

# Information and Corruption: Evidence from China's Land Auctions

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## Abstract

This paper examines how sellers' private information affects auction outcomes differently in two-stage auction and English auction, and how this difference affects auctioneer's incentive in choosing auction formats and gives rise to corruption in the context of China's land market. Using a theoretical model to endogenize the incentive of China's local governments, this paper finds that (1) two-stage auctions are more prone to corruption than are English auctions when information is asymmetric and (2) land with lower value faces a harder constraint for corruption. Consequently, local governments tend to use two-stage auctions on low-value land to maximize personal benefits and use English auctions on high-value land to maximize public benefits. Using a detailed data set that covers all land transactions in China between 2007 and 2017, I structurally estimate a common value auction model where bidders are asymmetric in information and private costs. Results show that land sold by two-stage auctions on average have a value lower than English auction by  $CNY343/m^2$ , explaining 43% of the observed price gap (selection effect); and the remaining 57% can be explained by the different bidding equilibrium of the two auction formats (corruption effect). Moreover, connected bidders have a significant information advantage over unconnected ones, allowing them to bid higher and win more often. The counterfactual results suggest that using English auction only and increasing public information disclosure, can both significantly reduce corruption, increase land revenues, and increase social welfare.

**Keywords:** China's land market, auction with asymmetric bidders, structural estimation of auctions, corruption

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# 1 Introduction

Land plays an important role in China's economic system. The state owns the land, and only the government can decide its usage and lease it to developers. Additionally, revenue from land sales constitutes an important source of fiscal income for the local government. Land leasing fees, as a part of the local extrabudgetary income, constitute about 50% of the formal budget at the provincial government level. In some areas, this percentage is as high as 170% (Tao et al. (2010)). Despite the financial significance of land, corruption manifests as a major problem.

Attempting to end widespread corruption, China launched a massive land reform in the early 2000s. The central government now requires all sales to be publicly conducted by either English or two-stage auctions. Each auction is usually publicly announced 20 working days before the sale. At announcement, basic details (e.g., use restrictions, reserve price, location) are publicized, and, for a small fee, potential bidders can obtain more detailed information, as well as inspect the site. English auctions are a standard ascending auction, in which bidders gather in a room and shout their bid(s). Two-stage auctions are a nonstandard auction format consisting of two consecutive periods. The first stage resembles a first-price sealed bid auction. In the first 10-day period, bidders may enter the auction by privately submitting their bids to local governments. At the end of the first stage, the highest bid is released to the public, and if at least one bidder claims that she would like to bid more, a second stage proceeds with the current highest bid being the reserve price, otherwise the bidder who posted the highest bid wins the land parcel and pays her bid. The second stage is the standard English auction previously described. In the remaining of the paper, I will model two-stage auction as a combination of first-price sealed bid auction and English auction.

Auctions appear to be more transparent than in the past, but corruption persists in the choice of the auction format and through preauction side deals between favored bidders and local officials. Everything else equal, the two auction formats should yield the same result

without leaving room for corruption (Goeree and Offerman (2003)). However, everything else is not equal.

Land auctions involve both private and common value components. While private value components typically consist of bidder-specific costs, common values can comprise common costs or the potential revenue from land development. In most auctions, the value of the object cannot be affected by the sellers' action. For example, in the auction of oil tracks, the value of the track is revealed immediately after the track is developed by the bidder. However, revenue from land development is usually realized after several years and, more importantly, crucially depends on local governments' development and infrastructure investment in the surrounding area. However, at the time of an auction, local governments' plans for the following years comprises their private information, which is unknown to the bidders. This leaves significant room for corruption. Some politically connected bidders can approach local officials and buy information by paying bribes, while unconnected bidders do not have this opportunity. This scenario in which some bidders have access to different information leads to a potential information asymmetry in future auctions. Because bidders do not observe the other bidders' bids and identities in the first stage of the two-stage auction, the better informed bidders have more room to secure profits from their extra information and thus leave more room for corruption. As a consequence, the corrupt local officials may find two-stage auction more attractive than English auction.

I construct a comprehensive land transaction data set with detailed information on land characteristics and winner firms' characteristics covering all land transactions in China from 2007 to 2017. I find that politically connected bidders bid significantly higher and make higher ex post profits than do unconnected bidders. Moreover, despite strong incentives for local governments to maximize land revenue and thus use English auctions, I find that governments use two-stage auctions, which are associated with lower prices on average, much more frequently than English auctions. This is partially because local governments' selection of the two-stage auctions for low-quality land sales and English auctions for high-quality land

sales.

In light of these empirical patterns, I develop a theoretical model with an anti-corruption central government, a corrupt local government, a politically connected bidder who can approach the local government and buy information by paying a bribe, and other unconnected bidders who cannot bribe government officials. I show that two-stage auctions are more prone to corruption than are English auctions when bidders' information about the common value of land is asymmetric. Moreover, low-value land yields lower information rent for connected bidders and thus has a harder constraint for corruption. Consequently, local governments tend to use two-stage auctions for low-value land to maximize personal benefits and English auctions for high-value land to maximize public benefits.

I then structurally estimate a common value auction model with bidders having asymmetric information and private costs. I show that land sold by a two-stage auction has, on average, a lower value than that in an English auction by  $CNY\ 343/m^2$ , explaining 43% of the observed price difference between the two auction formats (selection effect), and the remaining 57% is explained by the different bidding equilibrium of the two auction formats (i.e., the corruption effect). Moreover, that politically connected bidders have a significant information advantage over unconnected bidders allows the former to bid higher and win more often. My analysis, however, also finds that politically connected bidders have higher private costs, suggesting a great loss of efficiency, because land is not developed by the most cost-efficient firm.

Finally, I also evaluate the impacts of several alternative land market designs. The counterfactual analysis suggests that using only English auctions and increasing public information disclosure could significantly reduce corruption, increase land revenue, and increase social welfare.

### **Related Literature.**

Cai et al. (2013) first document the difference between two-stage auctions and English auctions. Relying on data on 2,302 completed auctions from 15 cities from 2003 to 2007,

they find that two-stage auctions are more corruptible, so city officials tend to divert higher-quality properties to this form. Their study focuses on a period during which the land market was still in transition, but I look at the land market once the land reform was complete and use a much larger data set that covers all cities. As a result, I document very different data patterns. For one example, they find that selection on land quality for two-stage auctions is positive, whereas, with a larger data set, I find selection to be negative. Moreover, while we both find that two-stage auctions to be more corruptible, the mechanism of corruption is very different: they argue that favored bidders can signal that auctions are “taken” in the first stage, so as to deter the entry of other bidders. For their argument to be true, two-stage auctions have to be noncompetitive such that only one bidder enters, the auction ends at the first stage, and the winner pays the reserve price. However, this pattern does not hold for the period of my study, and I focus on the role of information as a mechanism of corruption. I show that favored bidders acquire information advantage in the pre-auction period and make use of the information in the first stage of the auction.

Among the literature addressing corruption in China (e.g., Guo (2008), Wederman (2004), Dong and Torgler (2013)), only a few papers look at corruption in the land market despite its huge amount. Chen and Kung (2018) find that “princeling” firms obtain a significant price discount in land auctions, and the provincial party secretaries who provided the discount to these “princeling” firms are rewarded with promotions. Zhu (2012) documents the practices of corruption in China’s real estate industry, which ranges from local governments to lower-level functional units. I contribute to the literature by providing a complete overview of corruption in the market using a big data set covering all transactions in the past 10 years, and I am also able to characterize the mechanism of corruption with a structural model.

This paper directly speaks to the literature on the value of information in auctions. In their seminal paper, Milgrom and Weber (1982), studied whether the value of information in a first price auction is greater when it is observed by the other bidders. Larson (2009) and Hernando-Veciana and Tröge (2011) focus on the value of information in open auctions, and

Parreiras (2002) studies asymmetric common value auctions in a two-bidder case. Milgrom (1981), Engelbrecht-Wiggans et al. (1983), and Hernando-Veciana (2004) also derive some partial results as a by-product. My theoretical model builds on the work of Hernando-Veciana (2009), who suggest a new argument in favor of English auctions: more information about the private value and less information about the common value may improve efficiency and revenue. On the other hand, sealed bid auctions induce more information acquisition about a common component of the value than the English auction but less about the private component of the value.

Although one can find considerable theoretical discussions in the literature on common value auctions with asymmetric information,<sup>1</sup> the empirical evidence has remained relatively scarce because of known difficulties with structural identification in common value auctions (see, e.g., the discussion in Athey and Haile (2002)). In a seminal paper, Hendricks and Porter (1988) find that neighbor firms are better informed about the value of offshore drainage lease auctions than are nonneighbor firms. They also find that, when information is asymmetric, less competition occurs, and the profits of informed firms are much higher than in auctions in which information is more likely to be symmetric. Li and Philips (2012) tests the predictions of the Engelbrecht-Wiggans et al. (1983) theoretical asymmetric common value auction model with reduced-form analysis and shows that the private information of neighboring firms in drainage lease auctions leads to higher ex post profit. De Silva et al. (2009b) argue that asymmetric information about contract characteristics is a particularly important problem for new entrants and show that the release of information helps entrants in assessing the value of a procurement project. In a recent paper, Weiergraeber and Wolf (2018) structurally estimate an auction model with private and common value components and asymmetric bidders in both dimensions. I contribute to the literature by providing more empirical evidence, and moreover, by comparing two auction formats with a structural model.

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<sup>1</sup>See Hernando-Veciana (2009) for a more complete summary.

Some studies focus on bidder asymmetries in other dimensions (e.g., Andreoni et al. (2007), Dionne et al. (2009), Krishna (2003), Lebrun (1999)). For example, Maskin and Riley (2000) show theoretically that stochastically weaker firms bid more aggressively, and stronger firms win with higher profits. De Silva et al. (2003) empirically tests their theoretical predictions with an asymmetric procurement model. I contribute to this vein of literature by incorporating two types of asymmetries in the analysis, as well as comparing different auction formats in such a setting.

In terms of identifying common value auctions with asymmetric information, I rely on the large literature on the structural estimation of asymmetric auctions (e.g., Guerre et al. (2000), Guerre et al. (2000), Somaini et al. (2015)). Arguments in the literature rely on measurement error techniques and require one to observe all bids and understand that bidders' signals are a multiplicative function of private and common value signals. Because I only observe winning bids, I cannot use their methodology. Weiergraeber and Wolf (2018) develop an empirical strategy that relies on winning bid data and exogenous variation in the contract design. They have two auction formats, one of which is a standard asymmetric independent private value auction, which allows the authors to separately identify the distribution of private costs and common value signals. My estimation is in the same vein, but instead, makes use of the large sample of my data and is based on a mild assumption that bidders' development costs do not vary by land parcel.

I also build on the literature of political favoritism in auctions (e.g., Brogaard et al. (2015), Goldman et al. (2013), Muraközy and Telegdy (2016), Baltrunaite (2016), Szucs (2017)). Previous studies have mostly focused on documenting empirical relationships between political connections and auction outcomes. For example, Goldman et al. (2013) shows that political connections of the board of directors of publicly traded companies in the USA increase the chance of winning government procurement contracts. I contribute to this literature by providing additional empirical evidence, and moreover, building a structural model that formalizes the mechanisms by which governments' private information gives rise to

corruption. I also contribute to the literature by quantifying the welfare consequences of favoritism (Mironov and Zhuravskaya (2016), Schoenherr (2018), Schoenherr (2018), Szeidl and Szucs (2017), Bandiera et al. (2009)). I do so by providing a structural framework to quantify the level of corruption and simulate the effects of alternative policies that may reduce corruption in the presence of political connections.

Finally, this paper is closely related to a small but growing literature investigating the effects of information disclosure on corruption (e.g., Bandiera et al. (2009), DiRienzo et al. (2007), Barth et al. (2009)). Previous studies have mostly focused on cross-country evidence of the impact of information disclosure on corruption. I contribute to this vein of literature by providing micro-level evidence of how information disclosure can reduce corruption.

The remainder of the paper is structured as follows. Section 2 describes the institutional context. Section 3 describes the data. Section 4 presents my reduced-form evidence. Section 5 presents a model of corrupt local governments' auction format choice. Section 6 describes my estimation strategy for the common value auction model and presents the structural estimation results. Section 7 discusses two counterfactual experiments. Section 8 concludes.

## **2 Institutional Background and Data**

### **2.1 China's Land Market: Revenue Maximizing or Corruption?**

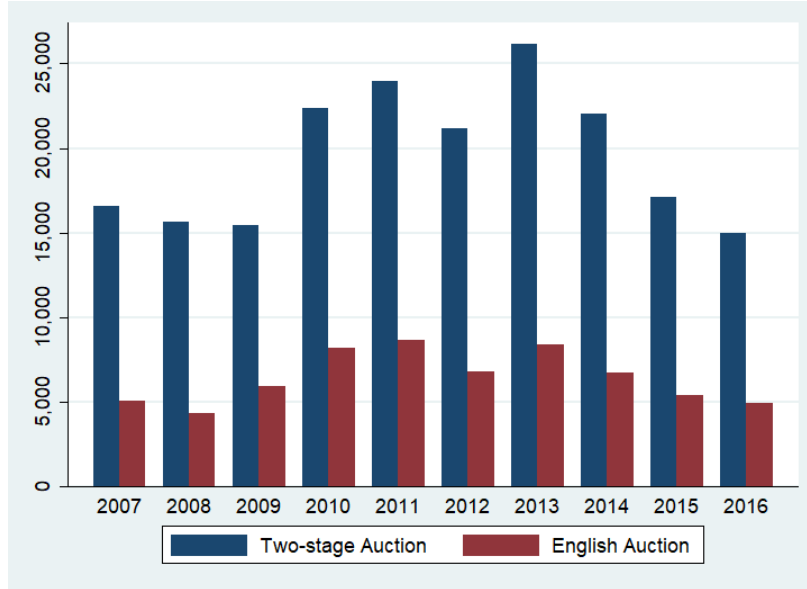
Different from most developed countries, urban land is owned by the Chinese state, and land use and land allocations are controlled by local governments. The Chinese central government carried out a massive tax reform in 1994 that essentially recentralized budgetary revenues and allowed the central government to control more spending. The impact was immediate, and the central share jumped from 22% to 56% in 1994 (Tsui and Wang (2004)). Local revenue shortfalls were further compounded by spending decentralization. As a result, the tax reform created acute revenue shortages and forced local governments to increase their efforts to meet expenditure needs. Opposite of intra-budgetary income, land revenues



are not subject to sharing with the central government, and, more importantly, the use of land revenue is subject to little central regulation. From 1999 to 2013, the ratio of land conveyance fee to the local budgetary revenue rose from 9% to 60% (Wang and Hui (2017)). The local governments' dependence on land revenue created a strong incentive among local officials to promote the real estate sector so as to maximize land revenue (Han and Kung (2015)).

On the other hand, because of the lack of central government regulation, China's land market is notorious for corruption. For one example, it has been estimated that in 2003, the country faced 168,000 violations of its Land Law (*China Daily* (2004)). Before 2002, most land was sold by "approved selling," which means that the local government sells the land by a one-on-one negotiation with a specific buyer. Such negotiations afford officials the opportunity to extract bribes and line their own pockets (Tao et al., 2010). Aimed at combating corruption, the central government started a massive land reform in the early 2000s, and the land market began transitioning from a planned process to a market-oriented one. In 2007, the central government completely banned the use of negotiation on the land market, after which more than 97% of land sales have been sold by public auction (Cai et al. (2013)).

Compared with negotiation, auction is believed to be more transparent for limiting sellers' ability to engage in corruption or political favoritism (Chong, Staropoli, and Yvrande-Billon (2011), Tran (2010)). However, even after the reform, local governments still have a lot of room for corruption, though in a less obvious way. First, local officials have whole discretion in determining the auction format for each piece of land being sold on the market. If they have a strong incentive to maximize land revenue, one may expect that they would choose the optimal auction format that maximizes the sale price. However, a first inspection of the data yields a confusing pattern. Figure 1 plots the number of land parcels sold by the two auction formats across my study period, and Figure 2 plots the average unit price ( $RMB/m^2$ ) weighted by land area for the two auction formats accordingly. Figure 2 shows



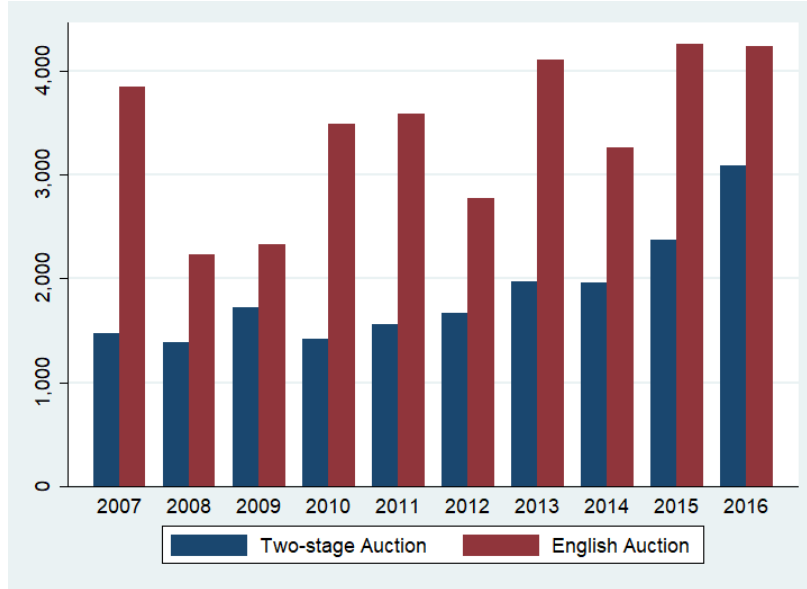
*Note:* This figure plots the number of land parcels sold by two-stage auctions and English auctions from year 2007 to 2017.

Figure 1: Number of land parcels sold by auction format

that the average sale price is much lower for two-stage auctions than for English auctions, but local governments employ two-stage auctions far more frequently in practice.

