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WHEN CAN WE INCREASE COMPETITION IN PUBLIC PROCUREMENT?

POTENTIAL BIDDERS AND A FRAMEWORK FOR PROCUREMENT PERFORMANCE

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When Can We Increase Competition in Public Procurement? Potential Bidders and a Framework for Procurement Performance*

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Abstract

Low participation in public procurement auctions may reflect either weak procurement practices or a genuinely limited pool of potential suppliers. Distinguishing between these explanations requires credible estimates of potential competition. This paper develops and compares three approaches to identifying potential bidders: firms that register in tenders, machine-learning predictions of bidding probabilities, and a novel algorithm based on similarities in previous procurement activity of firms. Using comprehensive data from Finnish procurement auctions, we quantify the level of potential competition for each procurement and develop a framework to examine how well the market potential is attained. In general, more than 40% of auctions attract too few bidders relative to their market potential, indicating that a large share of potential competition remains unrealized. Moreover, there is considerable heterogeneity in performance across procurers. We show that longer bid preparation periods and the use of lot division are associated with significantly higher realized competition, consistent with procurement design playing an important role in mobilizing potential bidders.

Keywords: Public procurement, Competition, Potential bidders, Market entry, Procurement performance

JEL: C51, C53, D44, H57

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1 Introduction

Increasing competition in public procurement is a central policy objective in the European Union (European Court of Auditors, 2023). However, low participation in procurement auctions may reflect either weak procurement policy or a genuinely limited pool of potential suppliers. Without credible estimates of potential competition, policymakers cannot distinguish between markets where additional entry is feasible and those that are structurally constrained. This distinction is crucial, as attracting additional bidders can substantially reduce procurement costs (Titl, 2025).

Information on potential bidders is valuable for procurers, policy makers, and researchers each. Procurers can use such information when designing tenders, for example, to reach out to firms that are likely interested of bidding. Policy makers need to understand where and how to best improve procurement outcomes. In research, measures of potential competition are often used to model and estimate firms' entry decisions. Despite its importance, there is limited research that directly estimates the magnitude of potential competition in public procurement markets.

In this paper, we analyse the extent of potential competition in public procurement by developing and implementing multiple methodological approaches to identify and quantify the number of potential bidders in procurement auctions. Particular attention is devoted to procurement contracts that attract only a small number of actual bidders. Furthermore, we assess the performance of individual procuring entities and examine how their various practices are associated with the degree of realised competition, measured as the ratio of actual bidders to potential bidders.

We implement three complementary approaches. First, we exploit information on firms that either formally register or otherwise indicate interest in a tender, which serves as a proxy for potential competition employed in the literature (e.g., Krasnokutskaya and Seim (2011), Jääskeläinen et al. (2026)). Second, we estimate firms' bidding probabilities using a machine learning model (random forest), which enables us to construct a predicted set of potential bidders as a function of observable firm- and contract-level characteristics. Although conceptually related methods have been applied in more restricted environments (García Rodríguez et al. (2020)), the richness and coverage of our data permit a considerably more comprehensive, market-wide analysis. Third, we propose a novel and simple algorithm to identify potential bidders based on observable similarities in firms' historical procurement activity. The transparency and computational tractability of this procedure make it particularly well suited for operational use by procurement authorities, for example, in pre-tender market consultations.

These methods confirms and quantifies the existence of many additional firms that could participate in procurement auctions. This market potential varies across geographic areas and industries, but in almost all settings, there appears to be scope to attract additional competition to procurement auctions.

The two algorithms differ in their strengths and limitations. The random-forest model predicts observed participation well, but it also assigns high bidding probabilities to many firms that ultimately do not bid. This feature inflates the implied number of potential bidders, especially in urban areas. By contrast, our algorithm is more anchored in firm-level bidding probabilities estimated from the data. As a result, it avoids implausibly high measures of potential competition in cities, but it may understate potential competition in Eastern and Northern Finland, where firms are geographically more distant from their typical core markets.

Whereas the estimates derived from both the random forest algorithm and, in particular, from the number of registered firms, serve mainly as proxies for the overall pool of potential bidders, our algorithm infers the number of likely potential bidders based on firm-specific bidding probabilities. This approach produces an estimate of the number of bidders that is arguably more realistic in terms of actual participation. Thus, we use this measure in the subsequent analysis of procurement performance.

Using the estimates for potential competition, we develop a framework to assess the extent to which potential competition is realized in procurements. The framework (i) identifies tenders with substantial unrealized market potential, (ii) distinguishes them from highly concentrated markets, and (iii) separates both from procurements that already attract so many bidders that additional entry is likely constrained by entry costs. Applying this framework, we find that 42% of ITTs attract only a few actual bidders despite having several potential bidders, which implies huge potential savings if this market potential could be realized. These ITTs are not concentrated in a narrow set of industries; rather, they broadly mirror the overall distribution of procurement contracts, with particularly large improvement potential in construction and IT services.

We also document substantial heterogeneity in performance across Finnish procurement units. While the performance of large cities is broadly comparable, other procurer types exhibit markedly different outcomes, as measured by their ability to attain the available market potential. We link these differences to procurement practices and show that several characteristics under procurers' control are associated with a higher probability that an ITT attracts only a few bidders even when more market potential is available.

Our results indicate that longer bid preparation periods and the division of tenders into multiple lots are both positively associated with the realized degree of competition. Furthermore, advance market notification of forthcoming procurement procedures and the use of standard, industry-typical selection criteria appear to be linked to an increase in the number of participating bidders. Overall, the results highlight considerable scope for efficiency gains in public procurement and suggest large returns to investments in procurement professionalism.

1.1 Literature

The number of potential bidders plays a central role in auction theory, as it shapes bidders' strategic behaviour and expected outcomes (e.g. Milgrom, 2004). However, in empirical public procurement research, measuring market potential remains a challenge. As a result, potential competition is often proxied indirectly, and systematic evidence on its magnitude is limited.

A common approach identifies potential bidders as firms that have expressed interest in a contract, for example, by acquiring project documentation (Li and Zheng, 2009; Krasnokutskaya and Seim, 2011) or by accessing tender materials in digital procurement systems (Jääskeläinen et al., 2026). More recent contributions use broader definitions, such as all previous winners within a product category (Best et al., 2023) or all suppliers of a given product in narrower institutional settings (Bucciol et al., 2020). These approaches move closer to measuring the underlying pool of feasible entrants, but it remains unclear how accurately they capture the true set of firms capable of bidding. At least, they limit the possible analysis to narrower settings and may omit other relevant dimensions, such as local market conditions, that may impact the market potential.

Our paper contributes to this literature by systematically comparing multiple methods for identifying potential bidders within a unified empirical framework. By quantifying and contrasting these measures across markets and institutional settings, we provide new evidence on the size and structure of potential competition in public procurement. In addition, our algorithm produces a method of estimating the number of likely potential bidders for each procurement auction, something that has been lacking the literature in the past.

More broadly, this paper relates to the growing literature examining the performance of procurement units. Our methodologies for estimating the level of potential competition can be used to examine the efficiency and professionalism of procurers. A procurer achieving only two bids on average is often considered a poor performer, but if the amount of potential competition is also low this might be a wrong conclusion. This measure has not been extensively used in the earlier literature. Instead, the literature has focused on using price variation between procurement units to measure their performance. Best et al. (2023) show that almost 40% of the price variation of standardized goods procured in Russia can be explained by behavior of individual bureaucrats and procurement units. Similarly, other studies have examined the differences between paid prices in other narrow markets, namely medical devices (Bucciol et al., 2020; Grennan and Swanson, 2020). More qualified procurement units and officials have also been shown to be able to improve non-price outcomes, such as reducing time delays, cost overruns (Decarolis et al., 2020), and speeding up the tender awarding process (Baltrunaite et al., 2023). Our methodologies provide new ways of identifying procurements with low levels of attained competition and those procurement units that exhibit worse procurement outcomes in general. It also allows examining inefficiencies in procurement processes and in which situations more competition could most easily be attained, requiring the least amount of additional resources.

We also contribute to the literature on machine learning estimation approaches in the context of public procurement. In the computer science literature, different machine learning methods are applied to various prediction problems related to public procurement, including predicting contract award prices (e.g. Chou et al., 2015; García Rodríguez et al., 2019), bidder participation (e.g. Ballesteros-Pérez et al., 2016; Oo et al., 2025), and making bidder recommendations (García Rodríguez et al., 2020). Machine learning methods are also used in collusion detection (Huber and Imhof, 2019). We extend this body of research toward its economic counterpart by applying and assessing methodological approaches developed in the computer science literature, thereby facilitating their dissemination and adoption within economics. Concurrently, by employing our algorithm, we introduce a novel predictive framework for public procurement outcomes, in particular by constructing an algorithmic tool capable of identifying potential bidders. Whereas the existing literature has primarily concentrated on construction contracts, we generalize the analysis to a substantially broader class of procurement contracts.

The rest of the paper is structured as follows. Section 2 describes the institutional setting and the data. Section 3 outlines the methodologies used to estimate potential competition. Section 4 presents the estimation results and evaluates the performance of the alternative methodologies. Section 5 introduces our framework for assessing the scope to increase competition in procurement auctions and examines heterogeneity in performance across procurement units. Section 6 concludes.

2 Institutional Setting and Data

Public procurement in Finland is based on the Act on Public Procurement and Concession Contracts (1397/2016), which implements the EU Procurement Directive 2014/24/EU. The legislation applies to contracting authorities such as state and municipal authorities, public enterprises, and other publicly controlled entities.

Under the law, contracts exceeding predetermined EU threshold values must be awarded through formal procurement procedures. The regulation also sets requirements for procurements below the EU thresholds through national rules.

When a contracting authority plans a purchase exceeding the relevant threshold, it must publish a contract notice and an Invitation to Tender (ITT) on the national electronic procurement portal Hilma. The ITT specifies the object of procurement, participation requirements, the award criteria, and the timeline of the procedure, ensuring equal access to information for potential bidders. Contracts exceeding EU thresholds must additionally be published in the EU-wide procurement portal TED (Tenders Electronic Daily).

2.1 Data

We use data from procurement software run by Cloudia Oy, containing 87,330 procurement ITTs from January 2017 to May 2025. This data set covers between 40 and 75 percent of Finnish procurement ITTs, the coverage increasing over the years. The data includes multiple characteristics regarding ITTs, such as their expected cost, procurer unit, possible secondary objectives used, selection criteria used, and also detailed descriptions of the procurement. These detailed procurement descriptions are also used to determine the more accurate location for the procurement than the location of the procurement unit.

The data also contains bids and bid prices from those firms that have bid in the procurement auctions. Finnish firm register data from Statistics Finland and

ALMA Talent are merged to include bidder characteristics such as their revenue and number of employees.

These data are merged with the data from national procurement notice board HILMA, containing all the tender notices in Finland. This allows as to include additional characteristics to our analysis, such as better information about the used selection criteria and expected cost, as well as whether the tender is divided into multiple lots or not.

