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Using beneficial ownership data for large-scale risk assessment in public procurement. The example of 6 European countries

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Abstract

This paper fills a critical gap in the literature, providing practical insights into employing beneficial ownership data for large-scale corruption risk assessment in public procurement, with potential implications for public policy and practice. Existing literature lacks systematic evidence on using beneficial ownership (BO) data for large-scale corruption risk assessment. Hence, this paper aims to validate common indicators of corruption and money laundering in BO data in relation to public procurement. By doing so it also generates hypotheses on the impact of beneficial ownership registers on the organisation of financial crime. Analyzing administrative datasets of public procurement contracts matched with beneficial ownership registers for 6 countries (Denmark, Estonia, Latvia, Slovakia, Ukraine, and the UK) this paper utilizes ordinary least squares regressions to identify the relation between risk variables of BO with corruption risk indicators in public procurement. We find that BO-based risk indicators capturing unusual and outlier BO features - high company frequency of BO, frequent information change, outlier BO age, and no BO data - all perform in line with expected results. However, BO-based risk indicators relating to BO country such as offshore jurisdictions largely fail to relate to public procurement corruption risks in line with expectations, even though there are notable examples where we find the hypothesized relationships. Finally, BO data-based risk indicators which have already been widely validated in the literature using different data sources - company age and political connections - also turn out to be valid in our regressions. Our findings lend support to the growing use of BO data in research, policy, and investigations.

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Introduction

In order to avoid the use of corporate structures for money laundering, corruption, and other financial crimes, beneficial ownership registers have been created in several countries since 2015. These registers contain information on the beneficial owners (BO) or natural persons who ultimately own or control a company, as well as other legal entities like funds and trusts. One of the reasons behind the creation of these registers is that having this information available on a central register that is public can deter individuals from misusing corporate structures for a number of crimes. Given the increasing availability of BO data, there is a great need for better understanding the quality of these datasets, as well as for evaluating their usefulness for anticorruption purposes. The interest that this transparency policy has sparked has made it a busy and contested policy field which, nevertheless, still lacks rigorous evidence.

Although a series of articles have been written regarding the potential benefits of having BO data, there is still a lack of systematic evidence that proves the use of these datasets for the prevention, detection, investigation, and sanctioning of financial crimes. Some articles have been written to analyze the effect that BO registers have in deterring crime in real estate (*Collin et al, 2023*), as well as to understand large-scale ownership data networks and financial secrecy (*Garcia-Bernardo et al, 2017*). Still, there is a need to map the mechanisms in place that explain the different impacts that this policy has as well as to derive risk indicators from BO data.

In light of this, the overarching objective of this paper is to lay the groundwork for the emerging literature related to the use of beneficial ownership data for systematic risk assessment as well as for policy-relevant impact studies. In order to do so, *this paper conducts validity tests of the most common indicators of money laundering and corruption in beneficial ownership datasets*. Validity testing is enabled by linking BO data and risk indicators to public procurement data and its already validated risk indicators. By doing so, it also generates testable hypotheses about the impact of beneficial ownership transparency on financial crime.

This paper tests the usefulness of risk indicators in beneficial ownership data for large-scale risk assessment in 6 countries: Denmark, Estonia, Latvia, Slovakia, United Kingdom, and Ukraine. The selection of these countries reflects a series of considerations. First, data with sufficient scope and quality has to be available in order to conduct large-scale indicator validity testing. This means that we needed public access to procurement and beneficial ownership datasets covering a prolonged and overlapping time period. Second, a diverse set of countries were selected in order to offer sufficient variation in integrity and prevalence of high-level corruption. Testing the same indicators with the same methods in countries experiencing different levels of corruption allows us to arrive at more generalisable results. Third, the countries selected in the analysed time period followed approximately the same legal frameworks regarding beneficial ownership information and public procurement. These similarities allow for keeping our cases, while separately analysed, roughly comparable in their fundamental legal and data infrastructures, holding a number of intervening variables constant.

We test the validity of a wide range of proposed BO risk indicators by using 2 core validity concepts (*Adcock and Collier, 2001*):



1) Theoretically, we conduct content validation, that is we show that each BO risk indicator is in line with our corruption definition and that they capture theoretically coherent actor strategies pertaining to corruption.

2) Empirically, we conduct convergent validity tests, by correlating BO risk indicators with public procurement corruption risk indicators while controlling for as many confounding factors as possible.

We define corruption in public procurement as the violation of open and impartial access to government contracts in order to benefit a favored company or network of individuals (Fazekas et al., 2023). Risky beneficial owners or ownership patterns point at potential corruption and related crimes, as they underpin corrupt rent extraction from government contracts and support hiding the corrupt. Hence, content validation means for us to explain why and how specific BO risk indicators point at likely efforts to hide owners or proceeds in public procurement; or alternatively how BO patterns reveal that there is a corrupt network at work in public tenders. An example for the former would be a company whose owner looks like a nominee or strawmen, hence we expect that corrupt motives would be ripe behind using such a company for winning a corrupted tender. An example for the latter case would be a company with conflict of interest such as one of the company's owners being a political office holder. In other words, we need to show that an indirect (signs of hiding) or direct (high risk relationship revealed) link is likely to exist between corruption in the winning supplier and corruption in its contract. For empirically testing convergent validity, we lean on already validated corruption risk indicators in public procurement (Fazekas and Kocsis, 2020). If corruption takes place in a public tender won by a particular company, we expect risks to show up both in the tender itself and the winning bidder. Naturally, public procurement corruption can happen through completely legit and non-risky firms, however it tends not to be the case. Hence, we claim that corruption is measured form 2 different angles: using 2 different datasets and 2 different sets of risk indicators. The correlation between BO and public procurement data-based risk indicators is hence evidence for validity. Given that there are many confounding factors in public procurement corruption, that is factors which lead to high-risk features in the data without necessarily corruption taking place, we need to control for a number of factors such as market or contract value.

However, given that corruption is a deliberately hidden phenomenon, we expect BO data to carry little direct evidence for corruption risks and instead indirect signs to be most indicative of corruption risks. This is because direct evidence of risky connections such as a political officeholder owning a company winning a government contract is relatively easy and comparatively cheap to hide. This can be done for example through the appointment of a nominee or registering the company in an offshore country where BO transparency regulations do not apply, or establishing an ownership complex structure, where beneficial owners remain hidden behind a trust (Knobel, 2017). This does not mean that there is no chance of direct evidence for corruption risks in BO datasets, it may well be that the risk of punishment is perceived to be so low by corrupt actors (e.g. they think that their political connections would block any investigation or court case against them) that they do not care to hide obvious risky connections visible in BO datasets. It may also be the case that linking data from different administrative datasets (either in different countries or different datasets) can reveal direct signs of corruption risks which is not anticipated by corrupt actors. Nevertheless, indirect evidence, indicative of the intent to conceal information, is what is more likely to correlate with public procurement corruption risks. Such tell-tale signs for circumventing transparency regulations could include missing values, data errors, unreasonable values, and unusual records in the BO registers. In our empirical, validity testing



below we will explore both content validity and convergent validity using indirect and direct risk indicators.

