UNCOVERING CORRUPTION RISKS IN PUBLIC PROCUREMENT USING BIG DATA: THE CASE OF UKRAINE

By

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Abstract

Corruption, favoritism and lack of public accountability have long been a central topic in academic research and policy debates. This study focuses on the phenomenon of corruption in a bureaucratic context, in one of the most corruption-prone sectors – public procurement. In their attempts to fight institutionalized grand corruption, governments all over the world improve the regulatory frameworks to ensure transparent and efficient public procurement market. One of the recent developments in the field was a successful launch of the ProZorro public procurement platform in Ukraine that achieved recognition all over the world as one of the best procurement reforms. Despite the enormous effort invested in the development of the transparent and efficient public procurement platform, it is too early to conclude that ProZorro successfully eliminated corruption. Hence, this study sets out to precisely estimate the prevalence and distribution of corruption risks in ProZorro. Overall, we find that ProZorro faces issues related to the lack of competition such as a low number of suppliers and a high share of single bidding contracts in some of the procurement markets. To tackle these issues, we develop a risk assessment tool for policymakers that could signal higher corruption risks in tendering processes.

Keywords: public procurement, corruption, governance, ProZorro, Big Data, networks

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Introduction

Corruption, favoritism and lack of public accountability have long been a central topic in academic research and policy debates. In some countries, these issues shift from unbounded academic and policy discussions to a nationwide problem affecting the lives of all citizens and communities. According to a survey conducted in 2019 in Ukraine, the anti-corruption reform, in the opinion of 55% of the population, is a top priority even as compared to the reforms of healthcare and social security (Democratic Initiatives Foundation, 2019). In Transparency International's 2019 "Corruption Perceptions Index", Ukraine ranks 126 out of 198 down from 120 in 2018 (Transparency International, 2020).

The definition of corruption, however, has an enormous number of variations and is context-dependent (Johnston, 1996). Transparency International defines corruption as "the abuse of entrusted power for private gain" (Transparency International, n.d.). Alternatively, the literature suggests the definition of corruption as a lack of "impartiality of institutions that exercise government authority" (Rothstein & Teorell, 2008). Irrespective of a selected definition, corruption in its various manifestations has proved to slow economic growth, and negatively affect the business environment, employment and investments (Šumah, 2018). Corruption slows down innovation (Dincer, 2019; Riaz & Cantner, 2020), increases inequality, stimulates the growth of a shadow economy and leads to a deterioration in public investment (Enste & Heldman, 2017).

When considering the phenomenon of corruption in a bureaucratic context, one of the most corruption-prone sectors is public procurement. Public procurement accounts for 12% of GDP and around 30% of general government expenditures in OECD countries (OECD, 2019b). Ukraine, in particular, has a public procurement sector amounting to roughly 13% of GDP (Ministry of

Economic Development and Trade of Ukraine, n.d.). The control over such a significant resource creates opportunities for corruption. Out of all possible forms of corruption, the focus of this research is institutionalized grand corruption in public procurement. As defined by scholars on good governance and corruption, institutionalized grand corruption in public procurement refers to “the allocation and performance of public contracts by bending universalistic rules of open and fair access to government contracts in order to benefit a closed network while denying access to all others” (Mihaly Fazekas et al., 2017).

In their attempts to fight institutionalized grand corruption, governments all over the world improve the regulatory frameworks to ensure transparent and efficient public procurement market. One of the recent developments in the field was a successful launch of the ProZorro public procurement platform in Ukraine.

In 2015 the Ministry of Economic Development and Trade of Ukraine had estimated the annual losses caused by grand corruption and intentionally restricted competition to have been at an average of 20% of a public procurement budget amounting to roughly 50 billion UAH (~1.7 billion EUR) a year. Inherited from the Soviet era, the Ukrainian public procurement system at the time had had a poor design with unnecessarily complex regulation. To add insult to injury, the sheer amount of paperwork in the system had limited transparency and increased proneness to exploitation by corrupt officials.

The first steps towards the development and implementation of the new public procurement system took place at the beginning of 2014, in the midst of the Revolution of Dignity. A group of civil society activists started advocating for a set of anti-corruption reforms, including the improvement and full digitalization of public procurement. Much excellent work has been accomplished over the following two years to develop the new system and adopt necessary laws. The new fully functional procurement platform was launched in April 2016. The system got the name “ProZorro”. In Ukrainian, “prozoro” means “transparently” that was spiced up by the nickname of a fictional character Zorro, a fighter against corrupt officials.

Ever since the implementation, ProZorro became the symbol of successful public reforms. This is because the system is based on values of transparency, effectiveness, responsibility, teamwork and innovative development. ProZorro achieved recognition all over the world as one of the best procurement reforms. ProZorro is listed as a recommended model for eProcurement reform by EBRD and a showcase of procurement reform by the Open Contracting Partnership (ProZorro, 2016). In 2016 Ukraine got the World Procurement Award and Open Government Award for the implementation of ProZorro (ProZorro, 2016).

Despite the enormous effort invested in the development of the transparent and efficient public procurement platform, it is too early to conclude that ProZorro successfully eliminated corruption. In light of this, the research aims to fill the empirical gap in the analysis of the corruption risks present in the ProZorro system. The study looks at corruption in public procurement by the case of ProZorro from a new perspective, exploring the following research questions:

- What are the corruption-related risks present in ProZorro?
- How does a level of corruption risk in ProZorro differ across markets, regions, and years?
- What are the public procurement contract parameters that are associated with a higher risk of corruption? What are the direction and the size of the effect each feature has on the corruption risk?

- How do network-based measures that illustrate the connectivity, link density and centrality of an entity in a market network associate with corruption risk in contract awards?

To answer these questions, we employ administrative dataset of all tendering processes that took place in ProZorro between the launch of the system and the end of the first quarter of 2020. We combine the analysis of procurement-specific risk indicators developed in the corruption literature (Mihaly Fazekas et al., 2017; Mihaly Fazekas & Kocsis, 2016) and network-based approach to map and analyze the presence and distribution of corruption risks in ProZorro. Furthermore, we employ the findings of the study to develop a risk assessment tool for policymakers that could signal higher corruption risks in tendering processes.

Despite a long history of studies focusing on corruption measurement and capturing and employing a variety of different approaches, we note that comprehensive objective measures of corruption risks in public procurement based on large administrative datasets and other types of big data are a recent invention and have a great potential for further employment and enhancement – on new geographies, data sources, and additional red flags. Furthermore, we note that network science-based corruption studies in public procurement are rather scarce and have been so far implemented only on European data. To further enhance data-driven approach in the field of public procurement and corruption research, we expand the developed methodology to new geography – Ukraine – and fill the gap on the employment of corruption risk indicators methodology and network-based approach in non-European realities on the case of a highly innovative public procurement system ProZorro.

To address the above research questions, the thesis is structured as follows: Chapter 1 presents the relevant literature and the most recent empirical approaches to the measurement of corruption in the general economy, public policy, and in the field of public procurement in particular. Chapter 2 focuses on ProZorro, its regulatory framework and the key definitions needed for the understanding of the public procurement context in Ukraine. Next, the first part of Chapter 3 presents the scale of the system, its development over time, and the trends stemming from regional and market differences. Further, the second part of Chapter 3 introduces network science methods to explore procurement markets from an interconnected systems point of view. Finally, the third part of Chapter 3 investigates corruption risks present in ProZorro and outlines the list of potential contract-level red flags. Chapter 4 presents data, features and methodology and develops a model that would help us understand how features of each procurement process can explain and predict the outcome level of corruption. Finally, Chapter 5 reiterates the main findings and present policy recommendations a risk assessment tool for policymakers to tackle corruption issues in ProZorro.

Chapter 1 – Related Work

Corruption, its definition, and measurement as well as ways of capturing, preventing, and fighting it have been always of interest to all social sciences with a variety of studies using different definitions, methods, and data. This chapter presents the review of the literature on the capturing and measuring corruption in economic systems to orient the thesis. In line with the empirical character of this study, we will further discuss the most recent relevant empirical approaches to the measurement of corruption in the general economy, public policy, and in the field of public procurement in particular.

Overall, experts group the approaches to the measurement of corruption into the following categories: i) perception- and experience-based surveys for macro-studies, ii) experiments at the micro-level, and a relatively new method that involves iii) big data and network science approaches using large administrative datasets (UNODC et al., 2018; Wachs et al., 2020). Further, we present widely used corruption measures as well as the most recent developments in the field of corruption assessment from each of the abovementioned groups of studies in a separate subsection.

1.1 Perception- and Experience-based Surveys for Macro-studies

Perception- and experience-based surveys rely on subjective opinions and experience of corruption by individuals, businesses, public servants, field experts, and other groups of population (Santamaría & Mihaljević, 2018). Most prominent perception- and experience-based surveys for further aggregation and comparison on country level were developed by international organizations – Transparency International (Corruption Perceptions Index), World Bank (Control of Corruption Indicator), and Global Integrity (Global Integrity Index) (United Nations Office on

Drugs and Crime, 2009). These indicators present universal global ranking of countries according to corruption level and usually attract considerable attention from policymakers, journalists and general public.

TI's Corruption Perceptions Index (CPI) was launched in 1995 and since then provides annual updates on ranking of countries according to aggregated perceptions of corruption by country experts (coming from surveys conducted by multiple organizations such as African Development Bank, Asian Development Bank, Bertelsmann Foundation, Economist Intelligence Unit, Freedom House, Global Insight and the World Bank) and business executives (surveyed by IMD, Political and Economic Risk Consultancy, and the World Economic Forum) (Transparency International, 2010). Interestingly, the Ukrainian branch of Transparency International has the local regional version of CPI that ranks 100 largest cities (Transparency International Ukraine, 2017) according to the quality of preventive measures against corruption and amount and quality of information on local governance that is available to citizens. According to this index published in 2019, larger cities in Ukraine (especially capital and regional centers) tend to be more transparent and less corrupt as compared to smaller towns, possibly due to higher control of use of public funds from the central government proportional to the amount of funds received (Transparency International Ukraine, 2019).

The World Bank's Worldwide Governance Indicators (WGI) present different measures of broad dimensions of governance, however, the most relevant to the study of corruption is Control of Corruption composite index, which is, similarly to CPI, based on perception surveys of general population respondents, non-governmental organizations, commercial business information providers, and public sector organizations worldwide (Kaufmann et al., 2011). In addition, Global Integrity, international non-governmental organization tracking governance and corruption trends, developed the Global Integrity Index which not only took into account perceptions of corruption overall, but also was based on existing legal measures and mechanisms against it (Global Integrity, 2008). However, in 2011 Global Integrity announced that the index will no longer be available due to a shift in the organization's strategy towards "more effective policy making or advocacy tool" arguing that corruption indices are rather public relation tools (Global Integrity, 2011). As a replacement for the dismissed Global Integrity Index, a group of researchers from Hertie School of Governance, developed an alternative New Index of Public Integrity which identically does not directly measure corruption, but rather indirectly evaluates opportunities for corruption based on institutional setting, anti-corruption tools and good governance strategies (Mungiu-Pippidi & Dadašov, 2016).

Despite a great popularity, influence, and wide use of perception-based macro indices of corruption and quality of governance, they have been subjected to much criticism and have been strongly challenged for difficulties and limitations in methodology used for weighting and aggregating scores, reliability of the data sources as well as differences in the definition of corruption they use, biased perception of corruption etc. (Heywood & Rose, 2013; Thompson & Shah, 2005). There have been two projects trying to resolve issues in the composition of perception-based macro indices on a global scale – Varieties of Democracy (Coppedge et al., 2018) and European Quality of Government Index (Charron et al., 2014). Varieties of Democracy (V-Dem) dataset is an open project headquartered in Gothenburg, Sweden that provides free access to a multidimensional and disaggregated dataset that reflects five high-level principles of democracy: electoral, liberal, participatory, deliberative, and egalitarian (V-Dem, n.d.). Out of the variety of indicators measuring different dimensions of democracy, the most corruption-relevant variables are i) political corruption index, ii) executive corruption index, and iii) public sector corruption index (Coppedge et al., 2018). Unlike CPI and WGI that mostly focus on public sector corruption, V-Dem corruption indices also take into account executive, legislative, and judicial corruption and more corruption forms previously not included in other measures (McMann et al., 2016).

The European Quality of Government Index by Quality of Government Institute (QoG) within the University of Gothenburg, in turn, also presents an alternative measure of corruption, however, on a more detailed, NUTS-1 and NUTS-2 regional level. QoG considers a novel measure of institutional quality defined as "a multi-dimensional concept consisting of high impartiality and quality of public service delivery, along with low corruption" (European Commission, 2017). Importantly, in the 2013 data release QoG expanded the analysis to some of the Ukrainian regions as well with all units of observation unanimously reporting relatively lowest quality of law services and high level of corruption in the sample (Charron, 2013).

There has been a smaller project led by European Bank for Reconstruction and Development (EBRD) "Life in Transition Survey" (EBRD, 2016) that is focused primarily on countries in transition to an open market-oriented economy – mostly post-Soviet countries. The survey covered many aspects from governance to gender issues and life satisfaction in those countries overall with the whole separate section on corruption which reveals very high however decreasing levels of perception-based corruption in the transition economies (16% in Eastern-European countries, 8% - Central Asia, 7% - Southeastern Europe) as compared to their more prosperous western neighbors (France, Germany, Italy, Sweden and the United Kingdom with average of 1-2% consistently) (European Bank for Reconstruction and Development, 2016).

Another contribution of the recent research introduces convictions-based measures which allow for very detailed level of analysis, narrowing down the unit of observation from a country, to a state, city, county. The corruption literature has widely examined different conviction-based measures: i) 5-year aggregate number of state convictions of public officials for corruption and ii) 30-year aggregate measure – and compared those to abovementioned perception-based survey measures. Remarkably, such comparative studies (Goel & Nelson, 2011; Treisman, 2007) discovered that perception-based measures tend to have low correlation with conviction-based indices highlighting the point that two groups of indicators are heavily influenced and biased by different factors such as, for instance, level of media exposure to high-profile corruption cases relevant for perception of corruption by population (Pellegrini & Gerlagh, 2008), while a number of convictions partially reflect quality of legal enforcement mechanisms (Glaeser & Saks, 2006).

1.2 Experimental Approach to Corruption Measurement

A large number of existing studies in the broader literature on corruption have employed the experimental approach to capture and measure corruption. Some of the studies presented laboratory experiments (Abbink et al., 2000; Banuri & Eckel, 2011; Frank & Schulze, 2000; Schulze & Frank, 2003), while others used field experiments (Armantier & Boly, 2011b; Olken, 2007; Peisakhin & Pinto, 2010; Seim & Robinson, 2019) to cover different aspects of corruption such as level of income (Azfar & Nelson, 2007; Van Veldhuizen, 2013), gender (Frank et al., 2011; Rivas, 2013), religion (Armantier & Boly, 2011a), ethnicity (Olken, 2009), culture (Banuri & Eckel, 2012), and legal enforcement mechanisms (Banuri & Eckel, 2011; Frank & Schulze, 2000; Schulze & Frank, 2003). While researchers highlight many strengths of experimental approach including high level of control over behavior of the subjects, a possibility to manipulate with the environment, and lower costs as compared to institutional arrangements (Dusek et al., 2005), experiments are subject to representative sample bias (Harrison & List, 2004), issue of representative stimuli (Carpenter et al., 2005), framing (Abbink & Hennig-Schmidt, 2006), and calibration (Barr et al., 2004).

Implementing the experimental approach in the ProZorro system, however, would pose many challenges. Experiments are expensive and difficult to implement. They are also hard to scale. Results of experiments are specific to the experimental setup and are difficult to compare with effects in a different environment. Most importantly, the literature does not present any examples of a central government body organizing randomized checks of its own and its participants' actions at a large scale (Wachs, 2019).

1.3 Big Data and Network Science Approaches

In the current era of rapid development of big data analytics, a growing body of literature on corruption switched the focus to the employment of large administrative datasets and different types of unstructured big data making attempts to address previously discussed weaknesses of other approaches and advance techniques of capturing and measuring corruption. Academia, governments, international organizations and NGOs all over the world invest efforts into exploring and building new data sources to develop data-driven approach for enhancing corruption risk assessment and early-warning anti-corruption system (A mu-la & Zhuang, 2016; Kim, 2014; Kornberger et al., 2017; OECD, 2019a). One of the recent innovative studies in this field was carried out by IMF (Hlatshwayo et al., 2018) in which researchers developed "cross-country news flow indices of corruption" based on nearly 700 million news articles. Interestingly, these new measures have significant correlation with CPI and WGI, however, have richer time-series variation. There have been also investigations into asset declarations in Romania (Klašnja, 2015), lobbying data (Borisov et al., 2016) and intellectual property data (Chiang, 2004) in the USA.

However, one of the fastest-developing subfields in the big data quantitative studies on corruption is research in public procurement. There have been various attempts to construct objective risk indicators and develop quantitative methods to capture corrupt practices. In their seminal paper, Fazekas and Kocsis (2016) construct two indicators of high-level corruption in public procurement based on EU-wide and Norwegian government contracts (nearly 3 million): i) single bidding and ii) composite corruption risk indicator (CRI) based on numerous procurement procedure parameters (call for tender publication, procedure type, length of advertisement, length of decision period, and weight of non-price evaluation criteria). In their later study, these researchers developed further the list of red flags by combining procurement contract parameters, bidding company's registry characteristics, financial information on a bidder's performance, its management and ownership structure (Mihaly Fazekas et al., 2017). This approach introduced an innovative inclusion of both procurement data and other company characteristics that initially were not meant to measure corruption, however, in combination provide a comprehensive view on a single entity and variety of possible channels through which it reveals its corrupt practices. CRI in its varied compositions were later employed by other studies to measure corruption in public funds, including OECD's project focused on infrastructure projects in Mexico (OECD, 2019a), institutional quality, campaign contributions, and favoritism in public contracting study in US (Ferrali & Wachs, 2018), and research on impact of bureaucratic meritocracy on public procurement in Europe (Lapuente & Fazekas, 2016).

In recent years, corruption studies have also advanced further and started implementing complex systems and network theory approaches that were made possible by developments in computing and data science. Innovative application of network analysis to politics and economics with the focus on corruption has revealed previously undiscovered patterns: for instance, the study based on Swedish local government data mapped networks of municipally-owned enterprises and principals and found substantial overlaps between the two that potentially lead to adverse effects on accountability (Bergh et al., 2019). Another study focused on Brazil analyzed almost 30-year long data on political corruption scandals shows that politicians in the network tend to co-occur in different scandals and create a large connected component with the risk of abrupt changes with every elections in the country (Ribeiro et al., 2018). The most recent development in this field presents the multi-layer network approach including all available entity-related data such as ownership structure, information on management and administrations, commissaries, notaries etc. (Luna-Pla & Nicolás-Carlock, 2020).

Some researchers have also combined network theory approach with the corruption risks in public procurement specifically. Wachs et al. (2019) described a methodological approach to inspection of public procurement markets and applied it to the procurement contracts data covering all EU member states from 2008 to 2016. This study concludes that high level of corruption in procurement is highly clustered, however, can be concentrated in both center and periphery of a network, depending on a country (Wachs et al., 2020). Similar logic was applied in other studies, for instance, in the research on cartels (Wachs & Kertész, 2019): network-based framework allows to see cases of frequently co-bidding firms and develop statistical red flags for cartel behavior. In the network-based approach, corruption in public procurement was also studied from a dynamic point of view – how it is affected by changes in political structures and government turnover (Mihaly Fazekas et al., 2018) and what is the relationship between social capital in settlements and corruption risk in public procurement, both presented as networks – social and transactional (Wachs et al., 2019).

Despite a long history of studies focusing on corruption measurement and capturing and employing a variety of different approaches, we note that comprehensive objective measures of corruption risks in public procurement based on large administrative datasets and other types of big data are a recent invention and have a great potential for further employment and enhancement – on new geographies, data sources, and additional red flags. Furthermore, we note that network science-based corruption studies in public procurement are rather scarce and have been so far implemented only on European data. To further enhance data-driven approach in the field of public procurement & corruption, we will expand the developed methodology to a new geography – Ukraine – and fill the gap on employment of corruption risk indicators methodology and network-based approach in non-European realities.

