Endogenous Joint Venture Formation in Procurement Auctions*

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Abstract

We examine the impact of joint ventures on the efficiency of procurement auctions. Even though procurers may expect some efficiency gains through cost synergies derived from such collaborations, joint ventures may discourage potential entrants' entry incentives, thereby lowering procurement efficiency. We develop and estimate a two-stage structural model by, explicitly considering these two forces. The estimation results indicate the existence of cost synergies and suggest two obstacles to joint venture formation: adjustment costs and search frictions. Our simulation demonstrates that excessive government support for joint venture formation lowers procurement efficiency.

JEL Classification Codes: L24; D22; D44; H57.
Keywords: Joint ventures; Cost synergies; Matching; Procurement auctions.

1 Introduction

In many auctions, participants are allowed, under certain conditions, to form a joint venture (JV hereafter), enabling them to submit a joint single bid. Researchers have analyzed the economic consequences of such joint ventures in various contexts, including Outer Continental Shelf (OCS) auctions (Hendricks and Porter, 1992), Official Development Assistance (ODA)

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procurement auctions (Iimi, 2004), and patent auctions (Asker, Baccara and Lee, 2021), and have found two opposing competitive effects: an anti-competitive effect from the reduction in the number of bidders and a pro-competitive effect from efficiency improvement (e.g., cost synergies). If the efficiency improvement is passed through to the bidding behavior efficiently, the bids can be more competitive even when the number of bidders is reduced, compared to the case when all parties bid as single bidders.[1]

In the context of procurement auctions, procurers must balance these two effects when designing auction rules, including whether to allow JV formation. In practice, only a few JVs are formed, although the literature provides strong evidence that the cost synergies exist. For example, just 5% of bids are submitted by joint ventures in Europe (Gugler, Weichselbaumer and Zulehner, 2021), whereas it has been found that 24% of bids are from joint ventures in Japanese procurement auctions, even when restricted to the largest-scaled auctions. Is the observed JV formation level suboptimal? If so, what hinders the achievement of the social optimum? The primary objective of this study is to answer these questions by quantifying the pro- and anti-competitive effects of JV formation and drawing implications for market outcomes.

For this purpose, we build a two-stage structural model. In the first stage, potential entrants face an entry problem in which they choose their intentions from (i) trying to form a joint venture, (ii) entering as a single bidder, or (iii) not entering. This set of intentions is mapped into the distributions of the number of joint ventures and the number of single bidders in the second stage. In the second stage, the participants compete in an asymmetric scoring auction, where asymmetry arises from the potential difference between joint ventures and single bidders; specifically, the cost synergy is expressed as the difference between the two distributions of cost types. An integrated model is required to study the net benefit of JVs because of the pro-competitive effect; that is, the cost synergy of JVs in the second-stage auction necessarily diminishes the entry incentive in the first stage. Our model allows for this secondary anti-competitive effect, in contrast to the existing literature, which might overestimate the pro-competitive effect of JVs.

[1] According to Bouckaert and Van Moer (2021), in antitrust cases in Nordic countries, two criteria are used to address these two effects: the no-solo-bidding test and efficiency pass-through.

In the first stage, we have two key obstacles to forming JVs: *adjustment cost*, which is required to manage the joint venture throughout the project period, and *search friction*, which means there is a possibility of not finding a partner. Adjustment costs affect the expected utilities in the intention choice problem. Search friction is incorporated in the structure of the mapping from the set of intentions to the entry patterns in the following way. For example, consider a set of intention patterns such that two potential entrants try to form a JV. When the mapping assigns a probability of one to the set of entry patterns in which one JV exists for this set, we can say that there is no search friction. In contrast, when the mapping assigns zero probability to the same set, we can say that there is search friction. Under the assumption that all the JVs are formed by two potential entrants, the number of formed joint ventures in the absence of search friction is determined by $\lfloor \frac{\#\text{intentions of JV}}{2} \rfloor$. We define search friction as the difference from this maximum for all the possible numbers of intentions to try to form a JV.

At first glance, it seems difficult to separately identify adjustment cost and search friction because both scenarios–(i) lower adjustment cost and more severe search friction, and (ii) higher adjustment cost and milder search friction–produce the same result: a reduction in the number of joint ventures. We show that these two parameters can be identified separately by focusing not only on the distribution of the number of JVs but also on the conditional distribution of the number of single bidders given the number of JVs. The conditional distribution is decomposed into a mixture of distributions over the number of single bidders, conditional on the number of potential entrants choosing JV. Because these mixture components are linearly independent of each other, for every number of realized JVs, we can identify the components necessary to generate the observed conditional distribution over the number of single bidders. This model structure allows us to pin down the relationship between the number of JVs and the number of intentions of JV.

We estimate the model using Japanese procurement data. In the first stage, we find that adjustment costs and search friction hinder JV formation. In particular, the estimated search friction suggests that at least four firms must choose the intention of trying to form a joint venture to observe at least one joint venture in a given auction. In other words, there is the possibility of failing to find a partner when forming a JV. Moreover, our estimates suggest that, compared to entering as a single bidder, managing a joint venture additionally requires approximately 6 million Japanese yen, which constitutes 23.72% of the expected payoff in small-scale procurement auctions. In the second stage, our recovered distributions of cost types show a clear difference between single bidders and JVs. Particularly, JVs are likely to draw a more competitive type than single bidders, implying the existence of cost synergy.

In a counterfactual scenario where we simulate the promotion of joint venture formation by reducing the adjustment cost, we find that a mild level of promotion leads to lower procurement costs, whereas excessive promotion results in higher procurement costs. This non-linearity arises from the transition of the relative strengths of the pro- and anti-competitive effects. Excessive promotion leads to a growing number of joint ventures which reduces the number of bidders and affects the entry incentives of others. This anti-competitive effect eventually overwhelms the pro-competitive effect generated by cost synergy.

1.1 Related Literature

The first strand of the literature to which this study contributes is the empirical literature on joint venture formation and endogenous merger formation. Forming a joint venture and mergers share some similarities in that parties commit to making collective decisions. The competitive effect of joint ventures has been studied intensively in the merger literature including Shapiro and Willig (1990), Estache and Iimi (2009), and Miller and Weinberg (2017). The incentives for mergers and for joint venture formation are complex due to externalities in subsequent competition, rendering it challenging to build a tractable and internally-consistent model. The literature has developed in two strands: (i) building a long-term horizon dynamic model, as seen in Gowrisankaran (1999) and Igami and Uetake (2020), and (ii) utilizing the matching model developed by Fox (2018), as shown in Akkus, Cookson and Hortaçsu (2016) and Uetake and Watanabe (2020). This study proposes a new tractable method to estimate an endogenous joint venture/merger formation model by extending the entry model developed by Seim (2006) and estimating the joint venture formation pattern directly from the data.

As a specific point of the literature on joint ventures, existing studies usually consider joint ventures as mechanisms for efficient reallocation. For example, the cost or type of a joint venture is often modeled as the minimum of the costs or the maximum of the type of the firms forming the joint venture (Asker, Baccara and Lee, 2021; Bouckaert and Van Moer, 2021). In contrast, recent industrial organization literature suggests that group formation, such as mergers and joint ventures, generates synergies, as reviewed by Asker and Nocke (2021). We incorporate this viewpoint into the context of joint ventures. Our model encompasses the possibility of cost synergies generated by forming a joint venture.

Broadly speaking, joint venture formation, the focus of this study, can be seen as a particular type of joint bidding, which has been studied by Cho, Jewell and Vohra (2002), Cantillon (2008), and Chatterjee, Mitra and Mukherjee (2017), including in specific contexts of procurement auctions (Gugler, Weichselbaumer and Zulehner, 2021), subcontracting (Bouckaert and Van Moer, 2021), and patent auctions (Asker, Baccara and Lee, 2021).[2] The empirical literature on the joint bidding, including Iimi (2004), Estache and Iimi (2009), and Branzoli and Decarolis (2015), has developed slightly independently from the theoretical literature. Its focuse is on examining whether joint bidding has pro-competitive effects or anti-competitive effects, and generally finds the pro-competitive effect of joint bidding. A notable exception is Gugler, Weichselbaumer and Zulehner (2021), who used a structural approach, endogenizing the entry and joint venture formation in a reduced-form way with heterogeneous bidders, and finding pro-competitive effects. Our study complements Gugler, Weichselbaumer and Zulehner (2021) by explicitly modeling the joint venture formation and imposing equilibrium restrictions, enabling us to conduct a richer set of counterfactual analyses.

The final contribution of our study is to the empirical works on procurement auctions. In particular, our modeling adds the joint venture formation process to procurement auction models with endogenous entry, such as those of Li and Zheng (2009) and Krasnokutskaya and Seim (2011). Their work demonstrated that decisions regarding endogenous *entry* are crucial for understanding the origins of efficiency in procurement auctions. Our study also finds that

[2]Another strand of literature investigates joint bidding in the context of common value auctions, where auctioneers sell natural resources such as petroleum. Although the theoretical papers, including Mead (1967) and Levin (2004), have argued that joint bidding functions as a bidding ring or a collusion and hence impedes the competitive bids among bidders, empirical studies, including Millsaps and Ott (1985), Moody and Kruvant (1988), and Hendricks and Porter (1992), found pro-competitive effects of joint bidding caused by pooling information, relaxing the budget constraint and risk sharing.

the *choice of joint venture formation* plays a decisive role in determining the efficiency of procurement auctions. Moreover, our empirical analysis focuses specifically on the scoring auction, which is categorized as multi-attribute auctions (Perrigne and Vuong, 2019). This type of auction incorporates non-monetary information to determine the winning bidder in procurement auctions and evaluates the quality of projects submitted by the bidders to aim for long-term value maximization. Recent studies by Lewis and Bajari (2011), Kong, Perrigne and Vuong (2022), and Hanazono et al. (2020) have empirically and theoretically examined this auction format.[3] We contribute to the literature by modeling and estimating the second stage as a scoring auction within a class of asymmetric auctions.

2 Background and Data

This study focuses on public procurement auctions held by five Regional Development Bureaus of the Japanese Ministry of Land, Infrastructure, Transport and Tourism (MLIT), the largest purchaser in Japan. We first provide the institutional background in Subsection 2.1, emphasizing the auction procedure and describing how we collect and construct the data. We then present descriptive statistics, in Subsection 2.2, highlighting differences between the bids from joint venture firms and those from non-joint venture firms (single bidders). Concerns about collusive behavior among Japanese construction firms, as noted by Kawai and Nakabayashi (2024), Chassang et al. (2022), Kawai et al. (2022), and Kawai and Nakabayashi (2022), prompted us to test whether this applies to our data by employing the screening method proposed by Kawai and Nakabayashi (2024) in Subsection 2.3.

2.1 Institutional Background and Descriptive Statistics

This study focuses on public procurement auctions held by five Regional Development Bureaus of the MLIT. We specifically focus on these regional offices to control for auction rules. Although municipal and prefectural government offices also use procurement auctions,

[3]There are other auction variants worth mentioning, such as the bid-preference or set aside policies, which aim to promote equity in procurement. Notable references in this regard include Corns and Schotter (1999), Marion (2007), Krasnokutskaya and Seim (2011), Athey, Coey and Levin (2013), Nakabayashi (2013), and Rosa (2019).

their auction rules do not perfectly coincide with each other. The main tasks of these regional offices include developing and maintaining public infrastructure, such as national routes, rivers, dams, and ports, under the direct control of the MLIT. Depending on these tasks, the procurement of construction work is categorized into 22 types, including civil engineering, bridge building, pavement, and landscaping.[4]

The auction format used by each Regional Development Bureau is a variant of a first price sealed-bid auction with secret reserved prices.[5] If the secret reserve price exceeds 100 million JPY in an auction, procurers are strongly encouraged to use a scoring auction, as explained in Subsection 2.3. Moreover, if the secret reserve price roughly exceeds 500 million JPY, each auction is encouraged to invite joint ventures, aiming to generate complementarities among participating firms and take advantage of scale economies. Although there are a few exceptions for large construction projects with short deadlines, the number of participating firms for each joint venture must be two or three firms in principle. Furthermore, if the secret reserve price exceeds 680 million JPY, each procurement is subject to the Agreement of Government Procurement, a multilateral agreement within the framework of the World Trade Organization (WTO), implying that equal treatment for the foreign firms must be guaranteed.[6]

Depending on their purposes, four types of joint ventures exist: (i) project-specific (Tokutei), (ii) fixed-term (Keijo), (iii) maintaining regional infrastructure-specific (Chiiki-iji), and (iv) restoration-project-specific (Fukkyu-Fukkou). In this study, we focus on the first type, which appears most frequently in the data.

We first collect the data from seven regional offices for all types of construction work between 2006 and 2022.[7] Procurement projects involving joint ventures are mostly observed in auctions with reserve prices above 680 million JPY, as shown in Panel (A) of Table

[4] See Table 1 for the list of the categories.

[5] Secret reserved prices are unknown *ex-ante* and the bidders whose bid exceed this secret reserved prices are disqualified.

[6] These threshold values vary across municipal and prefectural governments, hence why we focus on the auctions held by each regional offices of the Japanese MLIT.

[7] There are eight Regional Development Bureaus of MLIT, including Tohoku, Kanto, Hokuriku, Chubu, Kinki, Chugoku, Shikoku, and Kyushu. We exclude Tohoku area from our sample to remove the impact of the 2011 off the Pacific coast of Tohoku Earthquake. Note that there are several missing years for some regional development bureaus. See Appendix.

