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Research Article

Keywords: Public procurement, Corruption risk, Machine learning, Gradient boosting, Open data, Risk-based

Posted Date: October 19th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11209176/v1>

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Additional Declarations: No competing interests reported.

Expected versus Unexpected Non-Competition: A Corruption-Risk Approach to Public Procurement in Spain

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Abstract: Limited competition in public procurement, often operationalized as single or below-threshold bidding, is a widely used objective proxy for corruption risk and rent-seeking, yet static red-flag indicators cannot separate low competition that reflects legitimate market or institutional conditions from low competition that signals restricted access to public contracts. We address this measurement problem using contract-level data on 393,631 Spanish tenders awarded between 2018 and 2024. Estimating a gradient boosting model on pre-award characteristics, we predict the ex-ante probability that a tender attracts fewer than three bids and decompose realized non-competition into an expected component, driven by structural and procedural factors, and an unexpected residual component. We find that procurement sector and procedure type, proxies for market structure and administrative discretion, are the dominant determinants of competition, consistent with the political-economy view that discretion shapes the scope for favouritism. The unexpected component correlates with established corruption-risk indicators, supporting its interpretation as a refined, false-positive-reducing proxy for integrity risk. Our approach offers a transferable, ex ante measure of corruption risk relevant to the governance of EU-funded procurement, where Spain is among the largest recipients of Next Generation EU resources.

Keywords: Public procurement; Corruption risk; Machine learning; Gradient boosting; Open data; Risk-based.

JEL codes: C38, H57, D72, D73, O38

1. Introduction

Public procurement represents one of the most critical yet vulnerable areas of public sector governance (Dastidar and Jain, 2023; Davis et al., 2024). As governments allocate high amount of national expenditure to acquire goods, services, and infrastructure, procurement systems inherently combine large financial flows with complex administrative discretion, conditions that make procurement processes particularly vulnerable to inefficiency and corruption (Zhang, 2026). Within the European Union (EU), public procurement accounts for approximately 12% to 30% of GDP (European Commission, 2014; OECD, 2017). However, despite decades of reform and digital transparency initiatives, corruption risks in procurement remain a persistent challenge, particularly in countries with historically weak oversight or fragmented institutional frameworks.

From a political-economy perspective, limited competition is not merely an efficiency concern but a symptom of how administrative discretion, market structure, and institutional design shape the scope for rent-seeking and favouritism in the allocation of public contracts. Single or below-threshold bidding has accordingly become one of the most widely used objectives, contract-level proxies for corruption risk (Fazekas and Tóth, 2016; Fazekas and Kocsis, 2020). Yet the same low-competition outcome may reflect either benign market conditions or the deliberate restriction of access to favour a connected supplier, a distinction that static red-flag indicators cannot draw. This paper addresses that measurement problem directly.

Detecting irregularities and the control of corruption risk is a continuously evolving field, not only because data availability and analytical tools are rapidly advancing, but also because procurement practices and, consequently, corruption schemes, adapt over time. Efforts to detect corruption or inefficiency in procurement have traditionally relied on “red flags” or observable indicators such as single bidding, non-open procedures, or short advertising periods (Ferwerda et al., 2017; OECD, 2007). While these static checklists offer transparency and simplicity, they also produce numerous so-called false positives, especially in markets like Spain’s, where structural or sectoral characteristics often explain low competition without implying misconduct. Moreover, as corruption networks adapt to scrutiny, overt red flags become less informative (Decarolis and Giorgiantonio, 2022). Recent research thus highlights the need to move beyond descriptive red-flag systems toward predictive, data-driven approaches capable of distinguishing legitimate from suspicious tendering patterns. Recent research also suggests that corruption risks and irregularities cannot be fully understood through static indicators alone, as they emerge from complex interactions between institutional structures, incentives, and individual behaviour. This perspective highlights the limitations of purely rule-based monitoring systems and reinforces the need for more adaptive and context-sensitive approaches to risk detection (Røhl and Hansen 2024).

The increasing availability of open and standardized procurement data, through platforms such as *OpenTender*, *Tenders Electronical Daily*, and the *Open Contracting Data*

Standard, has transformed the empirical analysis of public contracting (Duguay et al., 2023; Felizzola et al., 2024). These datasets enable large-scale, comparative assessments of integrity and competition, fostering a new generation of analytical tools that leverage machine learning (ML) and explainable artificial intelligence (XAI). However, while ML has demonstrated strong predictive potential in detecting collusion and inefficiency (Fazekas and Kocsis, 2020), practical adoption in government oversight remains limited. At the same time, the growing integration of algorithmic and data-driven tools into public administration is reshaping how governments monitor and make decisions, raising important questions regarding transparency, accountability, and the role of human judgment in administrative processes (Mergel, 2016). Key challenges include the lack of labelled corruption data, limited interpretability of complex models, and the difficulty of translating predictions into actionable audit insights.

The literature reveals a clear trajectory: from reliance on simple red flags, with the shortcomings noted above, toward model-based approaches that estimate context-adjusted risk. A critical gap nonetheless remains in separating the component of low competition that is predictable from a tender's sectoral, procedural, and regional characteristics from the residual, unexpected component that is more plausibly informative about integrity risk. This study addresses that gap by constructing an interpretable, model-based counterfactual of expected competition for the universe of Spanish public tenders.

