Rating public procurement markets*

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Abstract

We develop a novel, scalable method to assess public procurement performance at the tender award stage using standard administrative data. Our measure, which we call the "Market Allocation Imbalance" (MAI), compares how total contract value is distributed across winning firms to how procurement opportunities are distributed across tenders. We show how governance failures can lead to significant deviations of winning firms' concentration from a theoretical benchmark we derive. We then use procurement data from Ukraine and EU member states in 2018–2021 to assess the MAI of five large sectors, and find that Ukraine's performance in four of the five is comparable to many other European countries. However, Ukraine's construction procurement displays large excess concentration among winners, consistent with anecdotal evidence of corruption in this sector. Overall, with minimal data requirements, our method offers a practical tool for comparing the competitiveness of procurement award outcomes across sectors and countries.

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1 Introduction

The quality of institutions and governance is widely recognized as a key driver of economic and social development (see e.g., Acemoglu, Johnson and Robinson, 2005, for a review). However, measuring institutional quality remains challenging, not least because governance is multi-dimensional and many important aspects—such as corruption—are illicit and hard to observe directly unless prosecuted by the legal system. Due to these challenges, many existing measures rely heavily on subjective perceptions.[1] As a result, there can be significant gaps between these perception-based indices and the actual situation on the ground. Russia's full-scale invasion of Ukraine in February 2022 has brought renewed urgency to this issue. While Ukraine has pressing needs for military support and reconstruction funding, donors, investors, the public, and other stakeholders are concerned about whether corruption could undermine the effective use of aid. Yet there remains little consensus about the exact extent of corruption in Ukraine, largely because of weaknesses in the available measures.

We develop a simple and transparent method to assess the competitiveness of countries' procurement markets at the tender award stage using publicly available administrative data. Public procurement constitutes a significant share of government expenditure and GDP (OECD, 2019) and is a critical interface between the public and private sectors. As such, it is particularly vulnerable to corruption (Transparency International, 2015) and other market distortions such as collusion among suppliers, creating a "procurement wedge" compared to the benchmark if the same projects were procured and delivered through a fully efficient process (Decarolis and Srhoj, 2026). The resulting distortions can create inefficient allocation of public resources, inflated costs, and diminished trust in public institutions. Yet measuring the quality of procurement markets is inherently difficult, especially in a consistent, comparable way across countries. Existing approaches (e.g., the EU Single Market Scoreboard) often rely on crude metrics—such as the share of auctions with only one bidder—or require

[1] A prominent example is the Corruption Perceptions Index compiled by Transparency International, which is frequently used in policy discussions but is based largely on subjective assessments, sometimes made by individuals outside the country in question.

detailed data on all bids, which are generally available in only a small number of countries (e.g., Asker, 2010; Hyytinen, Lundberg and Toivanen, 2018; Kawai and Nakabayashi, 2022; Kawai et al., 2023) and unavailable for most EU member states.

Our method relies only on publicly available data and and assesses the competitiveness of procurement award outcomes using a measure we call the "Market Allocation Imbalance" (MAI). The MAI compares how total contract value is distributed across winning firms to how procurement opportunities are distributed across tenders, with both distributions summarized using the Herfindahl–Hirschman Index (HHI). In a competitive environment with identical firms, contracts should be allocated roughly in proportion to the size and frequency of available projects, so that no small set of firms consistently captures a disproportionate share of total value. We show that, under these conditions, the HHI of winning firms should be determined by the HHI of auction values and the number of firms: larger contracts naturally induce some concentration, but overall the distribution of winnings should broadly mirror the distribution of opportunities after accounting for the number of firms. Corruption or other governance failures that undermine open competition—such as poor design of the procurement framework or failure to check collusion—will lead to systematic deviations from this benchmark, that is, higher-than-expected HHI among winning firms. The MAI, which measures these deviations, can therefore be used as a tool to identify sectors in need of regulatory attention.

MAI measure offers several advantages over other approaches. It is simple to compute; does not require information that is often confidential, such as the identity and bids of losing firms; and generates intuitive, scalable metrics that can be compared across countries or over time. Importantly, it does not require knowing which contracts are corrupt or uncompetitive; instead, it highlights outcome patterns that are difficult to reconcile with well-functioning procurement systems. Because the method incorporates the size distribution of auctions into the benchmark, it distinguishes between market concentration that can arise when there is a handful of extremely large projects and suspicious concentration that suggests corruption, collusion, or other procurement frictions. Although in principle firm cost heterogeneity could also generate a large MAI, a simulation exercise shows that explaining the largest observed MAI values would require implausibly high levels of cost dispersion among firms. At the same time, many country–sector MAIs are not statistically different from what a competitive market with homogeneous firms would imply, indicating that reasonable levels of cost heterogeneity alone are unlikely to account for the most extreme patterns we document.

We apply our method to procurement auctions in the EU and Ukraine that took place in 2018–2021. We restrict our attention to contracts valued at €250,000 or more to reduce the possibility of selective reporting in the EU dataset while also maintaining a sufficiently large sample size to allow for reliable inference. Focusing on large auctions also yields a sample where the return to corruption or collusion and thus the impact on public finances are likely higher. We further limit our main analysis to five sectors, defined by 2-digit Common Procurement Value (CPV) codes: medical procurement (CPV code 33); transport equipment (34); construction work (45); architectural, construction, engineering and inspection services (71); and sewage, refuse, cleaning, and environmental services (90). We select these sectors because (a) each of them accounts for at least one percent of all procurement auctions in Ukraine and (b) there are at least ten other European countries that have at least 200 auctions in each of these sectors.[2] Together, these auctions cover €35.1 billion (75% of auction value among all auctions over €250,000) of Ukraine's and €363 billion (53% of auction value among all auctions over €250,000) of the EU's procurement spending, respectively.

Our findings indicate meaningful heterogeneity in Ukraine's and other countries' performance across these five sectors, underscoring the usefulness of a method that can deliver sector-specific results. Focusing on Ukraine, we find that its MAI places it 11th out of 18 in the medical sector; 15th out of 16 in transport equipment; 26th out of 26 in construction; 10th out of 16 in architectural and engineering services; and 6th out of 19 in sewage and refuse services. In architectural and engineering services, Ukraine's MAI is not statistically

[2]We report findings for the next five sectors that fall slightly below the 200-auction threshold in the Online Appendix.

different from the competitive benchmark with 95 percent confidence, and in sewage and refuse services it is barely so. In the medical sector, Ukraine's MAI is significantly above the competitive benchmark but statistically indistinguishable from that of countries like Germany and Finland and is substantially better than Spain's.

In the construction sector, however, Ukraine shows by far the largest MAI compared to other countries, exceeding expected concentration by around 900 standard deviations. This result is highly robust across subsamples, and is driven largely by the highway and road construction subsector (CPV 45233), which faced significant allegations of corruption in the second half of our time period. Consistent with this, we find that the excess concentration is driven to a large extent by auctions that took place in 2021, which suggests that our measure is flagging genuine market distortions in Ukraine's construction sector and not a permanent difference in fundamentals, such as firms' cost structure.

Prior literature shows that an important part of the efficiency loss during public procurement, compared to the optimal benchmark, reflects corruption, collusion and distorted resource allocation, for example due to firms' political connections (e.g., Faccio, 2006; Baltrunaite, 2020; Schoenherr, 2019; Titl, Mazrekaj and Schiltz, 2024). While one way to measure procurement inefficiencies across countries is to study the degree of politically connected auction winners, comparing the prevalence of contracts granted via observable political connections across different countries/sectors would likely understate the true extent of the distortions generated by such connections, many of which are unobservable to outsiders. A distinct strand of literature instead focused on using directly observable procurement data to detect governance risks, such as analyses of single-bidder auctions, non-open procedures, subjective criteria, repeated awards, direct awards, departures from a buyer's baseline, renegotiations, bunching near reserves, or high winner concentration (e.g., Bandiera, Prat and Valletti, 2009; Decarolis, 2014; Fazekas and Tóth, 2016; Andreyanov, Davidson and Korovkin, 2018; Baránek, Musolff and Titl, ming; Bosio et al., 2022; Fazio and Zaldokas, 2025).[3] How-

[3]See Decarolis and Srhoj (2026) for a detailed discussion. In Online Appendix A, we also briefly review existing approaches used in antitrust practice to score procurement markets.

ever, as such flags could also arise in the competitive situations, they are likely to be noisy indicators and are at best suggestive than definitive (Chassang and Kawai, 2025).[4] Our goal is different: rather than suggest a new flag to identify bid-rigging in particular auction conditional on a its method and environment, we suggest an approach that allows easy cross-country comparisons while staying agnostic whether variations come from an explicit supplier misconduct or be an unintended outcome of flawed auction designs, bureaucratic capacity, transparency or integrity conditions (Decarolis and Srhoj, 2026). We emphasize, however, that our measure operates at the contract allocation stage of the procurement cycle. It does not speak *directly* to upstream design choices—such as lot structure, qualification thresholds, or advertising requirements—nor to downstream execution problems such as cost overruns and renegotiation, each of which can independently generate a wedge between authorized spending and delivered value (Decarolis and Srhoj, 2026).

With this, we also contribute to the literature on the cartel detection (e.g., Porter and Zona, 1993, 1999; Bajari and Ye, 2003; Chassang et al., 2022; Houde et al., 2022; Kawai et al., 2023). Unlike these existing indicators, however, our method explicitly benchmarks observed contract allocations against the underlying distribution of procurement opportunities. This allows us to distinguish between inequality that arises naturally from heterogeneous contract sizes and inequality that signals governance distortions. By focusing on deviations from a well-defined competitive benchmark, our metric provides a more interpretable and comparable measure of procurement system quality across industries and countries.[5]

The rest of the paper is organized as follows. Section 2 presents a simple model relating the Herfindahl–Hirschman index (HHI) of winning firms to market characteristics and shows how corruption or other governance failure can raise winning firms' HHI. Sections 3 and 4 describe our data and empirical methods, respectively. We present our results in Section 5,

[4] See Chen (2025), who shows that 65% of tenders exhibit patterns consistent with the manipulation of scoring rules and the presence of "zombie" bidders that formally satisfy the requirements but do not exert competitive pressure.

[5] In a conceptually similar approach, Ellison and Glaeser (1997) develop test for whether observed levels of geographic concentration are greater than would be expected to arise randomly.

assess the extent to which cost heterogeneity can affect our results in Section 6, and conclude in Section 7.

2 Conceptual framework

2.1 Firm HHI in the homogeneous competitive case

We derive the theoretical relationship between the Herfindahl–Hirschman index (HHI) of a country's auctions and the HHI of winning firms under the assumption that auction outcomes are uniformly distributed across these firms. A uniform distribution of awards would hold if, for example, firms were *ex ante* identical and procurement auctions were perfectly competitive, but this is a sufficient and not a necessary condition. In our empirical work, we estimate deviations from this benchmark at the country-sector level.

Suppose there are A auctions won by F unique firms. Let V_a denote the dollar value of procurement in the auction a, which we treat as fixed, and $V_{tot} = \sum_{a=1}^{A} V_a$ denote the total procurement value across all auctions. Define I_{af} to be an indicator for firm f winning auction a. Then the total value won by firm f is $S_f = \sum_{a=1}^{A} V_a I_{af}$. If each auction is independently awarded to one of the F firms with equal probability $1/F$, then $E[I_{af}] = \frac{1}{F}$.

We define *Auction HHI* to be:

$$\text{HHI}_{\text{auct}} = \sum_{a=1}^{A} \left(\frac{V_a}{V_{tot}} \right)^2 = \frac{1}{V_{tot}^2} \sum_{a=1}^{A} {V_a}^2$$

Similarly, we define *Firm HHI* to be:

$$\text{HHI}_{\text{firm}} = \sum_{f=1}^{F} \left(\frac{S_f}{V_{tot}} \right)^2 = \frac{1}{V_{tot}^2} \sum_{f=1}^{F} {S_f}^2$$

We now derive the relationship between HHI_{firm}, HHI_{auct}, and F. Given our assumptions that (1) auctions values are fixed and (2) each firm wins with an independent and equal probability, the expected value won by each firm and the variance of the value won are, respectively:

$$\mathbb{E}[S_f] = \sum_{a=1}^{A} V_a \cdot \mathbb{E}[I_{af}] = \frac{V_{tot}}{F}$$

and

$$\text{Var}(S_f) = \sum_{a=1}^{A} V_a^2 \cdot \text{Var}(I_{af}) = \sum_{a=1}^{A} V_a^2 \cdot \left(\frac{1}{F} \cdot \left(1 - \frac{1}{F}\right)\right) = \frac{F-1}{F^2} \sum_{a=1}^{A} V_a^2$$

With these results, we obtain the expected value of the *square* of the value won by each firm:

$$\mathbb{E}[S_f^2] = \text{Var}(S_f) + (\mathbb{E}[S_f])^2 = \frac{F-1}{F^2} \sum_{a=1}^{A} V_a^2 + \frac{V_{tot}^2}{F^2}$$

The expected value of winning firms' HHI is therefore:

$$\mathbb{E}[\text{HHI}_{\text{firm}}] = F \frac{\mathbb{E}[S_f^2]}{V_{tot}^2} = F \left[\frac{F-1}{F^2} \frac{\sum_{a=1}^{A} V_a^2}{V_{tot}^2} + \frac{1}{F^2}\right]$$

$$= \frac{1}{F} + \left(1 - \frac{1}{F}\right) \text{HHI}_{\text{auct}} \tag{1}$$

The expected firm HHI is therefore larger than HHI_{auct}, i.e., the distribution of contract values is, in expectation, more concentrated between winning firms than between auctions. As the number of firms grows, the two values converge. Yet because our approach adjusts for the number of firms, it is robust to differences driven solely by this factor, such as those arising from economies of scale.

Next, we extend this model to show how governance quality—which could include corruption and collusion—affects the measured firm HHI.

2.2 HHI, governance quality, and corruption

Equation (1) in the previous section is a special case of a more general result. Let $p_f := \mathbb{E}[I_{af}]$ denote the (possibly heterogeneous) expected probability that firm f wins an auction. We maintain the assumption that each auction is awarded independently, so p_f does not vary within firm. Recomputing the variance-decomposition but allowing p_f to vary yields

$$\mathbb{E}[\text{HHI}_{\text{firm}}] \;=\; \text{HHI}_{\text{auct}} \;+\; \left(1-\text{HHI}_{\text{auct}}\right)\sum_{f=1}^{F} p_f^2 \tag{2}$$

The term $\sum_f p_f^2$ is the sum of the squares of (ex-ante) winning probabilities; it equals $1/F$ under homogeneous productivity and perfect competition, nesting equation (1).

Now suppose that each auction is *competitive* with probability $\gamma \in [0,1]$ and *non-competitive* with probability $1-\gamma$. A subset of the F potential bidders, $M < F$, forms a cartel or attempts to bribe the auctioneer.[6] Conditional on a competitive auction, every firm is equally likely to win, and conditional on a non-competitive auction, the winner is chosen uniformly from the cartel. Therefore

$$p_f \;=\; \begin{cases} \dfrac{\gamma}{F} + \dfrac{1-\gamma}{M}, & f \in \{\text{cartel}\}, \\[2ex] \dfrac{\gamma}{F}, & f \notin \{\text{cartel}\}. \end{cases}$$

Substituting these probabilities into equation (2) gives an updated expression for expected firm-level concentration:

$$\mathbb{E}[\text{HHI}_{\text{firm}} \mid \gamma] \;=\; \text{HHI}_{\text{auct}} \;+\; \left(1-\text{HHI}_{\text{auct}}\right)\left[M\left(\frac{\gamma}{F}+\frac{1-\gamma}{M}\right)^2 + (F-M)\left(\frac{\gamma}{F}\right)^2\right]. \tag{3}$$

A useful closed-form for the latter bracketed term is

$$\sum_{f=1}^{F} p_f^2 \;=\; \frac{F(1-\gamma)^2 + M\gamma(2-\gamma)}{F\,M}.$$

Note that equation (3) nests the earlier extreme of perfect governance ($\gamma = 1$), where $\sum_f p_f^2 = 1/F$. In that case, equation (3) collapses to equation (1). Governance quality therefore affects firm-level concentration through $\sum_f p_f^2$, while heterogeneity in auction

[6] Note that it is possible for M to be equal to 1, i.e., a single firm could bribe the auctioneer.

sizes.[7] affects it through HHI_{auct}. Poor governance (lower γ) increases $\sum_f p_f^2$; the impact of that increase on the observed HHI_{firm} is attenuated when auction values themselves are unequal (HHI_{auct} large) and amplified when auctions are similarly sized (HHI_{auct} small).

This formulation provides a direct empirical prediction: controlling for auction-level concentration, lower-quality governance (or a stronger cartel) should raise the concentration of contract awards. Conversely, observing HHI_{firm} vastly exceeding the benchmark in (1) indicates that either γ is low, M is small, or both.

At the other extreme, when $\gamma = 0$ and only cartel firms ever win, $\sum_f p_f^2 = 1/M$, and

$$\mathbb{E}[\text{HHI}_{\text{firm}}] = \frac{1}{M} + \Big(1 - \frac{1}{M}\Big)\text{HHI}_{\text{auct}}. \tag{4}$$

2.3 Limitations and Strengths

We call the difference between expected and observed firm HHI the "Market Allocation Imbalance" (MAI) measure, which we formally define in Section 4. A positive MAI can occur for a number of reasons, not all of which necessarily indicate collusive or corrupt behavior. Most obviously, it is unlikely that every firm has a uniform chance of winning every auction. Firms differ in their productivity levels and cost structures. For this reason, our main empirical comparison is across countries within the same sector. Section 6 empirically examines the extent to which our results can be explained by cost heterogeneity.

The MAI cannot speak to *which* features of the procurement process—such as restrictive specifications, limited participation due to high bidding costs, or buyer discretion over who is invited to tender—may have generated the observed concentration. Two countries with similar MAI scores could therefore differ substantially in the underlying source of that concentration. Our measure also does not capture distortions that operate further upstream in the procurement process—most notably, the selection and design of projects that enter the procurement pipeline in the first place, including politically motivated project choices,

[7] Manipulation of tender sizes to favor particular suppliers can also reflect poor governance quality, however, we abstract from it as we focus on the procurement implementation process.

strategic auction timing, or the manipulation of tender sizes to favor particular suppliers (Decarolis and Srhoj, 2026). Nor can it flag downstream execution problems—such as cost overruns, delays, or opportunistic renegotiation—that can represent an important source of inefficiency in public procurement even when the initial contract allocation appears competitive (Decarolis and Srhoj, 2026).

We cannot observe losing bids for the vast majority of the countries in our sample. Our approach therefore cannot detect more sophisticated forms of collusion such as bid rotation when members of a collusion ring agree to take turns to win contracts and the members charge higher prices (see e.g., Kawai and Nakabayashi, 2022). This can be seen in Equation (4) when $\gamma = 0$: Without information on losing firms (or the total number of potential bidders), it is impossible to empirically distinguish the case where only firms in a cartel win from perfect competition among M firms.