Chapter 2 - The Regulatory Framework for Public Procurement in Ukraine

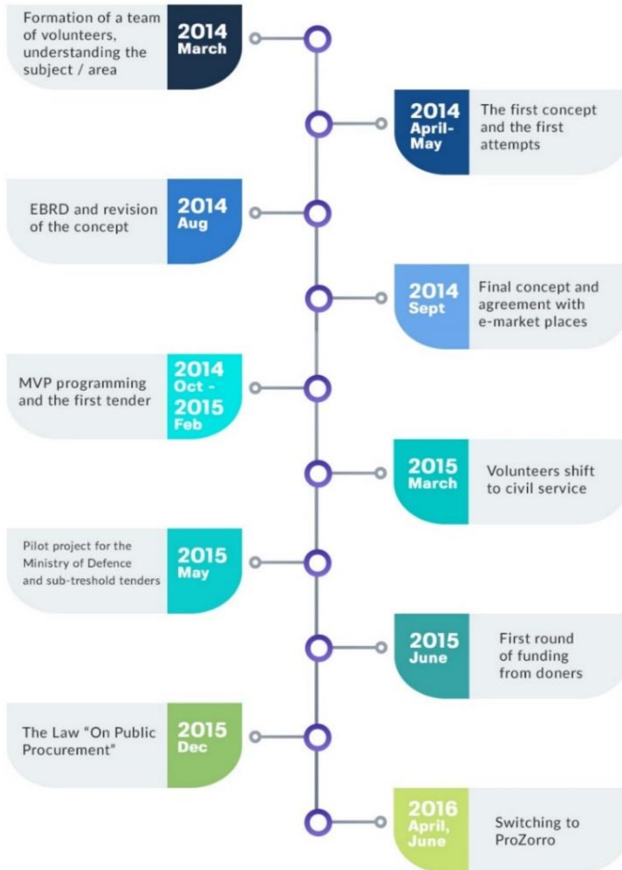
The thesis is focused on the analysis of the Ukrainian public procurement system ProZorro and the quantitative analysis of corruption patterns based on that. Currently, ProZorro is a large e-procurement platform in Ukraine where all public tenders take place and get reported. In addition to that, ProZorro provides unrestricted access to procurement data for all interested parties and citizens. However, such a transparent public procurement system is a relatively new concept in Ukraine. ProZorro was implemented only several years ago following dramatic revolutionary events and radical changes in the Ukrainian government. ProZorro presents a fundamental transformation of the public procurement market in Ukraine. In this section, we tell a story of the development of ProZorro, highlight achievements and challenges creators faced. The section further outlines the design of ProZorro, its regulatory framework and presents key definitions needed for further understanding of public procurement in Ukraine.

2.1. ProZorro: Development and Stakeholders

The first steps towards the development and implementation of the new public procurement system were made at the beginning of 2014, in the midst of the Revolution of Dignity. A group of civil society activists started advocating for a set of anti-corruption reforms, including the improvement and full digitalization of public procurement. ProZorro started as a volunteer initiative and was strongly supported by the then minister of economic development and trade. However, later that year the reform was weakened by the resignation of the minister as well as the re-election of the parliament. Luckily, the Deputy Head of the Presidential Administration proposed to develop the prototype of a new public procurement system on those tenders that were not covered by the then existing law on public procurement – below-threshold small-value tenders (ProZorro, 2016). ProZorro was designed as a hybrid system with a central database (CDB) and multiple platforms (marketplaces) that buyers and suppliers can use. The first round of financing was provided by those electronic marketplaces which later would play a role of the interface that users interact with. The prototype was launched in the spring of 2015. The Ministry of Economic Development and Trade issued the recommendation for public bodies to use the newly created online platform for public procurement. However, their response was not very active. In spring 2015, the system got its final "ProZorro" name. In Ukrainian, "prozoro" means "transparently" that was spiced up by the nickname of a fictional character Zorro, a fighter against corrupt officials.

Over the next year, the ProZorro team completed the development of the IT system and made the parliament pass the two necessary laws on public procurement. *The Law "On Public Procurement"* (2015) made the use of ProZorro mandatory by public buyers. The transition was divided into two stages. Since 1 April 2016 the use of the system became obligatory for the central government and some public monopolies in the market (mostly oil and gas, public utilities related state enterprises) spreading on all public bodies and state enterprises from 1 August 2016. Starting from that date, ProZorro became one and only platform for public procurement. Over 2016-2019 the Law "On Public Procurement" has been subject to change and modifications. The last set of changes to the Law took place in September 2019. The major change had been to harmonize the Ukrainian public procurement law with EU directives, improve control of suppliers and implement a new type of the procedure e-catalogue (*The Law "On Public Procurement,"* 2019).

Figure 2. 1 Roadmap of ProZorro development



Source: adapted from (ProZorro, 2016).

The system is based on values of transparency, effectiveness, responsibility, teamwork and innovative development. As the ProZorro team says, the system is aimed at uniting government, business and civil society to ensure a high level of trust and the most effective results of public funds management (ProZorro, 2016). However, the whole ProZorro ecosystem involves a larger number of stakeholders. Graph 8 shows a schematic representation of parties involved in the development and functioning of the public procurement ecosystem.

Placed in the center, the state enterprise “ProZorro” unites government, non-governmental organizations, international financial institutions, public buyers, suppliers, marketplaces, academic institutions. Out of all stakeholders, however, the system is focused on public buyers and the way they redistribute available public funds. With the help of ProZorro, public buyers announce and manage tenders. Buyers are able to do it individually or through the Central Procurement Body. The IT system, regulatory and legal frameworks were developed and are maintained by the government (the Ministry of Economic Development and Trade in particular) in cooperation with NGOs led by TI Ukraine and supported by international financial institutions such as EBRD. The business sector accesses the procurement market through e-marketplaces and is able to compete for public tenders transparently. Finally, the academic institutions are also actively involved in the process by providing expertise in the field and developing courses on how to use ProZorro for all interested parties, primarily for public buyers.

Figure 2. 2 ProZorro ecosystem and its stakeholders

Source: adapted from (ProZorro, 2016).

2.2. Public Procurement Procedure Types

The first version of the Law "On Public Procurement" introduced the regulation on all procurements above 50 000 UAH (~1 500 EUR). According to the law, low-value procurement below 50 thousand UAH could take place offline. In this case, a buyer's obligation is only to publish the concluded contract in ProZorro. Such a procedure type is called direct procurement or contract reporting procedure and belongs to non-competitive procedures (ProZorro, 2020e). Alternatively, a buyer could utilize ProZorro for below 50 thousand UAH purchases. However, it is not mandatory.

In case below 50 thousand UAH procurement takes place in ProZorro, it is called a sub-threshold procedure that is a competitive type of procurement (ProZorro, 2020e). The same procedure type must apply to procurements in 50 - 200 thousand UAH contract value range. The direct procurement is forbidden for this range of contract values. The last version of the *Law "On Public Procurement"* (2019) slightly modified and renamed a sub-threshold procedure to a simplified procurement procedure type.

To meet the increased procurement needs for medical equipment during COVID-19 pandemic, ProZorro introduced a separate contract reporting procedure for COVID-19 (ProZorro, 2020i). It does not have a value threshold, however, has strict requirements on the object of the procurement.

For procurements above 200 000 UAH the law presented three types of procurement procedures:

- Open tender and open tender with publication in English;

- Negotiated procedure;
- Competitive dialogue.

Open tender is a universal basic procedure type that should be used by procuring entities in ProZorro by default. Open tender assumes unrestricted access of suppliers to the bidding process and a selection of a winner based on a lowest price (ProZorro, 2020h). The Law also presents a subtype of open tender which is an open tender with publication in English. It is required for a high-value procurement. Both procedure types provide unrestricted access to submission of bids by suppliers and require a minimum length of submission period (15 days for open tender and 30 days for open tender in EN) (ProZorro, 2020h). Open tender is a competitive procedure type.

Negotiated procedure type, as defined by the Law, is the exception from rules. In case of negotiated procedure, a buyer does not need to produce and publish tender documentation, there is no auction and the length of a tendering process is minimal (up to 11 days for all stages overall) (ProZorro, 2020g). The later version of the Law "On Public Procurement" introduces a separate negotiated procedure type for military purposes and the one for "urgent needs" . A buyer is allowed to follow negotiated procedure type if there is a documentary evidence of one of the following conditions:

- if goods and services could be supplied or provided exclusively by a particular entity (in case if goods or services could be classified as a piece of art, software, or any other product subject to intellectual property rights);
- occurrence of special economic or social circumstances related to the immediate elimination of the consequences of emergencies that make it impossible for a buyer to meet the deadlines for the tender;

- if the open tender procedure has been canceled twice due to the lack of a sufficient number of bidders (ProZorro, 2020g).

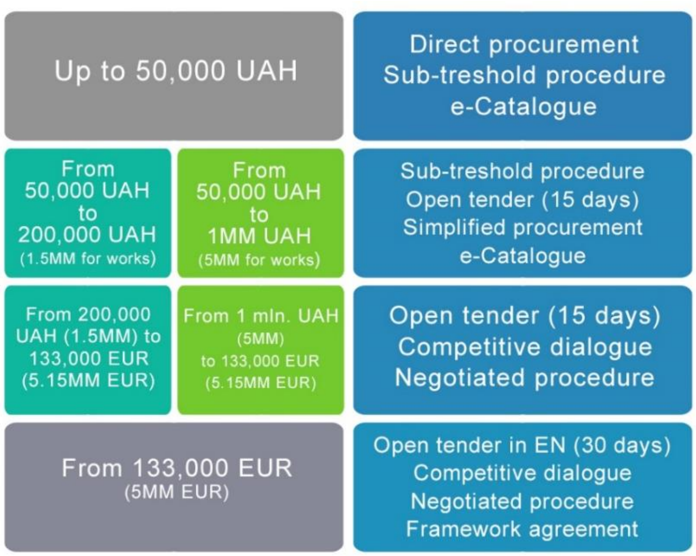
Competitive dialogue procedure type is meant for procurement for which a buyer cannot specify technical requirements or if the procured service is legal or consulting services that require additional discussion and negotiation (ProZorro, 2020b). The procedure of a competitive dialogue is split into two stages. First, bidders provide proposals on the basis of which technical requirement are specified. In case if less than three suppliers participate in a tendering process, a lot gets cancelled. If there are three or more potential suppliers, an auction takes place and a contract gets awarded to a bidder who offered the lowest price for the services defined in a first stage. The second stage of the process is regulated and can take place in a form of an open tender (in UA or EN depending on an expected contract value) only.

Recent developments in the regulatory framework of ProZorro have introduced two other procedure types: framework agreement and e-catalogue. Framework agreement is a commonly used procedure type in procurement systems of other countries. Framework agreements are arrangements between one or more buyers and several suppliers to determine the conditions of procurement of certain goods and services on a repetitive basis during the term of such agreement (ProZorro, 2020c). Framework agreements in ProZorro are divided into two stages. First, one or several buyers organize an open tender with publication in English in which they select suppliers that will supply goods and services (a minimum of three, otherwise the procedure is cancelled). At the second stage, buyers can organize multiple auctions with previously selected suppliers in a short term (4 days only). Framework agreements are a useful tool in public procurement as they avoid buyers' time investments needed to renegotiate standard terms of repetitive procurement contracts.

E-catalogues present an innovative public procurement solution. E-catalogues are an "Amazon" for public buyers, a marketplace where procuring body can easily buy standardized goods from already verified suppliers (ProZorro, 2020d). It is designed to simplify and improve control over low-value procurement. The launch of this procedure type is scheduled for June 2020.

It is necessary to highlight that the *Law "On Public Procurement"* (2019) specifies different contract value thresholds for two groups of public buyers. The Law separates public buyers involved in the provision of public utilities and infrastructure services. This group of buyers has higher value thresholds for starting from which it is necessary to follow open tender regulations. The summary of procedure types is presented in the graph below. In case if thresholds differ depending on a buyer type, value thresholds for the majority of public buyers are presented on the left. Value thresholds on the right apply to public buyers involved in the provision of public utilities.

Figure 2. 3 Summary on procedure types in ProZorro



Source: adapted from (ProZorro, 2016).
Note: specified contract value thresholds apply to goods and services. Contract value thresholds in parentheses apply to works. Value thresholds for the majority of public buyers are presented on the left. Value thresholds on the right apply to public buyers involved in the provision of public utilities.

2.3. Public Procurement Cycle

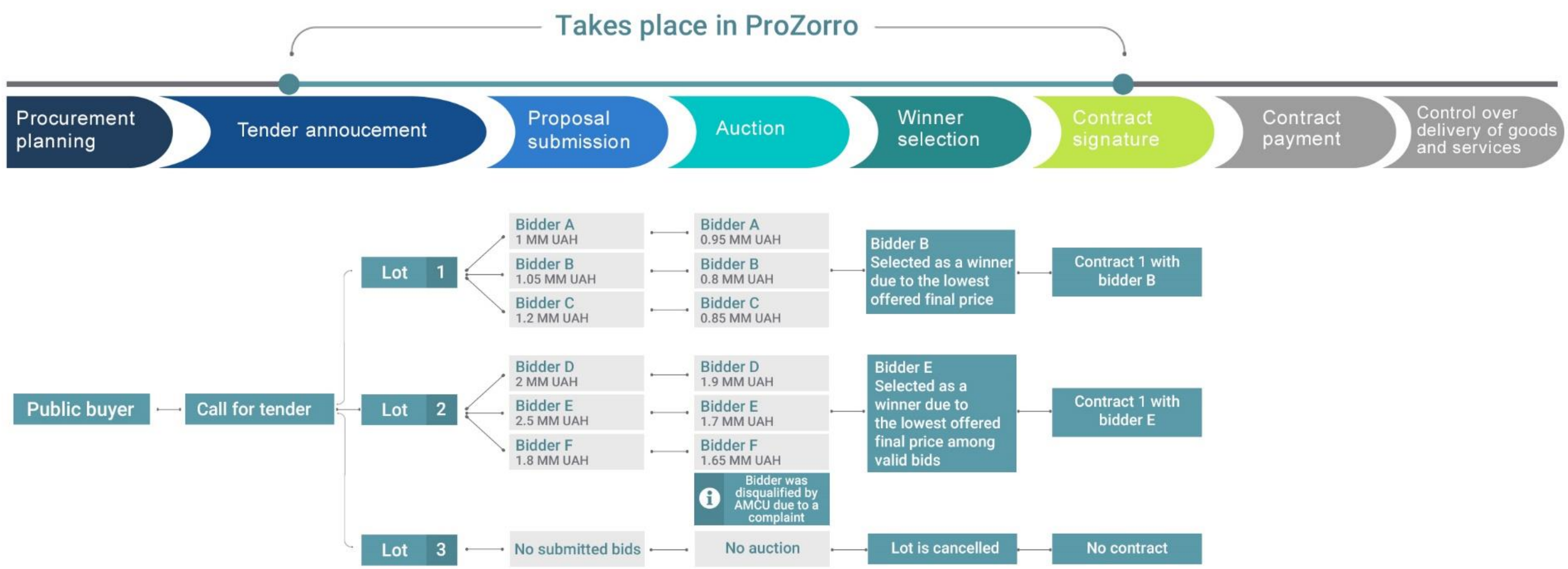
The length and stages of a tendering process depend on a selected procedure type and are strictly regulated by t*he Law "On Public Procurement"* (2019) as well as the ProZorro system itself. However, there is a sequence of procurement phases that is generally shared by all procedures and is important to understand for further analysis. The schematic representation of a procurement cycle is presented below.

The cycle starts with a procurement planning which takes place outside of the ProZorro platform. A buyer comes to the platform when it announces a tender. One tender can include one lot (a procurement object) as well as multiple lots. The unit of observation and monitoring in ProZorro is a lot, not a whole tender. All further steps of tendering process take place for each lot independently. After a call for tender was published, a buyer starts a period of bid submissions from suppliers. In this phase, bidders do not see price offered by competitors, they cannot see the legal name of a competing entity and a number of bidders overall. Then the auction starts. The date and the time of an auction is set automatically by the system. During the auction, suppliers already see bids of their competitors and have three rounds to modify their price offer (ProZorro, 2020a). The lowest price offer wins. Once a winner is selected, all information on a bidding process gets published. In some circumstances, a buyer can apply a non-price criterion for selecting a winner. Such non-price criteria include, for example, terms of payment, delivery deadline, warranty service, etc. (ProZorro, 2020f). The weight of a non-price criterion in the overall estimate cannot be higher than 30%.

When a winner is selected, tendering process comes to a concluding stage – signing of a contract. If there are no issues at this stage, a buyer signs contracts for each lot separately even in case several lots were awarded to the same supplier. However, once winner is selected, other bidders have an opportunity to appeal against the decision by the Anti-Monopoly Committee of Ukraine. The payment for the goods and services as well as control of their delivery take place outside of ProZorro.

All the published call for tenders as well as concluded contracts are publicly accessible on the ProZorro website. In addition to that, the ProZorro team also developed monitoring tools that allow users easily see aggregated data. “bi.prozorro.org” analytical module gives access to all concluded procurements and has online functionality to aggregate data by procedure type, time period, buyer, region, city, etc. (ProZorro, 2015). Furthermore, users of ProZorro data can see data on all payments going though State Treasury Service of Ukraine on the “E-Data” website (E-Data, n.d.). The group of investigative journalists and civil activists also developed “007” platform which helps to search and visualize data from open sources such as ProZorro on the use of public funds by the public bodies (007, n.d.). There is a separate platform on decisions of the Anti-Monopoly Committee on public procurement called “Clarity App” (Clarity, n.d.). Finally, ProZorro has a related project “DoZorro” that is a platform where anyone leaves reviews on tenders, buyers, suppliers (DoZorro, n.d.). In addition to reviews, DoZorro presents investigations on corruption in public procurement. Such a variety of monitoring and analytical tools presents a unique opportunity to track how public funds get redistributed and what are the potential and identified corruption risks related to them.

Figure 2. 4 Key stages of procurement cycle



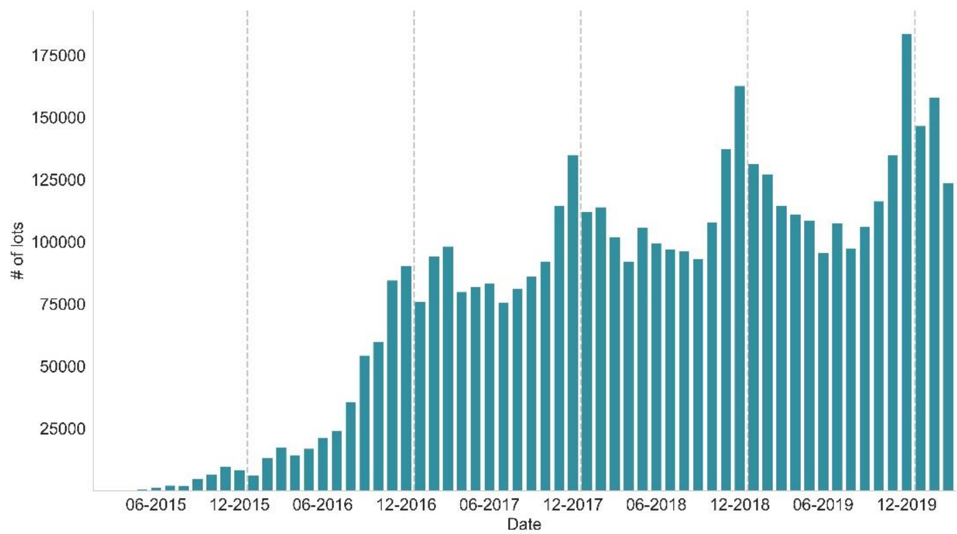
Chapter 3 - ProZorro: Overview of the System

This study attempts to analyze public procurement system, ProZorro, to assess as well as predict corruption risks in public spending going through this system. This chapter discusses the main features and trends related to ProZorro, starting from the first month of implementation in February 2015 to the end of the first quarter of 2020. We will present the scale of the system, its development over time, and the trends stemming from regional and market differences. Further, we observe the behavior of procurement participants – buyers and bidders – and apply network science methods to explore procurement markets from an interconnected systems point of view. Finally, the chapter will investigate corruption risks present in ProZorro and outline the list of potential contract-level red-flags that could be aggregated and analyzed on market and regional levels.

3.1. Trends and System Composition

The first steps towards the development and implementation of the new public procurement system were made in the beginning of 2014. However, the idea was turned into reality in the spring of 2015, when the first prototype of ProZorro was launched and the Ministry of Economic Development and Trade issued its recommendation for public bodies to use the newly created online platform for public procurement. Despite the recommendation, public buyers responded poorly, and their level of participation was low. Figure 3.1 below shows that in the year of 2015, there was a small number of tenders placed in the system. However later, in 2016 the Ministry made the use of ProZorro mandatory by public buyers. Thus, the transition was divided into two stages: starting on the 1st of April, 2016, the use of the system became obligatory for the central government and some public monopolies in the market (mostly oil and gas as well as public utilities related state enterprises). The system became mandatory for all public bodies and state enterprises from 1 August 2016, making ProZorro the only platform for public procurement. Since that date, ProZorro has been steadily growing in terms of number of contracts going through the system.