Spain provides a particularly relevant case for examining these dynamics. As one of the largest receivers of the EU's Next Generation recovery funds, amounting to nearly €160 billion in grants and loans, Spain faces the challenge of accelerating public investment while ensuring transparency and accountability in its allocation. Reports by Transparency International España (2022) consistently identify public procurement as one of the country's most corruption-prone sectors, with recurring issues of single-bid tenders, limited competition, and political influence over contract awards. The 2022 Eurobarometer indicates that 40% of Spanish companies reported losing contracts due to corruption, nearly twice the EU average, and that approximately one-third of national tenders attract only a single bidder. These structural inefficiencies not only distort market competition but also jeopardize the effective deployment of EU recovery resources.

This paper contributes to the political economy of corruption in public procurement by providing an *ex ante*, model-based measure of corruption risk grounded in the gap between expected and observed competition. Using a comprehensive dataset of 393,631 tenders from 2018 to 2024, compiled from OpenTender and the Spanish national procurement platform, we estimate a Gradient Boosting Model that predicts, using only pre-award information, the probability that a tender attracts fewer than three bids, a widely recognized proxy for limited competition and integrity risk. Crucially, the model decomposes realized non-competition into an expected component, driven by legitimate structural and procedural factors, and an unexpected residual component that may signal the restriction of access characteristic of favouritism (Teruel-Gutiérrez et al., 2025).

The results demonstrate robust predictive performance ($AUC \approx 0.78$ on testing data) and temporal stability across validation samples. The analysis of feature importance reveals that procurement sector and procedure type are the dominant predictors of competition levels, emphasizing the structural nature of bidder participation. The model displays strong correlations between the model's predicted risk and OpenTender's integrity indicators, confirming its conceptual validity and operational relevance. The model thus establishes a robust analytical basis for proactive, risk-based auditing, by demonstrating that a selective focus on a small subset of tenders, those whose competition levels deviate from predicted norms, can translate predictive insights into actionable oversight measures.

This paper contributes to the political economy of corruption in public procurement in three in three main ways. First, we build on the literature that uses single bidding and low competition as objective, contract-level proxies for corruption risk (Fazekas and Kocsis, 2020; Fazekas et al., 2016) and address its central limitation, the conflation of benign and suspicious low competition, by replacing static thresholds with a model-based counterfactual of expected competition. The unexpected residual provides an *ex ante*, continuous measure of integrity risk that reduces false positives relative to conventional red flags. Second, our finding that procedure type and sector dominate competition outcomes speaks directly to the discretion versus rules debate, in which the latitude afforded to procuring entities is a key channel for rent-seeking and favouritism (Broms et al., 2019; Coviello and Mariniello, 2014; Hoekman and Onur Taş, 2024). Third, we extend evidence that is largely Italian, French, German, and EU-panel-based (Hartlapp, 2025; Ravenda et al., 2020; Thomann et al., 2024) to the Spanish setting, a first-order case given Spain's role as a major recipient of Next Generation EU funds. In doing so, we position machine learning not as a methodological end but as a measurement device for the political economy of government contracting (Fazekas et al., 2022).

The remainder of the study is structured as follows. Section 2 reviews the literature on corruption risk and predictive modelling in procurement. Section 3 describes the data, variables and modelling approach. Section 4 presents the empirical results, including model performance, interpretability, and anomaly detection. Section 5 discusses implications for integrity monitoring and policymaking, and Section 6 concludes.

2. Literature review

This study connects to a growing body of political-economy research that uses large-scale contracting data to measure corruption risk and to test how institutional design shapes competition (Guerrero and Castañeda, 2021). One strand operationalizes corruption risk through single bidding and composite red-flag scores (Fazekas and Kocsis, 2020; Fazekas et al., 2016) and shows that these objective proxies track well-established perceptions-based indicators. A second strand examines how the latitude afforded to contracting authorities affects outcomes: greater discretion can lower prices but also widens the scope for favouritism and rent-seeking (Broms et al., 2019; Coviello and Mariniello, 2014). The integrity consequences of procurement design have been developed largely in Italian and

cross-country European settings, including work on criminal infiltration (Ravenda et al., 2020) and the strategic use of award clauses for favouritism (Maréchal and Morand, 2022). We contribute by supplying a transferable, ex ante measure of the unexpected component of non-competition, by extending the evidence to Spain, and by treating machine learning as a measurement device for the political economy of government contracting rather than as an end in itself (Fazekas et al., 2022).

Public procurement is widely recognized as one of the government activities most vulnerable to corruption. As nearly all state functions, from infrastructure development to healthcare provision, involve purchasing goods, works, or services, this sector represents a substantial share of public expenditure, accounting for approximately 12% to 30% of GDP in the EU (European Commission, 2014; OECD, 2017). This combination of substantial financial flows and delegated decision-making authority creates significant opportunities for abuse. The European Commission (2014) estimated that corruption costs EU countries around €120 billion annually. More recent survey data confirms the persistence of these issues, with over half of businesses perceiving illicit practices in public tenders as widespread; for instance, 57% report encountering tailor-made specifications designed to favour particular firms, and 52% observe evidence of collusive bidding (European Commission, 2022a). Such corrupt practices distort market competition, inflate public costs, and ultimately erode citizen trust in governmental institutions. A robust body of empirical research corroborates that corruption in procurement leads to market distortions and inefficient public investment, resulting in higher costs, wasted resources, and ultimately weaker economic growth (Fazekas and Kocsis, 2020; Pellegata and Memoli, 2016; Villoria and Jiménez, 2012).