Table 1. Summary Statistics

	# of Auctions	# of JV Auctions	Rate of JV auction	Prob. JV winning	Log of Engineer's Estimate Mean	Min	Med	Max	# Bidders Mean	Min	Med	Max
Panel (A): By Reserve Prices												
Non WTO	66733	4	0.000	0.750	18.374	4.787	18.523	22.929	4.057	1	3	52
WTO	1712	245	0.143	0.408	21.025	16.097	20.885	24.350	10.411	1	10	35
Panel (B): By Construction Types												
Civil Engr.	806	120	0.149	0.475	21.284	18.081	21.161	24.350	11.428	1	10	35
PC	177	10	0.056	0.200	20.731	19.604	20.634	22.513	11.006	1	12	19
Bridge	460	97	0.211	0.381	20.919	19.524	20.807	22.782	11.311	1	12	24
machine	63	0	0.000	NaN	20.814	19.988	20.639	22.544	3.714	1	4	9
building	99	11	0.111	0.182	21.083	19.399	20.914	23.126	6.606	1	5	28
electricity	29	1	0.034	0.000	20.517	18.066	20.533	21.857	4.069	1	3	12
airconditioner	31	5	0.161	0.400	20.780	20.281	20.683	22.525	6.516	1	6	14
dredging	15	1	0.067	0.000	20.821	20.287	20.738	21.933	4.400	1	5	8
CC	7	0	0.000	NaN	20.209	19.837	20.041	20.610	9.143	4	11	14
management	18	0	0.000	NaN	17.518	16.097	17.118	20.609	2.833	1	2	8
bridgerepair	1	0	0.000	NaN	20.796	20.796	20.796	20.796	4.000	4	4	4
painting	1	0	0.000	NaN	17.824	17.824	17.824	17.824	2.000	2	2	2
slope	4	0	0.000	NaN	20.815	20.115	20.767	21.610	13.000	1	10.5	30
pavement	1	0	0.000	NaN	19.288	19.288	19.288	19.288	14.000	14	14	14
Panel (C): By Regions												
Kanto	637	130	0.204	0.462	21.181	20.102	21.044	24.350	9.722	1	9	33
Chubu	195	6	0.031	0.167	20.896	20.107	20.783	22.935	12.354	1	12	35
Hokuriku	68	13	0.191	0.462	20.955	16.519	20.906	23.598	10.529	1	11	32
Kinki	402	16	0.040	0.188	20.909	17.028	20.790	23.334	10.846	1	10	32
Chugoku	39	2	0.051	0.500	20.935	17.824	20.752	22.743	9.718	2	10	19
Shikoku	110	18	0.164	0.333	21.019	19.837	20.803	22.934	8.918	1	8.5	22
Kyushu	261	60	0.230	0.383	20.955	16.097	20.891	23.482	10.670	1	10	32
Final Sample	793	194	0.245	0.459	21.244	18.416	21.114	24.350	10.810	1	10	33

Notes; The rate of JV auctions is the number of the auctions in which at least one joint venture participates in the total number of auctions for each construction type. The second and the third panels show the details about WTO type auctions.

1. Moreover, among these 1,712 auctions, joint ventures mostly appear in two types of construction work—Civil Engineering and Bridge Building—and in five regions—Kanto, Hokuriku, Kinki, Shikoku, and Kyushu—as shown in Panels (B) and (C) in Table 1. Therefore, we focus on civil engineering or bridge building projects with reserve prices above 680 million JPY, procured in Kanto, Hokuriku, Kinki, Shikoku, and Kyushu, which leaves 793 auctions out of 66,733.

In the auctions explained above, each bid submitted by both single bidders and joint ventures is weighted by a "score," which is calculated by the combination of bidder attributes and characteristics of the procurement project, according to pre-determined scoring rules.[8] The auctioneers then compare the "effective bids," defined as the ratio of the score to the submitted bid.[9] The bidder with the highest effective bid wins the auction, implying that submitting a lower bid or obtaining a higher score increases the likelihood of winning. The

[8] For joint ventures, we observe a score for a joint venture, not for individual firms.

[9] In our data, the bids are typically in order of 10^8 JPY, implying that the effective bids become tiny values. To visibility, in the data, we multiply effective bids $\times 10^8$.

minimum score is 100, whereas the maximum score varies by auction, depending on the difficulties and complexities of the projects, reaching a maximum of 200. Therefore, effective bids typically range from 0 to 200.

Figure 1 depicts the distributions of firm-level behavior in our sample: the logarithm of the effective bid, the logarithm of the bid, and the score. The blue and orange bins represent joint ventures and single bidders, respectively. The left column shows histograms of the three variables observed in all auctions, while the right column shows the bids observed in auctions where at least one joint venture exists. In Panel (a), we observe small effective bids by joint ventures, which Panel (b) shows this is due to selective entry. Panel (c) shows that joint ventures enter relatively expensive projects, even when focusing on WTO auctions. Regarding the score, both single bidders and joint ventures face similar distributions, and we do not find systematic differences in the auctions where at least one joint venture exists.

2.2 Motivating Facts

Here, we briefly examine our data to motivate the details of the structural model. We begin by observing a small number of realized JVs in the dataset. The second column of Table 1 displays the number of auctions where at least one JV exists for each construction type. The third column shows the ratio of these auctions to the total number of auctions. Even in the largest auction category, the WTO type, we find JVs in only 14.3% of the auctions. This percentage varies among construction types and regions hosting auctions. However, even in the pairing of construction types and regions where JVs are most common, the percentage is only 24.5%. When there are no obstacles to forming a joint venture, this small number appears surprising, given that JVs are more likely to win an auction once they enter, as seen in the fourth column of Table 1. Based on this observation, we identify two obstacles in forming a joint venture: adjustment cost and search friction.

Next, we consider the nature of cost synergy. First, as shown in the fourth column of Table 1, JVs are more competitive than single bidders in auctions. While this strength undoubtedly stems from a systematic reason, various possible explanations exist. Typically, in the literature, this competitiveness arises from efficient reallocation among the firms forming a joint venture (Asker, Baccara and Lee, 2021; Bouckaert and Van Moer, 2021).

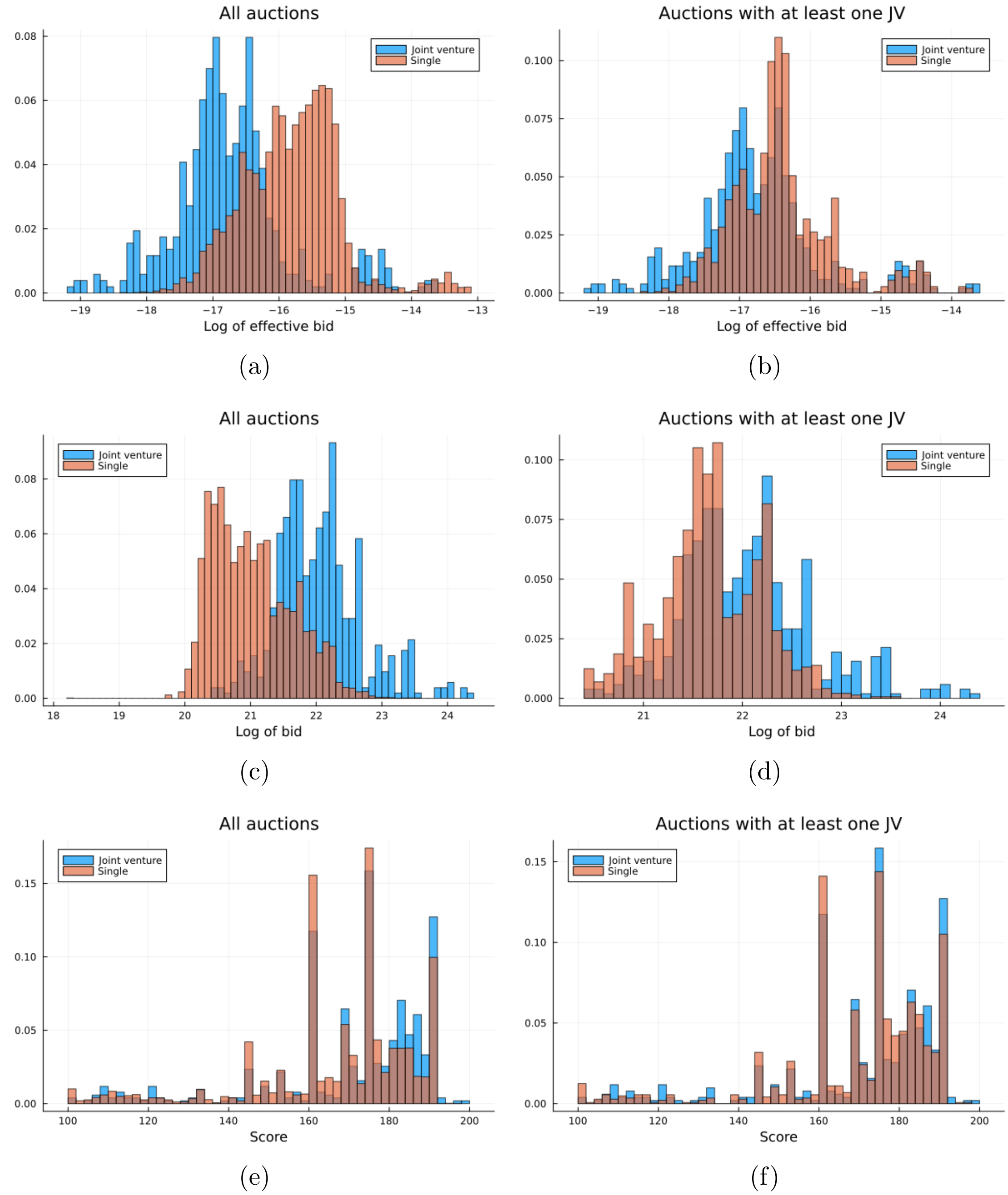
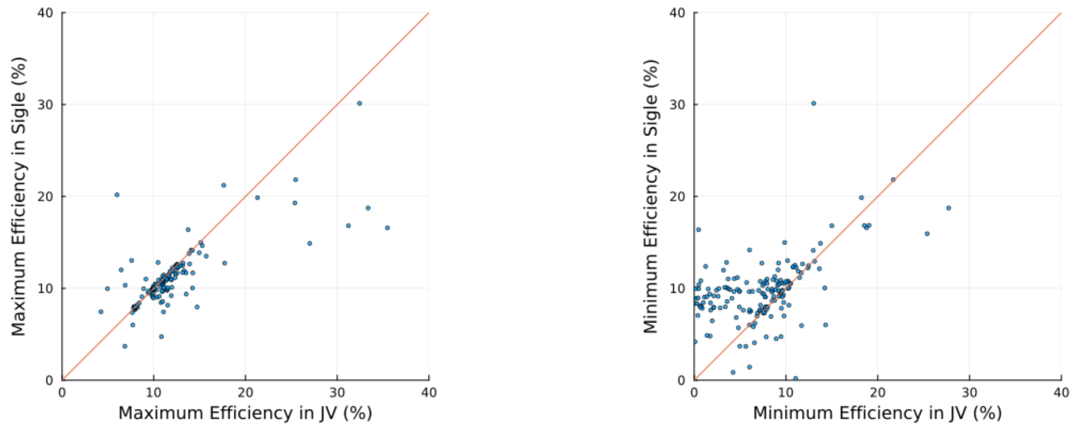


Figure 1. Histograms of effective bids, logarithm of bids, and entrants' scores.

Note: Blue bins represent joint ventures, and red bins represent single bidders. In the left column, we use all the auctions. In the right column, we use the auctions where at least one joint venture participates. The first row represents about the logarithm of effective bids, defined as the score's ratio to the bid. The second row represents about the logarithm of bids, whereas the third row displays about the score.



(a) Maximum of efficiency

(b) Minimum of efficiency

Figure 2. Comparison between single bidder and joint venture with respect to the submitted bids.

In our context, this corresponds to a situation where the project cost of a JV is determined by the lowest cost among the firms forming it. In this model, JVs consistently emerge more competitive than the individual firms before forming the JV. Therefore, we expect that in an auction, JV bids are not much larger than those submitted by single bidders, even if firms with higher costs are likely to form a JV to reduce project costs.

In our data, this is not the case; JVs might bid at significantly higher prices in auctions. To compare submitted bids across auctions with varying engineer's estimates, we define a cost-efficiency measure for each bidder in each auction:

$$\text{Cost-efficiency} = \frac{\text{Engineer's Estimate} - \text{Submitted Bid}}{\text{Engineer's Estimate}} \times 100.$$

Figure 2 compares the maximum and minimum cost-efficiencies within single bidders and joint ventures. Panel (a) indicates that a JV is likely to bid at a lower price, suggesting the existence of cost synergy. However, as shown in Panel (b), the competitiveness of JVs does not always materialize: the minimum cost efficiency of JVs is relatively larger than that of single bidders. Given that the distributions of the scores are similar, this suggests that JVs might be weaker in scoring auctions. We interpret Figure 2 as evidence that (i) JV formation is not merely an efficient reallocation and (ii) the degree of cost synergy in the second stage is unknown to potential bidders in the first stage. The second point shapes the information structure in the game of auction with an entry stage. Following Levin and Smith (1994), we assume that potential entrants are unaware of their type and the type obtained when forming a JV in the auction stage prior to entry but are aware of the distributions for both the single bidder and the JV cases.[10] In our model, the difference between these two distributions indicates the degree of cost synergy.

As argued above, we define the degree of cost synergy as the difference between the two types of distribution at the auction stage. To clarify this concept, it is essential to define the types in the context of this study. Typically, a firm's cost information is considered private and should be included in its type. In contrast, the score is not fully known to the bidders when submitting their bids. This is because the scoring rule may include elements of uncertainty in addition to deterministic parts based on the bidders' attributes.

However, in our model, we assume that the bidders decide their bids when they know their scores. In other words, the "type" in the auction stage also includes the bidder's score. There are several explanations for this assumption. First, 15 years have passed since the Japanese government introduced these scoring rules, and it is reasonable to believe that firms can now form appropriate expectations of their scores in advance.[11] Second, as summarized in Table 2, our regression analysis, in which we regress the logarithm of the submitted bids on the score and other variables, alongside some fixed effects, reveals a statistically significant positive correlation between the submitted bids and scores. This implies that the bids reflect the bidders' scores, and that such results would not occur if the bidders were unaware of their scores.