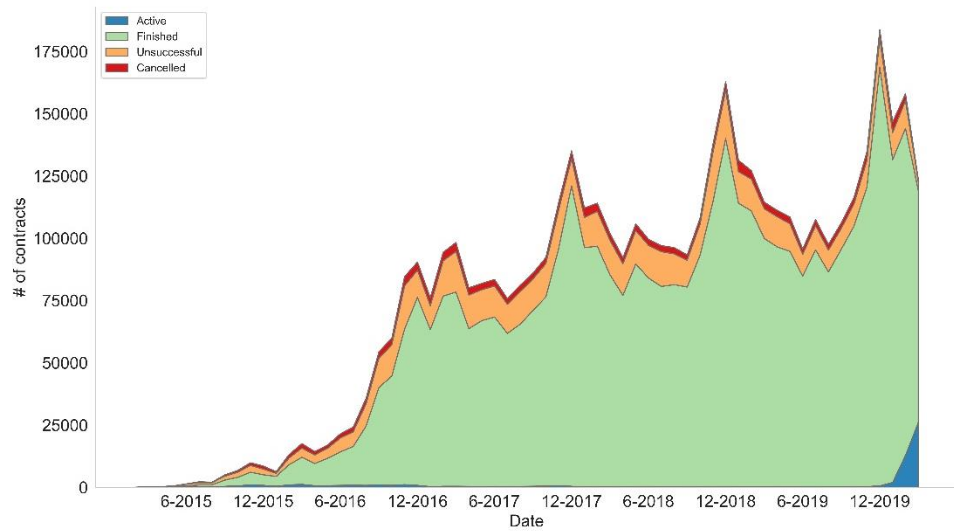
Figure 3. 1 Distribution of lots over time, all procedures (2015 – 1Q2020)



Out of the growing number of contracts, a high number of them were completed and awarded in the end. Up to 20% of contracts in the system were cancelled or turned out unsuccessful, as presented in Figure 3.2. According to Article 32 of *The Law "On Public Procurement"* (2015), such statuses are recorded in the system in case a buyer and a selected participant did not succeed in signing the contract. Failing to sign the contract can be due to violation of deadlines by a supplier, or the supplier's refusal to provide documents necessary to prove a clean criminal record and the absence of a tax debt of an entity bidding for a lot as well as other documents that might be required in a specific transaction due a large contract value or specific activities that require licenses and authorization. Additionally, a lot award could be cancelled by the Antimonopoly Committee of Ukraine in case one of the bidders submitted an official complaint that was accepted.

The figure below shows that over the observed period of the analysis, the share of unsuccessful and cancelled tenders remains rather stable with a slight decrease in the last year.

Figure 3. 2 Distribution of contracts by procedure status, all procedures (2015 - 1Q2020)



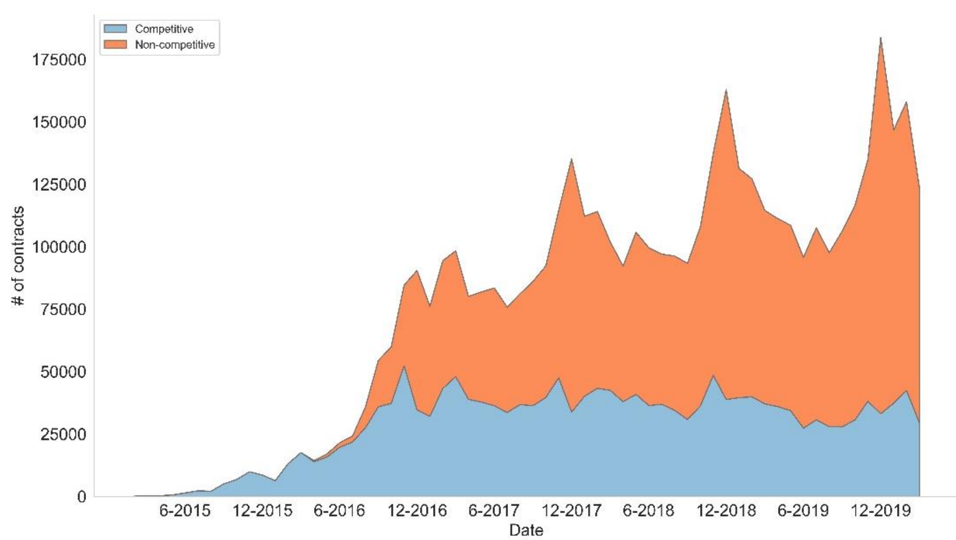
The same figure also shows a steady growing number of lots being awarded in the system and a strong pattern of seasonality. While there is an overall positive trend, in the first quarter of each year the number of contracts drops, followed by a gradual increase over the following two quarters and a significant spike in the fourth quarter. Such a pattern emerges due to the budget cycle. On December every year, the Ukrainian parliament approves the budget for the next year, subject to possible corrections and adjustments in the coming months. Following the approval of the budget, the State Treasury redistributes funds to proper recipients. However, the time lag caused by this stage of the budget process results in low volumes of procurement procedures in the beginning of the year.

Another feature of the Ukrainian budget process can also help us explain the spikes we see in the last quarter of each year. As per the Budget Code of Ukraine, all unused public funds will return to the central budget and cannot be kept at a local level for the next budget period. In an attempt to avoid loss of received funds, public bodies, state and municipal enterprises significantly increase purchases of goods and services by the end of each year.

All tenders taking place in the ProZorro system can be also examined by using the procedure type they follow. While we discuss all the procedure types in a great detail in Chapter 2, generally, procedures can be classified into two categories: competitive and non-competitive. Competitive procurement procedures by design open and advertise the tendering process to a large number of bidders in the respective market to ensure competition and obtain the best price-value combination. On the contrary, non-competitive procurement process allows a buyer to either significantly restrict the pool of potential bidders or unilaterally select a supplier.

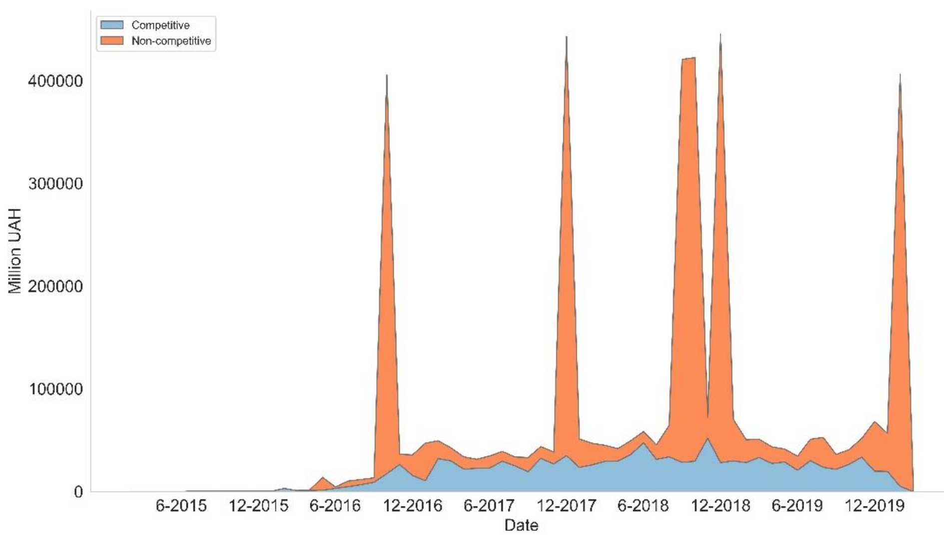
Figure 3.3 illustrates the division between competitive and non-competitive procedures in the aggregated volume of contracts being awarded in the entire ProZorro system. While we observe the overall growing number of contracts, the number of competitive procedures over the observed period remains relatively stable. The growth is driven predominantly by an increase in non-competitive share, mostly contract reporting procedure - the least regulated type of procurement.

Figure 3. 3 Distribution of contracts by procedure type, all procedures (2015 - 1Q2020)



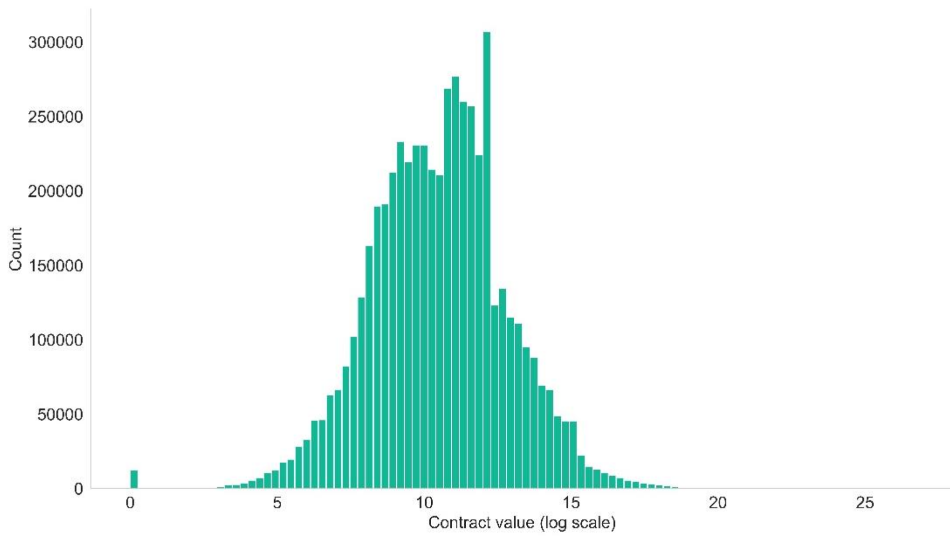
Interestingly, the spikes in the number of contracts awarded by the end of each year are linked to significant growth of solely non-competitive tenders. If we look at the dynamics of competitive vs non-competitive procedures over time from a perspective of contract value (Figure 3.4), the spikes of contract value awarded in non-competitive procedures in the last quarter of each year appear even more striking. The figure below shows a pattern of public buyers spending all the available funds by the end of each calendar year. Due to the poor timing and the overall mismanagement of the available public funds by buyers, a colossal amount of contract value gets awarded in a non-competitive manner, thus paving the way to all corruption risks associated with the intentional restriction of competition.

Figure 3. 4 Distribution of aggregated contract values by procedure type, all procedures (2015 - 1Q2020)



To gain further understanding of public funds volumes distributed through the system, we need to have a closer look at the distribution of awarded contract values. The values were rescaled to a logarithmic scale due to a wide highly skewed distribution of the variable. Most of the contracts have relatively low value while there are a few extremely highly priced lots. As presented in Figure 3.5, distribution of rescaled contract value is closer to a normal distribution, yet has a longer left tail with a group of outliers with dramatically low contract values.

Figure 3. 5 Distribution of contract values, awarded contracts (2015 - 1Q2020)



Note: contract value is presented on a natural logarithmic scale.

As discussed previously, most of the awarded contract value (up to 75%) gets redistributed through non-competitive procedures. When narrowing down to a specific procedure type level, we discover that out of all non-competitive procedures there is only one prevailing procedure type that covers 53.6% of the contract value – that is contract reporting procedure (Table 3.1). Other types of non-competitive procedures such as negotiated procurement procedure and negotiated procurement procedure on urgent needs present 17.9% of public spending. Newly developed e-catalogues and contract reporting procedures for the purpose of COVID-19 are not widely used in the system.

On the contrary, competitive procedures constitute 27.2% of public spending. In terms of a number of contracts, a sub-threshold procedure is the most frequently used competitive procedure. However, most of the sub-threshold contracts are low in value, thus represent a small part of the contract value awarded in a competitive manner. Open tender with publication in Ukrainian and in both Ukrainian and English languages are less frequently used, however, are, on average, higher in value (especially open tenders with publication in English that have a minimal value of 330k EUR) and represent most of the spending distributed in competitive procedures. Framework agreements that are considered to have restricted competition, which are classified as competitive in ProZorro, are the least used type of procedure partially due to the fact that it assumes long-term (up to 4 years) collaboration between a buyer and several bidders.

Table 3. 1 Main statistics on the contracts by specific procedure type, all procedures (2015 - 1Q2020)

Procedure type	Whether competitive	Number of contracts	Share of contracts, %	Aggregated contract value, MM EUR	Share of contract value, %
Open tender	Yes	307,040	7.7	13,735	9.7
Open tender with publication in English	Yes	25,993	0.7	19,499	13.8
Sub-threshold procedure	Yes	688,448	17.3	5,277	3.7
Framework agreement	Yes	91	0.0	21	0.0
Negotiated procurement procedure (for military purposes)	No	6,726	0.2	1,800	1.3
E-catalogue	No	794	0.0	1	0.0
Contract reporting procedure (COVID-19)	No	874	0.0	2	0.0
Negotiated procurement procedure	No	111,016	2.8	7,063	5.0
Negotiated procurement procedure on urgent needs	No	107,459	2.7	18,360	12.9
Contract reporting procedure	No	2,730,860	68.6	76,021	53.6

Note: a 30 UAH/EUR uniform exchange rate was applied.

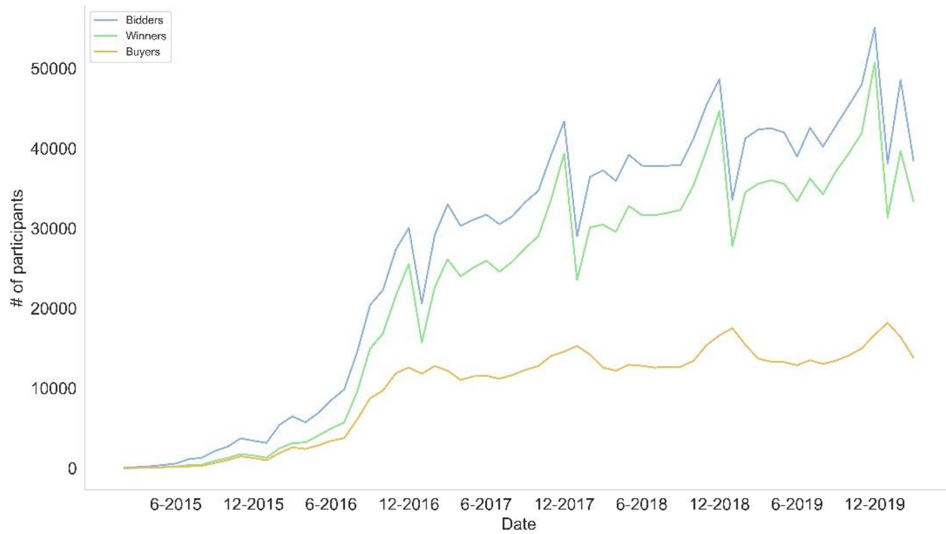
The rapid expansion of ProZorro can be seen in terms of overall number of participants in the system (Table 3.2). Starting from 2016 when the system became mandatory for use by public entities, the number of buyers reached 20k with a following growth to 27k in the next year. In the last two years we also see an increase in the number of public buyers, however these are mostly small state enterprises and local government offices in rural areas. The pool of bidders kept expanding year by year starting from 66k companies in 2016 to reach 160k by the end of 2019. Interestingly, the average number of bidders in competitive procedures over the period of full functionality of ProZorro (2016 - 2019) remains rather stable around 2.3 – 2.4 participants, bidding for an announced lot.

Table 3. 2 Main statistics on the number of overall participants in the system, all procedures (2015 - 2019)

	2015	2016	2017	2018	2019
Number of bidders	8,091	65,843	127,604	148,097	160,007
Number of buyers	2,313	20,144	27,072	28,339	28,852
Average number of bidders per competitive contract	2.76	2.43	2.29	2.29	2.40

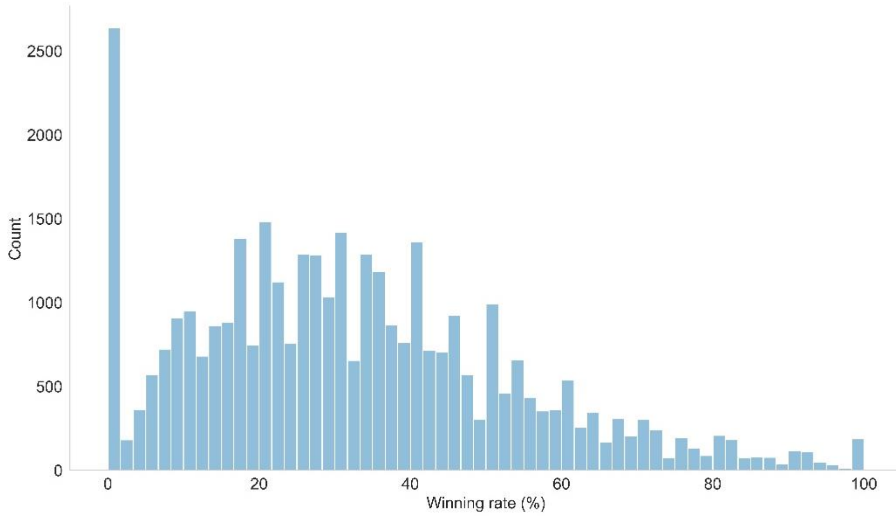
When we observe continuous dynamics on the number of participants in the system (Figure 3.6), we see that the seasonality pattern of number of bidders coincides with the last-quarter spikes we saw with the number of contracts and awarded contract value. A large share of bidders take part in the tendering process only in the fourth quarter while not being active in first quarter. Moreover, the share of winners (companies with at least 1 successful bid in a corresponding month) is relatively high and stable across the observed period. While such a high winner-to-bidders ratio could indicate high level of competition and equally distributed chances of winning for each participant, it could also be a sign of a large share of single bidding contracts when one company bids for one or a small number of contracts and wins them.

Figure 3. 6 Number of participants in the system, all procedures (2015 - 1Q2020)



A closer look at the distribution of winning rates of relatively active bidders (companies that submitted at least 10 bids for an aggregate contract value of at least 100k UAH (~33k EUR)) reveals an interesting pattern (Figure 3.7). A vast majority of bidders (approximately 2.5k) have not won any contracts. The distribution of winning rates for the rest of the firms is wide and asymmetric with a long right tale. The average winning rate is 28%, the median is 20%. On the right side we can observe approximately 200 firms (classified as outliers) winning all contracts they placed bids for. While such cases do not directly indicate corruption risks, they, however, require a closer investigation and a potential inclusion in the list of red flags of corruption in tenders.

Figure 3. 7 Distribution of winning rates, competitive procedures (2015 - 1Q2020)

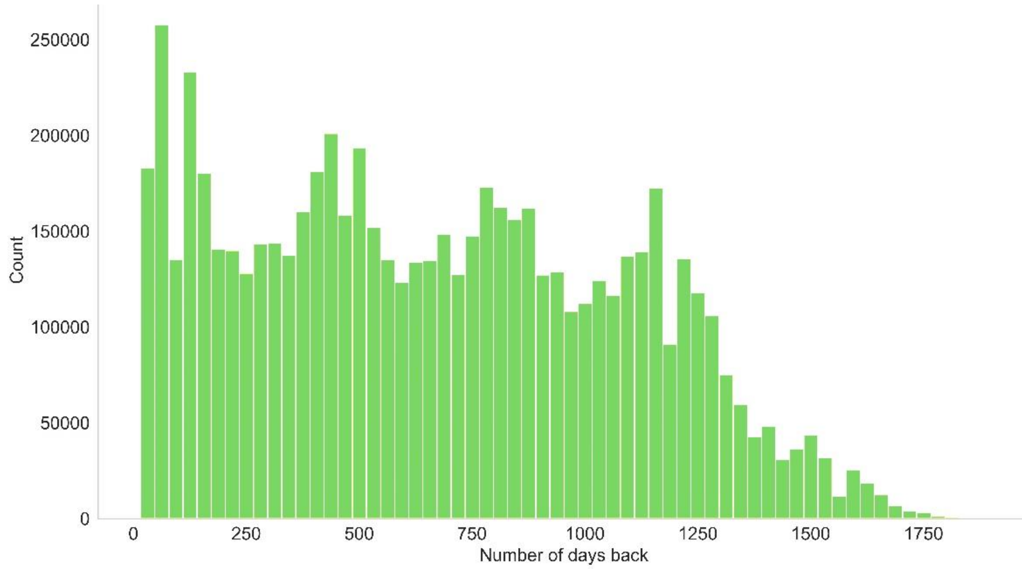


Note: only firms with ⩾10 bids and bidding for ⩾100k UAH of contract value are included.