These challenges are particularly severe in Spain and have gained renewed urgency due to the country's status as one of the largest beneficiaries of the EU's Next Generation recovery funds, having been allocated approximately €160 billion in grants and loans. This massive injection of public investment must be managed through public procurement systems which remain historically exposed to corruption risks. Transparency International España (2022) highlights that public procurement remains one of the most corruption-prone areas of Spanish governance. The European Commission (2022b) identified public contracting, political party financing, and infrastructure projects as sectors of elevated risk. According to a recent Eurobarometer edition, 40% of Spanish companies reported losing contracts due to corruption, nearly twice the EU average (European Commission, 2022a). Moreover, around one-third of Spanish public tenders in 2024 attracted only a single bidder, exceeding the European mean of roughly 29%. The European Commission notes that such single-bid tenders are especially suspicious, since limited competition often signals collusion or favouritism (OECD, 2014).

Recent scandals illustrate these risks. In late 2024, a former minister was indicted in a pandemic-related procurement case, and in 2025 the “Operación Delorme” investigation alleged that senior officials received kickbacks for infrastructure contracts (Deconinck, 2025; Sánchez Nicolás, 2025). In response, Spain’s Prime Minister announced new anti-corruption measures, including stricter tendering rules and blacklisting of companies

convicted of bribery (Pinedo and Landauro, 2025). Nevertheless, experts argue that addressing systemic corruption requires deeper institutional reforms (Jiménez-Sánchez, 2023; Mugellini et al., 2021). Spain thus provides an important context for studying how data-driven oversight can enhance procurement integrity.

Efforts to identify corruption in procurement have traditionally relied on red flags, *i.e.*, observable patterns in contracting data that signal potential misconduct (Ferwerda et al., 2017; Kenny and Musatova, 2010; Tátrai and Németh, 2018). Common red flags include tenders attracting only one bidder, use of non-open procedures, unusually short advertising periods, repeated awards to the same contractor, or ambiguous technical specifications (OECD, 2007; PricewaterhouseCoopers and Ecorys, 2013). Robust empirical evidence confirms that contracts awarded after receiving a single offer tend to have significantly inflated prices and exhibit a strong correlation with confirmed corruption and collusive practices (Decarolis, 2014).

However, simple red flags have important limitations. In many European markets, and particularly in Spain, procurement processes often exhibit low levels of competition. According to the CNMC (2019), approximately one out of three central government contracts attracts only a single bidder. Low competition can also stem from legitimate factors related to low government capacity, such as poor tender design, inadequate market outreach, or complex procedures that deter bidders, rather than malfeasance. Therefore, alerts based solely on low competition generate numerous false positives. Furthermore, corrupt actors can learn to avoid obvious indicators. Decarolis and Giorgiantonio (2022) demonstrated that in Italian public procurement, traditional corruption red flags are often ineffective due to strategic avoidance by officials. They revealed that subtle, less-monitored features in tender documents, particularly discretionary award criteria, are stronger predictors of corruption than obvious signals like emergency procedures. This evidence highlights the necessity of moving beyond static checklists toward predictive analytics that can distinguish legitimate low-competition scenarios from suspicious anomalies.

The emergence of large-scale open procurement data has transformed the fight against corruption. Over the past decade, European countries have made unprecedented efforts in publishing detailed contract-level data, aided by the *Open Contracting Data Standard* and platforms like *Tenders Electronic Daily*. These datasets have enabled the transition from traditional descriptive analyses, focused on reporting irregularities, to predictive approaches that estimate the likelihood of risk events, such as low competition or potential collusion.

Platforms such as OpenTender.eu have significantly improved access to procurement data; however analysts contend that this information remains insufficiently leveraged for oversight and policy-making (Transparency International España, 2022). (Transparency International España, 2022). By aggregating and scoring tenders based on indicators such as single bidding or opaque procedures, OpenTender provides a foundation for more advanced analytical tools. These data infrastructures serve as enablers of predictive

monitoring systems, allowing oversight bodies to transition from descriptive statistics to continuous, automated integrity monitoring (OECD, 2024; World Bank, 2024).

A challenge that arises in this domain is the scarcity of labelled corruption data (Sun and Xu, 2026). Researchers therefore use proxy labels, such as single-bid outcomes or non-competitive procedures, to train supervised learning models (Fazekas and Kocsis, 2020). Beyond standard classification models, network-based and deep learning approaches are emerging (Barone and Schneider, 2025; Çelik et al., 2026; Wang and Zhao, 2025). Huber and Imhof (2023) developed ML and deep learning methods to detect bid-rigging cartels. Their convolutional neural network achieved roughly 95% out-of-sample accuracy in identifying collusive patterns, demonstrating the capacity of AI to detect subtle irregularities invisible to rule-based screens.

Another important advancement comes from integrating non-traditional data sources. Decarolis (2014) studies auction formats and contract performance, and he underscores the value of deep, micro-level analysis of procurement data to understand the real-world consequences of awarding procedures. This aligns with broader trends toward combining diverse data types, from structured bidding information to network patterns, to capture complex signals of inefficiency and risk.

While ML enhances detection power, interpretability remains essential for accountability in government auditing. The OECD (2025) emphasizes that AI systems used in public integrity must be explainable, traceable, and aligned with ethical standards. Complex models like deep neural networks risk becoming “black boxes” if their decisions cannot be understood. To mitigate this, researchers increasingly use XAI methods. Shapley Additive Explanations has emerged as a prominent technique to interpret corruption risk predictions in procurement data, revealing which contract features, such as unusually high estimated budgets or procedural irregularities, contribute most to model alerts (Lundberg and Lee, 2017). Similarly, the OECD (2025) advocates for integrating explainability into predictive monitoring systems to enhance trust and accountability among auditors.

