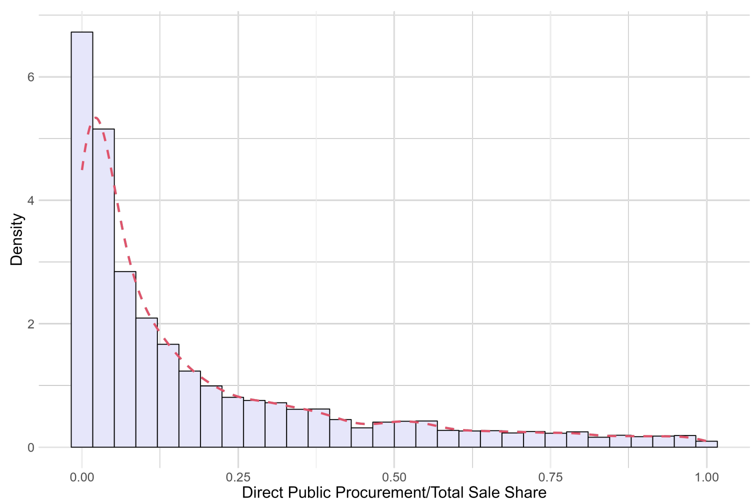
Both R and pp_i for any i can be directly calculated from the transaction data, and then pp_i^{Total} can also be directly measured.

3.4.2 Total Public Procurement Shares

After calculating the total public procurement share, we will plot the distribution of direct and total public procurement shares across firms within the province.

Just by looking at the direct public procurement shares, we find that only 0.5% of firms in the province signed a contract with the government in the year 2018. For firms with direct contracts, the distribution of the direct public procurement contract relative to the total sales share is shown in Figure 3.10. Among the firms that directly participated in the public procurement supply chain, the share of direct public procurement is low for most firms, with pp_i being smaller than 10%. However, there is a long right tail in the distribution, indicating that some firms are highly reliant on public procurement contracts.

Figure 3.10: Distribution of Direct Public Procurement Ratio pp_i



Notes: 99.5% of firms in the province did not participate in direct public procurement in 2018. This graph represents the 0.5% of firms that participated in public procurement in the province in 2018.

We will also investigate the heterogeneous distributions by sector. Specifically, we aim to distinguish between firms that have been corruptly predetermined winners and those that are competitive winners in public procurement contract competitions.

3.4.3 Firms Directly and Indirectly Linked to Public Procurement Supply Chain

With the total public procurement share measure in place, we can study the overall effect of public procurement contracts on firms. Similar to the specification used in Section 3.3.1 and Table 3.1, we will replace the direct public procurement contracts with the total direct and indirect public procurement projects' driven demand to present the results.

3.5 Propagation of Public Procurement Contracts

After exploring the direct and indirect effects arising from public procurement contracts, we would like to investigate how these contracts propagate through the production network and thus affect the overall sales of firms.

We can rewrite Equation 3.2 in the difference of logarithmic form with a time stamp as:

$$\Delta log S_{i,t} = \sum_j r_{ij,t-1} \Delta log S_{ij,t} + r_{iPC,t-1} \Delta log S_{iPC,t} + pp_{i,t-1} \Delta log S_{iPP,t}$$

Here, $r_{ij,t-1}$, $r_{iPC,t-1}$, and $pp_{i,t-1}$ represent the shares of sales to firm j, to final private market consumers, and to public procurement projects in the previous year $t-1$, respectively; and $S_{ij,t}$, $S_{iPC,t}$, and $S_{iPP,t}$ represent the sales from firm i to firm j, to the final consumer market, and to public sectors in year t, respectively. Unlike the notation in the previous equation (3.2), here we sum up all firms j regardless of whether they directly purchase inputs from i. If there is no direct purchase, then $r_{ij} = 0$. Therefore, the two equations are equivalent.

Following the previous assumptions in Section 3.4, Cobb-Douglas functions imply that inputs change proportionally to outputs, given by $\Delta \log S_{ij,t} = \Delta \log S_{j,t}$, and sales to private market consumers change proportionally to their expenditure, represented as $\Delta \log S_{iPC,t} = \Delta \log E_{PC,t}$. Consequently, the equation can be rewritten as:

$$\Delta log S_{i,t} = \sum_j r_{ij,t-1} \Delta log S_{j,t} + r_{iPC,t-1} \Delta log E_{PC,t} + pp_{i,t-1} \Delta log S_{iPP,t}$$

By recursively replacing $\Delta \log S_{j,t}$ with the same equation, we eventually derive an equation that breaks down $\Delta \log S_{i,t}$ into two components: expenditure by private market consumers and public procurement:

$$\Delta log S_{i,t} = \Delta log E_{PC,t} \sum_j (I - R_{t-1})^{-1} r_{jPC,t-1} + \sum_j (I - R_{t-1})^{-1} r_{jPP,t-1} \Delta log S_{jPP,t} \quad (3.4)$$

Here, similar to the equation (3.3), the ij element in the production network matrix R represents the ratio of revenue that firm i sells to firm j. $\Delta \log S_{jPP,t}$ measures the changes in public procurement contracts.

The equation above provides a good starting point for regression analysis to explore the impact of public procurement on total firm revenues. However, interpreting the results from regressing the change in total sales on the change in public procurement contracts as a causal relationship is challenging due to potential biases from unobservables such as productivity and political connections. Following Hummels et al. (2014); Dhyne et al. (2021), we construct the changes in direct public procurement demand for firm i to capture the reasonably exogenous variation in public procurement demand:

$$\Delta log S^{shock}_{iPP,t} = \sum_{c,p} r_{i,c,p,t-1} \Delta log PPDemand_{c,p,t}$$

where c represents the city, p represents the product industry, and $r_{i,c,p,t-1}$ is the share of firm i's public procurement sales in city c for product p relative to i's total public procurement sales at time $t-1$. $PPDemand_{c,p,t}$ denotes the city c's planned public procurement amount for product p at time t from city-level public procurement plan data.

Therefore, equation (3.4) can be reframed as a reduced-form regression:

$$\Delta logS_{i,t} = \alpha_0 + \alpha_{E_{PC,t}} \sum_j (I - R_{t-1})^{-1} r_{jPC,t-1} + \alpha_{PP} \sum_j (I - R_{t-1})^{-1} r_{jPP,t-1} \Delta logS^{shock}_{iPP,t} + \epsilon_{i,t}$$

The estimated α_{PP} captures the effect of public procurement demand shocks on a firm's sales revenue through both direct and indirect participation in the public procurement supply chain. The time-variant coefficients, denoted by $\alpha_{E_{PC,t}}$, capture changes in private consumer demand. We also include firm fixed effects and industry-year fixed effects.

3.6 Conclusion

This paper examines how public procurement contracts affect firms through direct and indirect channels. First, we find that winning public procurement contracts is positively related to firm performance, including total and net revenue, profit, assets, and liability growth. To quantify the effect of direct public procurement contracts on purchasing and selling activities, we use an event study design and compare firms that won public procurement contracts with those that did not. We find that winning public procurement contracts leads firms to consistently and significantly increase the purchase of inputs over the following four months. We also find that winning public procurement contracts increases the likelihood of winning other contracts from the private sector and leads to more sales. Additionally, the demand stimulation effects come from competitive auctions rather than corrupt ones.

Second, we propose a method to measure the total ratio of public procurement contracts to sales, including both direct and indirect contracts. We show that although only 0.5% of firms directly participate in the public procurement supply chain, more firms are involved through indirect production networks. Firms that directly win public procurement contracts are more likely located downstream in the input-output linkage.

Third, we explore the overall effects of public procurement contracts through the propagated supply chains on firm revenues.

Our findings underscore the important role of public procurement-driven demand in helping firms and the economy grow. Furthermore, our findings suggest that, given the current size of public procurement, winning public procurement contracts will not crowd out other private contracts. Instead, winning in public procurement competitions can provide more experience and show a positive signal to firms, helping them attract more contracts. Thus, government expenditure could provide extra demand by helping firms gain credit and reducing barriers to selling in larger markets.

Our measurements of total public procurement through the network show that government procurement policies, when leveraged as an industrial policy, need to carefully consider the overall input-output linkage to design the optimal policy. The results do not provide any suggestions on how to design public procurement policies since social planners have different goals to maximize. Also, the paper does not claim that public procurement policies are the best way to stimulate firm and economic growth. The comparison of different policy designs requires more discussion in future research.

Bibliography

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2017. "Microeconomic origins of macroeconomic tail risks." *American Economic Review*, 107(1): 54–108.

Acemoglu, Daron, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2012. "The network origins of aggregate fluctuations." *Econometrica*, 80(5): 1977–2016.

Alfaro-Urena, Alonso, Isabela Manelici, and Jose P Vasquez. 2022. "The effects of joining multinational supply chains: New evidence from firm-to-firm linkages." *The Quarterly Journal of Economics*, 137(3): 1495–1552.

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

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

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

Atalay, Enghin. 2017. "How important are sectoral shocks?" *American Economic Journal: Macroeconomics*, 9(4): 254–280.

Athey, Susan, and Philip A Haile. 2002. "Identification of standard auction models." *Econometrica*, 70(6): 2107–2140.

Atkin, David, Amit K Khandelwal, and Adam Osman. 2014. "Exporting and firm performance: Evidence from a randomized trial." National Bureau of Economic Research.

Aubert, Cécile, Patrick Rey, and William E Kovacic. 2006. "The impact of leniency and whistle-blowing programs on cartels." *International Journal of industrial organization*, 24(6): 1241–1266.

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.

Baqaee, David Rezza, and Emmanuel Farhi. 2019. "The macroeconomic impact of microeconomic shocks: Beyond Hulten's theorem." *Econometrica*, 87(4): 1155–1203.

Bobonis, Gustavo J, Luis R Cámara Fuertes, and Rainer Schwabe. 2016. "Monitoring corruptible politicians." *American Economic Review*, 106(8): 2371–2405.

Boehm, Christoph E, Aaron Flaaen, and Nitya Pandalai-Nayar. 2019. "Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake." *Review of Economics and Statistics*, 101(1): 60–75.

Bouakez, Hafedh, Omar Rachedi, and Emiliano Santoro. 2023. "The government spending multiplier in a multisector economy." *American Economic Journal: Macroeconomics*, 15(1): 209–239.

Boudreau, Laura E, Sylvain Chassang, Ada Gonzalez-Torres, and Rachel M Heath. 2023. "Monitoring harassment in organizations."

Brugués, Felipe, Javier Brugués, and Samuele Giambra. 2022. "Political connections and misallocation of procurement contracts: evidence from Ecuador."

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 efficiency 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."

Carpenter, Jeffrey, Andrea Robbett, and Prottoy A Akbar. 2018. "Profit sharing and peer reporting." *Management science*, 64(9): 4261–4276.

Carvalho, Vasco M, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi. 2021. "Supply chain disruptions: Evidence from the great east japan earthquake." *The Quarterly Journal of Economics*, 136(2): 1255–1321.

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

Chassang, Sylvain, and Gerard Padró I Miquel. 2019. "Crime, intimidation, and whistleblowing: A theory of inference from unverifiable reports." *The Review of Economic Studies*, 86(6): 2530–2553.

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. 2023. "Corruption in Public Procurement Auctions: Evidence from Collusion between Officers and Firms." *working paper*.

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, Zhao, Zhikuo Liu, Juan Carlos Suárez 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 Effects 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.

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.

Demir, Banu, Beata Javorcik, Tomasz K Michalski, and Evren Ors. 2024. "Financial constraints and propagation of shocks in production networks." *Review of Economics and Statistics*, 106(2): 437–454.

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

Dhyne, Emmanuel, Ayumu Ken Kikkawa, Magne Mogstad, and Felix Tintelnot. 2021. "Trade and domestic production networks." *The Review of Economic Studies*, 88(2): 643–668.

Di Giovanni, Julian, Andrei A Levchenko, and Isabelle Mejean. 2014. "Firms, destinations, and aggregate fluctuations." *Econometrica*, 82(4): 1303–1340.

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.

Felli, Leonardo, and Rafael Hortala-Vallve. 2015. "Collusion, blackmail and whistle-blowing."

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

Ferraz, Claudio, Frederico Finan, and Dimitri Szerman. 2015. "Procuring firm growth: the effects of government purchases on firm dynamics."

Foerster, Andrew T, Pierre-Daniel G Sarte, and Mark W Watson. 2011. "Sectoral versus aggregate shocks: A structural factor analysis of industrial production." *Journal of Political Economy*, 119(1): 1–38.

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

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 C hinese public procurement." *Regulation & Governance*, 9(1): 63–76.

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

Guerre, Emmanuel, Isabelle Perrigne, and Quang Vuong. 2000. "Optimal nonparametric estimation of first-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, Identification, 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.

Hendricks, Kenneth, and Robert H Porter. 1988. "An empirical study of an auction with asymmetric information." *The American Economic Review*, 865–883.

Heyes, Anthony, and Sandeep Kapur. 2009. "An economic model of whistle-blower policy." *The Journal of Law, Economics, & Organization*, 25(1): 157–182.

Hodges Jr, Joseph L, and Erich L Lehmann. 1956. "The efficiency 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.

Hummels, David, Rasmus Jørgensen, Jakob Munch, and Chong Xiang. 2014. "The wage effects of offshoring: Evidence from Danish matched worker-firm data." *American Economic Review*, 104(6): 1597–1629.

Huneeus, Federico. 2018. "Production network dynamics and the propagation of shocks." *Graduate thesis, Princeton University, Princeton, NJ*, 52.

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*a*. "Detecting large-scale collusion in procurement auctions." *Journal of Political Economy*, 130(5): 1364–1411.

Kawai, Kei, and Jun Nakabayashi. 2022*b*. "A Field Experiment on Antitrust Compliance."

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.

Kiefer, Jack, and Jacob Wolfowitz. 1956. "Consistency of the maximum likelihood estimator in the presence of infinitely 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.

Li, Tong, Isabelle Perrigne, and Quang Vuong. 2002. "Structural estimation of the affiliated private value auction model." *RAND Journal of Economics*, 171–193.

Liu, E, Y Lu, W Peng, and S Wang. 2023. "Court Capture, Local Protectionism, and Economic Integration: Evidence from China."

Liu, Yan, Shuming Zhao, Rui Li, Lulu Zhou, and Feng Tian. 2018. "The relationship between organizational identification and internal whistle-blowing: the joint moderating effects of perceived ethical climate and proactive personality." *Review of Managerial Science*, 12: 113–134.

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

Mechtenberg, Lydia, Gerd Muehlheusser, and Andreas Roider. 2020. "Whistleblower protection: Theory and experimental evidence." *European Economic Review*, 126: 103447.

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 field experiment in Indonesia." *Journal of Political Economy*, 115(2): 200–249.

Palguta, Ján, 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, and J Douglas Zona. 1993. "Detection of bid rigging in procurement auctions." *Journal of Political economy*, 101(3): 518–538.

Ramey, Valerie A. 2011. "Can government purchases stimulate the economy?" *Journal of Economic Literature*, 49(3): 673–685.

Reuben, Ernesto, and Matt Stephenson. 2013. "Nobody likes a rat: On the willingness to report lies and the consequences thereof." *Journal of Economic Behavior & Organization*, 93: 384–391.

Ryan, Nicholas. 2020. "Contract enforcement and productive efficiency: 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. "Identification and inference in first-price auctions with collusion." *Working Paper*.

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

Tybout, James R. 2000. "Manufacturing firms in developing countries: How well do they do, and why?" *Journal of Economic literature*, 38(1): 11–44.

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, Geoffrey 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.

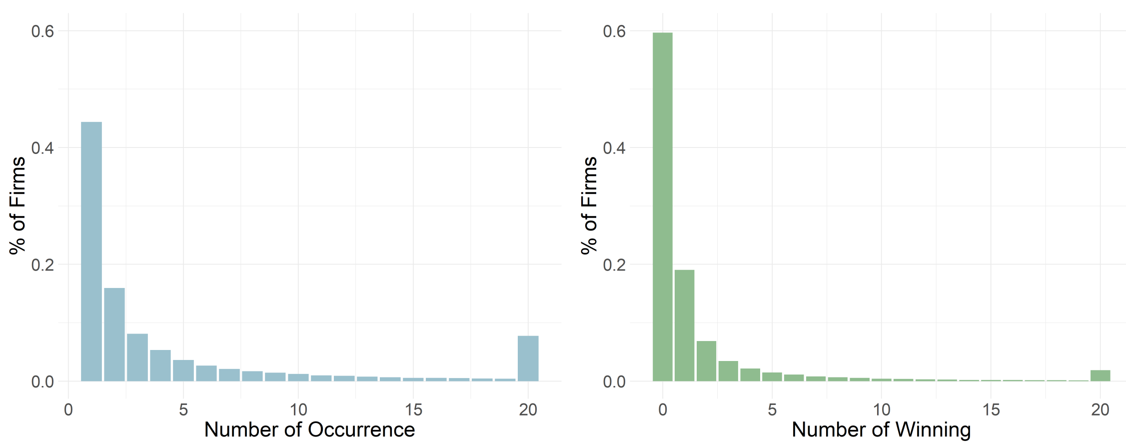
Yang, Jiawei, Susanto Rahardja, and Pasi Fränti. 2021. "Mean-shift outlier detection and filtering." *Pattern Recognition*, 115: 107874.