From a point of view of healthy competitive environment, it is also necessary to incentivize and maintain frequent participation of all bidders in the system unless they provide some highly seasonal goods and services such as agriculture products, printing services for education institutions etc. Figure 3.8 illustrates that last bidding activity in the system is spread over 5 years with no clear pattern. The number of days back is calculated as the difference between the 1 April 2020 and the date of a last bid of a company.

There is a large number of firms that have placed bids recently (between 1 to 6 months since the 1st April), although we also observe that around 50% of the pool of bidders did not participate in any tender over the last 24 months and longer. For these reasons, it is hard to say that the last activity pattern poses a serious problem from a competition perspective. However, it is an important consideration for further discussion on competition enhancement and the design of the ProZorro system.

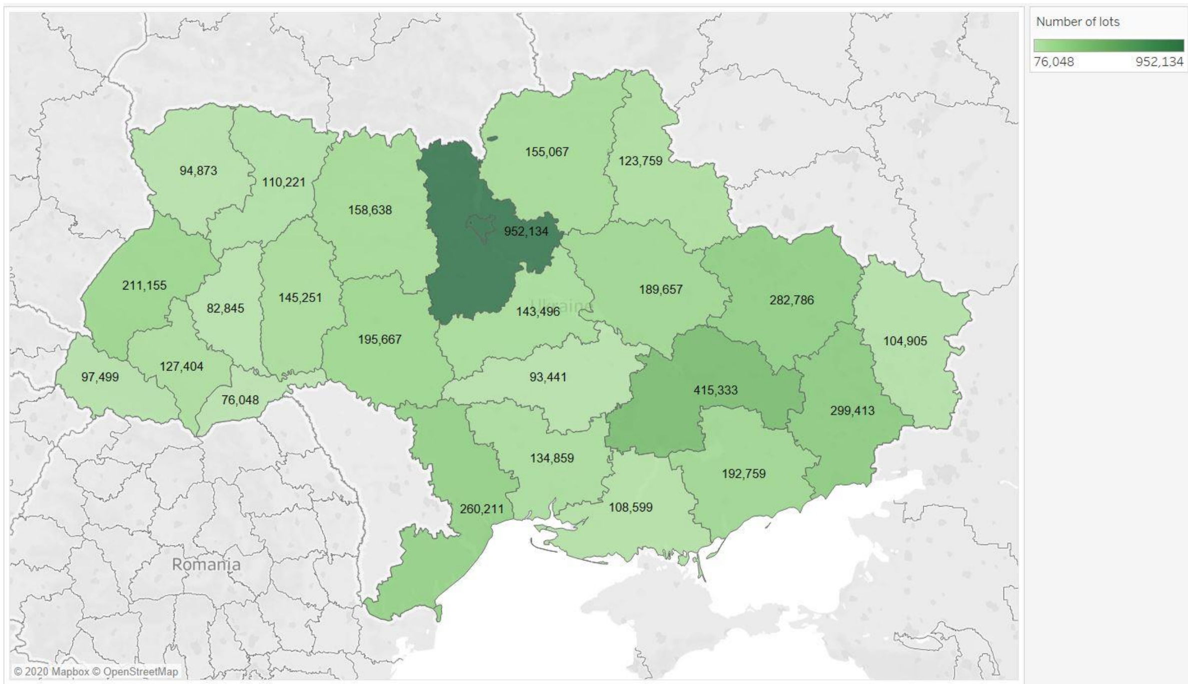
Figure 3. 8 Distribution of last activity of bidders, all procedures (2015 - 1Q2020)



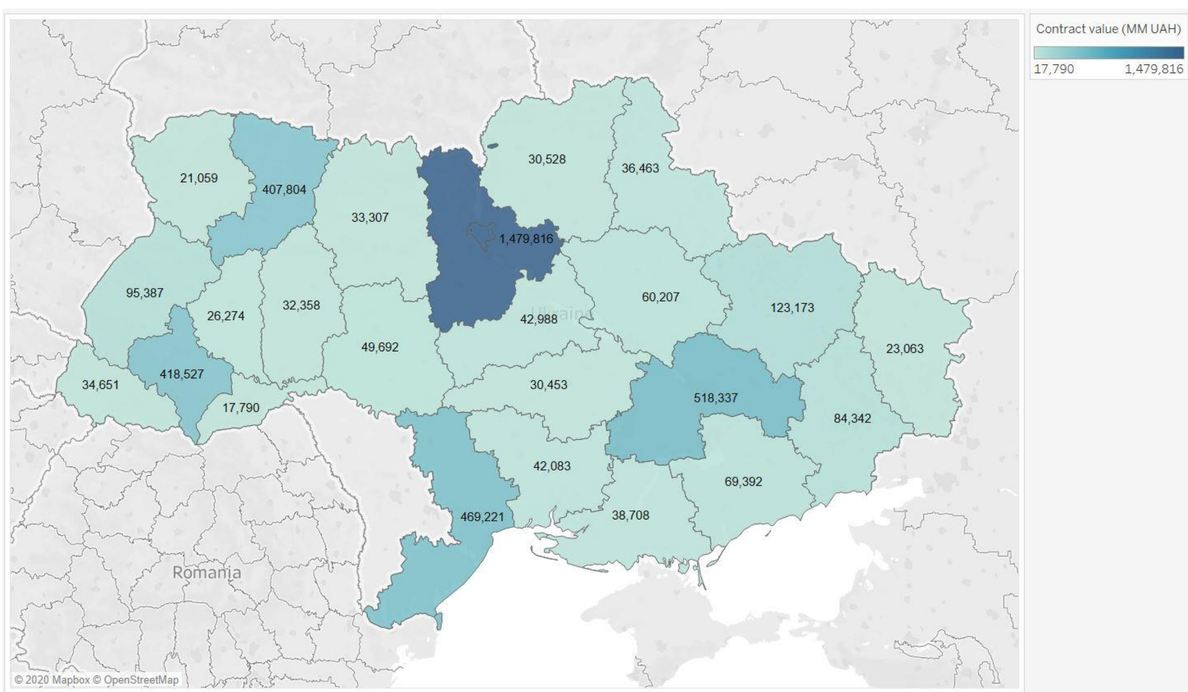
In our attempts to present the most comprehensive view on the ProZorro system, we further focus our analysis on regional and sectoral aggregation of public procurement activities. The regional maps presented below (Figures 3.9 A and 3.9 B) demonstrate that as of the first quarter of 2020, ProZorro has covered all the geographical regions. It is necessary to highlight that ProZorro is not used in the Autonomous Republic of Crimea as well as it has restricted application in undefined territories of Donetsk and Luhansk regions despite the absolute number of awarded contracts in these two regions being still comparable with some smaller regions of the country. Predictably, the capital region of Kyiv has a disproportionally higher share in terms of a number of contracts (Figure 3.9 A) as well as awarded contract value (Figure 3.9 B). Nevertheless, there are four other large regions that play an important role in distributing public funds through ProZorro: Odesa, Volyn, Dnipro, and Ivano-Frankivsk regions.

Figure 3. 9 Regional aggregation of public procurement activities

A) Regional distribution of lots, all procedures (2015 - 1Q2020)



B) Regional distribution of aggregated contract value, all procedures (2015 - 1Q2020)



The approach to the sectoral aggregation is, however, not as straightforward in the public procurement field, given various market definitions. The ProZorro system follows the widely used practice of the European Union and has the "Common Procurement Vocabulary" (CPV) as the main classification system. The classification of goods and services is organized in such a way that each code is made up of 8-digits and a wording that describes the types of works, supplies or services forming the subject of the contract. The purpose of the CPV is to make it easier for bidders to identify relevant tender notices. Bidders can find these by searching for CPV codes. The logic behind the CPV aims to increase competition and ensure a higher level of transparency. If relevant publications can be identified more easily locally and across borders, more bids will be placed, and the level of competition among bidders would increase. This contribution to a more transparent market should eventually lead to better value for money in public procurement.

The CPV is based on the Classification of Products by Activity (CPA) nomenclature. The overall logic model of the CPV structure is shown in the following figure:

Figure 3. 10 Tree structure of division "Construction work" (45000000)

The CPV system has a hierarchical tree structure with four levels. The most aggregated category is a division which is defined by first two digits and has 45 codes only. A more detailed level is a group that is represented by 3-digits and results into 272 markets. The next level is a class defined by 4 digits. A CPV category is defined by 5 digits. It is possible to develop an 8-digit CPV code which is the most detailed specification of goods and services.

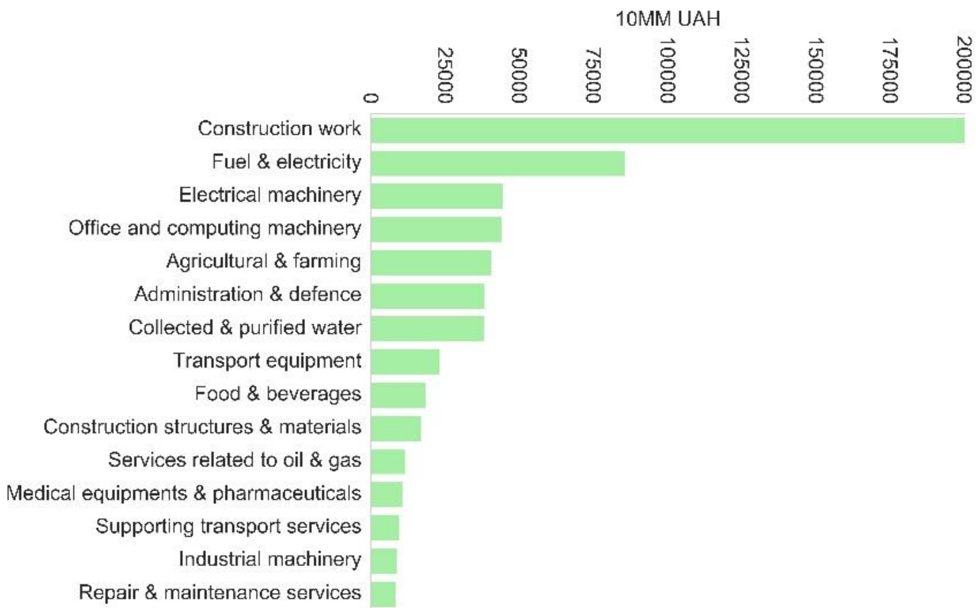
Since data and surveys on user experience of CPV use in ProZorro is not available, we further discuss European-wide experience with the CPV. The European Commission and DG Internal Market and Services surveyed both buyers and bidders across EU member-states. Out of the public buyers surveyed, 70% thought that the codes allow more bidders to become aware of their notices and 56% stated that the CPV leads to better value for money. Of the bidders surveyed, 57% stated that the CPV allows them to become aware of more tender notices, and 45% perceived that the CPV leads to more business opportunities. Both contracting authorities and bidders assessed the costs of applying the CPV as very low (European Commission, 2012).

This indicates that the current CPV system is an efficient and effective instrument. Despite that, bidders are not familiar enough with the CPV due to its difficulty to use. The hierarchical tree structure of the CPV is not always consistent. Some code classification levels are not conclusive (some codes should be on higher or lower levels), some codes do not match the subject of the superordinate level (they should be grouped under different superordinate codes) and some codes are not mutually exclusive. The different divisions, groups and classes each contain a very different number of single elements. The current CPV makes it possible to describe works/supplies/services in considerable detail. However, it turned out that the level of detail provided is neither fully used in practice nor necessary. Bidders usually search at a more general level than the level of codes provided by contracting authorities.

An alternative approach to market definition was developed with the help of network science methods which disregard already developed CPV codes currently used in public procurement. The idea is to analyze the public procurement market as a whole and investigate co-bidding networks of suppliers. For example, finding groups of bidders that tend to compete for the same lots. With the help of community detection algorithms, co-bidding networks of suppliers can reveal groups of firms having similar business profile and providing similar goods and services no matter what CPV code was specified in a tender documentation. While this method seems promising, it presents a standalone research challenge which is out of scope of this thesis. For our further discussion, we will define markets according to the traditional CPV classification and specify a market as CPV division (first 2 digits of the code) which leads us to 45 different markets.

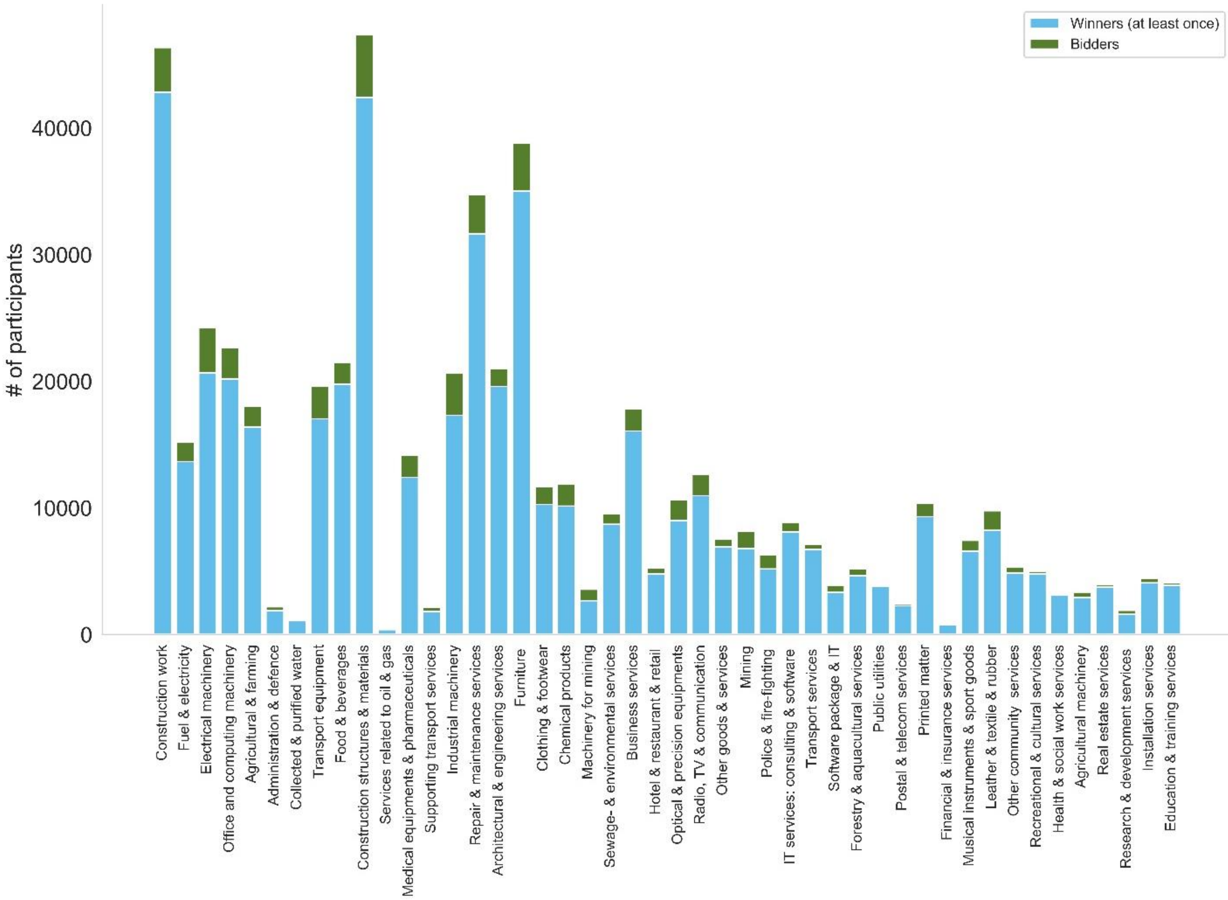
In the list of 45 markets, however, top 15 sectors (Figure 3.11) cover 82% of all public spending. Construction work is by far the largest market in ProZorro and it solely distributes 30% of the contract value in the system. Similarly, construction work stands as the largest industry in public procurement in the European Union and other countries worldwide. As presented in the graph below, there are two other markets in the top 10 that are closely related with construction work: Construction structures & materials and Repair & maintenance services. Next after construction work comes Fuel & electricity, Electrical machinery, Office machinery, and Agriculture, which are considered (especially the latter) as significant contributors to the Ukrainian GDP.

Figure 3. 11 TOP-15 procurement sectors by aggregated awarded contract value, all awarded contracts (2015 - 1Q2020)



If we look at the number of suppliers in each market, the size of the market is not necessarily positively associated with the higher number of bidders. While the largest construction work market indeed has one of the largest number of bidding suppliers (Figure 3.12), the other 4 largest markets - Fuel & electricity, Electrical machinery, Office machinery, and Agriculture – have significantly lower number of bidders, approximately half of the number of firms participating in construction market. Some of the other large markets – Agriculture & farming and Administration & defense – have surprisingly low number of bidders. For some niche markets with high entry barriers such as machinery for mining and services related to oil and gas, low number of bidders can be explained by a small pool of such companies in the market. However, such scarcity of companies seen in niche markets does not apply to industries like agriculture, hotels & restaurants, and retail, which are widely represented in the general economy in Ukraine.

Figure 3. 12 Number of winners and bidders per market, awarded contracts (2015 - 1Q2020)



Note: bars are sorted by aggregated awarded contract value per market in the ascending order.

Overall, we observe that ever since the implementation of the ProZorro system, the number of active contracting authorities, bidders, and the overall public spending being distributed through the system has been growing. The system is being actively used all over the country and provides access to goods and services in various markets. However, we discover that only top 10 largest markets cover around 80% of the public spending. We also note that markets are quite diverse in terms of the available pool of different bidders with varying levels of participation, contract values won, and likelihood of winning.

3.2. Overview of the System from a Network Science Perspective

After reviewing ProZorro from the angle of participants in the public procurement – bidders and buyers – different procedure types, markets, and geographies, we shift our focus to interconnectedness and interactions of all elements in the system. In this subsection, we employ network analysis and a set of straightforward network-based measures that illustrate the importance and centrality of an entity for a particular market as well as the public procurement field overall.

Utilization of network science methods for the analysis of public procurement systems is a new and rapidly evolving field of studies. The advantage of this approach is the ability to analyze public procurement system not as a sum of its components but as a complex network of interconnected and interacting elements. Wachs et al. (2019) described a methodological approach to inspection of public procurement markets with the help of network science. This approach was further developed in research on cartels, also based on procurement data (Wachs & Kertész, 2019). Network science methods allow observing corruption in a static state as well as from a dynamic point of view – how it is affected by changes in political structures and government turnover (Mihaly Fazekas et al., 2018).

By the nature of its design, the public procurement market is a bipartite network. The two sets of nodes in the public procurement network are buyers and bidders. It meets the criteria for a bipartite network given that buyers can only organize tendering processes and do not place bids in tenders of other buyers, while bidders that are private companies cannot organize tenders in the ProZorro system.

The bipartite network is a type of network in which there are two types of elements (vertices, nodes), and only nodes of different types can be connected and have one or multiple links. (Barabási, 2016)

For our analysis, we consider three network-based metrics: degree, clustering coefficient, and closeness centrality. While measured for each participant, it can be easily aggregated on the market and regional levels as well.

Node degree in a bipartite network is a number of links (edges) connected between the node and vertices in the other set of nodes. (Barabási, 2016)

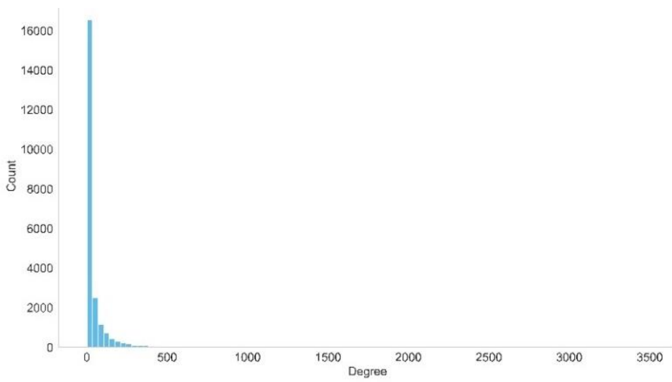
The clustering coefficient is a measure of the local link density that captures the degree to which the neighbors of a given node link to each other. (Barabási, 2016)

Closeness centrality is a key measure of the centrality of a node in a network. It reflects the sum of the length of the shortest paths between the node and all other nodes in the graph. Thus, the more central a node is, according to this measure, the closer it is to all other nodes. (Barabási, 2016)

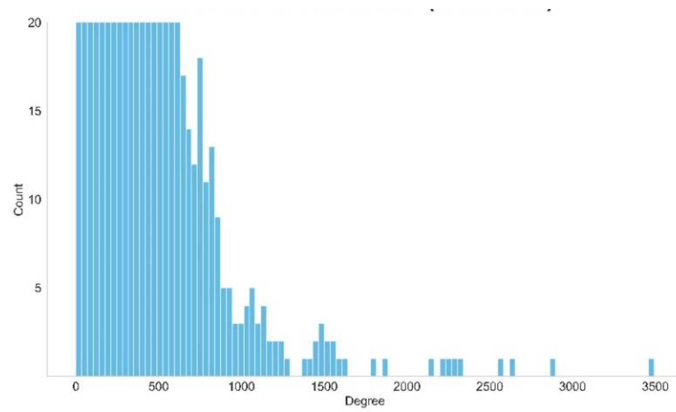
Starting with the most straightforward out of the three measures – node degree – we present the distribution of this metric for both buyers and bidders. According to the definition, the node degree of a buyer is the number of bidders that are connected to the buyer. The node degree of a bidder is the number of buyers they interacted with in tendering processes. The graph below demonstrates that degree distribution for both types of nodes is wide and highly skewed with a long right tail.