Among the various ML algorithms, gradient boosting machines (GBMs), particularly XGBoost, have emerged as a gold standard in tabular data prediction competitions and have seen successful application in public sector analytics. Their strength lies in handling mixed data types, capturing complex interactions, and providing high predictive accuracy. Their native support for feature importance metrics also makes them more interpretable than deep neural networks for structured data like procurement records.

3. Data and Methodology

3.1. Data sources and variables

In order to systematically distinguish tenders that are genuinely risky from those that are predictably uncompetitive for legitimate reasons, we utilize data extracted from

OpenTender¹, a transparency initiative developed by the Government Transparency Institute and the Open Contracting Partnership. OpenTender systematically collects and harmonizes public procurement information from both national and EU sources, adhering to the Open Contracting Data Standard. The platform offers structured, comparable, and downloadable datasets on tenders, awards, and suppliers across European countries, providing a robust foundation for large-scale integrity analytics. Specifically, OpenTender compiles data from the official Spanish national procurement portal (*Plataforma de Contratación del Sector Público*) and the European Commission's Tenders Electronic Daily database. The dataset includes detailed information on procurement procedures, including contract type, Common Procurement Vocabulary (CPV) sector, estimated value, procedure type, geographical location (NUTS² code), and the number of bids received.

We study all awarded contracts between January 2018 and December 2024. Following the European Union's "minor thresholds" established in Directive 2014/24/EU, we restrict the sample to awarded tenders with a base budget of at least €40,000 for works and €15,000 for services or supplies, excluding non-awarded or incomplete records. After applying these filters and performing quality checks, the final dataset comprises 393,631 tenders.

Data were downloaded as JSON (JavaScript Object Notation) files from OpenTender and processed in Python, using automated parsing and transformation scripts. This workflow allowed us to integrate core tender attributes with OpenTender's pre-existing integrity indicators, such as Integrity and Transparency scores, later used for external validation of the model. All variables have been constructed exclusively from pre-award information, ensuring that the model predicts competition outcomes based solely on data available before contract award. This avoids information leakage and enables ex-ante risk assessment, a critical requirement for operational audit and oversight.

To capture the different dimensions of the procurement process, we construct a balanced set of thirteen explanatory variables covering tender characteristics, award design features, and contextual attributes. This set includes financial measures (e.g., budget and per-lot value), procedural dimensions (procedure and contract types), sectoral and regional identifiers (CPV and NUTS codes), as well as textual proxies for contract complexity. Table 1 summarizes the explanatory variables included in the model, categorized by their type and source. The target variable, *LowCompetition*, is defined as a binary indicator where *LowCompetition* equals 1 if the number of received bids is fewer than three, and 0 otherwise. This threshold aligns with established literature on procurement competition and integrity risk assessment (Fazekas and Kocsis, 2020; OECD, 2024; OECD and ADB, 2007; Thomann et al., 2024), and reflects benchmarks used by European oversight authorities to flag potentially non-competitive tenders.

¹ <https://opentender.eu/>

² Nomenclature of territorial units for statistics

[Table 1 here]

To better contextualize this definition, Figure 1 presents the distribution of received bids across all tenders, revealing a highly skewed pattern: more than half of the tenders attract only one or two bids, while fewer than 5% receive more than 12 bids. This evidence supports the selection of the threshold and further motivates a predictive approach aimed at distinguishing between expected low competition, reflecting legitimate low participation and unexpected low competition, which may indicate potentially risky procurement outcomes.

[Figure 1 here]

Prior to model estimation, all explanatory variables were transformed and standardized to enhance interpretability and predictive performance. Following established practices in credit risk and public-sector modelling (Siddiqi, 2012), we applied Weight of Evidence (WoE) encoding to all continuous and categorical predictors.

The WoE transformation converts each variable into a monotonic numerical scale that reflects its statistical association with the binary target variable, thereby capturing non-linear relationships while preserving interpretability. This approach provides several methodological advantages: it handles missing values; it enforces monotonicity, limit overfitting and yields a consistent scaling across heterogeneous predictors (Giner-Baixauli et al., 2021; Raymaekers et al., 2021).

The binning process was optimized using information value maximization and monotonicity constraints to ensure that each variable's transformed representation aligned with the direction and strength of its association with low competition. This step produced a harmonized and interpretable feature set suitable for the subsequent Gradient Boosting modelling stage.

Table 2 summarizes WoE transformation for the type of contract, which distinguishes among works, supplies, and services tenders. This transformation converts each category into a continuous measure reflecting its relationship with the probability of low competition. This encoding allows both numerical and categorical variables to be incorporated into the model in a monotonic and interpretable way. As shown, works contracts represent about 23% of all tenders. Positive WoE values (e.g., *Works*) indicate a lower-than-average likelihood of low competition. In contrast, negative values (e.g., *Supplies* and *Services*) indicate a higher-than-average risk. In fact, supplies and services present 72% and 76% proportions of low-competition calls.

[Table 2 here]

To ensure robust model training and temporal validity, the dataset was divided into three mutually exclusive subsets corresponding to distinct time periods: training, testing, and validation. Specifically, tenders published before July 2024 were allocated to the training and testing sets, while those published after July 2024 were reserved exclusively for out-of-sample validation. Within the pre-July 2024 data, a 70/30 split was applied to create the training and testing subsets. To preserve the empirical class balance of the target variable (*LowCompetition*), stratified sampling was implemented, ensuring that both the training and testing sets maintained the same proportion of low-competition tenders as observed in the full dataset. This step is particularly relevant in procurement data, where the distribution between competitive and low-competition tenders tends to be highly asymmetric.