Appendix A

Chapter 1

A.1 Supplementary Tables and Figures

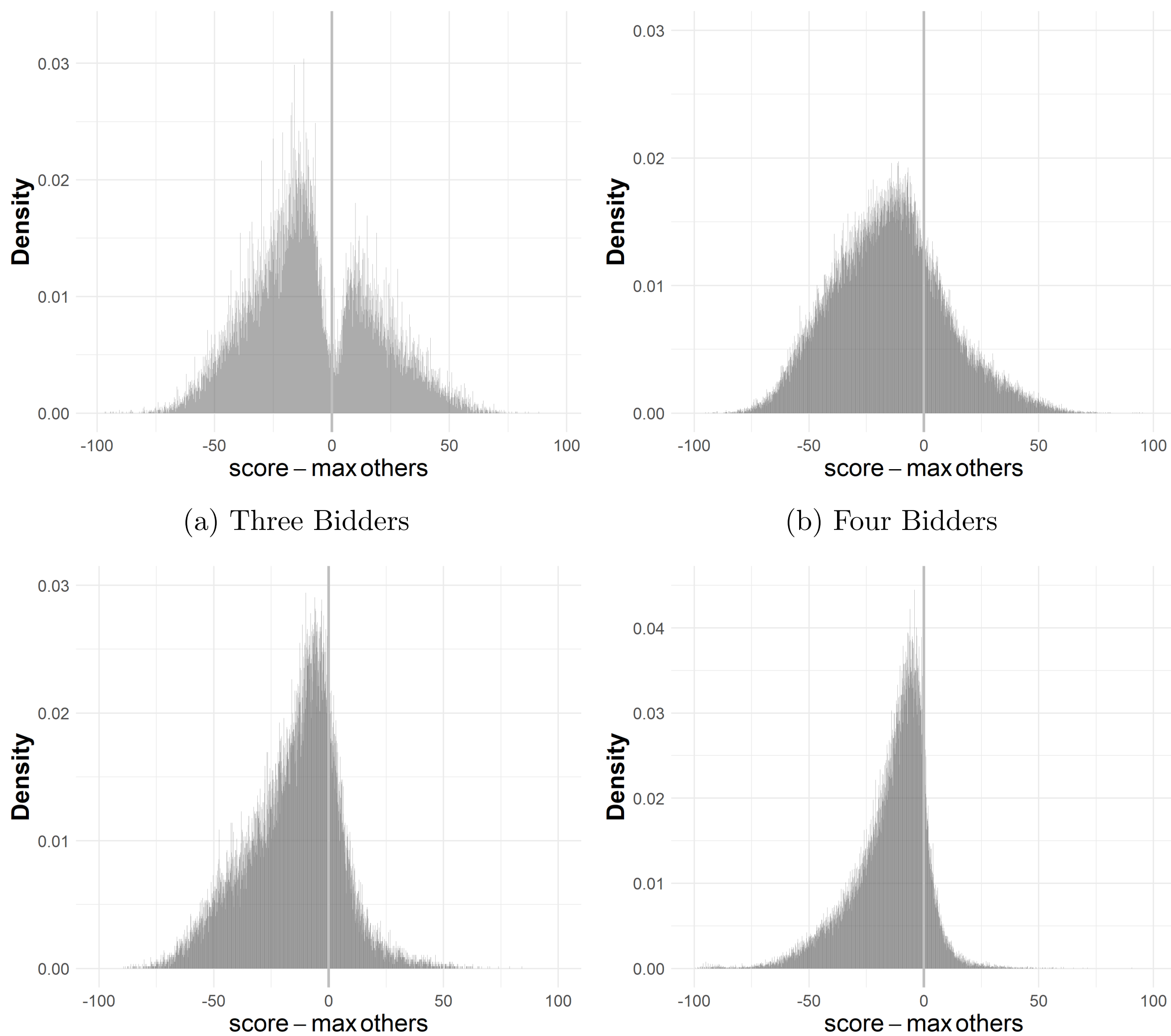
Figure A1: How frequently do firms participate in public procurement



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

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

Figure A2: Distribution of bid-differences over (bidder, auction) pairs



(a) Three Bidders

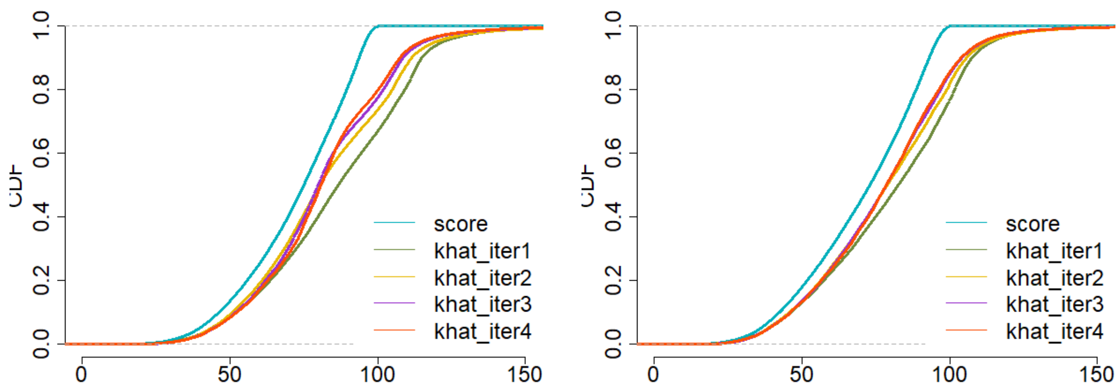
(b) Four Bidders

(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.

Figure A3: Estimated Khat by Each Iteration



(a) CDF of khat and score for 3-bidder cases (b) CDF of khat and score for 4-bidder cases

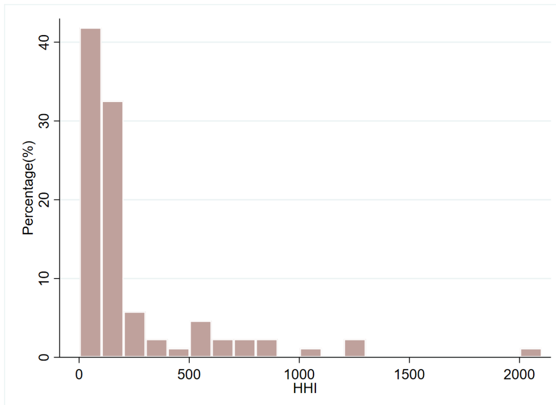
Notes: The X-axis represents the value of the score and pseudotype, while the Y-axis represents the cumulative probability.

Table A1: Auction Level Characteristics of Each Iteration

Variables	Iteration1	Iteration2	Iteration3	Iteration4
Number of Bidders	3.742	3.833	3.888	3.919
Year	2016	2016	2016	2016
Reserve Price	4.500 m	4.600 m	4.800 m	4.900 m
Win Price	3.900	3.800	3.800	3.900
Product%	0.555	0.540	0.530	0.522
Construction%	0.092	0.096	0.102	0.106
Service%	0.353	0.364	0.368	0.371
Winning Margin	18.440	10.496	7.746	6.233

Notes: Each column represents the characteristics of the remaining procurement auctions after each iteration.

Figure A4: Distribution of HHI for Industries



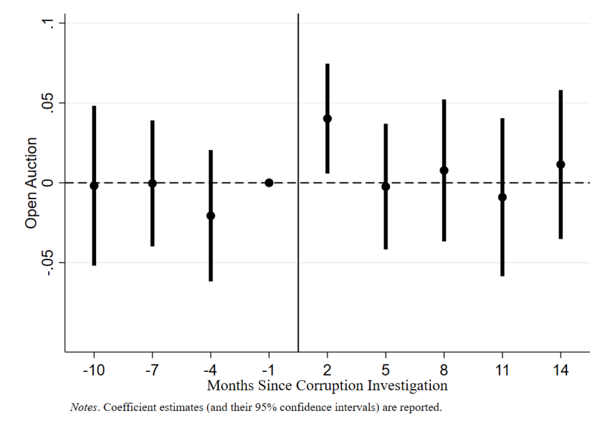
Notes: HHIs are derived from the 2016 Firm Tax data. Typically, an HHI exceeding 2500 signifies a highly concentrated market.

Table A2: Expert Survey and Model Prediction

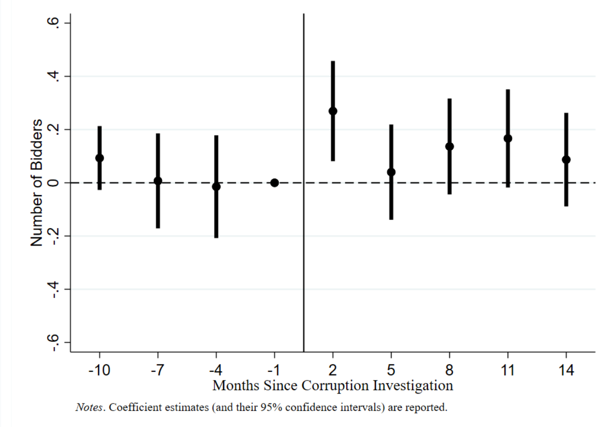
Accuracy Rate=78.2%	Total=500	Model Prediction		
		Corrupt (PP)	Not Corrupt (PN)	
Expert Survey	Corrupt (P)	288	87 False N	Test Power 76.8%
	Not Corrupt (N)	14(+8) False P	103	Test Size 17.6%(11.9%)

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 classification of model prediction uses adjusted p-values with a significance level of 0.1.

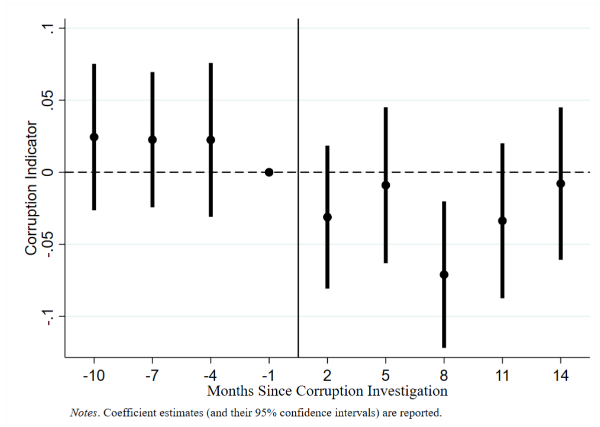
Figure A5: The Effect of Corruption Investigation



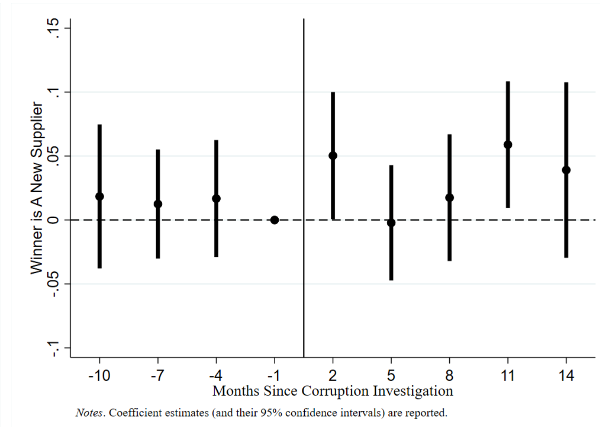
(a) Open Auction



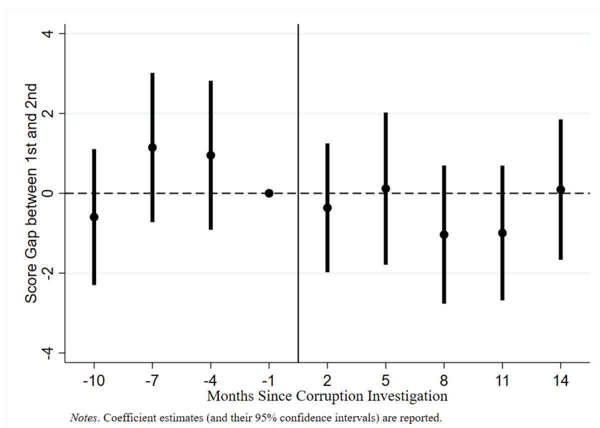
(b) Number of Bidders



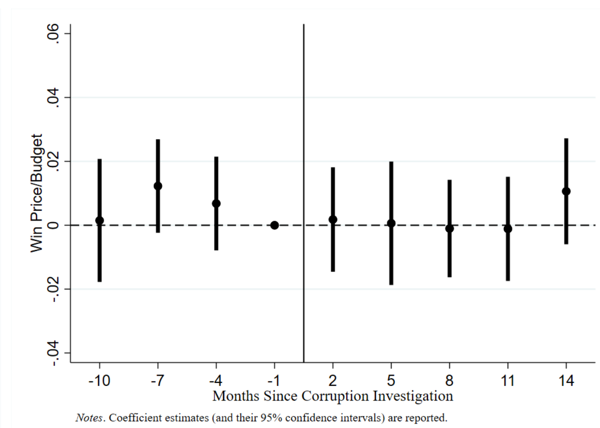
(c) Corruption Indicator



(d) New Winning Firm



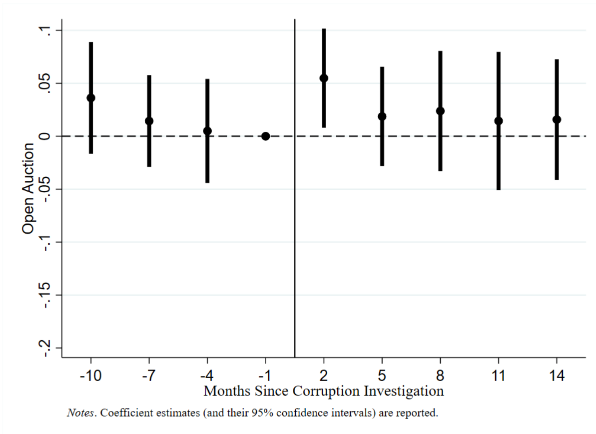
(e) Score Gaps



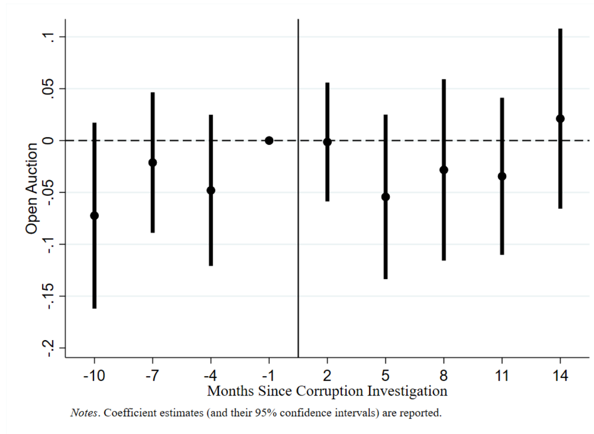
(f) Final Price/Budget

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

Figure A6: The Effect of Corruption Investigation by Officials with Different Levels