There are two possible reasons for the observed price difference between the two auction formats. First, local officials may employ two-stage auctions for low-value land and English auctions for higher-value land, either to maximize land revenue or for personal benefit. Second, two-stage auctions have a lower equilibrium price than do English auction; however, local governments still like to use two-stage auctions to maximize corrupt income. In fact, both channels work together in explaining the price differential, and I will distinguish these two channels from one another using a theoretical model, which I will discuss in more detail later in this paper.

How can local officials, acting as the auctioneer, acquire personal benefit from the auctions, and why is one auction format more corruptible than the other? To answer this question, one needs to understand local governments' role in China's land system. The local government not only runs the land auctions but also plays a very important role in the whole land development process. Local governments actively participate in building local



*Note:* This figure plots the average unit price of land parcels weighted by the area of the land parcel for two-stage auctions and English auctions from year 2007 to 2017.

Figure 2: Unit price of land by auction format

infrastructure, encouraging local businesses, attracting investment, and even directly engaging in enterprise investment and management, all of which may affect land value Tao et al. (2010). For example, Wu et al. (2014) show that complexes nearer to city centers or subway stations could achieve higher transaction prices. It usually takes developers at least 1 year, and sometimes up to several years, after winning land to finish a project for sale. This length of time can be even longer when developers decide to stock the land for future development (CRIC (2013)). This long period for land value realization increases uncertainty at the time of land sale. If the local government invests more into infrastructure in the surrounding area within this period, it can increase land value significantly and thus increase bidders' ex post profit. However, whereas local governments make careful plans about future land development and infrastructure investment, this information is not known to the public or to the developers at the time of a land sale. Other than the development plan, the local officials can influence land development along numerous other aspects as well. One typical case is in assisting in demolition. When conflicts arise between the developer and the current users,

bureaucrats may act as a mediator, exerting pressure on the current users and compelling them to accept the compensation clause. However, at the time of an auction, bidders do not have information about the extent to which the land development will be assisted by the central government. All uncertainties about land's value give rise to potential corruption. Bidders with a personal connection to local officials can access nonpublic information by paying a bribe. In reality, these bribes can be a huge amount. For example, *China Daily* (2006) reports that a former minister of land and resources was expelled from the Communist Party of the China Central Committee and refused Party membership on corruption charges for taking bribes of about \$600,000 for “misusing his powers”.

## **2.2 Data**

For my econometric analysis, I combine data from several sources. The data set contains detailed information on all land transactions and their winner firms during the post-reform period of 2007 to 2017. I also collect data on two relevant policy shocks: the anticorruption campaign and the establishment of online transaction systems for land auctions. The first one allows me to study the effect of corruption incentives on local governments' choice of auction formats, and the latter answers the question of how information asymmetry affects bidders' behavior and local governments' choice.

### **2.2.1 Land Transaction Data**

The land transaction data set is obtained from the website of the Land Transaction Monitoring System (<http://www.landchina.com/>). According to the Law of Land Management, the prefectural bureau of land and resources is required to report on the website every single land transaction in their jurisdiction. For each transaction, the Ministry provides detailed information about the size and location of the land parcel (with an address and postal code), total payment, date of transaction, the use restrictions, the stipulated plot ratio, the tenure

of lease, names of the seller and buyer, the specific method of transaction, a 2-digit code of land usage (e.g., industrial versus commercial), land parcel quality (as subjectively evaluated by the official-in-charge on a 12-point scale), a 3-digit industry code of the buyer's firm, and so forth.

The data set contains 1,865,513 total land transactions. As local governments have more complicated incentives in selling commercial land and industrial land (Su and Tao (2017)), I restrict my analysis to residential land only. Among the 299,769 residential land parcels, 60% were purchased by firms (the rest were acquired by private individuals), and I utilize these data for two reasons: First, I have information on all Chinese firms, and using these data only allows me to have more information about the winners. Second, the land parcels purchased by individuals are all in rural area, and the purpose of buying the land is not for development and profit, and therefore focusing on land purchased by firms illuminates a cleaner profit-maximizing buyer incentive.

One problem I encountered is that I was unable to identify errors in inputting key information, such as the land size. In practice, I deleted unreasonable observations (e.g., observations with land size  $\geq 100$  hectares or land size  $\leq 0.1$  hectares). Additionally, I calculated the land unit price (i.e., land price/land size), excluding any data with extreme values and retaining the remaining in the 199% interval. In addition, I also exclude land allocations for public projects (e.g., public rental housing, low-rent housing, and affordable housing), because firms not only bid on prices but also bid on the amenities they can offer for public projects. Finally, after removing observations with missing values on key variables, I had 181,045 land parcels.

I also obtained the satellite brightness measure of each piece of land for sale. Specifically, I locate each piece of land in the digital map from [bendi.google.com](http://bendi.google.com) using its street address. I then match the location with a time series of DMSP nighttime satellite images for the study period obtained from the National Geophysical Data Center (<http://ngdc.noaa.gov/eog/download.html>). The nominal data are at a 1-km resolution, and each pixel is represented by a digital number

between 0 and 1. A value of 0 represents the relative darkness, whereas very brightly lit central business districts (CBDs) typically saturate at a value of 1. The brightness measure constitutes one of the key variables that I use later on to estimate the value of the land. Moreover, in the reduced-form analysis, I use it as a proxy for land value. Although I do not observe the value of the land after years of transactions, the change in brightness offers an idea of how the value of the land changes over the years.

Table 1 presents summary statistics for the land transaction data set across the two auction formats. One can see from the table that, compared to land parcels sold by English auction, those sold by two-stage auction on average have larger area, lower limit for plot ratio, higher grade (i.e. lower official quality), and lower nighttime brightness, which all suggest that land sold by two-stage auction are of lower quality.

Table 1: Descriptive statistics of land transaction data

	Two-stage auction				
	Obs	Mean	SD	Min	Max
Price (CNY 10,000)	134,876	7272.27	17510.71	0.12	751000
Area (hectare)	134,876	3.78	4.50	0.1	99.09
Unit price (CNY/m <sup>2</sup> )	134,876	1751.61	2335.99	1	19986
Plot ratio (upper limit)	131,580	0.98	0.87	0	20
Plot ratio (lower limit)	131,148	2.48	1.31	0	20
Grade	110,415	4.97	3.07	1	12
Brightness	126,142	0.54	0.33	0	1
	English Auction				
	Obs	Mean	SD	Min	Max
Price (CNY 10,000)	31,595	10677.13	21321.51	1	479030.7
Area (hectare)	31,595	3.62	3.98	0.1	87.3
Unit price (CNY/m <sup>2</sup> )	31,595	2670.86	2956.44	2.43	19980.47
Plot ratio (upper limit)	30,950	1.06	0.79	0	20
Plot ratio (lower limit)	30,947	2.55	1.28	0	20
Grade	25,732	3.75	3.02	1	12
Brightness	29,498	0.63	0.33	0	1

*Notes:* This table compares descriptive statistics of the most important auction characteristics across different auction formats (two-stage vs. English). Grade is a 1 to 12 official measure of land quality. Brightness is a 0 to 1 measure of land brightness in the night.

### 2.2.2 Winner Firm and Political Connection

For each land transaction, the land data set contains the winner’s name, and this information allows me to match the data set to the firm data so that I can identify firms with connections. In particular, I code two connection indicators: whether or not the winner firm is a “princeling” firm and whether or not the winner firm is a local firm.

First, I search the winner firms’ names from qichacha.com. The website contains almost all Chinese firms registered at the State Administration of Industry and Commerce and contains detailed information about each firm’s establishing time, location, board members, registered capital, and business situation (existence, emigration, revocation, or cancellation), as well as historical information on the firm’s investment and shareholders.

Second, I construct a list of “princelings.” Princelings are defined as the offspring and other extended family members of China’s top leaders. Following Chen and Kung (2018), I first collect a list of the standing committee of the Politburo who served between 1997 and 2017. Furthermore, I also include the “Eight Immortals,” who are revered in communist lore as revolutionary fighters who led China’s economic opening after Mao Zedong’s death. Their families are believed to have long-lasting effects on China’s politics and economic activities (reference here). Upon identifying these political elites, I then searched online for their family members, that is, children and relatives. I mainly rely on Wikipedia and *Bloomberg*, which list political elites’ family members. I then supplement the data set with information from multiple sources, including Western media (*Bloomberg*, *New York Times*, *Washington Post*, and *Guardian*), and Chinese news groups (*China Digital Times* and *Boxun.com*). Altogether, I have identified xx family members related to xx Politburo Standing Committee members. Table xx reports the distribution of these xxx princelings in terms of both their relationship with the Politburo Standing Committee members and their reported occupation. For instance, about xxx of my sample is either a child or spouse of a Politburo member, and xxx (nearly half of them) are affiliated with the private sector (either as owners or investors).

Finally, a firm is coded as a “princeling” firm if its shareholders (including historical

shareholders) or its indirect shareholders (i.e., the shareholder of its shareholder) have a board member that is a “princeling” as defined above. A firm is coded as a local firm if its location is within the city or if its name contains the city’s name.

Table 2 presents summary statistics for the land transaction data set for firms with connections and without connections separately.

Table 2: Descriptive statistics by firm connection

	Nonprinceling				Princeling			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Price	7,794.53	18,142.82	0.12	751,000	14,503.45	26,112.05	15	356,000
Area	3.64	4.38	0.1	99.09	4.99	5.53	0.1	94.93
Unit price	1,914.06	2,478.72	1	19,986	2,564.17	3,049.63	3.2	19,887.37
PR (upper)	1.04	0.85	0	20	1.03	0.79	0	12.5
PR (lower)	2.50	1.30	0	20	2.44	1.13	0	12.5
Grade	3.91	3.05	1	12	4.83	3.53	1	12
Brightness	0.63	0.33	0	1	0.68	0.33	0	1

	Nonlocal				Local			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Price	8,053.47	19,598.02	0.12	751,000	7,778.20	16,940.79	0.94	661,489.9
Area	3.73	4.48	0.1	99.09	3.61	4.33	0.1	98.92
Unit price	1,888.12	2,555.18	1.06	19,984.65	1,965.52	2,423.93	1	19,986
PR (upper)	1.03	0.85	0	20	1.06	0.85	0	20
PR (lower)	2.45	1.27	0	20	2.55	1.33	0	20
Grade	4.04	3.21	1	12	3.82	2.90	1	12
Brightness	0.61	0.33	0	1	0.65	0.33	0	1

*Notes:* This table compares descriptive statistics for the most important auction characteristics by firm type (princeling vs. nonprinceling and local vs. nonlocal). PR, plot ratio. The variable units are the same as those used in Table 1.

### 2.2.3 Corruption

In November 2012, Xi Jinping initiated a wide-reaching anticorruption campaign in China. After Xi assumed office in the 18th National Congress, the Party’s Central Discipline Inspection Commission (CDIC) started to post the most influential cases on its official website. By September 2015, more than 1,000 names had been added to the CDICs list, at the rate of almost one per day.

During the campaign, the central government set up an organization called the Leading



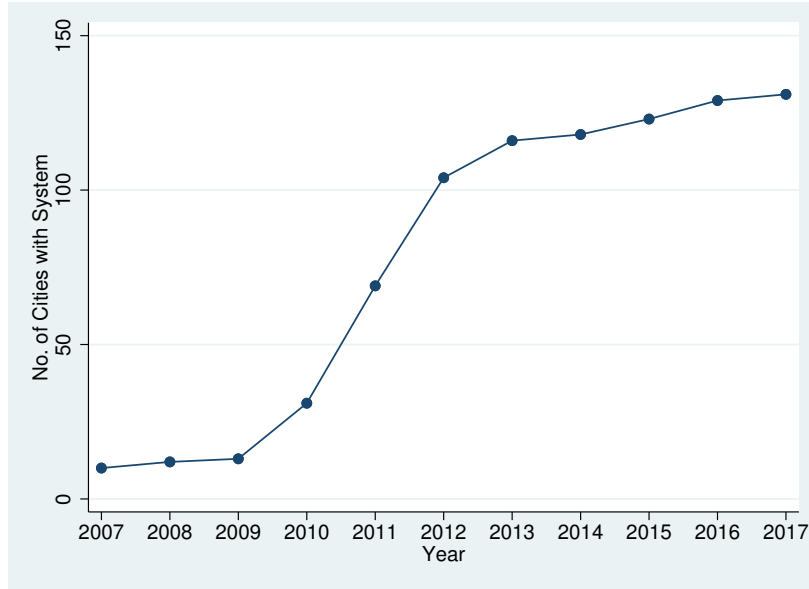
Group for Inspection Work.” This group subsequently accredited inspection teams (xunshizu) to the provinces, ministries, and state-owned enterprises. These teams assumed the responsibility of receiving tip-offs, conducting preliminary probes, and reporting useful information to the CDIC. In the 2 years after the anticorruption campaign began, four batches of inspection teams were sent to the provinces. In May 2013, the first batch was dispatched to five provinces. In November of the same year, another six teams were dispatched. Then, in March and July of 2014, two more batches were sent to the rest of provinces. In this paper, I use the dispatch of an inspection team to a province as the dividing line for defining whether or not a prefectural city in the province was affected by the anticorruption campaign.

To ascertain the details of the corruption in land sales, I collected a data set of all the cases posted by the CDIC between November 2012 and September 2015. For each investigated bureaucrat, I searched all of the reports, news, and legal documents regarding his or her downfall. By reading the materials, I then determined whether this bureaucrat was involved in the corruption related to land sales. A city is labeled as “corrupt” if any bureaucrat that worked in the city before the anticorruption campaign has been announced in an investigation.

Table B1 in the appendix gives more detail about the coding rules. The table summarizes the reasons for corruption revealed by the anticorruption campaign in the prefectural cities. Of the 308 cities, 218 cities, or two-thirds, had fallen bureaucrats inspected by the CDIC, and 95 cities, almost half of them, had corrupt bureaucrats involved in land issues. This further highlights the seriousness of the land corruption in China.

#### **2.2.4 Online Transaction Systems**

Since 2007, some provinces and cities started to establish online transaction systems for land auctions. Until the end of 2017, 131 cities had established online transaction systems. With online transaction systems, two-stage auctions become more transparent to the bidders. In the first 10-day stage of a two-stage auction, all bids are submitted online, and the highest



Note: The figure plots the number of cities that has established an online transaction system for land auctions across the study period.

Figure 3: Cities with online transaction systems for land auctions

bid is updated in a timely manner so that every bidder observes the bidding process, but not the identity of the submitting bidder. Therefore, one can expect that two-stage auctions leave less room for informed bidders to secure profits from their extra information and thus leave less room for corruption. As a result, the local government should have less incentive to use two-stage auctions.

I manually search the official website of each city’s land bureau for the official document that releases the establishment of their online transaction system. The document includes the date that the system was put into use. If the system was established by the provincial government, I assume that all cities within the province have an online system. Figure 3 plots the number of cities that have an online transaction system by year. The figure shows that the adoption of online transaction systems boomed around years 2010 to 2012, coinciding with a boom in the Chinese housing market. By 2017, almost half of the cities had already established systems, so new establishment has since slowed. In the next section I will provide some empirical evidence about how the land transaction system affects bidders’ behavior and local governments’ choice of auction formats.

### 3 Reduced-Form Evidence

In this part, I present suggestive evidence for my initial hypotheses of local governments' selection of auction formats and bidders' asymmetries. I also present evidence to guide the specification of the theoretical model developed in the next section.

#### 3.1 Comparison of Auction Formats

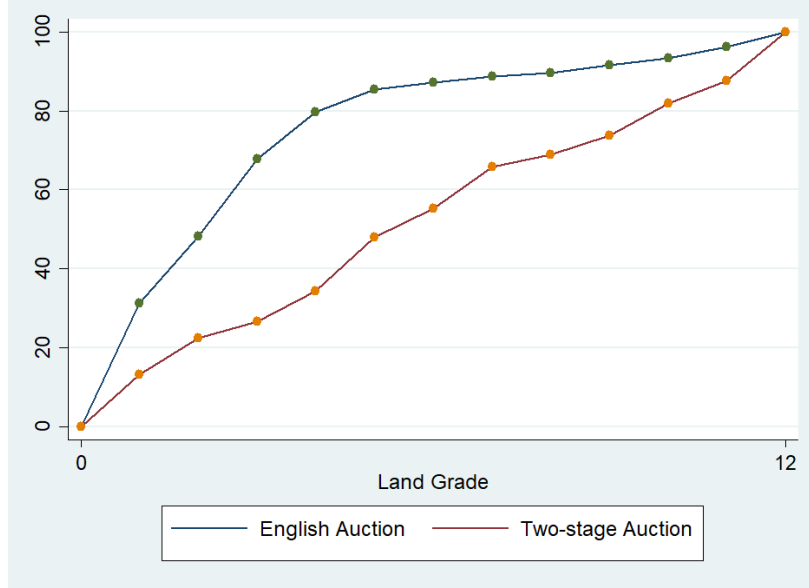
Table 3 presents the relationship between the land auction format and the unit price of a land sale. The first column displays the result from a simple ordinary least squares (OLS) regression of the unit price on the auction format without controlling for any covariates. The regression confirms the difference between the unit price of land sold by English auctions and two-stage auctions. It shows that land sold by English auctions is on average  $CNY951.3/m^2$  more expensive than land sold by two-stage auctions. In the second column, I control for a set of fixed effects including land usage, the winners industry, and city and year dummies. I found that land sold by English auctions still has a higher unit price than that sold by two-stage auctions, but the difference is slightly smaller. Finally, in the third column, I add more control variables for land characteristics, including the area of the land parcel, the official land grade, nighttime brightness of the land, and the lower limit of the land's plot ratio. As expected, some variables are a significant predictor of the unit price. For example, a unit increase in land grade, which means the land is worse by one grade, could decrease the unit price by  $CNY140.5/m^2$ , and a one unit increase in the brightness of the land could increase the unit price by  $CNY2,660/m^2$ . More importantly, as can be seen in the table, after controlling for these variables, the difference between the unit price of English auctions and two-stage auctions further decreased to  $CNY662.2/m^2$ . This indicates that the choice of land auction format is closely correlated with these variables and confirms that local governments employ English auctions when selling better-quality land.