These limitations do not necessarily undermine the value of the MAI. Existing methods likewise cannot speak to multiple stages of the procurement cycle. Many also require detailed bid-level data, consistent reporting standards, or administrative records that are unavailable for the vast majority of countries (Decarolis and Srhoj, 2026). Constructing the MAI, by contrast, requires only the identity of the winner and the contract value—information that is publicly available and consistently reported across a wide range of countries and sectors. The limitations listed above are therefore best understood as highlighting that the MAI is most informative as a comparative diagnostic: a country-sector combination that deviates sharply and consistently from the competitive benchmark is difficult to explain away with any single confound.

3 Data and summary statistics

3.1 Sample selection and data processing

We obtain data on government auctions and winners from the Prozorro database for Ukraine and from the Tenders Electronic Daily (TED) database for all European Union (EU) countries.[8] We focus on the years 2018–2021, when Ukraine's electronic public procurement process was well-established but before Russia's full-scale invasion, which disrupted the normal functioning of procurement markets.

Both datasets include information on the procurement category (Common Procurement Value or CPV code), the number of bidders, the identity of the winner (name, country, and sometimes national identifier), and the contract value.[9] TED also reports the country in which the procurement took place. The identities of losing bidders and their bids are *not* disclosed in TED.

The data include framework agreements, in which suppliers are commissioned to provide goods or services on an ongoing basis, and the value of the contract is not known *ex ante*. In such cases, the reported value can be €0 or a nominal amount such as €1. We therefore drop any tenders explicitly labeled as framework agreements or with reported values below €100. We also exclude unsuccessful procurements from the data and drop small countries that have very few procurement auctions in general: Croatia, Cyprus, Malta, Iceland, Ireland, Liechtenstein, and North Macedonia.

An auction can be won by multiple firms. We treat those cases as W separate equal-valued auctions, where W is the number of winning firms, and divide the total contract value by W. We treat firms that bid jointly as a consortium as a separate firm because we cannot

[8] Prozorro also discloses the identities and bids of losing firms. We attempted to obtain comparable bid-level procurement data from EU member states to build alternative competitiveness metrics and validate our approach; however, in most cases authorities indicated that such information is not publicly available.

[9] Prozorro also includes the estimated value of the tender. In principle, the TED database also contains the *ex ante* estimated tender value. In practice, it is incomplete, and in some cases reflects the lowest bid rather than the estimated value. Additionally, estimated values could be subjective, so we use the *ex post* contract value to the winner as our measure of auction value throughout. TED (2022) provides additional information on the TED dataset.

observe the identities of firms making up the consortium.

After adjusting for multiple winners, we further restrict both datasets to contract values of at least €250,000, for three reasons. First, smaller contracts may fall below various reporting or competitive procurement thresholds and therefore show up inconsistently in the data. Second, our focus is on grand corruption and collusion, which are arguably less likely to occur in smaller contracts. Third, restricting to larger contracts yields a more comparable range of project sizes, avoiding comparisons between very small and very large tenders. While higher thresholds (such as the official reporting threshold in some countries of €5 million for works) would further reduce concerns about selective reporting, they would also substantially reduce the number of observations, particularly in smaller countries and sectors, limiting our ability to draw reliable conclusions.

We construct the deviation of firm HHI from the competitive benchmark by country-sector, as defined by the 2-digit CPV code, thereby allowing ratings to vary within country. Figures 1a and 1b show the distribution of high-value (≥€250,000) auctions by the 2-digit CPV code for Ukraine and the other European countries in the sample, respectively, focusing on CPV codes that make up at least 1 percent of all high-value auctions in that sample.[10] In both groups, construction work (CPV code 45) dominates, accounting for over half of Ukraine's high-value auctions and almost a quarter of high-value auctions in other European countries. Medical equipment, pharmaceuticals and personal care products (CPV code 33) and transport equipment (CPV code 34) also account for a sizeable share of auctions in both countries.

Because our metric is likely to be more reliable in cases where there are many auctions, and a ranking of Ukraine against EU countries is more informative when there are more countries to compare to, we apply two filters when picking the sectors on which to focus our analysis. In particular, we only look at the sectors that in 2018–2021, (1) account for more than 1 percent of high-value auctions in Ukraine and (2) account for at least 200

[10]The full set of CPV codes and descriptions is available here: https://www.bipsolutions.com/news-and-resources/cpv-codes/.

high-value auctions in at least 10 other European countries.[11] There are five such sectors in the data: the three sectors mentioned above; architectural, construction, engineering and inspection services (CPV code 71); as well as sewage-, refuse-, cleaning-, and environmental services (CPV code 90). We identify five additional sectors that meet the first criterion and account for at least 100 high-value auctions in each of at least 10 other European countries in 2018–2021 and present rankings for them in the Online Appendix.

Prozorro reports the winning firm's numeric identifier, making it easy to identify all auctions won by the same firm. However, national winner identifiers are often missing in the TED dataset; even when present, they are not always reported consistently—for example, the same (unique) firm name may appear under different identifiers. Although winner names are almost always reported in the TED dataset, they are likewise not reported consistently and sometimes contain misspellings. Being overly conservative in grouping similar names risks underestimating concentration among winners, while being too permissive risks overestimating it. Our approach to standardizing winner names and national identifiers (IDs) aims to minimize the risks of both (1) artificially splitting the same firm and (2) merging distinct firms.

We first extract and validate national IDs, with some country-specific rules (e.g., parsing 11–digit Italian tax codes when relevant markers such as *C.F./P.IVA* are present). We identify reliable IDs by comparing their length with the modal ID length for that country and backfill consistent IDs for entries sharing the same firm name and country code. When reliable IDs exist, we reconcile all name variants sharing an ID and choose a canonical label.

Where IDs are missing or appear unreliable, we harmonize names (e.g., lowercasing; removal and standardization of punctuation, diacritics, and legal-form suffixes across languages; normalization of conjunctions). We then compare names within country–CPV–first–letter blocks and accept near–matches using conservative string–distance thresholds. Full details of the data standardization across countries appear in Section B of the Online Appendix.

[11] The 1 percent threshold for Ukraine also ensures that Ukraine has at least 200 auctions in each selected sector.

Although our main analysis focuses on 2-digit CPV codes, in some cases we also examine finer classifications. However, not all EU countries report more granular CPV codes consistently. To improve coverage, we predict the missing third-digit CPV codes using a supervised machine-learning approach (LightGBM).[12] The model uses the reported 2-digit CPV code, the auction title, and the winner's identity as predictors. We represent auction titles using n-gram TF-IDF features and include the title's language as an additional input. Model training is performed separately for each country to account for language and reporting differences.

3.2 Summary statistics

Table 1 shows the mean, median, standard deviation, minimum and maximum of the in-sample contract values by country.[13] As might be expected, the value distribution is highly skewed, with the standard deviation being generally several times larger than the mean and the mean significantly exceeding the median. After conditioning on the minimum value of the auction being at least €250,000, median values are similar across countries, and Ukraine does not stand out in the mean, median, or maximum values of its auctions.

Table 2 shows the number of high-value auctions and the number of distinct winning firms for each country and sector in the sample (including cases where countries do not meet the 200 auction threshold). In general, most of the auctions fall into the construction category, and larger countries generally have more auctions in a given category.

Figure 2a shows the distribution of auction values in the main sample, separately for Ukraine, all EU countries, and some Central and Eastern European EU countries, which we might expect to be more similar to Ukraine.[14] In general, the three distributions look

[12]Our median (mean) predicted accuracy is 0.73 (0.70). We do not attempt to predict additional digits of the CPV code because the accuracy would likely fall substantially.

[13]Online Appendix Tables E.1-E.5 show the same summary statistics by sector.

[14]These Central and Eastern European EU countries include Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, North Macedonia, Poland, Romania, Slovakia, and Slovenia. Online Appendix Figure E.1 shows the full distribution of contract values, including amounts below €250,000 (but above €100). In this case, the distribution of values is very different, with EU values being generally much higher

very similar, although there are slightly fewer very high-value auctions (over €3,500,000) in Ukraine compared to the other two groups.

Figure 2b shows the distribution of the number of bidders, with the right-most bar corresponding to 20 or more bidders for readability. Compared to all EU countries, Central and Eastern European EU countries are about twice as likely to have single-bidder auctions. Ukraine is much less likely to have single-bidder auctions and much more likely to have two bidders, which is attributable to Ukraine requiring at least two bidders for procurement auctions above a certain value. Overall, Ukraine's distribution of the number of bidders is much more compressed than that of other countries, with very few auctions attracting more than five bidders.

Finally, we match our winning firms to Orbis dataset—published by Moody's (Bureau van Dijk)—containing standardized financial, ownership, and business information on over 300 million public and private global companies and find that 7.14% of public procurement auction winning firms' revenues come from public procurements with little variation across sectors. [15]

4 Methodology

To construct each country-sector's deviation from its competitive benchmark, we calculate two HHI values for each county-sector combination: one based on the distribution of auction opportunities (*Auction HHI*) and one based on the distribution of awarded contract values (*Firm HHI*). Auction HHI reflects how procurement opportunities are distributed across auctions. As outlined in Section 2, when combined with the number of winning firms, this calculation helps define a benchmark that captures expected variation in outcomes across firms due to heterogeneity in project size alone. We then compare this benchmark to the

than Ukraine's and other Eastern European countries' values falling in between these two distributions. Online Appendix Figure E.2 show the distribution of large (≥€250,000) contract values separately by sector.

[15] We calculate the fraction for every firm that we can match between TED and Orbis datasets. We take overall awarded procurement values over 4 years (2018-2021) and divide by consolidated turnover values for these firms over the same 4 year period.

actual Firm HHI, which is computed based on the share of total awarded value captured by each firm. For most of our analysis, we use the whole sample period of 2018–2021 to calculate HHIs rather than computing them annually.

The deviation of Firm HHI from what would be expected given our homogeneous competitive benchmark as:

$$\Delta\mathrm{HHI}_{\mathrm{firm}}^{\mathrm{c,s}} := \widehat{\mathrm{HHI}}_{\mathrm{firm}}^{\mathrm{c,s}} - \mathbb{E}[\mathrm{HHI}_{\mathrm{firm}} |\, \mathrm{F}^{\mathrm{c,s}}, \mathrm{HHI}_{\mathrm{auct}}^{\mathrm{c,s}}], \tag{5}$$

where c indexes countries and s indexes sectors (e.g., construction). $\widehat{\mathrm{HHI}}_{\mathrm{firm}}^{\mathrm{c,s}}$ is the empirical HHI of winning firms in country c in sector s, calculated as $\sum_{f=1}^{F^{\mathrm{c,s}}} \left(\frac{S_f^{c,s}}{V_{tot}^{c,s}}\right)^2$. The variable $S_f^{c,s}$ denotes the total value won by firm f across all contracts it won in sector s in country c, and $V_{tot}^{c,s}$ is the sum of the values of *all* the relevant contracts. $F^{\mathrm{c,s}}$ is the total number of winning firms in that country and sector.

The second term, $\mathbb{E}[\mathrm{HHI}_{\mathrm{firm}} |\, \mathrm{F}^{\mathrm{c,s}}, \mathrm{HHI}_{\mathrm{auct}}^{\mathrm{c,s}}] = \frac{1}{F^{\mathrm{c,s}}} + \left(1 - \frac{1}{F^{\mathrm{c,s}}}\right) \mathrm{HHI}_{\mathrm{auct}}^{\mathrm{c,s}}$, is the expected firm HHI under the homogeneous competitive benchmark, where $\mathrm{HHI}_{\mathrm{auct}}^{\mathrm{c,s}} = \sum_{a=1}^{A^{\mathrm{c,s}}} \left(\frac{V_a}{V_{tot}^{\mathrm{c,s}}}\right)^2$, with a indexing all the procurement auctions in sector s and country c, $A^{\mathrm{c,s}}$ being the total number of such auctions, and V_a being the auction value.

Ranking procurement markets based on the raw deviations given by $\Delta\mathrm{HHI}_{\mathrm{firm}}^{\mathrm{c,s}}$ could be misleading because the baseline scale of Auction HHI, $\mathrm{HHI}_{\mathrm{auct}}$, varies substantially across countries and sectors. To address the issue of scale, we normalize $\Delta\mathrm{HHI}_{\mathrm{firm}}^{\mathrm{c,s}}$ by the standard deviation of Firm HHI, $\mathrm{HHI}_{\mathrm{firm}}^{\mathrm{c,s}}$, under the assumption of homogeneous competition. To obtain this standard deviation, which we denote by $\widehat{\sigma}_{c,s}^{\mathrm{firm}}$, we randomly and uniformly assign winners to each auction from the pool of winning firms in that sector-country combination. We then calculate the resulting Firm HHI, $\mathrm{HHI}_{\mathrm{firm}}^{\mathrm{c,s,d}}$, for each draw d. After repeating this process 500 times for each country-sector combination, we calculate $\widehat{\sigma}_{c,s}^{\mathrm{firm}}$ as the estimated standard deviation of $\mathrm{HHI}_{\mathrm{firm}}^{\mathrm{c,s,d}}$.

The Market Allocation Imbalance (MAI) is defined as $\mathrm{MAI}^{\mathrm{c,s}} := \frac{\Delta\mathrm{HHI}_{\mathrm{firm}}^{\mathrm{c,s}}}{\widehat{\sigma}_{c,s}^{\mathrm{firm}}}$. Intuitively, the MAI measures standardized excess concentration in a country-sector combination compared to a perfectly competitive market with homogeneous firms and the same project mix. The MAI is effectively a z-score that scales the excess concentration by this volatility. Values near zero are consistent with competitive allocation, whereas large positive values suggest corruption, persistent cost advantages, or collusion among some winners. Because some firms may plausibly have persistent cost advantages *ex ante*, we might expect MAI scores to exceed zero even in the absence of corruption and collusion; accordingly, we emphasize cross-country comparisons of MAI scores rather than their absolute levels. We assess the potential role of cost heterogeneity explicitly in Section 6.

We obtain confidence intervals for $\text{MAI}^{\text{c,s}}$ via a bootstrap, resampling auction-winner observations from each country-sector 500 times and calculating the resulting $\Delta\text{HHI}^{\text{c,s,b}}_{\text{firm}}$ for each bootstrap b. We then calculate the empirical standard deviation of $\Delta\text{HHI}^{\text{c,s,b}}_{\text{firm}}$, $\widehat{\sigma}^{\text{firm}}_{c,s,b}$, with 500 uniform reassignments of firms to auctions within each bootstrap, as in the main sample. Finally, we assume that $\text{MAI}^{\text{c,s}}$ is normally distributed to calculate 95% confidence intervals.[16]

We conduct a number of extensions and robustness checks. To allow for the possibility that not every firm is equally likely to win each auction, we repeat our exercise focusing on the top 25% of auctions by value. This restriction should exclude smaller firms that may not be capable of carrying out larger projects. To allow for the possibility that some auctions are naturally unique and have few potential winners, another set of robustness checks restricts the sample of auctions to those that had at least two or three offers. To check for the influence of outliers, we repeat our exercise excluding the top 1% or 5% of auctions in each sector. Finally, we also recalculate rankings when dropping the top or the top two winning firms in each country (by total value won). Out of computational considerations, we do not bootstrap confidence intervals in these cases.

[16]Let $\widehat{\text{MAI}} = \Delta\text{HHI}^{c,s}_{\text{firm}}/\widehat{\sigma}^{\text{firm}}_{c,s}$ and let $\widehat{\sigma}_{\text{MAI}}$ denote the bootstrap standard deviation of $\Delta\text{HHI}^{c,s,b}_{\text{firm}}/\widehat{\sigma}^{\text{firm}}_{c,s,b}$. The 95% confidence interval is $[\widehat{\text{MAI}} - 1.96\,\widehat{\sigma}_{\text{MAI}},\ \widehat{\text{MAI}} + 1.96\,\widehat{\sigma}_{\text{MAI}}]$.

5 Results

5.1 Main ranking

Figure 3 presents our main result, ranking countries based on by how many standard deviations the actual winner HHI exceeds the expected winner HHI.[17] Reassuringly, several countries in each sector do not deviate significantly from the competitive benchmark. As expected, however, many others exhibit MAI scores well above zero, potentially reflecting persistent cost advantages among certain firms. The distribution of lower MAI scores varies across sectors. In the medical sector, for instance, the middle tercile of countries has MAI scores between 18 and 35, values that would be extraordinarily unlikely under a normal distribution. In transport, the corresponding range is 6 to 17, with construction falling in between. Architectural and engineering services and sewage and refuse services display patterns similar to transport. Broadly, the lower end of each sector's distribution provides a sector-specific reference point for what "normal" competitive variation looks like, allowing higher MAI scores to be interpreted relative to this feasible competitive range.

In the medical sector (panel (a)), Ukraine ranks 11th out of 18, and we cannot reject that its standardized deviation is equal to that of the country ranked 6th in this sector. By contrast, Poland, Bulgaria, Lithuania and Spain all show very high excess concentration, with gaps ranging from about 180 standard deviations above the benchmark (Spain) to 860 standard deviations above the benchmark (Poland). We cannot reject the null of no excess concentration in Ukraine's procurement contracts in the architectural and engineering services sector (panel (d)) and barely reject it in the sewage and refuge services sector (panel (e)). The point estimates place Ukraine 10th out of 16 and 6th out of 19 in these sectors, respectively.[18]

Ukraine scores notably worse in the remaining two sectors. In transport equipment (panel

[17] Estimates and confidence intervals corresponding to this figure are available in Online Appendix Tables E.6-E.10.

[18] The number of countries included varies across sectors due to differences in data availability.

(b)), it is ranked 14th out of 16, with a highly statistically significant excess concentration of about 39 standard deviations. Although the confidence intervals are fairly wide, we can reject that the excess concentration is lower than around 16 standard deviations with 95 percent confidence.

Notably, Ukraine's performance in the construction sector (panel (c)) is a clear outlier, placing it last in a group of 26 countries. Ukraine's score is 900 standard deviations above the competitive benchmark, which is substantially above the next-worst-scoring country, Poland, where the score is 165 standard deviations above the benchmark. By contrast, 13 of the 26 countries' scores do not deviate significantly from the benchmark.

Online Appendix Figure E.3 shows rankings for five additional sectors that meet a 100-auction threshold but not our main 200-auction threshold. These sectors include petroleum products, fuel, electricity and other sources of energy (CPV code 9); office and computer supplies (CPV code 30); laboratory equipment (CPV code 38); industrial machinery (CPV code 42); and repair and maintenance services (CPV code 50). Ukraine ranks last in two of these sectors (energy and laboratory equipment). It is right above the bottom tercile in repair and maintenance services and is not statistically distinguishable from the competitive benchmark in the remaining two sectors.

A country's rankings across the five sectors are positively correlated in all but two of the cases (Table 3) but the magnitudes vary. The largest and only statistically significant correlation (between architecture and construction) is 0.42 while the smallest positive correlation (between medical and sewage) is 0.09. This heterogeneity underscores that corruption risks need not be evenly distributed across a country's economy: they may well be concentrated in a handful of sectors such as resource extraction (e.g., mining) contracts, construction/public works, and transportation and storage (OECD, 2016). Empirically, well-documented sectoral scandals sometimes coexist with otherwise well-functioning markets—for example, bid-rigging in Japanese public works (Hayashi, 2016) or systemic collusion in Quebec's construction industry (Commission of Inquiry on the Awarding and Management of Public Contracts in the Construction Industry, 2015). Such patterns highlight the value of sector-specific metrics compared to a single country-level measure.