Before proceeding to our main analysis, we must examine whether the bidding patterns in our data show any indications of collusion. This step is crucial because collusive behavior is a known concern in Japanese procurement auctions, as highlighted in previous studies

[10]This assumption regarding the information structure is reasonable and standard in the literature because a proper assessment of the project cost and score rating requires certain effort, and potential entrants must decide whether to exert such effort in the first place, which we view as the entry decision. Furthermore, for the score, potential entrants are not aware of the detailed formula in advance. All they know are the characteristics the government considers and the maximum points.

[11]Kawai and Nakabayashi (2024) provided evidence to support this information structure. They argued that some firms in the scoring auction of Japanese procurement engage in bid rotations based on the level of the score: after one firm with a high score wins an auction, another firm with a lower score takes a turn to win. Such behavior would not be observed if the firms did not know their scores in advance.

Table 2. Regression Results

	(1) ln(bid)	(2) ln(bid)	(3) ln(bid)
Score	0.003***	0.001**	0.002***
	(0.000)	(0.000)	(0.001)
# bidders		-0.021***	-0.004
		(0.001)	(0.008)
Score × # bidders			-0.000**
			(0.000)
Constant	20.537***	20.636***	20.403***
	(0.060)	(0.072)	(0.129)
Year FE		√	√
Region FE		√	√
Type FE		√	√
N	8572	8572	8572
R^2	0.010	0.172	0.173

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(e.g., Kawai and Nakabayashi, 2024; Chassang et al., 2022; Kawai et al., 2022; Kawai and Nakabayashi, 2022). If firms engage in collusion, our model and empirical strategy may not be applicable in the subsequent sections. Therefore, we use the screening method proposed by Kawai and Nakabayashi (2024) to analyze our data and confirm that it did not exhibit any suspicious bidding behaviors.

Following the approach of Kawai and Nakabayashi (2024), we first divide our data by region and year, and subsequently apply their screening method to each subset to identify any sets of auctions that may be affected by collusion.[12] The results are presented in Figures A1 and A2.[13] Unlike the findings of Kawai and Nakabayashi (2024), our data does not show any suspicious bidding patterns. This discrepancy between their results and ours is likely due to the difference in the types of procurements examined. Our focus is on relatively large-scale auctions compared to those studied in the existing literature, and the bidders

[12]This method utilizes the mathematical principle that, when considering marginally losing and winning bidders, the winner is randomly determined in the absence of collusion. If collusive behavior occurs, the submitted bid of the marginally losing bidder will differ unnaturally from the winning bid. For example, if a firm with a higher technology intends to lose, its submitted bids are unnaturally high. We can detect collusive bids by examining this gap. As shown in the case of the Nippo cooperation in Kawai and Nakabayashi (2024), this method can be applied to each firm, revealing a set of suspicious firms.

[13]A jump at point 0 in these figures suggests that high-quality bidders, who are likely to win carefully choose their bids to lose the auction. This is considered evidence of collusion.

in our data may face much stricter compliance requirements. Therefore, we retain all the observations described in the previous subsection for our main analysis.

3 Model

Given the institutional features explained in the previous section, we adopt a two-stage model. In the first stage, the *entry and joint venture formation stage*, potential entrants choose their intentions: forming a joint venture, entering as a single bidder, or staying out from the auction. Subsequently, a set of the intentions of the potential entrants is mapped onto a distribution over entry patterns, which includes the number of JVs and single bidders. In the second stage, the *bidding stage*, the realized entrants compete in a scoring auction. Note that two types of entrants exist: joint ventures and single bidders; therefore, the second stage is an *asymmetric* scoring auction. Here, we describe the details of the two stages in reverse order.

3.1 Bidding stage

We consider a scoring auction, whereom the bidders compete not only in the submitted bid but also in the score that combines the quality of project proposal and the competence of bidders into a one-dimensional measure. For a given auction, we use the following notations: i denotes the index of the entrants in the auction, s_i denotes the score of firm i, and b_i denotes the submitted bid of firm i. As described in Section 2, the bidders compete in an effective bid $B_i \equiv \frac{s_i}{b_i}$. Furthermore, the engineer's estimate of the project cost is computed ex-ante for every auction and denoted by p.

When the entrant i wins the auction, the payoff is given by

$$b_i - \tilde{c}_i p = \frac{s_i}{B_i} - \tilde{c}_i p,$$

where $\tilde{c}_i$ is the individual cost factor, and the actual cost of the entrant i is equal to $\tilde{c}_i p$. When determining the bid, we assume that the score and individual cost factor are private information. We call these pair types in the auction stage. Note that we directly observe

p, b_i and s_i in the data, whereas the individual cost factor, $\tilde{c}_i$, is not directly observed in the data

In the following section, the number of JVs is denoted by M, and the number of single bidders is denoted by N. In a slight departure from conventional notation, M and N also represent the sets of each type of bidder. For both a JV and a single bidder, the optimal bidding strategy is determined by solving the corresponding expected payoff maximization problem. Because they have similar structures, here we only outline a single bidder's problem:

$$\max_{B}\ Pr\left(\left\{B_j^{JV} \le B\ \forall j \in M\right\},\ \left\{B_j^{S} \le B\ \forall j \in N \setminus \{i\}\right\}\right)\left(\frac{s_i}{B} - \tilde{c}_i p\right),$$

where we denote the effective bid of a single bidder, B_j^S, and a joint venture, B_j^{JV} for entrant j. The objective function is the expected payoff, where the expectation is taken with respect to the realization of the scores and individual cost factors of other entrants. For later use, we take the logarithm of effective bids:

$$\max_{B}\ Pr\left(\left\{\ln B_j^{JV} \le \ln B\ \forall j \in M\right\},\ \left\{\ln B_j^{S} \le \ln B\ \forall j \in N \setminus \{i\}\right\}\right)\left(\frac{s_i}{B} - \tilde{c}_i p\right).$$

We can similarly define the problem for a joint venture bidder by replacing M by $M \setminus \{i\}$ and $N \setminus \{i\}$ by N.

Now, we have two distributions, denoted by G^S and G^{JV}, representing the type distributions for a single bidder and a joint venture, respectively. Both are two-dimensional distributions encompassing the scores and individual cost factors. As in the standard auction model, we assume that these types are drawn independently.

Assumption 1. *If the entrant i is a single bidder, $(s_i, \tilde{c}_i)$, is drawn independently from G^S. If i is a joint venture, $(s_i, \tilde{c}_i)$ is drawn independently from G^{JV}.*

To determine the optimal bidding strategy in this game, we directly consider the distributions of the effective bids of the other bidders. Let F^{JV} be the distribution of the logarithm of the JV's effective bids and F^S be the same for single bidders. Then, under Assumption 1, the expected payoff maximization problem described above can be written as follows:

$$\max_{B} \; F^{JV}(\ln B)^{M} F^{S}(\ln B)^{N-1}\left(\frac{s_i}{B} - \tilde{c}_i p\right). \tag{1}$$

For a single bidder and for a joint venture, the system of first-order conditions is as follows:

$$\begin{aligned} 1 - \frac{\tilde{c}_i}{s_i} pB = & \quad \frac{1}{(N-1)\frac{f^S(\ln B)}{F^S(\ln B)} + M\frac{f^{JV}(\ln B)}{F^{JV}(\ln B)}}, \\ 1 - \frac{\tilde{c}_i}{s_i} pB = & \quad \frac{1}{N\frac{f^S(\ln B)}{F^S(\ln B)} + (M-1)\frac{f^{JV}(\ln B)}{F^{JV}(\ln B)}}. \end{aligned} \tag{2}$$

This system indicates that the optimal effective bid depends not only on private information obtained through $\frac{\tilde{c}_i}{s_i}$. In other words, although our problem contains two-dimensional private information, the optimization problem is reduced to a one-dimensional problem. Hence, we can solve for these two first-order conditions and determine the optimal bidding strategies $B_S\left(\cdot\,; F^S, F^{JV}\right)$ and $B_{JV}\left(\cdot\,; F^S, F^{JV}\right)$, which map $\frac{\tilde{c}_i}{s_i}$ to an effective bid. We also denote the maximized expected payoff for a single bidder by $V^S(\frac{\tilde{c}_i}{s_i}; M, N, p)$ and the same for a joint venture by $V^{JV}(\frac{\tilde{c}_i}{s_i}; M, N, p)$. For later use, we denote the distributions of this fraction for joint ventures and single bidders by $\tilde{G}^{JV}$ and $\tilde{G}^S$.

Equilibrium is a version of the standard Bayesian Nash equilibrium considered in the auction literature. Because we have two types of entrants, our equilibrium comprises a pair of bidding strategies.

Definition 1. *The pair of two invertible functions mapping $\frac{\tilde{c}}{s}$ to an effective bid, $B^{\star}_S(\cdot)$ and $B^{\star}_{JV}(\cdot)$, is an equilibrium, if it satisfies*

$$\begin{cases} B^{\star}_S(\cdot) = B_S\left(\cdot\,; F^S, F^{JV}\right) \\ B^{\star}_{JV}(\cdot) = B_{JV}\left(\cdot\,; F^S, F^{JV}\right) \end{cases} \tag{3}$$

where

$$\begin{cases} F^S(\ln B) \equiv Pr\left(B^{\star}_S\left(\frac{\tilde{c}_i}{s_i}\right) \leq B\right) \\ F^{JV}(\ln B) \equiv Pr\left(B^{\star}_{JV}\left(\frac{\tilde{c}_i}{s_i}\right) \leq B\right). \end{cases}$$

The existence and the uniqueness of this equilibrium is discussed in Hanazono et al. (2020) and Lebrun (1999). Under mild regularity assumptions, the current asymmetric scoring auction always has a unique equilibrium. For completeness, we describe the basic existence and uniqueness argument in our case in Appendix B.

Theorem 1. *There exists the unique pair of* $(B_S^\star(\cdot), B_{JV}^\star(\cdot))$ *satisfying the equilibrium condition.*

For later use, we define the ex-ante expected payoff *conditional on* the realized entry pattern for each pair of (M, N, p), denoted by $u_{JV}(M, N; p)$ and $u_S(M, N; p)$ for joint ventures and single bidders, respectively.

$$\begin{cases} u_{JV}(M, N; p) \equiv E_{\frac{\tilde{c}_i}{s_i} \sim \tilde{G}^{JV}} \left[V^{JV}(\frac{\tilde{c}_i}{s_i}; M, N, p) \right], \\ u_S(M, N; p) \equiv E_{\frac{\tilde{c}_i}{s_i} \sim \tilde{G}^{S}} \left[V^{S}(\frac{\tilde{c}_i}{s_i}; M, N, p) \right]. \end{cases}$$

The expectations are taken with respect to the realization of the fraction $\frac{\tilde{c}_i}{s_i}$. Each value of this function corresponds to the ex-ante expected payoff conditional on the entry pattern (M, N) and the engineer's estimate p.

When potential entrants make their entry decisions, they are not yet aware of the realization of M and N. Given an engineer's estimate p, to compute the *unconditional* ex-ante expected payoff, they must take the expectation of u_{JV} and u_S with a probability distribution over the entry pattern. In the following section, we describe the entry and joint venture formation stage, where we endogenize the probability distribution over entry patterns as part of the equilibrium.

3.2 Entry and joint venture formation stage

In our model, a potential entrant initially indicates its intention of entry modes from three options: *JV*, *S*, and *O*. *JV* implies the intent to form a joint venture with another potential entrant. Choosing *S* indicates the intent to participate as a single bidder, resulting in actual entry as a single bidder. Intention *O* represents a withdrawal from the procurement process. While *S* and *O* lead directly to an entry decision, expressing *JV* does not guarantee the formation of a joint venture, as it requires at least one other potential entrant with a mutual agreement to form a joint venture. Therefore, we refer to this choice as the intention, and the corresponding decision making process as the intention choice problem. We denote the number of firms expressing each intention by L_1, L_2, and L_3 and refer to the triplet (L_1, L_2, L_3) as the *intention pattern.* In each auction, the specific intentions of each potential entrant cannot be observed. Instead, we observe the realized number of JVs, M, and single bidders, N. We refer to this pairing as the *entry pattern.* Consequently, to estimate our model, which includes the intention choice problem, we must model the correspondence between the *intention pattern* and the *entry pattern.*

Note that the set of potential entrants for any given procurement auction is finite. The number of potential entrants for a particular auction is determined by the number of firms qualified for that project. Let $\bar{N}$ represent the number of potential entrants. Consequently, $\bar{N}$ is the maximum number of single bidders that can participate in the auction, and $\bar{N} \equiv \lfloor \frac{\bar{N}}{2} \rfloor$ is the maximum number of JVs that can be formed. Additionally, in the intention-choice problem, the set of possible intention patterns is also finite, which we denote by $J \equiv_{\bar{N}+2} C_2$. Given this finiteness, the correspondence from an intention pattern to a realized entry pattern can be represented by a simple matrix.

3.2.1 Outcome mixing matrix

In a standard structural estimation, a detailed structure is required to construct this correspondence.[14] In this study, we adopt a different approach. Rather than detailed modeling, we treat the correspondence between the intention pattern and the entry pattern as a parameter and estimate it directly, similar to a semi-parametric model. For this purpose, we introduce an *outcome mixing matrix* that maps a distribution over intention patterns to a distribution over entry patterns. This approach helps us avoid potential misspecifications that might arise from the detailed modeling of the joint venture formation process. In the following

[14]For instance, we might consider a coalition formation model, as discussed byUetake and Watanabe (2020). Studies on coalition formation, such as the survey of Ray and Vohra (2015), have proposed numerous models for group formation. These models can analyze group formation even under externalities, as in the current situation. However, the outcomes of these models heavily depend on assumptions about players' farsightedness, as illustrated in example 5.5 in Ray and Vohra (2015), and on the protocol specifying the group formation process, like the order of proposers. For empirical work on group formation in procurement auctions, a model that avoids these specificities is needed, as the exact process of JV formation is unknown. This is why models from coalition formation literature are not adopted here.

sections, we explain the structure of the outcome mixing matrix and discuss the equilibrium in this entry and joint venture formation stage.