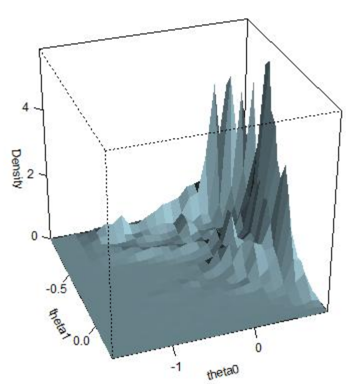
(a) Open Auction: High-level Officials



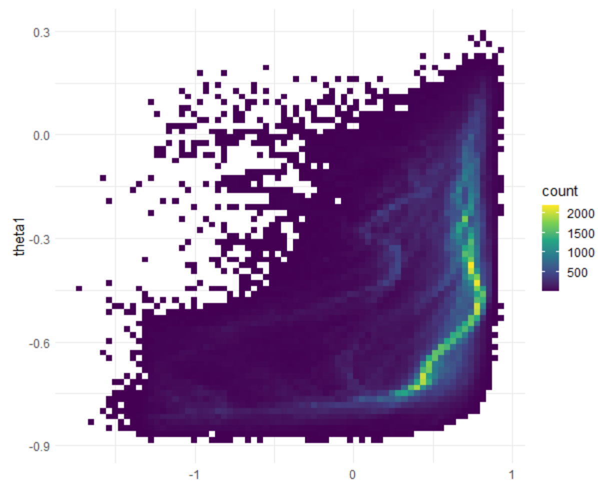
(b) Open Auction: Low-level Officials

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

Figure A7: $\boldsymbol{\theta}$ Distribution



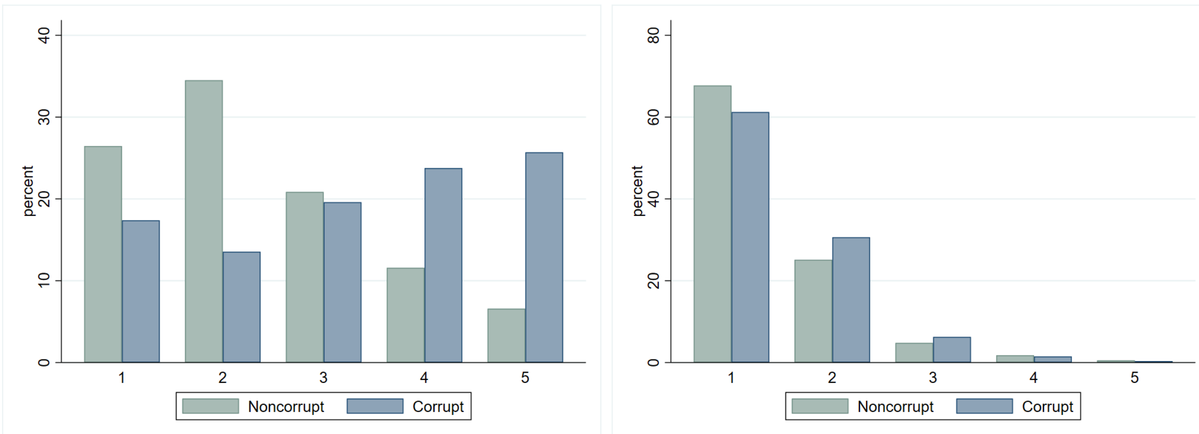
(a) 3D Density distribution of θ_0 and θ_1



(b) 2D Density distribution of θ_0 and θ_1

Notes: (a) shows the 3D density distribution of (θ_0, θ_1). (b) shows the 2D density distribution. Lighter colors are associated with larger density.

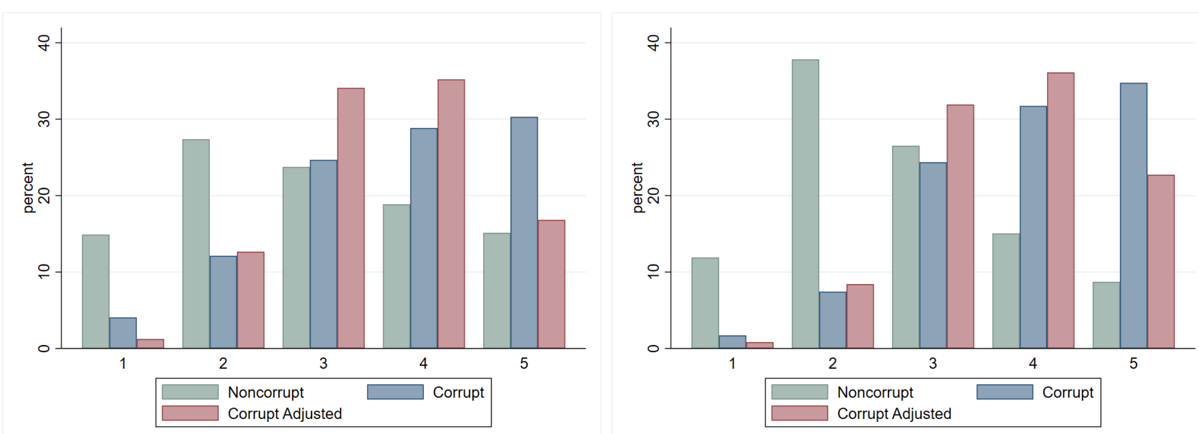
Figure A8: θ_1 Quintile Distribution



(a) All Bidders (b) Winners

Notes: I rank the estimated θ_1 within different groups based on procurement categories, number of bidders, price weights, and fixed quality weights. Lower ranking numbers indicate higher efficiency. (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 A9: θ Quintile Distribution for Losers



(a) θ_0 (b) θ_1

Table A3: Firm Characteristics and θ of Bidders

	Winners: Noncorrupt		Winners: Corrupt	
	θ_0	θ_1	θ_0	θ_1
Log(capital)	0.0000	0.0004	-0.0071***	-0.0015*
	(0.0023)	(0.0009)	(0.0022)	(0.0008)
Log(formal employee)	-0.0119***	-0.0051***	-0.0115***	-0.0047***
	(0.0019)	(0.0006)	(0.0012)	(0.0004)
Log(#members)	-0.0016	-0.0006	0.0013	-0.0003
	(0.0019)	(0.0006)	(0.0017)	(0.0004)
State-owned	0.0170	0.0150	-0.0063	0.0001
	(0.0268)	(0.0094)	(0.0199)	(0.0108)
Log(budget)	0.0099**	-0.0048***	0.0098**	-0.0055***
	(0.0046)	(0.0013)	(0.0038)	(0.0007)
Auction Characteristics	Y	Y	Y	Y
N	29951	29951	67690	67690

Notes: The first two columns present the estimated θ_0 and θ_1 for winners in non-corrupt auctions, while the third and fourth columns display the estimated θ_0 and θ_1 for winners in corrupt auctions. All regressions control for category fixed effects, number of bidders fixed effects, price weights fixed effects, fixed quality weights fixed effects, procurement year, and firm entry year. Standard errors are clustered at the procurement category level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Firm Characteristics and θ of Bidders

	Losers: Noncorrupt		Losers: Corrupt	
	θ_0	θ_1	θ_0	θ_1
Log(capital)	-0.0071***	-0.0079***	-0.0024***	-0.0034*
	(0.0019)	(0.0015)	(0.0006)	(0.0018)
Log(formal employee)	-0.0081***	-0.0069***	-0.0021***	-0.0051***
	(0.0015)	(0.0013)	(0.0005)	(0.0013)
Log(#members)	-0.0049***	-0.0040***	-0.0025***	-0.0047***
	(0.0014)	(0.0013)	(0.0007)	(0.0011)
State-owned	-0.0131	0.0172*	-0.0077	-0.0093
	(0.0196)	(0.0097)	(0.0071)	(0.0083)
Log(budget)	0.0093***	0.0013	0.0026	0.0040
	(0.0019)	(0.0022)	(0.0017)	(0.0032)
Auction Characteristics	Y	Y	Y	Y
N	85991	85991	193708	193708

Notes: The first two columns present the estimated θ_0 and θ_1 for losers in non-corrupt auctions, while the third and fourth columns display the estimated θ_0 and θ_1 for losers in corrupt auctions. All regressions control for category fixed effects, number of bidders fixed effects, price weights fixed effects, fixed quality weights fixed effects, procurement year, and firm entry year. Standard errors are clustered at the procurement category level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.2 Data

A.2.1 Large Performance Variance in Public Procurement Data

In the public procurement data, many firms perform substantially differently across different procurement auctions. This variability often defies straightforward explanation through differences in procurement requirements or scoring methodologies. While I assess the requisites 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 A10 (a), revealing its divergent performances. In the first 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 final case, Wonders seemingly regains its customary form, placing a reasonable bid despite stiffer 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.

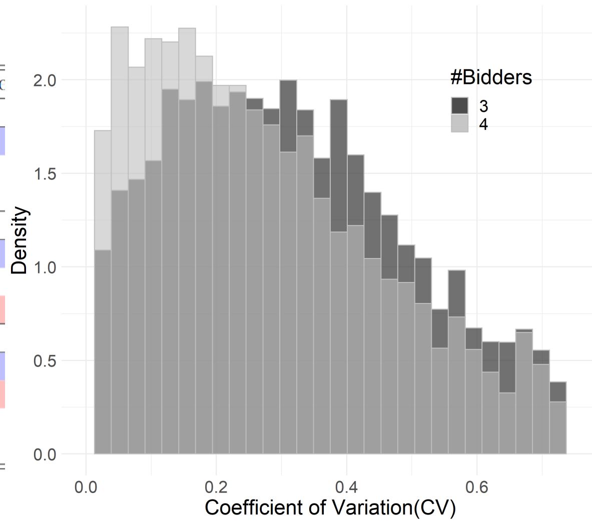
To quantitatively assess the varying bidding scores of firms across multiple auctions, I calculate the coefficient of variation of scores for each firm. The resulting distributions are presented in Figure A10 (b), differentiating between auctions featuring three bidders and those with four bidders. As depicted, the average coefficient of variation is substantial. A significant number of firms have a coefficient of variation exceeding 0.5, implying that their standard deviation is half the size of the mean score. When comparing the coefficient of variation between three-bidder and four-bidder auctions, it becomes evident that the former tends to exhibit a larger coefficient 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 firms may not consistently act as competitors across different auctions. Instead, they appear to assume varying roles, which encompass predetermined corrupt winners, genuine competitors, and even zombie bidders.

Figure A10: Performance Variance of the Same Firm

Company	price score	quality score	total score
Dominate Winner			
Wonders	18.51	77.63	96.14
F	18.51	27.07	45.58
G	20	25.32	45.32
Absolute Loser			
Wonders	28.12	7.4	35.52
H	30	4.6	34.6
I	28.52	47.3	75.82
Competitor			
Wonders	6.62	81.77	88.39
J	6.64	88.7	95.34
K	10	57.13	67.13
L	6.75	52.8	59.55

(a) A Case Study: Wonders Co.



(b) Distribution of CV

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

A.2.2 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 certificates 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 firms **B.** 5-10 firms **C.** 10-20 firms **D.** 20-50 firms **E.** 50+ firms

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

A.2.3 Estimation of TFP

The estimation of total factor productivity (TFP) for firms 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 firm-level records of tax payments and other financial 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 firm value-added r_{it} as:

$$\ln r_{it} = \frac{\theta - 1}{\theta}[\kappa \ln k_{it} + (1-\kappa)\ln l_{it} + \phi_{it}]$$

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

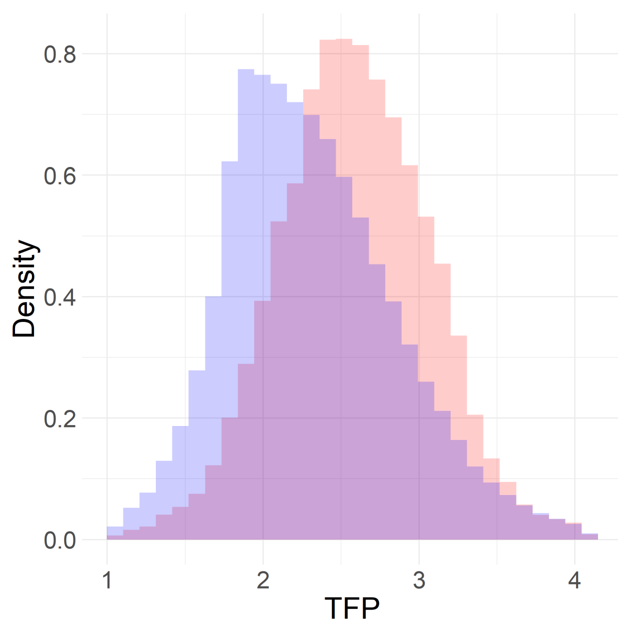
$$\ln \frac{wl_{it}}{r_{it}} = \ln[(1-\kappa)\frac{\theta}{\theta - 1}] + v_{it}$$

where w is the price of labor, and $v_{it} \sim iid$ 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 κ from the above equation. Finally, I can calculate the firm TFP:

$$\hat{\phi_{it}} = \frac{\theta}{\theta - 1}\ln r_{it} - \kappa \ln k_{it} - (1-\kappa)\ln l_{it}$$

I present the distribution of estimated Total Factor Productivity (TFP) for two sets of firms: the entire dataset from the State Administration of Tax (SAT) and firms that participated in public procurement. Figure A11 displays the distributions, with the blue distribution representing all firms in all available years, and the red distribution representing firms that have engaged in the procurement competition. The comparison of these distributions reveals that firms involved in public procurement tend to exhibit higher levels of TFP, indicating a general superiority in terms of productivity.

Figure A11: 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 firms that have matched records in the public procurement data.

A.3 Participation Test

I employ the participation test proposed by Conley and Decarolis (2016) to examine if there are specific groups of bidders who participate abnormally together in procurement auctions. The participation test compares the participation patterns of a suspected group of firms, denoted as g, in the auctions of interest with the participation patterns in reference groups, denoted as H. The objective is to determine whether the statistic reflecting the participation patterns of group g is an extreme event compared to the reference distribution, which follows a uniform distribution with support points represented by analogous statistics for all groups in H. Let T denote the total number of auctions, and the indicator variable d_{it} takes a value of 1 if firm i participates in auction t. For a group g with a size of N^g, the fraction of auctions participated in by $K \leq N^g$ members of group g is calculated as:

$$f_K^g = \sum_{t=1}^{T} \mathbb{1}\{K = \sum_{i \in g} d_{it}\}$$

Similarly, the count for firms in reference group $h \in H$ is defined as:

$$f_K^h = \sum_{t=1}^{T} \mathbb{1}\{K = \sum_{i \in h} d_{it}\}$$

I test the hypothesis that firms in group g do not exhibit unusually coordinated participation by assessing whether f_K^g is drawn from the distribution of f_K^h.

The test relies on the selection of the suspected group g and the reference group H. While theoretically applicable to any group, the computational demands of analyzing the extensive auction data make it impractical to consider all possible groups. To address this, I adopt the approach proposed by Conley and Decarolis (2016), which estimates the links between firms to predict the probability of belonging to the same cartel. The estimation involves three key steps. First, I compile the data on firm associations, including common ownership, temporary bidding consortia, subcontract exchanges, and location proxies. Next, I identify all pairs of firms that participated in the same procurement auction. Then, I employ the cartel membership probit model estimation from Conley and Decarolis (2016) to predict the probabilities of cooperative group membership for each pair of firms. To reduce the computational burden, I focus on the top 10% firms that participate in auctions most frequently. The complements of these predicted probabilities are interpreted as a dissimilarity array. In the third step, I construct the dissimilarity array using the hierarchical clustering algorithm (Gordon, 1999) to classify firms into different clusters. Finally, I conduct the statistical test by comparing the selected clusters with the remaining non-clustered firms.

A.4 Proof

Theorem 1. The competitive equilibrium bidding strategy is given by

$$P(s,q(s,\boldsymbol{\theta})) = \underbrace{C(q(s,\boldsymbol{\theta}),\boldsymbol{\theta})}_{\text{cost}} - \underbrace{P_s(s,q(s,\boldsymbol{\theta})\frac{G(s)}{(n-1)g(s)}}_{\text{Markup: relative advantage of MC}}$$

$$C_{q^l}(q(s,\boldsymbol{\theta}),\boldsymbol{\theta}) = P_{q^l}(s,q(s,\boldsymbol{\theta})) \text{ for any } l = 1...K$$

with the condition that $P_{q^l q^l} - C_{q^l q^l} < 0$ to ensure the profit maximizing.

Proof. If a bidder i with $\boldsymbol{\theta_i}$ bids $(p_i, \boldsymbol{q_i})$ and wins at $s_i = w_p \frac{p}{p_i} + w_q \boldsymbol{q_i}$. The winning probability is $Prob\{s > s_{-i}\}$. Rewrite the decision problem (3.2) as

$$max_s \pi(s,\boldsymbol{\theta})G(s)^{n-1}$$

Differentiating the above equation with respect to s, I have the first-order condition:

$$\pi_s(s,\boldsymbol{\theta})G(s)^{n-1} + \pi(s,\boldsymbol{\theta})(n-1)G(s)^{n-2}g(s) = 0$$

Rearrange the above equation,

$$\pi(s,\boldsymbol{\theta}) = -\pi_s(s,\boldsymbol{\theta})\frac{G(s)}{(n-1)g(s)} \tag{A.1}$$

Replace the $\pi_g(s,\boldsymbol{\theta})$ with equation (1.3) and $\pi(s,\boldsymbol{\theta})$ with equation (1.1), the first-order condition can also be written as

$$P(s,q(s,\boldsymbol{\theta})) = C(q(s,\boldsymbol{\theta}),\boldsymbol{\theta}) - P_s(s,q(s,\boldsymbol{\theta}))\frac{G(s)}{(n-1)g(s)}$$

At the equilibrium, the bid satisfies the profit-maximizing condition $P_{q^l} = C_{q^l}$. □

Corollary 1.1. The pseudotype k is monotone in $\boldsymbol{\theta}$ based on Assumption 3 and is a sufficient statistic for the bidder's type $\boldsymbol{\theta}$.