Institutional background

As beneficial ownership transparency requirements represent the key source of information for the subsequent analysis, we briefly review the common EU BO framework, its short history and a few key details of each country's regulatory framework. This sets the scene for understanding the strengths and weaknesses of the BO data analysed and potential ways to circumvent transparency requirements.

As part of strengthening the regulatory framework against money laundering, the financing of terrorism, and other financial crimes, the EU approved the 4th Anti-Money Laundering (AML) Directive in 2015. This directive required each Member State to establish a central register that contained information on the beneficial owners of companies. In this directive, a beneficial owner (BO) is defined as the natural person who ultimately owns or controls a company.¹ In response to the rise in new threats for money-laundering activities (e.g. cryptocurrencies) the 5th AML Directive was published in 2018, considerably extending the BO framework. Among others, this directive required Members State to make the existing central BO registers public. Although there had been considerable advances regarding the creation and publication of central beneficial ownership registers since the 5th AML Directive, the Court of Justice of the European Union (ECJ) ruled in 2022 that the publicity of BO data conflicts with privacy rights and therefore these registers should no longer be publicly accessible. After the publication of this sentence, many countries in the EU closed access to their beneficial ownership registers (*Martini, 2024*).

Each of the 6 countries analysed for this paper has comparable albeit somewhat different laws and regulations for BO registers. These establish the scope of the legal vehicles that are obliged to declare their beneficial owners, as well as definitions of direct and indirect ownership that further determine which companies and owners must comply with transparency requirements. Table 1. presents a brief summary of the main characteristics of each of the registers used in this paper. In the following section, we provide a brief recount of the beneficial ownership registers in these countries. Since the empirical analysis focuses on public procurement contracts awarded to companies that have beneficial ownership information available, the discussion concentrates on BO information of companies, excluding funds and trusts.

¹ <u>https://lexparency.org/eu/32015L0849/</u>



Table 1. Beneficial Ownership Registers characteristics

	Denmark	Estonia	Latvia	Slovakia	Ukraine	UK
Name	Central Business Register (CVR)	e-business register	Registry of Enterprises	Public Sector Partners Register (RPVS)	Unified State Registry (USR)	People with significant control register (PSC)
Launch date	May 2017	2018	2017	2017	September 2015	April 2016
Sector	Full-economy	Full-economy	Full-economy	Procurement	Full-economy	Full-economy
Authority	Danish Business Authority	Commercial Register	Ministry of Justice	Ministry of Justice	Ministry of Justice	Companies House
Laws involved	Act amending the Companies Act, the Certain Commercial Undertakings Act, the Corporate Funds Act and various other acts	Money Laundering and Terrorist Financing Prevention Act	Law On the Enterprise Register of the Republic of Latvia	Act on the Register of Public Sector Partners (ARPSP)	On State Registration of Legal Entities, Individual Entrepreneurs and Public Associations	Small Business Enterprise and Employment Act
Link	https://datacvr.vi rk.dk/artikel/cvr- webservices	https://ariregiste r.rik.ee/eng	https://info.ur .gov.lv/#/data -search	https://rpvs.g ov.sk/rpvs	<u>https://usr.minju</u> <u>st.gov.ua/</u>	https://find- and- update.compan Y- information.ser vice.gov.uk/
Open to public	Yes	Yes	Yes	Yes	Yes	Yes
Threshold to determine beneficial ownership	25%	25%	25%	25%	25%	25%



Denmark

Denmark launched its Central Business Register (Det Centrale Virksomhedsregister CVR in Danish) in 2017. This register is the responsibility of the Danish Business Authority and collects data on Danish companies and their ultimate beneficial owners. The CVR specifies that only natural persons can be considered beneficial owners, other legal vehicles like companies and trusts, cannot be considered BOs.² The threshold of ownership that is considered for the mandatory registration of a beneficial owner is to have above 25% ownership or control. Lower thresholds of ownership or voting rights of a company should be reported if they imply significant control over the company, as well as having the right to appoint members of the board. Indirect ownership of Danish companies, either via a Danish or foreign company or trust, is referred to as legal owners and are not considered beneficial owners; only natural persons can be registered as BOs. State-owned enterprises, publicly listed companies, and small personally owned businesses are excluded from registering their BOs.

Estonia

Following the publication of the Money Laundering and Terrorist Financing Prevention Act,³ Estonia launched its beneficial ownership register as part of its e-business register in 2018. According to Estonian regulation, a beneficial owner –in the case of a company– is considered a natural person who ultimately owns or controls the company by exerting direct or indirect control of it by holding a significant percentage of shares, voting rights, or other ownership interests. Following this act, we can establish that direct control of a legal vehicle is considered when a person owns more than 25% of a company, whereas indirect control refers to ownership through one or more companies that also own more than 25% of the referred company. The entities required to submit their BO information include private and public limited companies, partnerships, commercial associations, foundations, non-profit organizations, and trusts. Companies listed on regulated markets with sufficient disclosure requirements, as well as building and apartment associations, are exempted to declare their BOs.

Latvia

Latvia launched its Registry of Enterprises (Latvijas Republikas Uzņēmumu reģistrs) in 2017. The data of this register is collected by the Ministry of Justice and gathers information from companies, listed companies, European Companies (SE), associations, foundations, public-private partnerships, political parties, and religious organizations. According to Latvian regulation, the beneficial owner that is registered has to be a natural person, it cannot be a legal person. In order to be recognized as BO the threshold of ownership over 25% of shares or voting rights applies, as well as being a natural person who exercises significant control over the company.⁴

² https://danishbusinessauthority.dk/beneficial-

 $[\]underline{owners\#:} \sim: text = Companies\% 20 must\% 20 register\% 20 information\% 20 about, this\% 20 information\% 20 must\% 20 be\% 20 register and ered.$

https://danishbusinessauthority.dk/sites/default/files/media/act_amending_the_companies_act_ect._-_implementation_of_register_of_beneficial_owners.pdf

³ <u>https://www.riigiteataja.ee/en/eli/517112017003/consolide</u>

⁴ <u>https://www.ur.gov.lv/lv/patieso-labuma-guveju-skaidrojums/biedribas-arodbiedribas-politiskas-partijas/</u>

Slovakia

Slovakia has two beneficial ownership registers: the Register of legal entities, entrepreneurs and Public Authorities (RPO), which has data on beneficial ownership of all the Slovak companies, and the Public Sector Partners Register (RPVS), which has data on the beneficial owners of all companies and legal entities that have won a public procurement contract. The RPVS is the data we analyzed for this paper and was created in 2017. This register is under the administration of the Ministry of Justice of the Slovak Republic. In the RPVS a beneficial owner has to be a natural person, either Slovak or foreign that owns indirectly or directly 25% or more percentage of the shares or voting rights. If a person benefits from 25% of the company's dividends it also counts as a BO. A BO can also be a person who exerts significant control over the management and board of the company. If the owner is another legal entity, it still has to declare, who are the natural persons who benefit from it.⁵ In this register, there are few exemptions since this register reports all legal entities that conduct business with the state.