Figure 4 further confirms the selection of auction format on land quality. The figure plots the cumulative distribution of the official land grade and shows that more land parcels with low grade, that is, high quality, are sold by English auctions, and more land parcels with

Table 3: Unit price of land auctions and auction format

	(1)	(2)	(3)
English auction	951.3***	888.0***	662.2***
	(113.9)	(141.2)	(190.6)
Area (hectare)			-0.103
			(0.508)
Land grade			-140.5***
			(24.02)
Brightness			2,660***
			(210.6)
Plot ratio (lower bound)			3.815
			(18.53)
Plot ratio (upper bound)			9.159
			(6.783)
Land usage	No	Yes	Yes
Winner industry	No	Yes	Yes
City fixed effects	No	Yes	Yes
Year fixed effects	No	Yes	Yes

*Notes:* The table presents the relationship between the unit price of land and the auction format. Heteroskedasticity-robust standard errors appear in parentheses. English auction is a dummy equal to 1 for English auctions and 0 for two-stage auctions. The unit of the dependent variable is  $CNY/m^2$ . \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .



*Note:* The figure plots the cdf of land grade by English auction and two-stage auction. Land grade is an official measure of land quality with integers between 1 and 12, with grade 1 being the highest quality and grade 12 being the lowest quality.

Figure 4: CDF of land grades by English auctions and two-stage auctions

lower quality are sold by two-stage auctions.

**3.2 Bidder Asymmetries** To support my key idea about bidder asymmetries, I then test for bidders' different bidding behavior and profitability. First, I regress the land parcel's unit price on the two measures of bidders' political connection for the two auction formats separately. In all regressions, I control for land characteristics and city and year fixed effects. Table 6 presents the results for the OLS regressions. Contrary to common wisdom, where politically favored firms usually acquire purchases at a discounted price, all the results show that political connections have a significant positive effect on land price. For example, the first two columns of the table show that, on average, local bidders won land at a price  $CNY184.3/m^2$  higher than did other bidders in two-stage auctions and  $CNY292.7/m^2$  higher in English auctions, respectively. As for princelings, the price premium they pay are even higher ( $CNY315.3/m^2$  and  $CNY442.6/m^2$  for two-stage auctions and English auctions, respectively). It is worthwhile to note that although the coefficients are larger in English auctions, the premium as a percentage of the land's sale price is higher in two-stage auctions

because of the low price of two-stage auctions. This finding is consistent with my initial hypothesis that information has a larger effect in two-stage auctions than in English auctions. Overall, Table 4 suggests that political connected bidders actually won the land at a higher price than did other bidders. This finding confirms that, in China's land auction market, corruption was not reflected in the discounted prices of connected bidders. Instead, because these favored bidders have better information about the true value of the land, they are less affected by the winner's curse and thus are willing to pay a higher price.

Table 4: Land price and political connection

	Two-stage	English	Two-stage	English
Local	184.3** (57.1)	292.7*** (55.24)		
Princeling			315.3** (146.0)	442.6** (193.0)
Area	-22.79* (12.67)	-0.0827 (0.0945)	-22.95* (12.67)	-0.0780 (0.0946)
Brightness	2,557*** (256.7)	3,004*** (91.75)	2,575*** (256.2)	3,039*** (91.51)
Plot ratio	6.576 (7.516)	497.4*** (17.10)	6.584 (7.516)	498.5*** (17.11)
Grade	-130.6*** (29.54)	-123.8*** (10.14)	-130.9*** (29.56)	-124.1*** (10.15)
City fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

*Notes:* The table presents the relationship between the unit price of land and political connection for the two auction formats separately. Heteroskedasticity-robust standard errors appear in parentheses. Local is a dummy equal to 1 for local bidders and 0 otherwise. Princeling is a dummy equal to 1 for princeling bidders and 0 otherwise. The unit of the dependent variable is  $CNY/m^2$ . \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

Furthermore, I provide evidence to support my hypothesis that information incentivizes politically connected bidders to bid higher. Although it is difficult to measure information, especially when it is not observed by the public, I construct a proxy to measure the ex post profitability of the firms and show that politically connected bidders earn a higher profit than do other bidders because they knew ex ante that they have better information about the land's value ex ante. The proxy I use is the change in the nighttime brightness after

3 years of purchasing the land. As discussed in the data section, nighttime brightness is a good proxy for land value in China, and therefore the increase in the nighttime brightness indicates an appreciation of land value.

Table 5 presents the results for the OLS regression. To control for land characteristics at the time of the auction, I control for the land parcel's unit price and the brightness in the base period. The results remain robust if I control for land characteristics in the base period instead of land's sale price, but land sale price should capture more land characteristics that are observed by the bidders, but not observed by us. As can be seen in Table 5, land parcels purchased by local firms and Princeling firms experienced a larger increase in the land parcels' nighttime brightness after 3 years of purchasing the land, suggesting that political connected bidders were more likely to identify land parcels which have potential in appreciation and thus willing to pay a higher price to win the auction.

Table 5: Change in brightness and political connection

	Two-stage	English	Two-stage	English
Local	0.0359*** (0.0014)	0.0393*** (0.0024)		
Princeling			0.0245*** (0.0068)	0.00229 (0.0111)
Land grade	0.0024*** (0.0002)	-0.0009** (0.0004)	0.0026*** (0.0003)	-0.0009** (0.0004)
ln(Unit price)	0.0123*** (0.0006)	0.0119*** (0.0010)	0.0135*** (0.0006)	0.0129*** (0.0010)
Brightness in base period	-0.124*** (0.0022)	-0.0750*** (0.0042)	-0.119*** (0.0022)	-0.0651*** (0.0041)
Constant	-0.0037 (0.0792)	0.0021 (0.135)	-0.0012 (0.0797)	0.0084 (0.136)
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes

*Notes:* The table presents the relationship between the change in nighttime brightness on a land plot, which proxies for the change in land value, and political connection for the two auction formats separately. Heteroskedasticity-robust standard errors appear in parentheses. Local is a dummy equal to 1 for local bidders and 0 otherwise. Princeling is a dummy equal to 1 for princeling bidders and 0 otherwise. The unit of the dependent variable is  $CNY/m^2$ . \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

**3.3 Anticorruption Campaign** To identify the effect of local governments’ corruptibility on their incentives to choose between auction formats, I utilize the anticorruption campaign as a policy shock to conduct a difference-in-differences analysis. As discussed in the data section, in November 2012, Xi Jinping initiated a wide-reaching anticorruption campaign in China, during which inspection teams were dispatched to local governments, and thousands of local officials were demoted for corruption. A city is labeled “corrupt” if any bureaucrat that worked in the city before the anticorruption campaign has been since demoted in the campaign. This massive anticorruption campaign is analogous to a natural experiment that allows me to establish the variations in corruption. The dispatch of inspection teams created an exogenous shock in prefectural cities in terms of their cost of corruption. Because of the strength and long-lasting effects of the campaign, the cost of corruption has increased dramatically afterward. As a consequence, one should expect that local officials should be more cautious when trading off between land revenue and personal bribery income and thus use fewer two-stage auctions. Moreover, the effect should be stronger for cities whose leaders were more corrupt before the campaign, when they had been known to emphasize personal benefit. To empirically test how the anticorruption campaign has affected land sales in different types of cities, I use the following difference-in-differences model:

$$Area_{it} = \beta_0 + \beta_1 D_i + \beta_2 Campaign_t + \beta_3 D_i \times Campaign_t + \nu_i + \mu_t + \epsilon_{it}, \quad (1)$$

where  $Area_{it}$  is the total area of a specific type of land sold in city  $i$  and time  $t$ .  $Campaign_t$  is a dummy variable that is equal to 1 if an inspection team has been dispatched to the city’s province no later than time  $t$ .  $D_i$  is another dummy variable that equals to 1 if the CDIC has reported any bureaucrat of city  $i$  who is corrupt on land issues,  $\nu_i$  is citie fixed effect,  $\mu_t$  is time fixed effect, and  $\epsilon_{it}$  is the error term. The regression is conducted using a city-quarterly panel data covering my study period year 2007 to 2017. I do the analysis separately for each type of land (all usage, commercial usage, and residential usage) being sold and separately for two-stage auctions and English auctions. My coefficient of interest is  $\beta_3$ , which capture



the change of area of land sold by different auction formats in the city where any bureaucrat was corrupt on land issues after an anticorruption campaign compared to those cities where no bureaucrat was corrupt on land issues.

Table ?? presents the results for the DiD analysis. As can be seen in the table, cities in which land corruption was detected experienced a significant drop in the area of land sold by two-stage auctions, whereas there is no effect on the area of land sold by English auctions. For example, the first column shows that compared to uncorrupt cities, on average, the area of land sold by two-stage auction in corrupt cities decreased by 14.14 hectares after the anticorruption campaign. In contrast, the area of land sold by English auction has no significant change. To summarize, Table ?? suggests that corrupt local governments tend to use the two-stage auction less often after the central government started to put more effect in combating corruption, and this finding supports the idea that two-stage auction is more prone to corruption.

### 3.4 Online Transaction Systems

Lastly, I analyze the effect of information disclosure on local governments' choice of auction formats. As discussed in the data section, some cities started to establish online land transaction systems as early as 2007, and about 150 cities have since established such a system. Online transaction systems are mainly designed for use in two-stage auctions. With the online transaction system, the first stage of the two-stage auction is conducted online, so that bidders can observe the other bidders' bidding sequence. As a result, there is less room for better-informed bidders to make use of their private information, and one should expect local governments to have less incentive to use two-stage auctions. I use a difference-in-differences model to estimate the effect of online transaction systems on land sale. The model is as follows:

$$Area_{it} = \beta_0 + \beta_1 System_{it} + \nu_i + \mu_t + \epsilon_{it}, \quad (2)$$

where  $Area_{it}$  is the total area of a specific type of land sold by city  $i$  in year  $t$ ;  $System_{it}$

Table 6: Difference-in-differences analysis of land sale and anticorruption

Two-stage auction			
	All	Residential	Residential & commercial
Corruption*Campaign	-14.14*** (5.135)	-2.188*** (0.431)	-6.829*** (2.316)
Campaign	-7.621 (7.064)	-1.353 (1.968)	-1.287 (3.185)
Constant	185.9*** (20.34)	9.827* (5.666)	85.71*** (9.170)
City fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Observations	9,528	9,528	9,528
<i>R</i> -squared	0.666	0.431	0.519
English Auction			
	All	Residential	Residential & commercial
Corruption*Campaign	0.223 (1.641)	0.971** (0.462)	-0.0499 (1.076)
Campaign	6.623*** (2.257)	0.171 (0.635)	2.443* (1.480)
Constant	-3.242 (6.499)	-1.130 (1.828)	-1.726 (4.262)
City fixed effect	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes
Observations	9,528	9,528	9,528
<i>R</i> -squared	0.612	0.303	0.468

*Notes:* The table presents the results for the difference-in-differences analysis, which compares cities with and without corrupt local officials, before and after the anticorruption campaign. Heteroskedasticity-robust standard errors appear in parentheses. Local is a dummy equal to 1 for local bidders and 0 otherwise. Princeling is a dummy equal to 1 for princeling bidders and 0 otherwise. The unit of the dependent variable is *CNY/m*<sup>2</sup>. \**p* < 0.1; \*\**p* < 0.05; \*\*\**p* < 0.01.

is a dummy variable indicating whether an online transaction system existed in this city  $i$  in year  $t$ ;  $\nu_i$  is city fixed effect;  $\mu_t$  is time fixed effect; and  $\epsilon_{it}$  is the error term. The quantity of interest is  $\beta_1$ , which measures the change in land sale after this system was established compared to cities where this system did not exist.

Table 8 presents the results for the coefficient of interests of the DiD design. The table shows that the establishment of online transaction systems has caused a decrease in the total area of land sold by two-stage auctions, but an increase in the total area of land sold by English auctions. The result is significant for residential land only or together with commercial land. This suggests that, while the adoption of online transaction systems has little effect on local governments land supply, it does affect local governments' incentives in choosing between the two auction formats. With less room for corruption in two-stage auctions, local governments would choose English auctions, which yield higher land revenues.

Table 7: Difference-in-differences analysis of land sales and online transaction systems

	All	Residential	Residential & commercial
Two-stage auction	-9.935 (13.45)	-5.784* (3.172)	-10.810* (6.361)
English auction	8.064 (5.281)	6.527* (3.583)	3.714* (2.022)

*Notes:* The table presents the results for the difference-in-differences analysis, which compares cities with and without online transaction systems before and after the reform. Heteroskedasticity-robust standard errors appear in parentheses. Local is a dummy equal to 1 for local bidders and 0 otherwise. Princeling is a dummy equal to 1 for princeling bidders and 0 otherwise. The unit of the dependent variable is  $CNY/m^2$ . \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

## 4 Model

In this section, I present a model that involves four groups of players on China's land market: a central government who can investigate land auctions to combat corruption, a local

government who cares about local land revenues as well as personal bribe income, a politically connected bidder who can approach the local government and buy information by paying bribes, and  $(N - 1)$  unconnected bidders who can only bid according to their own information. I then solve the model backward. First, I show how information asymmetry affects two-stage auction and English auction differently in a common value auction environment, and then I show how this difference shapes local governments' choice of auction formats. The model highlights local governments' trade-off between corruption income from local governments' private information and land revenues from land sale.

## 4.1 Model Setup

The model proceeds in three stages. I index bidding developers by  $i$ , the central government by  $CG$ , and the local government by  $L$ . At date 0, everyone observes a common value signal  $r_i$ , and has a private development cost  $c_i$ . I assume that the common value signal  $r_i$  is i.i.d and follow a normal distribution,  $r_i \sim N(m_r, s_r^2)$ . Similarly, the private cost distributions also follow normal distributions,  $c_i \sim N(m_{cc}, s_{cc}^2)$  if the bidder is politically connected, and  $c_i \sim N(m_{cu}, s_{cu}^2)$  if the bidder is unconnected. Conditional on bidders' type, the private costs are also i.i.d.. Denote  $F_r(\cdot)$  to be the CDF of the common value signal,  $F_{cc}(\cdot)$  to be the CDF of the private cost signal for connected bidders, and  $F_{cu}$  to be the CDF of the private cost signal for unconnected bidders. Moreover, the local government also observes a common value signal  $r_L$  which is unknown to the bidders. The local government can later on sell this private information in exchange for bribes.

At date 1, the local government plays a game with the central government in which local officials choose the auction format, and the central government chooses whether to monitor and investigate each piece of transaction. The utility of the local government is additively separable in public and private benefits and the cost of corruption when investigated by the

Table 8: Payoff matrix for the corruption game

		Central government	
		$M$	$N$
Local	$E$	$U(E, X, 1), R(BR_E(X)) - I$	$U(E, X, 0), 0$
	$T$	$U(T, X, 1), R(BR_T(X)) - I$	$U(T, X, 0), 0$

central government,

$$U(L, X, q) = \lambda \log(P_L(X)) + (1 - \lambda) \log(BR_L(X)) - q \cdot c(BR_L(X)), \quad (3)$$

where  $\lambda$  is the weight on public benefit,  $X$  is a vector of land characteristics observed by everyone,  $L = \{T(Two-stage), E(English)\}$  representing local government's choice of auction format,  $q$  denotes the probability of investigation,  $c(\cdot)$  denotes the cost of corruption to the local government,  $P_L$  is the equilibrium bidding price solved from the third stage auction model, and  $BR_L$  denotes the equilibrium bribe which is determined optimally in the second stage's local government utility maximization problem. For the central government, it gets utility  $R(BR)$  from successfully detecting corruption level  $BR$  at an investigation cost  $I$ . It is worthwhile to note that there may exist a mixed strategy Nash equilibrium for the game between the local government and the central government,  $q$  can be any value between 0 and 1. The payoff for the two parties are summarized in Table 8.

At date 2, given the auction format being chosen and the central government's investigation possibility, local officials decide how much bribe to ask from the connected bidder, and the connected bidder decides whether to pay the bribe. For simplicity, I assume that there can be at most one connected bidder for each land auction. If the connected bidder pays the bribe proposed by the local government in exchange for an extra signal about the common value of the land parcel, bidders then have asymmetric information about the common value of the auction; however, if no bribe is paid, then bidders have symmetric information.

At date 3, all bidders bid according to the auction format being chosen and their common value signals and private costs. To model auctions, I follow Weiergraeber and Wolf (2018)

to extend the model by Goeree and Offerman (2003). Goeree and Offerman (2003) models the common value to be the sum of bidders' common value signals  $R = \sum_{i=1}^N r_i/N$ . To accommodate asymmetric precision of the common value signal of different bidder types, I use a generalized form to model the common value signal as the weighted sum of signals:  $R = \sum_{i=1}^N \alpha_i r_i$ , with  $\sum_{i=1}^N \alpha_i = 1$ . If the connected bidder rejects local officials' offer and does not pay the bribe,  $\alpha_i = 1/N$  as in the original Goeree and Offerman (2003) model. If the connected bidder pays the bribe and acquires additional information,  $\alpha_i = \alpha_c$  for the connected bidder,  $\alpha_i = \alpha_u$  for the unconnected bidder, and  $\alpha_c > \alpha_u$ . One can understand the difference between the connected bidder and the unconnected bidders  $(\alpha_c - \alpha_u)r_i$  as the extra information from the local government  $r_L$ . This auction model allows me to study the effect of extra information on auction outcomes in both English auctions and two-stage auctions.

## 4.2 Equilibrium of the Auction Model

I start by solving the equilibrium bidding strategy of the auction model and studying and comparing the effect of information in both auction formats. I will then solve the first two stages of the model backward.