Proof. From equation (1.7), I take derivatives of $k(.)$ in respective to θ^k:

$$\begin{aligned}
\frac{dk(S(\boldsymbol{\theta}),\boldsymbol{\theta})}{d\theta^k} &= S_{\theta^k}(\boldsymbol{\theta}) - \frac{[\pi_s S_{\theta^k}(\boldsymbol{\theta}) + \pi_{\theta^k}]\pi_s - \pi[\pi_{ss}S_{\theta^k}(\boldsymbol{\theta}) + \pi_{s\theta^k}]}{\pi_s^2} \\
&= -\frac{\pi_s\pi_{\theta^k} - \pi[\pi_{ss}S_{\theta^k}(\boldsymbol{\theta}) + \pi_{s\theta^k}]}{\pi_s^2} \\
&= \frac{\pi\pi_{s\theta^k} - \pi_s\pi_{\theta^k}}{\pi_s^2} + \frac{\pi\pi_{ss}S_{\theta^k}(\boldsymbol{\theta})}{\pi_s^2}
\end{aligned}$$

Assumption 3 gives the first part as negative. S_{θ^k} is negative. The final sign depends on π_{ss}.

$$\pi_{ss}(s, \boldsymbol{\theta}) = P_{ss}(s, q(s, \boldsymbol{\theta})) + \sum_{l=1}^{L} P_{sq^l}(s, q(s, \boldsymbol{\theta})) q_s^l(s, \boldsymbol{\theta})$$

Given the form of the scoring rule, P_{ss} is positive, and P_{sq^l} is negative. The equilibrium (1.6) in Theorem 1 gives

$$C_{q^l}(q(s, \boldsymbol{\theta}), \boldsymbol{\theta}) = P_{q^l}(s, q(s, \boldsymbol{\theta}))$$

Taking the derivative with respect to s:

$$P_{q^l s}(s, q(s, \boldsymbol{\theta})) = [C_{q^l q^l}(q(s, \boldsymbol{\theta}), \boldsymbol{\theta}) - P_{q^l q^l}(s, q(s, \boldsymbol{\theta}))] q_s^l(s, \boldsymbol{\theta})$$

Since Assumption 3 gives $C_{q^l q^l} - P_{q^l q^l} > 0$, therefore I have $q_s(s, \boldsymbol{\theta}) < 0$ and then $\pi_{ss} > 0$. Combined all together, k in monotone in $\boldsymbol{\theta}$. □

Theorem 2. In the competitive equilibrium, the winning scoring bid is the expectation of the strongest rival's pseudotype k:

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

Proof. Rewrite the decision problem (3.2) with type $\boldsymbol{\theta}$ distribution:

$$max_s \pi(s, \boldsymbol{\theta}) G(s)^{n-1} = max_s \pi(s, \boldsymbol{\theta}) F(S^{-1}(s))^{n-1}$$

The first-order condition is

$$\pi_s(s, \boldsymbol{\theta}) F(\boldsymbol{\theta})^{n-1} + \pi(s, \boldsymbol{\theta})(n-1) F(\boldsymbol{\theta})^{n-2} f(\boldsymbol{\theta}) \frac{1}{s'(\boldsymbol{\theta})} = 0$$

Since $\pi_s = P_s < 0$, I divide both sides by π_1 gives

$$F(\boldsymbol{\theta})^{n-1} + (s(\boldsymbol{\theta}) - k)(n-1) F(\boldsymbol{\theta})^{n-2} f(\boldsymbol{\theta}) \frac{1}{s'(\boldsymbol{\theta}, q_1)} = 0$$

Solving the differential equation, I get

$$s(\boldsymbol{\theta}) = \int_{\underline{\boldsymbol{\theta}}}^{\boldsymbol{\theta}} \frac{(n-1) f(\tau) F(\tau)^{n-2}}{F(\boldsymbol{\theta})^{n-1}} k \, d\tau = E[k^{rival(1)} | s^{win}]$$

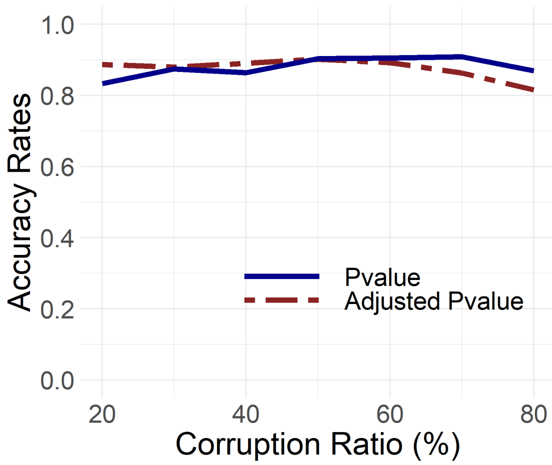
□

A.5 Monte Carlo Study of Test Steps

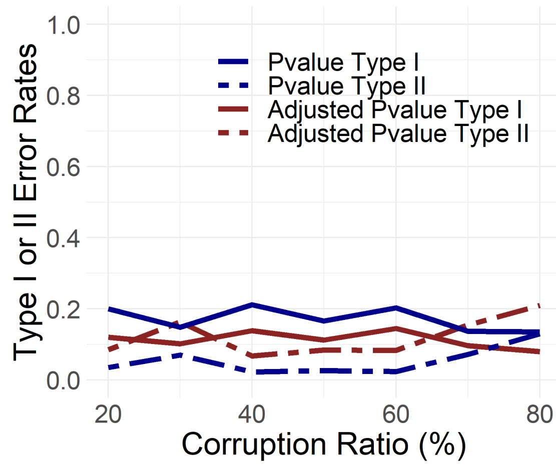
I replicate the Monte Carlo Study in Section 1.6 for cases with four and five bidders and present the summary of test accuracy rates, type I and II error rates in Figure A12. In comparison to Figure 1.9 (a), Figure A12 (a) and (c) indicate that auctions with more bidders exhibit higher overall accuracy rates. One consistent trend is that when the underlying real corruption ratio exceeds 50%, unadjusted p-values outperform adjusted p-values.

In Figure A13, the accuracy rates alongside type I and II errors are depicted for cases involving three bidders, employing 0.05 as the significance level. Generally, a high level of accuracy is still sustained as presented in Figure A13 (a). However, when contrasted with Figure 1.9, the test power is substantially reduced, particularly when the corruption ratio is exceedingly high, such as above 80%.

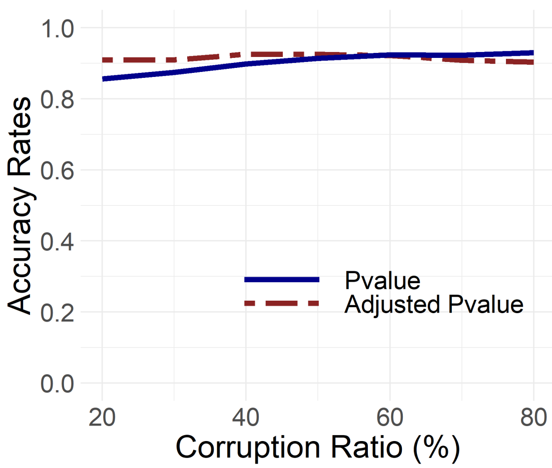
Figure A12: Comparison between Unadjusted and adjusted P-value



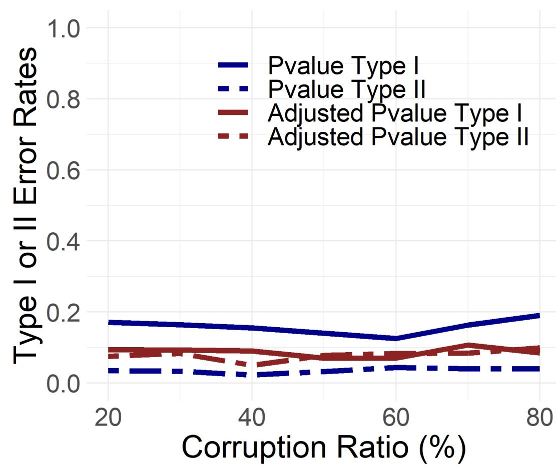
(a) Test Accuracy Rate (4 bidders)



(b) Type I and II Error Rate (4 bidders)



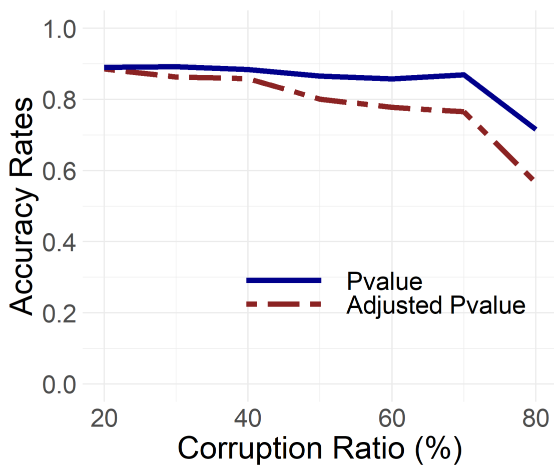
(c) Test Accuracy Rate (5 bidders)



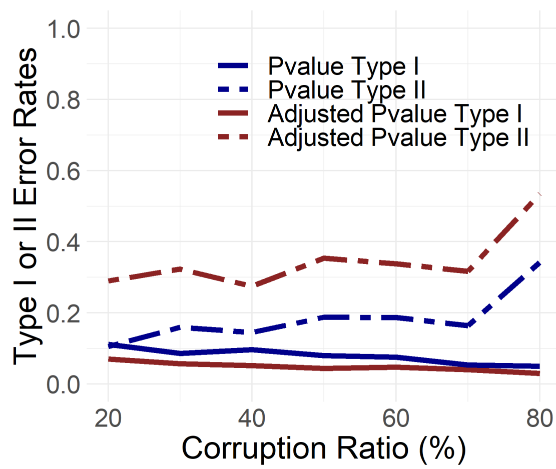
(d) Type I and II Error Rate (5 bidders)

Notes: (1) The accuracy rate is computed by adding the number of auctions from a competitive DGP failing to reject the null and the number of auctions from a corrupt DGP rejecting the null. The sum is then divided by 1000, the total number of auctions. (2) The Type I error rate is calculated by dividing the number of auctions from a competitive DGP but still rejecting the null hypothesis by the total number of competitive auctions. (3) The Type II error rate is calculated by dividing the number of auctions from a corrupt DGP but failing to reject the null hypothesis by the total number of corrupt auctions.

Figure A13: Comparison between Different Significance Levels



(a) Accuracy Rate (3 bidders with $\alpha = 0.05$)



(b) Type I and II (3 bidders with $\alpha = 0.05$)

Notes: (1) The accuracy rate is computed by adding the number of auctions from a competitive DGP failing to reject the null and the number of auctions from a corrupt DGP rejecting the null. The sum is then divided by 1000, the total number of auctions. (2) The Type I error rate is calculated by dividing the number of auctions from a competitive DGP but still rejecting the null hypothesis by the total number of competitive auctions. (3) The Type II error rate is calculated by dividing the number of auctions from a corrupt DGP but failing to reject the null hypothesis by the total number of corrupt auctions.

A.6 Model Extension with Bidder Asymmetry

In this Appendix, I extend the basic model to incorporate some bidder asymmetry using firm characteristics z. For example, local and non-local firms have different information and have different bidding strategies even when they have the same firm type $\boldsymbol{\theta}$.

A.6.1 Model

In a real competition, n potential ex-ante asymmetric and risk-neutral firms participate in the auction, denoted by $i = 1, 2, ..., n$. The number of competitors is known. Each firm draws its firm type $(\boldsymbol{\theta}|z)$ independently, conditional on firm characteristics z from a publicly known absolutely continuous conditional distribution function $F(\boldsymbol{\theta}|z)$. The type $\boldsymbol{\theta}$ and firm characteristics z are private information for each firm. The distribution of z, F_z, is also publicly known. Firms with different types have different costs $C(\boldsymbol{q}, \boldsymbol{\theta}|z)$, which depends on the quality bid $\boldsymbol{q}$ they submit and the firm type combination $(\boldsymbol{\theta}|z)$. Then Theorem 1 and Theorem 2 become the following.

Theorem 1. *The asymmetric, which is also conditional symmetric, Bayes–Nash equilibrium with interior-solution bids equilibrium is given by*

$$P(s, q(s, \boldsymbol{\theta}|z)) = \underbrace{C(q(s, \boldsymbol{\theta}|z), \boldsymbol{\theta}|z)}_{cost} - \underbrace{P_s(s, q(s, \boldsymbol{\theta}|z)) \frac{\int_z G(s|z) f_z(z)\, dz}{(n-1) \int_z g(s|z) f_z(z)\, dz}}_{Markup:\ relative\ advantage\ of\ MC} \tag{A.3}$$

$$C_{q^l}(q(s, \boldsymbol{\theta}|z), \boldsymbol{\theta}|z) = P_{q^l}(s, q(s, \boldsymbol{\theta}|z)) \tag{A.4}$$

with the condition that $P_{q^l q^l} - C_{q^l q^l} < 0$ *to ensure the profit maximizing.*

Proof. If a bidder with $\boldsymbol{\theta}_i$ bids $(p_i, \boldsymbol{q_i})$ and wins at $s_i = w_p \frac{p}{p_i} + w_q \boldsymbol{q_i}$. The winning probability is $Prob\{s(\boldsymbol{\theta}_j|z_j) < s_i, j \neq i\}$. Rewrite the decision problem (3.2) as

$$max_{s_i} \pi(s_i, \boldsymbol{\theta}_i|z_i) \int_{z_{-i}} \prod_{j \neq i} G(s_i|z_j) f_z(z_j) dz_{-i} = max_{s_i} \pi(s_i, \boldsymbol{\theta}_i|z_i) (\int_z G(s_i|z) f_z(z)\, dz)^{n-1}$$

Differentiating the above equation with respect to s, I have the first-order condition:

$$\pi_s(s_i, \boldsymbol{\theta}_i|z_i)(\int_z G(s_i|z) f_z(z)\, dz)^{n-1} + \pi(s_i, \boldsymbol{\theta}_i|z_i)(n-1)(\int_z G(s_i|z) f_z(z)\, dz)^{n-2} \int_z g(s_i|z) f_z(z)\, dz = 0$$

Rearrange the above equation,

$$\pi(s_i, \boldsymbol{\theta}_i|z_i) = -\pi_1(s_i, \boldsymbol{\theta}_i|z_i) \frac{\int_z G(s_i|z) f_z(z)\, dz}{(n-1) \int_z g(s_i|z) f_z(z)\, dz} \tag{A.5}$$

Replace the $\pi_s(s_i, \boldsymbol{\theta}_i|z_i)$ with equation (1.3) and $\pi(s_i, \boldsymbol{\theta}_i|z_i)$ with equation (1.1), the first-order condition can also be written as

$$P(s_i, q(s_i, \boldsymbol{\theta_i}|z_i)) = C(q(s_i, \boldsymbol{\theta}_i|z_i), \boldsymbol{\theta}_i|z_i) - P_s(s_i, q(s_i, \boldsymbol{\theta}_i|z_i)) \frac{\int_z G(s_i|z) f_z(z)\, dz}{(n-1)\int_z g(s_i|z) f_z(z)\, dz}$$

At the equilibrium, the bid satisfies the profit-maximizing condition $P_{q^l} = C_{q^l}$. From the equation (1.2) and Assumption 2, $P_q = \frac{w_q p^2}{w_p \underline{p}}$. I can get the equation (A.4). □