Is is worth emphasizing that the deviations we measure do not simply reflect oligopolistic market structure. Because the benchmark is computed conditional on the number of active winning firms, a sector with few firms will still meet the benchmark as long as winning probabilities are identical. In other words, our metric is not mechanically driven by limited competition per se, but by any asymmetries that push outcomes away from that homogeneous benchmark.

5.2 Comparison to other corruption metrics and procurement red-flag indicators

Table 4 compares our MAI metric to corruption metrics and a few other indicators that could identify red flags in procurement auctions. First, we compare MAI to countries' rankings based on the Corruption Perceptions Index (CPI) published by Transparency International, the consumption-income (C-Y) gap premium measure developed by Sarullo et al. (2026), as well as several other red-flag metrics that can be derived from procurement data (e.g., Adam, Sanchez and Fazekas, 2021; Fazekas et al., 2021). We emphasize that this exercise is not intended as a validation test of any specific measure. For example, the CPI is a broad, perception-based indicator of overall corruption at the country level, whereas our metric is an outcome-based, sector-specific measure derived from procurement data. As such, these two indices are conceptually distinct and need not be closely aligned even if both are informative.

We average each country's CPI rank over 2018–2021 and correlate it with countries' MAIs in each sector.[19] The correlation between our metric and the CPI rank is significantly positive for the construction sector, significantly negative in the sewage and refuse sector, and insignificantly positive in the remaining three sectors.

[19] Findings are similar if we retain Transparency International's country ordering but rescale CPI ranks to lie between 1 and N, where N is the number of countries in our sample.

This lack of systematic correlation is perhaps unsurprising given three key differences between the measures. First, the CPI aggregates perceptions of corruption across the entire economy, whereas our measure is sector-specific and reveals substantial within-country heterogeneity. Second, the CPI reflects subjective assessments, often by external observers, while our metric is constructed from realized allocation outcomes in procurement markets. Third, our measure isolates a particular mechanism—excess concentration relative to a competitive benchmark—rather than overall institutional quality. Yet the comparison is informative precisely because it highlights that the two approaches capture different dimensions of governance. These findings are broadly similar to Sarullo et al. (2026), who document that an alternative outcome-based corruption proxy—based on discrepancies between income and consumption of public-sector workers—is also uncorrelated with the CPI.[20]

Interestingly, our metric, although based on a very different dataset and methodology, is significantly and positively correlated with the consumption-income gap premium of Sarullo et al. (2026) in three of the five main sectors we consider (medical, construction, and architecture).[21]

Next, we compare the MAI to indicators that are commonly used to score public procurement markets. Our measure is positively—though not perfectly—correlated with the share of value captured by top firms, which is consistent with the fact that both capture aspects of allocation concentration. Unlike such top-share measures, however, the MAI explicitly accounts for heterogeneity in auction sizes, distinguishing between concentration that arises mechanically from a few large contracts and concentration that reflects systematic imbalances in how awards are allocated. In construction and transport, we find negative correlations between our metric and the average number of bidders (winsorized at the 99th percentile), which is consistent with our measure reflecting how competitive a procurement market is.

[20] Other often-used cross-country measures, such as German Exporter Corruption Index (GCI), are unavailable for our time period.

[21] Sarullo et al. (2026) use a very unbalanced panel of country-specific surveys to construct their metric. To maximize coverage (for example, the last survey from Ukraine is from 2012), we retain all surveys conducted in the year 2000 or later and average multiple metrics per survey to arrive at a single C-Y gap premium for each in-sample country.

By contrast, we find little to no correlation with the share of single-bidder auctions, which is among the most widely used procurement metrics among policymakers. While this could be interpreted as a limitation, it is also consistent with well-known concerns about the reliability of these indicators. In particular, bidder participation can be relatively easy to manipulate through the presence of non-competitive or "phantom" bidders, potentially weakening the informativeness of this metric about true competitive conditions.

Overall, the evidence indicates that our metric is not redundant with existing measures: it aligns with concentration-based indicators and alternative outcome-based proxies, while remaining largely orthogonal to perception-based indices and single-bidder red flags. This pattern is consistent with our measure capturing a distinct, outcome-based dimension of procurement performance.

5.3 Drivers of excess concentration in construction

In Figure 4, we rank countries within finer construction sector CPV codes. Only CPV codes that meet a minimum size requirement of at least 100 auctions in each country in at least ten countries (including Ukraine) are shown. The patterns suggest that the pipeline, railway, road and highway construction sector (CPV code 4523) drives Ukraine's poor performance in the construction sector. By contrast, building construction work (CPV code 4521) shows noticeably better performance, although Ukraine still ranks below the median country in that sample.

In Figure 5, we recalculate countries' rankings in the construction sector *excluding* some of the CPV codes in the previous figure. In panel (a), we drop the 5-digit CPV code 45233, corresponding to highway and road construction. Ukraine's ranking improves by only one position, but the deviation shrinks by more than two orders of magnitude, to just over 6 standard deviations above the competitive benchmark. In panel (b), we exclude the entire 4-digit sector 4523, which also encompasses pipeline, communication and power line, and airfield and railway construction. After this restriction, Ukraine's ranking improves to place it in the top half of the in-sample countries, and its score falls to less than one standard deviation away from the competitive benchmark. Further excluding additional auction categories (3-digit CPV code 452, panel (c)) does not meaningfully affect Ukraine's ranking or standard deviation. Note that the omitted sectors are not small: CPV codes 452, 4523, and 45233 represent, respectively, 75, 66, and 30 percent of Ukraine's construction procurement value during the time period of interest.

The finding of extreme excess concentration in Ukraine's construction sector, particularly in roads and related projects, is consistent with public accusations of corruption in the sector. For example, eligibility requirements for bidding on Ukraine's "Great Construction" (Велике Будівництво) program—for which auctions were held in 2020—were allegedly tightened to favor certain companies. As a result, only six large companies were eligible to bid.[22] Notably, the sharp increase in excess concentration also occurred in conjunction with the government substantially increasing funding for national roads in 2020 and 2021 as part of this program (Figure 14 in Zagreba, 2025), which may have made this sector more attractive for corrupt actors at that time.

5.4 Robustness and Extensions

In Figure 6, we consider alternative subsamples for each of the five main sectors, focusing on Ukraine's ranking. In each subsample, we first exclude the specified observations from each country's data and then recalculate each country's benchmark, deviation from the benchmark, and ranking. The gray bars denote the maximum ranking (i.e., the total number of countries in that sample). Ukraine's ranking is largely consistent when we exclude the largest procurement auctions in each country; restrict the sample to the top auction value quartile; restrict the sample to auctions that attracted at least two or three bidders; or remove the top one or two winners (and the auctions they won) from each country's data. Rankings

[22] See https://www.pravda.com.ua/news/2020/11/14/7273533/. Additional discussions of corruption in the program can be found here: https://zn.ua/ukr/internal/vijna-za-hroshi-velikoho-budivnitstva-druhij-front.html. Zagreba (2025) provides additional examples of corruption in Ukraine's road and bridge construction more generally.

are most volatile in the sewage and refuse services sector, where small and statistically insignificant deviations from the benchmark create idiosyncratic rank fluctuations across subsamples. By contrast, Ukraine continues to rank at the bottom in the construction sector in each subsample, which is perhaps unsurprising given how extreme its baseline metric is.

Figure 7 plots Ukraine's MAI measure by sector and year. For each sector–year, we treat the observations as a standalone sample, recompute the benchmark and the deviation from it. We see no clear trend in the MAI of the medical and transport sectors over this period, which additionally suggests the COVID-19 shock is unlikely to be a major confounder in our setting. By contrast, the MAI in architecture and engineering and in sewage and refuse falls from about five standard deviations in 2018 to approximately zero in 2019-–2021. The construction sector is a notable exception (plotted on a separate axis due to scale): its MAI rises from roughly 21 standard deviations in 2018 to 51 in 2019, 135 in 2020, and 750 in 2021, consistent with a rapid and accelerating deterioration in competitiveness and the documented corruption concerns in Ukraine's "Great Construction" program described above.

6 Cost heterogeneity

One natural concern is that departures from our benchmark could be driven by underlying cost heterogeneity across firms rather than corruption, collusion, or other procurement frictions. Among other reasons, such cost heterogeneity could come from production costs, scale economies, specialization, or capacity constraints, as well as differences in bidding costs. Indeed, it is likely that firms vary in their costs and this generates winning imbalances.[23] Two features of the data that we already presented argue against this being the main explanation. First, we observe many country-sector combinations in which outcomes do not differ significantly from the benchmark, which is hard to reconcile with deviations being due primarily to pervasive cost dispersion. Second, the benchmark is constructed from firms that have

[23] See, e.g., Krasnokutskaya (2011), who finds significant heterogeneity in both firm-specific and auction-specific costs, and Aryal et al. (2023), who estimate substantial cost heterogeneity across bidders but no auction-specific heterogeneity.

actually won auctions; this winner-only sample plausibly exhibits tighter cost distributions than the full set of potential suppliers (including firms that never win).

Nonetheless, an ideal metric would account for any cost heterogeneity. Unfortunately, we cannot do so explicitly because the vast majority of existing methods to back out cost heterogeneity require bid-level data and/or implicitly or explicitly assume that there is no corruption present (e.g., Hu, McAdams and Shum, 2013; Krasnokutskaya, Song and Tang, 2022; Carnehl and Weiergraeber, 2023). We would also require detailed firm-level product-specific cost data that is unavailable to us.

To assess the plausibility of cost heterogeneity being the sole explanation for our findings, we conduct a simulation exercise with permanent firm-level productivity dispersion. Specifically, within each country–sector combination, we take the set of firms that won at least one auction and assign to each firm a permanent cost parameter c_i drawn from a log-normal distribution. The dispersion of this distribution is governed by a single parameter, λ, which controls the degree of heterogeneity in firms' ex ante efficiency.

Conditional on these cost draws, we then simulate auction outcomes while holding fixed the empirical distribution of auction values and the observed number of bidders in each auction. For each auction, we draw a set of entrants of the observed size, allowing (1) for the possibility that more efficient firms more likely to participate and (2) for auction-specific shocks that are idiosyncratic across participating firms. Table 5 summarizes these parameters and the values they can take on. In particular, we assume that the probability that a firm enters a given auction depends on its cost through weights proportional to $c_i^{-\theta}$, where c_i denotes the firm's permanent cost parameter and $\theta \geq 0$ controls how strongly lower-cost firms sort into participation. When $\theta = 0$, as in our baseline scenario, entry is random and independent of costs; when $\theta = 1$, entry probabilities are inversely proportional to costs; $\theta = 2$ implies an even stronger sorting of more efficient firms into auctions.

Auction-specific variation in firms' performance is modeled by allowing realized costs to include an idiosyncratic shock. In particular, if firm i participates in auction a, its realized cost is given by $c_i \exp(s\,\varepsilon_{ia})$, where $\varepsilon_{ia} \sim N(0,1)$. The parameter s therefore governs the scale of auction-level shocks relative to persistent cost differences across firms. When $s = 0$, as in our baseline scenario, auction outcomes depend only on permanent firm efficiency; larger values of s ($s = 0.5$, 1, or 2) introduce greater idiosyncratic variation in realized costs and therefore reduce the persistence of winning firms across auctions. We then assume that the lowest-cost participating firm is chosen as the winner.

Repeating this procedure many times yields the distribution of firm-level concentration (HHI) implied by a purely competitive environment with heterogeneous costs. By varying λ over a wide range—including values that imply substantial dispersion in firm productivity—we obtain an upper bound on the degree of concentration that can plausibly be attributed to heterogeneity alone. Online Appendix Figure E.4 shows the 95th-5th and 90th-10th cost percentile ratios as a function of the degree of heterogeneity in firms' ex ante efficiency λ. For example, $\lambda = 1$ implies that the 90th percentile winner has costs that are 13 times larger than the 10th percentile winner ("90–10 cost ratio"), and the 95th percentile winner has costs that are 27 times larger than the 5th percentile winner. The most extreme assumption, $\lambda = 2$, implies a 90-10 percentile ratio of about 170 and a 95-5 percentile ratio of over 700.

Figure 8 shows the cumulative distribution of the 90—10 cost ratio required to rationalize observed firm HHI in each country-sector under alternative assumptions about auction-specific shocks and selection into entry. Panel (a) assumes that there are no auction-specific shocks ($s = 0$) and random entry into auctions ($\theta = 0$). In that case, 90–10 cost ratios around 4–8 can explain about half of the observed deviations, depending on the sector. To explain three-quarters of the observed deviations would require 90–10 cost ratios of around 8–22. Panel (b) shows the results of a more plausible scenario, where there are both moderate auction-specific shocks ($s = 0.5$) and moderate selection into participating in the auction ($\theta = 1$). In this case, 90–10 cost ratios of 4–5 can explain half of the observed deviations, and cost ratios of 5–10 can explain 75 percent.

Finally, in panel (c) we pick extreme values that would explain a significant portion of the deviations in the data. With no auction-specific shocks ($s = 0$), combined with our strongest selection assumption ($\theta = 2$), we would get cost ratios of 2 or less that could explain about 70–90 percent of the deviations. In other words, one would need a scenario that no only more cost efficient firms would be proportionally likely to select into winning, but they would be twice more likely to do so, and there would be no uncertainty with no auction-specific shocks.[24]

Even more so, even with in this extreme scenario, explaining the remainder would require greater cost heterogeneity than what has been found in the literature. For example, based on a sample of Michigan highway maintenance procurement auctions, Krasnokutskaya (2011)'s estimates of firm cost heterogeneity imply that a firm in the 90th percentile of the cost distribution has costs that are about 44% higher than a firm in the 10th percentile of the cost distribution. Based on a sample of Russian procurement auctions for printing papers, Aryal et al. (2023)'s estimates suggest a 90–10 cost ratio of about 1.5–2.0.[25]

Overall, the findings of these simulations are consistent with our former interpretations: on the lower end of our ranking, deviations from the benchmark can be explained by reasonable amounts of cost heterogeneity. However, explaining deviations at the upper end of our ranking would require unrealistic assumptions about the cost advantages enjoyed by the most efficient firms, the extent to which more efficient firms are more likely to enter the auction, or both. It is also worth re-emphasizing that our analysis compares deviations *across* countries: even if all countries exceeded the benchmark to some extent because of residual cost heterogeneity, systematic differences between countries are less naturally explained by cost differences. We cannot rule out all remaining heterogeneity, but these considerations make it unlikely that cost differences alone account for the core patterns we document. [26]

[24] Online Appendix Figure E.5 shows the results of three alternative parameterizations: (1) large auction-specific shocks with no selection ($s = 2$, $\theta = 0$); (2) large auction-specific shocks with moderate selection ($s = 2$, $\theta = 1$); and (3) moderate auction-specific shocks with no selection ($s = 0.5$, $\theta = 0$). These scenarios imply that an even larger amount of cost heterogeneity than in Figure 8 would be necessary to explain the outliers flagged by our metric.

[25] See Online Appendix Section C for details on these back-of-envelope calculations.

[26] As another test for whether we only capture differences in costs, we test whether the concentration of awards between firms reflects overall market structure in the country-sector. If cost heterogeneity is the

7 Conclusion

We develop and apply a novel Market Allocation Imbalance (MAI) measure to score countries' procurement auctions that compares realized concentration in contract value among winning firms to a homogeneous competitive benchmark, holding the distribution of auction values constant. While the MAI is designed to assess overall market functionality and identify sectors where performance can be improved rather than to distinguish between specific sources of distortion such as corruption, bid-rigging, or collusion, it offers a practical and scalable diagnostic tool for cross-sector and cross-country comparisons.

Both corrupt contracting authorities and colluding firms can manipulate many levers of a tender—the number of bidders, timelines, documentation requirements, and even the auction format—so common red flags like a high share of single-bidder awards, while also useful, can be rigged. Concentration measures based on the distribution of winners (e.g., the HHI) can also be influenced in principle—for example, by creating shell companies to spread wins and mimic competition. But doing so is costlier, must be sustained across many awards, and does not directly increase the rents from any single auction. No metric is tamper-proof, but in practice HHI-based measures, which are computed over sets of auctions within a country–sector–period rather than one award at a time, should be harder to manipulate, making them a robust and informative tool for assessing procurement risks.

Our method is not without shortcomings. First, public procurement has many stages (Decarolis and Srhoj, 2026), and the MAI only addresses one of them. For example, we take the auction values as given. If some corruption materializes through the creation of very large auctions that are then targeted to specific firms, our metric may not capture this manipulation if the winning firms are not also winning a disproportionate number of other

sole explanation, we should observe high within-sector correlation of auction winner HHI and overall sector HHI across different countries. We build the latter HHI based on firm-level data from the Orbis dataset. In Online Appendix D, we show that the correlations are small to modest in size and statistically insignificant. If we limit overall sector HHI concentration to only consider firms that appear in the TED dataset, i.e., participate in the procurements, the correlations are even smaller, suggesting that the overall size differences across auction winning firms do not translate into the differences in awards.

auctions. Second, our empirical work assumes that winning firms with distinct names are unrelated to each other. If companies that appear distinct on paper have a parent-subsidiary relationship, our approach will score a market as being more competitive than it really is. We note that this is not a conceptual problem but an empirical one: if data on firm linkages are available, then the linkages can be taken into account when constructing winner concentration (e.g., all firms connected through common ownership could be considered a single firm). Third, differences in firms' cost structures could also cause the firm HHI to deviate from the homogeneous competitive benchmark, although we show that such deviations are unlikely to explain the MAI of the lowest-ranked country-sectors. In that respect our findings should be interpreted from the necessary versus sufficient condition lenses: If we do not see significant deviations from the competitive benchmarks in most countries/sectors, what do a few extremely odd cases tell us?

References

Acemoglu, D., S. Johnson, and J. A. Robinson (2005). Institutions as a fundamental cause of long-run growth. Volume 1 of *Handbook of Economic Growth*, pp. 385–472. Elsevier.

Adam, I., H. A. Sanchez, and M. Fazekas (2021). Global public procurement open competition index. Working Paper GTI-WP/2021:02, Government Transparency Institute.

Andreyanov, P., A. Davidson, and V. Korovkin (2018). Detecting auctioneer corruption: Evidence from Russian procurement auctions. Working Paper.

Aryal, G., H. Charankevich, S. Jeong, and D.-H. Kim (2023). Procurements with bidder asymmetry in cost and risk-aversion. *Journal of Business & Economic Statistics 41*(4), 1143–1156.

Asker, J. (2010). A study of the internal organization of a bidding cartel. *American Economic Review 100*(3), 724–762.

Bajari, P. and L. Ye (2003). Deciding between competition and collusion. *Review of Economics and Statistics 85*(4), 971–989.

Baltrunaite, A. (2020). Political contributions and public procurement: Evidence from Lithuania. *Journal of the European Economic Association 18*(2), 541–582.

Bandiera, O., A. Prat, and T. Valletti (2009). Active and passive waste in government spending: Evidence from a policy experiment. *American Economic Review 99*(4), 1278–1308.

Baránek, B., L. Musolff, and V. Titl (forthcoming). Detection of collusive networks in multistage auctions. *American Economic Journal: Applied Economics*.