In addition, we use purchase invoice data from over 300 public organizations, including more than 180 municipalities. This data includes all the purchase recipes from these organizations, including all minor purchases from local grocery stores to huge construction projects.

Because cpv codes are often specified quite loosely by the procurement units, the industry of each ITT is determined using industries (5-digit TOL08 industry codes) of the actual bidders participating in the auction. Due to a large number of possible industries, some ITTs end up having very rare industries. This is problematic as the set of theoretically possible bidders in both algorithmic approaches depends on the determined industry of the auction. All industries with ten or fewer ITTs are dropped from the sample. Framework agreements and tender under dynamic purchasing systems (DPS) are also excluded from the sample as their entry dynamics may be different. Thus, the main sample includes 45,913 standard open procedure ITTs.

2.2 Registrations as a proxy for potential bidder

The main dataset from Cloudia Oy contains information on the number of firms that have opened a tender notice. This variable is commonly used in the procurement literature as a proxy for potential bidders. In particular, studies of procurement auctions in the United States often measure potential competition using the number of firms that obtain tender documentation (Krasnokutskaya and Seim, 2011). In the

Finnish context, firms do not need to formally request the tender documentation; instead, they can access the relevant information directly by opening the tender notice in the Cloudia procurement platform. We therefore use the number of firms that open the notice as a benchmark proxy for the pool of potential bidders in a procurement auction.

This proxy is imperfect. Opening a tender notice requires little effort, and firms that ultimately have no realistic intention or capability to bid may still access the information. For instance, firms outside the relevant industry may open notices to evaluate potential business opportunities. Consequently, the measure may overstate the number of genuinely potential bidders. Until August 2022, the data identify the specific firms that opened each notice but did not submit a bid. After this date, the dataset only reports the total number of registrations, without firm identifiers. Because the econometrician cannot reliably distinguish between firms that are plausible bidders and those that are not, we treat all registrations as potential bidders.

Registrations by other contracting authorities pose a related issue. Public procurement units may open notices for informational purposes, for example, when designing their own procurements, yet they are typically not potential bidders. These observations are easier to identify and exclude prior to August 2022. In the pre-August-2022 data, registrations by other procurement units account for approximately 20 percent of all registrations and remain relatively stable over time. For tenders after August 2022, when such observations cannot be separately identified, we therefore assume that 80 percent of total registrations correspond to firms.

At the same time, the measure may understate potential competition. Some firms that could plausibly bid may not observe a procurement opportunity if they are not registered on the platform or do not monitor it actively. As a result, the proxy is subject to both upward bias (from non-potential registrants) and downward bias (from unobserved potential firms). The net bias is therefore ambiguous and likely varies across industries and procurement types. Nevertheless, the number of registrations provides a useful approximation of the potential bidder pool, as it reflects the set of firms that at least became aware of the tender, while abstracting from additional participation constraints such as capacity limitations, transport costs, or other barriers that may prevent firms from bidding in every feasible procurement auction.

3 Methodology

To complement existing approaches that proxy potential competition using tender registrations or identify potential bidders within narrowly defined markets, we implement two additional methodologies to estimate the number of likely potential bidders in Finnish procurement auctions.

The first approach uses a machine-learning method, a random forest classifier, to estimate firm-level participation probabilities. Random forest algorithms have been applied in the computer science and engineering literature on public procurement to predict award prices (García Rodríguez et al., 2019), winning firms (García Rodríguez et al., 2019), and the number of bidders (Oo et al., 2025). In the economics literature on procurement, machine-learning methods have been used more sparingly, mainly to identify important predictors for subsequent econometric analysis (Kim and Jung, 2019).

The second approach is a transparent algorithm designed around key economic mechanisms governing firms' participation decisions, particularly geographical frictions and industry structure. This algorithm provides an interpretable benchmark that complements the data-driven predictions of the random forest model.

3.1 Random forest approach

In the first method, we estimate the probability that firm k participates in procurement auction l using a random forest classifier. The model is trained on observed firm–procurement pairs where the outcome variable is a bid indicator equal to one if the firm submits a bid and zero otherwise.

The estimation sample consists of the universe of observed bids as well as a broad set of theoretically feasible firm–procurement combinations. The latter includes all firms that have either previously submitted bids in public procurement or sold goods or services to public entities in the purchase invoice data within the relevant industry. Firms are excluded only if they were not yet established at the time of the procurement or had exited the market prior to it.

The data are randomly divided into a training sample (80 percent) and a testing sample (20 percent). A random forest classifier constructs a large number of decision trees using bootstrap samples of the training data and random subsets of explanatory variables at each split. Predictions are aggregated across trees using majority voting, which improves predictive accuracy and reduces overfitting relative to a single decision tree (Breiman, 2001). After training the model, predicted bidding probabilities are generated for all firm–procurement pairs.

The explanatory variables capture observable firm characteristics, past bidding behavior, industry characteristics, and geographical factors. Firm size is proxied by revenue, together with an indicator for missing revenue information. Past bidding behavior is captured by the share of a firm's historical bids within the industry of the procurement auction, which measures how typical it is for the firm to participate in that industry.

Geographical frictions are incorporated using several variables. First, industries are classified as either local or national. In local industries, firms typically participate in procurements close to their home markets due to transport or service-delivery costs. In contrast, firms in national industries can compete across the country with little geographical constraint. Industries are classified as national when the mean of the maximum observed bidding or delivery distances of firms exceeds 400 kilometers. Industries such as management consulting, IT services, and certain wholesale sectors fall into this category.

Second, the geographical location of each procurement is identified from procurement descriptions. For each firm k, the firm's main geographical market m_k is defined as the municipality in which the firm has participated in the largest number of procurement auctions. The road distance between the procurement location and the firm's main market is included as an input variable in the algorithm.

Finally, local market exposure is captured using municipality-level measures of firms' historical participation. Local geographical market from each municipality is defined as municipalities within a 30 minute driving distance from the center of each municipality. Local market exposure measures include indicators for whether the firm has previously bid in procurements in the municipality or sold in the area, as well as the firm's bid share in that area. Indicators for different Finnish regions are also included.

3.2 Algorithmic approach

As a complementary methodology, we construct a transparent algorithm that estimates the number of likely potential bidders based on firms' observed participation patterns and economically motivated assumptions about geographical market frictions.

The approach first computes firm-specific participation probabilities at the local geographical market level. Local geographical market in each municipality is defined to include all other municipalities within a 30 minute driving distance as such distance is assumed to have a negligible effect on supplier costs. For each firm k and municipality i, the baseline probability of participation is defined as

$$p_{k,i} = \frac{a_{k,i}}{A_{k,i}}, \tag{1}$$

where $a_{k,i}$ denotes the number of procurement auctions in municipality i's local market in which firm k has submitted a bid and $A_{k,i}$ denotes the number of procurement auctions in that local market in which the firm could plausibly have participated. Potential auctions are identified by observing procurements in which competing firms have submitted bids.

This measure captures participation probabilities in local geographical markets where the firm has previously been active. However, firms may also participate in procurements in areas where they have not previously bid. Such cases may arise due to frictions in procurement processes, including limited publicity of invitations to tender or temporary capacity constraints on the firm's side. To account for these cases, we allow participation probabilities to decline with geographical distance from the firm's main market.

For each firm k, the main geographical market m_k is defined as the municipality in which the firm has submitted the largest number of bids. The definition is the same as the one used in the random forest approach. The geographical distribution of these main markets is shown in Figure B.1 in the Appendix. Participation probabilities in other municipalities are assumed to decrease with road distance from this main market and its participation probability according to a Kaplan–Meier survival function:

$$p_{k,i} \cdot S(d_{i,m_k}) = p_{k,i} \left(1 - F(d_{i,m_k})\right), \tag{2}$$

where d_{i,m_k} is the road distance between municipality i and the firm's main market m_k, and $F(d_{i,m_k})$ denotes the cumulative distribution function of the distances at which firm k has previously participated in procurement auctions. The survival function equals zero beyond the maximum observed participation distance, reflecting the assumption that firms are unlikely to bid beyond their historical geographical reach. The participation probabilities in municipalities where the firm has not previously bid are interpolated from this survival function. Figure 1 illustrated non-scaled examples of survival functions for some firms in the data.

For industries classified as national, geographical frictions are assumed to be negligible. In these industries, participation probabilities are estimated at the national level:

$$p_{k,\text{nat}} = \frac{a_{k,\text{nat}}}{A_{k,\text{nat}}}, \tag{3}$$

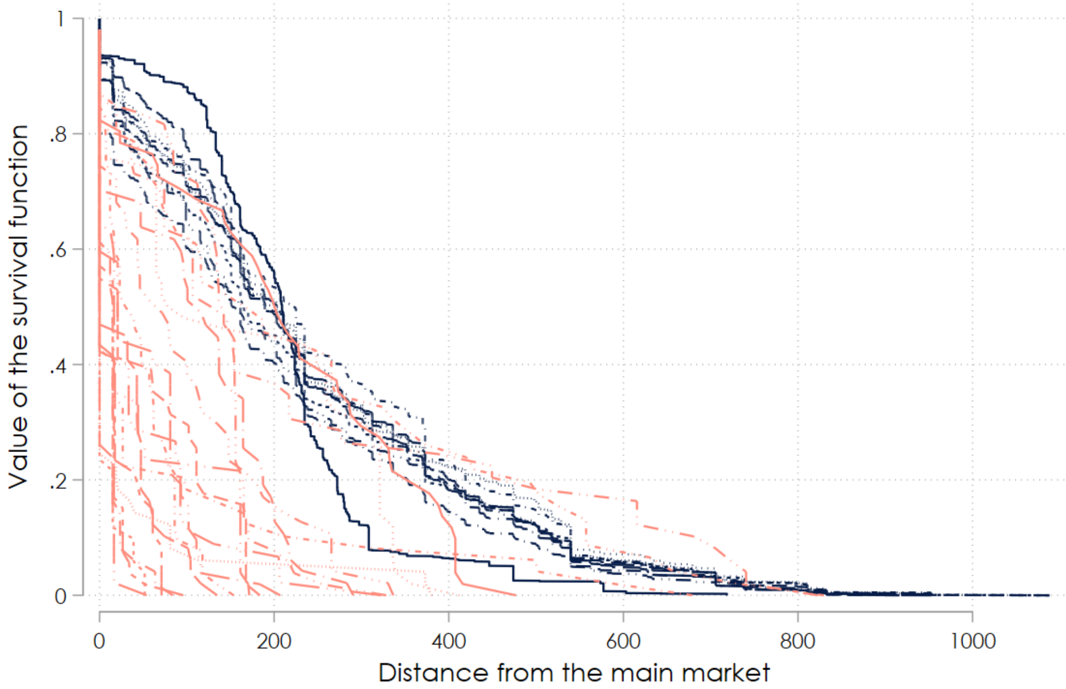


Figure 1: Examples of survival functions for larger (blue) and smaller firms (red). In the figure, survival functions are not scaled with the main market probability.

where $a_{k,\text{nat}}$ and $A_{k,\text{nat}}$ denote the number of procurement auctions in which firm k has submitted a bid and the number of potential procurement auctions nationwide, respectively.