Theorem 2. *In the competitive equilibrium, the winning scoring bid is the expectation of the strongest rival's pseudotype k:*

$$s^{win} = E[k^{rival(1)}|s^{win}] \tag{A.6}$$

Proof. Rewrite the decision problem (3.2) with type $\boldsymbol{\theta}$ distribution:

$$max_{s_i}\pi(s_i, \boldsymbol{\theta}_i|z_i)(\int_z G(s_i|z) f_z(z)\, dz)^{n-1} = max_{s_i}\pi(s_i, \boldsymbol{\theta}_i|z_i)(\int_z F(s^{-1}(s_i|z)) f_z(z)\, dz)^{n-1}$$

The first-order condition is

$$\begin{aligned} &\pi_s(s, \boldsymbol{\theta}|z)(\int_z F(\boldsymbol{\theta}|z) f_z(z)\, dz)^{n-1} \\ &\qquad + \pi(s, \boldsymbol{\theta}|z)(n-1)(\int_z F(\boldsymbol{\theta}|z) f_z(z)\, dz)^{n-2} \int_z f(\boldsymbol{\theta}|z) f_z(z)\, dz \frac{1}{s'(\boldsymbol{\theta}|z)} = 0 \end{aligned}$$

Since $\pi_s = P_s < 0$, I divide both sides by π_s gives

$$\begin{aligned} &(\int_z F(\boldsymbol{\theta}|z) f_z(z)\, dz)^{n-1} \\ &\qquad + (s(\boldsymbol{\theta}|z) - k)(n-1)(\int_z F(\boldsymbol{\theta}|z) f_z(z)\, dz)^{n-2} \int_z f(\boldsymbol{\theta}|z) f_z(z)\, dz \frac{1}{s'(\boldsymbol{\theta}|z)} = 0 \end{aligned}$$

Solving the differential equation, I get

$$s(\boldsymbol{\theta}|z) = \int_{\underline{\boldsymbol{\theta}}}^{\boldsymbol{\theta}} \frac{(n-1)\int_z f(\tau|z) f_z(z)\, dz (\int_z F(\tau|z) f_z(z)\, dz)^{n-2}}{(\int_z F(\boldsymbol{\theta}|z) f_z(z)\, dz)^{n-1}} k\, d\tau = E[k^{rival(1)}|s^{win}, z]$$

Then take expectations on both sides with respect to z:

$$s^{win} = E_z[s(\boldsymbol{\theta}|z)] = E_z[E[k^{rival(1)}|s^{win}, z]] = E[k^{rival(1)}|s^{win}]$$

□

A.6.2 Estimation and Test

The estimates of the distribution of scores also need to take the asymmetry of bidders into consideration. I have A independent scoring auctions, and for each auction a, there are n_a firms. I observe the bids (p_{ia}, q_{ia}), the score s_{ia} for each bidder, and some firm characteristics $\boldsymbol{z}_i$, as well as partial auction-specific covariates $\boldsymbol{x_a}$. The CDF and PDF of equilibrium scores can be non-parametrically estimated:

$$\hat{G}_s(s, n, \boldsymbol{x}, \boldsymbol{z}) = \frac{1}{Th_{g_n}h_{g_x}h_{g_z}} \sum_{a=1}^{A} \frac{1}{n_a} \sum_{i=1}^{n_a} \mathbb{1}(s_{ia} \leq s) K_G(\frac{n - n_a}{h_{g_n}}, \frac{\boldsymbol{x} - \boldsymbol{x_a}}{h_{g_x}}, \frac{\boldsymbol{z} - \boldsymbol{z_i}}{h_{g_z}})$$

$$\hat{g}_s(s, n, \boldsymbol{x}, \boldsymbol{z}) = \frac{1}{Th_s h_{g_n}h_{g_x}h_{g_z}} \sum_{a=1}^{A} \frac{1}{n_a} \sum_{i=1}^{n_a} K_g(\frac{s - s_{it}}{h_s}, \frac{n - n_a}{h_{g_n}}, \frac{\boldsymbol{x} - \boldsymbol{x_a}}{h_{g_x}}, \frac{\boldsymbol{z} - \boldsymbol{z_i}}{h_{g_z}})$$

where $\mathbb{1}(.)$ is the indicator function; K_G and K_g are kernels; and $h_{g_n}, h_{g_x}, h_{g_z}, h_s$ are bandwidths.

I can rewrite the definition of pseudotype k equation:

$$k(s(\boldsymbol{\theta}_i), \boldsymbol{\theta}_i|z_i) = s(\boldsymbol{\theta}_i|z_i) - \frac{\pi(s_i, \boldsymbol{\theta}_i|z_i)}{\pi_1(s_i, \boldsymbol{\theta}_i|z_i)} = s(\boldsymbol{\theta}_i|z_i) + \frac{\int_z G(s_i|z) f_z(z)\, dz}{(n-1)\int_z g(s_i|z) f_z(z)\, dz} \tag{A.7}$$

Therefore the pseudotype defined above can be estimated using:

$$\hat{k}_{it} = s_{it} + \frac{\int_z \hat{G}(s_i|z) f_z(z)\, dz}{(n-1)\int_z \hat{g}(s_i|z) f_z(z)\, dz}$$

Using the new estimates I can redo the test. The test results are shown in Table A5: Compare to the test prediction from the basic model, the proportions of auctions failing to

Table A5: Test Results

Proportion of Procurement Reject the Null				
	All	3 Bidders	4 Bidders	5 Bidders
Unadjusted p-value	64.71%	69.54%	51.57%	47.53%
Adjusted p-value	57.03%	62.14%	44.09%	39.38%

Notes: The first row represents the results using unadjusted p-values and the second row represents the results using adjusted p-values.

reject the null increase as some pseudotype gaps are attributed to the asymmetry of bidders, the differences are small.

Then I compare the new predictions with the expert survey results in Table A6. The allover accuracy rate is 80%, which is still pretty high and captures fewer corrupt cases than the basic model.

Table A6: Expert Survey and Model Prediction

Accuracy Rate=80.4%	Total=500	Model Prediction		
		Corrupt (PP)	Not Corrupt (PN)	
Expert Survey	Corrupt (P)	308	67 False N	Test Power 82.1%
	Not Corrupt (N)	31 False P	94	Test Size 24.8%

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 classification of model prediction uses unadjusted p-values with a significance level of 0.1.

A.7 Model Extension with Evaluation Randomness

In a more realistic setting, the outcomes of procurement auctions can be influenced by the subjective evaluations of experts. This uncertainty can cause the target quality that bidders aim to maximize their expected profit to differ from the final quality score that is observed. However, the quality score calculation that takes the average of quality evaluations from experts can reduce the impact of uncertainty. To account for this randomness, I have developed an extended model in this appendix, which is compared to the basic model presented in Section 1.5. The results demonstrate that randomness does not have an important effect in my setting.

A.7.1 Model

I introduce the i.i.d. error ϵ_{iea} into the quality evaluation of each expert e for the bidder i in auction a.[1] Therefore the observed quality score that each expert gives is the sum of real quality q_{ia} and error, $q^o_{iea} = q_{iea} + \epsilon_{iea}$. The final observed quality score that bidder i in auction t gets is $q^o_{ia} = \frac{\sum_{e=1}^{5} q_{iea}}{5} = \frac{\sum_{e=1}^{5}(q_{ia}+\epsilon_{iea})}{5} = q_{ia} + \epsilon_{ia}$. Then the observed score is the sum of real score plus the weighted error $s^o_{ia} = s_{ia} + w_q \epsilon_{ia}$

The new equilibrium under the extension now includes the expectation of the evaluation error. I rewrite the equilibrium conditions in Theorem 1 as follows:

$$P(s_{ia}, q(s_{ia}, \boldsymbol{\theta}_{ia})) = C(q(s_{ia}, \boldsymbol{\theta}_{ia}), \boldsymbol{\theta}_{ia}) - P_s(s_{ia}, q(s_{ia}, \boldsymbol{\theta}_{ia})) \frac{\int_\epsilon G(s_{ia} + w_q \epsilon_{ia})^{n-1} dF_\epsilon(\epsilon)}{\int_\epsilon (n-1) g(s_{ia} + w_q \epsilon_{ia}) G(s_{ia} + w_q \epsilon_{ia})^{n-2} dF_\epsilon(\epsilon)}$$

$$C_{q^l}(q(s_{ia}, \boldsymbol{\theta}_{ia}), \boldsymbol{\theta}_{ia}) = P_{q^l}$$

The new pseudotype is $k_{ia} = s_{ia} + \frac{\int_\epsilon G(s_{ia}+w_q\epsilon_{ia})^{n-1} dF_\epsilon(\epsilon)}{\int_\epsilon (n-1) g(s_{ia}+w_q\epsilon_{ia}) G(s_{ia}+w_q\epsilon_{ia})^{n-2} dF_\epsilon(\epsilon)}$. Theorem 2 still holds except the score is the real score s_{ia} not the observed s^o_{ia}. Since now I don't know the real target score s and I only know the observed score, for a given observed score, I can estimate the expected pseudotype:

$$E_s[k_{ia}|s^o_{ia}] = s^o_{ia} + \int_{s+\xi = s^o_{ia}} \frac{\int_\epsilon G(s_{ia} + w_q \epsilon_{ia})^{n-1} dF_\epsilon(\epsilon)}{\int_\epsilon (n-1) g(s_{ia} + w_q \epsilon_{ia}) G(s_{ia} + w_q \epsilon_{ia})^{n-2} dF_\epsilon(\epsilon)} dF_s(s)$$

$$= E_\epsilon[k_{ia}|s^o_{ia}] = s^o_{ia} + \int_\xi \frac{\int_\epsilon G(s^o_{ia} - w_q\xi + w_q \epsilon_{ia})^{n-1} dF_\epsilon(\epsilon)}{\int_\epsilon (n-1) g(s^o_{ia} - w_q\xi + w_q \epsilon_{ia}) G(s^o_{ia} - w_q\xi + w_q \epsilon_{ia})^{n-2} dF_\epsilon(\epsilon)} dF_\epsilon(\xi)$$

The new test is

$$H_0: \ E[E_\epsilon(k^{rival})|s^{winner}] \leq E[E_\epsilon(k_t^{rival})|s^{winner}]$$
$$\text{and } H_1\text{: } E[E_\epsilon(k^{rival})|s^{winner}] > E[E_\epsilon(k_t^{rival})|s^{winner}]$$

[1] The i.i.d. assumption is based on the random selection of experts for each auction and independent evaluation process.

Whether there are significant differences in the new test compared to the basic model test depends on how large the variance of the randomness is and whether there is systematic up or downward bias in the evaluation process. If the randomness is small, I will not see dramatically different test results.

A.7.2 Identification and Data

To conduct the test, I need to know the distribution of errors. Though I don't have a complete dataset including a quality evaluation of each expert for each bidder in every auction, I have a recent subsample from one city in Guangdong Province. The structure of the data is shown in Figure A14. For each bid, there are five randomly selected experts invited to evaluate the quality part of the bids. Each expert independently gives her or his own quality score. The final quality score is the average of the quality score given by the five experts.

Figure A14: A Example of Detailed Expert Evaluation Scores

Supplier	Detailed Quality Scores							Price Score	Total Score	Order
	Name	Name	Name	Name	Name	Sum	Average			
	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5					
Dongjin Co.	89.65	90	90	85	90	444.65	88.93	10	98.93	1
Biaosheng Co.	69	70.15	67.8	67.8	71.55	346.5	69.3	9.8672	79.1672	2
Chuangmeng Co.	53.8	59.95	53.1	53.1	56.85	272.8	54.56	9.886	64.446	3

The quality score q_{iea} given by each expert e for bidder i and in auction t is the sum of real quality q_{ia} and the expert-level evaluation error ϵ_{iea}. The identification of evaluation errors comes from a discrepancy in experts' evaluations:

$$q_{iea} - q_{ie'a} = \epsilon_{iea} - \epsilon_{ie'a}$$

The subtraction of quality evaluation from two different experts e and e' for the same bidder i in auction t helps me get rid of the real quality q_{ia}. The left is the subtraction between two i.i.d. variables. Therefore ϵ_{iea} is identified and further ϵ_{ia} is identified since $\epsilon_{ia} = \frac{\sum_e \epsilon_{iea}}{5}$ and ϵ_{iea} is i.i.d. The variance of ϵ_{ia} is much smaller than ϵ_{iea} because it is the average, $sd(\epsilon_{ia}) = \frac{sd(\epsilon_{iea})}{\sqrt{5}}$.

A.7.3 Estimation

I plot the histogram of $q_{iea} - q_{ie'a}$ for good, construct, and service procurement separately in Figure A15. The mean of $\hat{\epsilon}_{iea}$ is not different from 0. The standard deviations of ϵ_{ia} are 0.35 points for good procurement, 1.12 points for service procurement, and 2.29 points for construct procurement. The larger randomness in the evaluation of construction procurement may be due to a more subjective component in the evaluation of implementation plans. The demand and products in good procurement are more standardized compared to construction and service projects, resulting in lower variance.

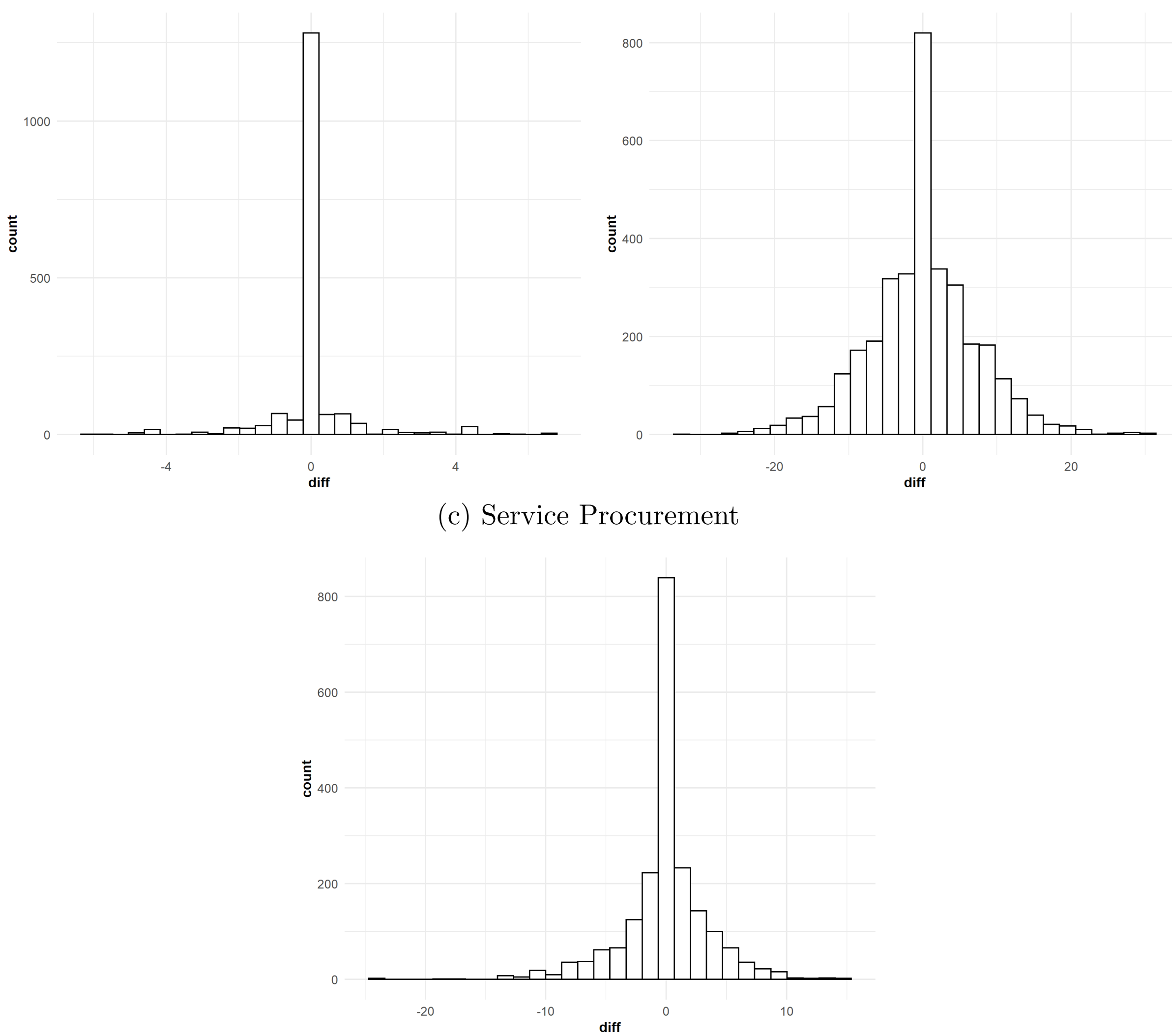
I then re-estimate the model and conduct hypothesis testing based on the extended model. The results are shown in Table A7. The proportion of procurement auctions that reject the null hypothesis under the extended model is similar to the results in the basic model. For all cases, the results fall within the 95% bootstrapped confidence intervals of the results in the basic model, indicating that randomness does not play a significant role in my setting.