Figure 3. 13 Degree distribution of participants, all awarded contracts (2015 - 1Q2020)

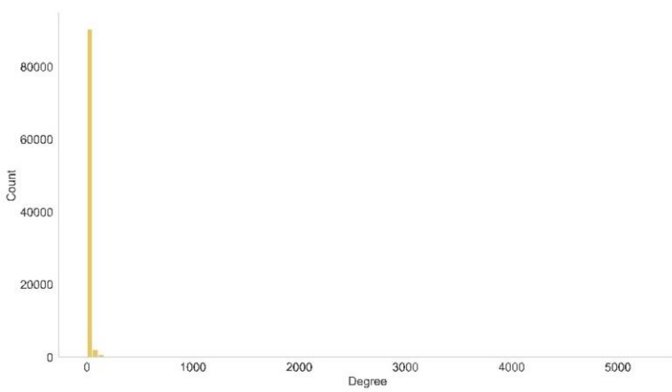
A) Buyers



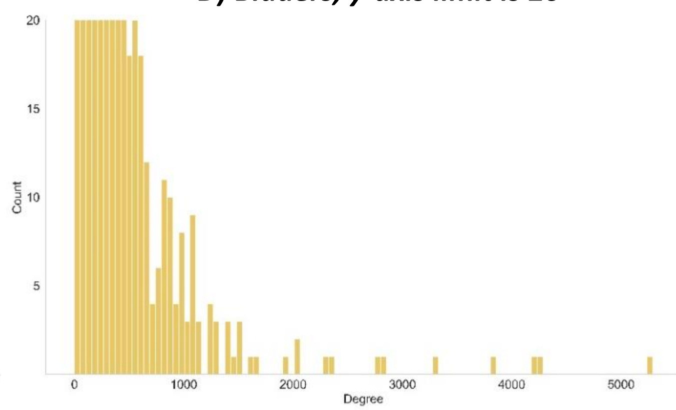
B) Buyers, y-axis limit is 20



C) Bidders



D) Bidders, y-axis limit is 20



This means that the majority of entities in ProZorro over their lifetime in the system have a relatively limited interaction, up to 10-50 links. The average node degree for a buyer is 11, for a bidder this indicator reaches 47. At the same time, there are also highly interconnected outliers with more than 1000 of connections, the observed maximum is 3492 links for a buyer and 5289 connections for a bidder.

To better illustrate the structure of the network and implications of such degree distributions, we further combine the analysis of node degrees as well as the clustering pattern. In this case, we additionally look at the clustering coefficients on the level of an individual entity and further aggregate them on the market level defined as 2-digit CPV codes. Interestingly, in the ranking of markets by clustering coefficient (the table with ranking is presented in the Appendix), public utilities market has the highest value, i.e. that it has the highest local link density. Therefore – simply put – neighbors of each node in the network have a high likelihood of having a connection as well.

The visual representation of the public utilities market is presented in the graph below. Each circle in the graph presents a separate node, an individual entity. Green nodes represent buyers, yellow – bidders. The size of the node is proportional to the degree of a node. We observe a link between a buyer and a bidder in case this bidder has ever placed a bid in the tendering process organized by this buyer.

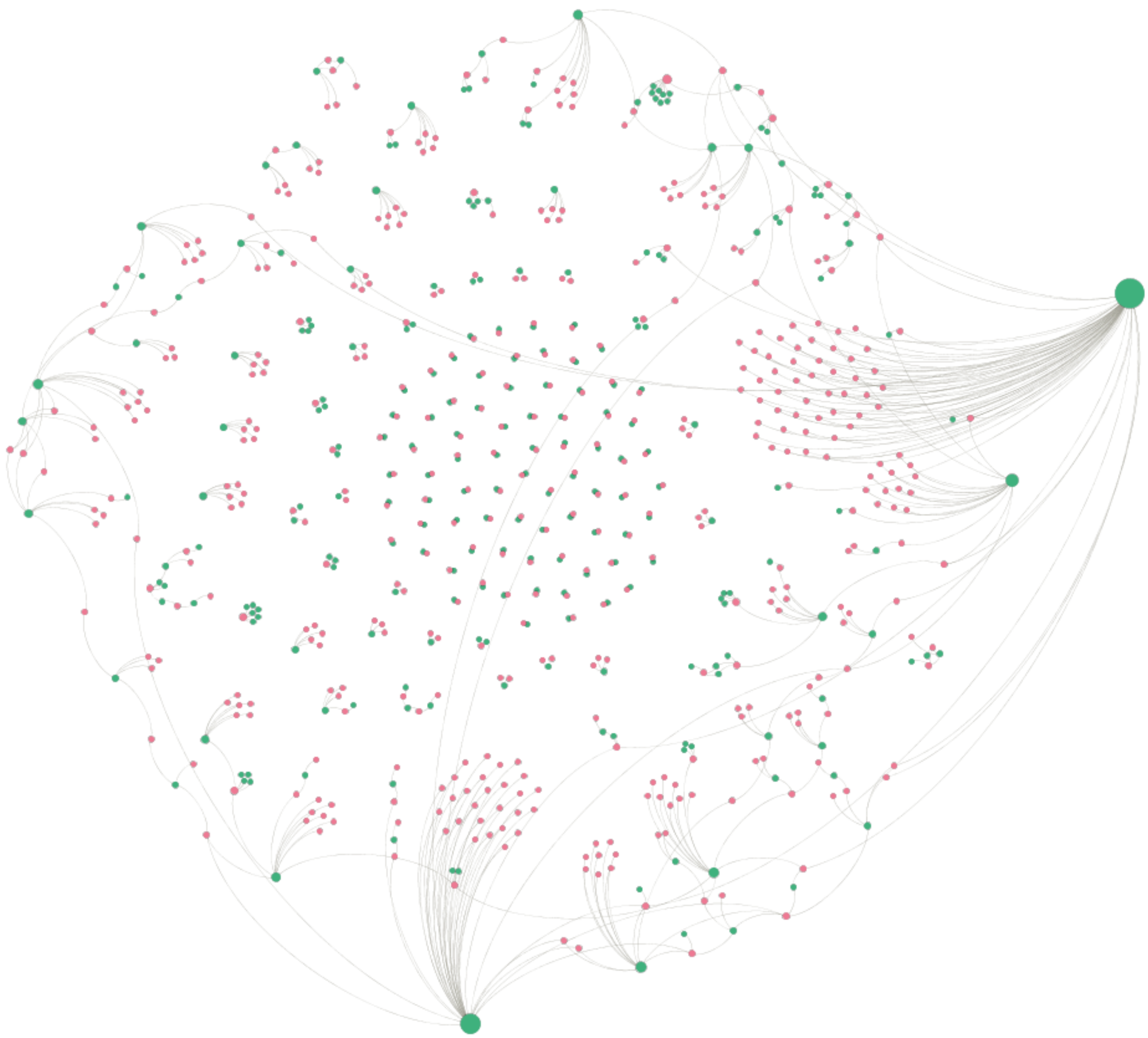
Given that the public utilities market has the highest clustering coefficient in public procurement, we observe that elements of the graph are highly interconnected. We also observe that, while most of the bidders participate in tenders of a relatively similar number of buyers (since they are similar in size, thus have close degree values), there is clearly a leader among buyers – the largest green node that attracted a significantly higher number of bidders. Nonetheless, we discover that the market has also a low number of small disconnected elements – groups of 2 to 4 participants interacting only with each other. However, this type of interaction is rather an exception in this market and the whole public utilities network is largely connected as represented visually and by the highest clustering coefficient in the public procurement overall.

Figure 3. 14 Visual representation of the public utilities market, all awarded contracts (2015 - 1Q2020)

Note: green nodes represent buyers, yellow – bidders. The size of the node is proportional to the degree of a node. The market has the highest Robins-Alexander clustering coefficient, a measure of the local correlation of connectivity in bipartite networks, analogous to the clustering coefficient in monopartite networks.

On the contrary, ProZorro has some markets that are rather sparse and disconnected. One of the clearest examples with the lowest clustering coefficient is the research & development services market. The visual demonstration of network structure in this sector is presented in the graph below.

Figure 3. 15 Visual representation of the research & development services market, all awarded contracts (2015 - 1Q2020)



Note: green nodes represent buyers, pink – bidders. The size of the node is proportional to the degree of a node. The market has one of the lowest Robins-Alexander clustering coefficients.

Green nodes in the graph represent buyers, pink – bidders. A link represents a procurement process. Unlike the previously discuss public utilities sector, the R&D services market presents mostly disconnected loose network. Most of the participants are grouped into small clusters of two to five entities. In this market, suppliers tend to bid for lots announced by one or maximum of two buyers. Buyers, in their turn, have a wider pool of bidders competing for the lots. There are also two clear market leaders – the largest green nodes grouping around a relatively high number of potential suppliers. Interestingly, in the center of the visualization, we observe disconnected bidder-buyer pairs which could pose significant corruption risks related to single bidding.

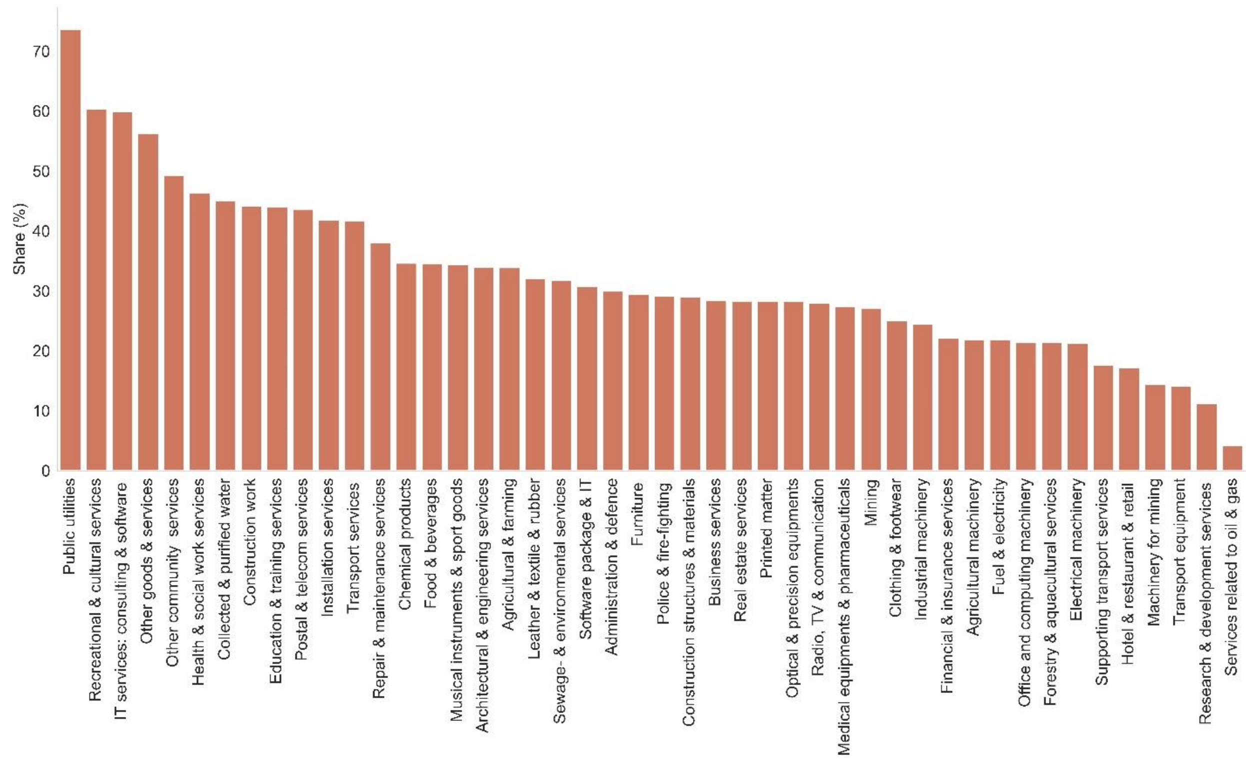
The application of network analysis approach to public procurement brings new perspectives and understanding of the procurement market as an interconnected system of interacting elements, not as separated individually acting entities. While the presented network-based measures are rather an introduction to network analysis, they reveal novel findings on interactions of participants in ProZorro. We observe that most of the participants over their lifetime in the system interact with a limited number of participants. The average degree for buyers is 11, for bidders – 47. When aggregated on the market level, the average degree and clustering coefficient combined present a wide variety of markets from a point of view of their interconnectedness. Markets with high average clustering coefficients present largely interconnected networks (such as public utilities market), while a low value of clustering coefficient for this indicator (R&D services) would result in sparse disconnected markets with a potentially higher risk of single bidding.

3.3. Distribution of Corruption Risks

As the next stage of our research, we extend our analysis to corruption risks in public procurement. To do so, we will focus on single bidding as one of the most prominent corruption risk indicators in public procurement across Europe (Mihaly Fazekas & Kocsis, 2016). The logic behind focusing on single bidding is that i) on the country level it significantly correlates with widely-used survey-based measures of corruption such as Perception of Corruption Index by Transparency International and Control of Corruption Index by the World Bank, ii) it predicts overpricing on the auction level (Wachs et al., 2020), and iii) it is available at the contract-firm-sector-country level, thus gives sufficient variation for the subsequent analysis. Furthermore, single bidding has been described as a key indicator of deliberately restricted access and partisan favoritism on otherwise competitive markets (Dávid-Barrett & Fazekas, 2019; Laffont & Tirole, 1991).

Based on this approach, we present an overview of single bidding distribution across different markets, regions, and how it developed over time. It is necessary to highlight that in further analysis of corruption risks and competition enhancement we will mainly focus on competitive procedures only. That is because non-competitive tendering processes by the design and regulatory framework are allowed (and in reality, in most of the cases) have an absence of competition, no bidding process, and a single supplier. When focusing on competitive procedures, however, we can also observe a high share of single bidding contracts. As presented in the histogram below, the majority of markets have more than 30% of the contracts awarded in a non-competitive manner, while some industries reach more than 50%. Interestingly, public utilities market that we previously discussed in a detail has the highest share of single biding (72%) despite a highly interconnected network and a large pool of potential suppliers. On the contrary, R&D services market that has a relatively small number of bidders and a loosely connected network ends up on the right-hand side of the distribution with the second-lowest share of single bidding contracts (12%). This empirical finding calls into question the common approach of concentrating policy efforts on markets with a low absolute number of bidders instead of considering the share of contracts that get no competition.

Figure 3. 16 Share of single bidding per sector, all awarded contracts, competitive procedures (2015 - 1Q2020)



As a next step, we further narrow down the focus of the analysis within markets to the level of a participant in the system. From a point of view of single bidding, the most interesting cases are buyers that actively issue tenders and have a high share of contracts awarded in a non-competitive manner. In Table 3.3, we list the largest buyers on the ProZorro platform that have more than 80% of single bidding contracts. From this table, the top ten firms are involved in construction activities, road building and public utilities, are leaders in the ranking of markets by single bidding.

Table 3. 3 TOP-10 largest buyers with a share of single bidding ⩾80%, all awarded contracts, competitive procedures (2015 - 1Q2020)

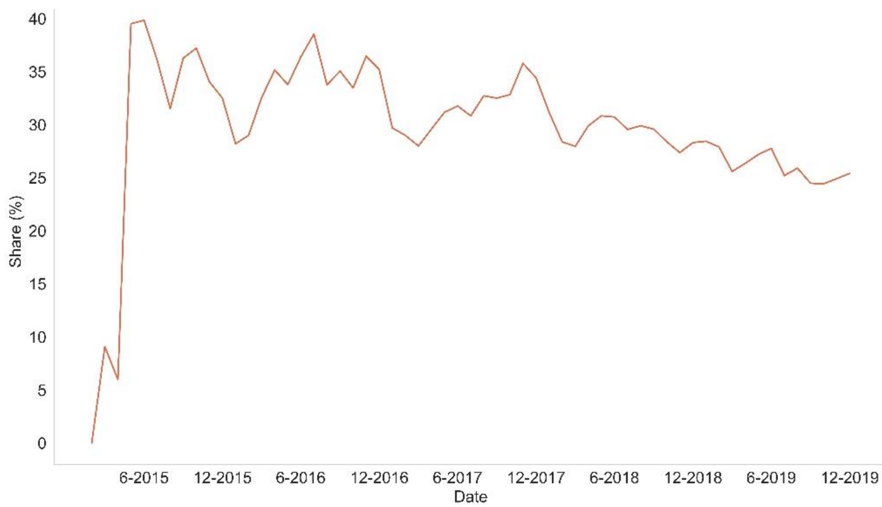
Buyer	Number of contracts	Aggregated contract value, MM EUR	Share of single bidding contracts, %
Municipal Enterprise "KyivBud Reconstruction"	2888	81.3	80.9
State Enterprise "Regional Highway in Vinnytsya"	63	30.1	84.1
Municipal Enterprise "Kyiv Residential Special Exploitation"	2321	20.8	85.3
Department of Construction and Architecture – Kyiv, Svyatoshyns'kiy district	827	19.5	88.1
Municipal Enterprise "Residential Service" in Kyiv	990	18.9	82.0
Department of Housing and Communal Services – Kyiv, Desn'ians'kiy district	1925	15.7	86.5
State Enterprise "Regional Highway in Kropyvnytskyi"	70	13.8	82.9
Department of Housing and Communal Services – Kyiv, Solom'yanskiy district	1267	11.1	84.8
Department of Housing and Communal Services – Kyiv, Dniprovs'kiy district	730	10.9	89.6
Department of Housing and Communal Services – Kyiv, Pechers'kiy district	657	8.0	84.9

Since the implementation and the full launch of ProZorro in 2016, the policy efforts were dedicated to competition enhancement and attraction of new bidders. While we saw a significant increase of an absolute number of suppliers over between 2016 and 2019, the share of single bidding contracts has been gradually decreasing, at a slower pace. Starting with 40% of single bidding at the launch date, the indicator reached 26% by the end of 2019 (Figure 3.17). As presented in Table 3.4, the share of single biding decreased by 14 percentage points over five years ProZorro, which was achieved despite significant growth in the volume of contracts.