Potential entrants do not necessarily enter the auctions in the manner they originally intended. For example, as discussed earlier, even though a firm chooses an intention to form a joint venture with another potential entrant, the firm may not be able to form a mutual agreement with other firms. Let $\delta \in \{JV, S, O\}$ denote the realization of entry modes, which is different from the intention of entry modes, and we call this realization of entry modes as *entry style*. From a viewpoint of each potential entrant, what matters for its expected utility is the distribution of realized (M, N) and its δ, and that is why we need to consider the correspondence between an intention pattern and the outcomes. We refer to the triplet (M, N, δ) as an *outcome*. When we express the total number of entry patterns as $K = (\bar{M}+1)(\bar{N}+1)$, where the addition of 1 accounts for the scenario of no entry, the total number of outcomes is $3K$.

Given an intention pattern (L_1, L_2, L_3) and an intention $I \in \{JV, S, O\}$, let $r(M, N, \delta \mid L_1, L_2, L_3; I)$ denote the probability that the outcome (M, N, δ) materializes. For example, $r(M, N, JV \mid L_1, L_2, L_3; JV)$ is the probability that a potential entrant choosing JV as its intention is assigned to the event that M joint ventures and N single bidders enter the second-stage auction and is able to form a joint venture when the intention pattern is (L_1, L_2, L_3). We naturally assume that the intentions of S and O directly determine the entry style: that is, $r(M, N, JV \mid L_1, L_2, L_3; S) = r(M, N, O \mid L_1, L_2, L_3; S) = r(M, N, JV \mid L_1, L_2, L_3; O) = r(M, N, S \mid L_1, L_2, L_3; O) = 0$ for all pairs of (M, N), and $\sum_{(M,N)} r(M, N, S \mid L_1, L_2, L_3; S) = 1$ for all (L_1, L_2, L_3) with $L_2 \geq 1$.

Given a specific intention I and an intention pattern (L_1, L_2, L_3), we can create a probability vector over outcomes by collecting $r(M, N, \delta \mid L_1, L_2, L_3; I)$ for all possible outcomes. For a given intention I, by stacking these probability vectors row-wise for all possible intention patterns, we construct a matrix R^I. R^I is a $3K \times J$ column stochastic matrix, where the jth column represents the probability vector over outcomes for the jth intention pattern. An R^I matrix is constructed for each intention in $\{JV, S, N\}$. Each of these matrices is referred to as an *outcome mixing matrix*.

Without further specifications, R^I represents a high-dimensional object. To define search

Table 3. An outcome mixing matrix when there are three potential entrants. Parameters: Φ and ρ.

	(0,0,3)	(0,1,2)	(0,2,1)	(0,3,0)	(1,0,2)	(1,1,1)	(1,2,0)	(2,0,1)	(2,1,0)	(3,0,0)
(0,0)	1	0	0	0	$1-\rho$	0	0	$(1-\rho)^2$	0	0
(0,1)	0	1	0	0	ρ	$1-\rho$	0	$2\rho(1-\rho)$	$(1-\rho)^2$	0
(0,2)	0	0	1	0	0	ρ	$1-\rho$	ρ^2	$2\rho(1-\rho)$	0
(0,3)	0	0	0	1	0	0	ρ	0	p^2	0
(1,0)	0	0	0	0	0	0	0	0	0	$1-\rho$
(1,1)	0	0	0	0	0	0	0	0	0	ρ

Table 4. An outcome mixing matrix when there are three potential entrants. Parameters: $\hat{\Phi}$ and $\hat{\rho}$.

	(0,0,3)	(0,1,2)	(0,2,1)	(0,3,0)	(1,0,2)	(1,1,1)	(1,2,0)	(2,0,1)	(2,1,0)	(3,0,0)
(0,0)	1	0	0	0	$1-\hat{\rho}$	0	0	0	0	0
(0,1)	0	1	0	0	$\hat{\rho}$	$1-\hat{\rho}$	0	0	0	0
(0,2)	0	0	1	0	0	$\hat{\rho}$	$1-\hat{\rho}$	0	0	0
(0,3)	0	0	0	1	0	0	$\hat{\rho}$	0	0	0
(1,0)	0	0	0	0	0	0	0	1	0	$1-\hat{\rho}$
(1,1)	0	0	0	0	0	0	0	0	1	$\hat{\rho}$

friction clearly, we impose a specific structure on R. We further parameterize R^I using two components: (Φ, ρ), where $\Phi : \mathbb{N} \to \mathbb{N}$ maps the number of potential entrants who choose JV as their intention to the number of successfully formed joint ventures, and $\rho : \mathbb{N} \to [0, 1]$ represents the probability of entering as a single bidder after a potential entrant, who has chosen JV as its intention, fails to form a joint venture when the total number of JV intentions is L_1. Then, we can calculate the number of potential but unformed joint ventures as $\lfloor \frac{L_1}{2} \rfloor - \Phi(L_1)$ for every feasible L_1. By examining this discrepancy, we can quantify the severity of search friction. In this formulation, the distribution of the number of single bidders, conditional on the number of JVs, becomes a mixture of multinomial distributions.

Assuming a deterministic relationship between L_1 and M significantly reduces the number of parameters in our model and provides a clear definition of search friction, as well as a basis for its identification. Fortunately, the number of feasible Φ functions is finite, given that it is bounded above by $\lfloor \frac{L_1}{2} \rfloor$ and below by the scenario where no JVs are formed. The number of all possible step functions between these bounds is also finite, which is beneficial for estimation purposes. For all intentions, we assume that the same Φ determines the outcome mixing matrix, therefore we do not append a subscript I to Φ.

Example 1. *We present a small example of an outcome mixing matrix. Imagine there are three potential entrants. For a fixed intention, an outcome mixing matrix can be represented as in Table 3, which is constructed using* Φ *and* $\rho \in [0, 1]$*, where we assume* ρ *is independent of* L_1*. In this scenario, we require three potential entrants choosing JV as their intention to form one joint venture. We also consider another outcome mixing matrix constructed by* $\hat{\Phi}$ *and* $\hat{\rho}$*, as depicted in Table 4. In this case, only two potential entrants are needed to form a joint venture. Accordingly, Table 3 represents the outcome matrix with more severe search friction.*

3.2.2 Equilibrium

Here we define the Bayesian Nash equilibrium in the entry and joint venture formation stage, given a set of outcome mixing matrices $R = \left(R^{JV}, R^S, R^O\right)$. First, we introduce a probability vector P with a length of $3K$, which serves as a *prediction* over the outcomes for each intention. The elements from the first to the Kth in P are the probabilities over the entry patterns, assuming that the potential entrant can form a joint venture. The subsequent K elements represent the probabilities over the entry patterns, assuming that the potential entrant enters as a single bidder. The final K elements of P are the probabilities over the entry patterns, assuming that the potential entrant does not enter.

Using the prediction vector P, a potential entrant calculates its expected payoff for each intention. At this stage, we introduce the entry costs for the two styles of entry: c_S as the entry cost for a single bidder and c_{JV} as the entry cost for a joint venture. The cost for a joint venture includes the management cost necessary to decide the bid in the subsequent auction as a joint venture, as well as any frictional costs associated with forming the joint venture. The additional execution cost incurred by forming and managing a joint venture is thus calculated by $c_{JV} - c_S$. It is important to note that we normalize the benefit of opting out (not entering) to 0.

$$\begin{cases} v_{JV}(P^{JV}) = \left(P^{JV}_{1:K} \cdot u_{JV} - c_{JV}\right) + \left(P^{JV}_{K+1:2K} \cdot u_S - c_S\right) + \left(P^{JV}_{2K+1:3K} \cdot 0\right), \\ v_S(P^S) = \left(P^S_{K+1:2K} \cdot u_S - c_S\right), \\ v_N(P^O) = P^O_{2K+1:3K} \cdot 0. \end{cases}$$

Note that the upper script of P represents the chosen intention. Hereafter we use $P = (P^{JV}, P^S, P^O)$. u_{JV} and u_S are vectors containing the ex-ante expected payoffs of each entry style.

Potential entrants face a discrete choice problem among the three intentions: $\{JV, S, O\}$. We incorporate additive disturbance terms $\epsilon_i = (\epsilon_i(JV), \epsilon_i(S), \epsilon_i(O))$ to account for unobserved costs. We assume that ϵ_i independently follows a Type I extreme value distribution. Consequently, the choice probabilities can be expressed as follows:

$$\begin{cases} m(JV; P) = \frac{e^{v_{JV}(P^{JV})}}{e^{v_{JV}(P^{JV})} + e^{v_S(P^S)} + e^{v_O(P^O)}} \\ m(S; P) = \frac{e^{v_S(P^S)}}{e^{v_{JV}(P^{JV})} + e^{v_S(P^S)} + e^{v_O(P^O)}} \\ m(O; P) = \frac{e^{v_O(P^O)}}{e^{v_{JV}(P^{JV})} + e^{v_S(P^S)} + e^{v_O(P^O)}} \end{cases}.$$

We denote $m(P)$ as the triplet of choice probabilities given a prediction vector P. Consequently, we obtain a distribution over the intention patterns, denoted as $Q(m(P))$, which is a multinomial distribution with the probability vector $m(P)$ and the total number of trials being $\bar{N} - 1$ (since we fix the intention of one firm and consider the distribution of intentions among the other potential entrants).[15] The distribution over the outcomes can now be expressed as a mixture of distributions for each intention pattern based on the outcome mixing matrices. For a potential entrant who chooses JV, the distribution over outcomes is represented by $R^{JV}Q(m(P))$. Similarly, for a potential entrant who chooses S or O, we have the analogous expressions, $R^S Q(m(P))$ and $R^O Q(m(P))$.

Following the definition of the Bayesian Nash equilibrium in Seim (2006), we characterize the equilibrium of this game by the prediction $P^\star$ which is equal to the realized distributions

[15] Because we fix the intention of one firm, we must consider the distribution of the intentions of the other potential entrants.

over outcomes. In other words, $P^\star$ solves the following fixed point problem, which is the equilibrium prediction of our model:

$$\begin{cases} P^{\star,JV} = R^{JV}Q(m(P^\star)) \\ P^{\star,S} = R^{S}Q(m(P^\star)) \\ P^{\star,N} = R^{N}Q(m(P^\star)). \end{cases}$$

This is equivalent to

$$P^\star = RQ(m(P^\star)) \tag{4}$$

where R is the stack of R^{JV}, R^S, R^N.

For this system, we have a unique equilibrium. This is because $RQ(m(P))$ is a contraction mapping with respect to P. This uniqueness is required for the following estimation procedure.

Theorem 2. *The system expressed as equation* (4) *has a unique fixed point. In other words, the entry and joint venture formation stage has a unique Bayesian Nash equilibrium.*

Proof. See Appendix B. □

The distribution over entry patterns can be calculated based on $P^\star$. First, we compute the marginal distributions over the entry patterns for each intention, and subsequently determine the weighted average of these marginal distributions. For future reference, we denote these equilibrium distributions over the entry patterns as $g(M, N)$.

4 Estimation and identification

In this section, we outline the estimation strategies for the two stages separately. In the auction stage, our aim is to estimate the distributions of $\frac{\tilde{c}_i}{s_i}$ for both a joint venture and a single bidder, which are denoted as $\tilde{G}_{JV}$ and $\tilde{G}_S$ in Section 3.1. Once we have estimated these distributions, we proceed to calculate the ex-ante expected payoffs, u_{JV} and u_S, for various levels of the engineer's estimates. In the entry and joint venture formation stage, we use the estimated ex-ante expected payoffs to estimate two key parameters: the adjustment cost associated with managing a joint venture and the outcome mixing matrices, as described in Section 3.2.

4.1 Estimation of bidding sage

Hereafter, we denote the auction index by j. From equation (2), we have the following inversions for the individual cost factors of both the JV and the single bidder: for a single bidder,

$$\tilde{c}_{ij} = \frac{s_{ij}}{p_j B_{ij}} \left(1 - \frac{1}{(N_j - 1)\frac{f^S(\ln B_{ij})}{F^S(\ln B_{ij})} + M_j \frac{f^{JV}(\ln B_{ij})}{F^{JV}(\ln B_{ij})}} \right), \tag{5}$$

and for a joint venture,

$$\tilde{c}_{ij} = \frac{s_{ij}}{p_j B_{ij}} \left(1 - \frac{1}{N_j \frac{f^S(\ln B_{ij})}{F^S(\ln B_{ij})} + (M_j - 1) \frac{f^{JV}(\ln B_{ij})}{F^{JV}(\ln B_{ij})}} \right). \tag{6}$$

Once we estimate the two distributions of effective bids for a single bidder and a joint venture, we can retrieve the individual cost factor for each firm using the above equations.

We now describe the estimation procedure for the distribution of effective bids. Note that the optimization problem implies that the optimal level of an effective bid depends on the combination of (p, M, N) and whether the firm is a single bidder or a JV. First, we assume that the logarithm of effective bids follows a normal distribution.

Assumption 2.

$$\ln B_{ij}^{JV} \sim N\left(\theta_j^{JV}, \sigma_j^{2,JV}\right), \ \ln B_{ij}^{S} \sim N\left(\theta_j^{S}, \sigma_j^{2,S}\right)$$

We estimate these distributions using sieve methods; that is, we estimate the mean and variance using the following regression model:

$$\ln B_{ij} = poly(d_{ij}^{JV}, p_j, M_j, N_j; \beta) + \epsilon_{ij}. \tag{7}$$

where d_{ij}^{JV} is the dummy variable for the joint venture and $poly(X, \beta)$ represents the polynomial function of the variables X with some degree when the coefficients are β. We denote the estimated coefficients by $\hat{\beta}$ and then the estimated distributions in auction j are as follows:

$$\begin{aligned}\ln B_j^{JV} &\sim N\left(poly(d_{ij}^{JV} = 1, p_j, M_j, N_j; \hat{\beta}),\ \hat{\sigma}^{2,JV}\right), and \\ \ln B_j^{S} &\sim N\left(poly(d_{ij}^{JV} = 0, p_j, M_j, N_j; \hat{\beta}),\ \hat{\sigma}^{2,S}\right).\end{aligned}$$

where the estimated variances are

$$\begin{aligned}\hat{\sigma}^{2,JV} &= \frac{1}{\#JV} \sum_{ij:d_{ij}^{JV}=1} \left(\ln B_{ij} - poly(d_{ij}^{JV} = 1, p_j, M_j, N_j; \hat{\beta})\right)^2, and \\ \hat{\sigma}^{2,S} &= \frac{1}{\#Single} \sum_{ij:d_{ij}^{JV}=0} \left(\ln B_{ij} - poly(d_{ij}^{JV} = 0, p_j, M_j, N_j; \hat{\beta})\right)^2.\end{aligned}$$

Based on the estimated distributions, we retrieve the individual cost factors using equations (5) and (6).