For each firm-municipality pair, we consider three participation probabilities: the local geographical market -specific probability $p_{k,i}$, the distance-adjusted probability $p_{k,m_k} S(d_{i,m_k})$, and the national probability $p_{k,\text{nat}}$. The participation probability used in the estimation is defined as the maximum of these three values.

Finally, for each procurement auction l, the estimated number of *likely potential bidders* in municipality i and industry j is then defined as

$$N_a = \mathcal{N}_{ij} = \sum_{k \in \mathcal{K}_{ij}} \max \left\{ p_{k,m_k} S(d_{i,m_k}),\ p_{k,i},\ p_{k,\text{nat}} \right\}. \tag{4}$$

For industries classified as local, the national participation probability $p_{k,\text{nat}}$ is set to zero.

4 Estimating potential competition

In this section, we estimate the level of potential competition using the three methods introduced above and assess their suitability for approximating the number of likely bidders in procurement auctions.

Because the true number of potential bidders is unobserved, model performance cannot be evaluated directly. Instead, we assess the models along three dimensions. First, we examine whether their estimates are consistent with theoretical predictions regarding the determinants of market participation. Second, we test whether the estimates are orthogonal to variables that should, in principle, not affect the size of the potential bidder pool. Third, we evaluate whether the implied bidding probabilities are economically meaningful and exhibit plausible statistical properties.

Potential competition is conceptualized as the set of firms that could plausibly submit a bid, and is therefore expected to be relatively stable over time and invariant to procedural features of the procurement process. Such features may influence realized participation but do not alter the underlying pool of feasible bidders.[1]

For this reason, we interpret potential competition as a distribution governing participation, rather than a fixed quantity. The realised number of bidders can, therefore, exceed or fall short of the estimated number of potential bidders in any given procurement.

Figure 2 presents the distributions of estimated potential competition across procurement auctions. The distribution based on the number of registered firms is more right-skewed and concentrated at higher values than those produced by the algorithmic methods. At the same time, the algorithmic approaches, particularly the random forest, more frequently generate very high estimates for a subset of ten-

[1]For example, both observed and unobserved factors—such as timing, market conditions, and temporary capacity constraints—affect the number of actual bidders in any given auction.

ders. By contrast, the estimates produced by our algorithm are more concentrated at lower values relative to the alternative methods.

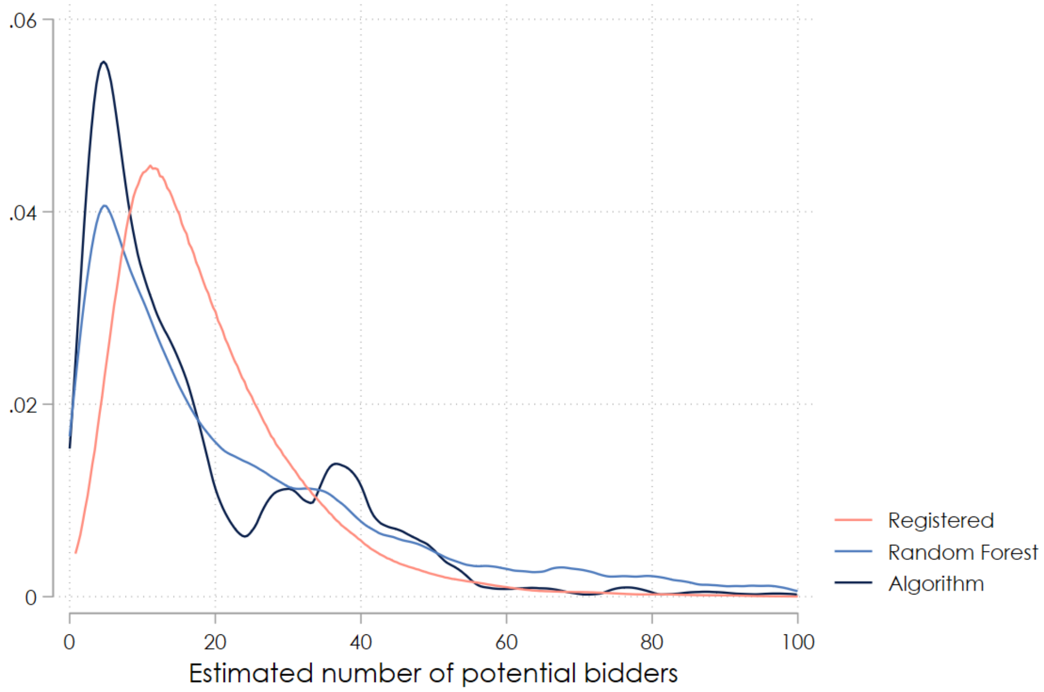


Figure 2: Distributions of the estimated number of potential bidders from different methodologies.

The aggregate estimates of potential competition are reported in Table 1. The first column denotes the number of registered firms (N_d). On average, slightly more than 19 firms register to access the tender documents. This figure is lower for procurements of products (approximately 14 firms) and higher for construction and service contracts, both of which exceed 20 registered firms on average.

The second column reports the estimates obtained from the random forest model (N_{rf}), which imply substantially larger bidder pools. On average, the random forest predicts approximately 14 more potential bidders than suggested by the number of registered firms, with differences of similar magnitude across sectors.

The third column presents the estimates from our algorithm (N_a). These are, on average, close to the number of registered firms, yielding approximately 21 potential bidders. Sectoral patterns are also similar: the estimated number of potential bidders is around 23 in construction, slightly below 20 in procurement of products, and just above 20 in services. The final column reports the realized number of bidders.

Table 1: The estimated number of potential bidders according to the different methods depending on the sector of the contract.

	N_d	N_{rf}	N_a	n
All ITTs	19.42	33.48	21.10	4.50
Construction	22.50	37.65	23.12	4.48
Products	14.08	28.86	19.59	3.35
Services	20.37	33.06	20.43	5.27

Since potential competition should be largely determined by structural market characteristics, its variation should primarily reflect geographical and industry-specific factors. By contrast, the procurement design choices of individual procurers should not systematically affect the size of the underlying bidder pool.

To assess whether the different measures of potential competition are consistent with these predictions, we regress each estimate on a set of procurement characteristics that are plausibly exogenous to market size, while also examining their relationship with geographical factors.

The results are reported in Table 2. Column (1) documents which characteristics are correlated with the number of registered firms. Both the timing of the procurement and the length of the bidding window are significantly associated with the number of registrations. One plausible interpretation is that shorter bidding windows or periods coinciding with holidays reduce the likelihood that potential bidders become aware of the tender or have sufficient time to respond.

Importantly, registrations do not need to reflect the true size of the underlying pool of potential bidders. Rather, they capture the subset of firms that observe the tender notice and choose to register. This group may include firms that are not credible bidders but register for informational reasons. The data are consistent with this interpretation: some registered firms operate in industries unrelated to the procured service. An example of this is infrastructure consulting firms registering for office furniture tenders. Moreover, the number of registered firms contains no information about firms' likelihood of submitting a bid.

Taken together, these findings highlight the limitations of using registrations as a proxy for potential competition. Because registrations are sensitive to procurement design features and may include firms with no realistic prospect of bidding, they provide a potentially misleading measure of underlying market potential.

The remaining columns report regression results for the algorithmic estimates of potential competition. In contrast to registrations, these estimates are driven primarily by geographical distance, with only a weak association between the length of the bidding window and the random forest–based estimate. Overall, the algorithmic measures appear largely invariant to procurement design features and therefore align more closely with the conceptual definition of potential competition.

Column (2) further shows that, in addition to distance, the population size of the municipality in which the procurement takes place is strongly associated with the random forest–based estimate of potential bidders. This relationship is illustrated more clearly in Table 3, which reports average levels of estimated potential competition by municipality size across methods. The random forest approach assigns substantially higher bidding probabilities in large municipalities, implying average potential bidder counts of approximately 45 to 65. In smaller municipalities, the corresponding estimates are considerably lower and fall below those implied by the alternative methods. This sensitivity to the size of the municipality suggests that the random forest model can overstate potential competition in large municipalities, or, equivalently, overestimate the bidding probabilities of firms in such locations.

To further investigate this, we examine the firm–tender–level bidding probability estimates in greater detail. Figure 3 presents the distributions of the estimated probabilities. For both algorithms, the distributions are heavily skewed toward

Table 2: The correlation between estimated potential number of bidders and procurement characteristics.

	(1) Registered N_d	(2) Random Forest N_{rf}	(3) Algorithm N_a
Distance to a large city	-0.014***	-0.020*	-0.026***
	(0.002)	(0.009)	(0.004)
Location population	0.002	0.083***	0.0003
	(0.001)	(0.013)	(0.005)
Bidding window	0.179***	0.054*	-0.001
	(0.037)	(0.024)	(0.003)
Summer	-2.263***	0.0508	0.099
	(0.327)	(0.733)	(0.061)
Autumn	1.425*	0.480	0.059
	(0.600)	(0.402)	(0.093)
Winter	1.247	-0.098	0.051
	(0.683)	(0.505)	(0.097)
N	45845	45697	45913
Sample mean	23.90	33.37	21.07
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Procurer type FE	Yes	Yes	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The omitted category is procurement auctions in spring. Standard errors are clustered in the broad industry (2-digit cpv code) level.

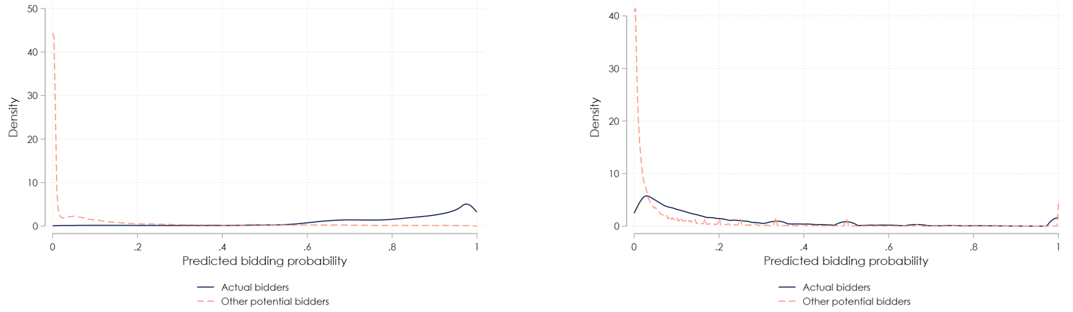
zero, indicating that most firm–tender pairs are assigned a low likelihood of bidding. However, for firms that do not submit a bid, the random forest assigns systematically higher probabilities than our proposed algorithm. The average predicted probability for non-bidders is 0.13 under the random forest, compared to 0.07 under our approach. Summary statistics are reported in Table 4.