Table 3. 4 Main statistics on single bidding, all awarded contracts, competitive procedures (2015 - 2019)

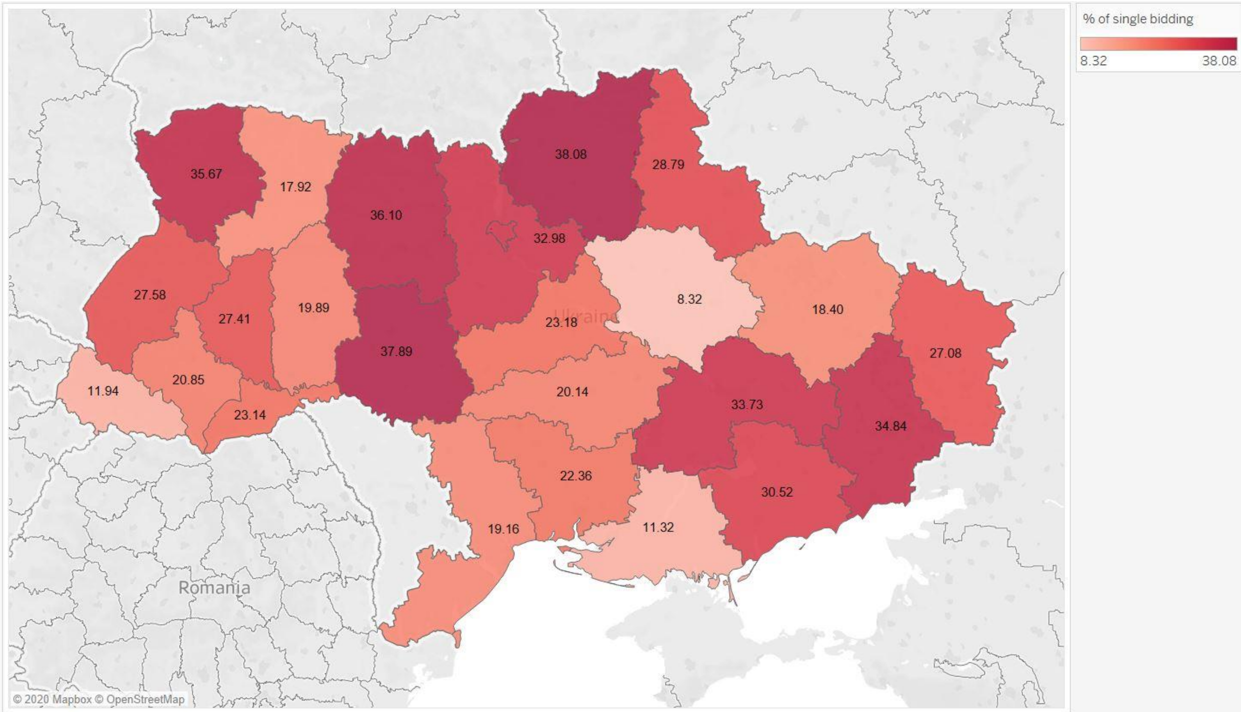
	2015	2016	2017	2018	2019
Single bidding contracts	6,079	60,665	86,651	78,856	64,316
Overall number of contracts	17,622	174,802	274,980	268,906	245,478
Share of single bidding, %	34.5	34.7	31.5	29.3	26.2

Figure 3. 17 Share of single bidding over time, all awarded contracts, competitive procedures (2015 - 2019)



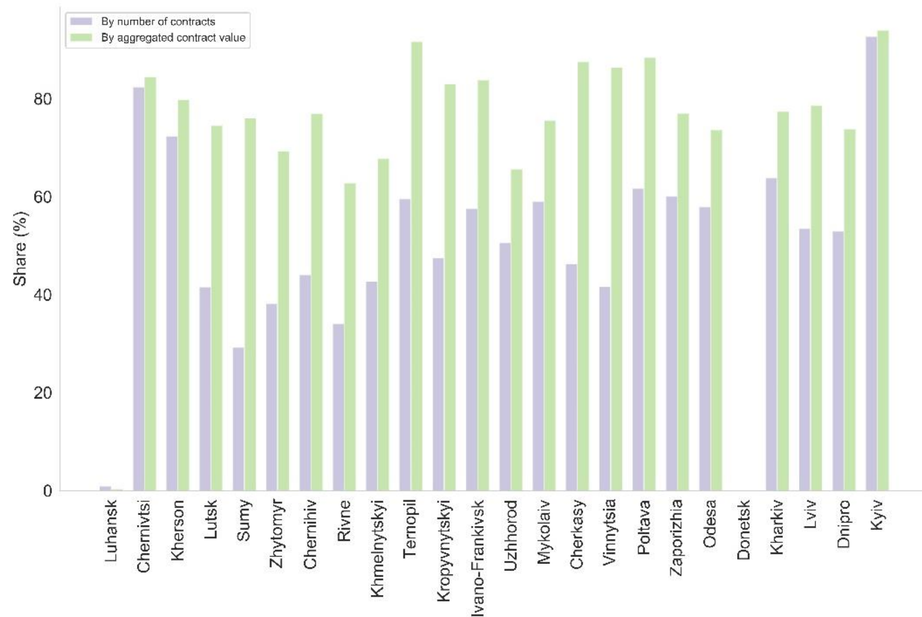
From a regional perspective, the distribution of a share of single bidding is uneven, ranging from the level of about 8% in Poltava region to highest level prevailing in the northern and capital regions as well as in Donetsk and two neighboring Zaporizhia and Dnipro regions reaching as high as 38%. Interestingly, if we compare the regional distribution of single bidding to the regional distribution of aggregated contract value discussed previously, we see that the highest levels of single bidding are present in regions with a lower aggregated value of awarded tenders. Regions with the highest spending through public procurement (Odesa, Dnipro, Ivano-Frankivsk), on the other hand, have an average level of the red flag. Capital region, however, ranks as one of the leaders in terms of share of single bidding.

Figure 3. 18 Share of single bidding by region, all awarded contracts, competitive procedures (2015 - 2019)



Furthermore, it is necessary to highlight that each region has a different level of concentration of public procurement activities in the capital vs the rest of the region. On average, a capital of a region in Ukraine redistributes around 50% to 70% of public procurement funds of the entire region (Figure 3.19). The two outliers with no procurement share going through the capital of a region are Donetsk and Luhansk given that the two cities are temporarily occupied territories that do not utilize ProZorro.

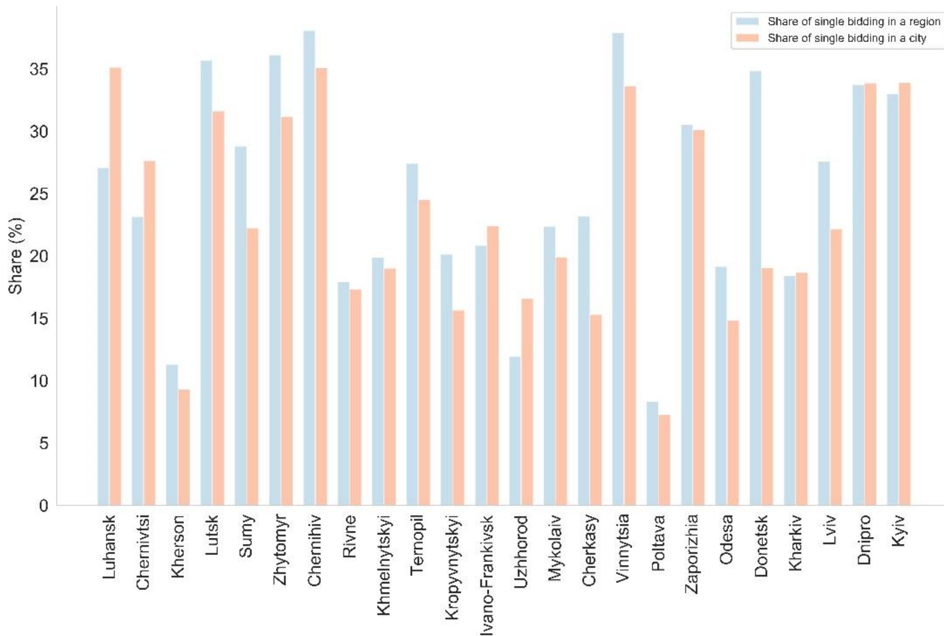
Figure 3. 19 Concentration of public procurement in a capital of a region, all awarded contracts, competitive procedures (2015 - 1Q2020)



Note: bars are sorted by aggregated contract value awarded in a region in the ascending order.

Comparing levels of corruption risks in a capital of a region vs the rest of the region (Figure 3.20) reveals a clear pattern: there is no large difference between a level of overall single bidding in the region vs capital. While we observe some regions with equal rate of single bidding in a capital vs region (Kyiv, Dnipro, Kharkiv, Poltava), others have differences of several percentage points. The two overall rates, however, are rather close. This finding invalidates the position of TI Ukraine stating that larger cities in Ukraine (especially capital and regional centres) tend to be more transparent and less corrupt as compared to smaller towns, possibly due to higher control of the use of public funds from the central government proportional to the amount of funds received.

Figure 3. 20 Share of single bidding in a capital city vs region, all awarded contracts, competitive procedures (2015 - 1Q2020)



Note: bars are sorted by aggregated contract value awarded in a region in the ascending order.

While in this study we mostly focus on single bidding as the most prominent corruption red flag in the field of public procurement, the literature suggests alternative and supplementary potential indicators (Mihaly Fazekas & Kocsis, 2016). The list of supplementary red flags includes the exclusion and disqualification of all bids except for one, relative price of a contract as compared to the initial estimate by the buyer, length of the decision period, number of complaints and disqualifications filed for a tendering process, etc. These indicators are discussed in length in the Modeling chapter.

In summary, corruption in the field of public procurement is a comprehensive issue that is difficult to capture and measure. The most common approach in the literature is the use of single bidding as the most notable red flag of corruption. When we analyze the issue of single bidding in

ProZorro, it turns out to be a significant issue. Approximately 30% of all competitive procedures has no competition, but with a gradually declining trend over time. In some markets, however, the share of single bidding reaches more than 50%. This is the case with public utilities, IT, health services, and construction work. From a regional perspective, the distribution of a share of single bidding is uneven. Furthermore, we note that the level of overall single bidding in the region vs capital the region is very close. In addition to single bidding, there are other potential indicators of corruption in public procurement that we will also further employ as supplementary red flags: exclusion of bids, relative price of the final contract value, complaints and disqualifications, and the length of decision period.

Chapter 4 - Modeling: Overview and Estimation

One of the goals of this study is to build upon existing literature on the determinants of corruption risks in the field of public procurement by investigating the relationship between characteristics and parameters of tendering processes and levels of corruption. While we previously described how the ProZorro is designed and functions and investigated corruption risks present in the system, the next step of our research is to develop a model that would link the two and help us understand how features of each procurement process can explain and predict the outcome level of corruption. In this chapter, we present the description of the data that will feed into the development of a model. We also describe the methodological approach and develop a model. We assess the model’s prediction power as well as interpret relevant findings.

4.1. Data, Variables, and Methodology

4.1.1. Data and Variables

To reiterate and as is common in literature (Mihaly Fazekas & Kocsis, 2016; Mihály Fazekas & Wachs, 2020; Wachs et al., 2019; Wachs & Kertész, 2019), we define corruption risk in public procurement as a share of single bidding (in case of aggregation on a market, region, or entity level) or as a binary feature on whether a particular tendering process has only one bidder. Single bidding as a binary variable on a contract level is selected as the outcome that we attempt to predict. The reason behind choosing the contract level instead of aggregating on entity or market level is the richness of the data and a long list of potential explanatory variables we observe on the contract level. Some of these features are either not available on a more aggregated level or might get noisy and skewed and lose some information due to the aggregation. Furthermore, we narrow down the sample to competitive procedures only. In the final dataset used for prediction, there are 1,022,366 contracts. It is necessary to highlight that data used for modeling excludes losing bids. The dataset contains parameters of a concluded contract and information on the winning bidder only. One contract with information on a supplier is one observation in the dataset. From a point of view of the dependent variable, the sample of contracts is unbalanced: 70% of observations have multiple submitted bids, while only 30% have the issue of single bidding.

The list of explanatory variables includes three groups of predictors: widely used control variables, supplementary red flags, and network-based measures. Confounding factors used in this study are market and procurement procedure parameters whose influence is to be controlled. As suggested by the literature (Broms et al., 2019; Dávid-Barrett & Fazekas, 2019; Mihaly Fazekas et al., 2017; Mihaly Fazekas & Kocsis, 2016) and in line with what ProZorro data offers, we include several control variables: procedure type, market code (2-digit CPV code), year, quarter, and issuer's region.

The literature (Mihaly Fazekas et al., 2013, 2017) also suggests alternative and supplementary potential indicators of corruption in public procurement. These indicators are presented in the table below and in every case are constructed in a way that their higher values are associated with higher corruption risks.

Table 4. 1 Descriptive statistics on corruption red flags, all awarded contracts, competitive procedures (2015 - 1Q2020)

	Count	Mean	StD	Min	25%	50%	75%	Max
Single bidder contract	1,022,366	0.30	0.46	0.00	0.00	0.00	1.00	1.00
Exclusion of all but one bid	1,022,366	0.08	0.28	0.00	0.00	0.00	0.00	1.00
Exclusion of all but one bid, when initial number of bids ⩾3	1,022,366	0.02	0.14	0.00	0.00	0.00	0.00	1.00
Relative price of contract documentation	1,022,366	0.87	0.16	0.00	0.79	0.93	0.99	1.00
Decision period	1,022,366	17.62	14.54	-165.00	9.00	14.00	22.00	993.0
Number of complaints	1,022,366	0.29	1.19	0.00	0.00	0.00	0.00	56.00
Number of disqualifications	1,022,366	0.25	0.65	0.00	0.00	0.00	0.00	42.00

One of such red flags is the exclusion and disqualification of all bids except for the winning single bid. In the ProZorro set of competitive procedures, we also observe such situations: 28% of all lots were awarded in a non-competitive manner due to the exclusion of other bids. Another indicator we consider is a relative price of a contract as compared to the initial estimate by the buyer. The logic behind this red flag is supported by the assumption that in case a tendering process has real competition, the final price will be lower than the initial expected value estimated by a buyer. Such a decrease of the contract value is achieved through competition by bidders lowering the offered price until the cheapest option wins (in case the decision criteria is the price, which is the case with competitive procedures in ProZorro). The average level of decrease of final contract value vs initial estimate is 13%, while the median value is only 7%. The third supplementary red flag is the length of the decision period. While bidders need time to find a lot that fits their business profile, make a decision on whether to bid and prepare the documentation needed for bidding, extremely short decision period signals attempts of a buyer to limit competition. On the other hand, overly lengthy decision period can be associated with complaints, disqualifications, and other legal challenges, suggesting that the issuer attempted to limit competition (Mihály Fazekas & Tóth, 2016). Finally, the number of complaints and disqualifications filed for a tendering process could also signal wrongdoings witnessed by bidders or monitoring organizations.

The introduction of network-based measures of participants' position and importance in the network is a novel approach to investigate corruption risks in public procurement. The utilization of network science methods in corruption research gained its popularity only over the last several years (Wachs, 2019; Wachs et al., 2020). While most of the existing studies in this narrow field focus on market- and community-level measures, only a few focus on a participant level. A recent study by Fazekas and Wachs (2020) has introduced network-based entropy and competitive clustering for buyers in the context of predicting corruption outcomes in public procurement contracts.

Building upon the existing approach, we expand network analysis to both buyers and suppliers. In our analysis, we incorporate basic and simple-to-understand network measures of connectedness and centrality for buyers and winning bidders. First, the list of network-based predictors includes the degree of a participant. Given that the public procurement network is bipartite, the degree of a buyer is a number of suppliers he awarded contracts to; the degree of a supplier is a number of issuers an entity got contracts from. Second, the model incorporates the clustering coefficient of a participant, i.e. local link density for each entity in a network. Finally, we include one of a key measure of centrality of a node – closeness centrality. It shows the sum of the length of the shortest paths between the node and all other nodes in the graph. The lower the closeness centrality a node has, the more central it is to the whole network.

Descriptive statistics on network-based measures are presented in the table below. Overall, in line with what is discussed in the Overview chapter, distributions of these indicators are very skewed: most of the participants in the network are weakly connected and play a peripheral role in the network. Distributions of all numeric predictors is presented in the Appendix.

Table 4. 2 Descriptive statistics on network-based measures, all awarded contracts, competitive procedures (2015 - 1Q2020)

	Count	Mean	StD	Min	25%	50%	75%	Max
Degree of a buyer	1,022,366	387.33	514.90	1.00	83.00	204.0	477.00	3492.0
Clustering coefficient of a buyer	1,022,366	0.66	0.32	0.00	0.41	0.79	0.94	1.00
Closeness centrality of a buyer	1,022,366	0.38	0.03	0.15	0.37	0.39	0.39	1.19
Degree of a supplier	1,022,366	316.40	791.21	1.00	13.00	57.0	201.00	5289.0
Clustering coefficient of a supplier	1,022,366	0.55	0.40	0.00	0.10	0.66	0.95	1.00
Closeness centrality of a bidder	1,022,366	0.50	0.06	0.22	0.46	0.48	0.51	1.81

4.1.2. Methodology

The models we develop aim at performing binary classification, i.e. to predict whether a public procurement contract has a single or multiple bid. Such a prediction model could serve as a risk assessment tool for policymakers in the process of improvement of the regulatory framework of ProZorro.

The type of regression analysis we employ is logistic regression (McCullagh & Nelder, 1989). It is used to model the probability of an event or any binary response variable. Logistic regression does not make assumptions of linear regression: linearity, normality of error terms, and homoscedasticity (Ruppert, 2004). Logistic regression requires i) the dependent variable to be binary, ii) observations to be independent from each other, iii) no multicollinearity between independent variables, iv) large sample size, and v) linearity between independent variables and log odds (Hastie et al., 2009; Ruppert, 2004). Logistic regression estimation is done through the probabilistic framework called maximum likelihood estimation.

Logistic regression has been widely used in the literature on corruption in the public sector and public procurement in particular. Such a modeling approach was employed to predict corruption-related outcomes on a macro-level (Debiel & Gawrich, 2013; Pellegrini & Gerlagh, 2008), regional/municipality level (Acar et al., 2019; Colonnelli et al., 2019; Wachs et al., 2019) as well as on the individual (Blake & Morris, 2009; Mangafić & Veselinović, 2020). In public procurement research, logistic regression served as a tool for prediction of corruption risks such as single bidding and other procurement-specific corruption outcomes (Mihaly Fazekas et al., 2013).

The advantages of using logistic regression in our prediction task is the ability to estimate and interpret coefficients and, more informatively, marginal effects (average partial effects), for each independent variable. Marginal effects show the average difference in the probability of a response variable between observations that are different in the value of an explanatory variable by one unit. With regard to our prediction task (predicting a single bidding outcome), the estimation of a logistic regression allows us to assess the likelihood of a public procurement contract having single bidding depending on a set of available characteristics. From a policy perspective, this helps identify what contracts tend to have a higher probability of not having multiple bids. Moreover, with this approach we are able to see marginal effects, and thus the direction and the size of the effect each feature has on the probability of single bidding. Such findings can guide and support policymaking efforts towards competition enhancement in ProZorro and other public procurement systems.

Nonetheless, this modeling approach has several limitations and difficulties we should consider. First, there should be no multicollinearity between explanatory variables. High correlation between independent variables would bias standard errors. This can be easily checked by the correlation matrix among independent variables. In our case, the correlation matrix heatmap presented in the Appendix demonstrates that explanatory variables do not have high correlations, thus it meets the required condition.

Another important consideration is overfitting (Ruppert, 2004). Certainly, adding more variables to a logistic regression will result in higher explanatory power, however, it can lead to overfitting, i.e. that the model works well on the available data, while performing poorly on new observations. To avoid that, we employ a machine learning technique called k-fold (in our case k=10) cross-validation to ensure the high performance of the model on the new data. Finally, we note that logistic regression does not use standard R^2. There is a variety of pseudo-R^2 developed for logistic regression, however, they tend to have computational difficulties that potentially skew the estimate. To prevent this, we use a combination of alternative measures such as the area under the ROC curve, root mean squared error, accuracy, precision, and recall.

Another issue that arises in this context is the endogeneity issue (Avery, 2005). While identifying the causal impact of procurement parameters and participants' characteristics on corruption risks is beyond the scope of this thesis, the selection of features for prediction of single bidding poses endogeneity concerns that can lead to biased parameter estimates. In the current modeling approach, endogeneity concerns arise due to the possibility that both single bidding and the set of independent variables are influenced by factors not accounted for in the model. For instance, a public buyer with corrupt intentions might tend to select a procedure type and modify procurement parameters such as technical requirements of goods and services in a way that would restrict the available pool of competitors and result in single bidding.

The conventional solution to the endogeneity problem in this situation could be i) the use of instrumental variable (IV) methods or ii) exclusion of potentially endogenous variables such as procedure type (Lousdal, 2018). Implementing the instrumental variable approach in this prediction task poses challenges. Finding and measuring valid IVs for potentially endogenous determinants of single bidding and other corruption outcomes is a difficult goal to attain (Jetter & Parmeter, 2016). While we include spatial and sectoral dependences that are widely used as an IV for corruption (Bai et al., 2019; Borsky & Kalkschmied, 2019; Faber & Gerritse, 2012; Jetter & Parmeter, 2016), it is elusive to design buyer- or contract-level IVs that are highly correlated with a procurement procedure type and do not have additional explanatory power. The exclusion of potentially endogenous variables – procedure type – might lead to an omitted variable bias (Leightner & Inoue, 2012). Furthermore, corruption studies in the field of public procurement widely employ procedure type variable in the modeling as an essential predictor of single bidding outcome (Mihaly Fazekas et al., 2013; Mihaly Fazekas & Kocsis, 2016).