Ukraine

Ukraine was the first country in the world to establish a public central beneficial ownership register in the year 2015. Following the Revolution of Dignity in October 2014 a series of anti-corruption laws were passed. The Unified State Register of Legal Entities, Individual Entrepreneurs and Civic Formations contains information about beneficial owners of Ukrainian companies. The government's "National Information System", part of the Ministry of Justice, is the authority in charge of this register. After a series of legal reforms, it was mandated to include in this register information on beneficial owners as well as a visual representation of the ownership structure, however, this last point has not been implemented yet.⁶ According to the previous changes, the beneficial owner is a natural person who directly or indirectly, independently or together with other individuals or entities, owns at least 25% of shares or voting rights of the company, or directly or indirectly performs ultimate control over management or business activities of a company, or has ultimate control over the conclusion of contracts by the company, or has a right to give obligatory instructions or perform functions of managerial body.

United Kingdom

The United Kingdom was also one of the first countries in the world to establish a public beneficial ownership register. In April 2016, the People with Significant Control Register (PSC) was launched. The data of this register is collected by the Companies House and has information on UK companies, European Companies (SE), Limited Liability Partnerships (LLP), and their beneficial owners. According to English law, a beneficial owner or person with significant control is someone that has one of the following characteristics: over 25% of shares or voting rights; the power to modify the company's board, the right to exercise control of the firm, or of the legal vehicle that controls the firm or company in

https://www.ur.gov.lv/en/explanation-of-beneficial-owners/general-and-limited-partnerships/

⁵ <u>https://register.openownership.org/data_sources/sk-rpvs-register</u>

https://deepnote.com/@open-ownership/Slovakia-RPVS-dashboard-fb4b6afa-2b39-4261-baaf-887071a2d62d

⁶ <u>https://openownershiporgprod-1b54.kxcdn.com/media/documents/oo-impact-story-ukraine-2022-02_z0DqeyY.pdf</u>

question. (complete the indirect ownership explanation) Companies that are listed in a US or European regulated markets are excluded from the PSC.⁷ It is important also to note that the UK has another register of beneficial owners: the Register of Overseas Entities (ROE). In 2022, the ROE was created as a response to the invasion of Ukraine, this register contains information on offshore companies and their beneficial owners that own real estate property in the UK. In this paper, the data of the ROE was not analyzed.

Data

This paper analyses administrative datasets of public procurement contracts matched with beneficial ownership registers in 6 countries (Denmark, Estonia, Latvia, Slovakia, UK, and Ukraine) considering a period between 2009 to 2022, although this changes by each country analysed. In the following section, we describe the beneficial ownership and procurement data that was used to conduct the analysis, as well as the matching process involved.

Beneficial Ownership data

Two data sources, the OpenOwnership Register and National BO registers, were used to collect BO data for the analysis. Although every country contains different BO information, all datasets contain the companies' unique IDs, the full name of the beneficial owner, and his or her nationality.

The Denmark and Slovakia datasets were collected from the OpenOwnership Register⁸. Denmark's dataset contains information about companies, including registration and dissolution dates, as well as historical data about the beneficial owners, type of ownership (shareholding or voting rights), and exact period of ownership. Danish data also has information on the percentage of shares controlled by a natural person. Slovakia's beneficial ownership dataset has information about the company that includes the entry date to the electronic register. The critical limitation of this dataset is that the data does not contain information about when a person becomes a company's controller. Previously, Slovakia's dataset had information only on approximately 11,000 companies, however, after the March 2024⁹ update it contains more than 30,000 companies.

Information about companies' beneficial owners in Estonia¹⁰, Latvia¹¹, Ukraine, and the UK¹² was collected from the respective national BO registers' websites. Neither Latvia's nor the UK's data has information about the companies' names, only company IDs. Hence, in these countries, company names had to be additionally collected in order to improve matching to public procurement data which often only has names of the winning suppliers, but not the IDs. The Latvian and UK datasets have BOs'

⁷ <u>https://register.openownership.org/data_sources/uk-psc-register</u>

https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/753028/170623_NON-STAT_Guidance_for_PSCs_4MLD.pdf

https://www.openownership.org/en/map/country/united-kingdom-of-great-britain-and-northern-ireland/

⁸ <u>https://bods-data.openownership.org/</u>

⁹ <u>https://bods-data.openownership.org/source/slovakia</u>

¹⁰ <u>https://avaandmed.ariregister.rik.ee/en/downloading-open-data</u>

¹¹ <u>https://data.gov.lv/dati/eng/dataset/patiesie-labuma-guveji/resource/20a9b26d-d056-4dbb-ae18-9ff23c87bdee</u>

¹² <u>http://download.companieshouse.gov.uk/en_pscdata.html</u>



dates of birth. This information allowed us to calculate the beneficial owners' age when the company bid on a procurement process. The Latvian dataset does not have a historical data and it only started on December 01, 2017, but it provides the date when a person became a beneficial owner of the company. The UK provides daily dumps of beneficial ownership data with historical data. The data for the analysis was collected in May 2022. Estonian beneficial ownership data contains information about the BOs and their unique identifiers as well as the date when the person became a beneficial owner.

Although Ukraine was the first country to open its beneficial ownership register publicly, it has the biggest limitations of the countries analysed for this paper. Firstly, Ukraine closed access to the machine-readable format of the data because of the Russan-Ukrainian war. This was done for security concerns as the BO dataset contains the full addresses of registered companies and of the companies' owners. Therefore, the last data available for Ukraine is a dump from February 22, 2022, which does not contain historical changes or the date when the beneficial owner was submitted. Secondly, addresses are not structured in the Ukrainian dataset, given that one owner can submit different passports and registration addresses. Because of the absence of a unique identifier (a tax ID is considered personal data), the algorithm will identify him/her as a different person. Finally, affiliate companies do not register as separate legal entities and do not provide any data to the register. However, they can participate in public procurement procedures and provide economic activity.

Public procurement data

Public procurement data for Denmark, Estonia, Latvia, Slovakia, and the UK were collected from <u>https://opentender.eu/</u> and have already been standardised to make them follow the same structure and data quality standards. As Ukraine is not part of opentend.eu, Ukrainian public procurement data was collected from the BI-Prozorro module¹³. Denmark has the smallest public procurement dataset, with only 55,000 unique contracts. However, it covers the period between 2006 and 2022. In contrast, Ukraine's procurement data consists of 7.6 million unique contracts but covers only the period from 2016 to 2022. Additionally, only Ukrainian procurement data contains almost all bidders' IDs, allowing high-quality data matching. However, because of the war, some procurement procedures were closed in 2022, and data was removed from the public domain. This caused the absence of key details about the procurement procedure and did not allow for calculating all corruption risk indicators for the Ukrainian data. The datasets of the rest of the countries have a limited number of bidder/supplier IDs. The UK procurement data has the lowest coverage of bidder ID information.