Table 3: The estimated number of potential bidders according to the different methods depending on the location of the contract.

	N_d	N_{rf}	N_a	n
Construction ITTs				
Small municipalities	20.07	14.89	21.82	3.95
Medium-sized municipalities	22.45	25.76	23.15	4.49
Large municipalities	23.76	65.42	23.72	4.72
Product ITTs				
Small municipalities	12.89	6.14	10.81	3.69
Medium-sized municipalities	13.57	12.29	16.85	3.19
Large municipalities	14.68	46.04	23.14	3.43
Service ITTs				
Small municipalities	15.41	9.15	12.12	4.22
Medium-sized municipalities	18.58	18.69	16.18	4.95
Large municipalities	23.79	55.69	27.52	5.95

The distributions for actual bidders differ significantly across the two methods. The random forest assigns high probabilities to firms that bid, indicating strong predictive performance with respect to those who actually bid. By contrast, our algorithm produces substantially more conservative probability estimates for actual bidders, resulting in a distribution that is noticeably less concentrated at high probability values. Nevertheless, only a small fraction of actual bidders are assigned very low bidding probabilities, suggesting that the algorithm still successfully distinguishes bidders from non-bidders. On average, the predicted bidding probability for actual bidders is 0.80 under the random forest, compared to 0.21 under our algorithm.

More generally, comparing mean bidding probabilities at the tender level shows that actual bidders are assigned higher probabilities than non-bidding firms under both models. For actual bidders, the random forest yields an average estimated probability of 0.81, whereas our algorithm produces a substantially lower estimate of 0.29. For other potential bidders, the corresponding averages are 0.19 under the



(a) Random Forest, estimated probability distribution

(b) Algorithm, estimated probability distribution

Figure 3: Distributions of predicated bidding probabilities for firm-tender pairs using (a) random forest algorithm and (b) our algorithm.

Table 4: Summary table of predicted bidding probabilities.

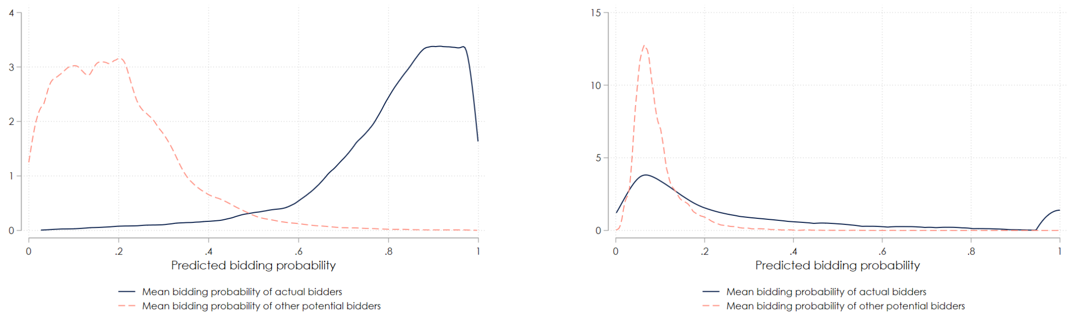
	Data	Random forest	Algorithm		
			Full sample	In-sample	Out-sample
Actual bidders	1	0.92	0.87	0.79	0.68
Bid rate, main geographical market	0.20				
Bidder level					
Mean bidding probability, bidders		0.80	0.21	0.33	0.25
Mean bidding probability, nonbidders		0.13	0.07	0.10	0.10
Tender level					
Mean bidding probability, bidders		0.81	0.29	0.42	0.30
Mean bidding probability, nonbidders		0.20	0.09	0.11	0.11
Mean difference in probabilities		0.61	0.20	0.31	0.19

random forest and 0.09 under our algorithm. These figures can be benchmarked against the observed bid rate in the main geographical markets of firms, which is approximately 0.20.

For robustness, the algorithm is validated using Monte Carlo simulation with 100 repetitions. In each repetition, the algorithm is run using a random sample containing 70% of tenders and recovering mean bidding probabilities for this sample (*in-sample*) and then for the rest of the tenders (*out-sample*). The results, shown in columns (5) and (6) in Table 4, remain relatively stable between in- and out-samples. The number of actual bidders detected in the data unsurprisingly drops from 87% in the whole sample to 79% in in-samples and 68% in out-samples, since there are less underlying data used to estimate the algorithm. Nevertheless, estimated bidding probabilities for bidders and nonbidders are in line with the whole sample, especially in the out-sample, validating the predictive power of the algorithm.

Comparison between bidding probabilities estimated by random forest and our algorithm further illustrates that the random forest model assigns very high probabilities to actual bidders while anchoring the baseline probability for other firms close to the observed bid rate. In contrast, our algorithm produces more conservative estimates for both groups, but still generates a clear and economically meaningful separation between actual bidders and non-bidders.

This pattern is further illustrated in Figure 4, which compares the tender-level average bidding probabilities of actual bidders and other potential bidders. Under the random forest model, the distributions for the two groups are sharply separated: actual bidders receive very high estimated probabilities, while other firms are assigned substantially lower values, resulting in nearly opposing distributions. By contrast, our algorithm predicts lower average probabilities for both groups. Nevertheless, the distribution for actual bidders remains clearly different and more skewer to the right, relative to that of other firms, indicating that actual bidders are still consistently assigned higher estimated probabilities of participation.



(a) Random Forest (b) Algorithm

Figure 4: Tender-level average bidding probabilities for actual bidders and other potential bidders using (a) random forest algorithm and (b) our algorithm.

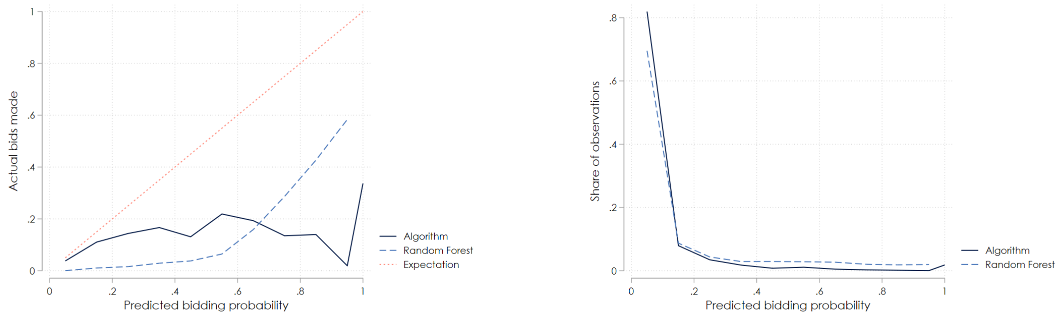
To further examine the estimated probabilities, we compare predicted bidding probabilities to realized bidding frequencies. Figure 5 plots, for each predicted bidding probability, the share of firm–tender pairs that result in an actual bid. The intuition is that if the probability is estimated to be 30%, on average 30% of those cases firms should have made their bid as well if the estimation was purely based on the underlying data, illustrated as 45-degree red line in the graph.[2]

The random forest estimates deviate substantially from this benchmark. Realized bidding frequencies remain low even at relatively high predicted probabilities: for instance, firm–tender pairs with estimated bidding probabilities around 50% result in bids only about 5% of the time. This indicates that the random forest systematically overestimates bidding probabilities and does not accurately reflect observed participation patterns.

The estimates from our algorithm exhibit a different pattern. While realized frequencies display more variation across probability bins, the estimates are substantially better aligned with observed outcomes for probabilities below 20%, which account for nearly 90% of observations (see Figure 5b). In this range, predicted probabilities closely track realized bidding behavior on average. For higher probability ranges, calibration remains imperfect, but these cases represent only a small share of the data. Overall, our algorithm yields probability estimates that are more consistent with observed participation patterns than those produced by the random forest.

The objective of the alternative methodologies considered in this paper is to estimate, for each procurement auction, the number of *likely* potential bidders. Table 2 shows that the number of registered firms is not a suitable proxy for this purpose. Registrations do not isolate underlying market potential and are instead correlated with the procedural and timing features of the tendering process. As a result, the registration count may lead to systematic bias if used as a proxy for

[2]Because the estimates are intended to capture underlying bidding propensities, realized bidding frequencies need not coincide exactly with predicted probabilities.



(a) Bidding probabilities (b) Distribution

Figure 5: Comparing estimated bidding probabilities to the actual bidding rates.

the level of potential competition. Furthermore, it does not provide information on firms' probability to submit a bid conditional on being aware of the tender.

In contrast, the random forest model performs well in predicting actual bidders, assigning very high participation probabilities to firms that actually do bid. However, these predictions do not take into account that even in firms' main geographical markets, capacity constraints and competing opportunities prevent them from bidding on every relevant tender. Consequently, while the random forest may be well suited for bidder prediction, its implied probabilities are not well calibrated for aggregating them to a tender-level measure of market potential, yielding implausibly high estimates in those settings.

Our proposed algorithm estimates bidding probabilities that are more closely aligned with observed participation rates and with the conceptual restrictions imposed by our definition of potential competition. The resulting tender-level measures are largely uncorrelated with procurement characteristics that should not affect the underlying market size, and they do not exhibit the same concerns as the random forest estimates in our application. For these reasons, we use the estimates from our algorithm in the subsequent analysis on how well the market potential is attained in the next section.

5 Measuring procurement performance

5.1 Framework

In principle, for highly similar procurements conducted within the same municipality, the underlying level of potential competition should be approximately constant, regardless of the identity of the contracting authority. Although auction-specific factors, such as firm capacity constraints and short-term market conditions, may affect realised participation, these do not alter the underlying pool of feasible bidders. As discussed above, potential competition is therefore best interpreted as a distribution governing participation rather than a fixed quantity. However, when averaged across sufficiently similar procurements, the expected level of potential competition should remain stable.

In practice, different procurers may attract different levels of realized competition even in otherwise comparable procurements. Such variation may reflect differences in expertise, procurement practices, or other demand-side factors, in addition to supply-side considerations.

The spatial distribution of estimated potential competition across Finnish municipalities is shown in Figure 6. The figure reveals substantial heterogeneity, including across neighboring geographical areas. Part of this variation reflects differences in the composition of procured goods and services across municipalities. When holding the type of procurements constant, the spatial variation becomes considerably smoother (see Appendix Figure B.2). Overall, potential competition is highest in and around large urban areas in southern Finland and lowest in Lapland and eastern Finland.