Figure A15: Distribution of $q_{iea} - q_{ie'a}$ by Procurement Categories

(a) Good Procurement

(b) Construct Procurement

(c) Service Procurement



Finally, I reconduct a validation test using expert surveys, and the results are shown in Table A8. The accuracy rate is 80.8%, which is slightly lower than the 81.4% accuracy rate in the basic model. However, the change is not significant.

Table A7: Test with Randomness Results

Proportion of Procurement Reject the Null				
	All	3 Bidders	4 Bidders	5 Bidders
Unadjusted p-value	65.51%	70.28%	52.75%	49.62%
Adjusted p-value	57.70%	62.90%	45.09%	40.95%

Notes: The first row represents the results using unadjusted p-values and the second row represents the results using adjusted p-values.

Table A8: Expert Survey and Model Prediction

<table>
<tr><td rowspan="2">Accuracy Rate=80.8%</td><td rowspan="2">Total=500</td><td colspan="2">Model Prediction</td><td rowspan="2"></td></tr>
<tr><td>Corrupt (PP)</td><td>Competitive (PN)</td></tr>
<tr><td rowspan="2">Expert Survey</td><td>Corrupt (P)</td><td>311</td><td>64
False N</td><td>Test Power
82.9%</td></tr>
<tr><td>Competitive (N)</td><td>32
False P</td><td>93</td><td>Test Size
25.6%</td></tr>
</table>

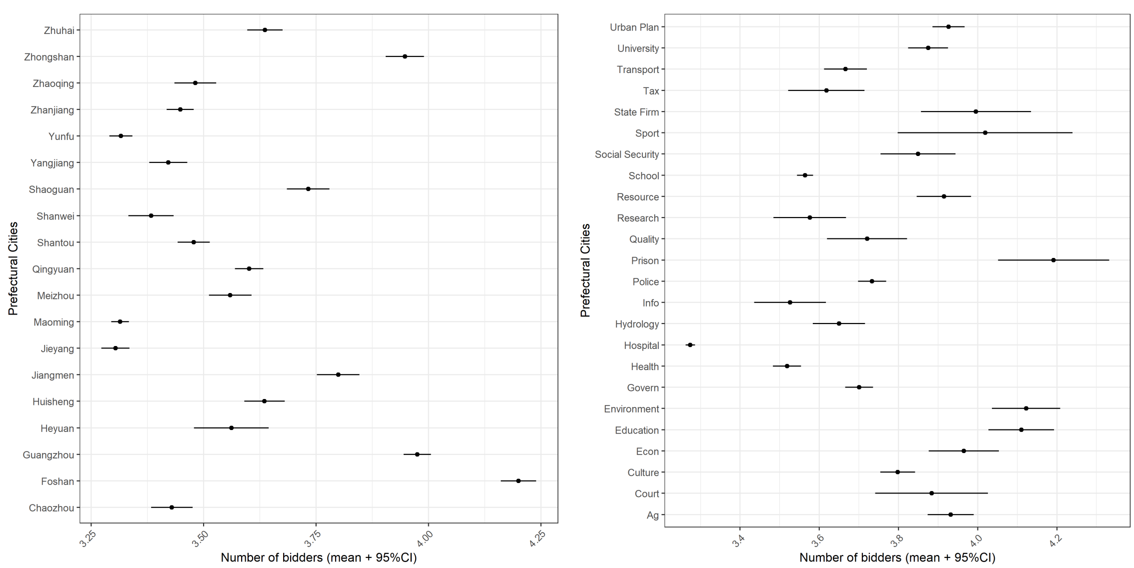
Notes: For the expert survey, if any evaluation survey reveals highlighted scoring rules accompanied by expert explanations and concerns, the procurement project is labeled as corrupt. The classification of model prediction uses unadjusted p-values with a significance level of 0.1.

A.8 City and Public Procurement Corruption

I conducted the statistical test for each public procurement auction and aggregated the auction-level predictions to specific department, county, or prefecture-city levels. This allows me to construct a corrupt index for each level, representing the proportion of public procurement auctions conducted by authorities rejecting the null hypothesis of a competitive auction.

In Figure A16, I plot the mean number of bidders with 95% confidence intervals by city and department. Cities such as Foshan, Zhongshan, and Guangzhou, the capital city of the province, have more bidders on average. Fiscal departments have the least number of bidders, which is consistent with the government's structure. The Fiscal Bureau monitors the procurement conducted by other departments, as it is responsible for local financial work, fiscal revenue organization, expenditure assurance, and the management of local financial funds.

Figure A16: Distribution of Number of Bidders



(a) Number of Bidders: by City

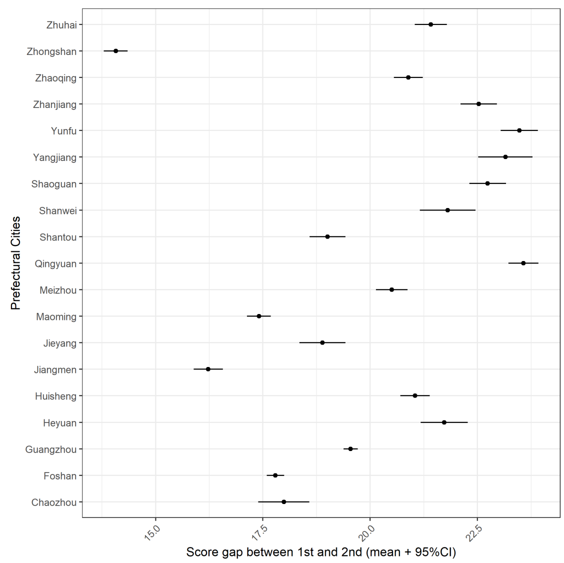
(b) Number of Bidders: by Department

Notes: Figure (a) is aggregating the procurement auction level data to the prefecture city level. In Figure (b), I relabeled the procurement departments by their functions, like the education department, the transportation department, the prison, etc.

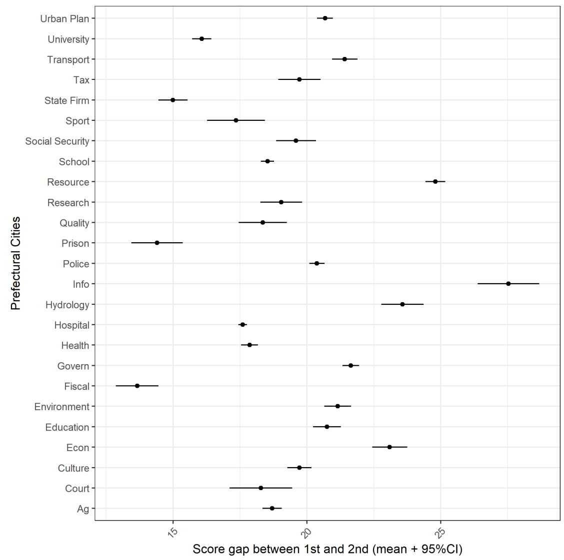
Next, I plot the distribution of score gaps between winners and the strongest losers by city and department in Figure A17. Similar to the number of bidders, cities like Foshan, Zhongshan, and Guangzhou have smaller winning margins on average.

To measure the corruption level more directly, I construct the corrupt index by city and department in Figure A18. Zhongshan City shows the lowest corruption index, followed by

Figure A17: Distribution of Winning Margins



(a) Winning Margin: by City



(b) Winning Margin: by Department

Notes: Figure (a) is aggregating the procurement auction level data to the prefecture city level. In Figure (b), I relabeled the procurement departments by their functions, like the education department, the transportation department, the prison, etc.

Jiangmen City and Foshan City. Interestingly, cities performing well in terms of corruption are mostly located around Guangzhou, except for Guangzhou itself.

To understand the city characteristics contributing to the corruption level, I collected city panel variables, including annual GDP, fiscal expenditure, and distance to the provincial capital government. I then ran city characteristics on city public procurement outcomes and the corruption index using the following specification at the city level:

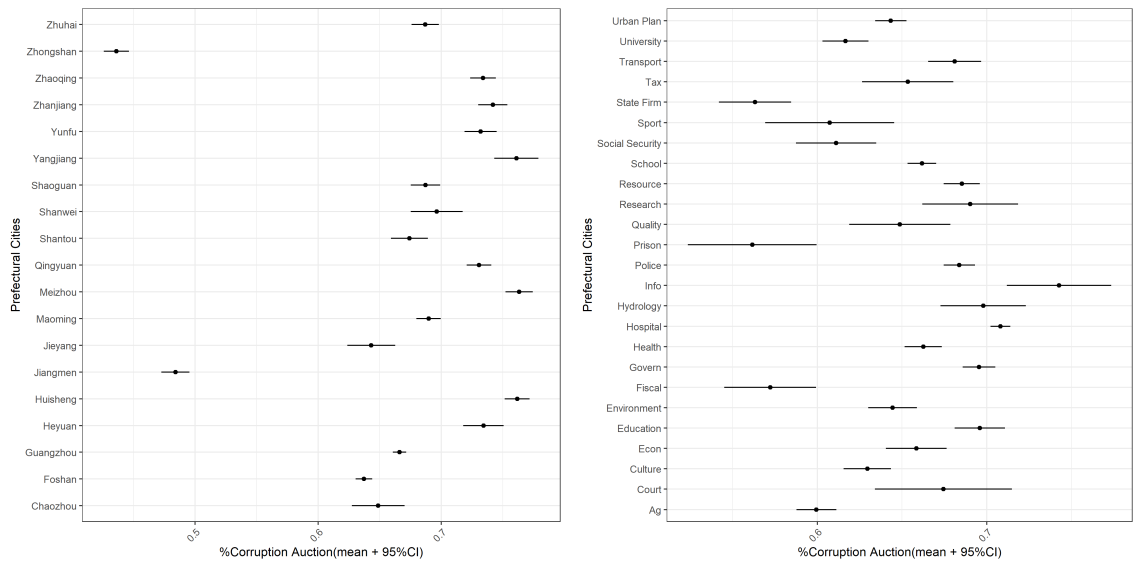
$$y_{ct} = \alpha_t + \beta_1 City\ Characteristics_{ct} + \epsilon_{ct}$$

where y_{ct} represents aggregate public procurement dependent variables in city c at year t, including the average number of bidders, winning margins, and the corruption index. I included city-level fiscal expenditure, the previous year's total GDP, GDP per capita, and the mean of public procurement budget size. Year fixed effects, α_t, are also controlled. Additionally, I conducted procurement project-level regressions using the specification:

$$y_{act} = \alpha_t + \beta_1 City\ Characteristics_{ct} + \beta_2 Auction\ Characteristics + \epsilon_{ct}$$

where y_{cat} represents the public procurement auction a dependent variables in city c at year t, including the number of bidders, score gaps between winners and the strongest losers, and the corruption test results. Procurement auction characteristics, such as public procurement

Figure A18: Distribution of Corruption Index



(a) Corruption Portion: by City (b) Corruption Portion: by Department

Notes: Figure (a) is aggregating the procurement auction level data to the prefecture city level. In Figure (b), I relabeled the procurement departments by their functions, like the education department, the transportation department, the prison, etc.

budget size and procurement category fixed effects, are added to control the variation in procurement projects.

The results in Table A9 show consistency between city-level and procurement-level regressions. The further the procurement is conducted away from the province's central government, the higher the corruption index and the higher the probability of rejecting the null hypothesis of real competition in procurement auctions. These results align with the Chinese proverb "The sky is high, and the emperor is far away," which describes a situation where local authorities or officials are not closely monitored or influenced by higher-level government authorities. Additionally, the results suggest that richer cities tend to have lower corruption levels, although this is not necessarily a causal relationship. Higher economic development could lead to more resources for regulation and increased transparency in public procurement. Conversely, lower corruption levels may make cities more attractive to investors and businesses, leading to further economic development.

Table A9: Firm Characteristics and θ of Bidders

	City Level			Public Procurement Level		
	Corruption	Score Gap	#Bidders	Corruption	Score Gap	#Bidders
log(Distance to Guangzhou)	0.0171**	0.2765	-0.0896***	0.0130**	0.3403*	-0.0591***
	(0.0070)	(0.2390)	(0.0316)	(0.0037)	(0.1418)	(0.0140)
Log(Procurement Budget)	0.0123	0.0692	0.0898**	0.0089***	-0.0414	0.1784***
	(0.0097)	(0.3218)	(0.0360)	(0.0016)	(0.1162)	(0.0411)
Log(Fiscal Expenditure)	0.0190	0.7037	0.0778*	0.0076	0.2283	0.0887**
	(0.0173)	(0.5784)	(0.0463)	(0.0171)	(0.5522)	(0.0258)
Lag Log(GDP)	-0.0572*	-1.4331	-0.1057	-0.1063***	-3.6705***	0.1521
	(0.0341)	(1.3381)	(0.1264)	(0.0202)	(0.7117)	(0.0892)
Lag Log(GDP)^2	0.0021	-0.0210	0.0025	0.0062***	0.1842***	-0.0130*
	(0.0031)	(0.1172)	(0.0105)	(0.0007)	(0.0297)	(0.0059)
Lag Log(GDP per capita)	0.0017	0.5907	0.2064***	-0.0125	-0.6534	0.1738***
	(0.0239)	(0.7174)	(0.0562)	(0.0078)	(0.3912)	(0.0354)
Observations	553	629	629	112594	112702	112702

Notes: The first three columns present the estimation for city panel data, while the second three columns display the estimation for public procurement auction data. All regressions control for year-fixed effects. The public procurement regressions also control for procurement category fixed effects and budget price. Standard errors are clustered at the city level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.9 Estimate the Proportion of Corruption

In this section, I discuss the method designed to directly estimate the proportion of corruption within a group of auctions, rather than assessing each auction individually. Subsequently, I juxtapose these findings with results obtained through the auction-level analyses.

A.9.1 Settings

Theorem 2 says in the competitive auction, the winning scoring bid is the expectation of the strongest rival's pseudotype k:

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

Corollary 2.1. *In a group of competitive auctions, the expectation of winning scores is equal to the expectation of the strongest rival's pseudotype k:*

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

Proof. Based on Equation A.6.1 in Theorem 2 and Law of total expectation:

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

□

The $k^{rival(1)}$ is estimated by utilizing the distributions of scores from competitive auctions using Equation 1.11. Theoretically, I can directly assess whether $E[s^{win}] = E[k^{rival(1)}]$ for a group of auctions. However, when the distribution of score s is biased by the mixture of corrupt auctions and non-corrupt auctions, $E[s^{win}] = E[k^{rival(1)}]$ doesn't hold for competitive auctions. When mixing the corrupt auctions and competitive auctions together, the k^{rival} is subject to an upward bias in competitive auctions, while it is tainted by a downward bias in corrupt ones due to the prevalence of low scores stemming from manipulations in the scoring rule. The mixture of corrupt and competitive auctions causes the separation of $E[s^{win}] - E[k^{rival(1)}]$:

$$\text{For competitive auctions: } E[s^{win}] - E[k^{rival(1)}] \leq 0$$
$$\text{For corrupt auctions: } E[s^{win}] - E[k^{rival(1)}] > 0$$

since the manipulation of scoring rules, denoted as m, is generally unobservable, a larger m corresponds to a larger positive gap, $E[s^{win}] - E[k^{rival(1)}]$. This distinctive separation provides a characteristic for conducting mixture analysis.