Data matching process and scope of datasets used for the analysis

In order to match procurement and beneficial ownership datasets, procurement data needed considerable pre-processing (Table 2). First, all contracts without bidder names were removed. Second, foreign bidders were removed from the Danish, Estonian, Latvian, and the UK datasets since these registers have no information about foreign companies. Finally, these procurement datasets were considered from the year when the BO register started operating, dropping public procurement

¹³ <u>https://bipro.prozorro.org/qlikview/FormLogin.htm</u>



data from earlier years. Slovakia represents an exception to the last 2 preparatory steps. As it also contains BO information for foreign firms, here we did not remove foreign suppliers. Also, as the Slovakian register includes sufficient historical data, we did not have to drop public procurement data from before the creation of the BO register.

Any citizen or tax resident in Ukraine can register as an Individual Entrepreneur, which is a form of sole proprietorship. Because of this, they are allowed to participate in public procurement processes and are not required to provide information about beneficial owners. Therefore, bids where individual entrepreneurs or sole traders are winners were removed from the Ukrainian procurement dataset. Additionally, Ukraine has a low threshold for reporting of public procurement, therefore, bids with a tender price lower than 250,000 UAH have been removed from the datasets.

In Slovakia, submission¹⁴ of beneficial ownership information is mandatory only for private companies participating in public procurement processes and also for companies winning contracts with the government for an amount of at least 100,000 EUR. Therefore, the data for contracts for a lower quantity were removed.

In our study countries, publicly listed joint-stock companies are not obliged to provide information about their beneficial owners. In Ukraine and the UK, a company can submit a notice that it does not have a beneficial owner or cannot identify one. At any rate, we removed publicly listed companies from the dataset as BO data for them was not available.

The matching process was adapted to context for each country. The first step was matching datasets by company IDs in each country. Because of recent transparency reforms in the Ukrainian public procurement system, procurement data is well structured and contains all companies' tax ID numbers. This allowed us to achieve high matching accuracy. Estonia's procurement dataset has almost all bidders' tax IDs and in addition, well-structured beneficial ownership data. Based on these factors, Estonia has the highest matching rate among all the countries analysed (Table 2). Given the availability of tax ID numbers, neither Ukrainian nor Estonian data needed matching by names of the companies. Only affiliate companies and foreign bidders were not covered by the matching process because removing them from the procurement dataset was impossible and there were no tax ID numbers for them. In contrast to Ukraine, the United Kingdom has the lowest coverage by bidders' IDs in its procurement dataset.

Matching by names, the second step, was applied in the case of Denmark, Slovakia, and the UK. Setting to lower case (removing capital letters) was applied first. For the UK and Slovakia, non-alfanumeric characters were removed. Companies' names in the UK have different forms of writing depending on the company types (for example, Ltd or Limited), therefore, company types were removed. This allowed us to significantly improve the percentage of matching. However, this also increased the possibility of mistakes.

The final step in matching for Denmark, Estonia, Latvia, and the UK was filtering by year. This allowed us to match information about beneficial owners while also taking into consideration a historical perspective. Since the BO data has a historical timeframe in the Danish dataset, we used all the records

^{14 &}lt;u>https://transparency.sk/wp-content/uploads/2017/06/Register-of-beneficial-ownership_study2017.pdf</u>



in the public procurement dataset as long as there was a matching rate higher than 10% of the sample. As a result, the matching period for Denmark is from 2016 to 2021.

Fable 2. Description of the matched dataset used in the analysis									
	Matched_years	No of companies in bo register	No of bid IDs	No of bids with BOs	% of bids with BOs				
Country									
Latvia	2017-2021	154418	138513	64890	46.8				
Denmark	2016-2021	429513	23277	7295	31.3				
UK	2016-2021	8317840	126282	40045	31.7				
Slovakia	2009-2021	11052	63699	38834	61.0				
Ukraine	2016-2022	2045940	7603582	5011844	65.9				
Estonia	2018-2022	275985	42376	32220	76.0				

One company in the matched dataset may have more than one beneficial owner. Therefore to work with the contract-level data of procurement BO data has been aggregated. For numerical variables, minimum or maximum values have been used.

Indicators and theoretical expectations

This section starts by introducing public procurement corruption risk indicators which serve as the dependent variable in our models. Give that they are already widely validity tested, they can be treated as a reference point for prospective BO data-based indicators. After that, this section enumerates widely discussed BO data-based risk indicators which are feasible to calculate given commonly available BO datasets. This discussion not only describes what each indicator is, but also discusses the rationale behind them, i.e. why they signal the risk of corruption and money laundering rather than other phenomena. Hence, we carry out a content validation exercise.

Dependent variable: Public procurement Corruption Risk Index

To identify possible cases of corruption in the public procurement data analyzed for this paper, we use the Corruption Risk Indicator (CRI), a proxy measure of high-level corruption (Fazekas and Kocsis, 2020). The methodology behind this indicator reflects the conceptualisation of corruption as the violation of open and impartial access to government contracts in order to benefit a favoured company or network of individuals (Fazekas et al., 2023). The CRI is a composite score that takes into consideration several risk indicators or "red flags" in procurement processes, like having a single bidder in the process or having a non-open procedural type (The full list of indicators used in each country can be found in Table 3). The CRI is constructed so that a higher indicator value signals a higher risk of corruption in a procurement contract. In line with the above definition of corruption, the red flags that make up the CRI approximate a range of strategies corrupt groups use to bias the tendering process and achieve favouritistic tendering results. Taken together the indicators composing the CRI represent



a robust measure of potential corrupt contracting spanning across many widely documented corrupt scenarios. For a full description of these public procurement corruption risk indicators used in the analysis see Fazekas et al (2024), while further theoretical background and evidence for indicator validity can be found in Fazekas and Kocsis (2020).

Table 3.	Descriptive statistic	s for the Corruption Risk Index a	nd its components by country

	corr_singleb	corr_proc	corr_subm	corr_nocft	corr_tax_haven	corr_decp	corr_buyer_concentration	cri
count	709002.000000	372299.000000	242220.000000	821660.000000	5791.000000	193962.000000	712948.000000	821660.000000
mean	0.525927	0.147081	0.392581	0.602042	0.461924	0.477235	0.092332	0.427724
std	0.499328	0.326826	0.442801	0.489477	0.498591	0.399139	0.180417	0.259675
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.003278	0.250037
50%	1.000000	0.000000	0.000000	1.000000	0.000000	0.500000	0.019398	0.369131
75%	1.000000	0.000000	1.000000	1.000000	1.000000	1.000000	0.088987	0.668365
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

Independent variables: beneficial ownership risk indicators

Following a comprehensive literature review and verifying whether BO datasets in the 6 countries enable indicator calculation, 10 BO-risk indicators were selected for in-depth analysis. These indicators not only indicate corruption but also money laundering and other financial crime according to the literature. Still our discussion narrows in on corruption in public procurement in order to remain succinct and focus on validity testing. The 10 indicators roughly fall into 3 broad categories: i) unusual and outlier BO features (high company frequency of BO, frequent information change, outlier BO age, and no BO data); ii) BO country (foreign BO, Chinese BO, BO from sanctioned countries; offshore-based BO); and iii) BO data-based risk indicators which have already been widely validated, as they are available from established sources other than BO registers (company age and owners' political connections).