Figure 7 compares the distributions of the actual and estimated potential bidder counts. The distribution of realised bidders is concentrated at lower values relative to the distribution of potential bidders. In a benchmark case where potential competition is fully realised on average, the two distributions would be expected to

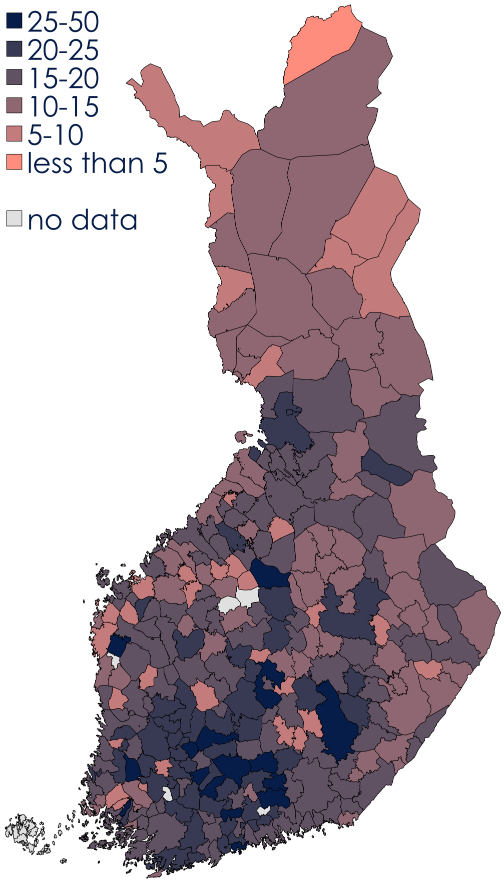


Figure 6: The estimated number of potential bidders in procurement auctions across Finnish municipalities.

align more closely, particularly for procurements with relatively small bidder pools. The observed gap, especially at lower bidder counts, indicates that a substantial share of procurements fall short of their estimated market potential. This motivates a more systematic analysis of the extent to which potential competition is realised across procurements.

We measure the level of attained competition by comparing the realized number of bidders to the estimated number of likely potential bidders at the tender level. A low ratio indicates that relatively few bidders participate compared to the estimated market potential, whereas a high ratio suggests that the procurement attracts a large share of the available bidders. This may reflect either particularly attractive procurement design or effective procurement practices.

Because our algorithm estimates the number of *likely* potential bidders rather

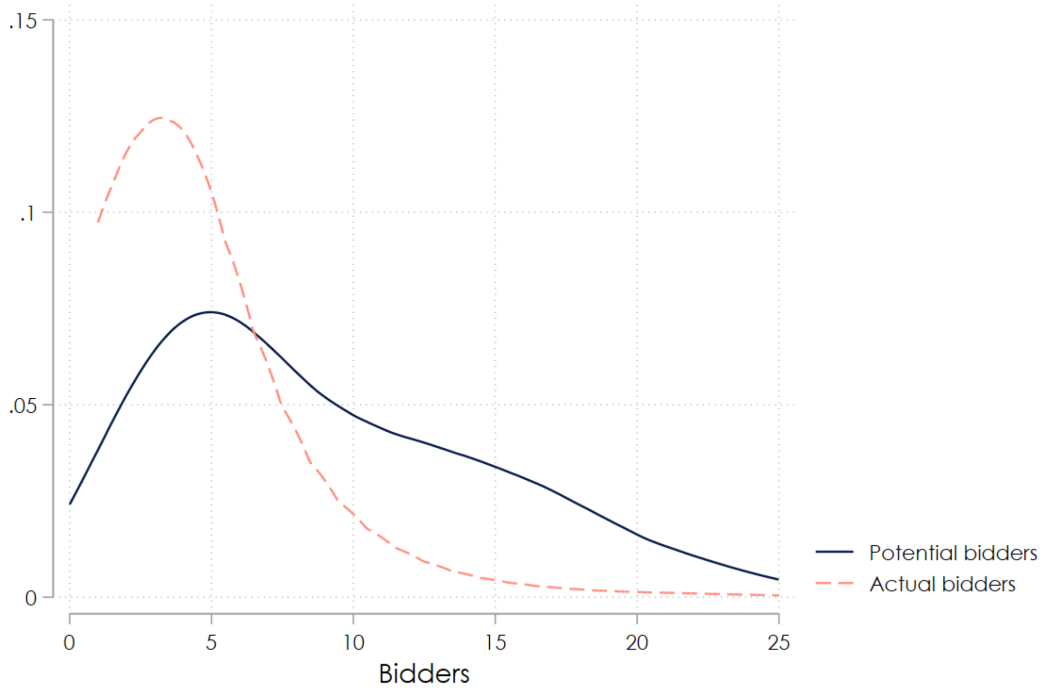


Figure 7: The distributions of actual and potential number of bidders in procurement auctions.

than the full feasible set, the measure should not be interpreted as an upper bound. In some cases, the realised number of bidders may exceed the estimate of potential competition. Such instances can be interpreted as procurements in which the contracting authority is particularly successful in attracting participation. Similarly, sometimes the actual number of bidders may fall short of the potential level, even if the procurement was conducted in a professional manner.

Table 5 summarizes the extent to which estimated potential competition is realized across sectors and types of procurement units. The median number of estimated potential bidders across all ITTs is 12.2. This varies across sectors: service ITTs having the lowest level of potential competition and construction contracts the highest level. This pattern mirrors the distribution of realized competition documented in Finnish procurement data (Ijäs, 2026; Hiilamo et al., 2023).

The results indicate that in 15% of ITTs, the estimated potential competition is fully realized. At the same time, in half of ITTs, at most 27% of the estimated potential competition is attained. In absolute terms, this corresponds to approximately eight additional potential bidders per procurement, on average. Differences across types of procurement units are relatively modest, whereas sectoral differences are more pronounced. Procurement units are more likely to realize a higher share of potential competition when procuring services.

Table 5: Summary statistics for potential and actual number of bidders.

	n/N			N-n			n	N
	25p	50p	75p	25p	50p	75p	median	median
All	0.12	0.27	0.64	26.0	8.04	1.85	3	12.2
Construction	0.11	0.20	0.42	32.1	15.9	5.05	4	19.7
Products	0.10	0.24	0.55	25.6	6.74	2.24	2	9.85
Services	0.16	0.40	0.85	14.3	4.79	0.68	4	9.71
Municipality, small	0.13	0.27	0.60	22.6	8.27	1.94	3	12.1
Municipality, medium	0.13	0.28	0.61	24.0	8.19	2.27	3	12.5
Municipality, large	0.13	0.30	0.72	23.9	6.90	1.24	4	10.5
Government entity	0.11	0.25	0.60	22.7	9.30	1.90	3	13.3
Other	0.11	0.26	0.64	27.6	8.20	1.78	3	12.5

While these results provide an overview of how effectively potential competition is realized, they do not fully capture the underlying mechanisms. When the realized share of potential competition is high, the interpretation is straightforward: the procurement likely succeeds in attracting available bidders, even if the total number of bidders remains limited due to a small underlying market.

When the realized share is low, however, two distinct scenarios may arise. First, the market may be highly competitive, with many potential bidders, but participation is limited by entry costs or capacity constraints, so that the observed number of bidders is already relatively high in absolute terms (Li and Zheng, 2009). Second, the number of actual bidders may be low despite a large estimated pool of potential bidders, suggesting that the contracting authority fails to attract available competition. The latter case is of particular policy interest, as it indicates procurements where additional competition could plausibly be achieved, potentially leading to more favorable procurement outcomes.

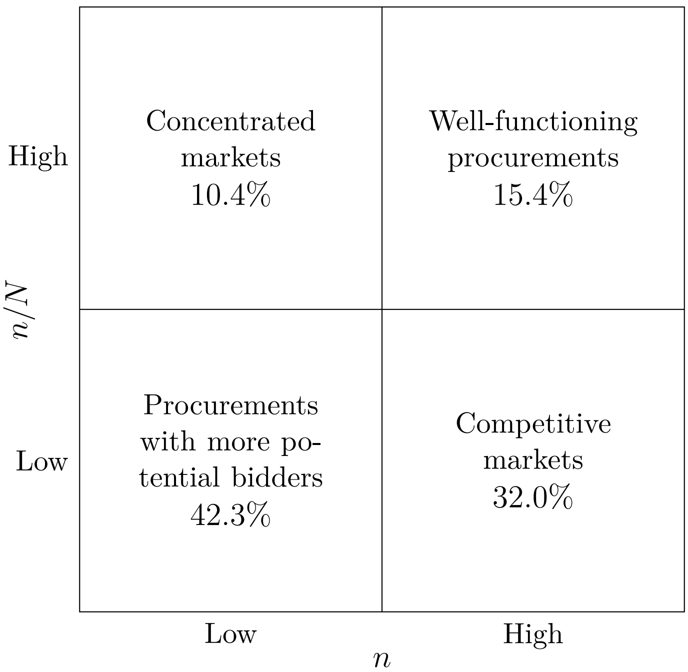


Figure 8: The framework for interpreting the level of attained potential competition (n/N). Low number of actual bidders is defined as $n \leq 3$ and low share of attained competition when $n/N < 1$ and $N - n < 2$.

Figure 8 illustrates the four-category framework. The low number of actual bidders (n) is defined as having three or fewer actual bidders in the procurement auction[3]. We define low attainment of competition (n/N) as cases where the ratio is below one and the gap between the number of actual bidders and the estimated number of likely potential bidders is at least two.

Under this classification, 15.4% of procurement auctions are categorized as *well-functioning procurements*, where participation is high relative to both the median and the estimated market potential. A further 32.0% fall into the *competitive market* category: these auctions attract more than the median number of bidders, but still fall short of their estimated potential, suggesting that participation may be constrained by entry costs.

In 10.4% of procurements, the estimated level of potential competition is itself

[3]Three corresponds to the median number of bidders in Finnish procurement auctions (Ijäs, 2026).

limited (*concentrated markets*), implying that low participation reflects underlying market structure rather than procurement performance. The remaining procurements, 42.3% of the sample, are classified as *problematic procurements*, characterized by both low participation and low attainment of potential competition.

These cases are of particular interest from a policy perspective. They represent situations in which achieving additional competition appears feasible and where the gains from increased participation are likely to be largest, as the marginal impact of additional bidders is typically strongest when the initial number of bidders is low (Ijäs, 2026). Accordingly, procurements with few bidders and substantial unrealized market potential are examined in greater detail in the subsequent analysis.

The classification depends on the choice of thresholds used to define low participation and sufficient potential competition. These thresholds are inherently somewhat arbitrary, and the distribution of procurements across categories may vary under alternative definitions. Figure 9 examines the sensitivity of the results to the cutoff used to define a low number of bidders. In the baseline specification, the median (three bidders) is used as the threshold.

The figure shows that the share of procurements classified as having unexploited potential competition is sensitive to this choice. As the cutoff increases, the share rises substantially. Under a stringent definition—where only procurements with a single bidder are considered to have low participation—the share of procurements with additional potential competition is approximately 15%. By contrast, if procurements with up to five bidders are classified as having low participation, the corresponding share increases to around 60%.

The shaded region in the figure reflects additional sensitivity to the second threshold, namely the minimum gap between actual and potential bidders required to classify a procurement as having unrealized potential. Taken together, these results indicate that while the precise magnitudes depend on the chosen thresholds, the qualitative conclusion, that a substantial share of procurements fails to fully exploit available competition, is robust.