Table 3 presents the sample sizes and target variable proportions after partitioning. This design supports a temporally informed out-of-sample evaluation, where the validation subset represents future procurement events unseen during model training, thereby aligning the predictive exercise with a real-world ex-ante risk assessment perspective. It can be seen that the training and test samples display identical proportions of low-competition cases (approximately 67%). The validation sample, corresponding to later tenders, shows a slightly higher share of low-competition outcomes (72%), reflecting realistic temporal variation in procurement dynamics.

[Table 3 here]

3.2. Methodology

The modelling approach employed Gradient Boosting Models (GBM) as the primary algorithm, selected after an extensive comparative analysis with several alternative methods. During preliminary experimentation, we systematically evaluated logistic regression (with L1/L2 regularization), Random Forests, and baseline decision trees. GBM consistently achieved the best trade-off between predictive performance and model stability. Detailed benchmarking results for alternative methods are available upon request.

The choice of GBM is theoretically grounded in its proven suitability for tabular and structured data prediction tasks (Grinsztajn et al., 2022). This algorithm effectively captures complex and non-linear relationships among tender characteristics, procedural attributes, and contextual factors, which are typical of procurement data. Unlike deep learning models that demand massive datasets and extensive computational resources, GBM performs exceptionally well on medium-sized administrative data (Borisov et al., 2022), making it particularly appropriate for large-scale, real-world policy analytics.

From an applied perspective, GBM also provides superior interpretability compared to other high-performance ensemble or neural methods.

To ensure robust model performance, we conducted hyperparameter optimization using a randomized grid search strategy across carefully balanced parameter configurations (Friedman, 2001; Grinsztajn et al., 2022; Prokhorenkova et al., 2018). The search procedure systematically explored the trade-offs between model complexity, generalization capacity, and computational efficiency, using Area Under Curve (AUC) as the optimization metric to align with our classification objective. Key parameters included the number of boosting iterations (50-300), learning rate (0.01-0.1), tree depth (3-5), and stochastic sampling ratios for regularization. This comprehensive optimization aimed to prevent overfitting while maintaining interpretability and temporal stability across data partitions. Detailed hyperparameter ranges and their theoretical justification are presented in Table 4.

[Table 4 here]

4. Results

As an initial step, we evaluate the overall performance of the model. The hyperparameter optimization process identifies an optimal configuration that balances model complexity and generalization capacity. The resulting model exhibits strong discriminative power, achieving an AUC of 0.778 on the test set, which indicates solid ability to distinguish between competitive and low-competition procurement procedures. The temporal validation set shows an expected decrease in performance (AUC = 0.727), reflecting realistic deployment conditions and confirming the model’s temporal stability and operational utility for forward-looking risk assessment. The stability of the Log Loss metric across training and testing sets further supports the model’s reliability and suggests consistent probabilistic calibration. The optimal configuration combines moderate model depth (max_depth = 5) with a balanced learning rate (0.08) and subsampling ratio (sample_rate = 0.75), ensuring both generalization and computational efficiency.

We then proceed to analyse the relative contribution of each variable or procurement characteristic to competition outcomes. Table 5 reports the relative importance of the explanatory variables in predicting low-competition cases. The procurement sector emerges as the most influential factor, accounting for nearly half of the total explanatory power.

Procedural characteristics also play a key role. In particular, procedure type ranks as the second most influential variable (19.6%), indicating that institutional design choices significantly affect bidder participation. Notably, contract value ranks only eighth in importance (accounting for 1.9% of the total explanatory power).

[Table 5 here]

Given the relevance of procedure type, we further examine the model's predictive performance across different categories. To this end, we define seven procedure types: negotiated without publication, negotiated with publication, minitender, open, restricted, approaching bidders, and others³. For each type, we compute the AUC for the training, test, and validation samples. Table 6 reports these discriminative performance metrics alongside the proportion of low-competition tenders. The results show that the model performs consistently well across all procedure types, with AUC values exceeding 0.70 in nearly every case. The highest AUCs are observed in procedures characterized by greater administrative discretion, such as negotiated without publication (AUC $\approx$ 0.87) and minitenders (AUC $\approx$ 0.85), which also correspond to the categories with the highest prevalence of low-competition cases. Even for open and restricted procedures, where competition is typically higher, the model maintains strong predictive ability (AUC > 0.70).

[Table 6 here]

We now turn to the question of the external validity of the model's predictive outcomes, and examine the relationship between the predicted probability of low competition and the integrity indicators provided by OpenTender. All OpenTender scores are normalized on a 0–100 scale, where higher values indicate greater procedural integrity and lower risk of irregularities. These indicators are designed to capture the likelihood of irregularities or inefficiencies in procurement processes and offer an external benchmark for evaluating competition-related risks. In particular, the integrity score is a composite measure that aggregates several red flags associated with limited competition, procedural risks, and potential favouritism. One of its main components is the single bid indicator, which flags tenders awarded after receiving only one valid offer, a direct signal of weak competition.