A key problem in auctions with private and common values is that each bidder's private information is two-dimensional, consisting of the private and the common value signal. The strategic variable, the bid, is only one-dimensional. In general, there is no straightforward mapping from two-dimensional signals into a one-dimensional strategic variable, and therefore structural identification becomes impossible with no additional assumption. However, the advantage of the Goeree and Offerman (2003) framework is that a reduction from two to one dimension is possible. I aggregate the common value and private cost information into a single statistic  $\rho_i = c_i - \alpha_i r_i$ , which serves as a sufficient statistic for bidders' bidding strategy. Therefore, standard auction theory methods following Milgrom and Weber (1982) can be applied. In this application, the scalar statistic,  $\rho_i$ , can be interpreted as a

net revenue signal (revenue minus cost) and is sufficient to capture all of bidder  $i$ 's private information in one dimension. Denote  $F_{\rho_c}(\cdot)$  and  $F_{\rho_u}(\cdot)$  to be the CDF of the net revenue signal for connected bidders and unconnected bidders respectively.

As explained in the background section, the first stage of the two-stage auction resembles a standard first-price auction, because bidders only observe the number of bidders but do not observe the other bidders' bids. If the auction ends at the first stage, the winner pays his bid. I first solve for the equilibrium of the sealed bid auction, and I will show later on that this equilibrium actually characterizes part of the equilibrium of the two-stage auction. The first lemma, which I borrow from Weiergraeber and Wolf (2018) and adapt to my setting, characterizes the bidding behavior for first-price sealed bid auction.

**Lemma 1** (*Weiergraeber and Wolf (2018)*) *The equilibrium of the first-price sealed bid auction  $B_i(\cdot)$  satisfies the following system of differential equations:*

$$b = \rho_i + \sum_{j \neq i} \alpha_j E[r_j | \rho_j = B_j^{-1}(b)] - \frac{F_{\rho_j}^{1:N \setminus i}(B_j^{-1}(b))}{f_{\rho_j}^{1:N \setminus i}(B_j^{-1}(b)) B_j^{-1}(b)}, \quad (4)$$

where  $\rho_i = \alpha_i r_i - c_i$ ,  $F_{\rho_j}^{1:N \setminus i}$  denotes the distribution of the  $(N-1)$ -th order statistic of the opponents' signals.  $B_j^{-1}(\cdot)$  denotes the inverse bid function of bidder  $j$ .

I defer the complete proof to Appendix A. The intuition is analogous to the classic Milgrom and Weber (1982) auction model: the first two terms together on the right side represents what the land parcel is worth (on average) to a bidder assuming that her surplus,  $\rho_i$ , is the highest and the second term shows how much she shades her bid.

Next, I turn to the bidding strategy of the English auction. For simplicity purpose, I model English auction as the "Button auction," in which bidders hold down a button as the auctioneer regularly raises the current price and everyone observes the price that each bidder quits. The next lemma characterizes then the equilibrium bidding behavior.

**Lemma 2** *The  $n^*n$ -tuple of strategies  $B_t^i(\cdot)$ , where  $i$  denotes the bidder's identity and  $t$  denotes the number of bidders that have quited, constitutes an equilibrium of the English auction.  $B_t^i(\cdot)$  is defined as follows,*

$$\begin{aligned}
B_0^i(\rho_i) &= \sum_{j \neq i} \alpha_j E(r_j | B_0^j(\rho_j) = B_0^i(\rho_i)) - c_i \\
B_k^i(\rho_i; b_1, \dots, b_k; Q_k) &= \rho_i + \sum_{j \notin Q_k} \alpha_j E(r_j | B_k^j(\rho_j) = B_k^i(\rho_i)) \\
&+ \sum_{t=0}^{k-1} \alpha_t E(r_j | B_t^j(\rho_j; b_1, \dots, b_t) = b_{t+1}, j = Q_t \setminus Q_{t-1}),
\end{aligned} \tag{5}$$

where  $Q_k$  denotes the pool of the  $k$  bidders that have already quit the auction.

Appendix A contains the complete proof. The intuition behind 5 is as follows: given her surplus and the information conveyed in others' drop-out levels, the highest a bidder is willing to go is given by the expected value of the commodity assuming that all other active bidders have the same surplus.

Now, I return to two-stage auctions. The first two lemmas characterize the equilibrium of the first and second stages of two-stage auctions separately, and the next lemma characterizes the equilibria of the two-stage auction.

**Lemma 3** *There exist two equilibria for the two-stage auction:*

1. *(Revealing Equilibrium) All bidders bid according to the equilibrium bidding strategy in the first-price sealed bid auction and do not enter the second stage.*
2. *(Babbling Equilibrium) All bidders bid reserve price in the first stage and enter the second stage and bid according to the equilibrium strategy in the English auction in the second stage.*

The interpretation of the lemma is as follows: the two-stage auction either ends in the first stage and adopt the equilibrium of the first-price sealed bid auction or ends at the second stage and adopt the equilibrium of the English auction. Consider first the revealing



equilibrium, given everyone else's bidding strategy, it is not profitable for a bidder to deviate from her current bid if she does not want to enter the second stage because of lemma 1. It is also not profitable for her to bid the reserve price and wait for the second stage because she will then need to compete with the bidder who posted the highest bid in the first stage, and bid up to her expected value of the project in the second stage which gives her lower expected profit. As for the "babbling equilibrium," given that everyone else bids the reserve price and enters the second stage, it is obvious not profitable for a bidder to reveal her signal in the first stage and become the only less informed bidder in the second stage.

It is worthwhile to note that no equilibrium appears to be the "focal" equilibrium: connected bidders are better off in the "revealing" equilibrium, where they get a higher expected revenue (as will be shown in Lemma 5). Unconnected bidders are better off in the "babbling" equilibrium, where they suffer less from being less informed. That being said, for the following two reasons, I focus on the revealing equilibrium in my analysis hereafter: First, the babbling equilibrium is essentially the same as the equilibrium in the English auction; however, one can see a significant difference between the two auction formats. Second, in real practice, most two-stage auction ends at the first stage and only a few of them enters the second stage, suggesting the "revealing equilibrium" is played by the bidders.

Next, I study the properties of the equilibrium of both auction formats and make a comparison between the two. Although theory gives contributes strong predictions about how bidding behavior differs across asymmetric participants in private value auctions, this is much less clear in the net auctions because of the additional asymmetric common revenue component. I give an intuition on the effect of the asymmetric precision in lemma 4 that assumes a symmetric and known cost component. Before the discussion, I need to make a mild functional form assumption of conditional stochastic dominance as in Maskin and Riley (2000).

**Assumption 1** Suppose  $\alpha_c > \alpha_u$ , then there exists  $\lambda \in (0, 1)$  and  $\gamma \in \mathbb{R}$  such that  $F_{\rho_c}(x) =$

$\lambda F_{\rho_u}(x), \forall x \in (-\infty, \gamma]$ , and  $\frac{d}{dx} \frac{F_{\rho_c}(x)}{F_{\rho_u}(x)} > 0, \forall x \in [\gamma, \infty)$

Conditional Stochastic dominance implies that

$$\frac{f_{\rho_c}(x)}{F_{\rho_c}(x)} \geq \frac{f_{\rho_u}(x)}{F_{\rho_u}(x)}$$

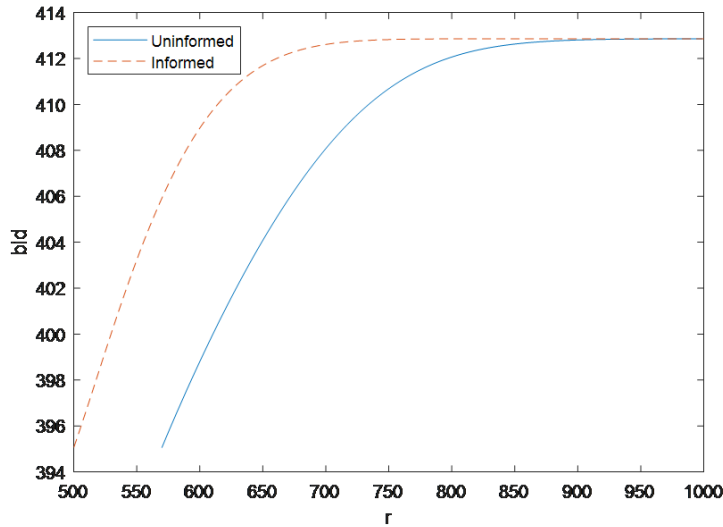
Given the assumption, I have the following lemma characterizing the effect of asymmetric information on bidders' bidding behaviors.

**Lemma 4** *Assume connected bidders have better information about the common value of land than do unconnected bidders, that is,  $\alpha_c > \alpha_u$ , and all bidders have the same private costs,  $c$ . Then, under assumption 1, in both auction formats, I have the following three properties:*

1. *Unconnected bidders shades their bids more than do the connected bidder given any revenue signal  $r$ . Moreover, the connected bidder's bid distribution is stochastically dominated by the unconnected bidders' bid distribution.*
2. *The connected bidder has higher chance of winning than do the unconnected bidders.*
3. *The connected bidder earn a higher expected profit than do the unconnected bidders.*

Lemma 4 shows that a less precisely informed bidder shades its equilibrium bid more than a more precisely informed bidder. This result is very intuitive as connected bidders have better information about the common value of land and are therefore less affected by the winner's curse. As a consequence, if bidders have the same costs, more informed bidders will have the stronger bid distribution (see Figure 8 for an illustration). For my application, this implies that connected bidders will bid more aggressively than will unconnected bidders.

I end the discussion of the auction model with a comparison of first-price sealed bid auctions versus English auctions. Although "revenue equivalence" still holds when bidders have symmetric information Goeree and Offerman (2003), it is no longer the case when the



*Note:* This figure plots the model simulation illustrating the bidding function of connected bidders and unconnected bidders.

Figure 5: Bidding function of sealed-bid auctions

connected bidder are better informed. As lemma 1 and 2 show, the effect on bids in both auctions happens through the hypothetical event that the bidder submits the same bid as the highest bid of the rivals. This hypothetical event is the intersection of two others: that the bidder's bid is a lower bound for the highest bid of the other bidders, the loser's curse, and that it is an upper bound, the winner's curse.

We may expect information acquisition by the better-informed bidder to have stronger effects on the loser's curse of the nondeviating bidders in the open auction than in the sealed bid auction. To see why, note that in this case, a noninformed bidder can determine that the informed bidder has the highest bid in the open auction, but not in the sealed bid auction. Thus, while the loser's curse determines a lower bound to the type of the deviating bidder in the open auction, it only implies that this may be the case with some probability in the sealed bid auction.

On the contrary, one may expect similar effects of information acquisition in the winner's curse in both auction formats. The reason being that the winner's curse fixes an upper bound on the type of the deviating bidder in either case: in the open auction because the

bidder can determine that the deviating bidder has the highest bid of the other bidders, and in the sealed bid auction because it implies an upper bound on the bids of all the other bidders.

The loser's curse means good news about the common value which information acquisition converts into better news, and thus induces higher bidding. This effect must be stronger in the open auction than in the sealed bid auction, so I expect the deviating bidder to face relatively fiercer competition and thus to win relatively less often in the open auction than in the sealed bid auction. The next lemma formalizes this conjecture.

**Lemma 5** *For any  $\alpha_C > \alpha_U$  and any number of bidders  $N$ ,  $\frac{\partial E(\pi^T)}{\partial \alpha_c}(\alpha_C, \alpha_U) > \frac{\partial E(\pi^E)}{\partial \alpha_c}(\alpha_C, \alpha_U) > 0$ , that is, the corrupt bidder gains more information rent in sealed bid auctions than in English auctions. As a consequence, English auctions lead to greater expected revenue for the auctioneer than do sealed bid auctions.*

The implication of lemma 5 is threefold. First, the better-informed bidder makes more profit than the other bidders, and this difference increases with the level of information asymmetry. I define information rent as the difference in expected profit for informed bidders minus expected profit from the symmetric information case. This is the extra profit that connected bidders make from extra information. Second, lemma 5 shows that information has a stronger effect on the bidding behavior, and thus the information rent, for sealed bid auction. Unlike in English auctions, where bidder's private information is revealed along the bidding process, in the sealed bid auction, informed bidders take more advantage of their information, and this gives them a higher information rent, and the seller less land revenue. Third, the auctioneer's expected revenue is equal to the difference between the expected social surplus generated in the auction and the expected utility of all the bidders. One can easily deduce from Lemma 4 that the bidders' expected utility is increasing in  $\alpha_c$ . The intuitive reason is that bidders' informational rents increase. As a consequence, the expected auctioneer's revenue decreases with  $\alpha_c$ .

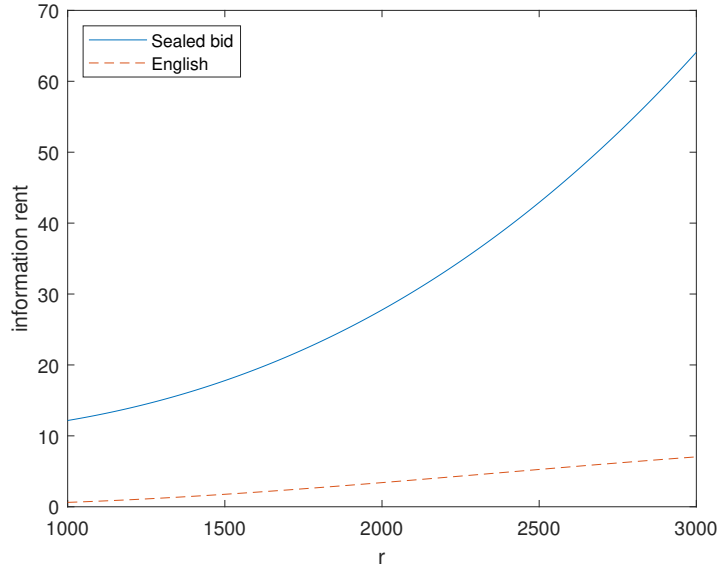
Lastly, to explain local governments' incentive for selection on land value, I study the connection between land characteristics and information rent. Lemma 7 offers intuition on the effect of the precision of the common value signal on the ex ante information rent of connected bidders assuming a fixed and known cost component.

**Lemma 6** *Assume there are two auctions, in which the connected firm has the same cost  $c$ . Then if  $\sigma_{r1} > \sigma_{r2}$ , and  $\alpha_{c1} = \alpha_{c2}$ , the ex ante information rent for connected bidders is higher in the first auction than in the second auction.*

Lemma 6 shows that the better-informed bidder gains more when the uncertainty of the land auction increases. The intuition behind the lemma is that as uncertainty increase, the uninformed bidder shades their bids more due to winner's curse, and, as a consequence, the informed bidder wins with higher probability and thus gaining higher information rent ex ante. Figure 6 illustrates the lemma with a simulation of the model and shows that information rent in both two-stage auctions and English auctions increases with the variance of the common value signal. Moreover, the gap between the two also increases with the variance.

While the mean of the common value signal does not affect bidders' bidding strategy, and thus does not affect the information rent, it is worthwhile to note that, empirically, the variance and the mean of the common value signal positively correlates with each other. This is intuitive, because the risk of land development always grows with the return. As a consequence, the information rent increases with the mean of the common value signal as well. When I observe in the data that local governments are selecting auction formats based on land quality, they are actually selecting on project uncertainties. Below, I refer this to the "value" of the land, denoted by  $V = V(X) = V(m_r(X), \sigma_r(X))$ , that is, the quality of the land as a function of land characteristics.

To summarize, information asymmetry crucially affects bidder's bidding behavior, and the effect differs by auction formats. The better-informed bidder bids more aggressively



The figure plots a simulation of the model illustrating the relationship between the ex ante information rent and the variance of the common value signal in two-stage auctions and English auctions.

Figure 6: Information rent

due to his information advantage, and this gives her higher expected profit. This effect is stronger in sealed bid auctions than in English auctions and therefore leaves local officials larger room to bribe bidders in two-stage auctions. As a result, expected land revenue from two-stage auctions is lower than is that from English auctions. This partially explains the price difference between two-stage auctions and English auctions. In the remaining part of this section, the game between the central government and the local government then explains the remaining difference by showing that local government tend to use two-stage auctions for lower-value land.

### 4.3 Equilibrium of the Bribery Game

Taking equilibrium winning bids and information rent in both auction formats as given, I then proceed to local government's utility maximization problem. For connected bidders to pay a bribe, the maximum bribe that the local government extracts cannot exceed the extra expected profit that the bidder can get from the information. Denote  $IR_l$  as the information

rent from auction format  $l$ . Local governments solve the following utility maximization problem:

$$\begin{aligned} \max_{BR} \lambda \log(P_l(X)) + (1 - \lambda) \log(BR) - q(X)c(BR). \\ \text{s.t. } BR \leq IR_l(X) \end{aligned} \tag{6}$$

We know from lemma 6 that information rent increases with land value. Therefore, when the value of the land is low, the condition that the bribe cannot exceed the information rent is binding, and the local government chooses to extract all information rent from the connected bidder. On the contrary, when the value of the land is high, local governments simply maximize the expected payoff from corruption by taking the probability of the central government's investigation as given. The equilibrium is summarized in the following lemma.

**Lemma 7**  $\forall \lambda \in [0, 1]$ , there exists  $\tilde{V}_l(\lambda)$ , such that the local governments' optimal choices of bribe given the auction format  $l$  is given by

$$BR_l^*(X) = \begin{cases} IR_l(X) & \text{if } V \in [0, \tilde{V}_l(\lambda)] \\ \bar{B}R(X) & \text{if } V \in (\tilde{V}_l(\lambda), \infty), \end{cases} \tag{7}$$

where  $\bar{B}R(X) = \arg \max_{BR} ((1 - \lambda) \log(BR) - q(X)c(BR))$ .

We know from lemma 5 that  $IR_T < IR_E, \forall X$ , and, therefore, the optimal bribe is always lower in English auctions than in two-stage auctions for all land parcels.

#### 4.4 Equilibrium of the Corruption Game

Finally, I am able to solve for the equilibrium of the game between the central government and the local government. As I am discussing the corruption incentive of local governments, I focus on the case in which  $\lambda$  is big enough that  $R(\bar{B}R) > I$ ; that is, local governments are corrupt enough to incentivize the central government's investigation.