Given a large number of predictors, we develop a model iteratively. We start from a baseline set of predictors widely used in literature and add a new feature/set of features at each next stage. The sequence of feature inclusion is presented in Table 4.3. All the features can be grouped into three categories: widely used control variables, supplementary red flags and network-based measures. It is necessary to highlight that the set of supplementary red flags consists of public procurement contract parameters used in the literature (Mihaly Fazekas & Kocsis, 2016; Mihály Fazekas & Wachs, 2020) as well as developed in this thesis as additional signals of corruption that are currently not monitored in ProZorro. Their inclusion in the development of a model will form the basis for the preparation of policy recommendations on what features can signal higher corruption risks in tendering processes.

The baseline logistic regression uses the first group of features – common control variables suggested by the literature. These are procedure type, 2-digit CPV code, year, and buyer's region dummies. At the second iteration, we include the quarter dummies to account for high seasonality. Later we transform the quarter dummies into three categories instead of four. The new quarter dummies are whether a tender took place in the i) 1st quarter, ii) 2nd /3rd quarter, or iii) 4th quarter of the year. The logic behind combining the 2nd and 3rd quarters is that we observed that the behavior of buyers and bidders is highly seasonal, and these quarters have a similar pattern. While there is a low number of lots awarded in the 1st quarter due to a budget cycle, it slightly increases over 2nd and 3rd quarters and goes up to the peak in the last quarter.

Model specifications 4-9 iteratively include supplementary red flags. First, we include a binary variable on whether a buyer's city is the capital of a respective region. As a second flag, the model incorporates the expected value of a contract as estimated by the issuing body. Then we add the difference between the final value and the initial estimate, i.e. savings achieved through competing bids lowering the offered price. Model 7 incorporates the number of complaints and disqualifications. In the next iteration, we include the length of a decision period. Finally, we add the dummy on whether a bidding company is a foreign entity.

To investigate the relationship of network-based measures of entities and procurement procedures in which they participate, we develop models 10 – 13. Models 10 – 12 sequentially include buyer-related network measures: first, degree, then clustering coefficient, and, finally, closeness centrality. Model 13 incorporates all three identical supplier-related network-measures.

The final model 14 simplifies 24 buyer's region dummies to three categories: whether a buyer's region is i) Kyiv, ii) one of the four largest regions that redistribute the highest contract volumes, or iii) a small region. The reason behind making such a modification of the region variable as the last step is the potential loss of prediction power that we want to be able to measure.

4.1.3. Performance Evaluation Framework

To evaluate the performance of the models, we employ a set of machine-learning techniques. For each model we measure several metrics: i) accuracy, ii) root mean squared error (RMSE), iii) precision, iv) recall, and v) area under the receiver operating characteristic curve (ROC) (Hastie et al., 2009; Ruppert, 2004).

In a classification task, accuracy is a metric that shows the percent of predicted values that a model gets right. Precision shows the share of correct true positives out of all positive predictions, while recall metric presents what is a percent of actual positives that were identified correctly. In the case of a single bidding prediction task, positives are contracts that have the issue of single bidding, and negatives are contracts that have multiple bids. True positives (TP) are contracts that are predicted to have only one bid and in fact have single bidding (SB). True negatives (TN) are contracts with multiple bids (nonSB) that were predicted to be so. False positives (FP) are procurement procedures that, according to a model, are supposed to be single bidding, while in reality have several bidders competing for them. Finally, false negatives (FN) are lots that are predicted to have several bids, but in fact have only one. In the current prediction task, a perfect model should have all three metrics as close as possible to 1. The summary of the discussed definitions is presented below:

$$Accuracy = \frac{Correclty\ predicted\ SB + Correclty\ predicted\ nonSB}{All\ contracts}$$

$$Precision = \frac{Correclty\ predicted\ SB}{All\ SB\ contracts} \qquad Recall = \frac{Correclty\ predicted\ SB}{Correclty\ predicted\ SB + Falsely\ predicted\ nonSB}$$

For the evaluation of the trade-off between precision and recall results, the precision-recall curve is then created. It shows the precision and recall for all thresholds for a logistic regression compared to a random ("no skill") model.

The ROC curve is an additional tool to evaluate the performance of a model (Bradley, 1997). It is a graphical plot that shows a trade-off between true positive and false positive rates depending on a classification threshold (ranging from 0 to 1). What we have to look at in this case, is the entire two-dimensional area under ROC curve. It provides an aggregate measure of the performance of a model with all possible thresholds. A model which has closest to 1 AUC is desirable.

It is necessary to highlight that the choice between precision-recall and ROC curves is dependent on how well the data is balanced. In case there is a relatively equal number of observations for each class of a dependent variable, ROC curve is preferred. In our case, when the data are imbalanced with ~70% of contracts with multiple bids and only ~30% of single bidding, precision-recall should be used as the main evaluation tool and ROC curve as a supplementary one.

The root mean square error (deviation) is a supplementary performance evaluation measure. It shows the difference between predicted value, therefore, our efforts will focus on minimizing RMSE (Hastie et al., 2009). The formula for RMSE calculation is presented below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N}}$$

Of note, for the estimation of the above-mentioned metrics for each of the 14 models, we employ a 10-fold cross-validation. Cross-validation is a resampling statistical method used to evaluate the performance of a machine learning model (Hastie et al., 2009). The logic of a technique is to split the data into k groups (10 in this case), take one group as a hold out (test) data, and train the model on the remaining k-1 groups. Then the evaluation score (accuracy, precision, RMSE, etc.) is calculated on test data, and such procedure is repeated k times. Finally, from the sample of model evaluation scores, we can take the average which will be the final evaluation score that we use for comparison of the performance of different models.

Table 4. 3 Model specifications

Group of variables	Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
Widely used control variables	Procedure dummies														
	2-digit CPV codes dummies														
	Year dummies														
	Buyer's region dummies														
	Quarter dummies														
Modified control variables	1Q, 2-3Q or 4Q dummies														
	Whether region is Kyiv, big region or small region dummies														
Red flags	Whether buyer's city is a capital of a region dummy														
	Expected value of a contract (log)														
	Savings as compared to expected value (%)														
	Number of disqualifications														
	Number of complaints														
	Length of decision period														
	Whether winner is a foreign company dummy														
Network-based indicators	Degree of a buyer in a network														
	Clustering coefficient of a buyer in a network														
	Closeness centrality of a buyer														
	Degree of a supplier in a network														
	Clustering coefficient of a supplier in a network														
	Closeness centrality of a bidder														

4.2. Model Estimation and Results

4.2.1. Model Estimation

The estimated logistic regressions perform a binary classification and predict whether a public procurement contract is more likely to have the issue of single bidding. The cross-section regression equation we estimate is:

$$y_i = \beta_0 + \beta_1 * RED\ FLAGS_i + \beta_2 * NETWORK\ MEASURES_i + \beta_3 * CONTROLS_i + e_i,$$

where yi is whether a contract i had single bidding (0 or 1), $RED\ FLAGS_i$ is the matrix of supplementary red flags variables, $NETWORK\ MEASURES_i$ is the matrix of network-based participants' characteristics, and, finally, $CONTROLS_i$ is the matrix of control variables. e_i is the error term.

All 14 model specifications employ a different set of predictors, thus our task is to compare their performance and select the best model. To reiterate, performance evaluation framework employs the following scoring metrics: i) accuracy, ii) RMSE, iii) precision, iv) recall, and v) AUC ROC.

Models 1 – 7 show improvement with each step and each included predictor. We observe increasing test accuracy, precision, recall, and AUC ROC and decreasing RMSE. Starting from the model 8, evaluation scores demonstrate only marginal improvements. Given that the goal of this thesis is not only to predict the probability of single bidding but also to be able to infer how co-variates contribute to the probability of single bidding, we aim to develop the fullest model with highest scoring results. Model 14 presents such a case that includes all features of interest yet has the highest prediction power. The table illustrating all performance evaluation scoring results is presented in the Appendix.

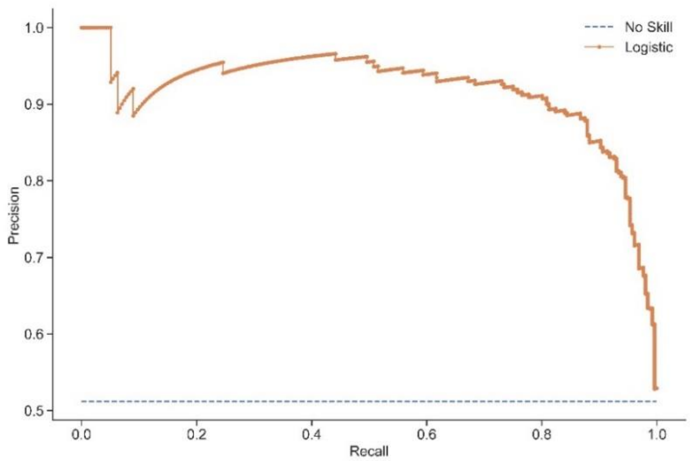
To further examine the performance of the model 14, we discuss each scoring result in more detail. The test accuracy of model 14 is 85% which means that the model predicts 85% of the observations and doesn't overfit the data. Subfigure 4.1 A shows a precision-recall curve, with an area under the curve 0.9. The result is close to a "perfect-skill" model with AUC of 1 and represents high precision (relates to a low FP rate) and high recall (relates to a low false negative). To better understand what it implies, we additionally present the respective confusion matrix (4.1 B).

Confusion matrix (Ting, 2017) presented in 4.1. B demonstrates that the model 14 has truly high true positives and true negatives rates. Those contracts that have multiple bids were accurately predicted to a large extent as negatives (north-western square on the matrix). In addition to that, contracts of our interest – those with the issue of single bidding – were precisely predicted as single bidding observations (south-eastern square). Nevertheless, we point out that some of the observations were classified incorrectly. There is a marginal error rate for false negatives (actual single bidding contracts that were classified as ones with multiple bids, south-western square). We observe a higher rate of contracts that in fact have multiple bids, however, were classified as single bidding observations (north-eastern square). From a policy perspective, such a model with high true positive and negative rates as well as a moderate level of false positives serves the initial purpose: the model accurately predicts single bidding cases, while slightly overestimating the risk of single bidding for multiple-bid contracts.

Subfigure 4.1 C demonstrates the ROC curve and calculated average AUC. Average AUC obtained through 10-fold cross-validation is 95%. This means that in 95% of the cases the developed model 14 ranks a random single bidding contract more highly that a random contract with multiple bids.

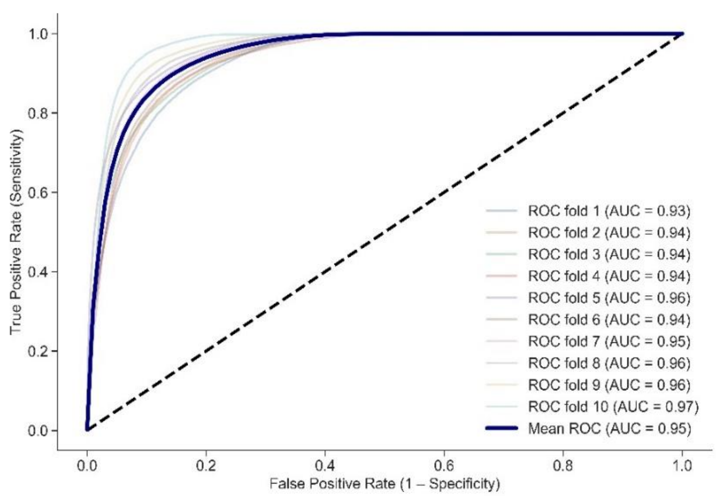
Figure 4. 1 Representation of scoring results for the best model (obtained through 10-fold CV)

A) Precision-recall curve



B) Confusion matrix

C) ROC curve



In view of the already proven high prediction power of the developed model, it is worth discussing how the model not only predicts but also explains the relationship between selected independent variables and the probability of single bidding. Table 4.4 shows the coefficients as well as marginal effects for 3 models: the baseline model, the model including all red flags, and the fullest model based on red flags and network-based measures. The reason for including results for 3 stages of model development is to be able to see changes in coefficients and marginals once new predictors are added. However, detailed interpretation of drivers of single bidding is provided for the most comprehensive model.

4.2.2. Interpretation of Results

Our results cast a new light on commonly used control variables and predictors suggested by the literature as well as newly introduced explanatory features. This analysis reveals that, first of all, procedure type (despite the fact that they are all competitive by their design) has an important role in predicting the single bidding outcome in the ProZorro system. Given that open tenders both in Ukrainian and English tend to have multiple bids in most of the cases, the model excluded these two dummies from the analysis. For the rest of the procedure types, the reference category is e-catalogues – the group with the highest share of single bidding in the observed sample. As compared to e-catalogues, subthreshold procedures tend to have a lower level of single bidding. The lowest share of single bidding is associated with framework agreements.

The results also demonstrate that, despite high seasonality of a number of awarded contracts that we observed previously, the likelihood of single bidding contract is rather stable throughout the year with a slight decrease by 2 pp in the last quarter of the year when we see a large spike in the participants' activity. The regional aspect does not seem to matter much when we compare two contracts with otherwise-identical features. While the capital region has one of the highest shares of single bidding, the top-4 regions with the highest awarded contract value have a similar, however, slightly lower (by 3 pp), the share of contracts with only one bid. The rest of the regions' share of single bidding is lower than in the capital region by 4 pp.

Table 4. 4 Logistic regressions output (logit coefficients and marginals)

	OUTCOME: SINGLE BIDDING	Baseline model (3)		Model including red flags (9)		Full model including red flags and network-based features (14)	
GROUPS OF PREDICTORS	PREDICTORS	(1) logit coefficients	(2) logit marginals	(1) logit coefficients	(2) logit marginals	(1) logit coefficients	(2) logit marginals
Control variables of interest	Framework agreement procedure dummy (reference group is e-catalogues)	-20.638	-4.76	-17.580	-2.24	-17.590	-2.22
		(863.416)	(199.32)	(545.777)	(69.47)	(601.783)	(76.04)
	Open tender procedure dummy = o	-	-	-	-	-	-
	Open tender procedure in EN dummy = o	-	-	-	-	-	-
	Subthreshold procedure dummy (reference group is e-catalogues)	-18.330	-4.23	-15.283	-1.95	-15.450	-1.95
		(863.415)	(199.32)	(545.776)	(69.47)	(601.781)	(76.04)
	1Q (reference category is 2-3Q)	0.165***	0.04***	0.015	0.00	0.014	0.00
		(0.020)	(0.00)	(0.026)	(0.00)	(0.026)	(0.00)
	4Q (reference category is 2-3Q)	-0.180***	-0.04***	-0.151***	-0.02***	-0.164***	-0.02***
		(0.021)	(0.00)	(0.028)	(0.00)	(0.028)	(0.00)
Red flags	Whether buyer's city is a capital of a region dummy			0.045*	0.01*	0.093***	0.01***
				(0.025)	(0.00)	(0.025)	(0.00)
	Expected value of a contract (log)			-0.058***	-0.01***	-0.074***	-0.01***
				(0.009)	(0.00)	(0.009)	(0.00)
	Savings as compared to expected value (%)			-11.515***	-1.47***	-11.313***	-1.43***
				(0.110)	(0.01)	(0.111)	(0.01)
	Number of disqualifications			-9.418***	-1.20***	-9.448***	-1.19***
				(1.001)	(0.13)	(1.001)	(0.13)
	Number of complaints			-0.943***	-0.12***	-0.954***	-0.12***
				(0.052)	(0.01)	(0.053)	(0.01)
	Length of decision period			-0.042***	-0.01***	-0.039***	-0.00***
				(0.002)	(0.00)	(0.002)	(0.00)
	Whether winner is a foreign company dummy			-0.048	-0.01	-0.051	-0.01
				(0.044)	(0.01)	(0.045)	(0.01)

Network-based measures	Degree of a buyer in a network					-0.000*** (0.000)	-0.00*** (0.00)
	Clustering coefficient of a buyer in a network					-0.339*** (0.062)	-0.04*** (0.01)
	Closeness centrality of a buyer					1.847*** (0.631)	0.23*** (0.08)
	Degree of a supplier in a network					0.000*** (0.000)	0.00*** (0.00)
	Clustering coefficient of a supplier in a network					-0.326*** (0.042)	-0.04*** (0.01)
	Closeness centrality of a bidder					-2.196*** (0.460)	-0.28*** (0.06)
Other control variables	Whether it is a small region (reference group is Kyiv region)			-0.182*** (0.030)	-0.02*** (0.00)	-0.342*** (0.032)	-0.04*** (0.00)
	Whether it is a big region (reference group is Kyiv region)			-0.141*** (0.034)	-0.02*** (0.00)	-0.233*** (0.034)	-0.03*** (0.00)
	Year Dummies	YES	YES	YES	YES	YES	YES
	Region Dummies	YES	YES	NO	NO	NO	NO
	2-digit CPV	YES	YES	YES	YES	YES	YES
	Constant	19.765 (863.415)		20.288 (545.776)		21.333 (601.781)	
	Observations	1,022,366	1,022,366	1,022,366	1,022,366	1,022,366	1,022,366
	Pseudo R^2 (Nagelkerke)	0.41		0.71		0.72	

Further novel findings focus on the group of red flags. As the model suggests, several supplementary red flags are significantly associated with higher risks of single bidding. First, from the estimated results, it is clear that higher contract values are associated with lower levels of single bidding. 10% increase in contract value is related to a 10 pp lower probability of single bidding. Second, the model demonstrates that lower or no savings achieved in a tendering process could be an additional signal of single bidding outcome. 10% lower final contract price is associated with 14pp lower likelihood of single bidding. Furthermore, the analysis reveals that the fact of disqualifications and complaints filed by bidders and external observers relates to a lower probability of a single bidding outcome.

On the contrary, some of the supplementary red flags do not seem to have a significant relationship with the single bidding outcome. These predictors are i) whether a supplier is a foreign company, and ii) whether the tender was issued in the capital of the region vs the rest of the region as well as iii) length of decision period. According to the estimated results, these features have either non-significant or very low, close to zero, impact on the single bidding outcome.

This analysis found evidence for a significant relationship between network-based features of both bidders and buyers and the single bidding outcome. While node degree of suppliers and buyers has a significant yet close to zero marginal effect on single bidding, clustering coefficient and closeness centrality seem to play a more important role. The model suggests that a buyer with a higher clustering coefficient tends to have a lower probability of awarding a contract in a non-competitive manner. On the other hand, the higher closeness centrality (higher values indicate a less central position) of a buyer is associated with a higher probability of single bidding. This result means that those buyers who tend to have a pool of frequently co-bidding suppliers (which clustering coefficient represents) have a lower probability of awarding a single bidding contract. Additionally, this could be a result of a "reputation effect": a buyer surrounded by a group of suppliers that monitor his tender announcements is constrained in awarding contracts in a non-competitive way (Campbell, 2007). At the same time, buyers that are highly central in the market network (that inverse of the closeness centrality demonstrates) are estimated to have a lower probability of non-competitive awards.

For winners, both clustering coefficient and closeness centrality are negatively associated with the probability of winning in a non-competitive way. We can infer that suppliers that bid against other suppliers, that, in their turn, frequently co-bid (which is indicated by higher clustering coefficient) have a lower chance of winning as a single bidder. In addition to that, more central suppliers in the network (that is expressed as lower closeness centrality) have lower chances of single bidding win.

In summary, the developed model casts a new light on the drivers of single bidding corruption risks in the public procurement system ProZorro. The modeling is based on a wide sample of awarded contracts (~1MM data points) from a subsample of competitive procedures. The models we develop aim at performing binary classification, i.e. to predict whether a public procurement contract has a single or multiple bid. The type of regression analysis we employ is logistic regression. The list of explanatory variables includes three groups of predictors: widely used control variables, supplementary red flags, and network-based measures. The fullest model with the highest performance reveals interesting suggestions of red flags of corruption:

1. Lower contract values are associated with higher levels of single bidding.
2. Lower or no savings achieved in a tendering process could be an additional signal of a single bidding outcome.

3. Buyer with a lower clustering coefficient tends to have a higher probability of awarding a contract in a non-competitive manner. Furthermore, buyers located in the periphery of a market network are estimated to have a higher probability of non-competitive awards.
4. For winners, both clustering coefficient and closeness centrality are negatively associated with the probability of winning in a non-competitive way.

These results form the basis for the preparation of policy recommendations on what features can signal higher corruption risks in tendering processes and how to capture such cases in advance.