Bosio, E., S. Djankov, E. Glaeser, and A. Shleifer (2022). Public procurement in law and practice. *American Economic Review 112*(4), 1091–1117.

Carnehl, C. and S. Weiergraeber (2023). Bidder asymmetries in procurement auctions: Efficiency vs. information–evidence from railway passenger services. *International Journal of Industrial Organization 87*, 102902.

Chassang, S. and K. Kawai (2025). Collusion in public procurement. *NBER Reporter 2025*(2), 9–13.

Chassang, S., K. Kawai, J. Nakabayashi, and J. Ortner (2022). Robust screens for noncompetitive bidding in procurement auctions. *Econometrica 90*(1), 315–346.

Chen, Q. (2025). Rigging the scores: Corruption through scoring rule manipulation in public procurement auctions. Policy Research Working Paper 11267, The World Bank.

Commission of Inquiry on the Awarding and Management of Public Contracts in the Construction Industry (2015). Report of the commission of inquiry on the awarding and management of public contracts in the construction industry. Final report (English translation).

Decarolis, F. (2014). Awarding price, contract performance, and bids screening: Evidence from procurement auctions. *American Economic Journal: Applied Economics 6*(1), 227–259.

Decarolis, F. and S. Srhoj (2026). The economics of public procurement. *CEPR Discussion Paper No. 21110*.

Ellison, G. and E. L. Glaeser (1997). Geographic concentration in U.S. manufacturing industries: A dartboard approach. *Journal of Political Economy 105*(5), 889–927.

Faccio, M. (2006). Politically connected firms. *American Economic Review 96*(1), 369–386.

Fazekas, M., A. Alshaibani, K. Aquino, and S. Cocciolo (2021). Market structure and value for money. Technical Report ProACT Research Paper 1, ProACT Project – Government Transparency Institute.

Fazekas, M. and I. J. Tóth (2016). From corruption to state capture: A new analytical framework with empirical applications from Hungary. *Political Research Quarterly 69*(2), 320–334.

Fazio, D. and A. Zaldokas (2025). Kamikazes in public procurements: Bid-rigging and real non-market outcomes. Working Paper.

Hayashi, S. (2016). Kansei-dango and antimonopoly law in Japan: The characteristics of collusion in Japan's public procurement. *CPI Asia Column (Competition Policy International).*

Houde, J. F., T. R. Johnson, M. Lipscomb, and L. Schechter (2022). Imperfect competition and sanitation: Evidence from randomized auctions in Senegal. Working Paper.

Hu, Y., D. McAdams, and M. Shum (2013). Identification of first-price auctions with non-separable unobserved heterogeneity. *Journal of Econometrics 174*(2), 186–193.

Hyytinen, A., S. Lundberg, and O. Toivanen (2018). Design of public procurement auctions: Evidence from cleaning contracts. *The RAND Journal of Economics 49*(2), 398–426.

Kawai, K. and J. Nakabayashi (2022, None). Detecting large-scale collusion in procurement auctions. *Journal of Political Economy 130*(5), 1364–1411.

Kawai, K., J. Nakabayashi, J. Ortner, and S. Chassang (2023). Using bid rotation and incumbency to detect collusion: A regression discontinuity approach. *The Review of Economic Studies 90*(1), 376–403.

Krasnokutskaya, E. (2011). Identification and estimation of auction models with unobserved heterogeneity. *The Review of Economic Studies 78*(1), 293–327.

Krasnokutskaya, E., K. Song, and X. Tang (2022). Estimating unobserved individual heterogeneity using pairwise comparisons. *Journal of Econometrics 226*(2), 477–497.

OECD (2009). Guidelines for fighting bid rigging in public procurement. OECD publishing, OECD.

OECD (2014). Ex officio cartel investigations and the use of screens to detect cartels. Roundtable on competition policy, OECD.

OECD (2019). Government at a glance 2019. OECD publishing, OECD.

OECD (2022). Data screening tools for competition investigations. OECD Roundtables on Competition Policy Papers 284, OECD.

Organisation for Economic Co-operation and Development (OECD) (2016). Preventing corruption in public procurement. OECD Public Governance.

Porter, R. H. and J. D. Zona (1993). Detection of bid rigging in procurement auctions. *Journal of Political Economy 101*(3), 518–538.

Porter, R. H. and J. D. Zona (1999). Ohio school milk markets: An analysis of bidding. *RAND Journal of Economics 30*(2), 263–288.

Sarullo, N., Y. Gorodnichenko, T. Deryugina, J. Hodson, I. Sologoub, and A. Fedyk (2026). Measuring corruption from household income and consumption micro-data: An international perspective. *Economic Modelling*, 107578.

Schoenherr, D. (2019). Political connections and allocative distortions. *The Journal of Finance 74*(2), 543–586.

TED (2022). Ted csv dataset information and codebook v3.4. Technical report, Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs (DG GROW).

Titl, V., D. Mazrekaj, and F. Schiltz (2024). Identifying politically connected firms: A machine learning approach. *Oxford Bulletin of Economics and Statistics 86*(1), 137–155.

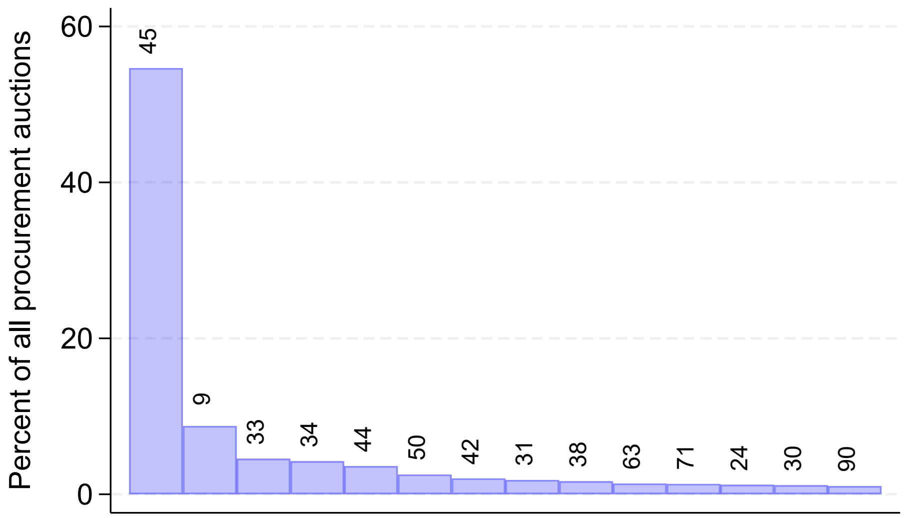
Transparency International (2015). Transparency in public procurement. Technical Report.

Transparency International (2017). The new electronic monitoring tool for *Prozorro* is launched.

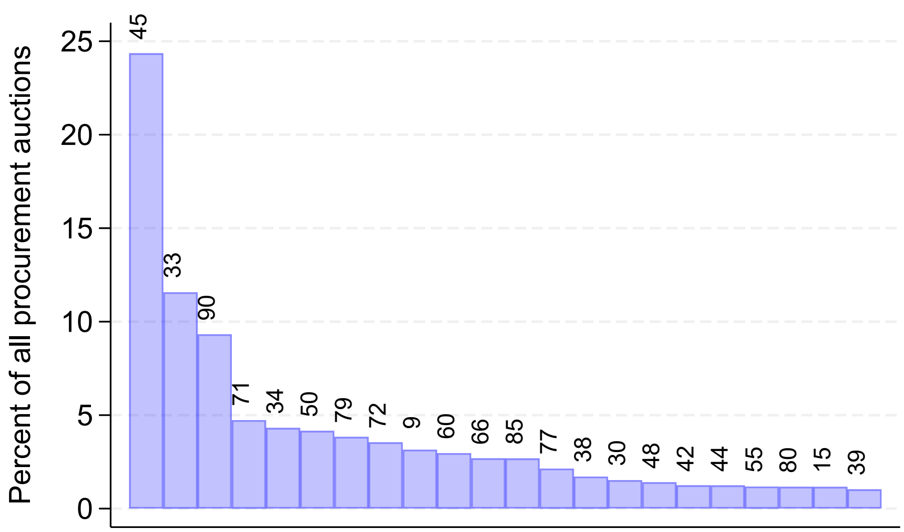
Zagreba, V. (2025). Bridges in Ukraine: Crisis, challenges and way forward. Policy paper.

Figures

Figure 1: Distribution of auctions across sectors



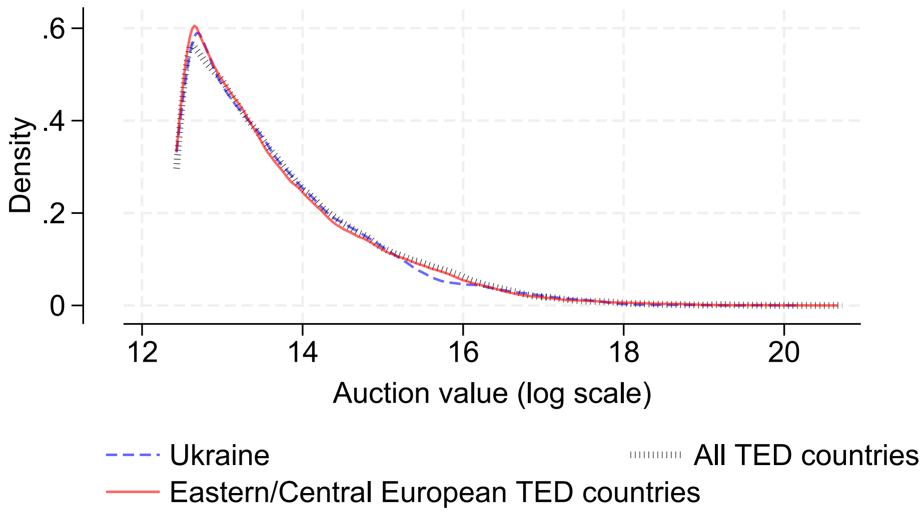
(a) Distribution of auctions across sectors, Ukraine



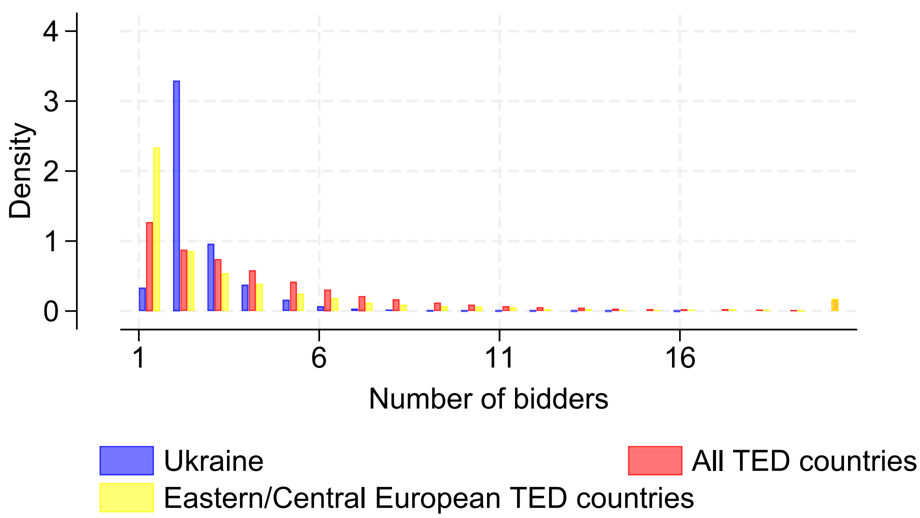
(b) Distribution of auctions across sectors, other European countries

Notes: Figure shows the share of all auctions worth at least €250,000 by 2-digit CPV code, based on ex-post contract values to winner. Panel (a) shows this distribution for Ukraine, while panel (b) shows it for the remaining European countries in the sample. CPV codes representing less than 1 percent of auctions are not shown. The full set of CPV codes and descriptions can be viewed here: https://www.bipsolutions.com/news-and-resources/cpv-codes/.

Figure 2: Distribution of auction values and number of bidders, Ukraine versus other European countries



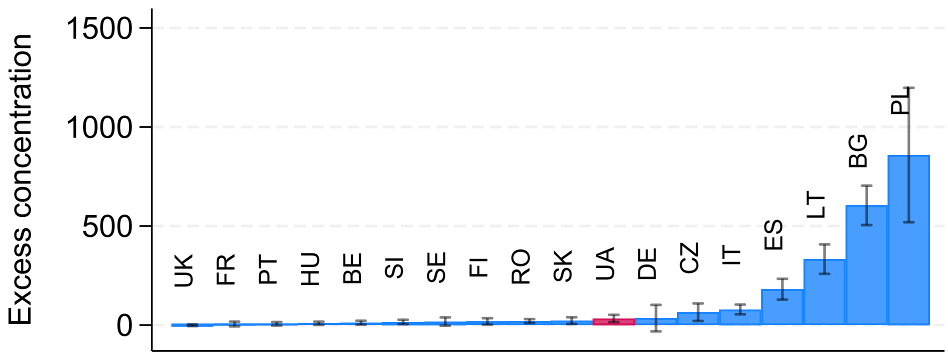
(a) Auction values



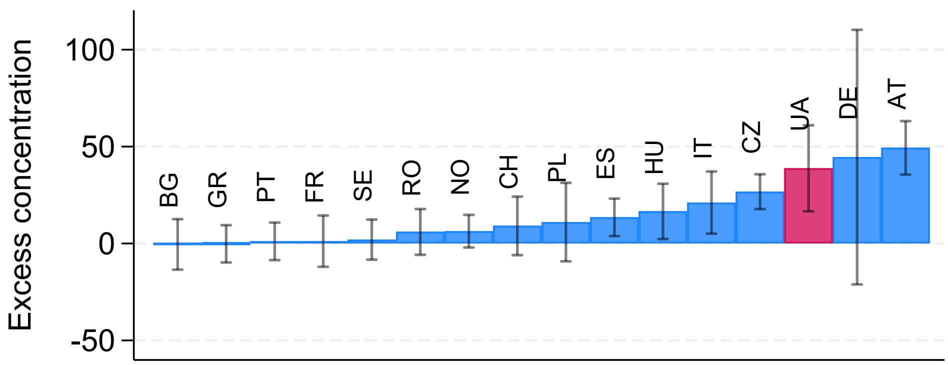
(b) Number of offers

Notes: Figure shows the distribution of the auction values and number of bidders in Ukraine, all TED countries, and a subset of Central and Eastern European TED countries (Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, North Macedonia, Poland, Romania, Slovakia, and Slovenia). Universe is procurement auctions with award values ≥ €250,000 from Ukraine's Prozorro and the EU's TED, 2018—2021, restricted to CPV codes 33 (medical), 34 (transport), 45 (construction), 71 (architectural and engineering), and 90 (sewage and refuse). Values are the *ex post* contract amounts to winners (in logs). For readability, the right-most bin in panel (b) aggregates auctions with 20 or more bidders.

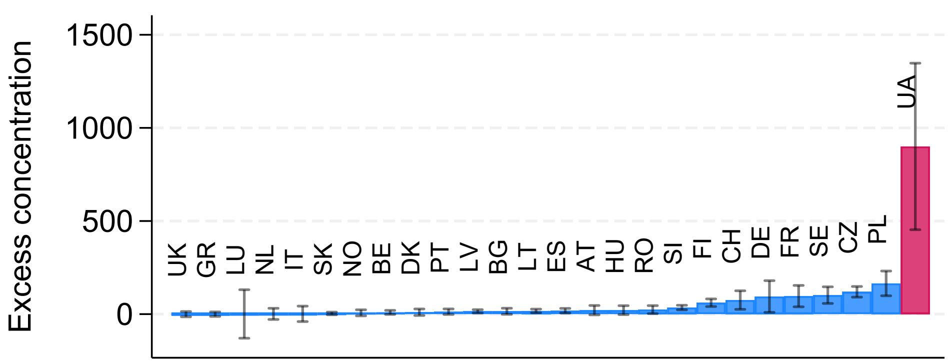
Figure 3: Procurement market rankings across selected European countries and sectors



(a) Medical equipments, pharmaceuticals and personal care products



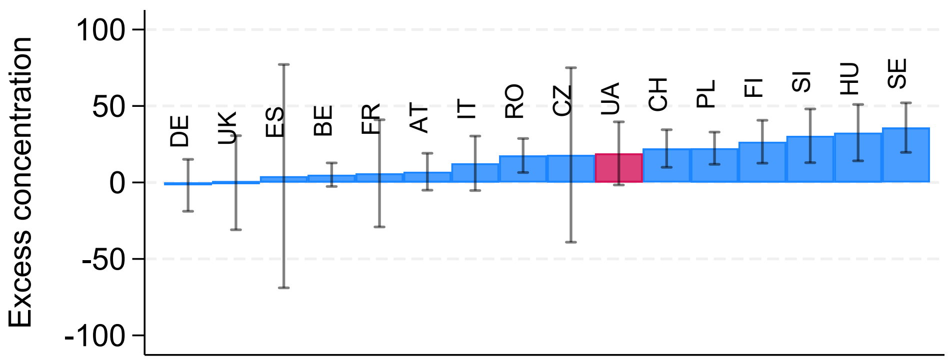
(b) Transport equipment and auxiliary products to transportation



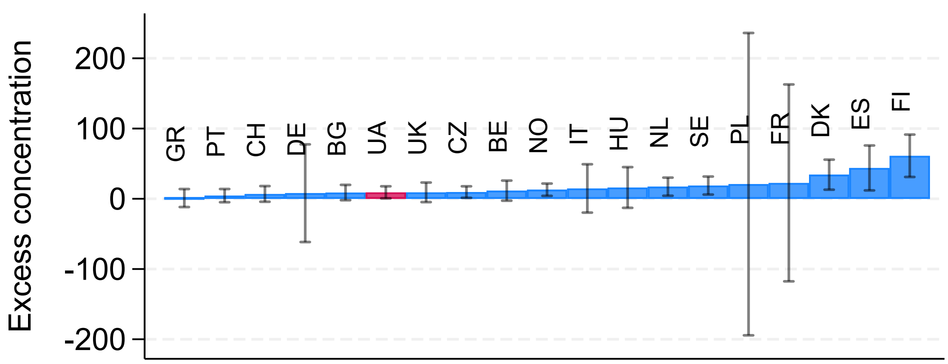
(c) Construction work

Notes: Each panel ranks countries by the standardized deviation (MAI score) of the winners' Herfindahl–Hirschman Index (HHI) from the competitive benchmark, $\frac{\Delta \mathrm{HHI}^{c,s}_{\mathrm{firm}}}{\widehat{\sigma}^{\mathrm{firm}}_{c,s}}$, where $\widehat{\sigma}^{\mathrm{firm}}_{c,s}$ is the within-country-sector standard deviation computed via random reassignment of winners. Positive values indicate excess concentration. Red bar denotes Ukraine. Error bars show bootstrapped 95% confidence intervals.