I first discuss the two extreme cases when land value is lower than a lower threshold or higher than a higher threshold, such that the central government has a dominant strategy of investigating or not.  $\forall \lambda, \exists \underline{V}(\lambda)$  and  $\bar{V}(\lambda)$ , such that:

**Case 1:** When  $V < \underline{V}(\lambda)$ , I have  $R(BR_E) \leq R(BR_T) \leq I$ .

When the value of the land is low enough that there is little room for the local government to extract a bribe, the benefit from investigating corruption cannot exceed the investigation cost. Therefore, the central government has a dominant strategy of never investigating. Given that the central government do not investigate and there is no cost for corruption, the corrupt local government should choose two-stage auction to maximize its bribery income. The equilibrium of the game is thus:  $U = N, L = T, BR = IR_T(X)$

**Case 2:** When  $V > \bar{V}(\lambda)$ , I have  $I \leq R(BR_E) \leq R(BR_T)$

When the value of the land is high enough that even English auction leaves too much room for corruption, investigation is the dominant strategy for the central government. Given that the central government always investigates, and land value is high enough that information rent from English auctions is not binding, the local government should employ English auctions, which lead to a higher land revenue. The equilibrium of the game is thus  $U = I, L = E, BR = \bar{B}R(X)$ .

**Case 3:** When  $\underline{V}(\lambda) < V < \bar{V}(\lambda)$ , I have  $R(BR_E) \leq I \leq R(BR_T)$

When the value of the land falls in between the two extreme cases, neither the central government nor the local government has a dominant strategy. There exists a unique mixed strategy Nash equilibrium:

$$C = \begin{cases} \text{M wp.} & \frac{(1 - \lambda)(\log(P_E) - \log(P_T)) + \lambda(\log(BR_E) - \log(BR_T))}{c(BR_E) - c(BR_T)} \\ \text{N wp.} & 1 - \frac{(1 - \lambda)(\log(P_E) - \log(P_T)) + \lambda(\log(BR_E) - \log(BR_T))}{c(BR_E) - c(BR_T)} \end{cases} \quad (8)$$



$$L = \begin{cases} \text{E} & \text{wp. } \frac{R(BR_T) - I}{R(BR_T) - R(BR_E)} \\ \text{T} & \text{wp. } \frac{I - R(BR_E)}{R(BR_T) - R(BR_E)}. \end{cases} \quad (9)$$

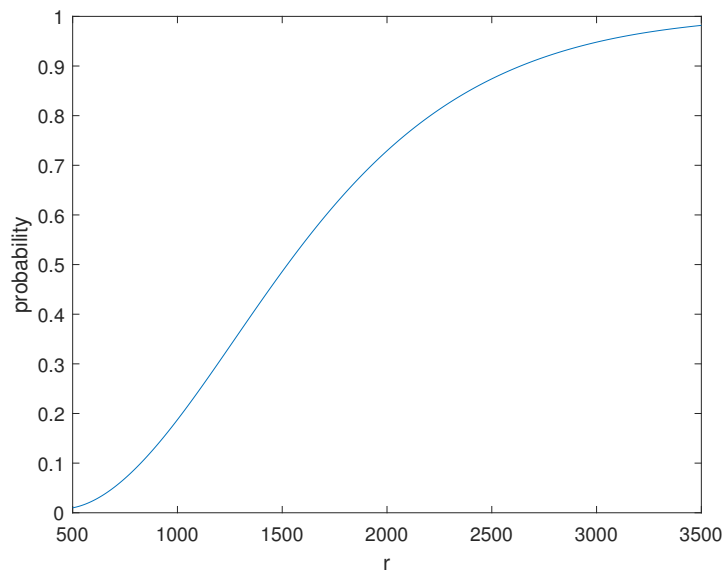
As no one has a dominant strategy in the game, both parties randomize between two options to make the other party indifferent. The next corollary discusses the property of the mixed strategy equilibrium.

**Corollary 8** *The probability that the local government chooses English auction increases with land value.*

The intuition behind the result is as follows: as land value increases, the optimal bribe increases for both auction formats. The increase in the corruption level makes investigation more profitable for the central government. To keep the central government indifferent between investigating and not investigating, the local government should employ English auctions, which lead to a lower corruption level, with higher probability.

## 5 Structural Estimation

In this section, I structurally estimate the auction model to get the distribution of common value signals and the distribution of bidders' private costs. I allow for bidders to have asymmetric information about the common value as well as asymmetric private cost distributions. With the estimation results, I will be able to decompose the observed price difference between two-stage auction and English auction into selection and corruption, as well as estimate the effect of corruption on the efficiency of the auction outcomes. In the next section, I will conduct counterfactual analysis based on the results of the structural estimation.



*Note:* The figure plots a simulation of the model illustrating the relationship between local governments' probability of choosing an English auction and the variance of the common value signal.

Figure 7: Model simulation: Choice of auction formats

## 5.1 Identification Arguments

The cost distributions in an asymmetric IPV model are nonparametrically identified from the winning bid, the number of bidders and the identity of the winner (see, e.g., the discussion in Athey and Haile (2002)). The identification of a common value component is more complicated. I need to recover two distributions: the distribution of common value signals and the distribution of private costs. But I only observe one variable: the winning bids. The advantage of using Goeree and Offerman (2003)'s framework is that the equilibrium bid, as characterized in lemma 2, is only a function of the compounded signal  $\rho_i$ , and do not depend on  $r_i$  and  $c_i$  separately. This gives rise to my estimation strategy.

The estimation proceeds in three steps. In the first step, I estimate the distribution of bids. Goeree and Offerman (2003) shows that the expected value of winning, and therefore the equilibrium bidding strategies, can be rewritten as a linear combination of the private signals,  $r_i$  and  $c_i$ , and terms independent of a bidder's private information. Therefore, standard auction theory methods following Milgrom and Weber (1982) can be applied. In

my application, this scalar statistic,  $\rho_i \equiv r_i - \alpha_i c_i$  can be interpreted as a net profit signal (revenue minus cost) and is sufficient to capture all of bidder  $i$ 's private information in one dimension. Then I can follow the standard practice to identify the distribution of  $\rho_i$  from the winning bid, the number of bidders and the identity of the winner (see, e.g., the discussion in Athey and Haile (2002)). I can then back out the distribution of the compounded signal  $\rho_i$  from the equilibrium bidding strategy described in lemma 2. In the second step, I identify the distribution of common value signals. Intuitively, identification of the distribution of the common value comes from the within-bidder variations. The key idea is that the bidders' private costs do not vary by land parcels, and therefore any systematic differences in bidding behavior by the same winner should be attributed to differences in the revenue uncertainty. This allows me to identify the distribution by comparing differences in the winning bids by the same winner across different land parcels. Lastly, I identify the distribution of bidders' private costs from the cross-bidder variations.

## 5.2 Estimation Strategy

I first estimate the bid distributions using data on winning bids following Weiergraeber and Wolf (2018). I assume that, in each auction, there is at most one connected bidder who is better informed about the common value. I make the assumption for two reasons: First, I do not observe the pool of bidders and therefore cannot identify the number of connected bidders in the data. Second, and more importantly, local officials usually only make deal with one bidder in practice to avoid the risk of being reported corruption by the losing bidders. Moreover, as I only observe the winning bid and winner's identity, if I observe a piece of land won by an unconnected bidder, there are two possibilities: there is no connected bidder or there is a connected bidder who did not win the land. Later on, in my estimations, I assume that the first case happens with possibility  $p$  and  $p$  is a parameter to be estimated that do not vary by land parcels.

Asymmetry complicates the estimation, because in general the differential equations in

the first-order conditions do not have a closed-form solution. An additional complication is that under asymmetry the markup term has to be computed for each bidder configuration, that is, for each number of bidders, separately. For computational purpose, I employ a parametric approach. As in Weiergraeber and Wolf (2018), Athey et al. (2011) and Lalive et al. (2015), I assume that the bid distributions for auction type  $j$  of bidder type  $i$ ,  $G_i^j$ , follow a Weibull distribution with distribution function

$$G_i^j(b_i|X, N) = 1 - \exp\left[-\left(\frac{b_i}{\mu_i^j(X, N)}\right)^{\nu_i^j(X, N)}\right], \quad (10)$$

where  $\mu_i^j$  and  $\nu_i^j$  are the bidder-specific scale and shape parameters. Both vary across corrupt and uncorrupt bidders as well as auction format and are modeled as a log-linear function of observed land parcel characteristics  $X$  and the number of bidders  $N$ . As I do not observe the number of bidders in my data set, I follow the literature (e.g., De Silva et al. (2009a), Hendricks et al. (2003)) to proxy it with the number of potential bidders who have participated in the market. Specifically, I divide the unit sale price into ten quantiles for each year and each city and calculate the number of firms that have won at least one piece of land in each quantile. I then use this number as a proxy of number of bidders. Although these bidders may not participate in each auction, they are the potential buyers on the market who are able to participate if they wish. The parameters of the distribution function are then characterized as follows:

$$\begin{aligned} \log(\mu_i^j(X, N)) &= \mu_{i,0}^j + \mu_{i,X}^j X + \mu_{i,N}^j N \\ \log(\nu_i^j(X, N)) &= \nu_{i,0}^j + \nu_{i,X}^j X + \nu_{i,N}^j N, \end{aligned} \quad (11)$$

where  $i \in C(\text{connected}), U(\text{unconnected})$  denotes bidders type, and  $j \in T, E$  denotes auction type.  $X$  denotes a vector of land characteristics that include area, the upper limit of plot ratio, land grade, and nighttime brightness. Because I only observe the winning bids in most of the data, I write the likelihood function relying on the first-order statistic, that is, the

highest realization of  $N$  random variables where  $N - 1$  bids are drawn from the uncorrupt bidders' distribution and one bid is drawn from the corrupt bidders' distribution. With one corrupt and  $N - 1$  uncorrupt bidders, the density of the first-order statistic conditional on the corrupt or not winning are given by

$$\begin{aligned} G_C^{j,(1:N)}(x) &= g_C^j(x)G_U^j(x)^{N-1} \\ G_U^{j,(1:N)}(x) &= (N - 1)g_U^j(x)G_U^j(x)^{N-2}G_C^j(x). \end{aligned} \quad (12)$$

Thus, the likelihood function is given by

$$LL(\lambda^t, \nu^t) = \sum_{j=1}^{T^t} \log (G_U^{t,(1:N)}(b_j)(1 - 1_{Cwins}) + G_C^{t,(1:N)}(b_j)1_{Cwins}), \quad (13)$$

where  $b_j$  denotes the winning bid in auction  $j$  with auction type  $j \in \{T, E\}$ , and  $T^t$  is the total number of auctions of type  $t$  in my sample.

Given the estimated parameters of the bid distributions, I can then back out the common value signal distribution and private cost distribution of each bidder on each track with characteristics  $X$ . Below, I will discuss the methods and computational details.

First, I borrow from Goeree and Offerman (2003) and define the expected valuation of the contract conditional on winning the auction with bid  $b$  by

$$R_i(b) \equiv \alpha_i r_i + \sum_{j \neq i} \alpha_j [r_j | \rho_j = B_j^{-1}(b)] - c_i.$$

I can compute the distribution of  $R_i(b)$  by inverting bidders' FOCs. Following Weiergraeber and Wolf (2018), I first draw a pseudo-sample of bids for both corrupt and uncorrupt bidders from the estimated bid distributions,  $G_C^T(b|X, N)$  and  $G_U^T(U|X, N)$ . I then invert the FOCs for all simulated bids results in a pseudo-sample of expected value realizations:

$$R_i(b_i) = b_i - \frac{G_i^{1:N_1}(b_i)}{g_i^{1:N_1}(b_i)}, \quad (14)$$

where

$$\begin{aligned}
G_i^{1:N \setminus i}(b_i|b_i, X, N) &= Pr(\max_{j \neq i} B_j \leq b_i) \\
G_u^{1:N \setminus i}(b_i|b_i, X, N) &= G_u(b_i|X, N)^{N-2} G_c(b_i|X, N) \\
G_c^{1:N \setminus i}(b_i|b_i, X, N) &= G_u(b_i|X, N)^{N-1},
\end{aligned} \tag{15}$$

where in the last two lines  $G_u(\cdot)$  and  $G_c(\cdot)$  denote the estimated bid distributions for unconnected bidders and connected bidders.  $G^{1:N \setminus i}(\cdot)$  describes the cumulative distribution function (CDF) of the highest rival bid evaluated at the observed winning bid  $b_i$ , conditional on the event that bid  $b_i$  was pivotal. The denominator of the markup term  $g$  is the derivative of  $G$  and is given by

$$\begin{aligned}
g_i^{1:N \setminus i}(b_i|b_i, X, N) &= \frac{\partial G_i^{1:N \setminus i}(b_i|b_i, X, N)}{\partial b_i} \\
g_u^{1:N \setminus i}(b_i|b_i, X, N) &= (N-2)g_u(b_i|X, N)G_u(b_i|X, N)^{N-3}G_c(b_i|X, N) + g_c(b_i|X, N)G_u(b_i|X, N)^{N-2} \\
g_c^{1:N \setminus i}(b_i|b_i, X, N) &= (N-1)g_u(b_i|X, N)G_u(b_i|X, N)^{N-2}
\end{aligned} \tag{16}$$

In this way, I transform the sample of winning bids into a sample of (winners') expected valuations. Afterward, I can take  $R_i$  as known. I know from lemma 1 that

$$R_i + c_i = \alpha_i r_i + \sum_{j \neq i} \alpha_j E[r_j | \rho_i = B_j^{-1}(b)]. \tag{17}$$

I assume that anything that varies by land parcels is common to all bidders, and, therefore, the bidders' private costs do not vary by land parcels. Luckily, the data size is large enough such that the same bidder wins many pieces of land parcels, and I can utilize the with-winner variation to estimate the distribution of common value signals. For all land parcels that are

won by the same bidder, I have

$$R_i - R_j = \alpha_i r_i + \sum_{k \neq i} \alpha_k E[r_k | \rho_k = B_k^{-1}(b)] - \alpha_j r_j - \sum_{k \neq j} \alpha_k E[r_k | \rho_k = B_k^{-1}(b)]. \quad (18)$$

I know  $R_i$  from the first step, so the distribution of the LHS is known from the data. The distribution of the RHS is only a function of  $r \sim F(\bar{r}, \sigma_r)$  and can be computed up to a vector of parameters  $(\bar{r}, \sigma_r, \alpha)$ . Thus, I can estimate the parameters using maximum likelihood.

An additional complication is that I need to compute the conditional expectation in the expected valuation of winning the land parcel with bid  $b$ , and this has to be consistent with the first-order conditions for equilibrium. I follow Weiergraeber and Wolf (2018) and implement the second step as follows.

To compute the likelihood, I need to specify a distribution for the common value signals and private costs. For computational purpose, I choose a Normal distribution for both. To capture revenue heterogeneity across tracks, I model the mean and variance of  $F_r$  as functions of land characteristics, so that for land parcel  $i$ :  $m_{ri} = \gamma_0 + \gamma_X X_i$  and  $\sigma_{ri} = \zeta_0 + \zeta_X X_i$ . Moreover, I specify the asymmetry parameter  $\alpha$  as a function of the number of bidders  $N$ :  $\alpha_c = \frac{\alpha}{\alpha + N - 1}$  implying  $\alpha_u = \frac{1}{\alpha + N - 1}$ . To allow for asymmetric cost distribution between connected bidder and unconnected bidder, I specify the cost distributions to depend on bidder's type:  $c_i \sim N(m_{cc}, \sigma_{cc}^2)$  for connected bidders and  $c_i \sim N(m_{cu}, \sigma_{cu}^2)$  for unconnected bidders.

The normal distribution offers an easy expression for the expected value:

$$E[r_i | \rho_i = B_i^{-1}(b)] = m_r + \frac{\alpha_i \sigma_r^2}{\alpha_i \sigma_r^2 + \sigma_{ci}^2} (B_i^{-1}(b) - \alpha_i m_r + m_{ci}). \quad (19)$$

Given the first step of the estimation procedure and for every winning bid  $b$ , I can compute the corresponding (compound) signal that induces opponents to bid  $b$ , that is, the opponents signal that makes  $b$  pivotal. If  $i$  is the winning bidder, denote this signal by  $B_i^{-1}(b)$ . I know

that in equilibrium:

$$R_i(b) = B_i^{-1}(b) + \sum_{j \neq i} \alpha_j E[r_j | \rho_i = B_j^{-1}(b)]. \quad (20)$$

Substituting equation (20) into equation (19) yields

$$E[r_i | \rho_i = B_i^{-1}(b)] = m_r + \frac{\alpha_i \sigma_r^2}{\alpha_i^2 \sigma_r^2 + \sigma_{ci}^2} (R_i - \sum_{j \neq i} E[r_j | \rho_j = B_j^{-1}(b)] - \alpha_i m_r + m_{ci}). \quad (21)$$

Applying this logic to every bidder for a given track, yields a sample of  $N$  expected valuations conditional on winning bid  $b$  and the winners identity. These equations have to be consistent with each other due to the following observation. In the expected value of  $i$ 's opponents' signals, the conditional expectation of  $i$ 's revenue signal appears again. Hence for each auction, I have  $N$  equations in  $N$  unknowns. This system is a fixed-point problem in  $N$  unknowns conditional on a set of parameters  $\{\alpha_i, m_r, \sigma_r, m_{ci}, \sigma_{ci}\}$ . These unknowns are the conditional expectations about the opponents' revenue signals.  $R$  can be computed from the estimation in the first step.