Table 7 reports the correlation coefficients between the model's predicted probability of low competition and the OpenTender integrity indicators across training, testing, and validation datasets. The results reveal a strong and consistent negative association between the model's predictions and both the integrity score and the single bid indicator. Specifically, the Pearson correlations with the integrity score are around -0.52 in the training and test sets, and -0.47 in the validation set. The single bid indicator also shows

³ These categories follow common classifications used in EU public procurement. Open and restricted procedures are fully regulated by Directive 2014/24/EU, while negotiated procedures (with or without publication) allow direct negotiation with suppliers under specific conditions. Minitenders refer to competitive calls within framework agreements. The “approaching bidders” category captures informal or simplified consultations used for low-value contracts, and “others” includes exceptional or non-standard procedures.

a significant correlation (approximately -0.47 in the training and test sets), consistent with its conceptual overlap with the model's target variable.

[Table 7 here]

Figure 2 illustrates these relationships for the single-bid indicator (left panel) and the integrity score (right panel). The predicted probability of low competition decreases as the number of bids increases and inversely follows the integrity score.

[Figure 2 here]

Considering the importance of situations involving very few bidders, we assess the model's operational utility in identifying unexpectedly low-competition tenders, defined as procedures that, based on their observable pre-award characteristics, were expected to attract multiple bids but ultimately received very few. To identify such anomalies, we define a tender as unexpectedly low-competition when it meets two simultaneous conditions. First, the model predicts a low probability of limited competition, specifically a predicted probability below a threshold such as $\tau = 0.30$. Second, the tender is actually observed ex post as low competition, that is, it received fewer than three valid offers. This dual condition isolates tenders that performed worse than expected in terms of competition, given their procedural, sectoral, and regional characteristics. The choice of $\tau = 0.30$ is illustrative and designed to strike a balance between coverage and precision. In practice, this threshold can be calibrated depending on the oversight capacity or risk tolerance of the reviewing authority. Lower thresholds (e.g., $\tau = 0.20$ – 0.25) identify a smaller number of highly exceptional cases, ideal for in-depth audits, whereas higher thresholds (e.g., $\tau = 0.35$ – 0.40) expand coverage at the cost of a larger review pool.

Table 8 summarizes the distribution of these anomalies applying this definition to the each type of procedure and to the complete dataset of tenders. The model identifies 2,195 cases, representing 0.56% of all observations, as unexpected low-competition tenders. The share of such cases is modest (below 1%) across all the procedure types, reflecting the model's conservative design and the rarity of truly unexpected outcomes.

[Table 8 here]

Most anomalies occur within procedure types that are generally competitive, such as approaching bidders and open procedures, whereas procedures that are structurally restrictive, such as negotiated without publication, show almost no anomalies.

5. Discussion

The results speak to both the political economy of public procurement and the practice of integrity oversight. First, the model's predictive performance indicates that low-competition outcomes are not random events but are systematically associated with observable characteristics of tenders. The test and validation results suggest that these patterns remain sufficiently stable over time to support forward-looking, *ex ante* interpretation in oversight settings.

Second, the feature-importance results show that competition in procurement is shaped primarily by structural and procedural factors rather than by contract value alone. Procurement sector accounts for nearly half of the model's explanatory power, while procedure type is the second most influential predictor. This finding suggests that the competitive environment of a tender depends heavily on market structure, supplier availability, and procedural design. In practical terms, this means that low competition should not be interpreted uniformly across tenders. Some procedures are predictably less competitive because of their institutional or market context, whereas others may warrant greater scrutiny because they perform worse than expected given their characteristics. This pattern is consistent with political-economy evidence that procedural design, and the discretion it affords, is a primary determinant of competition and, in turn, of the scope for favoritism (Broms et al., 2019; Hoekman and Onur Taş, 2024).

Third, the model performs consistently across procedure types, including those characterized by greater administrative discretion. This reduces concerns that the model is merely reproducing a single procedural category as a proxy for risk. Instead, the evidence suggests that the model captures broader and more generalizable patterns of bidder participation. For this reason, a unified model across procedure types appears preferable to separate procedure-specific models, which would add complexity while reducing robustness in smaller categories.

Fourth, the correlations with OpenTender's integrity indicators support the conceptual validity of the approach. These indicators are not direct measures of corruption, but they provide a relevant external benchmark for assessing whether the model captures meaningful dimensions of procurement risk. The strong negative association between predicted low competition and integrity-related scores suggests that the model is aligned with recognized signals of procedural weakness and limited competition. At the same time, these relationships should be interpreted cautiously, as integrity indicators remain proxies rather than confirmed evidence of misconduct.

These findings also help clarify the added value of predictive monitoring relative to traditional red-flag systems. Red flags remain useful for transparency and screening, but

they often treat all low-competition outcomes as equally suspicious. The present results suggest that this is too coarse an approach. By distinguishing between expected and unexpected low competition, predictive tools can reduce false positives and support a more proportionate allocation of audit attention. This makes them particularly valuable in procurement systems where oversight bodies face large volumes of contracts and limited investigative capacity. From a political-economy standpoint, the results point toward a shift from reactive, ex-post compliance control to proactive risk-based oversight of how access to public contracts is allocated. Rather than waiting for ex post outcomes to trigger review, oversight bodies can use pre-award information to identify tenders that deserve closer attention before irregularities become entrenched. This does not replace human judgment. Instead, it provides auditors and public managers with a structured basis for prioritization, helping them focus on the cases where observed outcomes deviate most sharply from reasonable expectations.

The anomaly analysis illustrates this practical contribution clearly. Only 0.56% of tenders are classified as unexpectedly low-competition cases under the selected threshold, which shows that the model is highly selective. This selectivity is important for implementation because it allows institutions to target a manageable subset of tenders rather than expanding review obligations across all low-bid contracts. In settings of constrained resources, such prioritization can improve both the efficiency and the credibility of integrity monitoring.