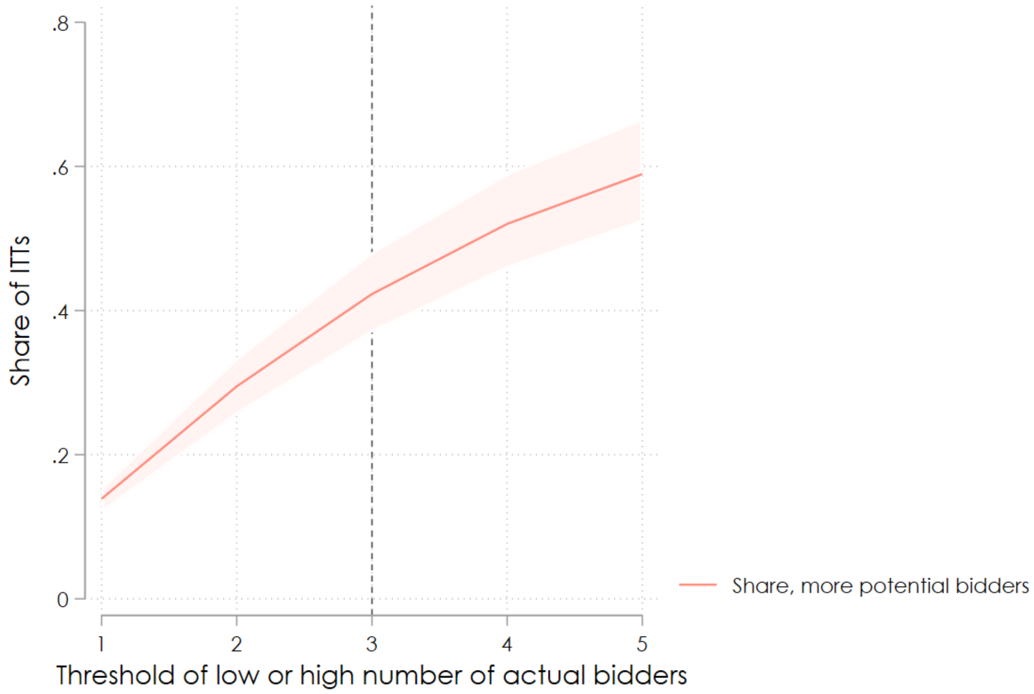


Figure 9: Volatility of the share of procurement with more potential bidders depending on how few actual bidders are required for a procurement to be considered as having low level of actual competition. As a baseline, at most three actual bidders is required. The shaded area denotes the possible flexibility in the requirement of how much potential competition needs to be acquired to be in the upper part of the framework.

5.2 Procurements with more potential bidders

The framework presented in Section 5.1 illustrates that for at least 42% of procurement contracts, there exist multiple additional potential bidders in the market. This raises a central question: to what extent can these additional bidders be attracted to participate?

First, the scope for increasing participation is typically substantial rather than marginal. Figure 10 presents the distribution of the estimated number of potential bidders among procurements classified as having unrealized competition. Only 9% of these procurements occur in markets that are sufficiently concentrated to support only a very limited number of potential bidders. In more than 90% of cases, the estimated pool of potential bidders is considerably larger. In this respect, there is also no significant variation between different kinds of procurement units (see Appendix Figure B.5). This suggests that, in the majority of these procurements, attracting additional bidders is a realistic objective.

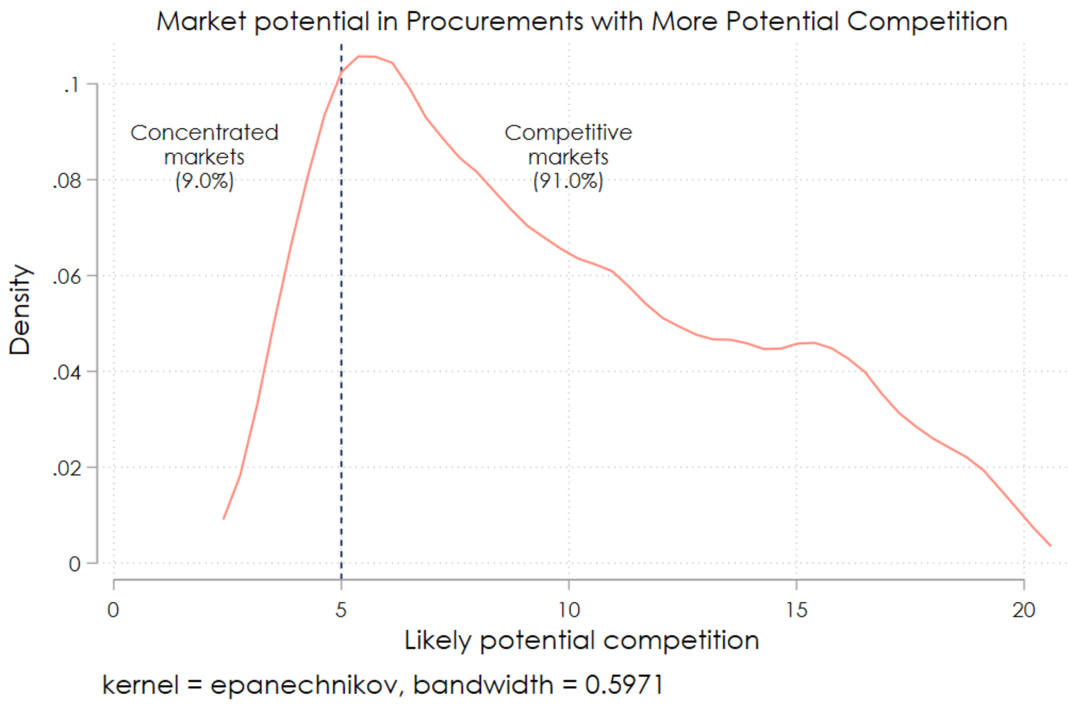


Figure 10: The estimated number of likely potential bidders among procurements with more potential competition.

Procurements with unrealized potential competition are not geographically concentrated but are distributed relatively evenly across the country (see Appendix Figure B.4). Similarly, they are not concentrated into particular broad industries but in absolute numbers, follow closely how procurement contracts are generally distributed across different industries in Finland (see Appendix Figure B.6). These patterns suggest that neither location nor broad industry classification alone explains why some procurements fail to attract available competition.

However, the distribution is not uniform across procurement units. Some procurers have a substantially higher share of contracts in the bottom-left category of the framework than others. This can be illustrated by comparing procurement units within the same category, which tend to face similar demand conditions and procure comparable goods and services. Figure 11 shows the distribution of such procurements across different types of procurement units.

In general, most procurement units have at least some contracts with unrealised potential competition. The share of these contracts is relatively stable among large municipalities, whereas there is greater dispersion across other types of procurement units. In particular, government entities and other public sector organizations exhibit substantial variation. These differences suggest that procurement practices, and not only market conditions, play an important role in determining the extent to which potential competition is realised.

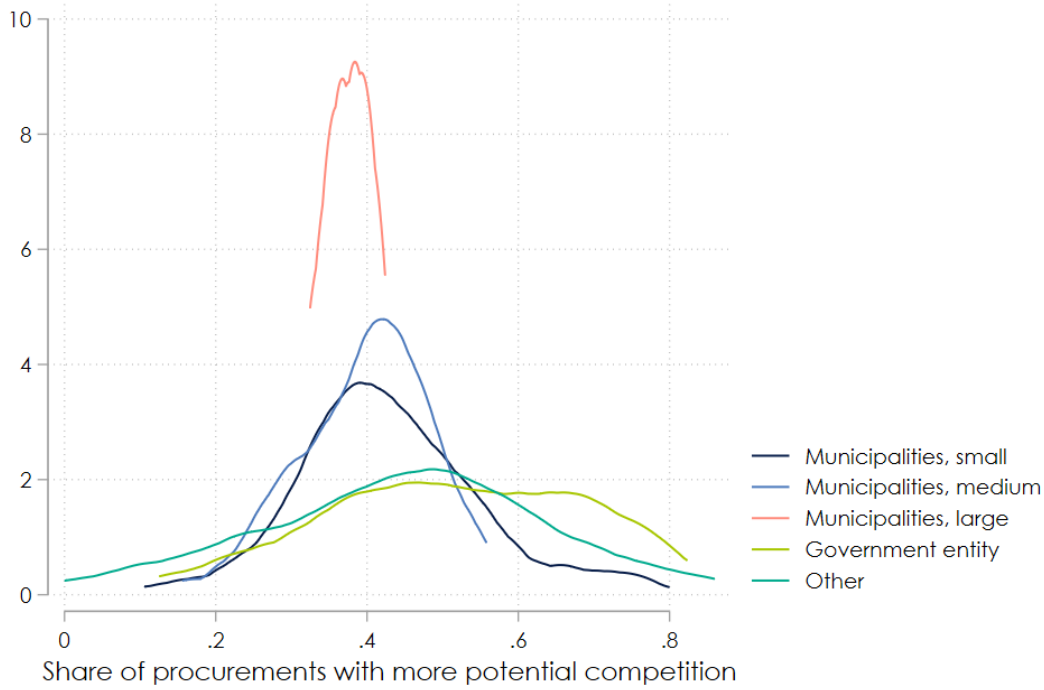


Figure 11: The distribution of the share of procurements with more potential bidders among different types of procurement units.

To better understand these differences, we examine which procurement practices are associated with a lower probability of ending up in the bottom-left category. We estimate linear probability, probit, and logit models in which the dependent variable indicates whether a procurement has both low participation and low attainment of potential competition. The explanatory variables capture procurement design choices that are, at least in part, under the control of the contracting authority.

The results are reported in Table 6. In particular, a longer bidding period, the use of smaller lots (i.e., dividing contracts into sub-auctions), avoiding procurements during peak holiday periods, and the use of industry-standard selection criteria are all associated with a lower probability of attracting only a small number of bidders when more competition would be feasible. Here, the findings are consistent with the existing literature. For example, Tukiainen and Halonen (2020) show that scoring auctions are associated with higher participation in industries where such mechanisms are commonly used, and Hiilamo et al. (2023) document lower participation in procurements conducted during the summer holiday period in Finland. We do not find as strong evidence for a similar phenomenon with the Christmas holiday, albeit the signs of the coefficients are in the same direction. It is shown in the literature that procurement units may conduct procurements more poorly and in a hurry at the end of the fiscal year (Liebman and Mahoney, 2017).

The number of subauctions in a tender is negatively associated with the probability of attracting only few bidders when there would be more potential bidders in the market. Splitting contracts into smaller lots may broaden participation by lowering entry barriers and enabling more firms to bid. While this may also affect the number of potential bidders, the results suggest that the increase in actual participation is relatively stronger, reducing the likelihood that such procurements fall into the bottom-left category.