4.1.1 Computation of ex-ante expected payoffs

Next, we compute the ex-ante expected payoffs based on the estimated joint distribution of $(\tilde{c}_i, s_i)$. Specifically, we calculate the following: $u_{JV}(M, N, p)$ and $u_S(M, N, p)$. Because p is a continuous variable, we cannot expect many auctions to have the same engineer's estimates. This necessitates approximating the set of auctions by using the same engineer's estimates. Here, we divide the space of p into two sub-groups and compute two sets of ex-ante expected payoffs. In other words, we consider auctions within the same group as homogeneous and use the variations within the group to infer the ex-ante expected payoffs.

The following notation is used to describe the specific inference process: $\bar{p}$ and $\underline{p}$ denote the maximum and the minimum of the engineer's estimate in our data. p_{cut} is the cutoff for dividing the total number of auctions into two equal-sized sets.[16] We compute two representative engineer's estimate for each group, $\tilde{p}_1, \tilde{p}_2$: these are the means of the engineer's

[16] This split is merely for simple execution. We can change the number of splitting and we can also rely on a kernel method to estimate the ex-ante expected payoffs as functions of the value of engineer's estimate.

estimates in each group. For each entry style, S and JV, we infer that the $2 \times \bar{M} \times \bar{N}$ expected payoffs.

When focusing on a single bidder, one entry pattern (M, N), and one auction size $k \in \{1, 2\}$, the inference process for the ex-ante expected payoffs is as follows:

1. Draw 2000 observed single bidders from auctions in group k. From the estimation of the bidding stage, we know their individual costs, as well as their scores from the estimation result in the second stage.

2. For each single bidder i, compute the maximized expected payoff under the entry pattern (M, N) given their pair of $(\tilde{c}_i, s_i)$ and the representative engineer's estimate $\tilde{p}_k$.

3. Take the average of these maximized expected payoffs among the drawn single bidders. This average corresponds to $u_S(M, N, \tilde{p}_k)$.

This same process is applied to all possible pairs of entry patterns, both auction sizes, and to entrants as joint ventures.

4.2 Estimation of entry and joint venture formation stage

Hereafter, we denote the equilibrium distribution over entry patterns as $g(M, N; c_{JV}, c_S, R)$ to emphasize its dependence on the parameters. To estimate the two entry costs and outcome mixing matrices, we adopt a Mathematical Programming with Equilibrium Constraints (MPEC) approach, as discussed by (Su and Judd, 2012). The estimation involves solving the following constrained maximization problem:

$$\max_{c_{JV}, c_S, \Phi, \rho} LL(c_{JV}, c_S, \Phi, \rho) \text{ subject to (4)},$$

where the objective function is the log-likelihood function constructed by the observed counts of every entry pattern. We denote the counts of the entry pattern of (M, N) by $T(M, N)$,

$$LL(c_{JV}, c_S, \Phi, \rho) \equiv \sum_{(M,N)} T(M, N) \times \ln g(M, N; c_{JV}, c_S, \Phi, \rho),$$

and the constraint corresponds to the equilibrium condition in the entry and joint venture formation stage described in Section 3.2.2.

The unique aspect of this estimation is that both Φ and ρ are functions. For ρ, which determines the probability of entering as a single bidder after an unsuccessful attempt to form a joint venture, we search across the probability values for each L_1. For Φ, our approach is as follows: we solve the MPEC problem with a fixed Φ to obtain the maximized log-likelihood. By comparing the log-likelihood values obtained for different Φs, we select the Φ that yields the largest log-likelihood as our estimate. This estimation strategy is feasible because, as discussed in Section 3.2.1, the total number of feasible Φs is finite.

To reduce the computation time, we further limit the set of possible Φ functions. This is because, while the total number of feasible Φs is finite, it increases rapidly with the number of potential entrants.[17] We consider the following set of functions:

$$\Phi(L_1; \alpha) = \max\left(0, \lfloor \alpha \times \ln \frac{L_1}{2} \rfloor\right). \tag{8}$$

Here the parameter α determines the shape of Φ. In the estimation, we first identify the set of α's which give feasible Φ's and then solve MPEC for each possible α to determine the best set of estimates. The number of feasible Φ in our estimation is seven. Therefore, we solve seven MPEC problems to obtain the estimation results and then compare the values to determine the best estimate.

This procedure can be viewed as a method for estimating a static entry game under incomplete information, similar to the approach outlined in Seim (2006) but executed via MPEC. In the standard entry game model, researchers are assumed to be aware of how the outcome mixing matrix non-stochastically maps intention patterns to entry patterns. However, in our scenario, because the detailed mechanism governing joint venture formation is unknown, it is necessary to include the unknown matrix R as a parameter in our estimation.

[17] To align the model with realistic scenarios, we require at least eight potential entrants; this number allows for the possibility of observing up to four JVs in an auction, which is the maximum number recorded in our sample. In this context, there are 143 feasible Φ functions. Additionally, we set the number of potential entrants at 11 to accommodate the possibility of search friction; in this situation, the total number of feasible Φs rises to 1423.

4.3 Identification and Monte Carlo simulation

Suppose we know Φ. Then, we know which intention patterns correspond to each of the possible number of JVs. As c_{JV} and c_S determine the probability distribution assigned to each intention pattern, c_{JV} and c_S are identified to match the empirical distribution of the number of JVs. However, Φ and (c_{JV}, c_S) are not jointly identified from the distribution of the number of JVs alone. Conditional on the realized number of JVs, we may have multiple pairs of Φ and (c_{JV}, c_S) that rationalize the observation; For example, a pair of (c_{JV}, Φ) and (c'_{JV}, Φ') with $c_{JV} < c'_{JV}$ and $\Phi(x) < \Phi'(x) \quad \forall x$ may leads to the same distribution of JV because lower cost of JV increases the probability assigned to intention patterns with JVs which may be offset by higher friction in the matching function.

To jointly identify Φ and cs, we must rely on the conditional distribution of the number of single bidders given the number of JVs. Given M and L_1, where $L_1 \geq 2 \times M$, we have $\bar{N} - L_1 + 1$ columns, which are the mixture components of the conditional distribution in an outcome mixing matrix. Note that the number of non-zero elements in each column is $\bar{N} - 2M + 1$. We denote the corresponding part of the outcome mixing matrix for L_1 by $R(L_1) \subset \mathbb{R}^{(\bar{N}-2M+1)\times(\bar{N}-L_1+1)}$. We further denote the corresponding weights on the columns in $R(L_1)$ by $q(m)_{L_1}$ where m is the choice probability vector over the three intentions and q is the function computing the multinomial choice probability vector.[18]

We define the set of mixture distributions generated by $R(L_1)$: $\mathcal{D}(L_1) \equiv \{R(l_1)q \mid q = q(m)_{l_1},\ m \in \Delta^3\}$. By the construction of the outcome mixing matrix, the conditional distribution of the number of single bidders is a mixture distribution where the set of mixture components is $\mathcal{D}_M \equiv \{D(L_1) \mid D(L_1) \in \mathcal{D}(L_1), L_1 \geq 2 \times M\}$ and the weight on each component is the probability that L_1 potential entrants will choose JV. Hence, we can decompose the identification problem of Φ into the sub problems for every possible M's, i.e., $\lfloor \frac{\bar{N}}{2} \rfloor$: the identification problem of the mixture components from the observation of a mixture distribution.

We first show that the set of mixture distributions generated by the set of $\bar{N} - L_1 + 1$

[18] This is different from Q in Section 3.2.2 because q must be a probability vector with length $\bar{N} - L_1 + 1$. From Q, by taking the ratio of the probabilities to the probability of L_1 potential entrants choose JV, we get q.

columns is distinct for every $L_1 \geq 2 \times M$. In other words, the mixture components are

Lemma 1. *Given $\frac{\bar{N}-3}{2} > M$ and take any two $l_1, l_2 \geq 2 \times M$. Then, we have $\mathcal{D}(l_1) \cap \mathcal{D}(l_2) = \phi$.*

Proof. Assume the contrary. Take one distribution from the product set of the two sets and denote. Then, we have $\bar{N} - 2M + 1$ equations for the equality of the probability vector and four parameters, $m \in \Delta^3$, $\rho(l_1)$ and $\rho(l_2)$. Then, when $\frac{\bar{N}-3}{2} > M$, there are no parameters to satisfy this system. Therefore, when M is less than the maximum possible number of JVs, we obtain the statement above. □

We define a similar set of mixture distributions including several different L_1: $\mathcal{D}(l_1, \cdots, l_n)$ for $2 \leq n \leq \bar{N}$ and a continual sequence of l_1 to l_n. By a similar argument, we have disjoint sets of mixture distributions in the transition from from $n-1$ to n.

Lemma 2. *Given $M \geq 0$, for $n < \bar{N} - 1 - 2M$, $\mathcal{D}(l_1, \cdots, l_{n-1}) \cap \mathcal{D}(l_n) = \phi$.*

We assume that this condition is satisfied for every M. This assumption serves as a lower bound for Φ. For example, when we have $\bar{N} = 11$ and there is no joint venture, the corresponding intention patterns has $L_1 = 0, \cdots, 8$. After 9 or more potential entrants choose JV, we assume there is at least one joint venture is formed.

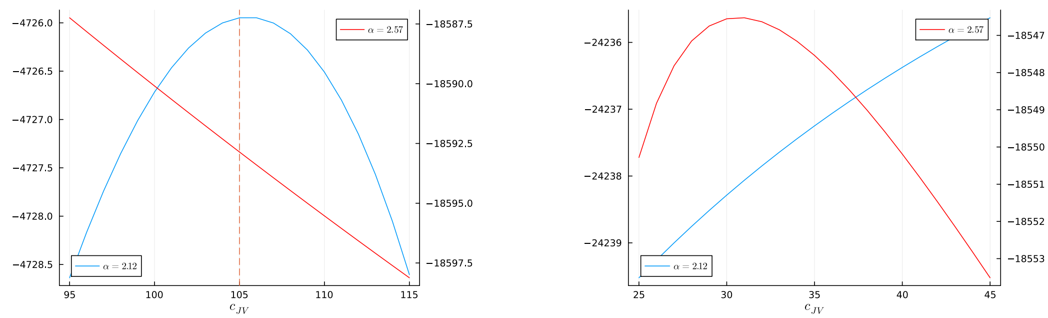
Assumption 3. *For every M, there are $n < \bar{N} - 1 - 2M$ different L_1 in the corresponding intention patterns.*

Under Assumption 3, Lemma 2 directly implies that we can identify the mixture components for M lower than $\frac{\bar{N}-3}{2}$. This is because every decision on whether to include a new set of intention patterns with l_n yields a completely new set of mixture distributions.

Finally, we assume on the number of potential entrants. This ensures that $2 < \bar{N} - 1 - 2$ and hence we have at least two cases for M, i.e., $M = 0$ and $M = 1$ to identify the correct form of Φ.

Assumption 4. $\bar{N} > 5$.

As argued at the beginning of this section, when we have two number of JVs, we can identify the values of the two costs, c_S and c_{JV}. After cost identification, we can decrease the



(a) Maximizer for the true α (b) Maximizer for the wrong α

Figure 3. The log-likelihood function of the two different α's.

Note: The blue line is obtained when we use the true α and the red line is the obtained when we use one wrong α. Panel (a) is the snapshot around true entry cost. Panel (b) is the snapshot around the maximizer of the log-likelihood of the wrong α.

number of parameters by two. We can then consider the case of $\frac{\bar{N}-3}{2} \leq M < \frac{\bar{N}-1}{2}$. Because the case with the maximum number of JVs is redundant, this implies that our identification argument covers all the possible M's. In short, we have the following identification, and the proof is as argued above.

Theorem 3. *Under Assumptions 3 and 4, all the parameters in the entry and joint venture formation game,* Φ, ρ *and* (c_{JV}, c_S)*, are identified.*

4.3.1 Monte carlo simulation

We conduct a Monte Carlo simulation to demonstrate our estimation strategy and validate the identification. For visibility, we assume that c_S is already known. Then, it is possible to identify all the parameters when the number of potential entrants is five and the maximum number of joint ventures is two. In this setting, we solve the equilibrium of our model under a set of ex-ante expected payoffs computed from our actual data. Based on this equilibrium distribution, we create a set of realized entries.

Our parameter setting is as follows: $c_{JV} = 105$, $c_S = 55$, and $\alpha = 2.12$. As an alternative, we consider another possible $\alpha = 2.57$, which also yields a feasible Φ. Figure 3 summarizes the two log-likelihood functions. The left axis represents the value of the log-likelihood for the true α, and the right axis represents the same for the higher α. Panel (a) of Figure

3 displays the log-likelihood functions around the true value of c_{JV}, which is 105. We observe that when using the true α, the log-likelihood reaches its maximum around the true value. Conversely, Panel (b) of Figure 3 illustrates the region around the maximizer of the log-likelihood function for the incorrect α. The maximized log-likelihood for the true α is around -4726, while for the incorrect α, it is approximately -18547. This significant difference enables us to accurately identify the true shape of Φ.