As unconnected bidders are symmetric, the equations reduce to a two-dimensional system with unknowns  $X_c = E[r_c | \rho_c = B_c^{-1}(b)]$  and  $X_u = E[r_u | \rho_c = B_u^{-1}(b)]$ , where for connected bidders,

$$X_c = m_r + \frac{\alpha_c \sigma_r^2}{\alpha_c^2 \sigma_r^2 + \sigma_{cc}^2} (R^c(b) - (n-1)X_u - \alpha_c m_r + m_{cc}). \quad (22)$$

For unconnected bidders,

$$X_u = m_r + \frac{\alpha_u \sigma_r^2}{\alpha_u^2 \sigma_r^2 + \sigma_{cu}^2} (R^u(b) - (n-2)X_u - X_c - \alpha_u m_r + m_{cu}). \quad (23)$$

This is a simple system of linear equations with two unknowns. Given the values of the conditional expectation terms,  $X_c$  and  $X_u$ , for any vector of parameters  $\{\alpha_i, m_r, \sigma_r, m_{ci}, \sigma_{ci}\}$ , I can construct the likelihood function from the first-order conditions for equilibrium bidding



using the estimated values  $R_i$ :

$$R_i - R_j = \alpha_i r_i + \sum_{k \neq i} \alpha_k X_k - \alpha_j r_j + \sum_{k \neq j} \alpha_k X_k, \quad (24)$$

where the left-hand side is the “dependent variable”  $R_i - R_j$  that I back out in the first stage. The right-hand side depends on the parameters  $\{\alpha_i, m_r, \sigma_r, m_{ci}, \sigma_{ci}\}$ , and is the sum of two independent random variables.

It is worthwhile to note that, while the left-hand side does not contain the private cost terms  $c_i$ , the expected value term are functions of bidders’ private cost parameters  $\{m_{cc}, \sigma_{cc}, m_{cu}, \sigma_{cu}\}$ . Therefore, I need to estimate the distribution of common value signals in conjunction with the next step such that the private cost parameters are consistent with what I get from the next step.

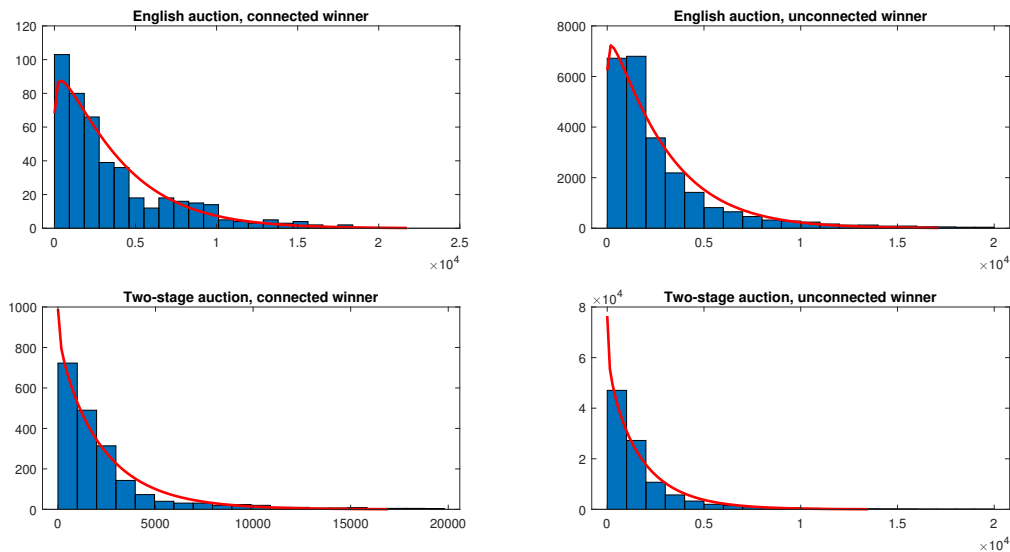
In the third step, I identify the distribution of private cost  $c_i$  utilizing the variations across different winners. I can isolate the private cost signal part of  $R$  via

$$c_i = \alpha_i r_i + \sum_{j \neq i} \alpha_j E[r_j | \rho_j = B_j^{-1}(b)] - R_i \quad (25)$$

I know  $R_i$  from the first step and the distribution of  $r_i$  as a function of private costs parameters from the second step. Consequently, I can compute the distribution of  $c_i$  separately for corrupt and uncorrupt bidders.

### 5.3 Estimation Results

In this section I present results of the structural estimation. I will present estimation results for the bid distribution, common value signal distribution, and private cost distribution. These results also allow me to evaluate the efficiency of the auction outcomes for both auction formats.



This figure plots the empirical fit of the bid distribution assuming that bids follow a Weibull distribution.

Figure 8: Empirical fit of bid distribution

### 5.3.1 Bid Distribution

Table ?? in the appendix presents the estimates for the bid distribution parameters in two-stage auctions and English auctions for both connected bidders and unconnected bidders. Interpreting the magnitude of the coefficients is difficult to do in a highly nonlinear auction model. Therefore, I focus on the shape of the implied bid functions and the cost distribution estimates.

Figure 8 displays the empirical distribution of bids and the empirical fits of the estimation. One can see that the estimation of bid distribution fits the data well.

### 5.3.2 Common Value Cost Estimates

As discussed in the previous section, the difference between the winning price of two-stage auction and English auction can be decomposed into two sources: selection effect, that is, local government chooses to use two-stage auction more often on land parcels with lower value, and information effect, that is, the equilibrium winning bid in two-stage auction is

lower than that in English auction when information about common value is asymmetric. To quantify the two effects separately, I estimate the distribution of common value from two-stage auction data, and then I extrapolate to English auction assuming that the distribution of common value as a function of land characteristics does not vary by the auction format being used.

Moreover, I learn from the reduced-form evidence that the bids of connected bidders are significantly higher than those of unconnected ones. In line with my theoretical model, this can be due to two reasons: connected bidders have an information advantage over unconnected ones, or connected bidders have lower private costs than do unconnected ones. To disentangle the two reasons, I estimate the information parameters  $(\alpha_c, \alpha_u)$  of my theoretical model, and, in the next part, I estimate the distribution of private costs separately for connected bidders and unconnected bidders.

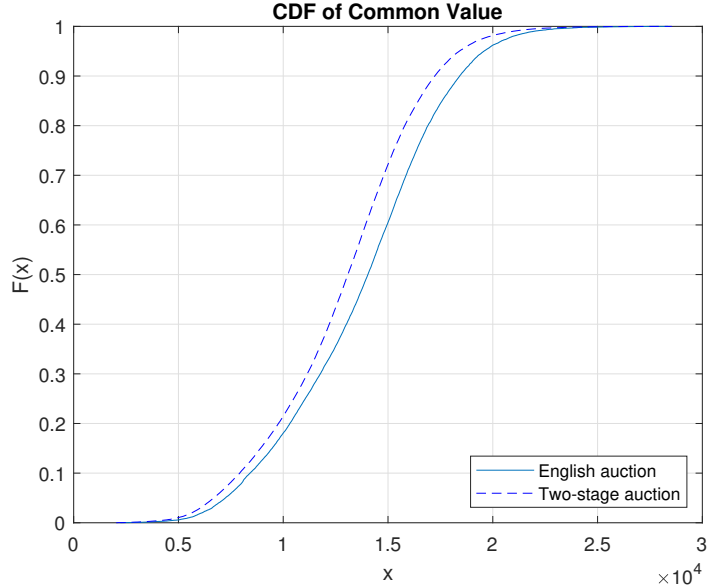
Table 9 presents the estimates for the common value distribution parameters. Consistent with the reduced-form evidence, the value of land increases with the plot ratio limit, the official land quality, and the land's brightness, while decreases with the area of the land.

Using the estimated parameters, I obtain the distribution of common value signals for each piece of land sold by two-stage auctions. I then extrapolate the estimation to English auctions. Figures 9 and 10 plot the cumulative distribution of the estimated mean and standard deviation of land's common value for both auction formats. As one can see from the figures, the distribution of English auctions stochastically dominates that of two-stage auctions, which suggests that two-stage auctions have a lower mean and lower variance than do English auctions. In line with my theoretical model, the lower mean and lower variance of two-stage auctions both contribute to the lower equilibrium winning bid of the auctions themselves. Quantitatively, the mean of the common value signal for two-stage auction is lower than that for English auction by  $CNY\ 343.6186/m^2$  on average, explaining 37% of the price difference between the two auction formats, and the standard deviation of the common value signal is lower by  $CNY\ 203.6871/m^2$ , explaining 6% of the price difference between the

Table 9: Estimation results: Common value signal distribution

$m_r$	
Area	-193.282*** (25.386)
Plot ratio upper bound	1,644.254*** (109.490)
Land grade	-1,085.285*** (329.551)
Brightness	3,868.557*** (538.749)
Constant	20,133.8454** (10,382.689)
$\sigma_r$	
Area	103.735 (278.332)
Plot ratio upper bound	264.462* (182.990)
Land grade	-532.339** (211.297)
Brightness	1,029.626** (445.411)
Constant	204.929 (1,256.552)

*Notes:* The table presents the estimation results for the common value signal distribution assuming it follows a normal distribution. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .



*Note:* This figure plots the CDF of the estimated mean of the distribution of the common value signal for two-stage auctions and English auctions.

Figure 9: Distribution of a common value signal ( $m_r$ )

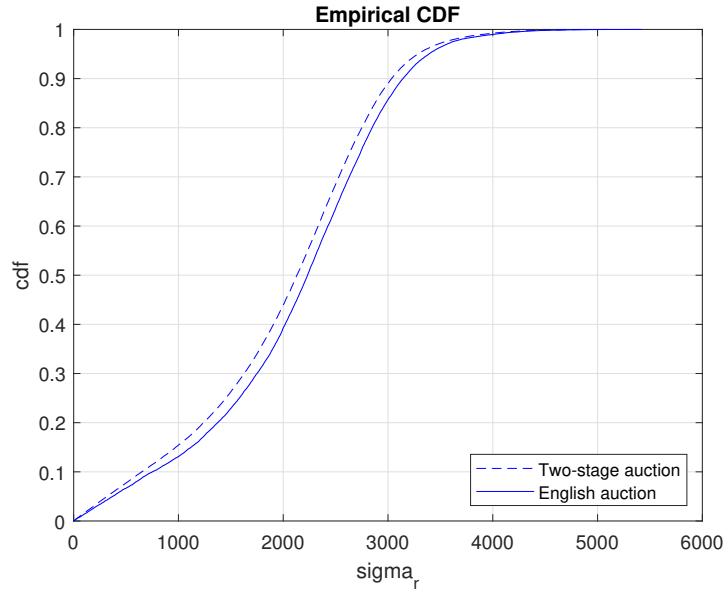
two auction formats. Altogether, the selection on land quality explains 43% of the observed price difference.

As for the information asymmetry parameter, I specify  $\alpha_c = \alpha\alpha_u$ , where  $\alpha$  measures the level of asymmetry, so that

$$\begin{aligned}\alpha_c &= \frac{\alpha}{\alpha + N - 1}; \\ \alpha_u &= \frac{1}{\alpha + N - 1}.\end{aligned}\tag{26}$$

The estimation is  $\hat{\alpha} = 1.891$  with a standard error of 0.537. This suggests that a connected bidder has 89% more information about the common value than does an unconnected bidder. Table 10 presents the estimated asymmetry parameters for several bidder configurations  $N$ . Most importantly, the results reveal that connected bidders have a substantial informational advantage over unconnected ones.

In line with my theoretical model, information asymmetry gives rise to the difference in the expected winning bid between two auction formats, and this explains the remaining 53%



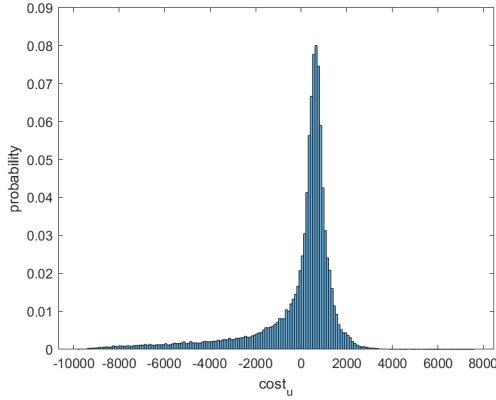
*Note:* This figure plots the CDF of the estimated variance of the distribution of the common value signal for two-stage auctions and English auctions.

Figure 10: Distribution of a common value signal ( $\sigma_r$ )

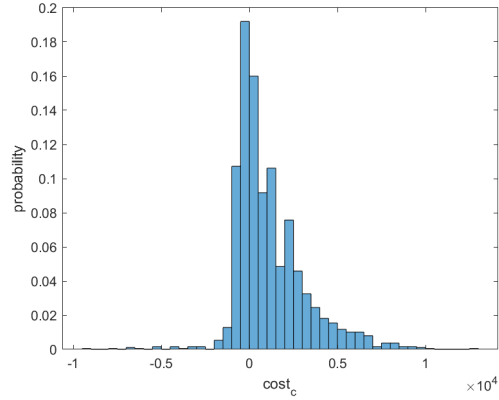
Table 10: Estimation results: Informational asymmetry

	N = 5	N = 10	N = 20	N = 30
$\alpha_c$	0.321** (0.062)	0.174** (0.041)	0.091** (0.023)	0.061** (0.016)
$\alpha_u$	0.170** (0.015)	0.092** (0.005)	0.048** (0.001)	0.032** (0.001)

*Notes:* This table presents the estimation results for the information asymmetry parameter for some number of bidders. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$  (testing  $H_0 : \frac{1}{N} = 1$ ).



(a) Unconnected Bidder



(b) Connected Bidder

Note: This figure plots the distribution of the private costs of the connected bidders and the unconnected bidders.

Figure 11: Distribution of Private Costs of Connected and Unconnected Bidders

of the observed price difference.

### 5.3.3 Private Cost Estimates

After I estimate the common value distribution, I am able to estimate the distribution of bidders' private costs. Figure 6 displays the histogram of bidders' private costs. Surprisingly, while connected bidders are making higher bids on average, they actually have higher private costs. Table xx summarizes the estimated parameter values for private cost distributions. The private costs of connected bidders are higher than those of unconnected bidders by  $CNY435.7/m^2$ . This result suggests that there is a significant number of land parcels that are not developed by the most cost-efficient firm, and I examine the implications on efficiency in more detail in the next part.

### 5.3.4 Efficiency

While local bidders only takes 30% of the total firm, they win almost 50% of the land parcels. Similarly, the princeling firms takes 1% of the total firms, but wins around 2% of the land parcels. Obviously, connected bidders are winning much more land than they “deserve.” The auction outcome is efficient if the land is sold to the firm with the lowest private cost. However, the information advantage of connected bidders gives these bidders a higher chance

of winning despite that they have higher costs on average. In this part, I follow Weiergraeber and Wolf (2018) and construct the measure for efficiency, that is, the probability of the lowest cost bidder wins the auction.

Consider bidder  $i$  winning with bid  $b$  resulting from the cost realization,  $c$ . The probability that this outcome is efficient is given by

$$Pr(c_i \leq \min_{j \neq i} c_j | b_i \leq \min_{j \neq i} c_j) = Pr(c_i \leq \min_{j \neq i} c_j | \rho_i \leq \min_{j \neq i} B_j^{-1} B_i(\rho_i)). \quad (27)$$

It is worthwhile to note that each bidder's signal consists of a private (cost) and a common value (revenue) signal, and therefore the bidder with the lowest compounded signal  $\rho_i$  may not be the one with the lowest private cost. To compute the ex ante probability of selecting the efficient developer, I have to aggregate over all possible compounded signals and the winner's identities so that the ex ante probability of selecting the efficient bidder is given by

$$\int_{-\infty}^{\infty} E^c(\rho) f_{\rho_c}(\rho) F_{\rho_u}(B_u^{-1} B_c(\rho))^{N-1} d\rho + (N-1) \int_{-\infty}^{\infty} E^u(\rho) f_{\rho_u}(\rho) F_{\rho_u}(B_u^{-1} B_c(\rho))^{N-2} F_{\rho_c}(B_c^{-1} B_u(\rho)) d\rho, \quad (28)$$

which integrates over all possible compounded signals and aggregate over winner identities weighted by the respective efficiency probabilities, where the efficiency probability  $E(\rho)$  are given by

$$\begin{aligned} E_c(\rho) &= \int_{-\infty}^{\infty} (X^u(c))^{N-1} f_{c|\rho_c}(c|\rho) dc, \\ E_u(\rho) &= \int_{-\infty}^{\infty} X^c(c) (X^u(c))^{N-2} f_{c|\rho_u}(c|\rho) dc. \end{aligned} \quad (29)$$

$E^c$  denotes the probabilities of connected bidders being the efficient firm when winning with compounded signal  $\rho$ , and  $E^u$  denotes that of unconnected bidders.  $f_{c|\rho}$  denote the conditional pdf of cost given the compounded signal. The efficiency terms integrate over all



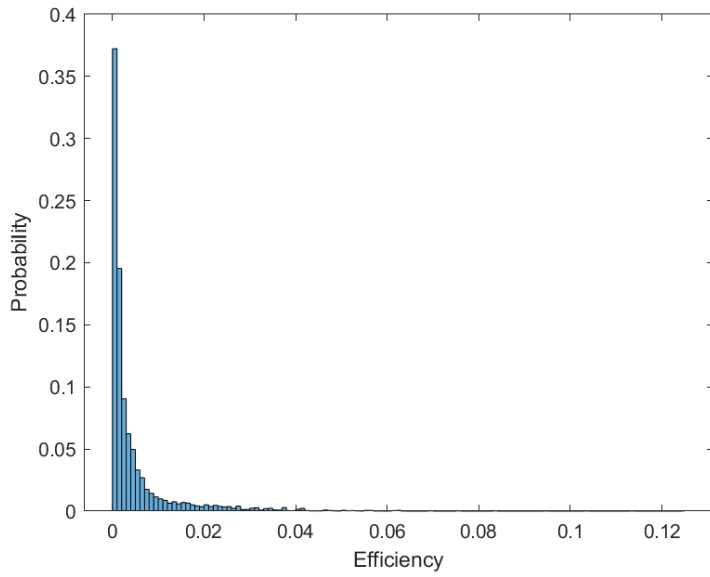
potential winner's costs that rationalize the compound signal with

$$\begin{aligned}
 X^c(c) &= \int_{-\infty}^{B_c^{-1}B_u(\rho)} (1 - F_{c|\rho_c}(c|\tilde{\rho})) \frac{f_{\rho_c}(\tilde{\rho})}{1 - F_{\rho_c}(B_c^{-1}B_u(\rho))} d\tilde{\rho} \\
 X^u(c) &= \int_{-\infty}^{B_u^{-1}B_c(\rho)} (1 - F_{c|\rho_u}(c|\tilde{\rho})) \frac{f_{\rho_u}(\tilde{\rho})}{1 - F_{\rho_u}(B_u^{-1}B_c(\rho))} d\tilde{\rho}
 \end{aligned} \tag{30}$$

and  $X^i(c)$  being the probability that the cost realization for competitor  $i$ , integrated over all compounded signals that lose against the winner's compounded signal  $\rho$ , is higher than the currently fixed (winner's) cost  $c$ .