Figure 3: Procurement market rankings across selected European countries and sectors (continued)



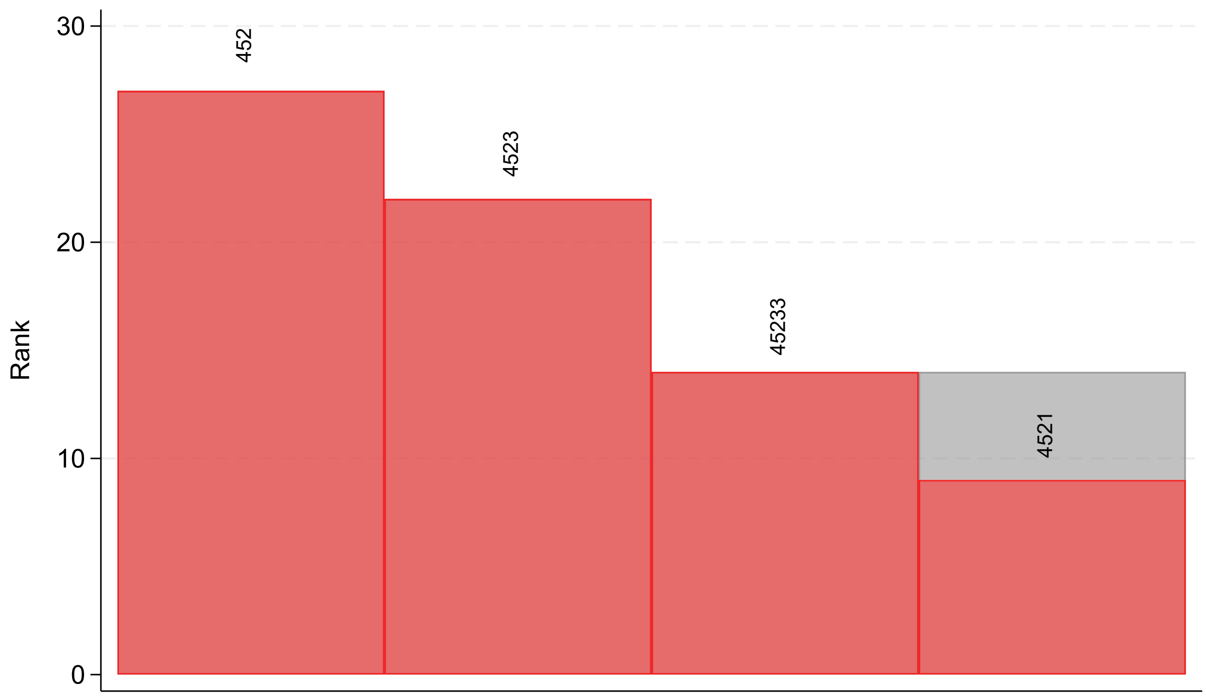
(d) Architectural, construction, engineering and inspection services



(e) Sewage-, refuse-, cleaning-, and environmental services

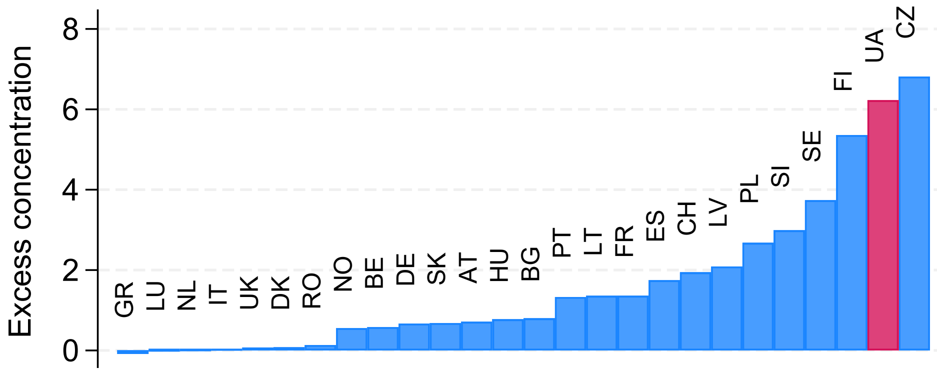
Notes: Each panel ranks countries by the standardized deviation (MAI score) of the winners' Herfindahl–Hirschman Index (HHI) from the competitive benchmark, $\frac{\Delta \mathrm{HHI}^{\mathrm{c,s}}_{\mathrm{firm}}}{\widehat{\sigma}^{\mathrm{firm}}_{c,s}}$, where $\widehat{\sigma}^{\mathrm{firm}}_{c,s}$ is the within-country-sector standard deviation computed via random reassignment of winners. Positive values indicate excess concentration. Red bar denotes Ukraine. Error bars show bootstrapped 95% confidence intervals.

Figure 4: Ukraine's ranking in finer construction CPV codes

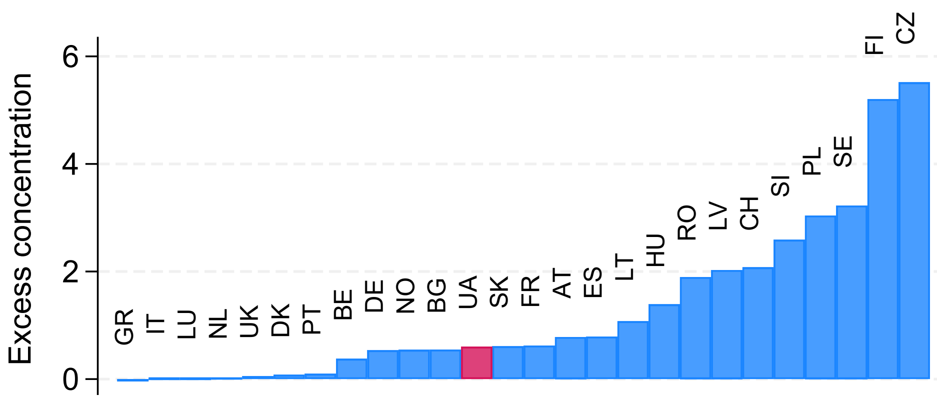


Notes: Each bar corresponds to a different construction CPV code, as indicated above the bar. Only CPV codes with at least 100 auctions and at least ten ranked countries are shown.

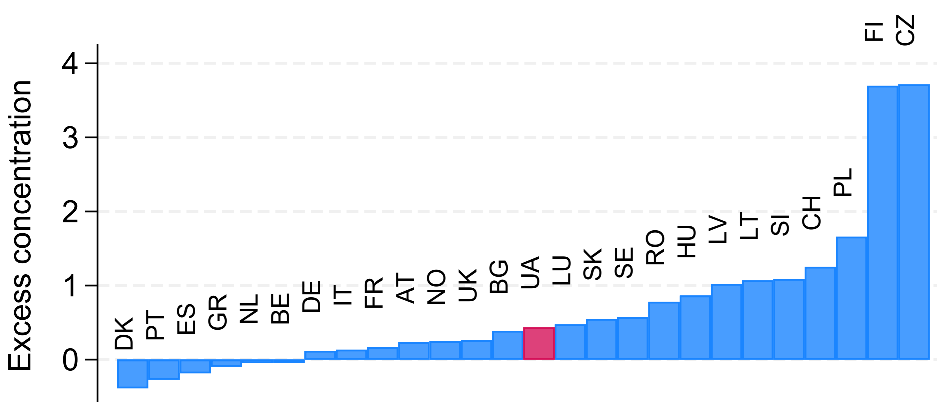
Figure 5: Procurement market rankings excluding certain construction CPV codes



(a) Excluding highway and road construction (CPV 45233)



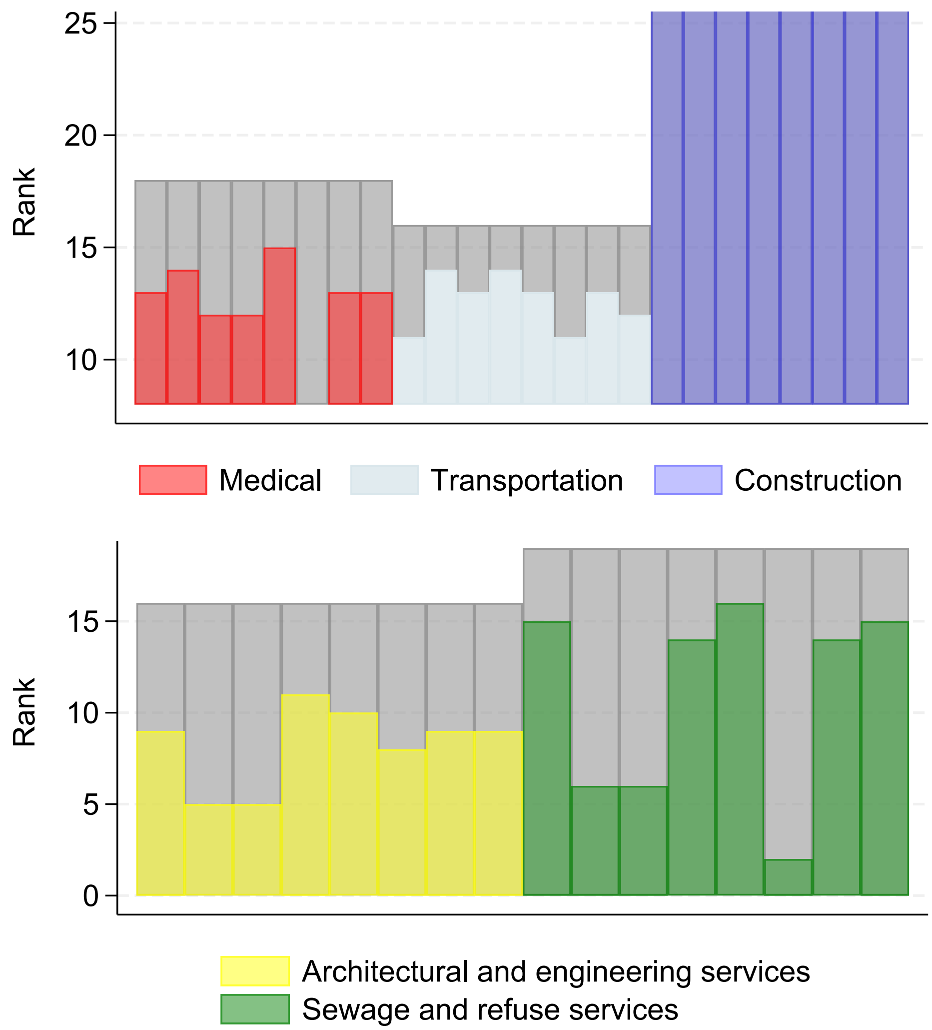
(b) Excluding pipeline, communication and power line, and highway, road, airfield and railway construction (CPV 4523)



(c) Excluding construction and civil engineering work (CPV 452)

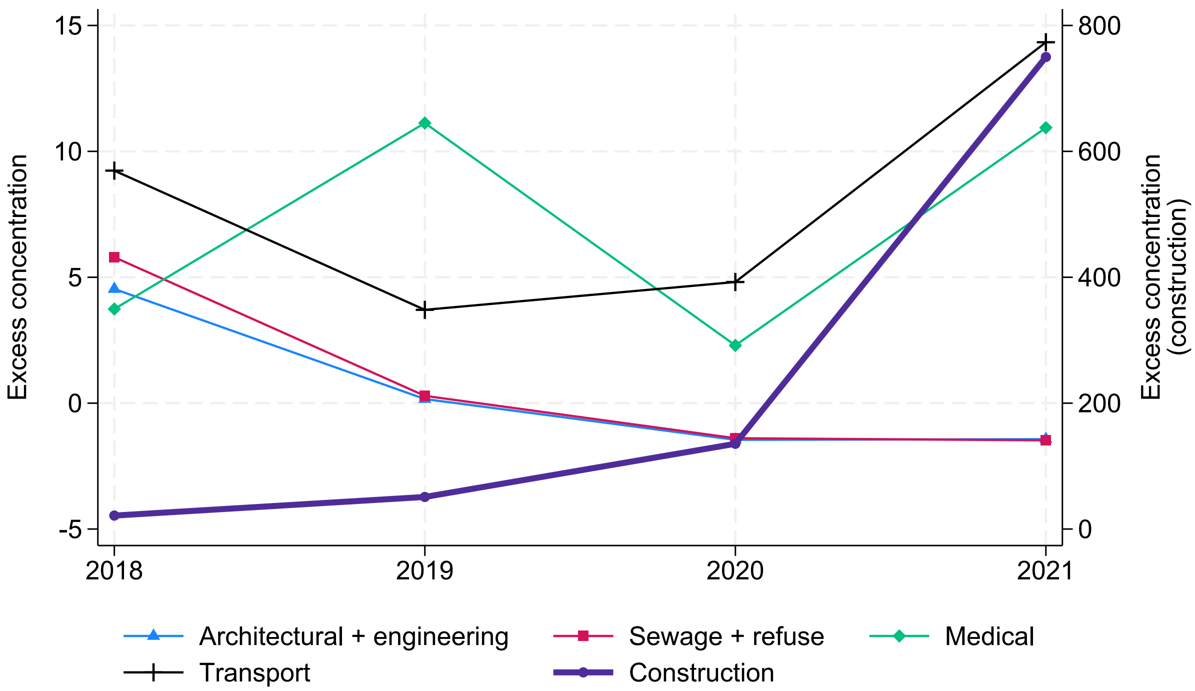
Notes: Each panel shows countries ranked by the deviation of their winner Herfindahl–Hirschman Index (HHI) from the expected value in the construction sector, dropping the specified CPV codes. Red color denotes Ukraine.

Figure 6: Ukraine's rankings in alternative subsamples



Notes: Each bar color corresponds to a different sector, as indicated in the legend. Grey bars denote the maximum ranking in that scenario. The first bar in each set corresponds to the baseline scenario. The subsequent bars correspond to, respectively: dropping the top 1% of auctions; dropping the top 5% of auctions; keeping only the top 25% of auctions; keeping only auctions with two or more offers; keeping only auctions with three or more offers; dropping the top winning firm (by value) from each country's data; and dropping the top two winning firms from each country's data.

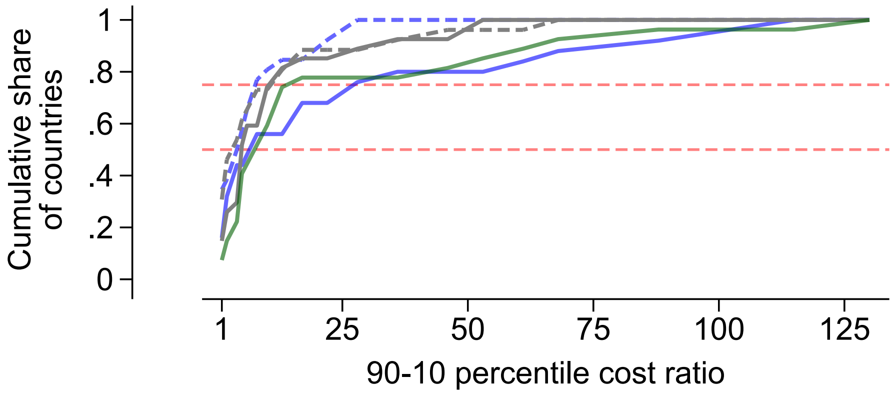
Figure 7: Excess concentration by year: Ukraine



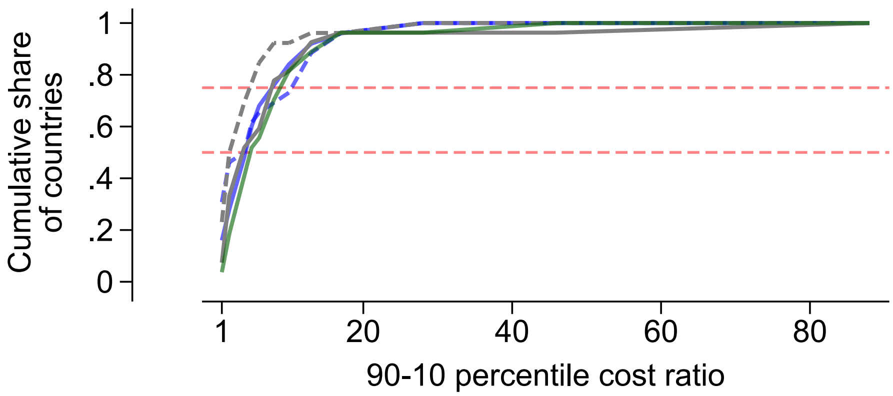
Notes: The figure reports the standardized deviation of the winners' Herfindahl–Hirschman Index (HHI) from the competitive benchmark by sector and year (2018–2021) for Ukraine. For each sector-year, we recompute the benchmark $\mathbb{E}[\text{HHI}_{\text{firm}}]$ using only that year's auction HHI and winning firms. We also recalculate the within-sample standard deviation by randomly reassigning winners among the set of winning firms in that sector–year (500 draws). The figure then plots $(\widehat{\text{HHI}}_{\text{firm}} - \mathbb{E}[\text{HHI}_{\text{firm}}])/\widehat{\sigma}$ in each year. The sample includes awards with value $\geq$ €250,000 in CPV codes 33, 34, 45, 71, and 90. Construction is displayed on a separate axis due to scale.

Figure 8: Distribution of cost heterogeneity necessary to rationalize deviations from benchmark

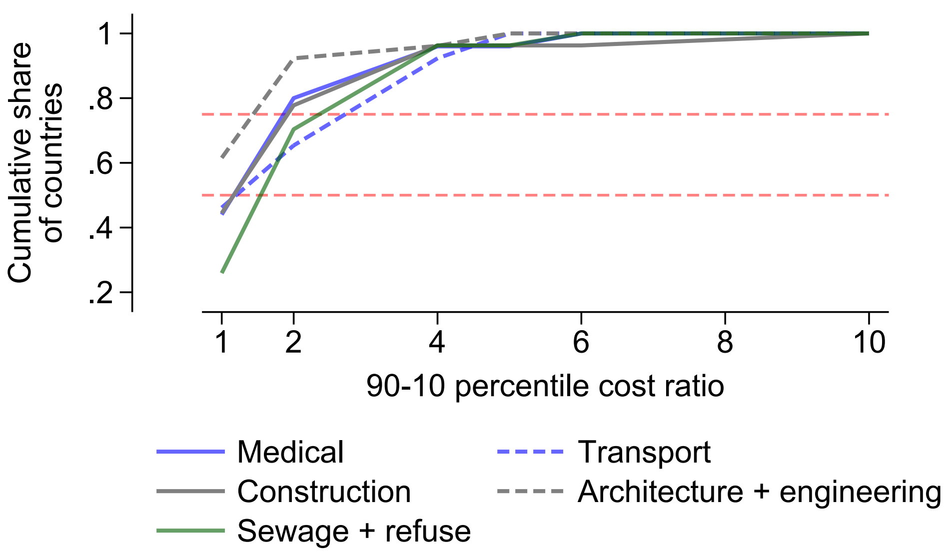
(a) No auction-specific shocks, random entry



(b) Moderate auction-specific shocks, moderate selection



(c) No auction-specific shocks, strong selection



Notes: The figure plots the cumulative distribution of the 90–10 cost ratio required to rationalize observed firm HHI in each country-sector under various assumptions about cost-related selections into auctions and auction-specific shocks. The horizontal axis shows the implied ratio of costs between high- and low-cost firms, while the vertical axis shows the share of country–sector observations with a required ratio at or below that level. Panels (a)–(c) correspond to $(s, \theta) = (0, 0)$, $(0.5, 1)$, and $(0, 2)$, respectively. Horizontal dashed lines drawn at values of 0.5 and 0.75.

Tables

Table 1: Summary statistics: auction values

	Mean	Std. dev.	Min	Median	Max
Austria	28	116	2.5	9	3255
Belgium	35	83	2.5	9	1500
Bulgaria	19	51	2.5	7	1406
Czechia	28	79	2.5	8	1320
Denmark	33	71	2.5	10	917
Finland	32	66	2.5	10	1560
France	16	79	2.5	6	10000
Germany	16	81	2.5	6	5704
Greece	45	171	2.5	9	2556
Hungary	48	246	2.5	8	9425
Italy	35	168	2.5	8	7055
Latvia	34	37	2.5	21	190
Lithuania	12	25	2.5	5	267
Luxembourg	47	367	2.6	12	8002
Netherlands	34	124	2.5	11	3080
Norway	62	248	2.5	14	6336
Poland	23	117	2.5	6	6664
Portugal	31	93	2.5	7	1489
Romania	50	215	2.5	13	6158
Slovakia	50	152	2.5	8	1500
Slovenia	21	32	2.5	9	384
Spain	36	163	2.5	7	8461
Sweden	44	132	2.5	10	4435
Switzerland	27	97	2.5	9	3189
Ukraine	23	96	2.5	6	5940
United Kingdom	107	367	2.5	11	2871

Table shows auction value summary statistics by country. All values are in hundreds of thousands of nominal euros.

Table 2: Summary statistics: number of auctions and winners

	Medical		Transport		Construction		Architecture		Sewage and refuse	
	Auctions	Winners	Auctions	Winners	Auctions	Winners	Auctions	Winners	Auctions	Winners
Austria	108	56	289	66	2028	880	355	229	188	88
Belgium	254	141	146	86	816	463	257	194	538	246
Bulgaria	2889	150	253	134	1730	880	176	138	286	165
Czechia	1677	196	450	149	1300	353	426	170	380	132
Denmark	90	42	119	57	257	169	104	54	325	142
Estonia	86	38	38	32	197	58	54	32	124	35
Finland	825	197	182	68	809	370	263	106	537	187
France	452	266	620	413	15613	8234	1536	1037	2924	1319
Germany	308	119	2109	501	19941	8860	926	713	2395	990
Greece	150	100	291	161	342	264	57	55	269	208
Hungary	433	152	377	169	1057	416	430	166	311	155
Italy	3688	1037	1084	525	2233	1522	727	561	3086	1583
Latvia	133	44	66	35	321	120	55	40	130	48
Lithuania	1780	109	182	81	308	120	52	26	140	55
Luxembourg	24	17	48	26	484	276	33	27	41	26
Netherlands	45	38	161	99	287	195	123	89	480	199
Norway	144	81	200	80	431	253	172	96	322	171
Poland	9398	1024	1335	478	4390	2144	1169	537	6306	2053
Portugal	405	166	231	135	584	264	151	97	413	156
Romania	776	200	390	165	1490	698	318	140	96	63
Slovakia	262	76	80	48	243	96	147	58	73	41
Slovenia	284	82	172	72	394	136	211	78	162	51
Spain	2515	549	1138	418	1318	827	1559	956	2610	775
Sweden	2047	522	463	195	1166	514	1076	476	770	336
Switzerland	105	55	347	175	3640	1553	1300	697	238	137
Ukraine	1064	213	989	355	12727	2789	313	161	246	83
United Kingdom	487	278	180	145	507	349	306	260	524	350

Table shows the number of auctions and winners in the relevant 2-digit CPV code classification (33, 34, 45, 71 and 90, respectively) by country.

Table 3: Correlations of rankings across sectors

	(1) Medical	(2) Transport	(3) Construction	(4) Architecture
Transport	0.203			
Construction	0.191	0.356		
Architecture	–0.059	–0.315	0.424***	
Sewage	0.090	0.178	0.167	0.297

Table shows pairwise Spearman (rank) correlations of a country's rank across sectors. A */**/*** indicates significance at the 10/5/1 percent level. Each entry corresponds to a separate regression. Each column corresponds to a different 2-digit CPV code classification (33, 34, 45, 71 and 90, respectively).

Table 4: Correlation between Market Allocation Imbalance (MAI) and other metrics

	(1) Medical	(2) Transport	(3) Construction	(4) Architecture	(5) Sewage and refuse
CPI rank	0.021	0.13	0.095***	0.52	–0.69**
	(0.022)	(0.67)	(0.013)	(0.57)	(0.32)
Sarullo et al. metric	0.076**	–0.92	0.072***	3.4**	0.81
	(0.029)	(1.1)	(0.025)	(1.2)	(0.98)
Pct. with one bidder	0.036	–0.010	–0.00042	0.36	–0.30*
	(0.022)	(0.25)	(0.0030)	(0.38)	(0.17)
Average number of bidders	0.0023	–0.016***	–0.0040***	–0.015	0.015
	(0.0055)	(0.0050)	(0.0010)	(0.073)	(0.019)
Top 10 winners pct.	0.013	0.11	0.011*	0.58*	0.27**
	(0.017)	(0.23)	(0.0060)	(0.28)	(0.12)
Top 5 winners pct.	0.014	0.14	0.011**	0.45**	0.27**
	(0.016)	(0.20)	(0.0043)	(0.21)	(0.094)

Table shows pairwise correlations between a country's Market Allocation Imbalance metric and the Corruption Perception Index ranking; the income-consumption gap metric developed by Sarullo et al. (2026); and other red-flag metrics that can be calculated from procurement data. Robust standard errors are shown in parentheses. A */**/*** indicates significance at the 10/5/1 percent level. Each entry corresponds to a separate regression. Each column corresponds to a different 2-digit CPV code classification (33, 34, 45, 71 and 90, respectively).

Table 5: Interpretation of simulation parameters

Parameter	Value	Interpretation
Auction-specific shocks (s)		
$s = 0$	None	Outcomes fully determined by permanent costs
$s = 0.5$	Moderate	Realized costs vary by factor $\approx e^{\pm 0.5} \approx [0.61, 1.65]$
$s = 1$	Large	Realized costs vary by factor $\approx e^{\pm 1} \approx [0.37, 2.72]$
$s = 2$	Very large	Realized costs vary by factor $\approx e^{\pm 2} \approx [0.14, 7.39]$
Cost-based entry (θ)		
$\theta = 0$	None	Entry is random and independent of cost
$\theta = 1$	Moderate	Lower-cost firms are more likely to enter (probability $\propto 1/c_i$)
$\theta = 2$	Strong	Entry strongly favors lower-cost firms (probability $\propto 1/c_i^2$)

Notes: Realized costs are $c_i \exp(s\varepsilon_{ia})$, where $\varepsilon_{ia} \sim N(0, 1)$. Entry probabilities are proportional to $c_i^{-\theta}$.

Online Appendix

Rating Public Procurement Markets

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A Other approaches to scoring procurement

We summarize several existing approaches to ranking the "quality" of public procurement processes by converting transaction-level datasets into summary competition scores. The most widely used building blocks are (i) the share of tenders receiving a single bid, (ii) the incidence of non-competitive procedures such as direct awards, (iii) the average number of bids per tender, and (iv) supplier-side concentration measures.

OECD guidelines and indicators. OECD (2009) provides one of the earliest standardized lists of suspicious patterns that act as warning signs for collusion. These lists include qualitative indicators based on the bid submission, documents submitted, pricing and behavior, that may act as tell-tale signs for the presence of bid-rigging. While these indicators are not definitive proof of misconduct, they can act as red flags that warrant further investigation.

EU Single Market Scoreboard. The European Commission reports a performance indicator sets for public procurement within its Single Market and Competitiveness Scoreboard. The headline measures include the percentage of contract awards with only one bidder, the percentage of direct awards without a prior call for competition, total publication value as a share of GDP, and others. Each metric is benchmarked against green–yellow–red thresholds (e.g., less than 10% single-bidder auctions for satisfactory performance, more than 20% for unsatisfactory performance).[1] Member-state performance is color-coded and published annually, facilitating cross-country comparison. The European Court of Auditors recently relied on these scoreboard metrics to show that EU-wide competition has worsened over 2011–2021, with the single-bid share almost doubling over the decade.[2]

[1] See European Commission, Access to Public Procurement Performance Indicators, https://single-market-scoreboard.ec.europa.eu/business-framework-conditions/public-procurement_en.

[2] European Court of Auditors, *Special Report 28/2023: Public Procurement in the EU*, https://www.eca.europa.eu/ECAPublications/SR-2023-28/SR-2023-28_EN.pdf.

Composite outcome indices. Sometimes different indicators are combined into composite indices. For example, the *Global Public Procurement Open Competition Index* (GP-POCI) averages z-scores of four components—single-bid share, trimmed mean bid count, market-share HHI within narrow CPV markets, and the entry rate of new suppliers—thereby controlling for sectoral mix while retaining cross-country comparability (Adam, Sanchez and Fazekas, 2021). Other thin-market scoring frameworks similarly combine bidder-count indicators with supplier-concentration metrics. For example, Fazekas et al. (2021) construct dashboards for Portuguese procurement markets that include both average bidder counts and top-supplier revenue shares.

Use of screens to detect cartels. To detect bid rigging, regulators have also started screening their bidding processes. There are two general approaches to screening, i) a structural approach, which involves identifying structural features of the product or the market that the bid was made which may make collusion more likely; and ii) a behavioral approach, where the behavior of markets and its participants are analyzed to see if there are any signs of collusion (OECD, 2014). By utilizing a mix of both approaches, regulators try to screen and flag suspicious bids that may signal collusion. We provide a few examples from various countries of the screening systems their antitrust authorities use to identify bid rigging behavior (OECD, 2022).

In Switzerland, the Swiss competition authority (COMCO) uses two simple screening techniques: the coefficient of variation (standard deviation of the bids divided by the mean of the bids for a given tender), and the relative distance (distance between two lowest bids divided by the standard deviation of the losing bids for a given tender). By flagging out tenders with low coefficient of variance and high relative distance, COMCO then launches further investigations into the suspicious activities of the firms and identify if there are any signs of collusion.

In Korea, the Korean Fair Trade Commission (KFTC) uses the Bid-Rigging Indicator

Analysis System (BRIAS) which weighs different indicators to produce a score on the likelihood on bid rigging, based on weights tailored to the specific sector in question. BRIAS automatically collects and analyses bid data from public tenders provided by government agencies. The system calculates a collusion risk score for each tender by weighting various indicators such as bid-winning rates, number of bidders, bid prices relative to estimated prices, competition methods, and gaps between winning and losing bids. BRIAS operates by gathering all bid- related data and information, analyzing it and generating a score on the likelihood of bid rigging by assessing each relevant factor for the analysis, and then weighting its scores.

Brazil's competition authority CADE developed Cérebro, a tool that utilizes data-mining and statistical tests to detect suspicious bidding patterns. It integrates a data warehouse that consolidates information from public and private databases into a searchable platform, employs advanced data mining techniques to identify collusive behavior based on competitor patterns, suspicious anomalies, and signs of simulated competition and applies statistical models to automate analysis and find indications of cartels in public bids. The system searches for key cartel indicators such as bid suppression, cover bidding, bid rotation, superfluous losing bidders, stable market shares, pricing anomalies, textual similarities in bids, and metadata patterns of submitted files.

Ukraine's *Prozorro* monitors each tender against a list of binary "risk indicators"—including single bidding, repeated wins by the same supplier, and abnormally high savings—and routes flagged tenders to auditors (Transparency International, 2017). Although designed for enforcement rather than scoring, aggregating the share of flagged tenders at buyer or product level offers a comparable quality metric.

Limitations of current screening methods. While current screening methods are comprehensive and consider various indicators, there always runs a risk of screens providing false positives or false negatives. False positives are costly, as it induces competition authorities to take up cases where collusion is not happening, thus wasting time and resources. One such example the BRIAS in Korea, which produced too many positives when it was first introduced in 2006, leading to difficulties in selecting cases for investigation (OECD, 2022). Another limitation is that meaningful screens require a large amount of data. In countries where data and information are limited, data crucial for effective screening may not be available (OECD, 2022).

B Winner name and identifier cleaning

We minimize both spurious fragmentation (splitting one firm across variants) and false mergers (combining distinct firms) in the TED database through the following data cleaning pipeline. To maximize the reliability of the cleaning procedure, we perform it on the full TED database (i.e., before dropping contract values below €250,000). Note that because all concentration metrics are calculated within a country-CPV-code combination, misidentifying the same firm in different countries or different 2-digit CPV codes does not affect our analysis.

(1) National ID extraction and validation. We lowercase and trim the winner national ID field and remove separators (`- - . ( ) ' + / :` and spaces). Where the name string contains Italian tax-code markers (*C.F./P.IVA*), we parse 11-digit numeric sequences and assign at most one candidate ID per winner. We set IDs to missing if they contain no digits, include a "+", have ≤4 digits but many letters, or match obvious non-identifiers (e.g., country names, cities, "n/a", all zeros). Country-specific reliability rules are applied: for Liechtenstein we drop IDs; for Germany we retain only plausibly formatted entries (must include "de" and have length ≥10). We also strip frequent registry prefixes/suffixes (e.g., *SIRET*, *REGON*, *RCS*, *VAT*, Greek tax-office markers) and country codes embedded in IDs.

(2) ID-length rationalization and backfilling. For each country, we compute the modal ID length among non-missing IDs and drop IDs with non-modal lengths for names that also appear with the modal length. We then compute the modal ID for each country-winner-name combination and carry forward/backfill that ID across the same winner's records when there is no internal inconsistency; ambiguous cases are left unchanged.

(3) Reconciliation with reliable IDs. Within each country, all records sharing the same validated ID are treated as the same firm. Because that firm may also appear in other auctions without a valid ID and under a slightly different name variant, we compute Levenshtein distances on space-stripped names sharing the same valid ID and collapse minor variants; when multiple labels remain, we keep the shortest non-empty winner name.

(4) Name normalization and harmonization. We apply Unicode fixes and convert names to lowercase; trim whitespace and collapse multiple spaces; and remove punctuation. We harmonize conjunctions to a single token (e.g., Spanish *y*, Portuguese/Italian *e*, German *und*, French *et*, Polish ł). We standardize and then remove legal-form tokens across languages (e.g., *SA*, *SAS*, *SARL*, *SPA*, *GmbH/GesmbH*, *KG*, *BV/NV*, *SRO/SRL/SL/LLC/Ltd*, *APS/OU/OY/AS/AB/AG/AE*, *KFT*, etc.), including fused or trailing variants. We normalize diacritics and transliterate common non-Latin characters (e.g., *é*→*e*, *ł*→*l*, *ß*→*ss*, *č*→*c*, *ţ*→*t*, *ñ*→*n*), and correct frequent typos observed in the raw data.

(5) Reconciliation without reliable IDs. When IDs are missing or determined to be unreliable, we compare names within country, 2-digit CPV code, and first letter of the cleaned name. The latter is done for computational reasons. We consider a merge a match only if calibrated thresholds are met: for one-character differences, scaled Levenshtein distance < 0.12; for two-character differences, < 0.075 (and < 0.07 in Bulgaria to avoid merging short engineering acronyms). A small number of deterministic corrections from visual inspection are also applied.

C 90–10 cost ratio approximations

Krasnokutskaya (2011) decomposes firm i's cost for project j multiplicatively as $c_{ij} = Y_j \times X_i$, where Y_j is a common auction-level component and X_i is a firm-level efficiency component. For regular (as opposed to fringe) bidders, X is normalized so that $E[X] = 1$. A firm with $X < 1$ is therefore cheaper than average. Krasnokutskaya (2011) estimates a standard deviation of $\hat{\sigma}_X = 0.14$ for the regular-bidder distribution of X. Approximating the distribution as normal, the 10th and 90th percentiles and their ratio are:

$$X_{0.10} = 1.000 - 1.28 \times 0.140 = 0.82$$

$$X_{0.90} = 1.000 + 1.28 \times 0.140 = 1.18$$

$$\frac{X_{0.90}}{X_{0.10}} = \frac{1.18}{0.82} \approx 1.44$$

A 90th-percentile firm therefore has costs approximately 44% higher than a 10th-percentile firm.

Aryal et al. (2023) estimate cost distributions on a [0,1] support normalized by the reserve price for three bidder types in Russian printing-paper procurements. While they do not report percentile-level cost statistics directly, the posterior predictive cost densities are heavily right-skewed with mass concentrated near the reserve price. Based on these figures, the 10th percentile of the pooled cost distribution appears to lie roughly in the 0.5—0.6 range while the 90th percentile approaches 1.0, suggesting a 90–10 ratio of around 1.5—2.0. We note that this should be treated as an informal visual approximation rather than a computed estimate.

D Differences in market structure

We test whether the concentration of awards between firms reflects overall market structure in the country-sector. We extract firm-level data from the Orbis dataset—published by Moody's (Bureau van Dijk)—containing standardized financial, ownership, and business information on over 300 million public and private global companies. We match winning firms from the

TED dataset to the Orbis dataset. We note the CPV codes of the auctions that winning firms are associated with in the TED dataset and their corresponding NACE industry codes in Orbis sector (e.g., firms in auctions CPV code 33, "Medical/pharma" have NACE code 4646 (pharma wholesale) in 83% cases, NACE code 21 (pharma manufacturing) in 5% cases). We only include NACE codes with over 5% representation in the relevant 2-digit CPV code and calculate industry HHIs of these sectors based on the revenues of all firms in that sector/country, including firms that do not participate in procurement auctions in our sample.