Pre-notifications of upcoming tenders, which potentially capture elements of market dialogue, are negatively associated with the probability of unrealized competition, although the estimates are mostly not statistically significant. This likely reflects measurement limitations, as the variable is primarily observed for larger contracts above EU thresholds. As a result, the relationship between pre-notification and bidder participation cannot be estimated precisely and warrants further investigation.

Column (4) in Table 6 presents procurement unit -level regression estimates, capturing indications whether procurement units systematically differ in their procuring behavior. Procurement units that systematically have longer bidding periods and divide ITTs into multiple subauctions more often are associated with having a lower share of their ITTs in the bottom-left corner in the framework. The estimate for the usage of industry-standard selection criteria is also negative, albeit not statistically significant. These results indicate that there are systematic differences between procurement units in how they conduct their procurements, but there also exists within-procurer variation as seen in columns (1) to (3).

Overall, these results indicate that procurement practices play a meaningful role in shaping participation outcomes, and that effective strategies may be context-specific. There is also substantial heterogeneity in procurement practices across Finnish municipalities. Saastamoinen et al. (2025), for instance, document large differences in resources, procedures, and organizational capacity across procurement units. In addition, municipalities differ in their procurement guidelines, particularly for contracts below national thresholds.

Some municipalities, for example, maintain detailed procurement schedules on their websites, occasionally including smaller tenders. Anecdotally, such practices appear to be associated with a lower share of procurements with unrealized competition, suggesting that transparency and predictability may facilitate participation.[4]

Finally, we consider the potential magnitude of efficiency gains in monetary terms. Figure 7 shows that the distribution of actual bidders is shifted left relative to the distribution of potential bidders. If estimated potential competition were realized on average in low-bidder procurements, i.e., if the two distributions coincided

[4]For example, municipalities of Sauvo and Siikalatva perform very well according to the algorithm and also maintain a procurement timetable on their websites.

Table 6: The level of attained competition and its correlation with different procurer-side measures

	(1) Low low, LPM	(2) Low low, Probit	(3) Low low, Logit	(4) Share of low lows
Bidding window	-0.001***	-0.001***	-0.001***	-0.006***
	(0.0002)	(0.0002)	(0.0002)	(0.002)
N of subauctions	-0.017***	-0.046***	-0.058***	-0.052**
	(0.001)	(0.002)	(0.003)	(0.016)
Pre-notified	-0.052*	-0.040	-0.038	0.313
	(0.023)	(0.023)	(0.024)	(0.246)
Summer holiday	0.058***	0.059***	0.058***	-0.003
	(0.011)	(0.011)	(0.011)	(0.133)
Christmas holiday	0.028	0.025	0.025	0.193
	(0.021)	(0.023)	(0.023)	(0.277)
Typical selection criteria	-0.027***	-0.031***	-0.031***	-0.082
	(0.006)	(0.006)	(0.006)	(0.059)
N	30738	29561	29561	520
Sample mean	0.428	0.444	0.444	0.440
Industry FE	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	No
Tender notice type FE	Yes	Yes	Yes	No
Procurer FE	Yes	Yes	Yes	No
Region FE	No	No	No	Yes
Procurer type FE	No	No	No	Yes

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 'Low low' refers to the ITTs in the bottom-left corner of the framework in Figure 8. Probit and logit coefficients refer to the average marginal effects. Models include controls for the size of the procurement unit, the actual location of the procurement in municipality level, and the distance to a large city from the location. Bidding window denotes the length of the bidding period in days. N of subauctions denotes the number of lots the tender has divided. Summer holiday is an indicator for whether the procurement is conducted between the midsummer and the beginning of August. Christmas holiday is an indicator for whether the procurement is conducted between Christmas (24th of December) and Epiphany (7th of January). Typical selection criteria refers to the usage of a typical selection criteria (lowest-bid or scoring rules) for the industry in question. If certain criteria is used over half of the ITTs in the industry, then the criteria is assumed to be typical for the industry. The last column provides the estimates from procurement unit -level regression. In column (4), the coefficients are estimated for the procurer-specific means of the same covariates.

for procurements with three or fewer bidders, a back-of-the-envelope calculation implies annual savings of EUR 390–650 million (roughly 1–1.6% of Finland's annual procurement expenditure). This figure is best viewed as an upper bound under the model assumptions, as it requires that all estimated potential competition be attained on average. In that case, procurements would fall into the bottom-left category only by chance, because the realized number of bidders would be drawn from the potential distribution.

More conservative calculations that reduce the share of procurements in the bottom-left corner of the framework to 20% imply annual savings of EUR 200–335 million. Finally, following the approach of Best et al. (2023), suppose that each procurement unit attained the share of procurements with unrealised competition observed among the top 25% of procurement units within its procurer type. Table A.1 in the Appendix reports these benchmark shares. Under this scenario, the overall share of procurements in the bottom-left category would fall to 34.8%, implying annual savings of EUR 68–110 million. The implied aggregate improvement is modest relative to the earlier estimates, reflecting that even the best-performing procurement units do not dramatically outperform others.

These calculations assume that moving a procurement out of the bottom-left category increases the number of bidders by at least one, which, according to prior research, can reduce procurement costs between 6% (Titl, 2025) and 10% (Ijäs, 2026). We consider this assumption plausible because in over 90% of the cases the estimated pool of potential bidders is sufficiently large for the market to be considered competitive. In such settings, increased participation would shift procurements towards the right-hand side of Figure 8, where competitive pressure is stronger. In practice, savings may be larger for single-bid contracts and smaller for contracts that already attract three bidders.

6 Conclusion

This paper studies the extent of potential competition in Finnish public procurement auctions using three complementary approaches. We develop a novel algorithm to estimate the number of *likely* potential bidders in each auction. In contrast to approaches that approximate the theoretical maximum number of suppliers, our method aims to capture the level of competition that could plausibly be realized in practice. We compare the estimates from our algorithm with two proxies used in the previous literature: the number of firms that register for a tender and predictions from a random forest model.

The results indicate that procurement markets typically feature a substantial pool of potential suppliers. This potential is unevenly distributed geographically, with lower levels in eastern and northern Finland and higher levels in urban areas. Despite this, realized participation frequently falls short of market potential. According to our estimates, the full level of likely competition is reached in only about 15 percent of auctions, and in more than 40 percent of contracts the number of bidders is below its estimated potential.

We further examine the relationship between procurement design and bidder participation. The findings suggest that practices such as longer bid preparation periods and the division of contracts into lots are associated with higher realized competition. This suggests that contracting authorities should be able to increase participation through procurement design and outreach to potential suppliers.

More broadly, the methodology developed in this paper can be applied in other settings where procurement data are available. Even in datasets that contain information only on winning firms, sufficiently rich auxiliary data can be used to approximate the pool of potential bidders. Our approach therefore provides a practical tool for evaluating the competitiveness of procurement markets and for identifying opportunities to increase participation and reduce procurement costs.

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Appendix

A Tables

Table A.1: The procurer-level share of low low ITTs in different procurer types.

	25p	Median	75p	Mean	SD
Procurer type					
Municipalities, small	0.36	0.41	0.50	0.43	0.12
Municipalities, medium	0.34	0.41	0.45	0.40	0.08
Municipalities, large	0.34	0.38	0.41	0.38	0.03
Hospital district (-2022)	0.43	0.49	0.55	0.50	0.09
Wellbeing services county (2023-)	0.39	0.49	0.57	0.50	0.13
Government entity	0.40	0.50	0.67	0.51	0.17
Municipality owned corporation	0.25	0.40	0.54	0.40	0.20
Joint procurement unit	0.43	0.47	0.55	0.49	0.15
Higher education	0.53	0.57	0.69	0.59	0.13
Church	0.36	0.44	0.48	0.42	0.15
Other	0.29	0.41	0.47	0.40	0.22
Total	0.34	0.43	0.54	0.44	0.16

B Figures

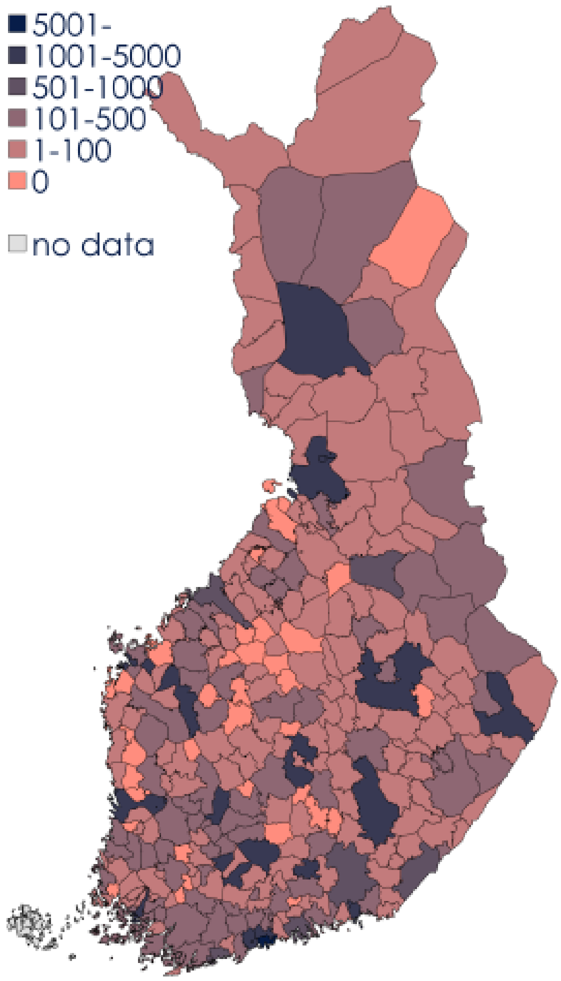

Figure B.1: Distribution of geographical main markets of Finnish firms across municipalities.

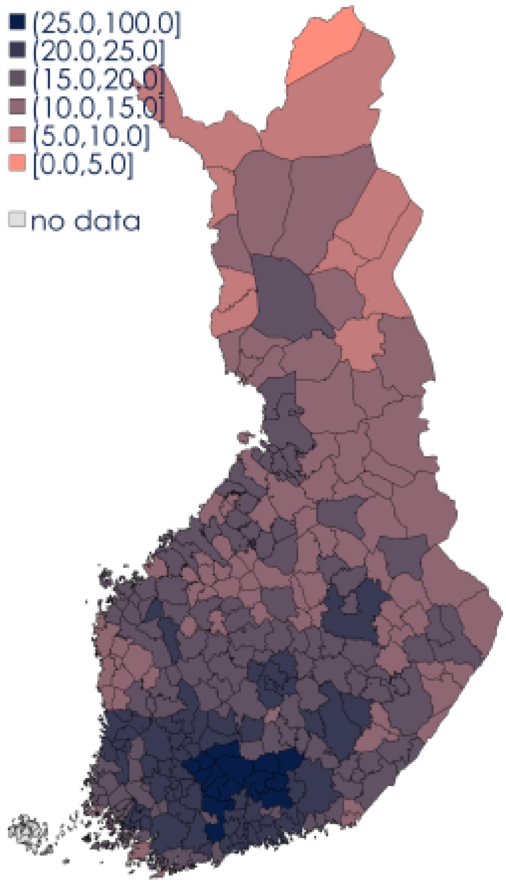

Figure B.2: Standardized procurement auctions for 25 largest industries in every Finnish municipality.