Chapter 5 – Discussion and Policy Recommendations

The findings of the previous chapters offer crucial insights for the analysis of public procurement system ProZorro and prediction of corruption outcomes in procurement contracts, and they might potentially offer insights for other countries and corruption studies. In this chapter, we summarize our findings and reflect on their contribution to the understanding of ProZorro and corruption risks present in this system. We highlight the most significant weaknesses of the system and develop a set of policy recommendations to address these challenges.

ProZorro, as a relatively new public procurement platform introduced in Ukraine, combines sophisticated IT solutions and a comprehensive regulatory framework to ensure highly competitive, transparent and efficient public procurement market. ProZorro has achieved recognition all over the world as one of the best procurement reforms. However, as it has been shown, despite the efforts, ProZorro continues to face corruption risks inherent in the public procurement market.

Our detailed empirical analysis revealed that since the launch of a fully functional ProZorro platform the volume of competitive procedures has been rather stable, while the volume of non-competitive awards – for which corruption risks are naturally much higher – has been steadily increasing. The difference becomes even more striking if we look at aggregated contract values awarded in a competitive vs non-competitive way. By the end of each year, buyers tend to increase the share of a contract value awarded through non-competitive procedures dramatically. This is due to a budget law that limits the usage of available public funds in the next budget period. Poor timing and the overall mismanagement of the available public funds by buyers paves the way to all corruption risks associated with the non-competitive procedure types.

Such seasonality pattern in public buyer's behavior is a common feature of many public procurement systems in countries with a similar to Ukrainian budget regulation on potential budget reduction in case of unused funds. As the review of the literature and different public procurement regulatory frameworks has revealed, there are no examples of policies aiming to tackle this issue to be found. On the contrary, different consulting firms issue reports on how to maximize efficiency in redistributing remaining funds by the end of the fiscal year (BakerHostetler, 2014). Therefore, the following recommendations can be made:

- One line of action might be for public buyers to set quarterly budget goals and follow a quarterly budget plan instead of the current approach of having the only annual deadline. This would allow public buyers to distribute spending over the year more evenly.
- A second way forward might be to partially alleviate the budget rule on the reduction of funds in case if not all the funds were spent. While this might be difficult to achieve in the situation of persistent budget deficits in Ukraine, the implementation of such a policy would alleviate burdens faced by the public buyers trying to maintain a stable budget.

Furthermore, our results demonstrated that ProZorro faces issues related to the lack of competition. This study found evidence for an extremely low number of suppliers in some of the procurement markets. Interestingly, the size of the market is not necessarily positively associated with a higher number of bidders. While the largest construction work market is a leader by the number of suppliers, the other four largest markets – Fuel & electricity, Electrical machinery, Office machinery, and Agriculture – have a significantly lower number of bidders. Some of the other large markets – Agriculture & farming and Administration & defense – have a surprisingly low number of bidders. For some niche markets with high entry barriers such as machinery for mining and services related to oil and gas, a low number of bidders can be explained by a small pool of such companies in the market. However, such scarcity of companies seen in niche markets does not apply to industries like agriculture, hotels & restaurants, and retail, which are widely represented in the general economy of Ukraine.

In addition to the low number of bidders in some markets, the results demonstrate that around 50% of the suppliers are not active in the system and have not placed any bids over the last 24 months or longer. While it is hard to define at what length of inactive period a bidder should be considered to have left the system irrevocably, the policy efforts should be focused on increasing the share of active participants.

To improve the share of active bidders as well as increase the number of bidders in some markets with a small pool of available suppliers, the following recommendations could be adopted:

- The evidence points, first, to the improved and more user-friendly than CPV-based system tender search (European Commission, 2012). Bidders are not familiar enough with the CPV system due to its difficulty to use. While it is possible to search by keywords in ProZorro, this option still retrieves many results that a buyer has to go through to find a matching tender.
- The second line of action might be the creation of personalized tender suggestions based on a company profile and previous history of bidding.
- Additionally, the use of network science methods could contribute to this task by analysis of co-bidding networks of suppliers. The idea of this approach is to recommend active tenders to bidders based on the activity of their former competitors. For example, if Company A competed against Company B for several lots previously, the recommendation system could suggest tenders that Company B places bids for to Company A and the other way around.

- Last but not least, policy efforts should focus on providing support and assistance in the preparation of tendering documentation and other aspects of the tendering process.

The results of this study also provide a base for the development of a corruption assessment framework. The developed models could help identify what contracts tend to have a higher probability of single bidding – the most prominent indicator of corruption in the field of public procurement. The developed models also show marginal effects, and thus the direction and the size of the effect each feature has on the probability of single bidding. Such findings can guide and support policymaking efforts towards competition enhancement in ProZorro.

According to the findings from the best performing model, a typical single bidding contract tends to be awarded in a low contract value range with low or no savings achieved in a tendering process. To reiterate, the savings achieved in a tendering process are measured as a percentage difference between the expected value of a contract provided by a public buyer and final contract value. Besides that, typical single bidding contracts have no filed complaints and disqualifications.

A category of buyers that tend to have a higher probability of awarding a contract in a non-competitive way is public bodies with a sparse network of connections. While these buyers are surrounded by a number of bidders that ever participated in their tenders, these suppliers do not tend to co-bid in the same tender. What happens in this situation is that each supplier becomes a single bidder and wins a contract with no competition. Furthermore, buyers who have a higher probability of single bidding tend to be placed in the periphery of a market network.

Network-based supplier characteristics are also significantly associated with a probability of single bidding. In line with the buyers' estimate, suppliers with a sparse network of connections end up having no competition. On the contrary to buyers, centrally positioned suppliers have a higher likelihood of winning as a single bidder.

Together, the present findings could serve as a risk assessment tool for policymakers and signal higher corruption risks in tendering processes. Therefore:

- While it is time-consuming and labor-intensive to perform an audit of all ongoing tendering processes, such a risk assessment tool would narrow down the sample to contracts with higher corruption risks as predicted by the developed model.

These empirical findings call into question the common approach of concentrating policy efforts on markets and contracts with a low absolute number of bidders. The new approach developed in the study analyzes public procurement market as a complex network of interconnected and interacting elements and draws attention to network aspects of procurement activities. In combination with the use of single bidding – simple to understand and at the same time powerful indicator of corruption – the developed framework can assist in policy making and audit by providing more knowledge on the chances of a single bidding award.

Conclusion

Mapping and analysis of the prevalence and distribution of corruption risks in public procurement systems are essential aspects of ensuring transparent and cost-effective use of public resources. While this thesis analyzes one of the most successful public procurement reforms ProZorro, the empirical findings suggest that even such transparent and innovative procurement systems are prone to corruption. Based on a large administrative dataset of all tendering processes that took place in ProZorro between the launch of the system and the end of the first quarter of 2020, this study combines the analysis of procurement-specific risk indicators developed in the corruption literature and a network-based approach. Our detailed empirical analysis reveals mismanagement of public funds and a lack of competition in a large share of awarded contracts.

Building upon these findings, we develop a risk assessment tool for policymakers that could signal higher corruption risks in ongoing tendering processes. The risk assessment framework is based on procurement parameters such expected value of a contract, length of decision period, type of procedure, etc. It additionally incorporates participants' network-based measures of connectivity, link density, and centrality. While it is time-consuming and labor-intensive to perform an audit of all ongoing tendering processes, such a risk assessment tool will narrow down the sample to contracts with higher corruption risks as predicted by the developed model. This will increase the efficiency of an audit of public buyers by ProZorro as well as other interested parties such as investigative journalists and civil activists.

Further work needs to be done on the improvement of a market definition in this research context. While the present study employs a commonly used CPV system as a proxy for market definition, the network science approach presents the opportunity to analyze public procurement market as a whole and investigate co-bidding networks of suppliers instead of grouping them by CPV. With the help of community detection algorithms, co-bidding networks of suppliers can reveal groups of firms having a similar business profile and providing similar goods and services no matter what CPV code was specified in the tender documentation.

Furthermore, future work should concentrate more on the investigation of corruption patterns in non-competitive procedures. The present study develops the modeling aspect on a set of competitive procedures only. That is because non-competitive tendering processes by the design and regulatory framework are allowed (and in reality, in most of the cases) have an absence of competition, no bidding process, and a single supplier. In the set of non-competitive procedures, the lack of variation in the corruption proxy employed in this study – single bidding – does now allow us to use a similar modeling approach. Corruption patterns in a subgroup of non-competitive procedures could further be investigated along similar lines to this study with the only difference being the use of a different corruption proxy. The overall aim would be to foster informed policy choices by providing a risk assessment tool that could signal higher corruption risks in tendering processes.

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Appendices

Table A. 1 Market-level network measures

2-digit CPV code	Sector name	R-A clustering	Density	Buyer's average degree	Bidders's average degree
65	Public utilities	0.3139	0.0161	1.77	2.13
85	Health & social work services	0.2628	0.0056	3.57	3.04
41	Collected & purified water	0.2622	0.0156	4.10	3.58
55	Hotel & restaurant & retail	0.2507	0.0022	3.75	4.03
60	Transport services	0.2284	0.0021	1.79	3.07
66	Financial & insurance services	0.2118	0.0233	20.39	6.70
98	Other community services	0.2007	0.0026	2.44	3.43
80	Education & training services	0.1763	0.0041	3.45	4.08
15	Food & beverages	0.1538	0.0018	8.67	14.97
76	Services related to oil & gas	0.1454	0.0292	1.46	7.94
16	Agricultural machinery	0.1439	0.0039	5.23	4.16
18	Clothing & footwear	0.1314	0.0025	6.96	10.94
33	Medical equipments & pharmaceuticals	0.1262	0.0037	16.41	24.78
63	Supporting transport services	0.1240	0.0074	1.36	5.24
90	Sewage- & environmental services	0.1231	0.0022	5.26	6.34
64	Postal & telecom services	0.1107	0.0054	2.20	2.54
75	Administration & defence	0.1072	0.0045	3.17	4.11
22	Printed matter	0.1063	0.0027	8.37	9.35
24	Chemical products	0.1036	0.0021	6.35	10.58
30	Office and computing machinery	0.1028	0.0016	15.78	13.64
92	Recreational & cultural services	0.0987	0.0039	1.64	3.62
70	Real estate services	0.0959	0.0099	1.67	4.57
48	Software package & IT	0.0926	0.0028	4.82	4.80
37	Musical instruments & sport goods	0.0906	0.0024	5.77	6.75
77	Forestry & aquacultural services	0.0887	0.0025	1.82	4.73
14	Mining	0.0837	0.0026	2.82	8.68
31	Electrical machinery	0.0821	0.0015	6.21	15.02
43	Machinery for mining	0.0813	0.0028	3.40	5.26
39	Furniture	0.0809	0.0013	8.95	16.12
34	Transport equipment	0.0803	0.0011	6.33	8.03
50	Repair & maintenance services	0.0735	0.0009	3.65	10.45
19	Leather & textile & rubber	0.0712	0.0020	3.44	8.32
44	Construction structures & materials	0.0649	0.0010	5.25	14.54
35	Police & fire-fighting	0.0649	0.0020	4.35	5.66
51	Installation services	0.0610	0.0023	1.71	2.88
32	Radio, TV & communication	0.0600	0.0014	6.24	7.59
38	Optical & precision equipments	0.0597	0.0013	4.65	6.64
73	Research & development services	0.0576	0.0057	1.43	4.75
79	Business services	0.0558	0.0013	3.26	6.80
42	Industrial machinery	0.0549	0.0012	4.24	10.67
72	IT services: consulting & software	0.0542	0.0015	3.12	3.82
71	Architectural & engineering services	0.0530	0.0013	3.86	8.36
99	Other goods & services	0.0490	0.0024	1.18	4.11
45	Construction work	0.0417	0.0005	4.00	8.23

Note: the table is sorted by R-A clustering in the descending order. R–A clustering stands for Robins–Alexander clustering, a measure of the local correlation of connectivity in bipartite networks (Robins & Alexander, 2004).

Figure A. 1 Correlation heatmap of variables used in modeling

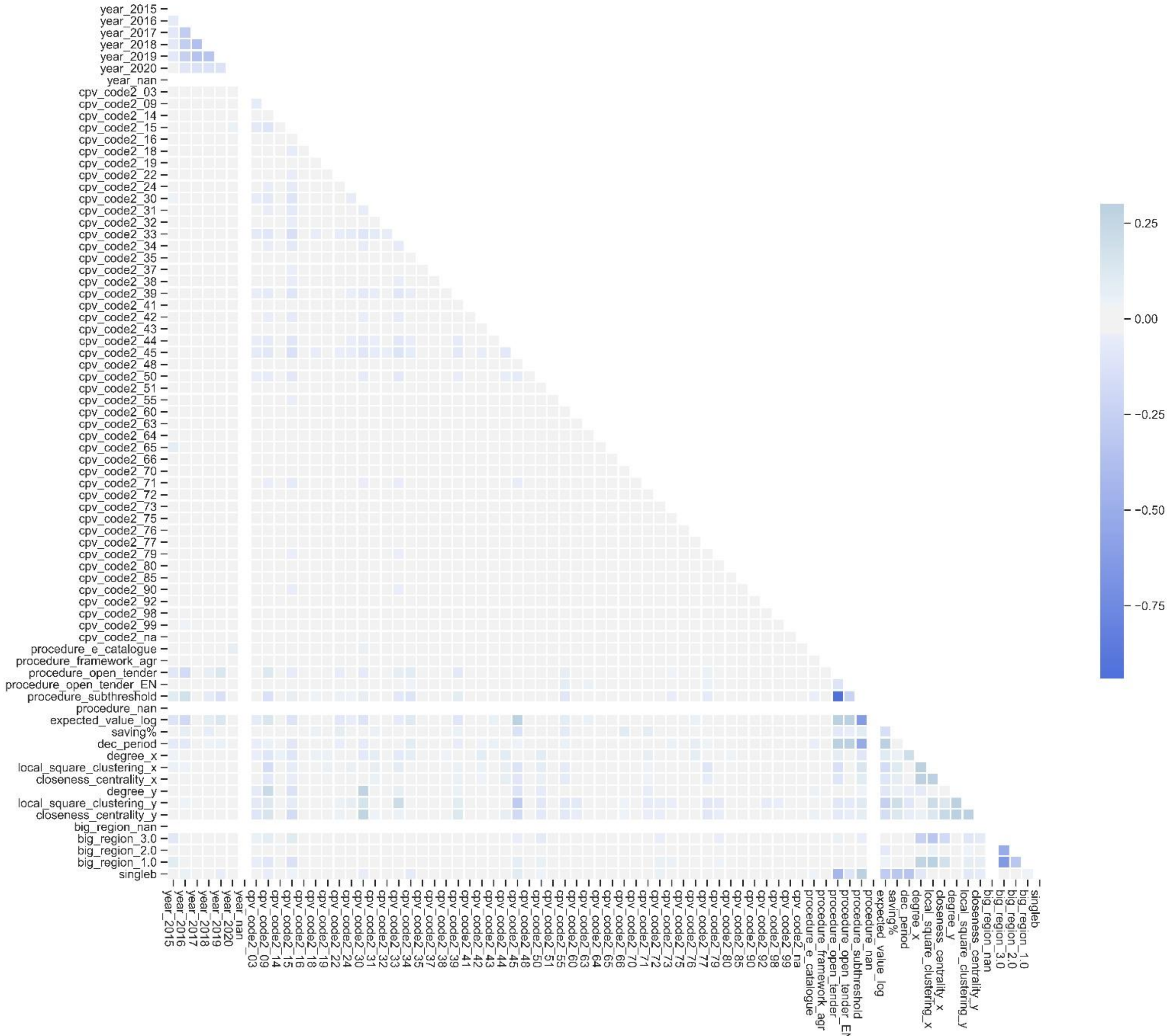

Figure A. 2 Histograms of numeric variables used for modeling

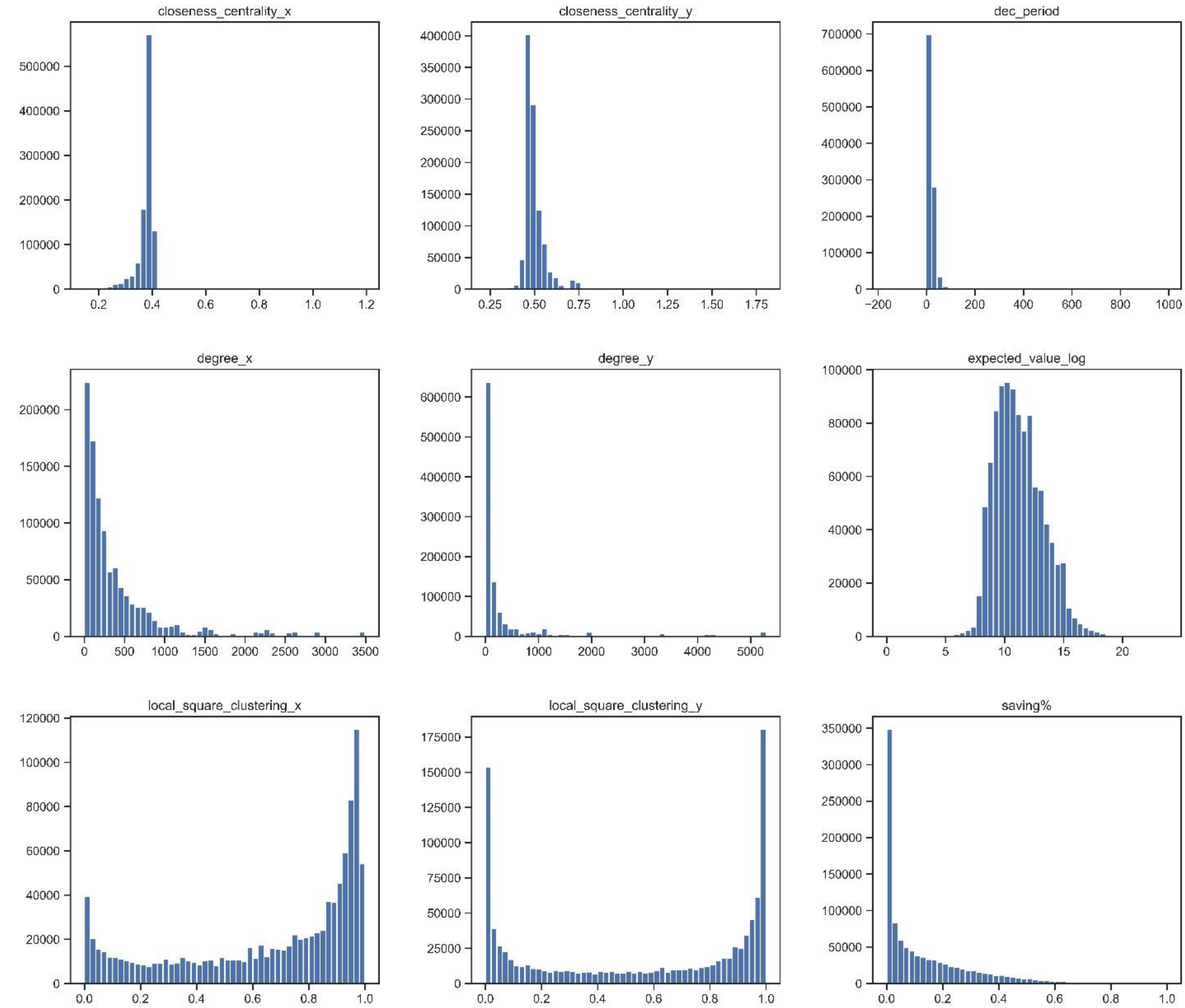

Table A. 2 Evaluation scores for developed models obtained through 10-fold cross-validation

	Test Accuracy	Root mean square error	Test Precision	Test Recall	Area under ROC curve	Pseudo R^2 (Nagelkerke)
Model 1	0.661	0.582	0.472	0.913	0.778	0.213
Model 2	0.663	0.581	0.473	0.912	0.782	0.364
Model 3	0.663	0.581	0.473	0.912	0.782	0.414
Model 4	0.663	0.581	0.473	0.912	0.781	0.491
Model 5	0.666	0.578	0.476	0.907	0.784	0.532
Model 6	0.799	0.449	0.615	0.903	0.905	0.598
Model 7	0.847	0.391	0.682	0.929	0.944	0.654
Model 8	0.849	0.389	0.686	0.929	0.946	0.677
Model 9	0.849	0.389	0.686	0.929	0.946	0.711
Model 10	0.849	0.388	0.686	0.929	0.946	0.719
Model 11	0.849	0.388	0.687	0.929	0.946	0.720
Model 12	0.849	0.388	0.686	0.929	0.946	0.720
Model 13	0.849	0.388	0.687	0.928	0.946	0.720
Model 14	0.850	0.387	0.687	0.929	0.948	0.724