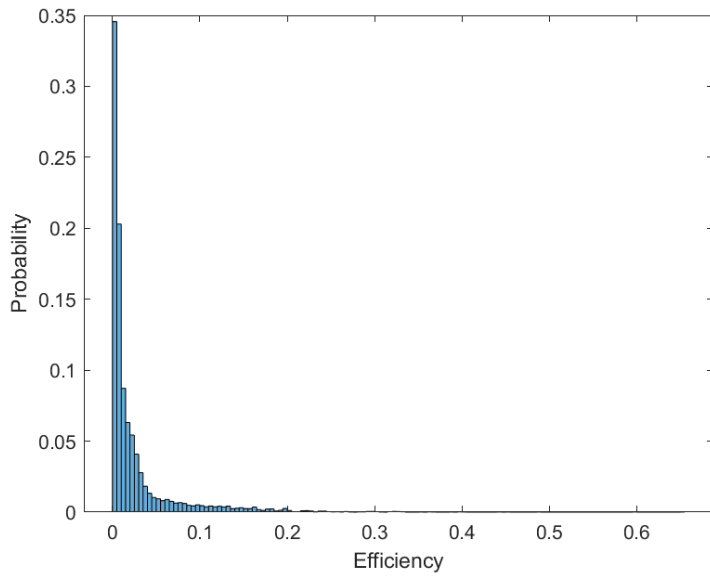
The estimation shows that the probability of selecting the efficient firm is 0.0079 for two-stage auctions and 0.015 for English auctions, both of which are low. Two factors simultaneously contribute to this low efficiency result: connected bidders have significantly higher private costs than do unconnected bidders; however, an information advantage allows the former to win with a much higher probability. Therefore, it is very unlikely that the auction ends with an efficiency result. Because information asymmetry has a much larger effect in two-stage auctions than in English auctions, efficiency is even lower in two-stage auctions.

Figure 12 displays the histogram of the estimated ex ante efficiency for two-stage auctions, and Figure 13 displays the same for English auctions. The figures show that the estimated value for efficiency for both auction formats gathers close to zero, a finding that explains the low value of average efficiency in both auction formats.



*Note:* This figure plots the distribution of estimated ex ante efficiency for two-stage auctions.

Figure 12: Histogram of efficiency for two-stage auctions



*Note:* This figure plots the distribution of estimated ex ante efficiency for English auctions.

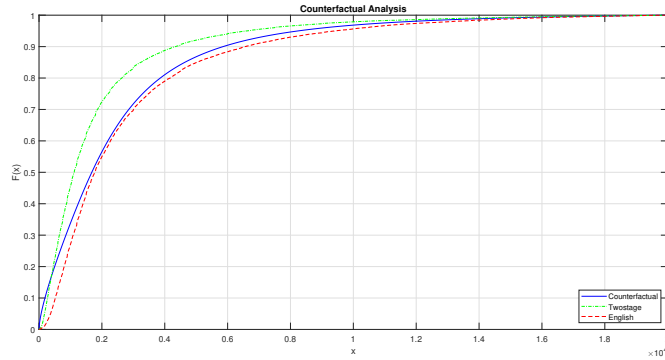
Figure 13: Histogram of efficiency for English auctions

## 6 Counterfactual Analysis

In this section, I use the estimated model to perform two sets of counterfactual experiments. First, I evaluate the effect of auction format choice by limiting local governments' ability in choosing auction formats. Second, I examine the effect of information by varying the information asymmetry parameter. For both experiments, I calculate the counterfactual winning bid, the change in information rent, as well as the change in efficiency.

### 6.1 English Auction Only

In the first analysis, I limit the local government's discretion in choosing auction formats, such that local governments can only use English auction for all land parcels. Figure 14 plots the counterfactual bid distribution if all land is sold by English auctions. The green line represents the bid distribution for two-stage auctions; the red line represents the bid distribution for English auctions; and the blue line in the middle plots represents the counterfactual bid distribution assuming the land parcels sold by two-stage auctions are now sold by English auctions. As can be seen in the figure, using English auctions, as expected, leads to higher winning bids and thus more land revenues than using two-stage auctions. The difference between the counterfactual bids and the bids from English auction can be explained by selection, that is, the value of the land parcels is lower for two-stage auctions than for English auctions.

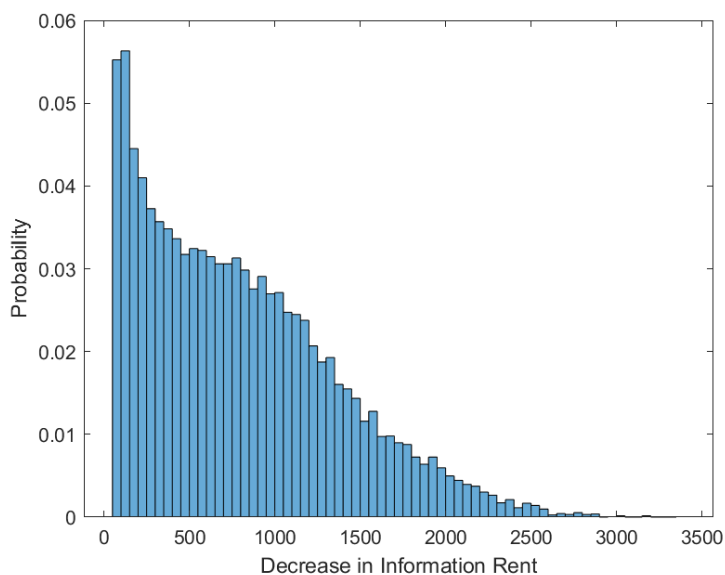


*Note:* This figure plots the CDF of the counterfactual bid distribution if only English auctions are used.

Figure 14: CDF of bid distribution

I then examine the effect of the policy on corruption. While I cannot identify the local governments' preference parameters, it is impossible to calculate the exact amount of corruption. However, information rent can be calculated from the estimated auction model. Recall from the equilibrium of the bribery game that the optimal bribe equals to the information rent when land value is below certain threshold and cannot not exceed the information rent otherwise. Therefore, information rent serves as a good proxy and upper limit for corruption, and I examine the change in information rent under the counterfactual policy.

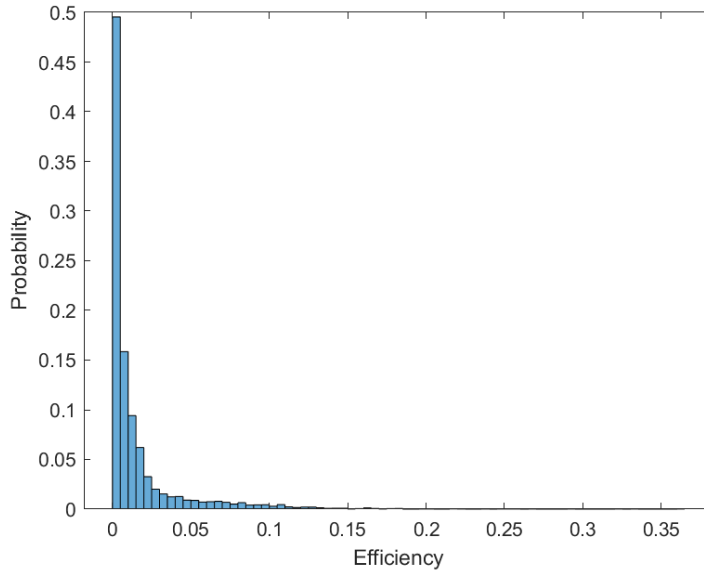
The counterfactual analysis shows that, on average, using English auction only can reduce information rent by 88% ( $CNY581/m^2$ ). Figure 15 displays the histogram of the change in the information rent under the counterfactual policy. As can be seen in the figure, using English auction instead of two-stage auction leads to a significant reduction in information rent, and therefore one can expect corruption to decrease significantly.



*Note:* This figure plots the distribution of the reduction in information rent if only English auctions are used.

Figure 15: Histogram of difference in information rent

Lastly, I examine the effect of the policy on the ex ante efficiency of the auctions. Figure 16 displays the distribution of the ex ante efficiency under the counterfactual policy. While efficiency is still low because of the asymmetric cost distributions of connected bidders and unconnected bidders, it is still higher than in the case of a two-stage auction.



*Note:* This figure plots the CDF of estimated ex ante efficiency if only English auctions are used.

Figure 16: Histogram of efficiency for English auctions only

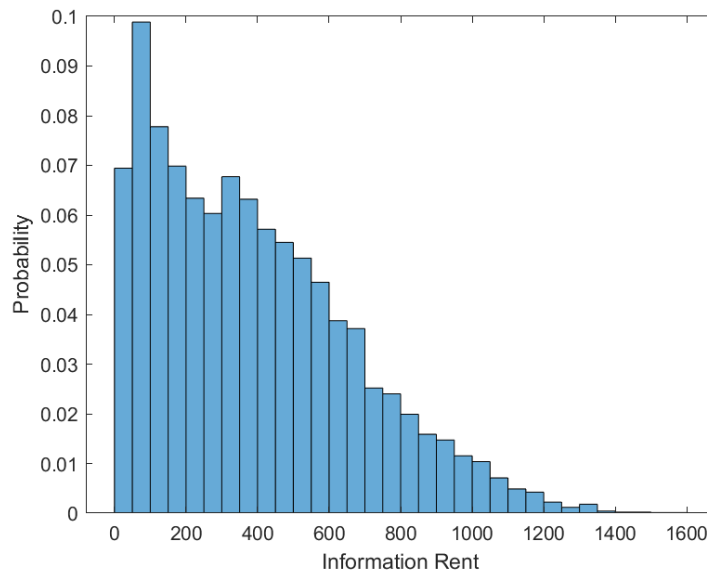
To summarize, using English auctions instead of two-stage auctions can lead to an increase in land revenue, a reduction in corruption, and an increase in efficiency.

## 6.2 Information Disclosure

While English auction yields higher land revenues and improves the efficiency of auction outcomes, two-stage auction may be easier to operate in practice. If two-stage auction ends at the first stage, there is no need for local governments to gather all bidders at a certain date to hold an on-site auction. Therefore, it may not be feasible to stop using two-stage auction completely. Instead, in the second analysis, I consider the policy of information disclosure. If the central government requires local governments to announce their cities' development plan in more detail periodically, the local government will have less private information about the land value, and therefore information asymmetry between bidders would be reduced. Another possible method to reduce information asymmetry, as discussed in the previous section, is to conduct two-stage auctions through online transaction systems,

so that bidders can observe other bidders' bids in the first stage.

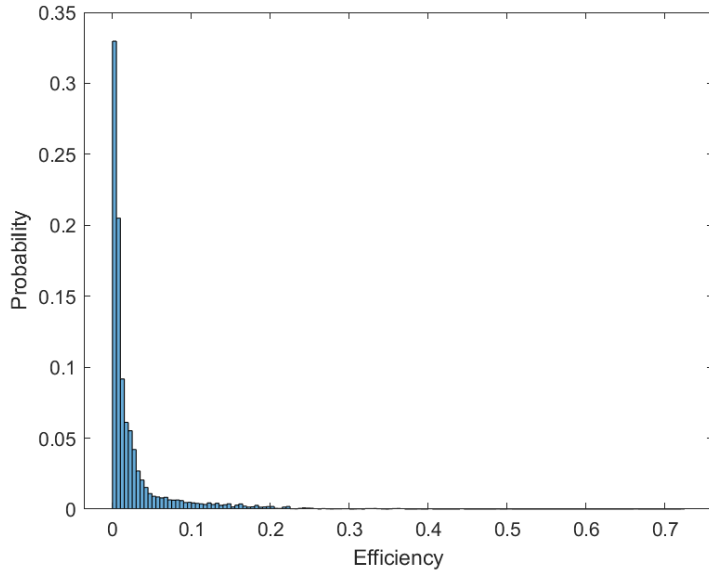
I conduct the second analysis by assuming that with better information disclosure, information asymmetry between the informed bidder and the uninformed bidders is reduced by 50%, that is,  $\alpha$  is reduced to 1.445 from 1.891. The counterfactual analysis shows that, on average, reducing information asymmetry can reduce information rent by 38% ( $CNY251/m^2$ ). Figure 17 displays the histogram of the change in information rent. As can be seen in the figure, reducing information asymmetry also leads to a significant reduction in information rent, but the magnitude is not as big as using English auctions instead.



*Note:* This figure plots the distribution of the reduction in information rent if information asymmetry is reduced by 50%.

Figure 17: Histogram of information rent

Figure 18 displays the efficiency distribution under the counterfactual policy, and one can see that efficiency remains low, but is certainly higher than that without the policy.



*Note:* This figure plots the CDF of estimated ex ante efficiency if information asymmetry is reduced by 50%.

Figure 18: Histogram of efficiency for reduced information asymmetry

To summarize, reducing information asymmetry may also lead to higher land revenue, less corruption, and higher efficiency, but to match the effect of the English-auction-only policy, officials would need to reduce information asymmetry by a large percentage.

## 7 Concluding Remarks

In this paper, I studied the role of information in shaping corruption in the context of China’s land auctions. When local governments, acting as auctioneers, have private information about the common value of land, they may sell information to bidders with political connections in exchange for bribes. This corruption leads to a loss in land revenue and efficiency. I construct a large data set with detailed information about land transactions, winning bidders, and local officials and use the novel data set to uncover empirical patterns that show that local officials employ English auctions to sell high-value land and two-stage auctions to sell low-value land, and politically connected bidders are paying more but are



also making higher ex post profit than are other bidders.

I develop a theoretical model in light of the reduced-form evidence. The model features corrupt a local official who has private information about land's common value and chooses auction formats to maximize his compounded utility in land revenue and personal benefit. I also endogenize bidders' behavior with a common value auction model that can be asymmetric across two dimensions: bidders' information on the common value and bidders' private cost distribution.

I then structurally estimate the auction model. I disentangle the two effects that explain the observed price differential between two-stage auctions and English auctions: the selection effect accounts for 43% of the difference, and the corruption effect accounts for the remaining 57%. Surprisingly, I also find that politically connected bidders have higher private costs in land development even though they are paying higher prices and winning with higher probability in land auctions.

I use the model estimates to evaluate policies that may reduce corruption in China's land market. I find that limiting local governments' discretion in choosing auction formats and increasing information disclosure can both decrease corruption and increase land revenue significantly, as well as improve the efficiency of land development.

This paper sheds light on how sellers' private information can be used in corruption. Moreover, I develop a new approach in estimating common value auction models with asymmetric bidders. I also provide new empirical evidence of how political favoritism affects auction outcomes.

This paper focuses on local governments who make independent decisions for each piece of land parcel in the residential land market. To this end, a simple local government's utility function consisting of land revenue and corrupt income is suitable. Dynamic problems could arise, however, if there is strong interaction between the residential land market and industrial land market. Local governments may have a more complicated goal in using the land as a tool to compete with other jurisdictions or to maximize total revenue from the

whole land market over a certain period. This would be an interesting dimension to explore in future work.