5 Estimation results

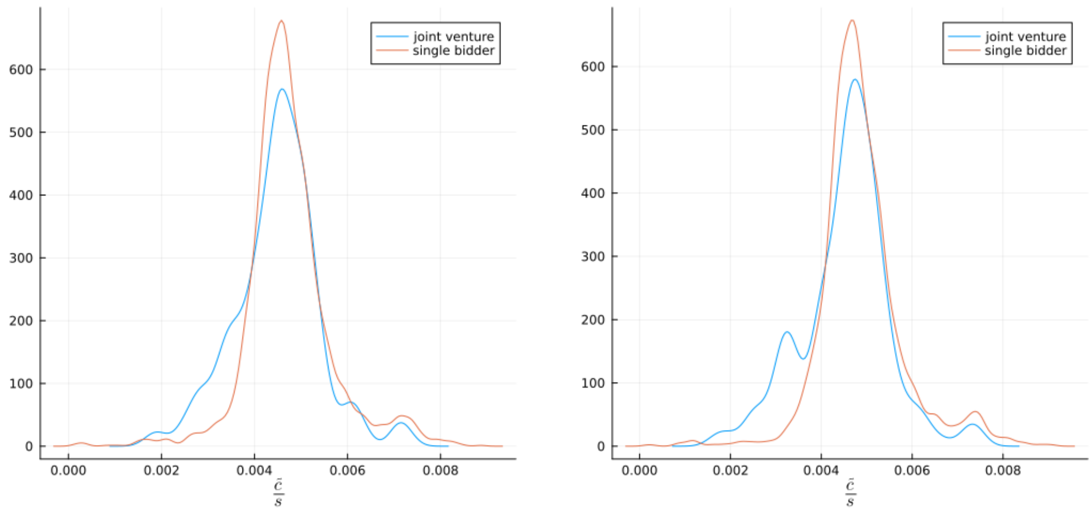
This section presents a series of estimation results for the two-stage structural model discussed above. Section 5.1 shows the estimation results for the bidding stage: the retrieved individual costs and ex-ante expected payoffs. Section 5.2 presents the estimation results for the entry and joint venture formation stage. Here, our main interest lies in estimating (i) Φ, which determines the number of successfully formed joint ventures and (ii) the two entry costs c_S and c_{JV}.

5.1 Bidding stage

First, we present the estimation results for the bidding stage. Our main result is obtained when the degree of the polynomial representing the mean of the logarithm of the effective bids, as specified in equation (7), was set to 1.[19] Figure 4 illustrates the estimated densities of $\frac{\tilde{c}_i}{s_i}$ for a single bidder and a joint venture: Panels (a) and (b) correspond to the case of homoskedastic and heteroskedastic variance, respectively. We retrieve $\tilde{c}_i$ based on the inversion discussed in Section 4.1 and compute the fraction $\frac{\tilde{c}_i}{s_i}$ for every bidder. The estimated densities are then plotted based on these empirical data points. In each panel, the blue line represents the density of a joint venture, and the red line represents the density of a single bidder.

There are two observations: (i) a joint venture is likely to draw a smaller value of $\frac{\tilde{c}}{s}$, and (ii) the density of the cost-score ratio of a joint venture exhibits a bimodal distribution in

[19] We check the robustness of our results by changing this degree of polynomial. Figure A3 in Appendix demonstrates the results when we set the degree of polynomial equal to 2.



(a) A Homoskedasticity Case

(b) A Heteroskedastic Case

Figure 4. Density estimations of $\frac{\tilde{c}_i}{s_i}$

Note: Panel (a) demonstrates the result when we assume homoskedastic variances, whereas Panel (b) demonstrates the result when we use type-dependent variance estimations. In each panel, the blue line represents the density for joint venture and red line represents the density for single bidder.

Panel (b). As discussed in Section 3.1, the optimal bidding strategy is a monotone function of the fraction. Hence, this difference in distributions reflects that a joint venture is more likely to win an auction than a single bidder. Additionally, as shown in Panel (f) of Figure 1f, where the distributions of scores for single bidders and joint ventures are almost identical, it is evident that joint ventures are more competitive due to their cost-effectiveness, which we attribute to cost synergies.

The second observation suggests that two types of joint ventures exist: one that realizes cost synergies and another that does not benefit from them. The joint ventures of the latter type have a cost distribution similar to that of single bidders, indicating that the social benefits of joint ventures are primarily derived from the former type, which effectively harnesses cost synergies. Importantly, this study does not impose any specific structure on how cost synergies are materialized. Questions such as "What makes a joint venture more cost-effective?" and "How can cost efficiency be facilitated?" are topics for future studies.

Based on the estimated distribution of $(\tilde{c}_i, s_i)$, we proceed to estimate the ex-ante expected payoffs for each auction. Figure A4 displays the estimated ex-ante expected payoffs for both a single bidder and a joint venture. We categorize the auctions into two groups based on the engineer's estimate, as outlined in Section 4.1.1. Auctions with an engineer's estimate below the median are classified as *small-sized auctions*, whereas those above the median are classified as *large-sized auctions*. For each combination of the number of joint ventures, M, and the number of single bidders, N, we present the estimated ex-ante expected payoff. Generally, we observe that the payoffs are larger when there are fewer entrants, which is consistent with theoretical predictions.[20]

To assess the accuracy of our model, we compare the observed bids with the optimal bids derived by solving the expected profit maximization problem, as defined in Equation (1). Figure A5 compares the observed and simulated optimal effective bids for each auction size. The orange line represents the estimated density of the observed effective bids and the blue line represents the estimated density of the simulated bids. Notably, the simulated and observed bid distributions peak at similar points, although the simulated distributions exhibit thinner tails than the observed distributions.

Given that our model fits using a limited number of parameters and assumes smooth distributional characteristics, the simulated distribution inevitably has thinner tails. While a better fit might be achievable by incorporating more auction heterogeneity, such an approach would increase the computational complexity and possibly reduce the reliability of the estimates owing to outlier observations.[21] Considering this trade-off, we adopt the current specification.

5.2 Entry and joint venture formation stage

This section presents the estimation results for the entry and joint venture formation stage. Figure 5 illustrates the estimated Φ with an orange line, and the upper bound of the number of joint ventures is shown by a blue line. The horizontal axis represents the number of potential bidders choosing JV (L_1), and the vertical axis displays the number of realized joint ventures (M). The estimated Φ suggests that no joint ventures are formed when

[20] The value for the case of a single entrant is set to the corresponding expected cost in Figure A4.

[21] Examples of such methodologies include dividing the sample of auctions into three or more classes based on size, using a kernel method as discussed in Section 4.1, or considering other characteristics of the auctions.

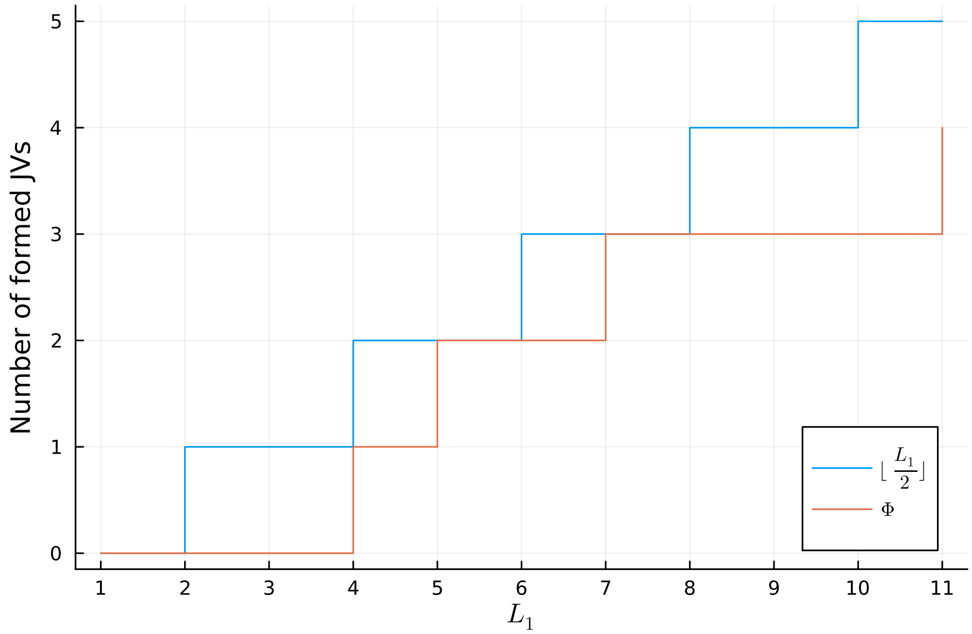


Figure 5. Estimated pattern of the formation of joint ventures.

Note: The horizontal axis is the total number of potential entrants who choose JV. The vertical line is the number of formed joint ventures. Blue line is the upper bound for the number of joint ventures, i.e., $\lfloor \frac{L_1}{2} \rfloor$.

fewer than four potential entrants attempt to form a joint venture. Beyond this threshold, the number of realized joint ventures begins to increase proportionally with the number of potential entrants choosing JV up to $L_1 = 7$. When L_1 exceeds 7, we observe another flat region in the Φ function.

The discrepancy between the two lines in Figure 5 represents the search friction encountered during joint venture formation. This friction arises when potential entrants seek partners willing to form a joint venture. Various factors could contribute to this friction. For example, a potential entrant might discover significant differences in firm culture with a prospective partner, making continued collaboration challenging after the initial meetings. Our concept of search friction encompasses all possible reasons for this deviation from the theoretically maximum number of joint ventures.

The estimated Φ implies that search friction is minimized when L_1 is at a medium level. This could be because (i) finding a partner is more feasible when there is a sufficient number of potential partners, avoiding a situation of too few options, and (ii) a congestion effect may occur when the number of potential entrants choosing JV is large. In such cases, finding an optimal partner becomes critical for outcompeting other JVs in the subsequent auction stage.

Table 5. Estimation Results in Entry Stage

α	LL	c_{JV}	c_S
2.373	-1963	18.651	11.013
2.413	-1955	19.368	11.002
		(0.511)	(0.032)
2.453	-2065	14.266	10.662
2.563	-2062	14.104	10.665
2.683	-2054	14.053	10.667
2.794	-2039	16.408	10.608
2.904	-2722	2.570	0.474

Notes: The unit of c_{JV} and c_S is one million yen. Standard errors are computed only for α that gives the highest log-likelihood, which are contained in the brackets below the estimated values.

Table 5 presents the estimated entry costs for a joint venture (c_{JV}) and a single bidder (c_S) across different values of α as specified in equation (8). The α that yields the highest log-likelihood, along with the corresponding estimated entry costs, are $\alpha = 2.413$, $c_{JV} = 19.368$, and $c_S = 11.002$. The standard errors demonstrate that the difference between c_{JV} and c_S is statistically significant.[22] Entering as a joint venture necessitates additional spending of approximately 8.37 million yen by potential entrants. This underlines the presence of adjustment costs in managing a joint venture, a concept widely acknowledged in the merger literature.

These adjustment costs represent approximately 0.21% of the average engineer's estimates in larger-sized auctions and 0.85% in smaller-sized auctions. While these percentages might seem small, they become significant when compared to the inferred ex-ante expected payoffs, especially considering the low probability of winning an auction. For instance, in smaller-sized auctions with one joint venture and one single bidder, the adjustment costs constitute

[22] In computation of standard errors, we fix the selected Φ and also treat the estimated ex-ante expected payoffs as fixed.

approximately 23.72% of the expected payoff for a joint venture. Therefore, it can be concluded that these adjustment costs may be a critical factor in explaining the relatively small number of joint ventures observed, despite their competitive advantage in the auction stage.

6 Counterfactual analysis

We conduct a counterfactual analysis in which we change the entry cost of joint ventures to investigate whether the government should further promote joint venture formations in procurement auctions. According to our estimation results, joint venture formation should be encouraged because of cost synergies. However, an increasing number of joint ventures may decrease the incentive to participate in an auction due to the competitiveness of joint ventures. Therefore, we must quantify the gross benefits of this policy by considering the two countervailing effects.

In principle, there are three possible policy interventions to encourage joint venture formation: (i) lowering the entry cost for joint ventures, (ii) mitigating search friction, and (iii) changing scoring rules to provide preferential treatment to joint ventures. In this study, we focus on the first intervention. We opt not to pursue the second intervention due to its complexity: since search friction in our model is expressed as the function Φ, there are numerous ways to modify Φ to bring it closer to the upper bound, making it challenging to effectively reduce search friction. Regarding the third intervention, our data lacks the detailed information necessary to compute a counterfactual score for each bidder, which inhibits us from performing counterfactual simulations of this nature.

To measure the efficiency of auction outcomes, we define *procurement efficiency* for a set of auctions as follows:

$$\frac{\sum_j \left(\text{Engineer's Estimates}\right)_j - \sum_j \left(\text{Winning bid}\right)_j}{\sum_j \left(\text{Engineer's Estimates}\right)_j} \times 100.$$

In small-sized auctions, the observed level of procurement efficiency is 11.31, and that for large-sized auctions is 12.25. In the following counterfactual analysis, we compute this value for each auction class in a scenario where the government alters the adjustment cost.

For this counterfactual analysis, we require simulated sets of auctions and entrants. Below, we describe how they are generated based on our estimation results.

1. Set the total number of auctions, T, for a class of auction, which we divide by an engineer's estimate.

2. From the empirical distribution of the engineer's estimate within a class of auction, we draw T engineer's estimates.

3. Within a class of auction, based on the estimated values of (α, c_S, ρ) and ex-ante expected payoffs and an arbitrarily chosen c_{JV}, compute the equilibrium prediction P^{fp} and the distribution over the entry patterns.[23]

4. Draw an entry pattern for each auction within a class based on the above equilibrium distribution.

5. Draw an individual cost factor and score for each firm from the estimated distributions for single bidders and joint ventures.

6. Compute the optimal bid by solving the optimization problem for each bidder.

7. Determine the winner in each auction and decide the winning bid by comparing the effective bids.

6.1 Simulation results

Figure 6 illustrates the simulated procurement efficiencies for each auction class. The blue solid line corresponds to the simulated procurement efficiencies for small-sized auctions, whereas the orange solid line represents those for large-sized auctions. The green dotted

[23] We have a technical remark on this counterfactual simulation. We set the range of c_{JV} as $c_{JV} \in [7, 30]$ to compute the procurement efficiencies. In the range, we check the model can be solved, i.e., we compute the equilibrium level of predictions and the corresponding distribution over the entry patterns. Out of this range, our fixed-point problem might not behave well, which makes it difficult to compute the counterfactual distribution. Regardless, we still believe that $[7, 30]$ is enough to consider the realistic situations.

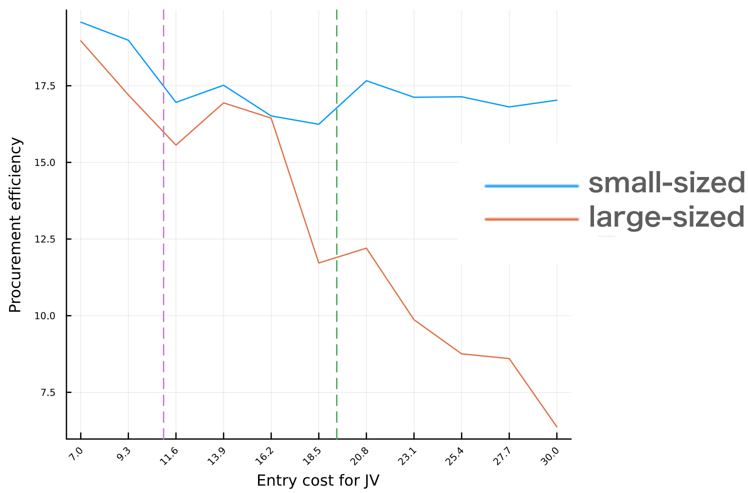


Figure 6. Counterfactual procurement efficiency vs the entry cost as a joint venture

Notes: The blue solid line represents the computed procurement efficiency in the smaller-sized auctions, whereas the orange solid line represents the same one for the larger-sized auctions. The green dotted line corresponds to the estimated value of the entry costs as joint venture, $\tilde{c}_{JV}$*, and the purple dotted line represents the estimated value of the entry costs as single bidders,* $\tilde{c}_S$*.*

vertical line marks the estimated entry cost for a joint venture ($\tilde{c}_{JV}$), and the purple dotted vertical line indicates the estimated entry cost for a single bidder ($\tilde{c}_S$).

The effects of altering the adjustment cost for joint venture formation vary depending on the auction size. In small-sized auctions, an increase in the adjustment cost for a joint venture does not significantly impact procurement efficiency. This is attributed to an increase in the number of bidders resulting from the reduced formation of joint ventures. Specifically, potential entrants who might have entered as a joint venture choose to enter as single bidders instead, leading to more competitive bids. Conversely, in large-sized auctions, an increase in the adjustment cost leads to a decrease in procurement efficiency. In these auctions, the negative impact of diminished cost synergies due to fewer joint venture formation outweighs the positive effect of having more bidders.

Next, we analyze the effect of encouraging joint venture formation by decreasing adjustment costs. The area between the two dotted vertical lines in Figure 6 corresponds to this policy. Although the overall effects vary depending on the size of the auctions, particularly in larger auctions, we find that a mild reduction in the adjustment cost is key to increasing procurement efficiency. Excessive reduction leads to more joint venture entries, potentially deterring other potential entrants. Consequently, the pro-competitive effect of cost synergy is overwhelmed by the anti-competitive effect of the decreasing number of bidders. On the other hand, by slightly reducing the adjustment cost, auctioneers can benefit from the cost synergies of joint ventures, as indicated by the sharp decrease just to the left of the green dotted line.

Overall, altering the adjustment cost for a joint venture has a more significant impact on large auctions compared to small auctions. The blue line, representing small-sized auctions, remains almost constant regardless of the value of c_{JV}. This heterogeneity in responses can guide policymakers to focus on the types of auctions that are most sensitive to these changes. Additionally, policymakers should be aware of the delicate nature of implementing cost-changing policies. In large auctions, procurement efficiency is notably sensitive to small changes in c_{JV}, which is a consequence of the low expected payoffs at the auction stage.

7 Conclusion

We examine joint bidding in procurement auctions using Japanese procurement data, developing a two-stage model. In this model, a potential entrant decides on entry and joint venture formation in the first stage, and the realized bidders compete in a scoring auction in the second stage.

The estimation results from the second stage show the presence of cost synergies for joint ventures. This is apparent when comparing the estimated joint distribution of individual costs and scores for single bidders with that of joint ventures.

Our empirical findings from the first stage reveal the existence of search frictions and adjustment costs associated with joint venture formation, which hinder their formation. Furthermore, the presence of joint ventures may reduce entry incentives for single bidders, as joint ventures are often more competitive when successfully formed. Therefore, from the procurers' perspective, optimizing government procurement efficiency requires balancing the pro-competitive effects of cost synergies with the anti-competitive impacts of a reduced number of bidders. Our counterfactual simulations indicate that, depending on the auction size, overly promoting joint ventures by lowering their entry costs could worsen procurement efficiency due to a decrease in the number of participating firms.

Finally, we acknowledge the limitations of our study and outline potential directions for future research. Our model assumes homogeneity among potential entrants and focuses solely on the realized number of joint ventures and single bidders, without delving into their individual identities. This approach is driven by the empirical context of our study, where all potential bidders for World Trade Organization (WTO) type auctions are required to be pre-registered and qualified companies. Therefore, we argue that the heterogeneity among potential entrants may not be a decisive factor in evaluating the efficacy of joint ventures. Nevertheless, incorporating identity information into the analysis could allow for a more detailed examination of cost synergies, search frictions, and adjustment costs. Policymakers would benefit from understanding which specific pairs of companies are more effective in achieving the desired outcomes.[24]

Incorporating the dynamic aspects of joint venture formation is another important area for future research. For instance, the adjustment cost associated with forming a joint venture might decrease over time as firms gain experience from repeated joint venture formations or even from unsuccessful attempts at forming them. This potential for a "learning-by-doing" effect could significantly impact how firms approach joint ventures and the overall dynamics within procurement auctions.

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[24]Our estimation method accommodates such heterogeneity by expanding the range of possible entry patterns and intention patterns. Although in this paper we define the entry pattern as the combination of the number of joint ventures and the number of single bidders, it is possible to consider the power set of entry decisions made by each potential entrant, thereby accounting for their identities.

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Appendix A Additional figures

Appendix A.1 Kawai-Nakabayashi test for collusion

We demonstrate a series of results for the collusion screening test developed by Kawai and Nakabayashi (2024) for each subset of region in Figure A1 and for each year in Figure A2.

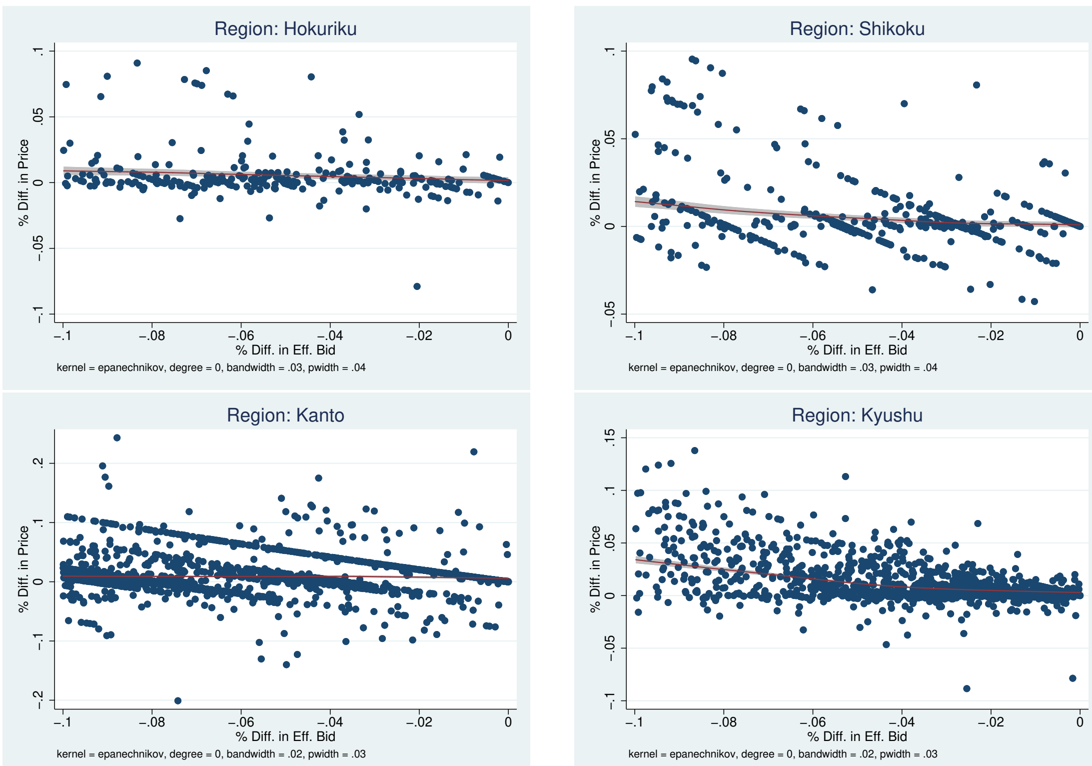


Figure A1. Region-by-Region Collusion Screening Tests by Kawai and Nakabayashi (2022)

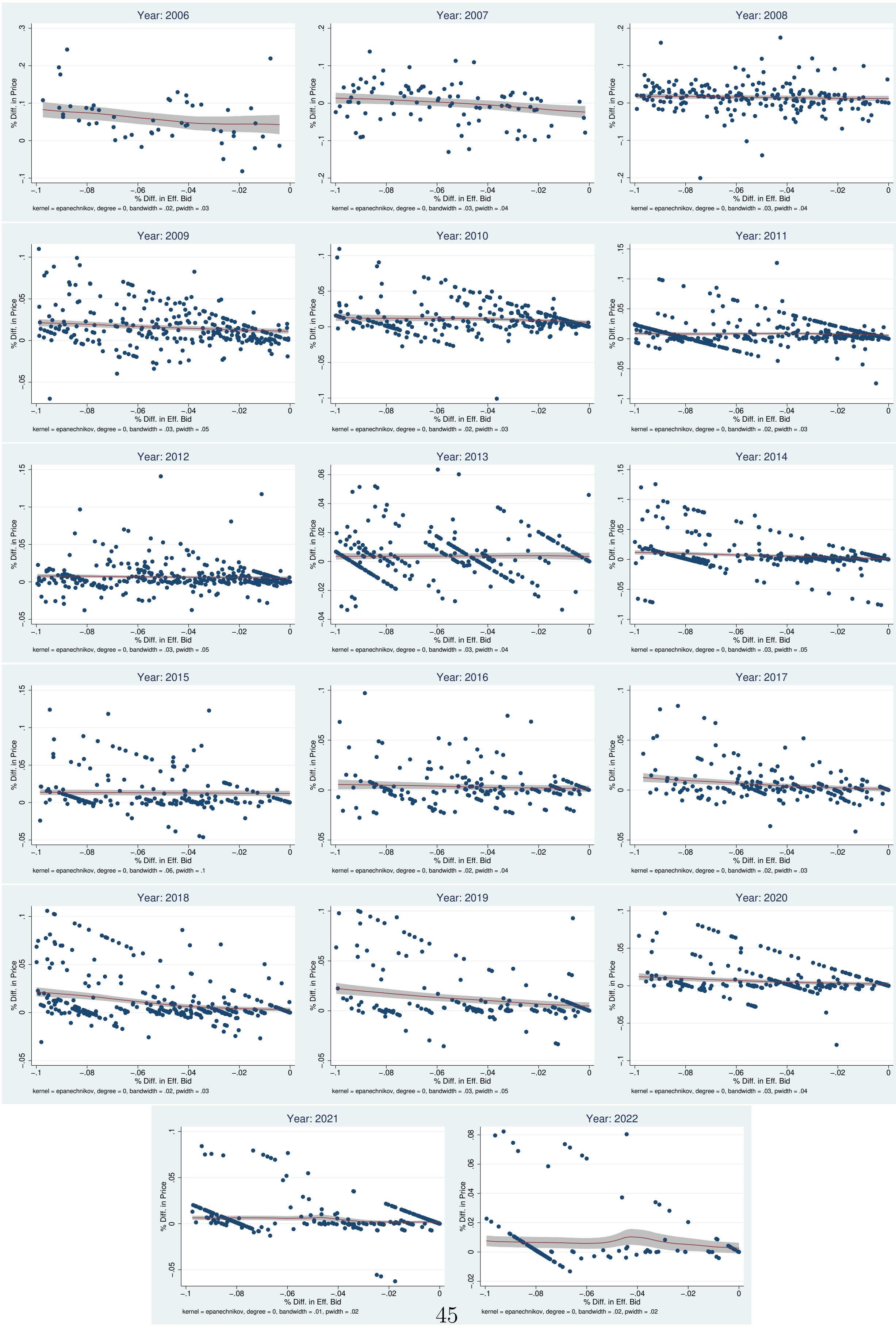
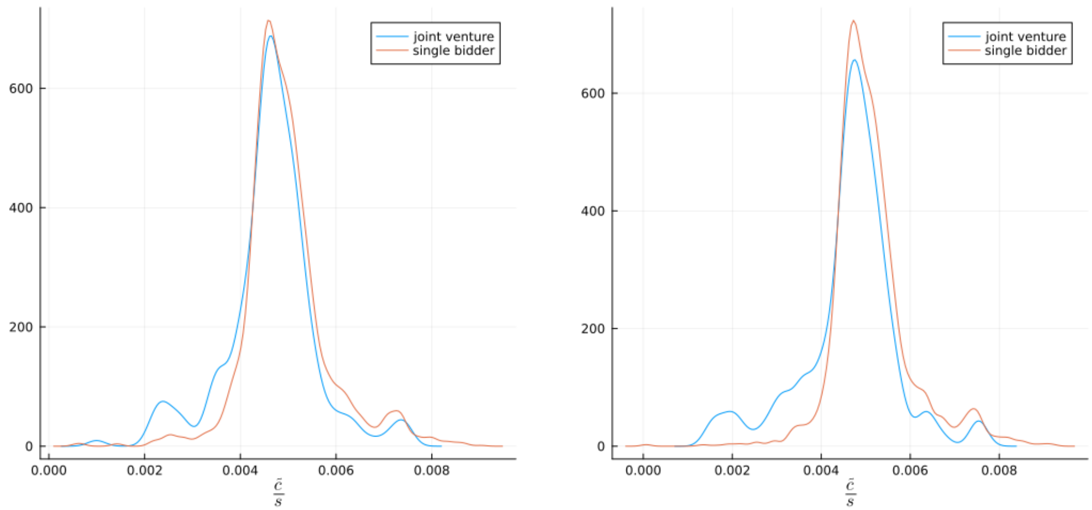


Figure A2. Year-by-Year Collusion Screening Tests by Kawai and Nakabayashi (2022)

Appendix A.2 Estimates of the density of cost-score ratio

Figure A3 shows the estimation results when we use the polynomials with degree 2. Basically, we see the same pattern as in the case of degree 1.



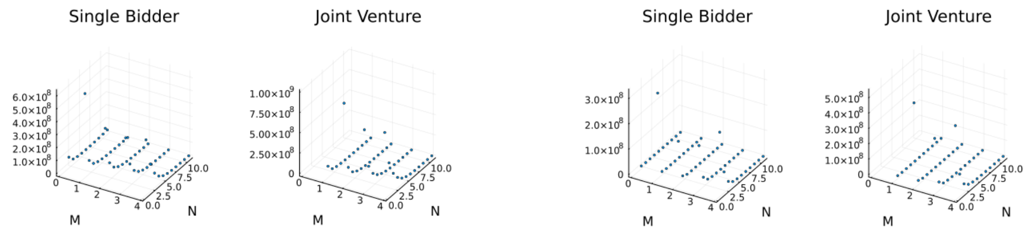
(a) Homoskedasticity case (b) Type dependent variance case

Figure A3. Density estimations of $\frac{\tilde{c}_i}{s_i}$.

Notes: We focus on the entrants in the auctions in which at least one joint venture participate. Blue line represents the density for joint venture and red line represents the density for single bidder. Panel (a) is the result when we assume homoskedastic variances. Panel (b) is the result when we use type-dependent variance estimations.

Appendix A.3 Ex-ante expected payoff

Figure A4 shows the ex-ante expected payoffs for each class of auctions. The results here are obtained when assuming the polynomial of degree 1.



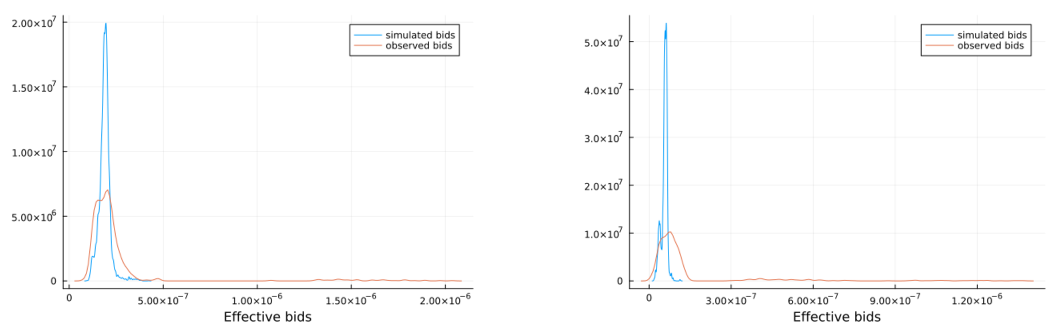
(a) Smaller size (b) Larger size

Figure A4. Estimates of the ex-ante expected payoffs.

Notes: For each category of auctions, we compute the expected payoffs by entering the auction for a single bidder and a joint venture given the number of entering single bidders and joint ventures.

Appendix A.4 Model fit

Here we compare the simulated optimal effective bids with the observed effective bids. Figure A5 shows the comparison results for all the classes of auctions.



(a) Smaller size (b) Larger size

Figure A5. Comparison of the observed bids with the computed optimal bids.

Notes: For each category of auctions, the blue line represents the estimated density function of computed optimal effective bids solving the profit maximization problem and the orange line is the estimated density of the observed effective bids.

Appendix B Proofs

Appendix B.1 Uniqueness of the equilibrium in the second stage

Here, we discuss the existence and the uniqueness of the equilibrium in this auction according to the argument of Lebrun (1999), which argues the existence and the uniqueness of the Bayesian Nash equilibrium in the first price asymmetric auction. Though our model are different from its setting in several aspects, we can still apply the similar argument to prove the existence and uniqueness of the equilibrium.

Now, assume that there is an equilibrium in this game and the bidding strategy is decreasing in $\frac{\tilde{c}_i}{s_i}$. This means that when the firm faces a higher cost or the score is lower, i.e., the firm is more competitive, the firm submits lower effective bids. If the bidding strategy is increasing in $\frac{\tilde{c}_i}{s_i}$, the reverse is true; then each entrant has an incentive to deviate to submitting more competitive bids. Hence it is not restrictive that we assume the bidding strategy is decreasing in $\frac{\tilde{c}_i}{s_i}$. Under an equilibrium, the problem (1) is transformed into the following:

$$\max_{B} \left(1-\tilde{G}^{S}\left(B_{S}^{\star,-1}\left(B\right)\right)\right)^{N-1}\left(1-\tilde{G}^{JV}\left(B_{JV}^{\star,-1}\left(B\right)\right)\right)^{M}\left(\frac{s_i}{B}-\tilde{c}_i p\right).$$

Here, we use the fact that $B_S^{\star}\left(\cdot\right)$ and $B_{JV}^{\star}\left(\cdot\right)$ are decreasing. We have an analogous problem for a joint venture. By taking the first order conditions for both types and solving the system of differential equations, we have the following two differential equations:

$$\begin{cases} \frac{d}{dB}B_{JV}^{\star,-1}(B) = \frac{1}{N+M-1}\frac{1-\tilde{G}^{JV}\left(B_{JV}^{\star,-1}(B)\right)}{\tilde{g}^{JV}\left(B_{JV}^{\star,-1}(B)\right)}\frac{1}{B}\frac{1}{B_{JV}^{\star,-1}(B)Bp-1}, \\ \frac{d}{dB}B_{S}^{\star,-1}(B) = \frac{1}{N+M-1}\frac{1-\tilde{G}^{S}\left(B_{S}^{\star,-1}(B)\right)}{\tilde{g}^{S}\left(B_{S}^{\star,-1}(B)\right)}\frac{1}{B}\frac{1}{B_{S}^{\star,-1}(B)Bp-1}. \end{cases}$$

Note that the right hand side is continuous in B over $[0, \frac{s_i}{\tilde{c}_i p}]$ for each i in both equations. We assume that the right hand side is Lipschitz continuous w.r.t. $B_{JV}^{\star,-1}(B)$ in the first equation and $B_{S}^{\star,-1}(B)$ in the second equation.

Assumption 5. *$\frac{1-\tilde{G}^{JV}(\alpha)}{\tilde{g}^{JV}(\alpha)}\frac{1}{\alpha Bp-1}$ and $\frac{1-\tilde{G}^{S}(\alpha)}{\tilde{g}^{S}(\alpha)}\frac{1}{\alpha Bp-1}$ are Lipschitz continuous w.r.t. α.*

Then there is a solution to the differential equation of each type and that is unique given an initial condition. This implies that the equilibrium of this auction is unique up to the initial condition if there is at least one equilibrium. Note that no firm bids the bid bigger than the cost: for every entrant i, we have $b_i > \tilde{c}_i p \;\Leftrightarrow\; \frac{\tilde{c}_i}{s_i} p B_i - 1 < 0$. This implies that $\frac{d}{dB} B_{JV}^{\star,-1}(B)$ and $\frac{d}{dB} B_S^{\star,-1}(B)$ are negative, which does not contradict with our assumption as $B_{JV}^{\star}(\cdot)$ and $B_S^{\star}(\cdot)$ are decreasing.

Appendix B.2 Uniqueness of the equilibrium in the first stage

We define the domain of the prediction vector attached with the intention: Δ^{3K} which is the simplex over the entry patterns for each its own entry result. The full prediction vector, P, is the stack of the prediction vectors attached with every intention and so its domain is $\mathcal{D} \equiv \Delta^{3K} \times \Delta^{3K} \times \Delta^{3K}$. $\mathcal{D}$ is a compact set in $\mathbb{R}^{9K}$. We define a function $\Psi : \mathcal{D} \to \mathcal{D}$ as follows:

$$\Psi(P) \equiv RQ(m(E(P))).$$

$E(P)$ is a three dimensional vector containing the expected ex ante payoffs obtained in the second stage auction: i.e., $E(P) = \left(v_{JV}^{P^{JV}}, v_S^{P^S}, v_N(P^N)\right)$. We redefine $m(E(P))$ is the two dimensional vector which includes the probability of choosing JV and S as intention. We omit the third elements because that should be on a simplex.

What we show is Ψ is a contraction mapping. Then, by Banach fixed point theorem, we know that the prediction vector satisfying the equilibrium condition is unique: in other words, there is a unique $P^\star$ such that $P^\star = \Psi(P^\star)$. For Ψ to be a contraction mapping, it is sufficient to argue that (1) Ψ has continuous partial derivative and (2) the matrix norm of its Jacobian is bounded above by 1. In our model, the mapping Q, m and E are all differentiable and so the first point is satisfied. So the remaining task is to show the second point.

We consider $L1$ matrix norm which is defined as follows: for a matrix $A \in \mathbb{R}^{n \times n}$,

$$\|A\|_1 \equiv \sup_{x \neq 0} \frac{\|Ax\|_1}{\|x\|_1}.$$

It is well known that $\|A\|_1$ is computes as follows:

$$\|A\|_1 = \max_{1 \leq j \leq n} \sum_{i=1}^{n} |a_{ij}| .$$

Using this norm we evaluate the Jacobian of Ψ.

First, we have the following decomposition of the Jacobian of Ψ:

$$\nabla_P \Psi(P) = R \nabla_m Q(m) \nabla_E m(E) \nabla_P E(P)$$

Because we assume that Q is the probability vector generated by a multinomial distribution, $\nabla_m Q(m)$ is computed as follows:

$$\nabla_m Q(m(P)) = n \left(\tilde{Q}^{JV} - \tilde{Q}^{N}; \tilde{Q}^{S} - \tilde{Q}^{N} \right),$$

where for every $I \in \{JV, S, N\}$, $\tilde{Q}^I$ is the distribution over the intention patterns when the total number of potential entrants is less than the current situation by one. Note that its support is still set to all the intention patterns of the original number of potential entrants. These three distributions are different only in the location of non zero entries. Second, based on the Logit choice probabilities, we have the following:

$$\nabla_E m(E(P)) = \begin{pmatrix} m(JV)(1 - m(JV)) & -m(JV)m(S) & -m(JV)m(N) \\ -m(S)m(JV) & -m(S)(1 - m(S)) & m(S)m(N) \end{pmatrix}. \quad (9)$$

Lastly,

$$\nabla_P E(P) = U$$

where the first row of U contains all the expected payoffs in the second stage auction for every entry patterns when the firm chooses JV as its intention, and the second and third rows are set in a similar manner.

Then, we evaluate the norm of the Jacobian. We define the maximum element in U by

$\bar{u}$.

$$
\begin{aligned}
\|\nabla_P \Psi(P)\|_1 &= \|R \nabla_m Q(m) \nabla_E m(E) \nabla_P E(P)\|_1 \\
&\leq \|R\|_1 \|\nabla_m Q(m)\|_1 \|\nabla_E m(E)\|_1 \|\nabla_P E(P)\|_1 \\
&= 1 \times n \|\tilde{Q}^{JV} - \tilde{Q}^N; \tilde{Q}^S - \tilde{Q}^N\|_1 \times \|\nabla_E m(E)\|_1 \times \|U\|_1 \\
&< 1 \times 2n \times \frac{1}{2} \times \bar{u} \\
&= n\bar{u}.
\end{aligned}
$$

For the fourth line we first bound $\|\tilde{Q}^{JV} - \tilde{Q}^N; \tilde{Q}^S - \tilde{Q}^N\|_1$. Because $\tilde{Q}^{JV}$, $\tilde{Q}^S$ and $\tilde{Q}^N$ are probability distribution and the sum of its elements is equal to 1, from the triangle inequality, we have $\|\tilde{Q}^{JV} - \tilde{Q}^N; \tilde{Q}^S - \tilde{Q}^N\|_1 < 2$. Then, we compute the upper bound of $\|\nabla_E m(E)\|_1$. From (9), the upper bound of the matrix norm is obtained as

$$
\max\{m(JV)(1 - m(JV) + m(S)),\ m(S)(1 - m(S) + m(JV)),\ m(N)(1 - m(N))\}.
$$

Under the constraint that $m(JV) + m(S) + m(N) = 1$ and $0 < m(JV), m(S), m(N) < 1$, by solving the constrained maximization problem, we can show that

$$
m(JV)(1 - m(JV) + m(S)) < \frac{1}{2},\ m(S)(1 - m(S) + m(JV)) < \frac{1}{2},\ m(N)(1 - m(N)) < \frac{1}{4}.
$$

Then we know that

$$
\|\nabla_E m(E)\|_1 < \frac{1}{2}.
$$

Hence, by normalizing the scale of the expected payoffs in the second stage auction so that $n\bar{u} < 1$, Ψ is a contraction mapping on $\mathcal{D}$ and by Banach fixed point theorem the equilibrium of our system uniquely exists.