At the same time, the results highlight several limits. The model predicts a proxy for integrity risk rather than corruption itself, and its usefulness depends on the quality and completeness of available procurement data. Its outputs should therefore be interpreted as decision-support signals, not as proof of wrongdoing. For this reason, predictive monitoring is best understood as a complement to existing audit procedures, investigative work, and professional judgment rather than as a substitute for them.

6. Conclusions

This study develops a predictive model to estimate the likelihood that a public procurement tender receives fewer than three bids, with the aim of identifying ex-ante cases of potentially limited competition. The results show that low-competition outcomes can be predicted with solid performance and temporal stability using only pre-award information.

The findings highlight that competition levels are primarily driven by structural and procedural factors, particularly procurement sector and procedure type, rather than by financial characteristics alone. This allows the model to distinguish between tenders that are predictably less competitive and those that exhibit unexpectedly low participation. Correlations with OpenTender's integrity indicators further support the conceptual validity of the approach. The model is particularly useful in identifying a small subset of tenders where observed competition deviates from expected patterns, which are more relevant for oversight. From a practical perspective, the model provides a pathway from

descriptive monitoring to proactive, risk-based supervision. By focusing on a very small proportion of tenders (approximately 0.56% in our sample), public authorities can improve the allocation of limited audit resources and enhance targeting efficiency. The study also has limitations. Low competition is an indirect proxy for integrity risk, and the model depends on the availability and quality of open procurement data. Future research could incorporate richer data sources and validate predictions against confirmed cases of irregularities.

The study also has limitations. Low competition is an indirect proxy for integrity risk, and the model depends on the availability and quality of open procurement data. Future research could incorporate richer data sources and validate predictions against confirmed cases of irregularities. Overall, the results suggest that interpretable predictive tools can complement traditional red-flag systems and support more targeted and efficient auditing in public procurement.

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Tables and Figures

Table 1. Variable description and sources

“Derived” indicates variables engineered from original OpenTender fields (e.g., transformations, aggregations, or text metrics).

Variable	Description	Type	Source
Contract duration	Estimated contract duration in days, transformed using Weight of Evidence	Continuous	OpenTender
Tender budget	Estimated base budget (EUR), transformed and log-scaled	Continuous	OpenTender
Criteria number	Number of award criteria included in the tender	Continuous	OpenTender
Minimum weight	Minimum relative weight among all award criteria	Continuous	Derived
Maximum weight	Maximum relative weight among all award criteria	Continuous	Derived
Lots	Number of lots in the tender	Continuous	OpenTender
Price	Logarithm of the estimated price per lot	Continuous	Derived
Procedure type	Type of procurement procedure (e.g., open, negotiated, restricted)	Categorical	OpenTender
Type of contract	Type of contract (works, services, supplies, concessions)	Categorical	OpenTender
Nuts	NUTS-2 region of the contracting authority	Categorical	Derived
Procurement sector	Sector of procurement (first two digits of CPV code)	Categorical	Derived
Tender words	Length of the tender title in words	Continuous	Derived
Tender characters	Length of the tender title in characters	Continuous	Derived

Table 2. Weight of Evidence transformation for contract type

This table presents the Weight of Evidence (WoE) transformation applied to the variable Type of contract.

Categories	Obs (%)	#Obs (Bids > 3)	#Obs (Bids <= 3)	Low Competition rate	WoE
Works	0.234	32,916	25,351	0.435	0.965
Supplies	0.368	25,564	66,129	0.721	-0.246
Services	0.398	23,960	75,234	0.758	-0.440
Total	1.000	82,440	166,714	0.331	

Table 3. Data partitioning and target variable distribution

This table presents the distribution of observations and the proportion of low-competition tenders across the training, test, and validation datasets.

Dataset	Period Covered	Observations	LowCompetition = 1	LowCompetition = 0
Training set	Before July 2024	249,154	66.9%	33.1%
Test set	Before July 2024	106,781	66.9%	33.1%
Validation set	After July 2024	37,720	72.3%	27.7%

Table 4. Hyperparameter configurations of the Gradient Boosting Model

Table details the grid of hyperparameter values tested during model optimization. The selection aimed to balance predictive performance, interpretability, and computational efficiency. The ranges chosen for parameters such as *number of trees*, *each tree depth*, and *learning rate* reflect a trade-off between model flexibility and overfitting control. Sampling parameters (*row sampling fraction* and *feature sample fraction*) introduced stochastic regularization, while *min. leaf size* ensured stability in leaf node estimation.

Hyperparameter	Values Tested	Meaning and theoretical rationale
Number of trees	[50, 75, 150, 300]	Controls the number of boosting iterations. Lower values (50-75) prevent overfitting, while higher values (150-300) capture complex patterns. We excluded extreme values (>300) to maintain computational efficiency.
Each tree depth	[3, 4, 5]	Determines tree complexity and interaction depth. Shallower trees (3-4) enhance interpretability and reduce overfitting, while depth 5 captures higher-order interactions without excessive complexity.
Learning rate	[0.01, 0.03, 0.05, 0.08, 0.1]	Controls the contribution of each tree. Lower learning rates (0.01-0.03) provide smoother convergence but require more trees; higher rates (0.08-0.1) accelerate training but increase the risk of overshooting optimal solutions.
Annealing factor	[0.99, 0.995, 1.0]	Reduces learning rate over iterations. Values lower than 1 enable finer convergence in later stages, while 1 maintains constant learning throughout training.
Row sampling fraction	[0.6, 0.75, 0.9, 1.0]	Row sampling fraction for stochastic gradient boosting. Lower values (0.6-0.75) introduce regularization and improve generalization; 1.0 uses all data.
Feature sampling fraction	[0.6, 0.75, 0.9, 1.0]	Feature sampling fraction per tree. Enhances diversity and reduces correlation between trees, with lower values providing stronger regularization.
Min. leaf size	[5, 10, 20, 50]	Minimum observations per leaf node. Higher values (20-50) create more conservative trees, while lower values (5-10) allow finer granularity for complex patterns.