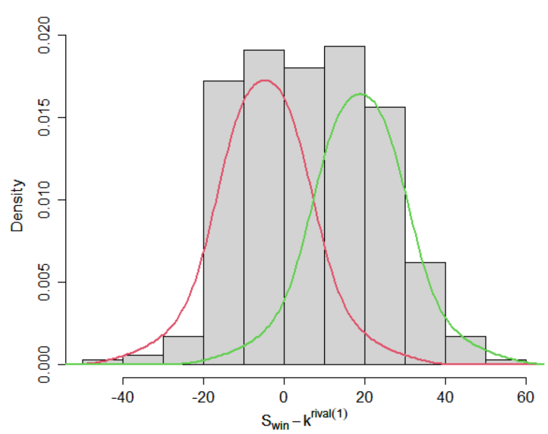
I adopt the approach of nonparametric maximum likelihood estimation to recover the distribution F of $s^{win} - k^{rival(1)}$ based on methods in Jiang and Zhang (2009), Koenker and Mizera (2014), Gu, Koenker, and Volgushev (2018), and Gilraine, Gu, and McMillan (2020). These papers establish a general framework for quantifying unobserved heterogeneity, without putting any parametric assumptions on the unobserved heterogeneity. This application to corruption within auctions fits within this established framework, as the manipulation of scoring rules, m, remains unobservable. Consequently, the resultant $s^{win} - k^{rival(1)}$ can be considered a manifestation of unobserved heterogeneity within the auction environments. The distribution F of $s^{win} - k^{rival(1)}$ is unobserved, but can be estimated non-parametrically from the data:

$$\hat{F} \equiv argmax_{F \in \mathcal{F}} \{ \sum_{t=1}^{\mathcal{T}} log \int \varphi_d((s_t^{win} - k_t^{rival(1)}) - \theta) dF(\theta) \}$$

where φ_d represents the standard d-dimensional normal density and $\mathcal{F}$ denotes the set of all probability distributions on $\mathbb{R}$. Here, $\hat{F}$ is the nonparametric maximum likelihood estimator (NPMLE) for F. Kiefer and Wolfowitz (1956) have demonstrated the consistency of the NPMLE for the mixing distribution F. Subsequently, integrating the density for $\theta > 0$ yields the proportion of auctions that are corrupt.

A.9.2 Monte Carlo Simulation

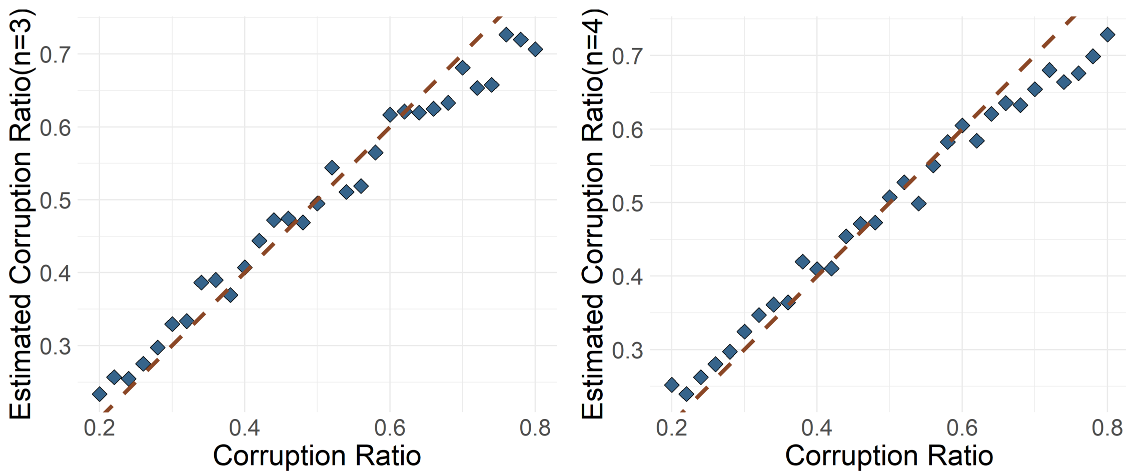
Figure A19: An Example of NPMLE on Mixture Analysis



Notes: The example is mixing 500 competitive auctions with 500 corrupt auctions. By estimating the pseudotype together, I plot the distribution of $s_{win} - k^{rival(1)}$.

Employing the same setting as detailed in Section 1.6, I estimate the NPMLE and the proportion of corrupt auctions under varied corruption ratios and contrast the estimation with the DGP. Figure A19 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 corresponding probabilities are 51.2% and 48.8%, respectively, which closely align with the actual corruption ratio of 50%.

Figure A20: The Comparison between Estimation and DGP



(a) Auctions with Three Bidders

(b) Auctions with Four Bidders

Notes: 1000 auctions are simulated with the different number of bidders as Section 1.6. The red dashed line is a 45-degree line to show the comparison between the estimation and the real DGP.

Figure A20 illustrates the estimation in comparison with the DGP. The x-axis represents the corruption ratio in the DGP, and the y-axis depicts the estimated proportion of corruption. A closer mass of dots to the dashed red 45-degree line implies higher estimation accuracy. As demonstrated in the graphs, across differing corruption ratios, the estimations approximate the actual corruption ratio, typically rendering a slightly inflated corruption proportion when the actual corruption ratio is minimal and slightly deflated when it is substantial. Overall, the results provided by the NPMLE are closely aligned.

A.9.3 Compare with Main Results

Then I apply the method to the public procurement data and compare the results. The results are shown in Table A10. For auctions with three bidders, the estimated proportion is 70%, closely aligning with the 70.03% from aggregating auction-level test results. As indicated in the preceding subsection's Monte Carlo exercise, the estimated proportion tends to underestimate the actual ratio when the inherent corruption ratio is high. Consequently, the actual corruption ratio is likely above 70%. This comparison also reveals that the auction-level test tends to be more conservative for cases involving three bidders. Regarding instances with four or five bidders, the estimated proportions align closely with the figures on the first row. In summary, the estimations of corruption proportions generally corroborate the main findings presented in Section 1.6.

To evaluate the accuracy of the estimation compared to actual public procurement data, I use two subgroups of data and plot how well the estimation fits the data in Figure A21.

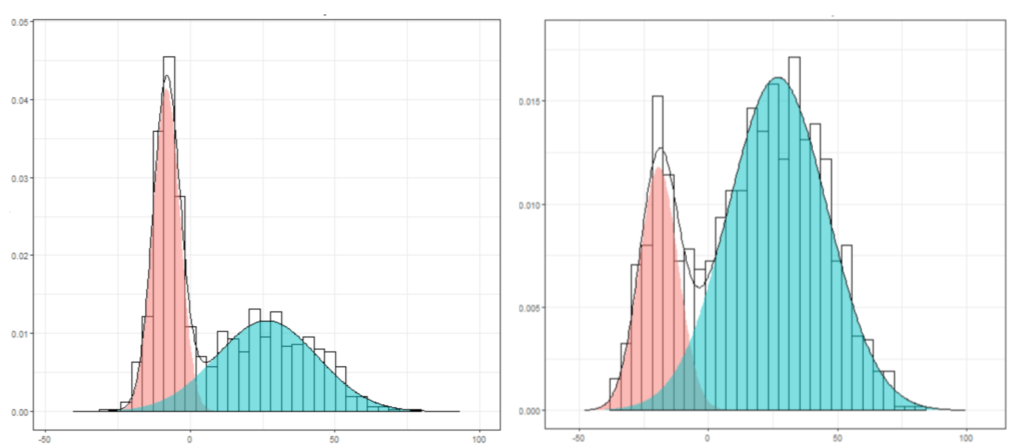
Table A10: Estimation of Corruption Proportion V.S. Main Results

	All	3 bidders	4 bidders	5 bidders
Unadjusted P-value $\alpha = 0.1$	65.06%	70.03%	51.52%	48.13%
Adjusted P-value $\alpha = 0.1$	57.23%	62.72%	43.76%	38.62%
Unadjusted P-value $\alpha = 0.05$	54.83%	60.31%	41.06%	34.76%
Adjusted P-value $\alpha = 0.05$	45.58%	50.38%	33.98%	27.45%
Proportion Estimation	63.70%	70.00%	47.58%	43.70%

Notes: The corruption proportions are calculated for each subgroup conditional on auction characteristics including the number of bidders, procurement categories, budget size, and price weights, then weighted by the number of auctions.

Both graphs represent professional service projects, albeit with varying budget bins and numbers of bidders. As illustrated in Figure A21, the estimation, which includes a mixture of both corrupt and non-corrupt groups, closely matches the observed data distribution.

Figure A21: 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.

A.10 An Alternative Corruption Test

Instead of estimating an unbiased pseudotype through the iterative approach proposed in Section 1.6, I can also use the biased pseudotype and clustering method to identify the corrupt auctions. In the following sections, I provide a detailed implementation of this clustering approach and a comparison with the main method in Section 1.6. Overall, the main method from Section 1.6 consistently outperforms the clustering method in terms of prediction accuracy, as evidenced by both Monte Carlo simulations and real data validated through expert surveys.

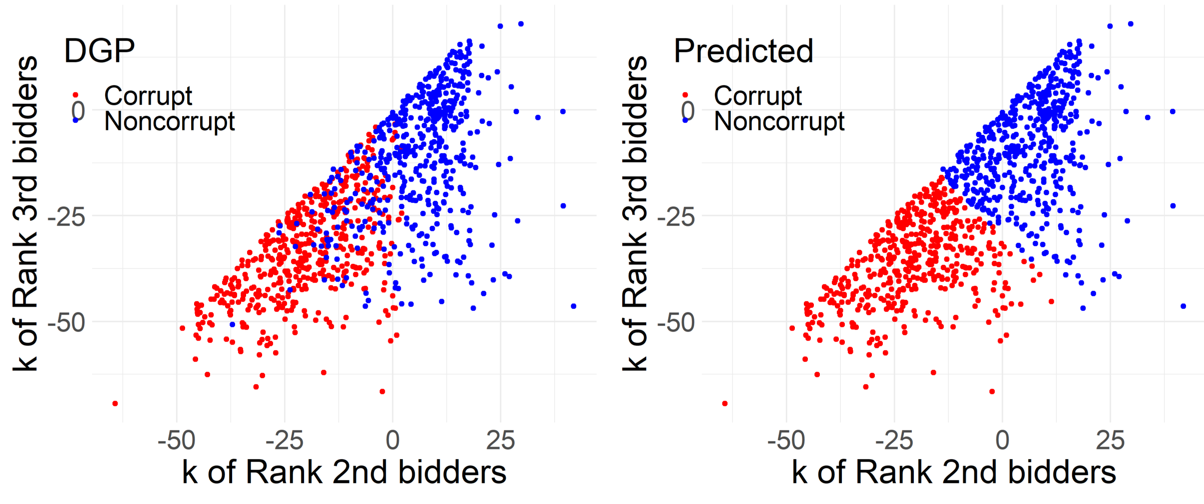
A.9.1 k-means Clustering

In Section 1.5, it's demonstrated that in the presence of scoring rule manipulation, both scores and pseudotypes k are downgraded, such that $E[k^{rival}|s^{win}] > E[k_t^{rival}|s^{win}]$. As a result:

$$E[k^{rival}_{noncorrupt} - s^{win}] > E[k^{rival}_{corrupt} - s^{win}]$$

This distinction provides a rule for employing the clustering method to categorize auctions as either corrupt or noncorrupt.

Figure A22: k-means Clustering: Observed V.S. Predicted



(a) DGP observed corruption labels (b) K-means predicted corruption labels

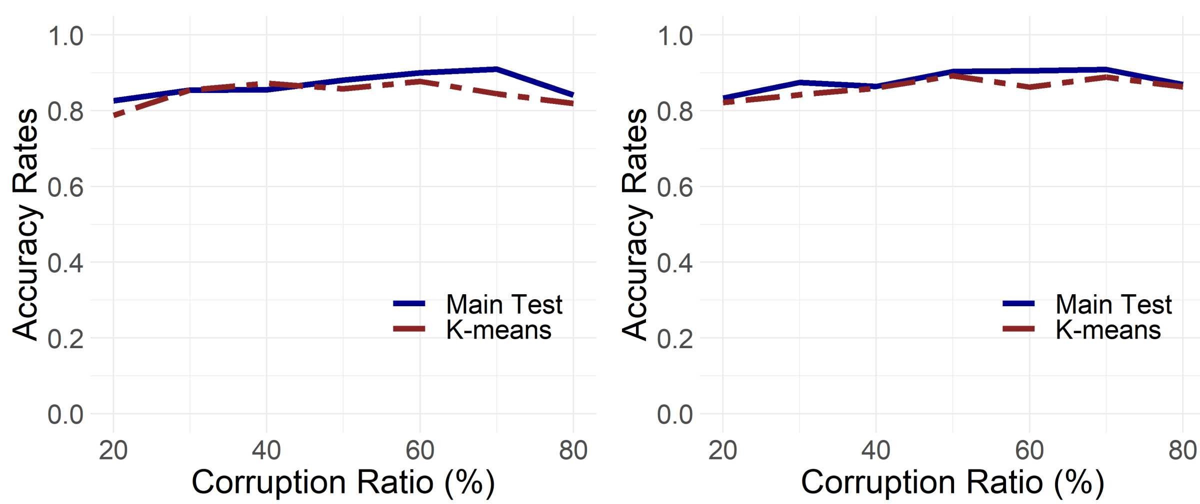
Notes: (a) plots the real corrupt auctions in red v.s. noncorrupt auctions in blue. (b) plots the predicted corrupt auctions in red v.s. predicted noncorrupt auctions in blue.

For each auction t with n bidders, I construct an observation vector composed of the demeaned pseudotypes $k^{rival} - s^{win}$ of all rivals. This vector, of dimension $n-1$, takes the form $[k^{rival(1)} - s^{win}, k^{rival(2)} - s^{win}, ..., k^{rival(n-1)} - s^{win}]$. To classify this multi-dimensional data, I use the k-means clustering method, a popular unsupervised learning clustering method in computer science. To show how the vectors of noncorrupt auctions and corrupt auctions behave differently, I use the 50% corruption ratio with three bidders in the Monte Carlo study as an example. In such a scenario, given three bidders, there are two rival bids, resulting in a 1x2-dimensional vector. This can be visualized on a 2D plot. Figure A22 (a) presents the corruption labels based on the data-generating process (DGP). Noncorrupt auctions concentrated on the upper position of the 45-degree line while corrupt auctions are mainly located in the lower area. Despite some overlap in the central region, a clear separation is evident. Implementing the k-means clustering to identify different clusters, the predicted results, shown in Figure A22 (b), perform pretty well, with some discrepancies observed in the overlapping middle area.

A.9.2 Comparison with the Main Method

I compare the accuracy rates of the main test results with the k-means predictions across varying corruption ratios, as shown in Figure A23 (a). Overall, for auctions with three bidders, the main test surpasses the k-means method in performance under most corruption ratio conditions. Figure A23 (b) shows the auctions with four bidders, and in all scenarios, the main test outperforms the K-means.

Figure A23: Comparison between Main Test and K-means in Monte Carlo

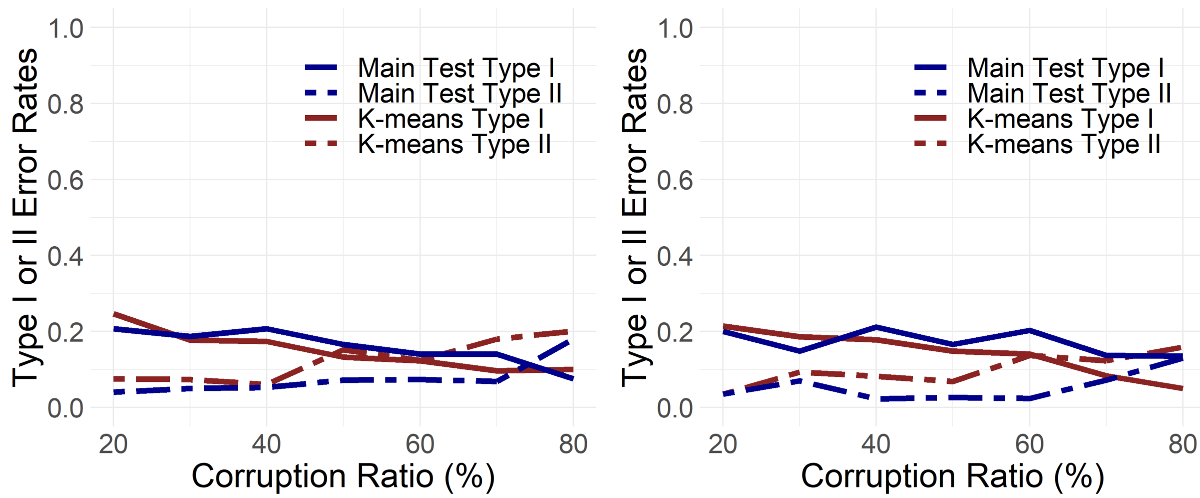


(a) Accuracy Rates with 3 Bidders (b) Accuracy Rates with 4 Bidders

Notes: (a) plots the accuracy rates under different corruption ratios, with the blue solid line representing the main test results and the red dashed line representing the k-means cluster prediction. (b) plots the accuracy rates for the auctions with four bidders.

Figure A24 (a) and (b) show the type I and II errors for auctions consisting of three or four bidders. Evidently, in both scenarios, the test power of the main method surpasses that of the k-means approach.