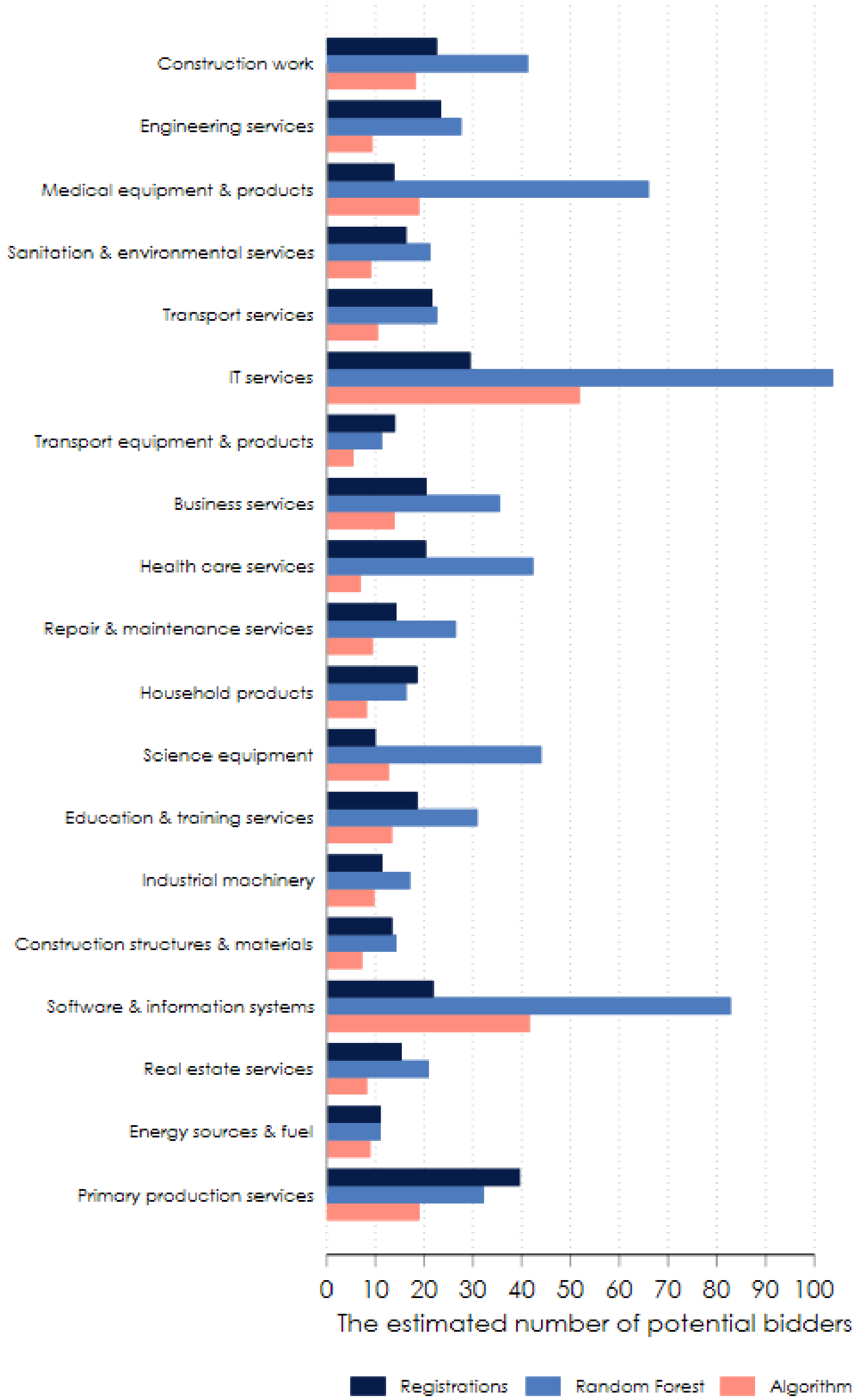

Figure B.3: The average number of estimated potential bidders in 20 most common industries (cpv codes).

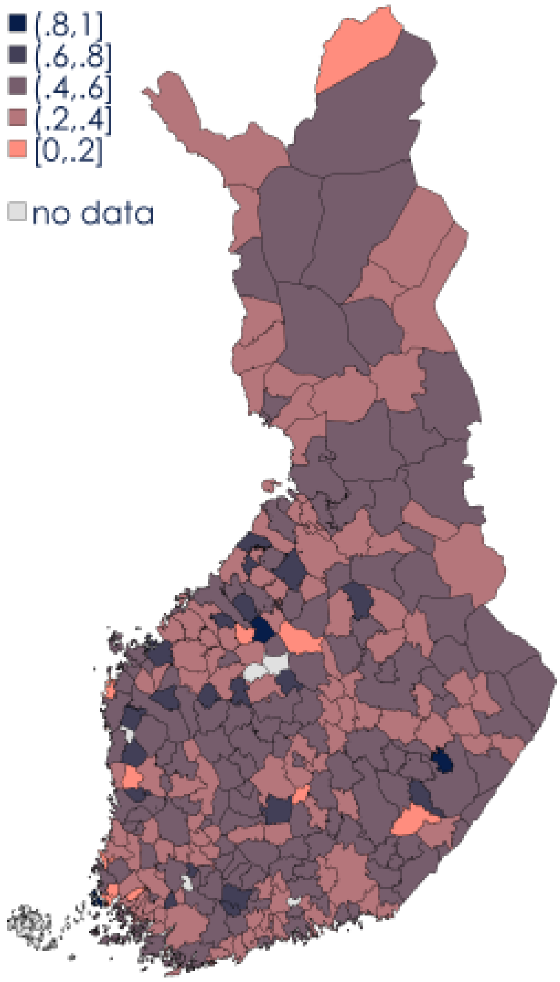

Figure B.4: The geographical distribution of ITTs with more potential competition.

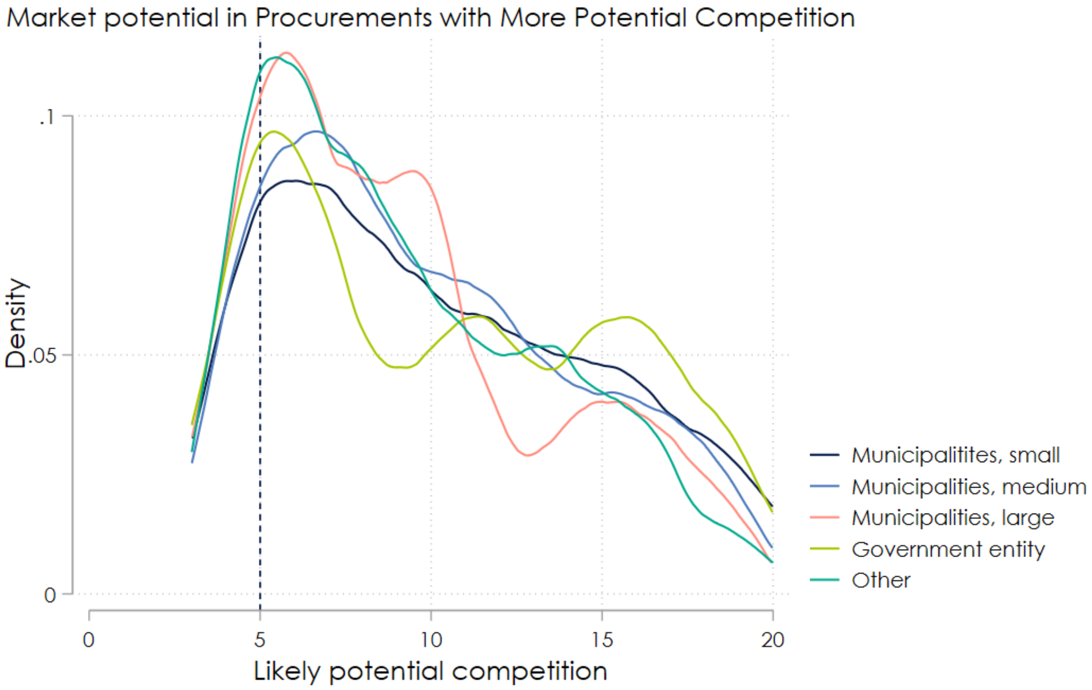

Figure B.5: The estimated number of likely potential bidders among procurements with more potential competition, different procurement units.

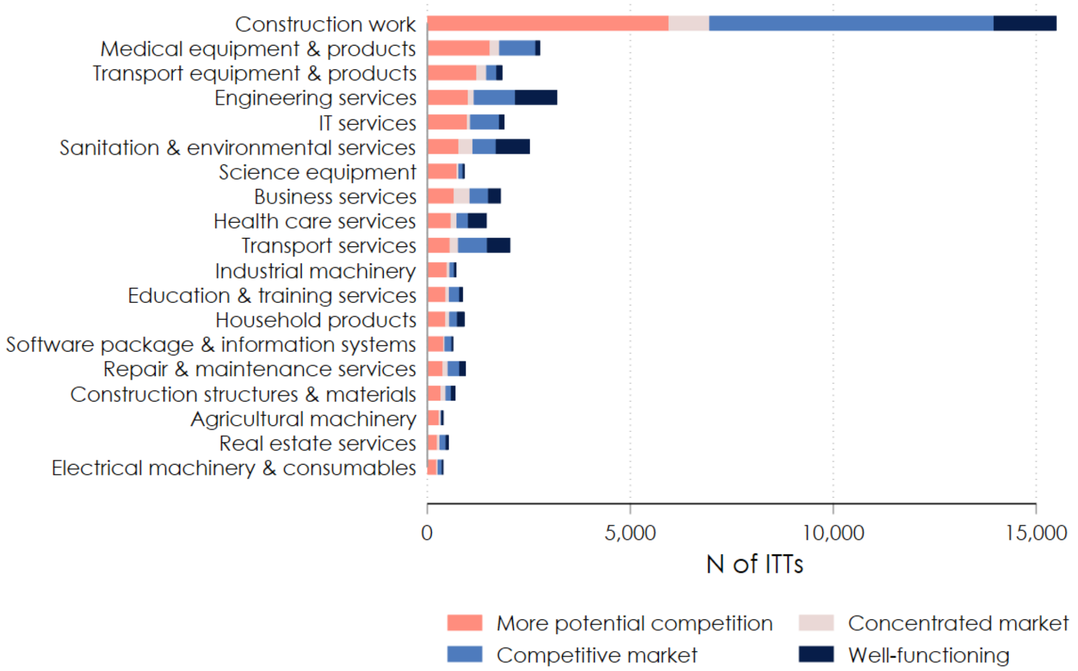

Figure B.6: Industries with the highest number of ITTs with more potential competition.