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## Appendix A. Proofs

### Proof of Lemma 2

*Proof.* The expected payoff of winning with bid  $b$  given signal  $\rho_i = \alpha_i r_i - c_i$  is given by

$$\pi_i(b) = \left( \rho_i + \sum_{j \neq i} \alpha_j E[r_j | \rho_j \leq B_j^{-1}(b)] - b \right) F_{\rho_j}^{1:N \setminus i}(B_j^{-1}(b)) \quad (\text{A1})$$

where  $F_{\rho_j}^{1:N \setminus i}$  denotes the first-order statistic of the opponents' signals. The FOC is given by

$$\begin{aligned} 0 &= \left( \rho_i + \sum_{j \neq i} \alpha_j E[r_j | \rho_j \leq B_j^{-1}(b)] - b \right) f_{\rho_j}^{1:N \setminus i}(B_j^{-1}(b)) B_j'^{-1}(b) \\ &+ \left( \sum_{j \neq i} \alpha_j \frac{f_{\rho_j}^{1:N \setminus i}(B_j^{-1}(b))}{F_{\rho_j}^{1:N \setminus i}(B_j^{-1}(b))} B_j'^{-1}(b) (E[r_j | \rho_j = B_j^{-1}(b)] - E[r_j | \rho_j \leq B_j^{-1}(b)]) - 1 \right) F_{\rho_j}^{1:N \setminus i}(B_j^{-1}(b)) \\ &= \left( \rho_i + \sum_{j \neq i} \alpha_j E[r_j | \rho_j = B_j^{-1}(b)] - b \right) f_{\rho_j}^{1:N \setminus i}(B_j^{-1}(b)) B_j'^{-1}(b) - F_{\rho_j}^{1:N \setminus i}(B_j^{-1}(b)) \end{aligned} \quad (\text{A2})$$

Rearranging for  $b$  gives the result. Note that again Reny and Zamir (2004) offers the existence of a pure monotone strategy equilibrium.  $\square$

### Proof of Lemma 3

*Proof.* Note that each  $B_k^i$  is strictly increasing in  $\rho_i$ . Suppose bidders 2,...,n bid according to 5. When bidder 1 wins the auction her expected profit is:

$$\rho_1 + \sum_{j=2}^N \alpha_j E[r_j | \rho_j] - B_{n-2}(\rho_2; b_1, \dots, b_{n-2}) \quad (\text{A3})$$

where the  $\rho_j$  are the realizations of the others' surpluses arranged in reverse bidding order. Using the definition of  $B_{n-2}$  the expected payoff can be written as

$$\rho_1 + \alpha_2 E[r] - \rho_2 \quad (\text{A4})$$

So bidder 1s expected profit is positive only when her compounded signal satisfies:

$$\rho_1 \geq B_{n-1}^{-1}(B_{n-2}(\rho_2)) \quad (\text{A5})$$

and using  $B(\cdot)$  she wins iff the equality of A5 holds. Hence,  $B(\cdot)$  is the optimal bidding strategy for player 1.  $\square$

## Proof of Lemma 4

*Proof.*  $\rho_u(\rho_c)$  = denotes the signal of unconnected bidders who induce the same bid as connected bidders given signal  $\rho_c$ . For simplicity,  $b = B_c^T(\rho_c)$  denotes the equilibrium bid for connected bidders with type  $\rho_c$ . I know from lemma 2 that, for connected bidders,

$$\frac{f_{\rho_u}(\rho_u)(B_u^T)^{-1}(b)}{F_{\rho_u}(\rho_u)} = \frac{1}{(N-1)(\rho_c + (N-1)\alpha_u E[r|\rho_u] - b)} \quad (\text{A6})$$

Consider now unconnected bidders with type  $\rho_u(\rho_c)$ . I substitute equation A6 into his bidding function, and after some trivial algebra, I have

$$\begin{aligned} & \frac{f_{\rho_c}(\rho_c)(B_c^T)^{-1}(b)}{F_{\rho_c}(\rho_c)} \\ &= \frac{1}{\rho_u + (N-2)\alpha_u E[r|\rho_u] + \alpha_c E[r|\rho_c] - b} - \frac{N-2}{(N-1)(\rho_c + (N-1)\alpha_u E[r|\rho_u] - b)} \end{aligned} \quad (\text{A7})$$

$$\frac{(B_c^T)^{-1}(b)}{(B_u^T)^{-1}(b)} = \frac{f_{\rho_u}(\rho_u)}{F_{\rho_u}(\rho_u)} / \frac{f_{\rho_c}(\rho_c)}{F_{\rho_c}(\rho_c)} \times \left( \frac{(N-1)(\rho_c + (N-1)\alpha_u E[r|\rho_u] - b)}{(\rho_u + (N-2)\alpha_u E[r|\rho_u] + \alpha_c E[r|\rho_c] - b)} - (N-2) \right) \quad (\text{A8})$$

Denote  $Q((B_c^T)^{-1}(b)) = (B_u^T)^{-1}(b)$ , which has derivative  $\dot{Q}((B_c^T)^{-1}(b)) = \frac{(B_u^T)^{-1}(b)}{(B_c^T)^{-1}(b)}$ . The interpretation of function  $Q(x)$  is that it gives the signal of connected bidders who place the same bid as unconnected bidders given signal  $x$ . Together with equation A8, this yields

$$\dot{Q}(x) = \frac{f_{\rho_c}(x)}{F_{\rho_c}(x)} / \frac{f_{\rho_u}(Q(x))}{F_{\rho_u}(Q(x))} / \left( \frac{(N-1)(x + (N-1)\alpha_u E[r|Q(x)] - b)}{(Q(x) + (N-2)\alpha_u E[r|Q(x)] + \alpha_c E[r|x] - b)} - (N-2) \right) \quad (\text{A9})$$

When  $Q(x) > x$ ,  $E[c|Q(x)] < E[c|x]$ , and therefore

$$\begin{aligned} & \frac{(N-1)(x + (N-1)\alpha_u E[r|Q(x)] - b)}{(Q(x) + (N-2)\alpha_u E[r|Q(x)] + \alpha_c E[r|x] - b)} - (N-2) \\ &= \frac{(N-1)(x + (N-1)Q(x) + (N-1)E[c|Q(x)] - b)}{(x + (N-1)Q(x) + (N-2)E[c|Q(x)] + E[c|x] - b)} - (N-2) \\ &< (N-1) - (N-2) \\ &= 1 \end{aligned} \quad (\text{A10})$$

Given the assumption of conditional stochastic dominance, I also have that  $\forall x$

$$\frac{F_{\rho_u}(x)}{f_{\rho_u}(x)} > \frac{F_{\rho_c}(x)}{f_{\rho_c}(x)} \quad (\text{A11})$$



Hence, when  $Q(x) > x$ , I have

$$\frac{F_{\rho_u}(Q(x))}{f_{\rho_u}(Q(x))} > \frac{F_{\rho_u}(x)}{f_{\rho_u}(x)} > \frac{F_x(\rho_c)}{f_{\rho_c}(x)} \quad (\text{A12})$$

Together, I have  $\dot{Q}(x) > 1$  when  $Q(x) > x$ .

Finally, it is straightforward to show that connected bidders will never submit a bid higher than the highest possible bid of unconnected bidders. So  $\lim_{x \rightarrow \infty} Q(x) - x \geq 0$ . Therefore, given the assumption of conditional stochastic dominance, I have  $Q(x) > x$  for all  $x$ ; that is, connected bidders always bid higher than unconnected bidders given the same signal.  $\square$

### Proof of Lemma 5

*Proof.* For the ease of notation, let bidder 1 be the connected and informed bidder, and bidder 2 to N to be the uninformed bidders.

First, Hernando-Veciana (2009) shows that the equilibrium of English auction satisfies

$$E[c_1 | \rho_1] = E[c_i | \rho_i = (B_u^E)^{-1}(B_u^E(\rho_1))], \forall i \in 2, \dots, N. \quad (\text{A13})$$

$\rho_c = \rho_1$  denotes the compounded signal of connected bidders, and  $\tilde{\rho}_u = (B_u^E)^{-1}(B_u^E(\rho_c))$  denotes the compounded signal of unconnected bidders that induces the same bid in English auctions.  $\hat{\rho}_u = (B_u^T)^{-1}(B_u^T(\rho_c))$  denotes the compounded signal of unconnected bidders who induce the same bid in two-stage auctions. From lemma 2, I have

For connected bidders,

$$b_c = \rho_c + (n-1)\alpha_u E[r | \hat{\rho}_u] - \frac{F_{\rho_u}(\hat{\rho}_u)}{(n-1)f_{\rho_u}(\hat{\rho}_u)(B_u^T)^{-1}(b_c)} \quad (\text{A14})$$

For unconnected bidders,

$$b_c = \hat{\rho}_u + (n-2)\alpha_u E[r | \hat{\rho}_u] + \alpha_c E[r | \rho_c] - \frac{F_{\rho_u}(\hat{\rho}_u)F_{\rho_c}(\rho_c)}{(n-2)f_{\rho_u}(\hat{\rho}_u)F_{\rho_c}(\rho_c)(B_u^T)^{-1}(b_c) + f_{\rho_c}(\rho_c)F_{\rho_u}(\hat{\rho}_u)(B_c^T)^{-1}(b_c)}. \quad (\text{A15})$$

Note that

$$\alpha_i E[r_i | \rho_i] = \rho_i + E[c_i | \rho_i] \quad (\text{A16})$$

Equation (A2) and (A3) can be simplified after some trivial algebra to the following equation,

$$E[c | \hat{\rho}_u] - \frac{F_{\rho_u}(\hat{\rho}_u)}{(n-1)f_{\rho_u}(\hat{\rho}_u)(B_u^T)^{-1}(b_c)} = E[c | \rho_c] - \frac{F_{\rho_u}(\hat{\rho}_u)F_{\rho_c}(\rho_c)}{(n-2)f_{\rho_u}(\hat{\rho}_u)F_{\rho_c}(\rho_c)(B_u^T)^{-1}(b_c) + f_{\rho_c}(\rho_c)F_{\rho_u}(\hat{\rho}_u)(B_c^T)^{-1}(b_c)} \quad (\text{A17})$$

Given the assumption of conditional stochastic dominance, I have that

$$\frac{F_{\rho_u}(\rho_c)}{f_{\rho_u}(\rho_c)} > \frac{F_{\rho_c}(\rho_c)}{f_{\rho_c}(\rho_c)} \quad (\text{A18})$$

I know from Lemma 4 that  $\hat{\rho}_u > \rho_c$ , and, therefore, I have

$$\frac{F_{\rho_u}(\hat{\rho}_u)}{f_{\rho_u}(\hat{\rho}_u)} > \frac{F_{\rho_u}(\rho_c)}{f_{\rho_u}(\rho_c)} > \frac{F_{\rho_c}(\rho_c)}{f_{\rho_c}(\rho_c)} \quad (\text{A19})$$

Moreover, by the monotonicity of the bidding function, I have

$$(B_u^T)^{\prime-1}(b_c) > (B_c^T)^{\prime-1}(b_c) \quad (\text{A20})$$

Equation (A7) and (A8) implies that:

$$\frac{F_{\rho_u}(\hat{\rho}_u)}{(n-1)f_{\rho_u}(\hat{\rho}_u)(B_u^T)^{\prime-1}(b_c)} > \frac{F_{\rho_u}(\hat{\rho}_u)F_{\rho_c}(\rho_c)}{(n-2)f_{\rho_u}(\hat{\rho}_u)F_{\rho_c}(\rho_c)(B_u^T)^{\prime-1}(b_c) + f_{\rho_c}(\rho_c)F_{\rho_u}(\hat{\rho}_u)(B_c^T)^{\prime-1}(b_c)} \quad (\text{A21})$$

Therefore, from equations (A5) and (A1), I have

$$E[c|\hat{\rho}_u] > E[c|\rho_c] = E[c|\tilde{\rho}_u] \quad (\text{A22})$$

, and this implies:

$$\hat{\rho}_u > \tilde{\rho}_u \quad (\text{A23})$$

Now, I show that the equilibrium profit of connected bidders is higher in two-stage auctions than in English auctions. The envelope theorem implies that the derivative of the equilibrium profit  $\pi^*(\rho) = \pi(B(\rho))$  with respect to a bidders surplus  $s$  equals the equilibrium probability of winning. The expected equilibrium profit of a connected bidder with surplus  $\rho_c$  is thus given by

$$\pi^l(\rho_c) = \int_{-\infty}^{\rho_c} F_{\rho_u}^{n-1}((B_u^l)^{-1}(B_c^l(\rho)))d\rho, \quad l \in \{E, L\} \quad (\text{A24})$$

As I show in equation (A11),  $(B_u^T)^{-1}(B_u^T(\rho)) > (B_u^E)^{-1}(B_u^E(\rho)), \forall \rho$ , so I have  $\pi^T(\rho_c) > \pi^E(\rho_c)$ .

Moreover, Goeree and Offerman (2003) show that, when information is symmetric, expected profit for the bidder is the same under first-price sealed bid auctions and under English auctions. I define information rent as the difference between the expected profits of connected bidders in the asymmetric case and the expected profits in the symmetric case, so

I am able to conclude that information rent is higher in two-stage auctions versus English auctions.  $\square$

### Proof of Lemma 7

*Proof.* Denote the ex ante information rent of the bidder as

$$E[IR] = \int_{-\infty}^{\infty} E[IR|\rho_c = \rho]f_{\rho_c}(\rho)d\rho$$

Following the proof of lemma 5, note that  $Q((B_c^T)^{-1}(b)) = (B_u^T)^{-1}(b)$ , such that it gives the signal of unconnected bidders that place the same bid as connected bidders given signal  $x$ . First, I derive the formula for the ex ante information rent

$$\begin{aligned} E[IR] &= \int_{-\infty}^{\infty} E[IR|\rho_c = \rho]f_{\rho_c}(\rho)d\rho \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\rho} F_{\rho_u}^{N-1}(Q(x))dx f_{\rho_c}(\rho)d\rho \\ &= \int_{-\infty}^{\infty} F_{\rho_u}^{N-1}(Q(x))(1 - F_{\rho_c}(x))dx, \end{aligned} \tag{A25}$$

where the last expression is obtained by changing the order of integration.

I then perform a mean preserving transformation of the common value signal  $r$ , such that

$$\tilde{r} = \gamma r + (1 - \gamma)m_r$$

where  $m_r$  denotes the mean of the common value distribution and  $\gamma > 1$  such that the variance of the common value signal increases after the transformation. As private costs  $c$  are a fixed number, the compounded signal for connected bidders then can be transformed as

$$\tilde{\rho} = \alpha_c(\gamma r + (1 - \gamma)m_r) - c = \gamma(\rho + c) + \alpha(1 - \gamma)m_r - c$$

.

Denote the distribution of the compounded signal for the first auction as  $\tilde{F}_{\rho_u}(\cdot)$  and  $\tilde{F}_{\rho_c}(\cdot)$ . When the variance of the common value increases, the ex ante information rent can then be express as

$$E[\tilde{IR}] = \int_{-\infty}^{\infty} \tilde{F}_{\rho_u}^{N-1}(Q(x))(1 - \tilde{F}_{\rho_c}(x))dx \tag{A26}$$

Let  $x = \gamma(t + c) + \alpha(1 - \gamma)m_r - c = \gamma t + A$  and perform a change of variable, so I have

$$\begin{aligned}
E[\tilde{I}R] &= \int_{-\infty}^{\infty} \tilde{F}_{\rho_u}^{N-1}(Q(x))(1 - \tilde{F}_{\rho_c}(x))dx \\
&= \gamma \int_{-\infty}^{\infty} \tilde{F}_{\rho_u}^{N-1}(Q(\gamma t + A))(1 - \tilde{F}_{\rho_c}(\gamma t + A))dt \\
&= \gamma \int_{-\infty}^{\infty} F_{\rho_u}^{N-1}\left(\frac{Q(\gamma t + A) - A}{\gamma}\right)(1 - F_{\rho_c}(t))dt \\
&> \gamma \int_{-\infty}^{\infty} F_{\rho_u}^{N-1}\left(\frac{\gamma Q(t) + Q(A) - A}{\gamma}\right)(1 - F_{\rho_c}(t))dt \\
&> \gamma \int_{-\infty}^{\infty} F_{\rho_u}^{N-1}(Q(t))(1 - F_{\rho_c}(t))dt \\
&= E[IR],
\end{aligned} \tag{A27}$$

where the equality holds by the properties of the mean-preserving transformation; the first inequality holds because  $\dot{Q}(x) > 1$  as I showed in the proof of Lemma 5; and the second inequality holds because  $Q(x) > x$ . Therefore, I show that the ex ante information rent increases when the variance of the common value signal distribution increases.  $\square$

### Proof of Corollary 8

*Proof.*

$$\frac{\partial Pr(L = E)}{\partial V} = \frac{\frac{\partial R(BR_T)}{\partial V}(R(BR_T) - R(BR_E)) - (R(BR_T) - I)\left(\frac{\partial R(BR_T)}{\partial V} - \frac{\partial R(BR_E)}{\partial V}\right)}{(R(BR_T) - R(BR_E))^2} \tag{A28}$$

We know that  $R(BR_T) > I > R(BR_E)$ , hence  $R(BR_T) - R(BR_E) > R(BR_T) - I > 0$ . Moreover, I know from Lemma 7 that  $\frac{\partial R(BR_T)}{\partial V} > \frac{\partial R(BR_T)}{\partial V} - \frac{\partial R(BR_E)}{\partial V}$ . Therefore, I have  $\frac{\partial Pr(L=E)}{\partial V} > 0$ .  $\square$

## Appendix B. Additional Tables

Table B1: Corruption of Prefectural Cities

Corruption on Land Issues	Corruption on Other Issues	No Corrupt Bureaucrats Reported
Corruption in Transaction Stage	Corruption beyond Transaction Stage	
Over-reimbursing remising fees	21 Approving use-rights certifi-cates	15
Over-compensating demolition fees	6 Approving development project plans	30
Manipulating auctions	23 Approving adjustment of plot ratio	10
Causing huge losses to the nation in land sales	26 Helping in coordinating demolition	27
	Seeking profits for developers	33
95 cities		

*Notes:* This table shows the results reported by the CDIC inspection teams in its first-round nationwide inspection tour (up to November 2015). The provinces of Beijing, Shanghai, Tianjin, Chongqing (the directly controlled municipalities), and Xinjiang, Qinghai, and Xizang (Tibet) are not included. The total number of prefectural cities is 308.

Table B2: Estimation results: Bid distribution parameters

		English Auction		Two-stage Auction	
		Unconnected	Connected	Unconnected	Connected
$\mu$	Constant	0.0030** (0.0010)	0.0334*** (0.0017)	23.8234*** (4.2966)	-0.0001*** (0.0000)
	Area	-0.0651 (0.1023)	-0.0001 (0.0001)	-0.0006 (0.0385)	-0.0058*** (0.0007)
	Plot Ratio	0.0008*** (0.0002)	0.0518*** (0.0099)	0.0041* (0.0018)	16.2768 (11.2556)
	Grade	-16.9098*** (3.7582)	-19.965 (26.9385)	-0.0006* (0.0003)	-52.7825 (36.7758)
	Brightness	2.3184* (1.1009)	0.0405** (0.0101)	8.6061** (2.8961)	0.0086*** (0.0008)
	N	0.102 (0.2933)	78.9836*** (11.3254)	0.0007 (0.0011)	21.1198*** (1.0293)
	$\nu$	Constant	0.0029*** (0.0004)	0.0420* (0.0195)	0.3442*** (0.0017)
Area		0.0068 (0.0133)	0.0119 (0.0136)	-0.0020 (0.1758)	-0.0001 (0.0005)
Plot Ratio		0.0277 (0.7556)	0.0148* (0.0053)	-0.0012 (0.0009)	0.0014** (0.0002)
Grade		0.0364** (0.0085)	0.0564 (0.0822)	0.0002* (0.0001)	-0.0059** (0.0018)
Brightness		0.0028 (0.0023)	0.3723** (0.0996)	0.0021*** (0.0002)	-0.0001 (0.0464)
N		0.0064*** (0.0007)	0.0122 (0.0089)	0.0013 (0.0055)	-0.0010 (0.0004)

*Notes:* The table presents the estimation results for the bid distribution assuming it follows a Weibull distribution. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .