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# ABSTRACT

## Rating Government Procurement Markets*

We develop a novel, scalable method for assessing the quality of public procurement systems using standard administrative data. Our approach compares the distribution of procurement opportunities to the distribution of contract awards across firms. We first derive a simple theoretical benchmark that relates the expected distribution of contract value winning firms, measured as a Herfindahl-Hirschman index (HHI), to the distribution of auction values, measured as a respective HHI, and the number of winning firms. Significant deviations of winning firms' HHI from this benchmark indicate potential governance failures such as corruption or unchecked collusion. Our method requires no subjective input, is transparent and reproducible, and allows for meaningful comparisons across countries, industry sectors, and over time. We use procurement data from Ukraine and EU member states in 2018-2021 to assess the performance of five large sectors. Ukraine's procurement performance in four of the five sectors is comparable to many other European countries, but Ukraine's construction sector consistently displays the largest excess concentration among all countries considered, consistent with anecdotal evidence of corruption in this sector.

**JEL Classification:** D73, L10, H11
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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. 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. As a result, there can be significant gaps between these perception-based indices and the actual situation on the ground. Although these limitations have long been known, and efforts to improve measurement have been ongoing, Russia's full-scale invasion of Ukraine in February 2022 has brought renewed urgency to the 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 the 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 broadly applicable and transparent method to rate the quality of countries' procurement markets. Public procurement constitutes a significant share of government expenditure (Bosio et al., 2022) 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. 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., European Union (EU) Single Market Scoreboard) often rely on crude metrics—such as counting the share of auctions that attract only one bidder—or require 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 in most EU member states.

Our method relies only on publicly available data and identifies lower-quality procurement environments by comparing the distributional outcomes among firms that won at least one auction to the distribution of the procurement auction values themselves. If the procurement system operates competitively and firms are homogeneous, we show that firms' outcomes should be a function of the variation in auction sizes and the number of firms: larger contracts naturally skew some results, but the distribution of winnings should broadly mirror the distribution of opportunities after adjusting for the number of firms. Systematic deviations from this benchmark signal disproportionate concentration of public contracts among a small set of firms. Such concentration is consistent with the presence of corruption or other governance failures that undermine open competition.

Our method offers several advantages over other approaches. It is simple to compute; does not require generally confidential information, 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 normal market concentration and suspicious concentration that suggests corruption or collusion. Although in principle firm cost heterogeneity could also generate deviations from the benchmark, and we find that it is not atypical for sectors to exceed the benchmark by 10–20 standard deviations, many countries' auctions are not statistically different from the benchmark, suggesting that cost heterogeneity is an unlikely primary explanation for the larger deviations we find.

We apply our method to procurement auctions in the EU and Ukraine that took place in 2018–2021, focusing on commonly procured items and contracts valued at €250,000 or more to reduce the possibility of selective reporting in the EU dataset and to focus on auctions where the return to corruption or collusion and thus the impact on on public finances are likely higher. We focus on 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 a given sector.[1] 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, demonstrating the usefulness of a method that can deliver sector-specific results. Focusing on Ukraine, we find that it ranks 11 out of 18 in the medical sector; 15 out of 16 in transport equipment; 26 out of 26 in construction; 10 out of 16 in architectural and engineering services; and 6 out of 19 in sewage and refuse services. In architectural and engineering services, Ukraine's performance is not statistically 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 performance 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 excess market concentration 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 42533), 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

[1] We report results for the next five sectors that fall slightly below the 100-auction threshold in the Online Appendix.

extent by auctions that took place in 2021, which suggests that our measure is flagging real problems in Ukraine's construction sector and not a permanent difference in fundamentals, such as firms' cost structure.

Our approach builds on and complements prior work that uses procurement data to detect governance risks, such as analyses of single-bidder auctions, direct awards, 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, 2021; Bosio et al., 2022; Fazio and Zaldokas, 2025). 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.[2]

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 and conclude in section 6.

[2]We briefly review existing approaches used in antitrust practice to score procurement markets in Online Appendix A.

# 2 Conceptual framework

## 2.1 Firms' HHI in the homogeneous competitive case

We derive the 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. This 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 will 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 $\text{HHI}_{\text{firm}}$, $\text{HHI}_{\text{auct}}$, 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

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

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

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

The expected value of winning firms' HHI is therefore:

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

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

Note that the expected firm HHI is larger than $\mathrm{HHI}_{\mathrm{auct}}$, 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.

Because our approach adjusts for the number of firms, it is robust to factors (e.g., economies of scale) that would lead to diverging distributions because of different number of firms existing in a given sector in equilibrium.

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 $p_f$ represents the probability for each auction. Recomputing the variance-decomposition but allowing $p_f$ to vary yields

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

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 bribes the auctioneer.[3] Conditional on a competitive auction, every firm is equally likely to win $(1/F)$; conditional on a non-competitive auction, the winner is chosen uniformly from the cartel $(1/M)$. 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:

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

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 sizes affects it through $\mathrm{HHI}_{\mathrm{auct}}$. Poor governance (lower $\gamma$) increases $\sum_f p_f^2$; the impact of that

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

increase on the observed $\mathrm{HHI}_{\mathrm{firm}}$ is attenuated when auction values themselves are unequal ($\mathrm{HHI}_{\mathrm{auct}}$ large) and amplified when auctions are similarly sized ($\mathrm{HHI}_{\mathrm{auct}}$ 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 $\mathrm{HHI}_{\mathrm{firm}}$ vastly exceeding the benchmark in (1) indicates that either $\gamma$ is low, $M$ is small, or both.

One might note that low $\gamma$ could also be interpreted as reflecting high heterogeneity in firm productivity levels in the sector. As we do not observe the identity and the characteristics of losing bidders, high observed $\mathrm{HHI}_{\mathrm{firm}}$ in a particular sector (e.g., construction) in one country (e.g., Ukraine) versus the other (e.g., France) could also be interpreted as Ukraine having few productive construction firms as compared to those in France.

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

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

## 2.3 Limitations and Strengths

Deviations from these described relationships in real-world data can happen for a number of reasons, many of which do not 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. In other words, if we see a deviation from the competitive benchmark, it should be interpreted as a necessary condition to infer anti-competitive behavior, but not a sufficient one.

Another limitation is that across a wide number of countries we only observe the winning bids but not the losing bids. Because we do not have information on the distribution of all bids, our approach is not able to 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). Our approach would not flag such behavior as potentially problematic. This is highlighted 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.

We do not view these issues as relevant shortcomings for our empirical work, however. Often, due to data limitations and lack of data standardization, different auction formats and public procurement rules, the comparisons between countries (or even within jurisdictions within countries) and across industries is challenging. While our estimated effects are easily interpretable as standalone statistics, they are likely to be informative about market failures in relative terms.

# 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.[4] We focus on the years 2018–2021, when Ukraine's public procurement database 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 and sometimes address and/or national id), and the contract value.[5] TED also reports the country in which

[4]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.

[5]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

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 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 two 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.

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 ($\geq$€$250,000$) 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.[6] 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

information on the TED dataset.

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

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 focus our analysis on sectors that, in 2018–2021, (a) account for more than 1 percent of high-value auctions in Ukraine and (b) account for at least 200 such auctions in each of at least 10 other European countries.[7] There are five such sectors in the data: the three sectors mentioned above; architectural, construction, engineering and inspection services (CPV code 71); and 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; and even when present, they are not always used consistently (for example, the same firm name may appear under different identifiers). Although winner names are almost always reported in the TED dataset, they are not recorded consistently and sometimes contain misspellings. Being overly conservative in grouping similar names risks underestimating concentration among winners, while being too permissive risks overestimating it. We therefore standardize winner names and national identifiers (IDs) to avoid artificially splitting the same firm or merging distinct firms.

First, we extract and validate national IDs, with country-specific rules (e.g., parsing 11–digit Italian tax codes when *C.F./P.IVA* are present; dropping unreliable formats in Liechtenstein and filtering most German entries). We identify reliable IDs partly by comparing their length with the modal ID length for that country and backfill consistent IDs. When reliable IDs exist, we reconcile all name variants sharing an ID and choose a canonical

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

label. Second, where IDs are missing/unreliable, we harmonize names (e.g., lowercasing; removal/standardization of punctuation, diacritics, and legal-form suffixes across languages; normalization of conjunctions). We then compare names within country–CPV(2–digit)–first–letter blocks and accept near–matches using conservative string–distance thresholds.

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).[8] 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.

Full details of the data standardization across countries appear in the Online Appendix.

## 3.2 Summary statistics

Table 1 shows the mean, median, standard deviation, minimum and maximum of the in-sample contract values by country.[9] 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.

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

[8]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.

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

we might expect to be more similar to Ukraine.[10] In general, the three distributions look 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/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 probably attributable to Ukraine requiring at least two bidders for procurement auctions above a certain value to be considered valid. 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.

# 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, accounting for auction sizes. 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 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 perform the estimations annually.

[10] 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 B.1a 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 than Ukraine's and other Eastern European countries' values falling in between these two distributions. Figure B.2 show the distribution of large (≥€250,000) contract values separately by sector.

The deviation of Firm HHI from what would be expected given our perfectly competitive benchmark is:

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

where $c$ indexes countries and $s$ indexes sectors (e.g., construction). $\widehat{\mathrm{HHI}}^{\mathrm{c,s}}_{\mathrm{firm}}$ 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 $S_f$ 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, $\mathbb{E}[\mathrm{HHI}_{\mathrm{firm}} |\, \mathrm{F}^{\mathrm{c,s}}, \mathrm{HHI}^{\mathrm{c,s}}_{\mathrm{auct}}]$, is expected firm HHI under a homogeneous cost structure and perfect competition. It is calculated as $\frac{1}{F^{\mathrm{c,s}}} + \left(1 - \frac{1}{F^{\mathrm{c,s}}}\right) \mathrm{HHI}^{\mathrm{c,s}}_{\mathrm{auct}}$. In turn, $\mathrm{HHI}^{\mathrm{c,s}}_{\mathrm{auct}} = \sum_{a=1}^{A^{\mathrm{c,s}}} \left(\frac{V_a}{V_{tot}^{\mathrm{c,s}}}\right)^2$, where $a$ indexes all the procurement auctions in sector $s$ and country $c$, $A^{\mathrm{c,s}}$ is the total number of such auctions, and $V_a$ is the auction value.

Ranking procurement markets based on the raw deviations given by $\Delta\mathrm{HHI}^{\mathrm{c,s}}_{\mathrm{firm}}$ could be misleading because the baseline scale of Auction HHI, $\mathrm{HHI}_{\mathrm{auct}}$, varies substantially across countries and sectors. To address this issue of scale, we normalize $\Delta\mathrm{HHI}^{\mathrm{c,s}}_{\mathrm{firm}}$ by the standard deviation of Firm HHI, $\mathrm{HHI}^{\mathrm{c,s}}_{\mathrm{firm}}$, under the assumption of cost homogeneity and perfect competition. To obtain this standard deviation, which we denote by $\widehat{\sigma}^{\mathrm{firm}}_{c,s}$, 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, $\mathrm{HHI}^{\mathrm{c,s,d}}_{\mathrm{firm}}$, for each draw $d$. After repeating this process 500 times for each country-sector combination, we calculate $\widehat{\sigma}^{\mathrm{firm}}_{c,s}$ as the estimated standard deviation of $\mathrm{HHI}^{\mathrm{c,s,d}}_{\mathrm{firm}}$. We then divide $\Delta\mathrm{HHI}^{\mathrm{c,s}}_{\mathrm{firm}}$ by $\widehat{\sigma}^{\mathrm{firm}}_{c,s}$ to obtain the final statistic used for ranking each country-sector combination: the number of standard deviations by which the HHI of winning firms in that sector-country combination exceeds the perfectly competitive benchmark.

Intuitively, our statistic measures standardized excess concentration compared to a perfectly competitive market with homogeneous firms and the same project mix. We estimate the competitive variability by repeatedly reassigning winners at random among the observed active firms (holding auction sizes fixed) and taking the resulting standard deviation; the z-score scales the excess 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 z-scores to exceed zero even in the absence of corruption and collusion; accordingly, we emphasize cross-country comparisons of z-scores rather than their absolute levels.

We obtain confidence intervals for $\frac{\Delta\mathrm{HHI}^{\mathrm{c,s}}_{\mathrm{firm}}}{\widehat{\sigma}^{\mathrm{firm}}_{c,s}}$ via a bootstrap, resampling auction-winner observations from each country-sector 500 times and calculating the resulting $\Delta\mathrm{HHI}^{\mathrm{c,s,b}}_{\mathrm{firm}}$ for each bootstrap $b$. We then calculate the empirical standard deviation of $\Delta\mathrm{HHI}^{\mathrm{c,s,b}}_{\mathrm{firm}}$, $\widehat{\sigma}^{\mathrm{firm}}_{c,s,b}$, with 500 uniform reassignments of firms to auctions within each bootstrap, as in the main sample. Finally, assuming the standardized statistic $\frac{\Delta\mathrm{HHI}^{\mathrm{c,s}}_{\mathrm{firm}}}{\widehat{\sigma}^{\mathrm{firm}}_{c,s}}$ is approximately normal, we take its bootstrap standard deviation and form 95% confidence intervals as the point estimate plus/minus 1.96 times that standard deviation.[11]

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 in the full sample, we repeat our exercise focusing on the top 25% of auctions by value to the winner. 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.

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

# 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.[12] Reassuringly, several countries in each sector do not deviate significantly from the competitive benchmark. As expected, however, many others exhibit z-scores well above zero, potentially reflecting persistent cost advantages among certain firms. The distribution of lower z-scores varies across sectors. In the medical sector, for instance, the middle tercile of countries has z-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 z-scores to be interpreted relative to this feasible competitive range.

In the medical sector (panel (a)), Ukraine ranks 11th out of 18,[13] 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.

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

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

[13]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.

A country's rankings across the five sectors are positively correlated in only about half the cases (Table 3). The largest correlation in absolute terms (between the sewage and transport sectors) is $-0.88$; the largest positive correlation (between architecture and construction) is 0.42. This lack of consistent correlations across sectors highlights the value of using sector-specific metrics rather than a single country-level measure.

Figure 4 compares our rankings in each sector to countries' rankings based on the Corruption Perceptions Index (CPI) rankings published by Transparency International. We average each country's 2018–2021 CPI rank and plot it against its rank for each sector.[14] To account for statistical significance, we weight our ranking by the negative natural log of the p-value (i.e., $-ln(p)$, where $p$ is the p-value) for the null hypothesis that allocation of contracts across firms in a given country-sector is uniform (i.e., competitive). We use the natural logarithm to moderate the influence of very small p-values, preventing them from receiving extremely large weights. In cases where the p-value is reported as zero, we replace it by $1e - 30$ before taking the log.

The Spearman (rank) correlation between our rankings and the CPI rank is positive in two of the five sectors and negative in the remaining three. None of the correlations is statistically significant. The weak and inconsistent relationship with the CPI suggests that

[14] Results are similar if we keep Transparency International's country ordering but compress CPI ranks to the range 1–$N$ where $N$ is the number of countries in our sample.

our approach captures distinct, data-driven aspects of procurement integrity rather than simply reflecting existing subjective perceptions of corruption.

Online Appendix Figure B.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.

The heterogeneity apparent in Figures 3, 4, and B.3 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).

More generally, we should not necessarily expect sector-level rankings within a country to be highly correlated: a jurisdiction can appear well-governed in one area while underperforming in another. Consequently, sector-specific metrics provide information that a single national ranking cannot, pinpointing where risks concentrate and enabling more targeted cross-country comparisons. In other words, sectoral diagnostics can be the more informative lens for policy and benchmarking.

One natural concern is that departures from our benchmark could be driven by underlying cost heterogeneity across firms rather than corruption or collusion. Two features of the data 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 actually won auctions; this winner-only sample plausibly exhibits tighter cost distributions than the full set of potential suppliers (including firms that never win).

It is worth 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.

Finally, 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 under symmetric homogeneous-cost competition. 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 Drivers of excess concentration in construction

In Figure 5, 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 6, 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.[15] 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.

## 5.3 Extensions

In Figure 7, 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. Ukraine's ranking is largely

[15] 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.

consistent when we exclude the largest procurement auctions in each country or focus on the top quarter by value; focus on auctions that attracted at least two or three bidders; or remove the top one or two winners from each country's data. Rankings are most volatile in the sewage and refuse services sector, where small and statistically insignificant deviations from the benchmark likely result in 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 8 plots Ukraine's excess concentration 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 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, excess concentration 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 excess concentration 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.

# 6 Conclusion

We develop and apply a novel method to score countries' procurement auctions that compares realized concentration in contract value among winning firms to a perfectly competitive benchmark, holding the distribution of auction values constant. While our approach cannot distinguish between corruption and other forms of bid-rigging or collusion in procurement auctions, it is useful for assessing overall market functionality and identifying sectors where performance can be improved.

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 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. Because single-bidder indicators attach to specific awards, the immediate payoff from gaming them is higher. 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, 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 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 perfectly competitive benchmark. 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?

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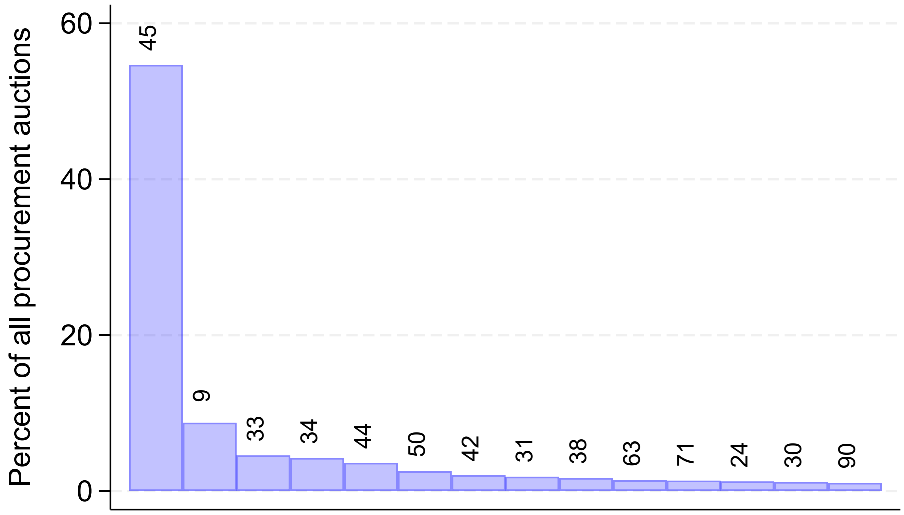
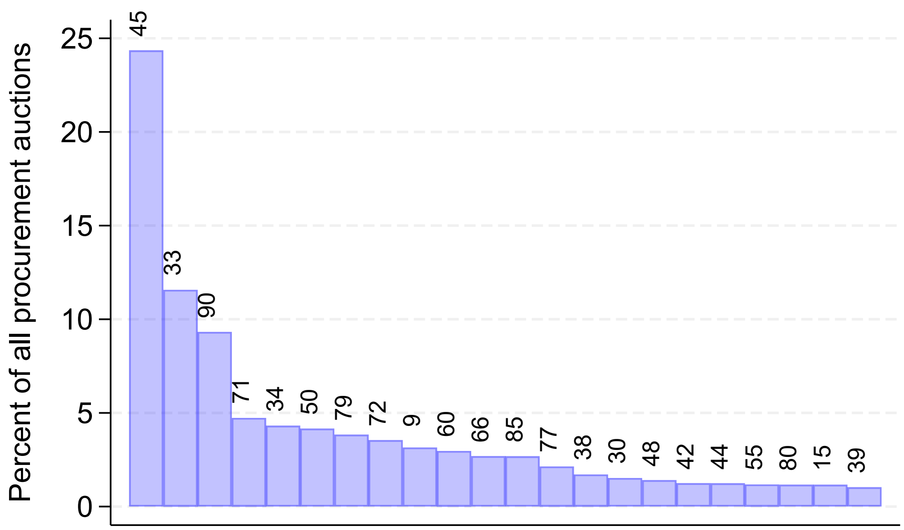
# Figures

**Figure 1:** Distribution of auctions across sectors



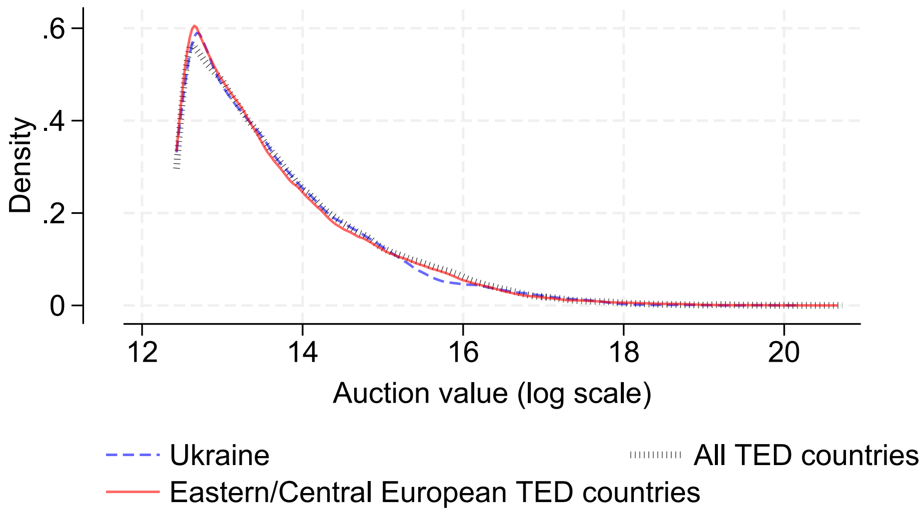

**(a)** Distribution of auctions across sectors, Ukraine



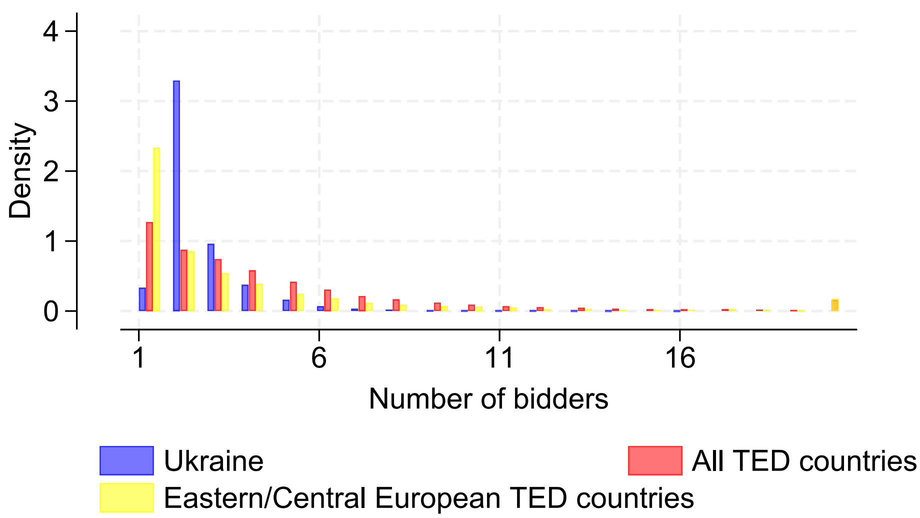

**(b)** Distribution of auctions across sectors, other European countries

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



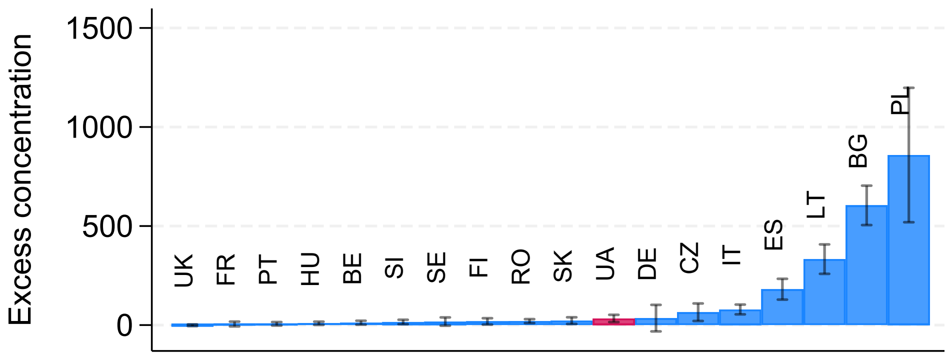

**(a)** Auction values



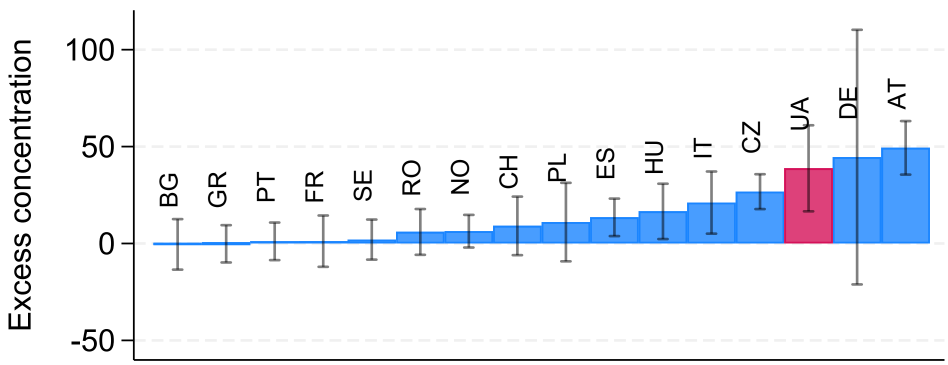

**(b)** Number of offers

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 $\geq$ €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.

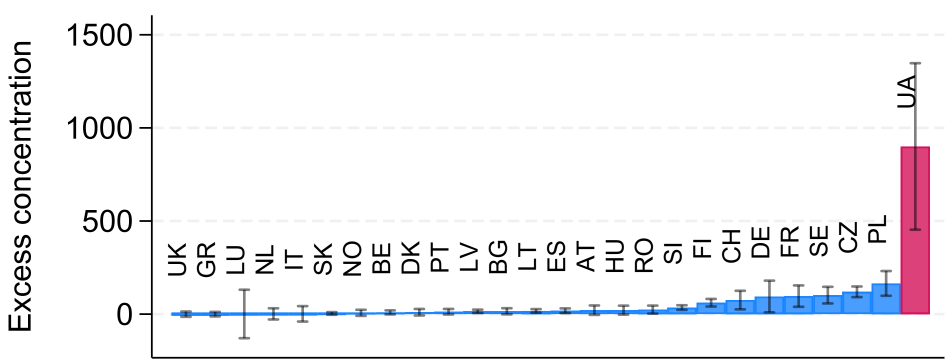
**Figure 3:** Procurement market rankings across selected European countries and sectors




**(a)** Medical equipments, pharmaceuticals and personal care products



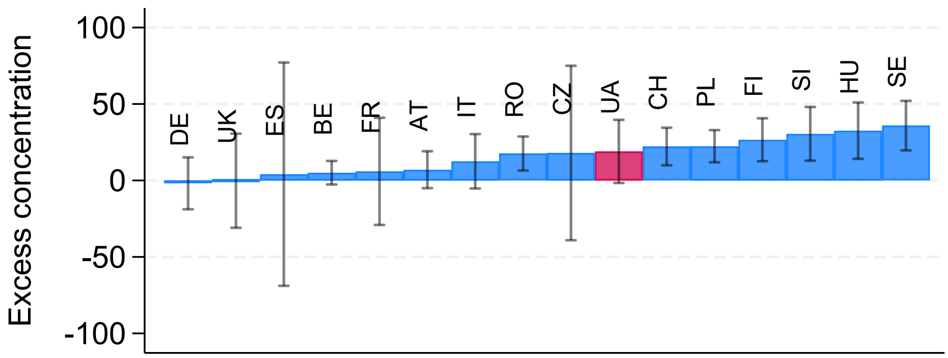

**(b)** Transport equipment and auxiliary products to transportation



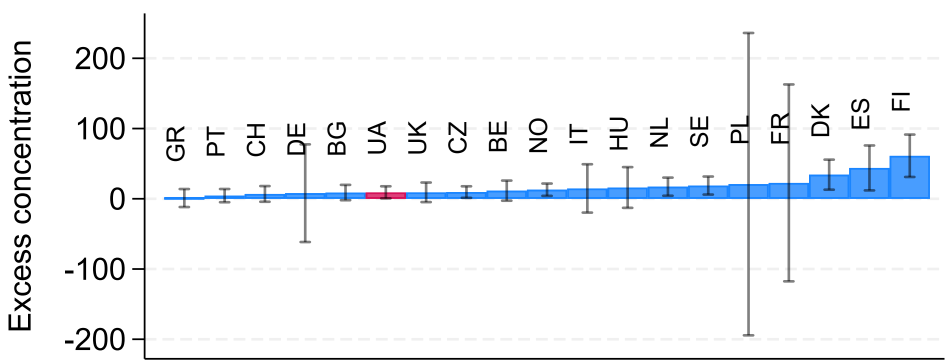

**(c)** Construction work

Notes: Each panel ranks countries by the standardized deviation (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. 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)



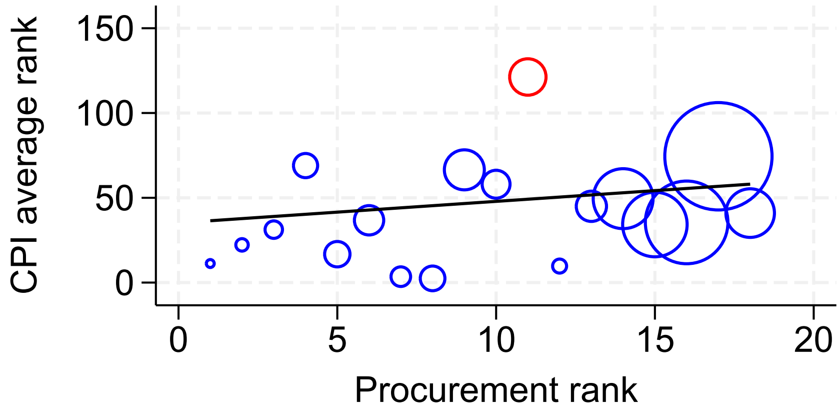

**(d)** Architectural, construction, engineering and inspection services



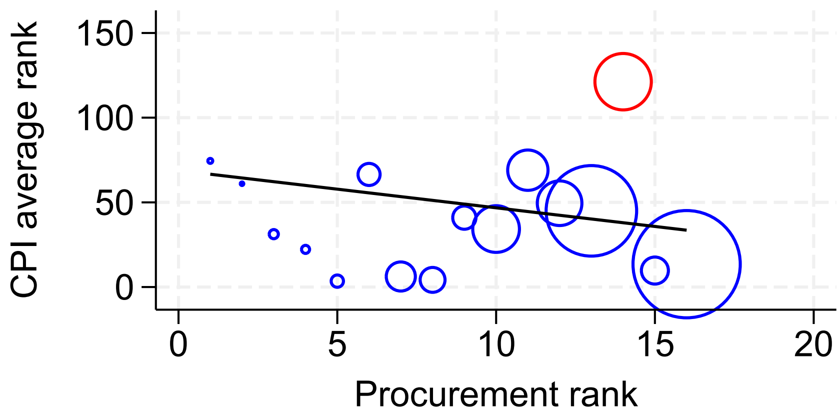

**(e)** Sewage-, refuse-, cleaning-, and environmental services

Notes: Each panel ranks countries by the standardized deviation (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. Positive values indicate excess concentration. Red bar denotes Ukraine. Error bars show bootstrapped 95% confidence intervals.

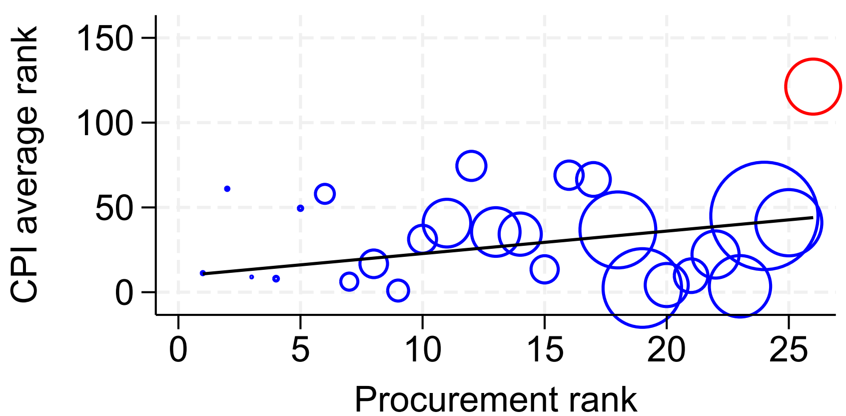
**Figure 4:** Procurement market rankings compared to Corruption Perceptions Index rankings




**(a)** Medical equipments, pharmaceuticals and personal care products



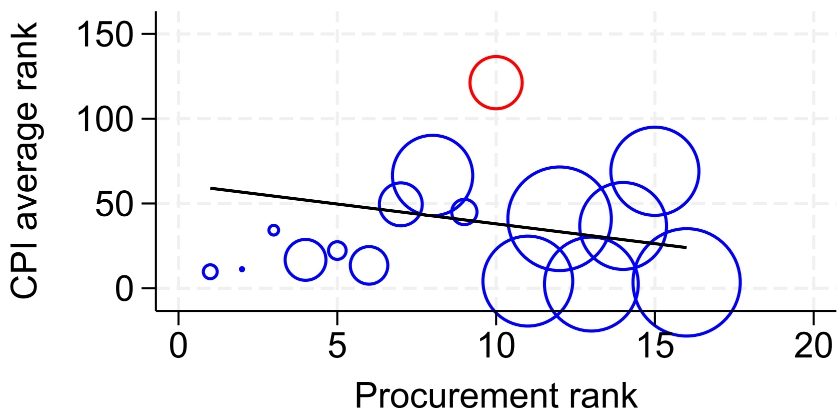

**(b)** Transport equipment and auxiliary products to transportation



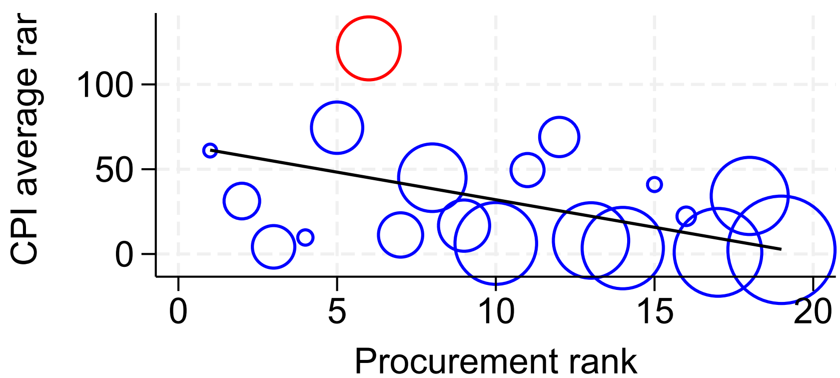

**(c)** Construction work

Notes: Each panel plots the HHI-based ranking against the Corruption Perceptions Index (CPI) ranking. The black line shows the linear fit, weighted by the negative log of the p-value. Blue circles denote countries in TED, and red circles denote Ukraine. Both the linear fit and the markers are weighted by the negative log of the p-value.

**Figure 4:** Procurement market rankings compared to Corruption Perceptions Index rankings (continued)



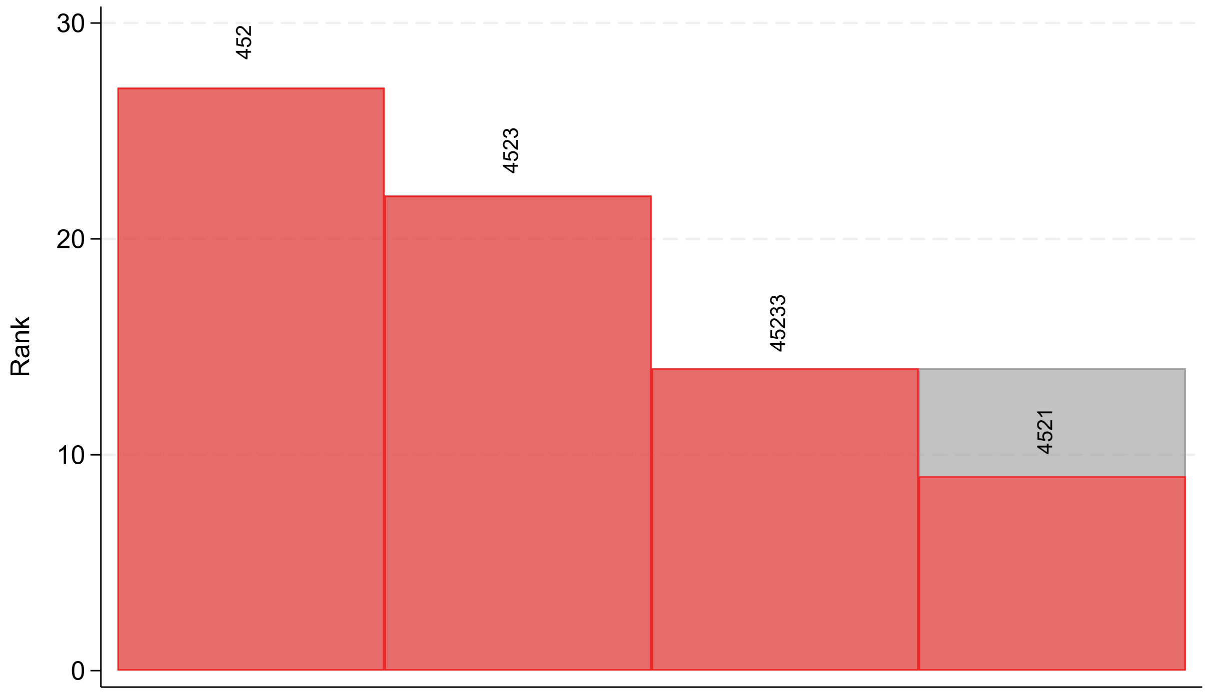

**(d)** Architectural, construction, engineering and inspection services




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

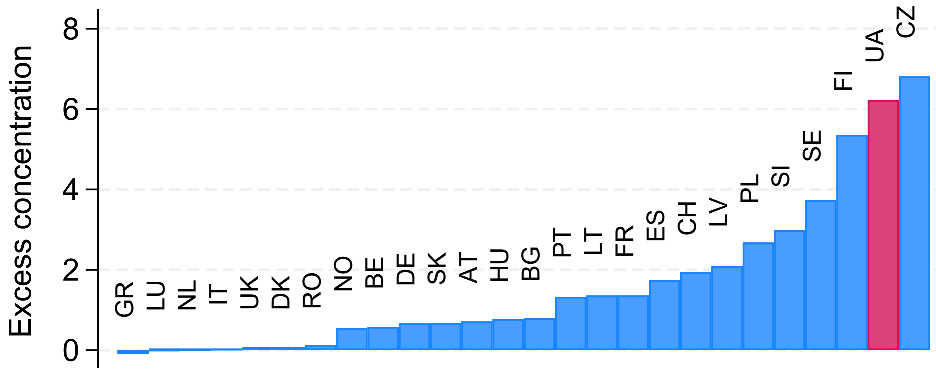
Notes: Each panel plots the HHI-based ranking against the Corruption Perceptions Index (CPI) ranking. The black line shows the linear fit, weighted by the negative log of the p-value. Blue circles denote countries in TED, and red circles denote Ukraine. Both the linear fit and the markers are weighted by the negative log of the p-value.

**Figure 5:** Ukraine's ranking in finer construction CPV codes

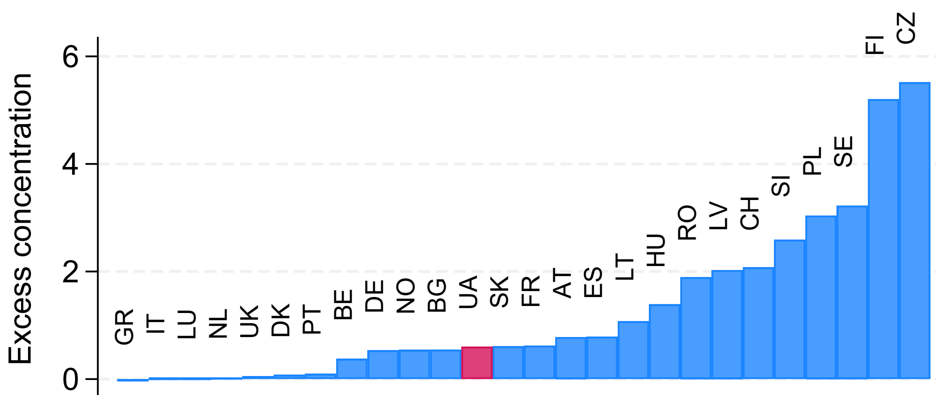



Notes: Each bar corresponds to a different construction CPV code, as indicated above the bar. Only CPV codes with at least 100 auctions and at least ten ranked countries are shown.

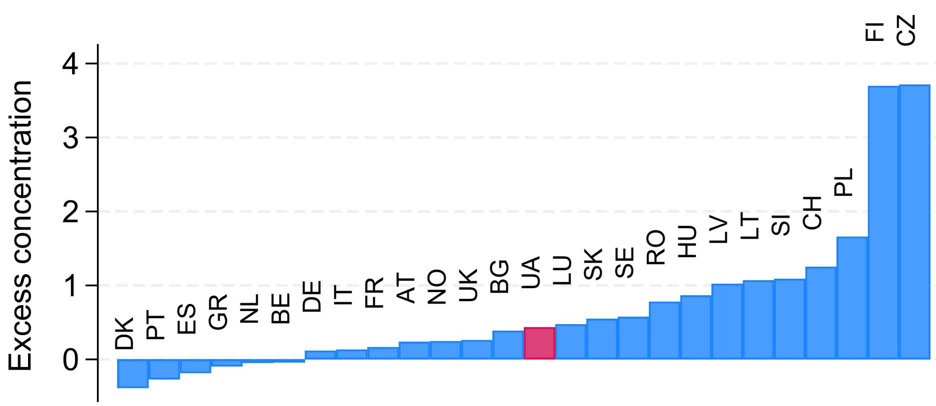
**Figure 6:** Procurement market rankings excluding certain construction CPV codes




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



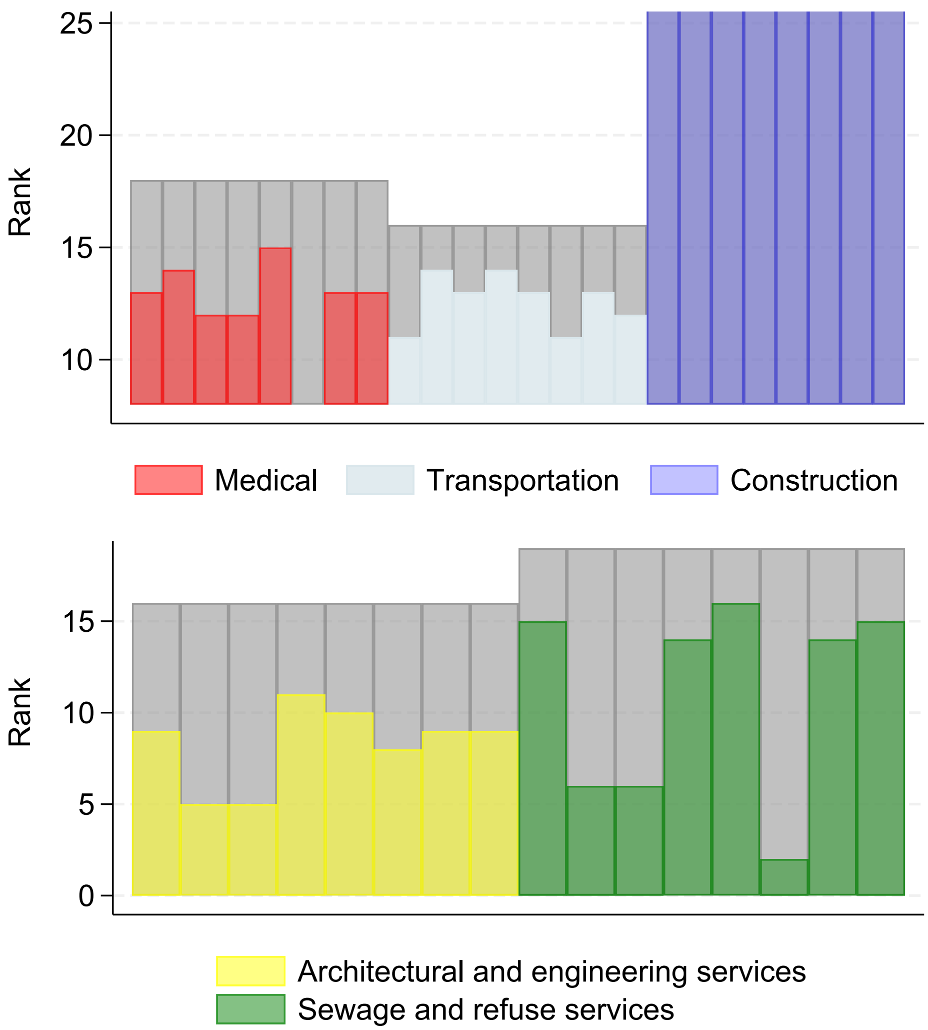

**(b)** Excluding pipeline, communication and power line, and highway, road, airfield and railway construction (CPV 4523)




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

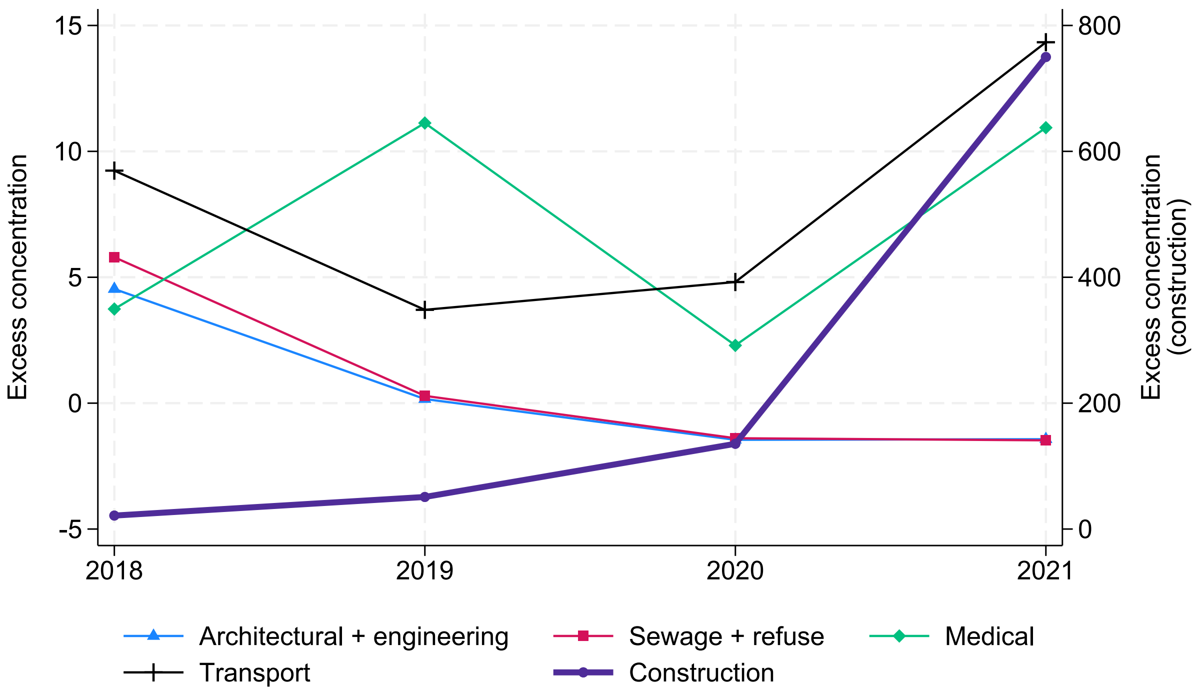
Notes: Each panel shows countries ranked by the deviation of their winner Herfindahl–Hirschman Index (HHI) from the expected value in the construction sector, dropping the specified CPV codes. Red color denotes Ukraine.

**Figure 7:** 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 8:** 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 $\mathbb{E}[\mathrm{HHI}_{\mathrm{firm}}]$ 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 $(\widehat{\mathrm{HHI}}_{\mathrm{firm}} - \mathbb{E}[\mathrm{HHI}_{\mathrm{firm}}])/\widehat{\sigma}$ 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.

# 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

| | Medical | Transport | Construction | Architecture | Sewage |
|---|---|---|---|---|---|
| Medical | 1.0000 | | | | |
| Transport | 0.2000 | 1.0000 | | | |
| Construction | -0.0500 | 0.0330 | 1.0000 | | |
| Architecture | -0.2170 | -0.3170 | 0.4170 | 1.0000 | |
| Sewage | 0.0830 | -0.8830 | -0.2170 | 0.0670 | 1.0000 |

Table shows pairwise Spearman (rank) correlations of a country's rank across sectors.

# Online Appendix

"Rating government procurement markets"


Tatyana Deryugina, University of Illinois

Alminas Žaldokas, National University of Singapore

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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]

**Composite outcome indices.** Sometimes different indicators are combined into composite indices. For example, the *Global Public Procurement Open Competition Index* (GPPOCI) 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, countries 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, countries 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

[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.

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 $\leq$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 $\geq$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.

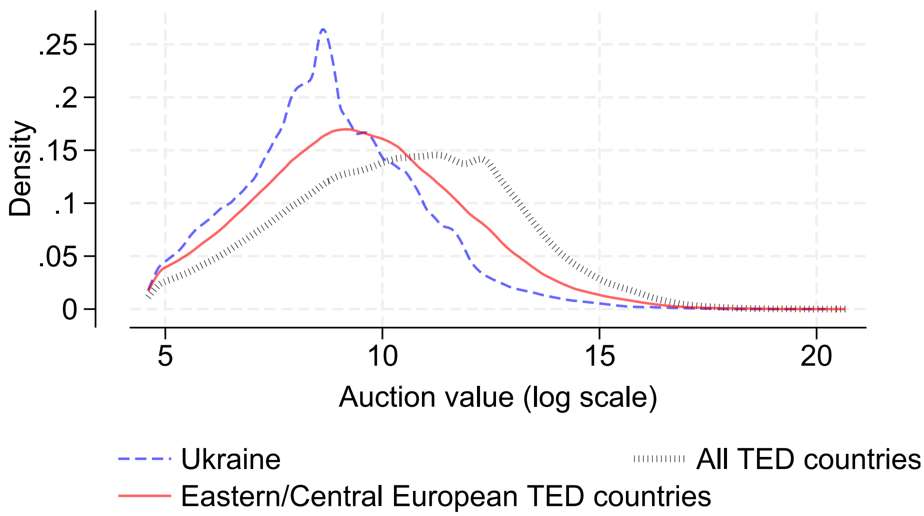
**(3) Reconciliation with reliable IDs.** Within each country, all records sharing the same validated ID are treated as the same firm. Because that firm may also appear in other auctions without a valid ID and under a slightly different name variant, we compute Levenshtein distances on space-stripped 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*$\rightarrow$*e*, *ł*$\rightarrow$*l*, *ß*$\rightarrow$*ss*, *č*$\rightarrow$*c*, *ţ*$\rightarrow$*t*, *ñ*$\rightarrow$*n*), and correct frequent typos observed in the raw data.

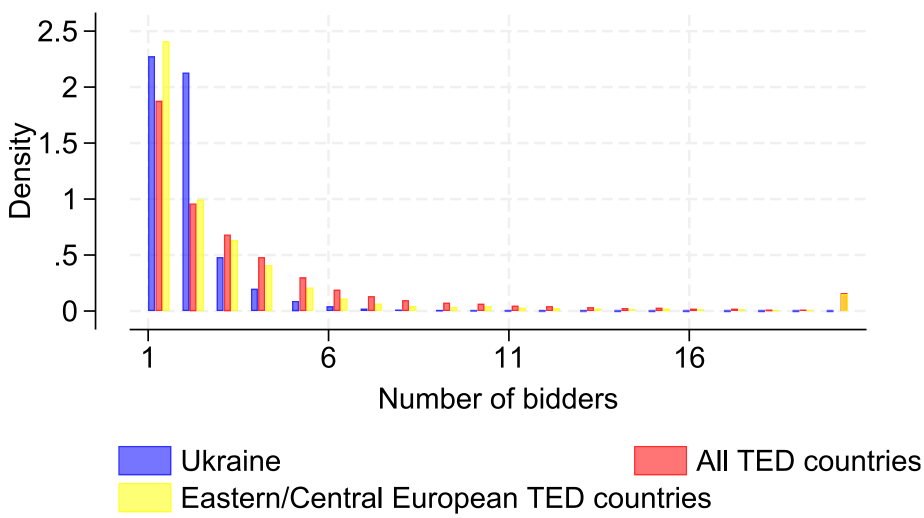
**(5) Reconciliation without reliable IDs.** When IDs are missing or determined to be unreliable, we compare names within country, 2-digit CPV code, and first letter of the cleaned name. The latter is done for computational reasons. We consider a merge a match only if calibrated thresholds are met: for 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.

# Appendix Figures

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



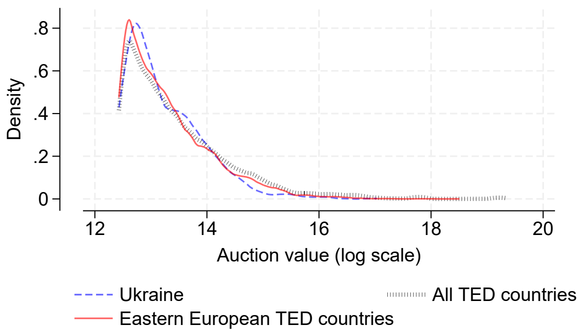

**(a)** Auction value



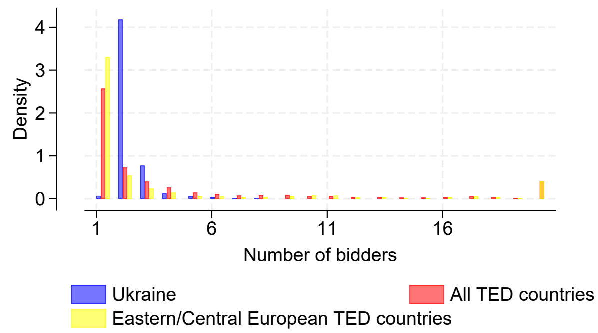

**(b)** Number of bidders

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.

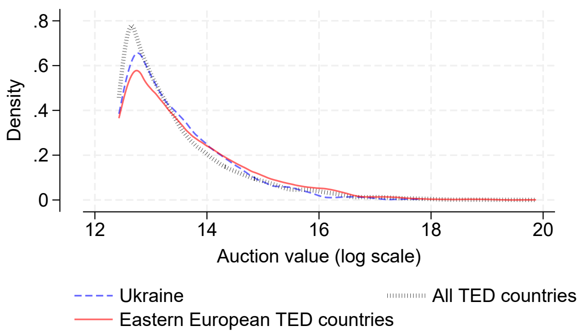
**Figure B.2:** Distribution of auction values and number of bidders, by CPV code



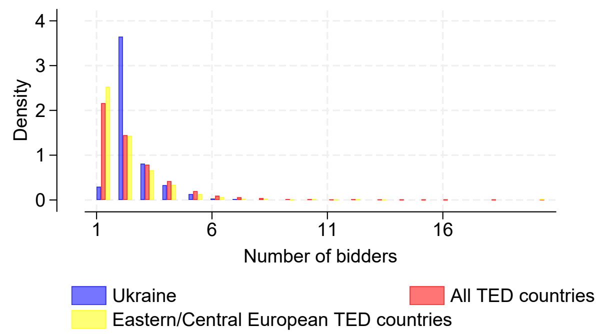

**(a)** Auction value, medical



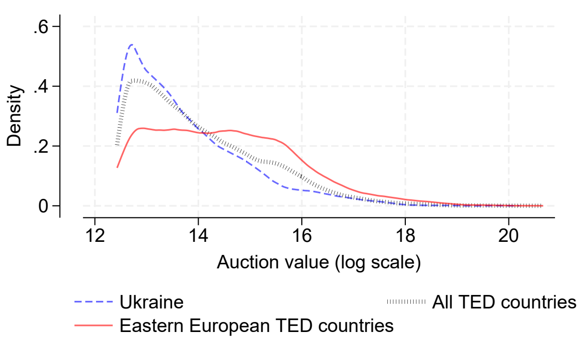

**(b)** Number of bidders, medical



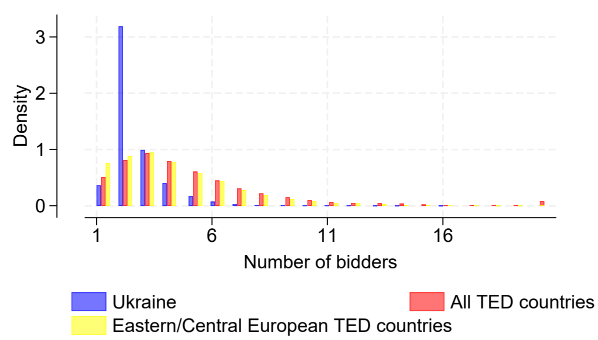

**(c)** Auction value, transport




**(d)** Number of bidders, transport



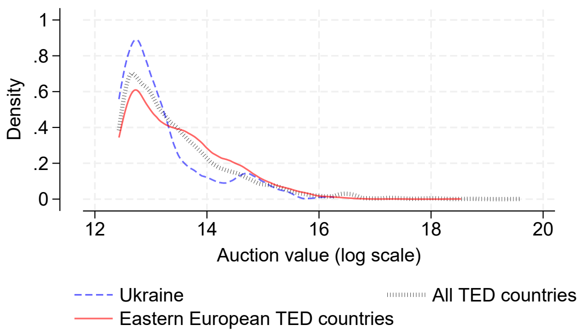

**(e)** Auction value, construction



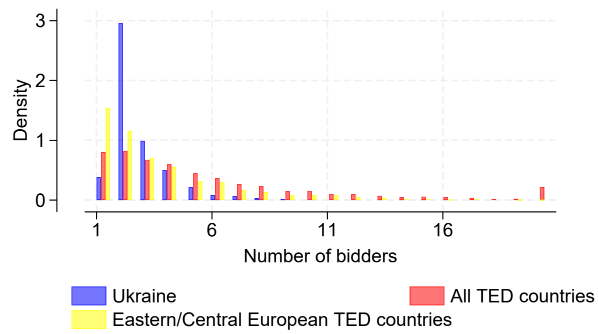

**(f)** Number of bidders, construction

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.

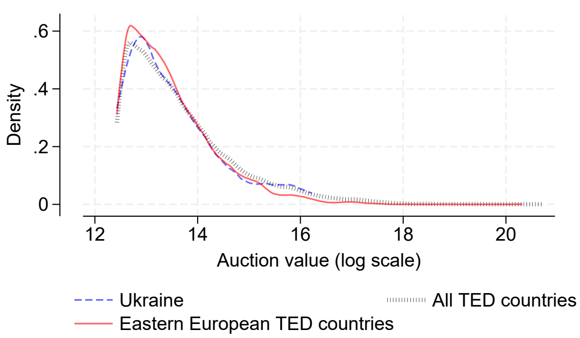
**Figure B.2:** Distribution of auction values and number of bidders, by CPV code (continued)



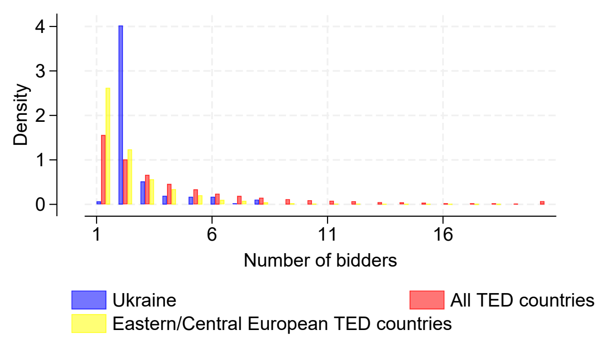

**(g)** Auction value, architectural and engineering




**(h)** Number of bidders, architectural and engineering



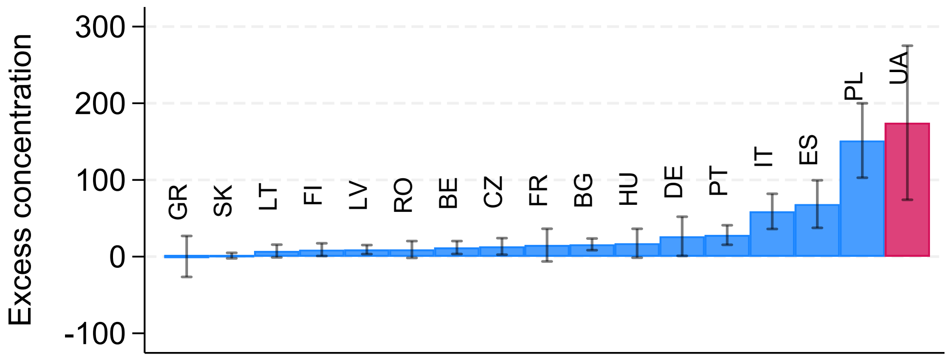

**(i)** Auction value, sewage and refuse



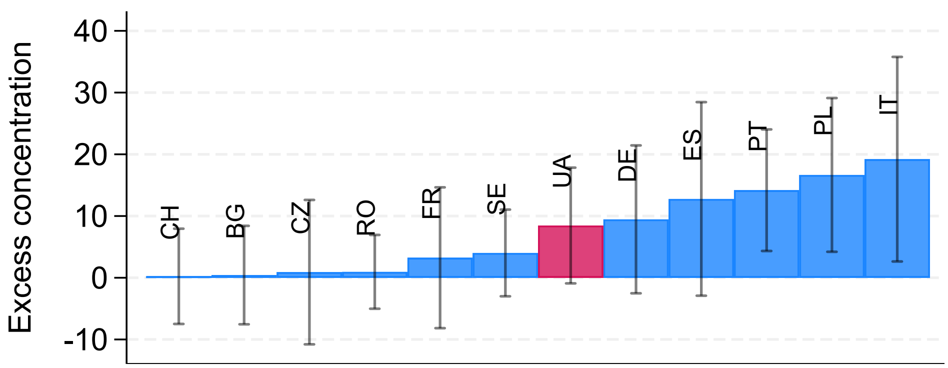

**(j)** Number of bidders, sewage and refuse

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.

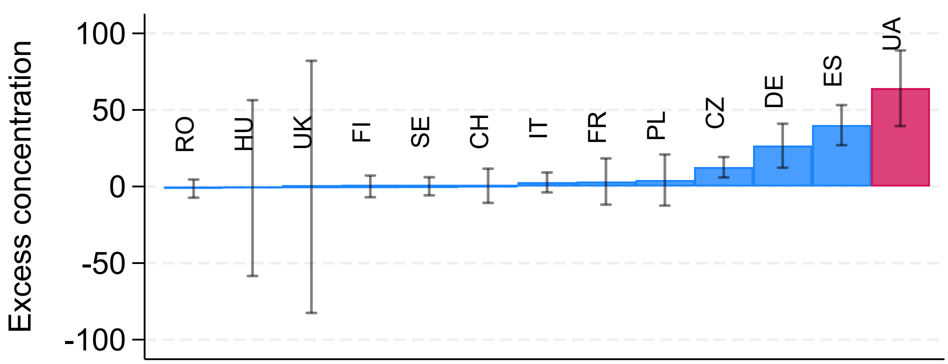
**Figure B.3:** Procurement market rankings across additional European countries and sectors




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



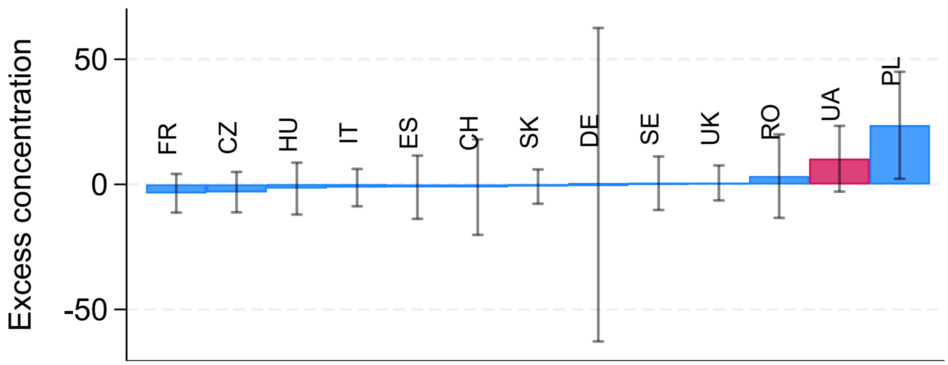

**(b)** Office and computing machinery, equipment and supplies except furniture and software packages



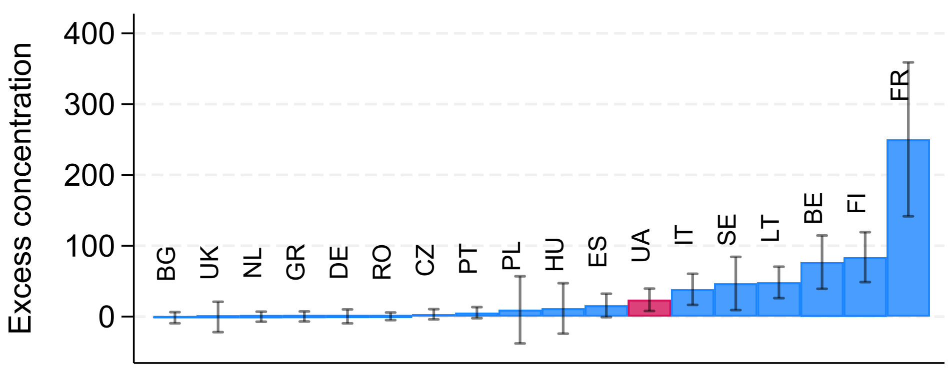

**(c)** Laboratory, optical and precision equipments (excl. glasses)

Notes: Each panel ranks countries by the standardized deviation (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. Positive values indicate excess concentration. Red bar denotes Ukraine. Error bars show bootstrapped 95% confidence intervals.

**Figure B.3:** Procurement market rankings across additional European countries and sectors (continued)




**(d)** Industrial machinery




**(e)** Repair and maintenance services

Notes: Each panel ranks countries by the standardized deviation (z-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.

# Appendix Tables

**Table B.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 B.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 B.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 B.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 B.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 B.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, $\frac{\Delta \mathrm{HHI}^{c,s}_{\mathrm{firm}}}{\widehat{\sigma}^{\mathrm{firm}}_{c,s}}$, 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 B.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, $\frac{\Delta \mathrm{HHI}^{c,s}_{\mathrm{firm}}}{\widehat{\sigma}^{\mathrm{firm}}_{c,s}}$, 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 B.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, $\frac{\Delta \mathrm{HHI}^{c,s}_{\mathrm{firm}}}{\widehat{\sigma}^{\mathrm{firm}}_{c,s}}$, 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 B.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 B.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.