If the auction winner HHI measure that we develop in the paper simply reflects general concentration differences across countries, we should observe high within-sector correlation of auction winner HHI and overall sector HHI across different countries. Instead, the correlations are small to modest in size and statistically insignificant. We report the regressions betas from regressing country-sector-level auction winner HHI measure on overall sector HHI concentration in that country-sector (with robust standard errors):

- Medical (CPV 33): N=27, Spearman = 0.195, p = 0.341
- Transport (CPV 34): N=27, Spearman = 0.108, p = 0.601
- Construction (CPV 45): N=27, Spearman = 0.067, p = 0.744
- Arch/Engineering (CPV 71): N=27, Spearman = 0.205, p = 0.316
- Sewage/Environment (CPV 90): N=27, Spearman = -0.040, p = 0.846

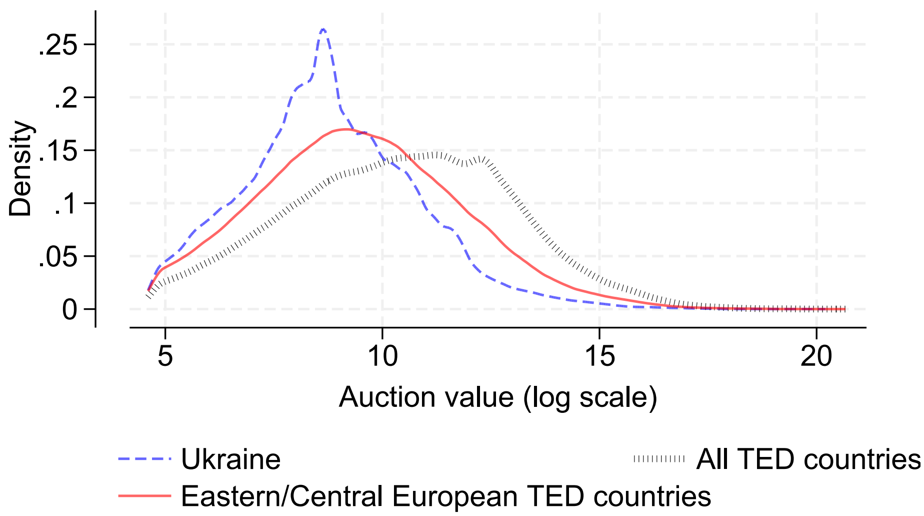
If we limit overall sector HHI concentration to only consider firms that appear in the TED dataset, i.e., participate in the procurements, the correlations are even smaller, suggesting that the overall size differences across auction winning firms do not translate into the differences in awards:

- Medical (CPV 33): N=27, Spearman = 0.195, p = 0.341

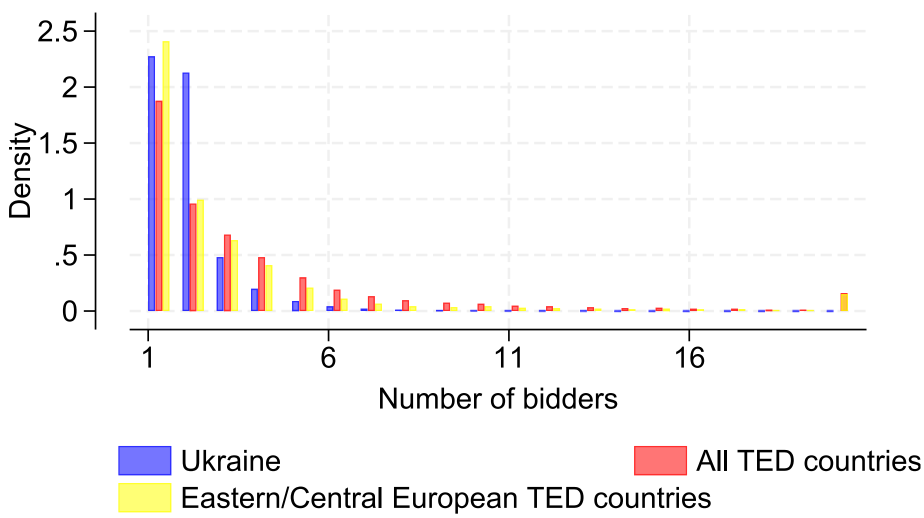
- Transport (CPV 34): N=27, Spearman = 0.108, p = 0.601
- Construction (CPV 45): N=27, Spearman = 0.067, p = 0.744
- Arch/Engineering (CPV 71): N=27, Spearman = 0.205, p = 0.316
- Sewage/Environment (CPV 90): N=27, Spearman = -0.040, p = 0.846

E Supplementary Figures and Tables

Figure E.1: Distribution of auction values and number of bidders, all sectors of interest



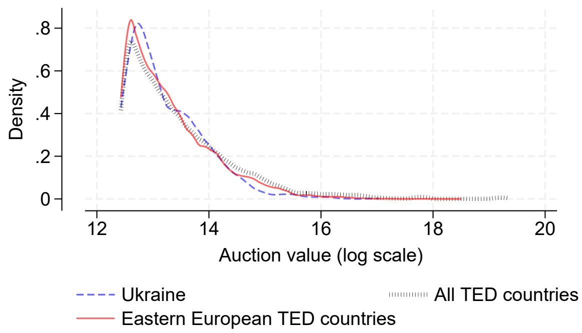
(a) Auction value



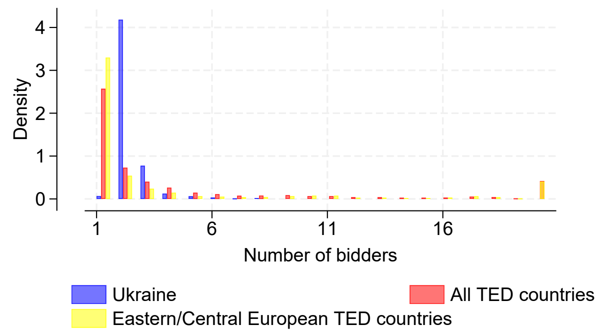
(b) Number of bidders

Notes: Figure shows the distribution of the auction values and number of bidders in Ukraine, all TED countries, and a subset of Central and Eastern European TED countries (Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, North Macedonia, Poland, Romania, Slovakia, and Slovenia). Universe is procurement auctions with award values $\geq$ €100 from Ukraine's Prozorro and the EU's TED, 2018—2021, restricted to CPV codes 33 (medical), 34 (transport), 45 (construction), 71 (architectural and engineering), and 90 (sewage and refuse). Values are the *ex post* contract amounts to winners (in logs). For readability, the right-most bin in panel (b) aggregates auctions with 20 or more bidders.

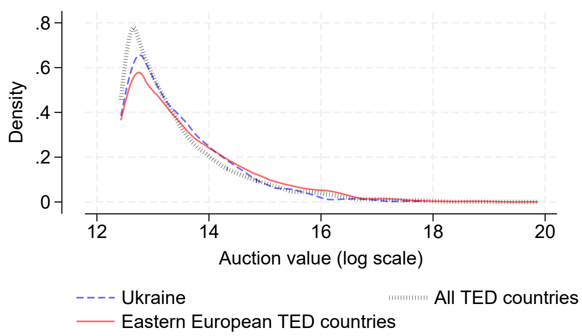
Figure E.2: Distribution of auction values and number of bidders, by CPV code



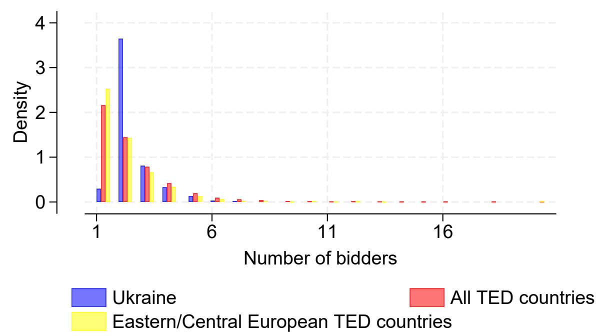
(a) Auction value, medical



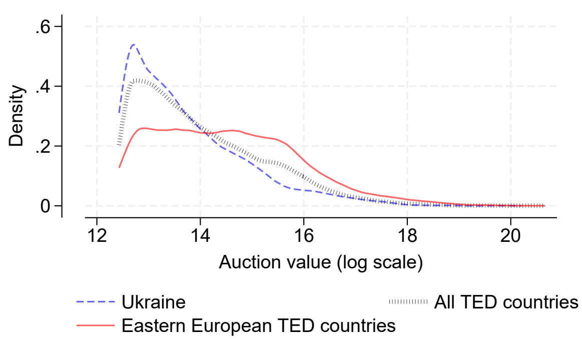
(b) Number of bidders, medical



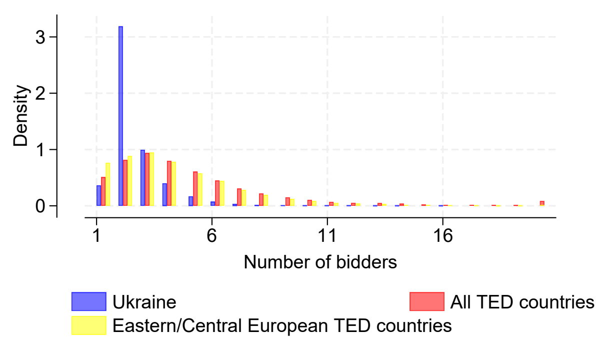
(c) Auction value, transport



(d) Number of bidders, transport



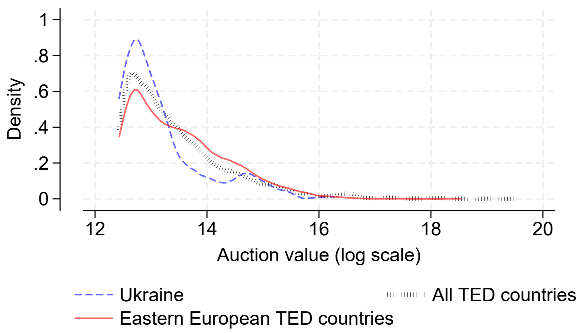
(e) Auction value, construction



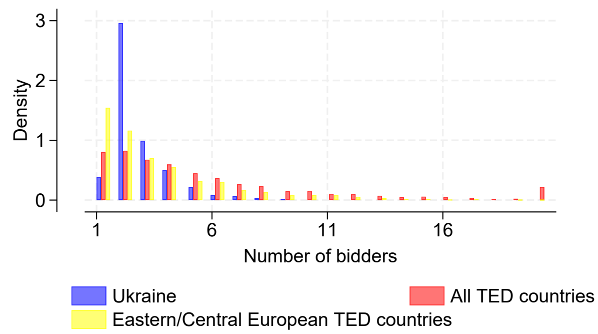
(f) Number of bidders, construction

Notes: Panels show the distribution of (left) *ex post* contract values to winners and (right) the number of bidders for awards ≥ €250,000 in 2018–2021 by 2-digit CPV code. Values are plotted in logs. The right-most bin in the bidder histograms aggregates auctions with 20 or more bidders.

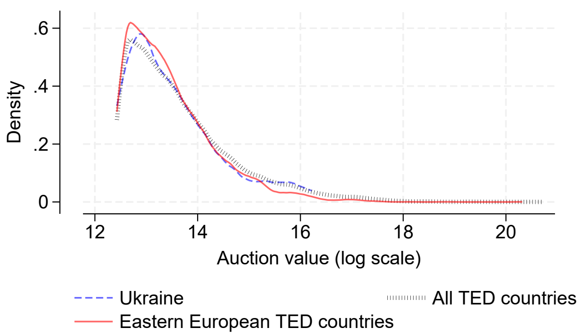
Figure E.2: Distribution of auction values and number of bidders, by CPV code (continued)



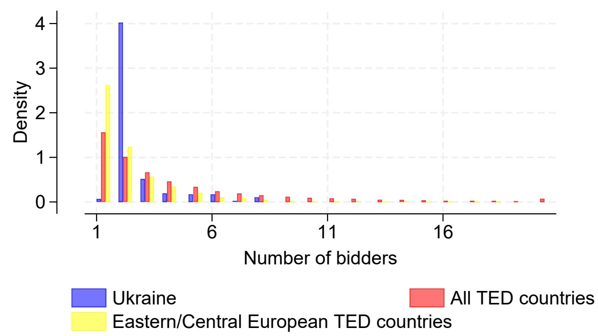
(g) Auction value, architectural and engineering



(h) Number of bidders, architectural and engineering



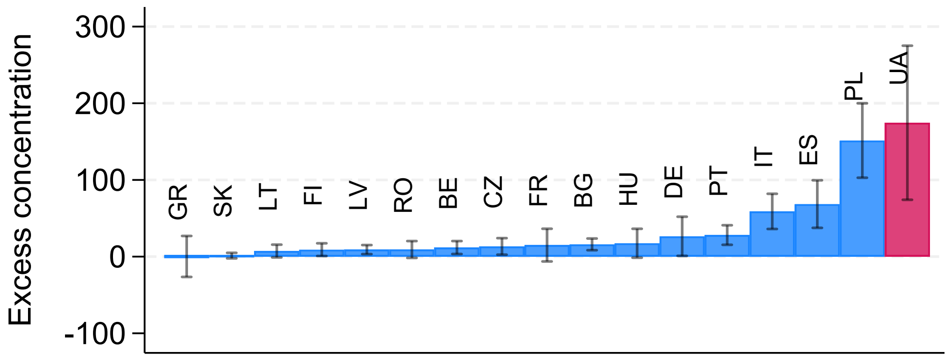
(i) Auction value, sewage and refuse



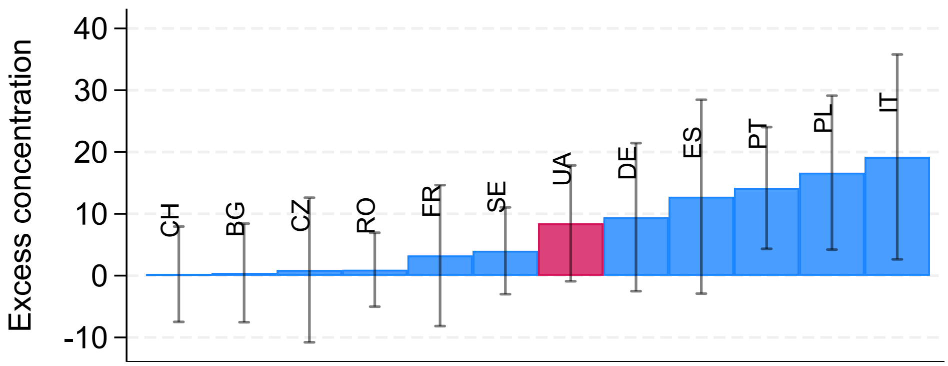
(j) Number of bidders, sewage and refuse

Notes: Panels show the distribution of (left) *ex post* contract values to winners and (right) the number of bidders for awards $\geq$ €250,000 in 2018–2021 by 2-digit CPV code. Values are plotted in logs. The right-most bin in the bidder histograms aggregates auctions with 20 or more bidders.

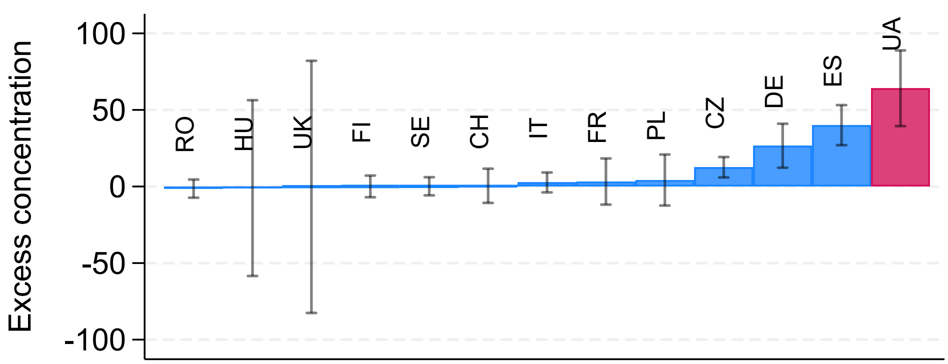
Figure E.3: Procurement market rankings across additional sectors



(a) Petroleum products, fuel, electricity and other sources of energy



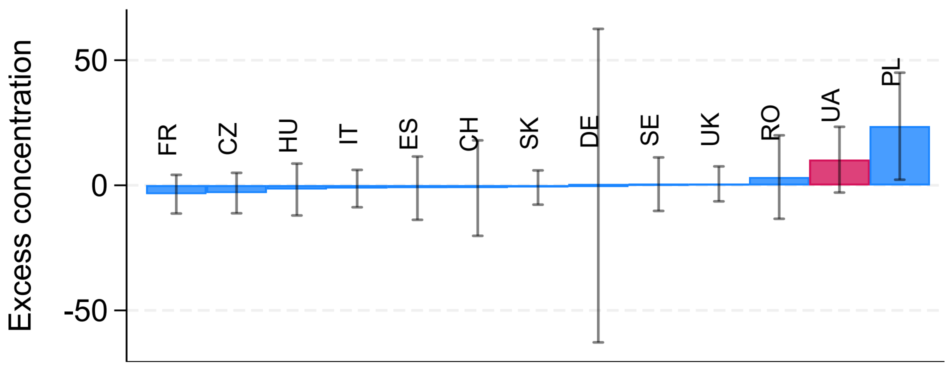
(b) Office and computing machinery, equipment and supplies except furniture and software packages



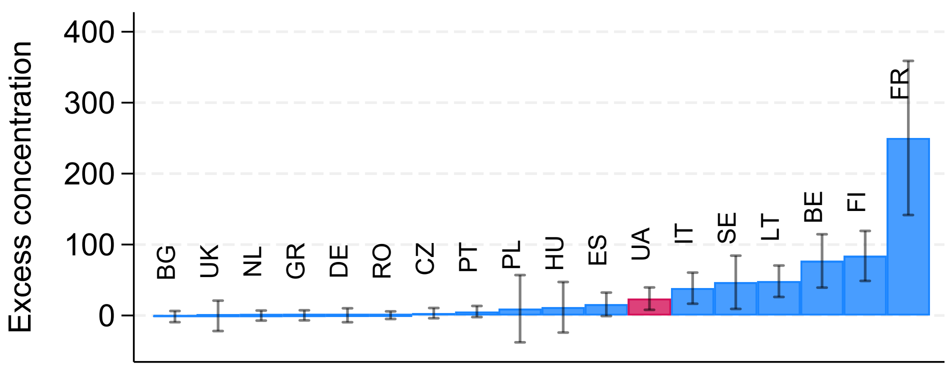
(c) Laboratory, optical and precision equipments (excl. glasses)

Notes: Each panel ranks countries by the standardized deviation (MAI score) of the winners' Herfindahl–Hirschman Index (HHI) from the competitive benchmark, $\frac{\Delta \text{HHI}^{c,s}_{\text{firm}}}{\widehat{\sigma}^{\text{firm}}_{c,s}}$, where $\widehat{\sigma}^{\text{firm}}_{c,s}$ is the within-country-sector standard deviation computed via random reassignment of winners. Positive values indicate excess concentration. Red bar denotes Ukraine. Error bars show bootstrapped 95% confidence intervals.

Figure E.3: Procurement market rankings across additional sectors (continued)



(d) Industrial machinery



(e) Repair and maintenance services

Notes: Each panel ranks countries by the standardized deviation (MAI score) of the winners' Herfindahl–Hirschman Index (HHI) from the competitive benchmark, $\frac{\Delta \text{HHI}^{c,s}_{\text{firm}}}{\widehat{\sigma}^{\text{firm}}_{c,s}}$, where $\widehat{\sigma}^{\text{firm}}_{c,s}$ is the within-country-sector standard deviation computed via random reassignment of winners. Positive values indicate excess concentration. Red bar denotes Ukraine. Error bars show bootstrapped 95% confidence intervals.

Figure E.4: Cost ratios of high- and low-cost firms in simulation scenarios

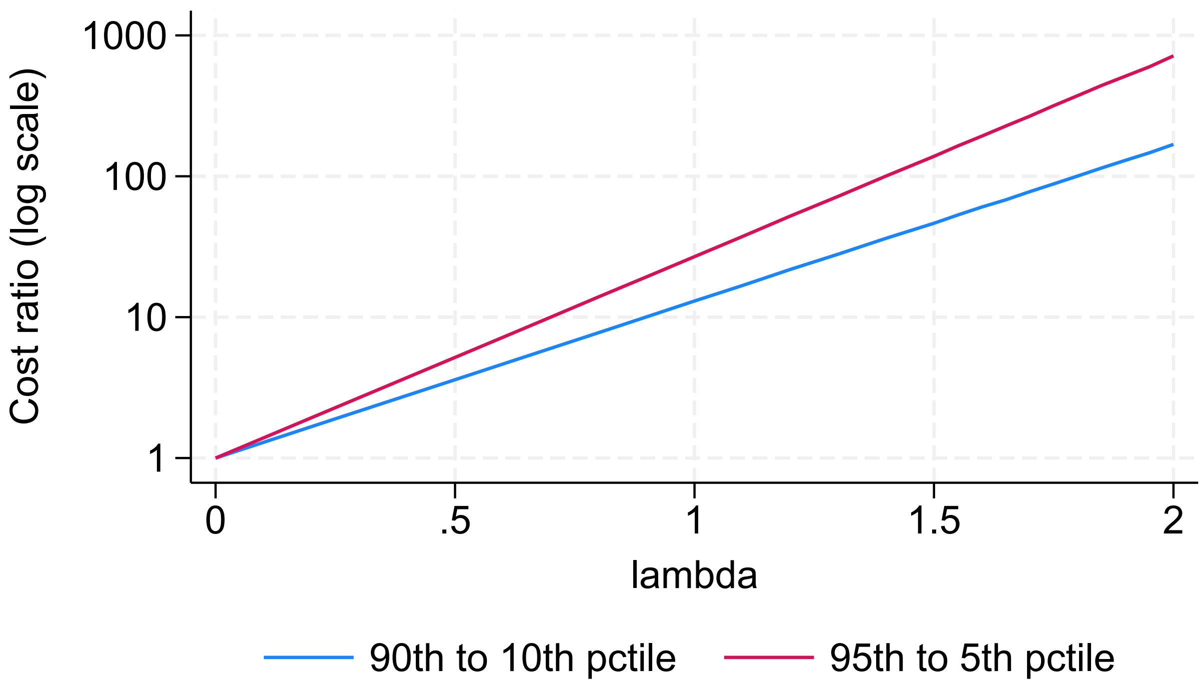
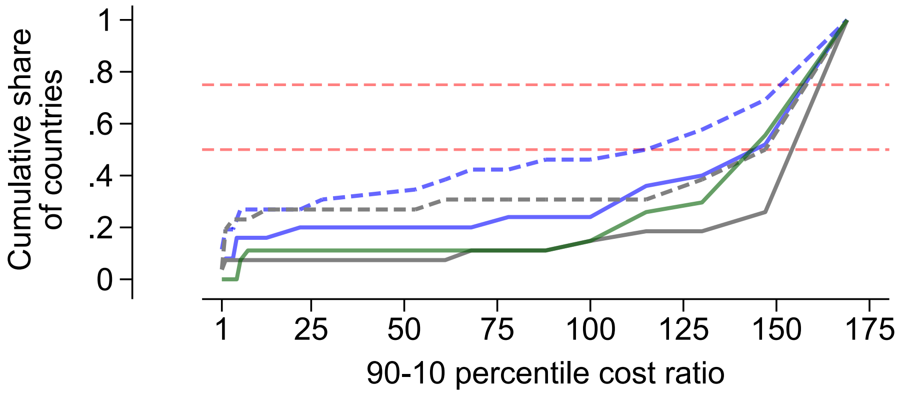
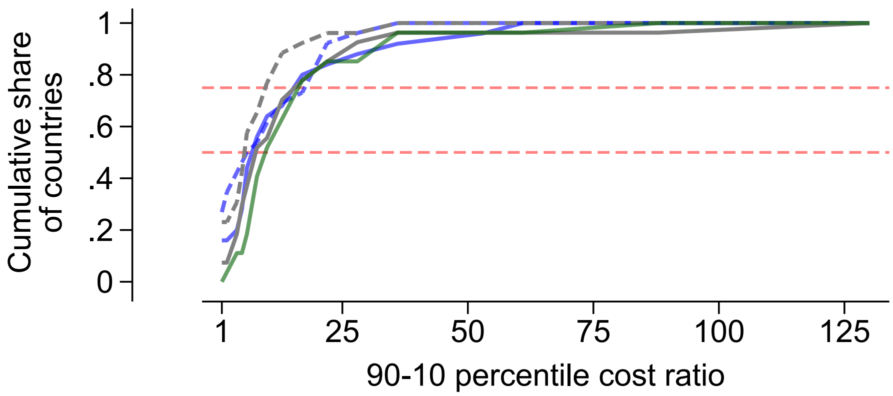


Figure E.5: Distribution of cost heterogeneity under alternative parameterizations

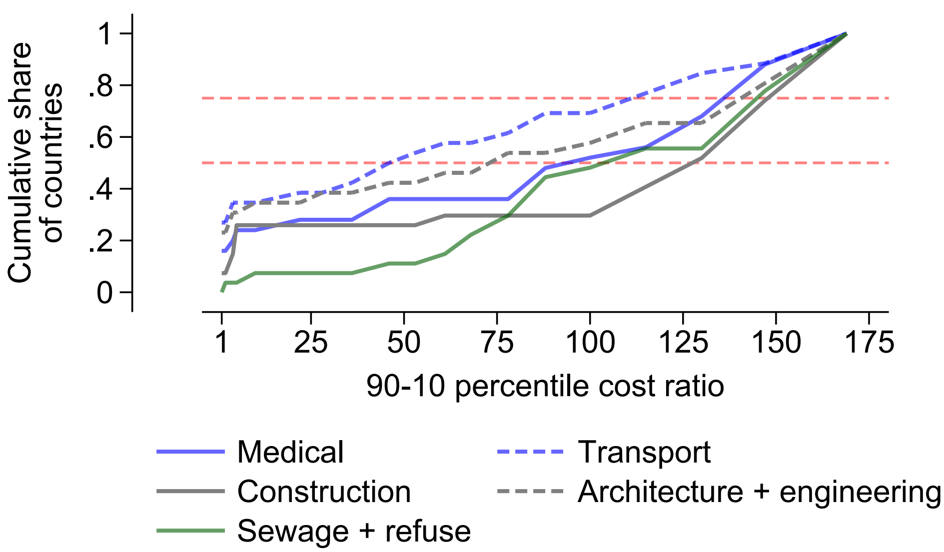
(a) Large auction-specific shocks, no selection



(b) Large auction-specific shocks, moderate selection



(c) Moderate auction-specific shocks, no selection



Notes: The figure plots the cumulative distribution of the 90–10 cost ratio required to rationalize observed firm HHI in each country-sector under alternative assumptions about auction-specific shocks and selection into entry. Panels (a)–(c) correspond to $(s, \theta) = (2, 0)$, $(2, 1)$, and $(0.5, 0)$, respectively. Horizontal dashed lines drawn at values of 0.5 and 0.75.

Table E.1: Summary statistics: Auction values, medical sector

	Mean	Std. dev.	Min	Median	Max
Belgium	11	16	2.5	6	124
Bulgaria	13	19	2.5	6	323
Czechia	13	38	2.5	6	1091
Finland	18	60	2.5	8	1560
France	20	47	2.5	6	581
Germany	14	89	2.5	5	1544
Hungary	8	10	2.5	5	78
Italy	18	46	2.5	7	1387
Lithuania	6	6	2.5	4	72
Poland	8	16	2.5	5	606
Portugal	9	13	2.5	4	120
Romania	8	14	2.5	5	223
Slovakia	8	10	2.5	4	77
Slovenia	10	18	2.5	5	188
Spain	23	85	2.5	5	528
Sweden	28	86	2.5	10	1971
Ukraine	8	12	2.5	5	250
United Kingdom	257	636	2.5	22	2518

Table shows auction value summary statistics by country for 2-digit CPV code 33. All values are in hundreds of thousands of nominal euros.

Table E.2: Summary statistics: Auction values, transport

	Mean	Std. dev.	Min	Median	Max
Austria	6	6	2.5	4	41
Bulgaria	12	34	2.5	4	413
Czechia	10	15	2.5	5	170
France	8	14	2.5	4	181
Germany	8	50	2.5	4	2167
Greece	17	51	2.5	6	542
Hungary	24	62	2.5	6	666
Italy	26	73	2.5	7	1011
Norway	7	15	2.5	4	125
Poland	28	153	2.5	7	4276
Portugal	18	62	2.5	5	524
Romania	30	113	2.5	6	1709
Spain	21	59	2.5	6	734
Sweden	13	33	2.5	5	500
Switzerland	51	237	2.5	7	2878
Ukraine	13	32	2.5	6	568

Table shows auction value summary statistics by country for 2-digit CPV code 34. All values are in hundreds of thousands of nominal euros.

Table E.3: Summary statistics: Auction values, construction work

	Mean	Std. dev.	Min	Median	Max
Austria	34	133	2.5	12	3255
Belgium	67	115	2.6	46	1500
Bulgaria	29	80	2.5	9	1406
Czechia	64	125	2.5	26	1320
Denmark	32	63	2.5	11	491
Finland	64	83	2.5	36	672
France	15	37	2.5	7	2553
Germany	18	87	2.5	7	5704
Greece	92	266	2.6	33	2556
Hungary	98	376	2.6	24	9425
Italy	53	243	2.5	19	6509
Latvia	34	37	2.5	21	190
Lithuania	42	53	2.5	19	267
Luxembourg	47	367	2.6	12	8002
Netherlands	57	192	2.6	29	3080
Norway	122	359	2.6	57	6336
Poland	70	222	2.5	15	4370
Portugal	59	138	2.6	14	1489
Romania	85	294	2.5	33	6158
Slovakia	95	210	2.5	30	1500
Slovenia	32	40	2.6	19	384
Spain	94	155	2.5	53	1877
Sweden	119	241	2.5	66	4435
Switzerland	29	93	2.5	9	3189
Ukraine	25	105	2.5	7	5940
United Kingdom	85	208	2.5	30	2871

Table shows auction value summary statistics by country for 2-digit CPV code 45. All values are in hundreds of thousands of nominal euros.

Table E.4: Summary statistics: Auction values, architectural and engineering services

	Mean	Std. dev.	Min	Median	Max
Austria	12	20	2.6	5	194
Belgium	7	8	2.5	4	45
Czechia	12	55	2.5	5	1123
Finland	9	11	2.5	5	109
France	8	19	2.5	4	605
Germany	7	10	2.5	4	194
Hungary	13	18	2.5	7	167
Italy	63	260	2.5	5	3260
Poland	11	16	2.5	6	331
Romania	14	19	2.5	6	144
Slovenia	14	19	2.5	7	186
Spain	10	42	2.5	5	1526
Sweden	22	46	2.6	7	700
Switzerland	17	27	2.5	9	341
Ukraine	8	12	2.5	4	116
United Kingdom	23	101	2.5	6	1625

Table shows auction value summary statistics by country for 2-digit CPV code 71. All values are in hundreds of thousands of nominal euros.

Table E.5: Summary statistics: Auction values, sewage and refuse services

	Mean	Std. dev.	Min	Median	Max
Belgium	11	27	2.5	6	530
Bulgaria	21	44	2.5	6	460
Czechia	13	23	2.5	6	240
Denmark	33	77	2.5	10	917
Finland	18	39	2.5	8	300
France	25	193	2.5	7	10000
Germany	12	58	2.5	6	2546
Greece	14	30	2.5	6	294
Hungary	17	92	2.5	4	1506
Italy	40	188	2.5	8	7055
Netherlands	20	46	2.5	8	700
Norway	17	25	2.5	8	253
Poland	13	87	2.5	6	6664
Portugal	18	51	2.5	6	585
Spain	40	263	2.5	7	8461
Sweden	24	60	2.5	7	690
Switzerland	16	27	2.5	8	223
Ukraine	12	18	2.5	6	111
United Kingdom	38	121	2.5	7	1382

Table shows auction value summary statistics by country for 2-digit CPV code 90. All values are in hundreds of thousands of nominal euros.

Table E.6: Main estimates, medical sector

Rank	Country	Deviation	5 pct. lower bound	95 pct. upper bound
1	United Kingdom	-.89	-5.16	3.38
2	France	5.28	-6.86	17.43
3	Portugal	6.27	-2.51	15.04
4	Hungary	9.1	.89	17.31
5	Belgium	11.78	1.79	21.76
6	Slovenia	15.65	4.56	26.74
7	Sweden	17.68	-3.34	38.69
8	Finland	18.41	2.19	34.63
9	Romania	20.05	10.17	29.92
10	Slovakia	22.36	5.49	39.22
11	Ukraine	33.41	15.07	51.76
12	Germany	34.99	-31.96	101.93
13	Czechia	64.85	20.57	109.13
14	Italy	78.78	54.02	103.55
15	Spain	181	128.49	233.51
16	Lithuania	332.95	258.61	407.28
17	Bulgaria	604.38	504.82	703.94
18	Poland	858.57	519.22	1197.91

Table shows estimates and confidence intervals from Figure 3 for 2-digit CPV code 33. The "deviation" column shows the standardized deviation (z-score) of the winners' Herfindahl–Hirschman Index (HHI) from the competitive benchmark, $\frac{\Delta \text{HHI}^{c,s}_{\text{firm}}}{\widehat{\sigma}^{\text{firm}}_{c,s}}$, where $\widehat{\sigma}^{\text{firm}}_{c,s}$ is the within-country-sector standard deviation computed via random reassignment of winners. 95% confidence intervals are computed via the bootstrap described in Section 4.

Table E.7: Main estimates, transport

Rank	Country	Deviation	5 pct. lower bound	95 pct. upper bound
1	Bulgaria	-.46	-13.49	12.57
2	Greece	-.17	-9.8	9.45
3	Portugal	1.11	-8.58	10.8
4	France	1.2	-12.05	14.44
5	Sweden	2.01	-8.33	12.35
6	Romania	5.97	-5.84	17.79
7	Norway	6.34	-2.08	14.76
8	Switzerland	9.08	-6.02	24.19
9	Poland	11.05	-9.2	31.3
10	Spain	13.48	3.8	23.15
11	Hungary	16.56	2.28	30.83
12	Italy	21.1	5.06	37.14
13	Czechia	26.75	17.76	35.74
14	Ukraine	38.78	16.58	60.98
15	Germany	44.57	-21.12	110.26
16	Austria	49.35	35.53	63.17

Table shows estimates and confidence intervals from Figure 3 for 2-digit CPV code 34. The "deviation" column shows the standardized deviation (z-score) of the winners' Herfindahl–Hirschman Index (HHI) from the competitive benchmark, $\frac{\Delta \text{HHI}^{c,s}_{\text{firm}}}{\widehat{\sigma}^{\text{firm}}_{c,s}}$, where $\widehat{\sigma}^{\text{firm}}_{c,s}$ is the within-country-sector standard deviation computed via random reassignment of winners. 95% confidence intervals are computed via the bootstrap described in Section 4.

Table E.8: Main estimates, construction work

Rank	Country	Deviation	5 pct. lower bound	95 pct. upper bound
1	United Kingdom	-.27	-14.47	13.94
2	Greece	-.25	-12.46	11.95
3	Luxembourg	.76	-129.36	130.89
4	Netherlands	1.25	-28.8	31.31
5	Italy	1.5	-39.98	42.98
6	Slovakia	3.6	-3.56	10.75
7	Norway	6.93	-9.29	23.16
8	Belgium	9.22	-1.51	19.95
9	Denmark	10.16	-7.31	27.63
10	Portugal	12.96	-1.89	27.81
11	Latvia	15.1	6.23	23.96
12	Bulgaria	15.14	-1.27	31.55
13	Lithuania	17.07	7.28	26.87
14	Spain	18.24	5.87	30.61
15	Austria	21.18	-3.95	46.32
16	Hungary	21.35	-2.69	45.4
17	Romania	24.18	2.55	45.8
18	Slovenia	35.28	23.06	47.5
19	Finland	61.15	40.75	81.54
20	Switzerland	75.49	25.59	125.38
21	Germany	94.58	9.5	179.66
22	France	96.71	39.29	154.12
23	Sweden	101.91	57.26	146.57
24	Czechia	119.69	91.08	148.3
25	Poland	164.9	98.46	231.33
26	Ukraine	900.34	453.27	1347.41

Table shows estimates and confidence intervals from Figure 3 for 2-digit CPV code 45. The "deviation" column shows the standardized deviation (z-score) of the winners' Herfindahl–Hirschman Index (HHI) from the competitive benchmark, $\frac{\Delta \text{HHI}^{c,s}_{\text{firm}}}{\hat{\sigma}^{\text{firm}}_{c,s}}$, where $\hat{\sigma}^{\text{firm}}_{c,s}$ is the within-country-sector standard deviation computed via random reassignment of winners. 95% confidence intervals are computed via the bootstrap described in Section 4.

Table E.9: Main estimates, architectural and engineering services

Rank	Country	Deviation	5 pct. lower bound	95 pct. upper bound
1	Germany	-1.87	-18.85	15.1
2	United Kingdom	-.18	-30.95	30.59
3	Spain	4.11	-68.92	77.14
4	Belgium	5.06	-2.65	12.76
5	France	5.95	-29.09	40.99
6	Austria	7.01	-5.07	19.09
7	Italy	12.52	-5.29	30.33
8	Romania	17.61	6.49	28.74
9	Czechia	17.97	-39.07	75
10	Ukraine	18.98	-1.66	39.61
11	Switzerland	22.19	9.9	34.48
12	Poland	22.39	11.85	32.93
13	Finland	26.62	12.6	40.65
14	Slovenia	30.49	12.92	48.06
15	Hungary	32.55	14.11	51
16	Sweden	35.85	19.65	52.04

Table shows estimates and confidence intervals from Figure 3 for 2-digit CPV code 71. The "deviation" column shows the standardized deviation (z-score) of the winners' Herfindahl–Hirschman Index (HHI) from the competitive benchmark, $\frac{\Delta \mathrm{HHI}^{c,s}_{\mathrm{firm}}}{\widehat{\sigma}^{\mathrm{firm}}_{c,s}}$, where $\widehat{\sigma}^{\mathrm{firm}}_{c,s}$ is the within-country-sector standard deviation computed via random reassignment of winners. 95% confidence intervals are computed via the bootstrap described in Section 4.

Table E.10: Main estimates, sewage and refuse services

Rank	Country	Deviation	5 pct. lower bound	95 pct. upper bound
1	Greece	1.06	-11.76	13.88
2	Portugal	4.5	-4.9	13.9
3	Switzerland	6.94	-4.23	18.1
4	Germany	7.97	-61.56	77.49
5	Bulgaria	8.88	-2.06	19.81
6	Ukraine	9.16	.55	17.78
7	United Kingdom	9.2	-4.74	23.14
8	Czechia	9.57	1.35	17.78
9	Belgium	11.59	-2.73	25.91
10	Norway	12.92	4.15	21.68
11	Italy	14.76	-19.68	49.19
12	Hungary	16.08	-12.93	45.09
13	Netherlands	17.24	4.33	30.16
14	Sweden	18.84	5.99	31.69
15	Poland	20.85	-194.38	236.09
16	France	22.63	-117.54	162.79
17	Denmark	34.33	12.93	55.72
18	Spain	43.93	11.95	75.91
19	Finland	61.24	31.07	91.41

Table shows estimates and confidence intervals from Figure 3 for 2-digit CPV code 90. The "deviation" column shows the standardized deviation (z-score) of the winners' Herfindahl–Hirschman Index (HHI) from the competitive benchmark, $\frac{\Delta \mathrm{HHI}^{c,s}_{\mathrm{firm}}}{\widehat{\sigma}^{\mathrm{firm}}_{c,s}}$, where $\widehat{\sigma}^{\mathrm{firm}}_{c,s}$ is the within-country-sector standard deviation computed via random reassignment of winners. 95% confidence intervals are computed via the bootstrap described in Section 4.