Table 5. Relative importance ranking in predicting low competition

This table presents the relative importance of the explanatory variables used in the model to predict low-competition tenders.

Variable name	Variable description	Relative Importance
Procurement sector	Sector of procurement (first two digits of CPV code)	48.30%
Procedure type	Type of procurement procedure (e.g., open, negotiated, restricted)	19.60%
Contract type	Type of contract (works, services, supplies, concessions)	8.30%
Lots	Number of lots in the tender	7.90%
NUTS	NUTS-2 region of the contracting authority	4.90%
Criteria	Number of award criteria included in the tender	4.30%
Duration	Estimated contract duration in days, transformed using Weight of Evidence	3.30%
Contract budget	Estimated base budget (EUR), transformed and log-scaled	1.90%
Minimum weight	Minimum relative weight among all award criteria	0.80%
Price	Logarithm of the estimated price per lot	0.50%

Table 6. Model performance by procurement procedure type

This table presents the AUC across different procurement procedure type.

Procedure Type	# Obs.	AUC (Train)	AUC (Test)	AUC (Val.)	Low Competition (%)
Negotiated without publication	36,962	0.878	0.874	0.874	98.50%
Negotiated with publication	2,224	0.768	0.777	0.694	96.00%
Minitender	30,733	0.857	0.844	0.85	91.10%
Open	110,117	0.757	0.753	0.704	74.20%
Approaching bidders	200,432	0.721	0.717	0.673	66.60%
Restricted	4,216	0.653	0.617	0.712	62.50%
Other	8,947	0.804	0.804	0.791	84.00%

Table 7. Correlation between predicted low-competition probability and OpenTender integrity indicators

This table reports the correlation coefficients between the model's predicted probability of low competition and OpenTender integrity indicators.

OpenTender Variable	Pearson	Spearman	Sample
Integrity Score	−0.525	−0.519	Train
Single Bid indicator Score	−0.472	−0.476	
Integrity Score	−0.524	−0.518	Test
Single Bid indicator Score	−0.470	−0.473	
Integrity Score	−0.474	−0.452	Validation
Single Bid indicator Score	−0.399	−0.397	

Table 8. Unexpected low-competition tenders by procedure ($\tau = 0.30$)

This table summarizes the proportion of tenders identified as unexpectedly low-competition cases using a probability threshold of $\tau = 0.30$.

Procedure Type	N	Low Competition %	Anomalies %
Approaching bidders	200,432	60.93	0.73
Open	110,117	65.51	0.53
Negotiated without publication	36,962	94.83	0.01
Minitender	30,733	80.22	0.32
Other	8,947	80.52	0.28
Restricted	4,216	62.64	0.33
Negotiated with publication	2,224	72.66	0.13
Total	393,631	64.84%	0.56%

Figure 1. Distribution of the number of bids received per tender

This figure shows the distribution of the number of bids received across all tenders, highlighting the prevalence of low-competition outcomes.

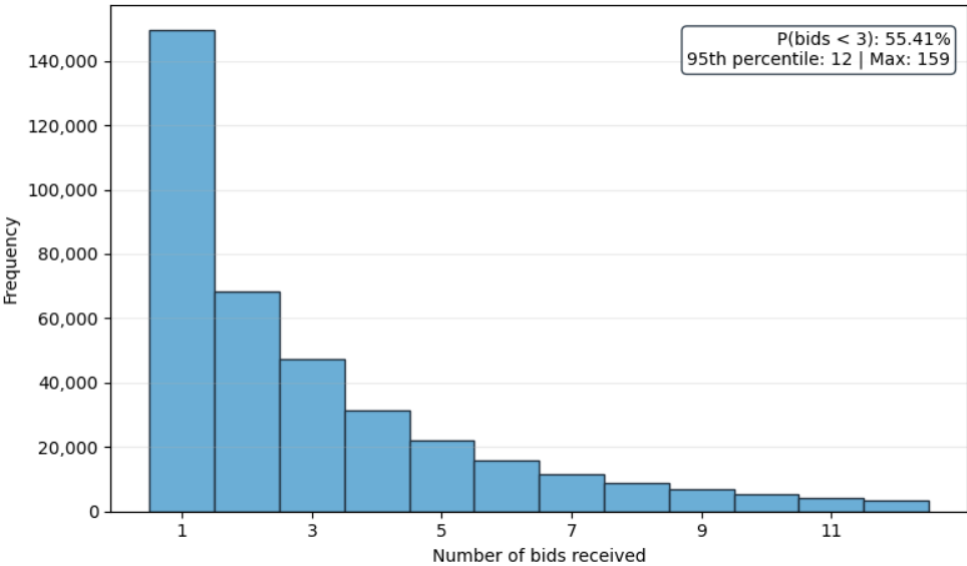


Figure 2. Relationship between predicted low-competition probability and OpenTender integrity indicators

These figures illustrate the relationship between the model’s predicted probability of low competition and the OpenTender integrity indicators. The left panel plots the average single-bid indicator, while the right panel displays the integrity score, both against the number of bids received.