Figure A24: Comparison between Main Test and K-means in Monte Carlo



(a) Errors with 3 Bidders

(b) Errors with 4 Bidders

Notes: (a) plots the Type I and II errors under different corruption ratios in auctions with 3 bidders. (b) plots the Type I and II errors under different corruption ratios in auctions with 4 bidders.

Then I apply the k-means method to all the public procurement data. The results are presented in Table A11. The proportions of auctions labeled as corrupt by the K-means method align closely with the primary results that employ Unadjusted P-values in cases of 3 and 4 bidders. For instances with 5 bidders, the proportion approximates the adjusted P-values. The comparison further provides evidence for the assertion in Section 1.6 that with a greater number of bidders, the adjusted p-value is the preferable choice. The overall prediction consistency rate between the unadjusted p-value in the main results and the K-means method is 82.83%. Comparing the results with the expert audit study, the K-means results reach a consistency (accuracy) rate of 79.59%, less than the main results of 81.4%.

Table A11: K-means Estimation V.S. Main Results

	All	3 bidders	4 bidders	5 bidders
Unadjusted P-value $\alpha = 0.1$	65.06%	70.03%	51.52%	48.13%
Adjusted P-value $\alpha = 0.1$	57.23%	62.72%	43.76%	38.62%
K-means Estimation	64.75%	71.72%	52.86%	38.61%
Same as Unadjusted P	82.83%	83.36%	75.91%	75.18%

Notes: The corruption proportions are calculated from the main test method and the K-means clustering method, conditional on auction characteristics.

Appendix B

Chapter 2

B.1 Supplementary Tables and Figures

Table B1: A Complaint Case

Company	Busi Score (20)	Tech Score (50)	Price Score(30)	Final Score	Order
A	17	48.8	25.183	90.98	1
Complainant	20	40.4	27.278	87.68	2
B	20	36.8	30	86.8	3
C	20	40.6	25.511	86.11	4
D	14	37	23.492	74.49	5
E	16	28.4	27.121	71.52	6
F	17	15.2	24.54	56.74	7

Notes: This procurement project was initiated by a county-level urban planning and water supply department in 2014. The outcomes of the procurement auction are shown on the public procurement website.

Figure B1: A Complaint Case: Submission at Call-for-tender Stage

中财采购决〔2015〕7号

政府采购投诉处理决定书

投诉人：广州市鑫德力科技有限公司

法定代表人：詹德仁

地址：广州市黄埔区黄埔东路5号东城国际907房

电话：020-22197563 邮编：510700

电子邮箱：xindeli@163.com 传真：020-22197562

委托代理人姓名：许春泽 职业：销售经理

联系电话：18620052681

被投诉人：中山市小榄人民医院 法定代表人：何淑明

地址：中山市小榄菊城大道中段65号

电话：0760-88662120

我局对广州市鑫德力科技有限公司于2015年1月8日提起的中山市小榄人民医院放疗辅助设备一批采购项目（采购项目编号：YY2014058）"投诉，已依法调查终结。经审查，我局认为：

一、投诉人的投诉事项

该项目由中山市小榄人民医院委托中山市小榄镇采购中心开展采购活动，采购文件于2014年12月18日在指定媒体上发布。在采购文件公示期间，投诉人认为招标文件损害其利益，并于2014年12月25日向中山市小榄镇采购中心提出了质疑，因对被投诉人的质疑答复不满意，向本局提起投诉。主要的投诉事项如下：

投诉人认为招标文件中带★条件制约及需原装进口之条件违反《政府采购货物和服务招标投标管理办法》第21条"招标文件不得要求或者标明特定的投标人或者产品，以及含有倾向性或者排斥潜在投标人的其他内容"之规定。

二、处理投诉过程

在处理投诉期间，我局对投诉人提供的相关资料进行了认真审阅，并对投诉人投诉材料真实性进行取证，就投诉事项要求被投诉人中山市小榄人民医院向我局作出书面说明，并两次组织了投诉方及被投诉方进行质证，听取投诉人及被投诉人的陈述和申辩。

三、查明事实

经查实，该项目已按照《关于印发〈政府采购进口产品管理办法〉的通知》（财库〔2007〕119号）的规定，履行了采购进口产品审批的相关程序。但在招标文件需求参数中设置"★需原装进口，国际知名品牌"条件，违反了《关于政府采购进口产品管理有关问题的通知》（财办库〔2008〕248号）第五点第二款"财政部门审核同意购买进口产品的，应当在采购文件中明确规定可以采购进口产品，但如果因信息不对称等原因，仍有满足需求的国内产品要求参与采购竞争的，采购人及其委托的采购代理机构不得对其加以限制，应当按照公平竞争原则实施采购"的规定。因此，该项目招标文件不应只限定采购进口产品。

另外，经我局对投诉资料的审查及向相关部门取证，发现投诉人提供的投诉书附件材料中的中山大学附属第一医院医疗设备（重招）（招标编号：0724-1441D60W1100）的招标文件与我局向有关机构调取的原始资料不符，具体表现在投诉人提供的招标文件无原始招标文件中近18处星号的技术参数条款。鉴此，我局将进一步予以调查，并根据调查结果依现行法律法规相关规定另行追究相关主体的法律责任。

四、处理决定

本局根据以上事实，依据《政府采购供应商投诉处理办法》（财政部令第20号）第十八条第二款（一）规定，对本投诉事项作出如下决定：

责令采购人修改招标文件，并按修改后的采购文件开展采购活动。

如贵公司不服本决定，可在决定书送达之日起六十日内依法向中山市人民政府或广东省财政厅申请行政复议，或在本决定书送达之日起三个月内向中山市人民法院提起行政诉讼。

中山市财政局

2015年3月9日

Notes: This procurement project was initiated by a county-level public hospital in 2015. The outcomes of the procurement auction are shown on the public procurement website. The complete complaint file is shown here.

Figure B2: A Complaint Case: Submission at Auction Complete Stage

政府采购投诉处理决定书

三财采决〔2014〕01号

投诉人：深圳市鸿盈鸿科技有限公司

法定代表人：季红伟

地址：深圳市龙岗区布吉街道京南工业区5号5楼南

被投诉人：广州群生招标代理有限公司佛山三水分公司

法定代表人：邓志彪

地址：佛山市三水区西南街道广海大道中39号一座1011

2014年9月9日，本机关依法受理了投诉人深圳市鸿盈鸿科技有限公司对“佛山市三水区三防物资采购项目（项目编号为：GZQS1401HG07051S）”提起的投诉，投诉人认为此次项目中技术评审未严格遵守评审方法和评审标准，严重影响中标结果，请求“认定中标结果无效，并从中标候选供应商中按顺序另行确定中标供应商或重新组织进行招标。”

本机关对投诉人提供的投诉相关资料进行了认真审阅，依法调取、审阅了有关材料，听取了被投诉人的陈述和申辩，经核实，情况如下：

广州群生招标代理有限公司佛山三水分公司（以下简称“群生招标”）组织了“佛山市三水区三防物资采购项目”（项目编号为：GZQS1401HG07051S）的采购活动，于2014年7月31日进行评审，推荐佛山市鹏洋商贸有限公司为预中标供应商。根据《招标文件》要求，评标委员会决定投标文件的响应程度只依据投标文件本身的真实无误的内容，而不依据外部的证据。本项目的评标委员会对于客观评分项的评分是一致的，对投诉人的评审均依据其投标文件。

综上，本机关认为，本项目评审委员会在进行技术评审时，已严格依照评标标准和方法对投标文件进行评审及比较，未发现存在投诉人所称“技术评审未严格遵守评审方法和评审标准，严重影响中标结果”等情形，本次采购过程也未发现存在违法违规影响采购结果公平公正的行为。根据《政府采购供应商投诉处理办法》第十七条的规定，本机关决定：

投诉缺乏事实依据，驳回投诉。

如对上述决定不服，可在收到本决定书之日起60天内向三水区人民政府或佛山市财政局申请行政复议，或在收到本决定书之日起3个月内向人民法院提起行政诉讼。

佛山市三水区财政局　　2014年 10月21日

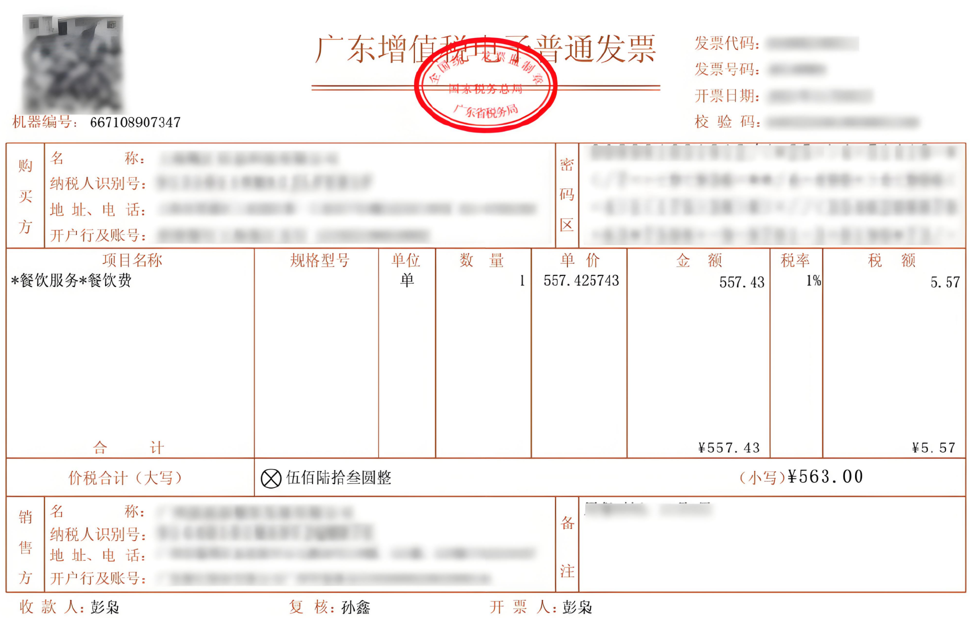
Notes: This procurement project was initiated by a county-level urban planning and water supply department in 2014. The outcomes of the procurement auction are shown on the public procurement website. The complete complaint file is shown here.

Appendix C

Chapter 3

C.1 Supplementary Tables and Figures

Figure C1: An Example of Invoice



广东增值税电子普通发票

发票代码:
发票号码:
开票日期:
校 验 码:

机器编号: 667108907347

购买方 名称: 纳税人识别号: 地址、电话: 开户行及账号: 密码区

项目名称	规格型号	单位	数量	单价	金额	税率	税额
*餐饮服务*餐饮费		单	1	557.425743	557.43	1%	5.57
合计					¥557.43		¥5.57

价税合计（大写） ⊗伍佰陆拾叁圆整 （小写）¥563.00

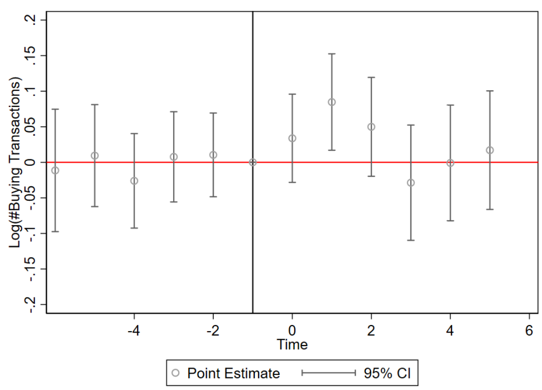
销售方 名称: 纳税人识别号: 地址、电话: 开户行及账号: 备注

收款人：彭枭 复核：孙鑫 开票人：彭枭

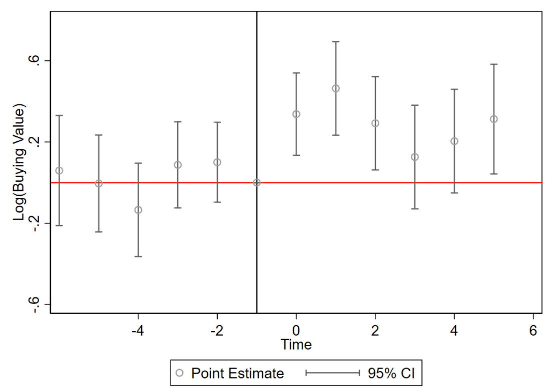
Table C1: Summary Statistics between Winners and 2nds

Variable	Winner	Losing 2nd	P Value
Capital Size	11230.69	7261.99	0.00***
Employee Size	334.2	204.79	0.00***
State Owned	0.04	0.03	0.00***
Registration Year	2004.71	2005.45	0.00***
Foregin Connected	0	0	0.00***
Small Business	0.01	0.01	0.57
Public Listed	0.03	0.02	0.00***
#Corp Member	47.52	29.92	0.00***
Branch	0.02	0.01	0.00***

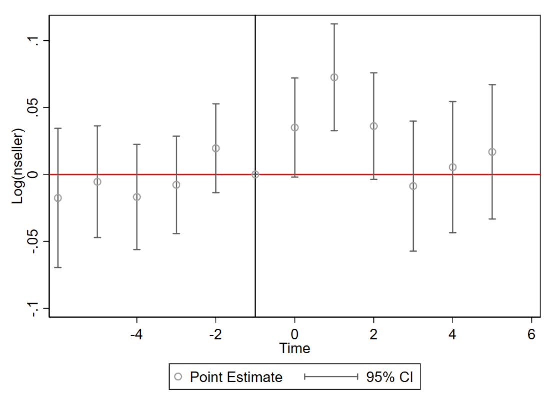
Figure C2: Direct Effects of Winning Public Contract on Upstream Purchase



(a) Number of Purchase Transactions



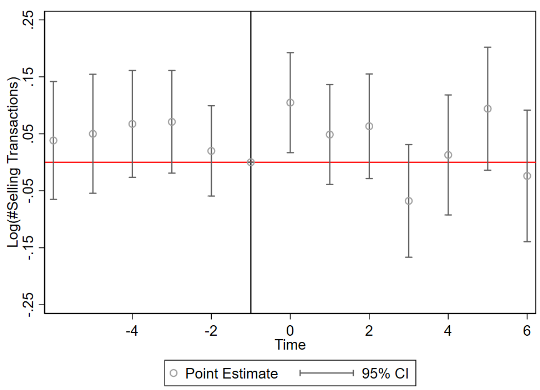
(b) Log(Purchase Transaction Amount)



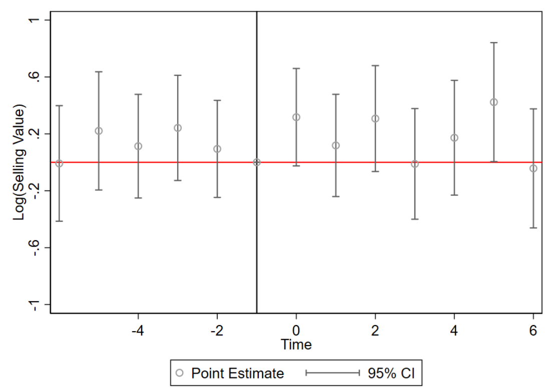
(c) Number of Sellers

Notes: In the event study, we control for public procurement project fixed effects, firm fixed effects, month fixed effects, and city-industry-project time fixed effects. We only use public procurement projects whose winners won only once during the event window to rule out the possible overlap of multiple projects. Standard errors are clustered at the firm level.

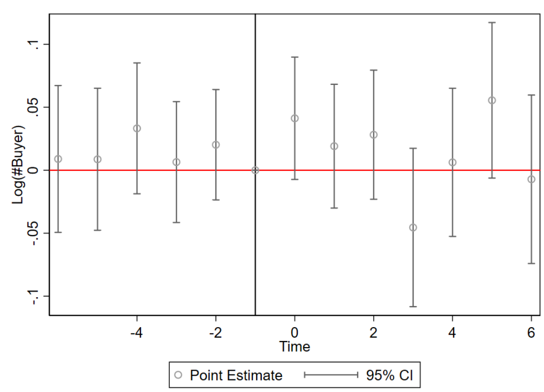
Figure C3: Direct Effects of Winning Public Contract on Downstream Sell



(a) Number of Sell Transactions



(b) Log(Sell Transaction Amount)



(c) Number of Buyers

Notes: In the event study, we control for public procurement project fixed effects, firm fixed effects, month fixed effects, and city-industry-project time fixed effects. We only use public procurement projects whose winners won only once during the event window to rule out the possible overlap of multiple projects. Standard errors are clustered at the firm level.