Number of companies owned by the same beneficial owner

The first BO data-based risk indicator we discuss is the number of companies that are owned by the same person (Table 4). Although there are legitimate reasons why one person can own several companies, this can also be a signal that the owner is a nominee or strawmen and that the underlying personal data is fraudulent. If a powerful corrupt group decides to put nominees to front its companies winning public contracts it might want to spread its risks of detection by setting up a great number of companies and bid independently with them in public tenders. Given the initial set-up cost of identifying and controlling nominees, it is optimal for the corrupt group to use one or a small set of nominees rather than one nominee for each company. This gives rise to our BO-based risk indicator, unusually high number of companies registered to the same person, given of course the person is not a known millionaire/billionaire of the country legitimately owning a great number of companies. The ease with which fake identities can be used for setting up companies and the lack of verification of personal

information make this corruption scheme low risk and low cost for corrupt groups¹⁵. As this indicator aims to track unusually high company frequency, when aggregating from the individual to the company level (note that one company can have multiple beneficial owners), we took the highest value among the company's owners as the aggregate company value.

Table 4. Descri	otive	statistics	of the	indicator:	Number	of	companies	owned	by	the	same
beneficial owner	r, by d	country									

	bo_freq_DK	bo_freq_LV	bo_freq_SK	bo_freq_UA	bo_freq_UK	bo_freq_EE
descriptive						
count	7295	57057	32067	1234966	21381	27316
mean	14	3	2	7	4	6
std	18	4	2	32	24	8
min	1	1	1	0	1	1
25%	4	1	1	1	1	2
50%	8	2	1	1	2	3
75%	17	4	3	3	4	6
max	202	122	16	495	1324	311

Frequency of BO information change

The number of changes, especially outlier and very frequent changes, in a company's BO information is our second risk indicator (Table 5). A high number of changes in ownership structure could indicate the intent to avoid regulatory scrutiny, for example by changing owners just for the period when the company's owners are checked for bid assessment. It could also represent a change in ownership structure intending to evade sanctions levied at some of the true or original owners, or circumventing conflict of interest rules preventing political office holders to own a company winning government contracts. Nevertheless, the number of BO data changes is only a crude proxy for these tactics, as only 1 or a few changes could achieve corrupt goals on their own, if the corrupt group is skilled and careful. While, when the corrupt group is incompetent or faces considerable infighting within the group, our indicator might be closer to corrupt behaviours. Changes in ownership to evade sanctions represent a typical manoeuvre performed by corrupt and high-profile actors. For example, Arkady Rotenberg, a close friend of Vladimir Putin and owner of two of Russia's biggest construction contractors, changed the ownership of one his firms, Milasi Engineering, to his son to evade sanctions after the annexation of Crimea in 2014.¹⁶ Similarly, Alexey Mordashov used this technique to transfer the ownership of several of his companies (Nordgold and TUI) to his wife after being targeted with EU sanctions in

¹⁵ See some recent investigations on such schemes in: <u>https://www.bbc.co.uk/sounds/play/m001qtdy</u> and

https://www.accountingweb.co.uk/business/finance-strategy/companies-house-registration-reform-tackles-fraud

¹⁶ <u>https://www.forbes.com/sites/giacomotognini/2022/03/09/evading-sanctions-a-how-to-guide-for-russian-billionaires/</u>

relation to the invasion of Ukraine.¹⁷ This risk indicator could only be calculated for the Danish and Estonian BO datasets due to data constraints.

bochanges_freq_EE	bochanges_freq_DK	descriptive
31217	7295	count
1	1	mean
0	0	std
1	1	min
1	1	25%
1	1	50%
1	2	75%
7	11	max

Table 5. Descriptive statistics of the indicator: Frequency of BO information change, by country

No Bo data

A straightforward indication of the intent to circumvent transparency rules and hence potentially aiming to hide corruption, is when a company's owner does not comply with BO reporting requirements. Hence, missing BO information is our third BO data-based risk indicator. When a company bids for a government contract, often ownership information and various declarations by the owners are required which could be checked against a BO register. However, when the company fails to submit the information on its BOs, it can submit incomplete or misleading documentation to the bid evaluation committee, hence it may avoid proper scrutiny or hide conflict of interest.

Failing to submit BO information is a technique for avoiding scrutiny and hence represents a risk factor in real estate too. More than two thirds of corporate-owned real estate in France are owned anonymously, meaning by companies that have not declared their BOs (*Brimbeuf et al., 2023*). This is enabled by the lack of verification of BO data by authorities. Although in France it is mandatory for companies to declare their ultimate Beneficial Owners, a third of legal entities (more than 1.53 million legal entities registered in France) have not declared their ultimate BOs.

While this indicator is straightforward conceptually, it is hard to measure because there are a wide range of exceptions to BO transparency requirements (see Institutional background section above); and also because data matching errors might lead to missing BO information in our database even if it is de facto available. Moreover, it is also possible, if unlikely, that BO data is missing because of an error in submitting information or the company not being able to identify a BO. Hence, this indicator was calculated using the lack of matched BO-procurement data with some modifications taking into account these potential biases. Whenever possible we removed sole entrepreneurs and joint stock

¹⁷ https://www.reuters.com/article/business/germany-investigates-ownership-change-at-tuis-top-russian-shareholder-idUSKCN2LF0W1/



companies without BO requirements. In Ukraine and the UK, BO data contains a specific notification of not being able to identify or find a BO which we used as the no BO information flag in the analysis.

Age of beneficial owners

A further indication of hiding the true BOs and instead using a nominee BO is the anomalous age of the beneficial owner, this is our fourth BO risk indicator. Although there is nothing illegal about having a minor or an elder as the ultimate BO of a company, there has been extensive documentation of corruption risks involved having minors and elders as nominees (*Bosisio et al., 2021; European Banking Authority 2021; Carbone et al., 2023*). For example, in Mexico, elders from rural provinces were asked to give their personal information to be declared as legal representatives of shell companies used to divert public funds in exchange for some small economic compensation in a national corruption scheme brought to light thanks to the famous journalistic investigation "La Estafa Maestra".¹⁸

This indicator could be calculated in Latvia, Slovakia and the UK (Table 6). Aggregating from the individual to the company level, both the age of the oldest and youngest beneficial owner of the company were used.

	bo_age_SK	bo_age_LV	bo_age_UK
descriptive			
count	32067	8792	21381
mean	54	58	54
std	9	10	12
min	15	26	0
25%	48	51	47
50%	55	58	55
75%	61	68	63
max	92	86	93

 Table 6. Descriptive statistics of the indicator: Age of beneficial owners, by country

Beneficial Owner with foreign nationality

BOs from foreign countries typically represent additional challenges to verifying the individual's true identity and personal information such as address. Such additional hurdles might open the door for using a nominee or a non-existent person as BO for a company which bids in public tenders. If the true owners face conflict of interest restrictions or other risky relations in the country of the tender, hiding behind a foreign nominee could fuel corrupt contracting.

According to FATF recommendations related to beneficial owners, it is important that countries have a risk-based approach to foreign-created legal persons that have considerable links to the country in

¹⁸ <u>https://contralacorrupcion.mx/web/estafamaestra/</u>



question, like winning public procurement contracts. This includes having access to up-to-date and verified information regarding the ultimate BOs of legal entities, to avoid the use of nominee arrangemenents (*FATF, 2023*). The World Bank also considers that multijurisdiction splitting, the case where networks of legal structures split their structures of ownership and asset administration, through the use of bank accounts and intermediaries located in different juridictions, could be done to avoid the imposition of sanctions and detection of illicit activities, which is why it is important to detect the persons involved in this type of administrative scheme (*World Bank, 2022*).

This indicator takes all foreign countries as a potential source of corruption risk while subsequent BO country-based indicators will only focus on specific groups of countries which represent particular risks (Table 7). In this sense, this BO risk indicator is rather broad-based, hence potentially biased, compared to the other BO country-based indicators. Still, given the complexity of individual national rules, we argue that such a generic risk factor could already be informative.

When aggregating from the individual to the company level, we flagged companies as risky whenever at least one of the company's BOs is a foreigner compared to the country where the public tender takes place.

	Count_UA	Count_DK	Count_SK	Count_LV	Count_UK	Count_ES
Category						
Domestic	1205096	7224	33974	56862	19384	27264
No data	20248	15839	25610	73623	108840	10156
Developed countries	13877	81	11613	8760	1861	4727
Developing countries	16978	0	449	65	745	0
Risky foreigners:	7479	59	4650	270	434	182
China	542	11	18	6	37	2
Sanction countries	4296	0	924	189	184	9
Offshore	3183	48	3708	75	213	171

Table 7. Descriptive statistics of the indicator: Foreign BO by country group

Beneficial owner from China

A company having at least one beneficial owner who is a Chinese citizen is our next BO country-based indicator. China and Hong Kong appear on a number of lists related to money laundering risks as well as lists based on media investigations related to corruption and money laundering scandals. For example, China appears in the United States' International Narcotics Control Strategy Report (INSCR) of "Major money laundering countries".¹⁹ It also appears as one of the top 20 countries most frequently cited in the Panama and Pandora Papers in relation to the number of companies, companies' directors and intermediaries they had in these two investigative journalism investigations (*Riccardi, 2022*). Given

¹⁹ https://www.state.gov/wp-content/uploads/2019/03/INCSR-Vol-INCSR-Vol-2-pdf.pdf

Chinese companies' high corruption risks and presence on a range of sanctions lists, BOs from China could be more ready to engage in corruption than domestic firms or firms with owners from high integrity countries such as Finland.

Beneficial owner from a sanctioned country

Similarly to the logic behind considering Chinese BOs as risky, we also put forward a risk indicator flagging companies with at least one BO from a sanctioned country: Russia, Belarus, Iran and North Korea. Many beneficial ownership regulations include the need to identify and check BOs that appear on a sanctions list. Nonetheless, sometimes there is a lack of verification of this information by the authorities in charge of public BO registers (*Russell-Prywata et al., 2023*). Given that individuals from sanctioned countries, already before the imposition of sanctions, are more likely to carry out corrupt acts, often in pursuance of their home country's strategic interests, we consider them as an indication of potential corruption.

Beneficial owner from an offshore jurisdiction (citizenship or

residence)

A company having at least one BO residing in or being the citizen of an offshore jurisdiction our strongest BO country-based risk indicator. One of the prime motivations for creating BO registers has been to track corrupt individuals hiding behind secrecy jurisdictions. For example, the UK passed the Economic Crime Bill (ECB) in 2022 mandating the creation of the Register of Overseas Entities, to list the beneficial owners of companies that own real estate in the UK. According to the analysis of Collin et al. (2023), after passing this bill, the purchase of property by companies based on tax havens fell substantially. One of the findings of the Panama Papers and the Pandora Papers is the systematic use of offshore companies for tax evasion, money laundering, and corruption (*ICIJ, 2016 & 2021*). Such jurisdictions allow the corrupt to hide their identity, avoid conflict of interest regulations, and move their corrupt proceeds without detection.

Latvian and UK datasets contain information not only on nationality but also on the residence of the beneficial owner. Offshore jurisdictions usually have regulatory deficiencies regarding their anti-money laundering and combat corruption regulations. This makes them an ideal place to set up residence to avoid the declaration of ownership rights of a company.

Although there exists an agreement on identifying companies registered in high-risk jurisdictions, the problem is that there is not a unique list of flagged offshore countries since each has a unique set of anti-AML/CTF regulatory deficiencies. For the purposes of this paper, we identified companies registered in the "consensus list" of tax havens used by Menkhoff and Miethe (2019); Bomare and Herry (2022); and Collin et al. (2023).

Company age

If a company wins a big procurement contract the same year it was founded this could signal to a corruption risk given the lack of experience and skills (*Fazekas and Tóth, 2017*). Having a relatively new company win a contract could signal to a corruption scheme where companies are founded to win a tailored tender and end up subcontracting other companies with more experience. The age of a company when it participates in procurement processes is a risk factor that could be calculated with



the data of some beneficial ownership registers which is relevant for us, even though such information has already widely been available from company registers.

Only with the BO data of Denmark and Slovakia could this BO risk be calculated (Table 8). It is important to state that Slovakia's BO data has the entry date to the electronic BO register which in some cases is later than the actual company registration, which gives a negative number in some cases.

	company_age_SK	company_age_DK
descriptive		
count	57906	7295
mean	16	19
std	7	13
min	-5	0
25%	11	10
50%	17	17
75%	22	28
max	68	90

Table 8. Descriptive statistics of company age, by country

Beneficial Owner that is a Politically Exposed Person

A widely documented and used corruption risk indicator is the government supplier having a political connection that is at least one of its BOs being flagged as a Politically Exposed Person (*Goldman et al, 2013*). Political office holders owning a company bidding in public tenders can use their connections and knowledge of the inner functioning of government agencies to secure favoured treatment for their firms. Hence, companies with a PEP BO are expected to engage in high corruption risk tenders more often.

Nonetheless, the availability of PEP data only for Ukraine could allow for the identification of BOs of companies who were also PEPs in the Ukrainian dataset (Table 9). Ukraine does not have an official register of PEPs, however, we had access to the data of the Anti-Corruption Action Centre –which was the first register of PEPs in the country.

Table 9. Number of contracts by PEP link, Ukraine

BO PEP	Count
PEP	7838
Not PEP	1246563



Methods

The empirical validity testing logic employed in this paper follows Adcock and Collier (2001), specifically relying on the concept of convergent validity. By implication, we are looking for associations among indicators of corruption and money laundering in public procurement between BO data-based risk factors and already validated public procurement data-based risk indicators. Specifically, we conduct a series of linear regressions for each country with the public procurement-specific Corruption Risk Index (CRI) as the dependent variable and the BO data-based risk factors as independent variables (IVs) of interest. Each BO indicator is tested on its own while controlling for a range of confounding factors. Control variables are the following: the year of the tender, the main product market (Common Procurement Vocabulary-CPV codes), the estimated tender price, buyer type, and buyer location (NUTS code). Taken together, these control variables account for structural and market conditions determining background risk levels such as the expected rate of single bidding even in the absence of corruption. We run our models country by country in order to fully consider country-specific risk patterns and data systems.

As some of the variables of interest and control factors have relatively high missing rates, we typically transform them into deciles with an additional missing category. This allows us to keep all relevant observations in the model while explicitly tracking the impact of missing values. This is crucial also for risk indicator development, given that often the lack of information can signal corrupt intent. In addition, we expect non-linear relationships whereby a wide range of indicator values have little to no bearing on risks, while at a certain threshold, risks jump. To model such effects, turning our key predictors of interest in the BO data into deciles is useful as it can trace null effects and sudden jumps by decile. Even though linear regressions are not adept at capturing non-linear associations and thresholds, the use of deciles and the careful assessment of each category's coefficients allow us to sufficiently model the expected relationships.

Results

This section presents the main results concerning the relationships between BO data- and public procurement data-based indicators. First, we offer a high-level overview of each country and BO indicator; second, we highlight some typical relationships to provide a detailed interpretation reflecting on our theory.

Results overview

Table 10 summarises the results from the OLS regressions for each BO indicator in each country (for full regression details see Annex C). Additionally, we also report simple linear correlation coefficients in Annex A as a reference. Whenever the BO risk indicator derives from a continuous distribution such as the number of companies a BO owns, we look for extreme values and outliers which would indicate likely wrongdoing. We sliced continuous distributions into deciles and verified which category increases CRI in the regressions. This approach reflects on the expectation that a wide range of indicator values are plausible, hence low risk (e.g. a person owning 2-3 or even more companies), while unusually high or low values could indicate deliberate hiding or obfuscation (e.g. a person owning hundreds of companies). In the case of binary indicators, no such approach was needed, we could simply test them

as is. Not all tests were possible (see n/a values in Table 10) due to lack of data. This typically means that the necessary variable was missing in the BO dataset (e.g. many BO datasets do not record company foundation year, hence company age risk indicator cannot be calculated). N/a can also mean that while the underlying data is theoretically available, in practice there was little to no variation for conducting meaningful statistical tests (e.g. only a handful of public procurement suppliers with owners linked to China).

Table 10. Summary of main results: BO features impacting public procurement corruption	n
risks	

Risk Indicator	Denmark	Estonia	Latvia	Slovakia	Ukraine	UK
Company frequency by BO	Yes (top 10%: 31-202)	Yes (top 20% 8 - 312)	Yes (top 10% 7-122)*	n/a	Yes (top 10%: 8-495)	Yes (top 10%:9-1324)
BO information change frequency	Yes (top 1%: 4 - 11)	Yes (top 1%: 3 - 7)	n/a	n/a	n/a	n/a
No BO data	No	No	Yes	Yes	Yes	Yes
BO age in years (max)	n/a	n/a	Yes (top 10% 71-86)	Yes (top 1 % 78-92)	n/a	Yes (bottom 10%: 0-37)
BO country: Foreign	No	No	No	Yes	No	Yes
BO country: China	n/a	n/a	n/a	n/a	No	Yes (residence)
BO country: Sanctions	n/a	n/a	No	No	No	Yes (residence)
BO country: Offshore jurisdictions	No	n/a	Yes (residence)	Yes	No	Yes (residence)
Company age in years	Yes (bottom 10%: 0-4)	n/a	n/a	Yes (bottom 3%: 0-2)	n/a	n/a
BO PEP	n/a	n/a	n/a	n/a	Yes	n/a

Notes* 1 outlier was removed

While unfortunately not all hypothesized relationships could be tested in all countries, an overwhelmingly positive and varied picture of BO-based risk indicator validity emerges in Table 10. First, BO-based risk indicators capturing unusual and outlier BO features - high company frequency of BO, frequent information change, outlier BO age, and no BO data - all perform very well, as expected. The no BO data indicator occasionally works in the opposite direction which may indicate matching quality issues rather than a lack of indicator validity. Second, BO-based risk indicators relating to BO

countries such as offshore jurisdictions largely fail to relate to public procurement corruption risks in line with expectations, even though there are notable examples where we find the hypothesized relationship. This is, hence, unsurprising, the very goal of BO registers was to uncover individuals hiding behind secrecy jurisdictions. Nevertheless, the fact that a large number of BOs from offshore and other high-risk jurisdictions can still be found among public procurement winners with high corruption risks is unexpected and notable. It may indicate that enforcement risk is perceived to be low among BOs in high-risk jurisdictions, so they do not consider revealing their identity as threatening. Finally, BO-based risk indicators which have already been widely validated using different data sources - company age and political connections - also turn out to be valid in our regressions. This provides further evidence of the value of BO datasets and the robustness of our methodology.

Detailed results by BO-based risk indicator

Regarding the *company frequency by BO indicator*, we expect that unusually high values indicate elevated corruption risks in public procurement, unless the individual is a known billionaire which is expected to be rare. This is exactly the relationship we find in all countries where such information is reliably available, that is in Denmark, Estonia, Latvia, Ukraine, and the UK. Taking the example of the UK, we find that a low to moderate number of companies owned by the BO of the public procurement supplier are associated with average CRI after controlling for a host of confounders. However, when the number of companies is very large or outlier, we find a distinct jump in procurement risks. The riskiest interval of this indicator corresponds to the top 10% of values, ranging from 9 to 1324 companies owned by the very same person (Figure 1). The UK has the most extreme outliers for this indicator, while other countries also have implausibly high values going up to 100-300 companies per individual. This risk indicator however could not be reliably calculated for Slovakia, where not all companies are required to provide information about their beneficial owners²⁰ only companies that have contracts with the government of an amount higher than 100 thousand euros have to declare their BOs.

²⁰ <u>https://transparency.sk/wp-content/uploads/2017/06/Register-of-beneficial-ownership_study2017.pdf</u>



Using beneficial ownership data for large-scale risk assessment in public procurement.



Figure 1. CRI and the number of companies owned by the same BO in the UK

Regarding the indicator on *BO information change frequency*, we expect that multiple changes in the data for a company's BOs relates to higher public procurement corruption risks. This is because changes in BO administrative records may obfuscate real ownership, for example around checks on the company bidding for a contract. Although we could only calculate this indicator in Denmark and Estonia, both countries' results point at the hypothesized positive relationship. In Estonia, the range of risky values fall between 3 and 7 changes, corresponding to the top 1% of the BO information change distribution (Figure 2). In Denmark, high risk BO indicator values are rather similar, 4 to 11 changes, again corresponding to the top 1% of the continuous distribution.

Figure 2. CRI and the number of changes to BO data in Estonia





With regards to the no BO data indicator, we expect that having no beneficial owner information is associated with higher public procurement corruption risks, as not fulfilling reporting requirements can effectively block scrutiny. This hypothesized relationship could be identified in 4 out of 6 countries: Latvia, Slovakia, Ukraine, and the UK (Figure 3). In Ukraine, after the passing of legislation where a bidder can be banned from participating in procurement processes due to the lack of submitting information about its beneficial owners, we appreciated a decrease in the number of companies with no BO information, which can explain the strong relationship we see between having no BO data and higher risks in CRI. In all of our countries, the no BO information is most likely a noisy measure of actually neglecting legal requirements. This is due to a number of potential data errors and complications. Public procurement datasets have a limited number of bidder ID codes that make the matching less accurate, for example in the UK. A further problem is posed by subsidiaries of publicly listed companies from abroad. While we could identify domestically listed companies and hence remove them from the analysis (listed companies do not have to submit BO data), if the ultimate owner company is listed abroad we could not reliably identify the relevant domestic subsidiaries so they remain in the analysis even though they have legitimate reasons for not submitting BO data.





Regarding the age of the BO, we expect extremely young or old owners to be related to higher CRI as these individuals are more likely to be nominees or strawmen. We saw such relationships in all the countries where we have the necessary data: Latvia, Slovakia, and the UK. Nevertheless, the particular age group related to a higher risk of corruption in public procurement changes by country. In the UK, BOs younger than 37 years (i.e. bottom 10% of the age distribution) are riskier (Figure 4-Panel A); while in Latvia, BOs older than 71 years (i.e. top 10%) are related to higher public procurement risks (Figure 4-Panel B). Slovakia is similar to Latvia, showing higher risks among older BOs.



Figure 4. CRI and the age of the beneficial owner Panel A. UK



Panel B. Latvia



Now we turn to *BO country, either citizenship or residency*. Regarding foreign BOs, the expectation is that foreign BOs might escape scrutiny by virtue of being foreigners, e.g. identity checks. However, this indicator is likely very noisy grouping a range of more or less risky countries under one category. In line with this, foreign BOs are not associated with higher corruption risks in 5 out of 6 countries, with the UK being the only exception where foreigners are of higher risk across the board. We also put forward specific hypotheses relating to several specific categories of BO countries (citizenship or residence) most of which do not find empirical support in most countries. The only country where we find consistent support for higher public procurement corruption risks associated with BOs from specific groups of countries - China, sanctioned countries (Russia, Belarus, Iran), and offshore jurisdictions (e.g. Cayman Islands) – is the UK (Figure 5). The foreign China and sanctioned countries indicators do not work with any of the other public procurement country datasets where tests could be conducted.

However, the indicator of BOs linked to offshore jurisdictions works as expected not only in the UK, but also in Latvia and Slovakia; while we do not find the expected relationship in Denmark and Ukraine. These partially confirming results suggest that some BOs do not find it threatening to reveal their association with secrecy jurisdictions, probably assessing that their risk of prosecution remains low. Unfortunately, due to the too low number of observations, we could not test many of the BO country-based indicators, data was especially sparse in Estonia.





Now we turn to testing ownership-based indicators already established in the literature. With regards to the relationship between the age of the company at the time of receiving the contract and corruption risks in public procurement, we expect to see very younger companies to have higher CRI. This is exactly what we saw in both countries where we had the necessary information to calculate this indicator: Denmark and Slovakia. In Denmark, companies younger than 4 years, i.e. those in the bottom 10% of the company age distribution, display considerably higher public procurement corruption risks (Figure 6). For Slovakia, the interval for heightened corruption risks corresponds to less than 2 years, that is the bottom 3% of the distribution.









Regarding the validity of Politically Exposed Persons (PEPs) or companies with political connections, we expect that PEP BOs display higher corruption risks in public procurement. This is exactly the empirical relationship we find in Ukraine, the only country where the necessary political connections data is available (Figure 7). These findings coincide with a number of well-documented cases. Some of the country's high-profile PEPs, like Rinat Akhmetov, Mykola Zlochevskyi, Oleksandr Novynskyi, are connected with companies that provide services to the state, specifically in the energy sector (oil, gas, and electricity). Regarding this issue, there are several journalistic investigations²¹ that show a tendency of overpriced services and unfair procurement competition connected with PEP's companies in Ukraine.



Figure 7. CRI and BOs that are Politically Exposed Persons in Ukraine

Conclusions and implications

The above analysis has amply demonstrated the value of linked beneficial ownership data and the new horizons it opens up for analysing risks related to companies but also to government contracts. We showed at scale, across 6 very different European countries that some, albeit not all, theoretical expectations for BO data-based risk indicators are valid. In particular, indicators that relate to BO features, other than country, and indicators related to the company (e.g. company age at the time of winning contract) are promising. The prime indicator types motivating BO registry creations, related to secrecy and high-risk jurisdictions turned out to be only moderately valid. This result, we speculate, might be driven by corrupt actors switching from hiding behind secrecy jurisdictions to using brokers and nominees.

One of the underlying goals of BO risk indicator validation is to use them for systematic risk assessment across countries as well as over time within the same country; or looking at mezo and micro actors such as regions or individual procuring authorities. In order to demonstrate the scale of the uncovered

²¹ <u>https://nashigroshi.org/2020/02/04/yaku-marzhu-ziat-zlochevs-koho-maie-na-hazovykh-tenderakh/</u>



valid BO risk indicators and their relevance we tabled the share of government contracts going to a flagged supplier (Table 11). This simple descriptive statistics reveals that Denmark and the UK often, albeit not always, harbour lower BO risks than their lower integrity peers such as Ukraine. Even though, the lack of comparable data and valid indicators across all 6 countries limits the cross-country comparability of results. Nevertheless, the prevalence of various risk factors range from the niche (0.03, 0.6, 0.7, etc.) to widespread (50-60% of contracts). This is hardly surprising as the BO risk indicators capture very different potential corruption schemes and they suffer from data quality errors to different degrees. Unsurprisingly, lack of BO data is the most wide-spread risk factor which almost certainly include both benign administrative errors and corrupt intent.

In order to additionally demonstrate the statistically desirable properties of the validated BO risk factors, we also show that they vary over time within the same country (Figure 8). Denmark and the UK show a stable low prevalence of this BO risk factor, while Ukraine substantially lowers its prevalence.

Risk Indicator	Denmark	Estonia	Latvia	Slovakia	Ukraine	UK
Company frequency by BO	4.0%	13.8%	7.7%	n/a	12.3%	1.6%
BO information change frequency	0.2%	3.2%	n/a	n/a	n/a	n/a
No BO data	not valid	not valid	53.2%	39.0%	25.9%	68.3%
BO age in years (max)	n/a	n/a	0.7%	0.6%	n/a	1.7%
BO country: Foreign	not valid	not valid	not valid	5.9%	not valid	0.2%
BO country: China	n/a	n/a	n/a	n/a	not valid	0.02%
BO country: Sanctions	n/a	n/a	not valid	not valid	not valid	0.2%
BO country: Offshore jurisdictions	not valid	n/a	0.2%	5.8%	not valid	0.03%
Company age in years	3%	n/a	n/a	1.5%	n/a	n/a
BO PEP	n/a	n/a	n/a	n/a	0.6%	n/a

Table 11. Prevalence of validated BO risk features in public procurement





Our results also point out the diversity of company and procurement system contexts and the corresponding diversity of risky transactions and features. While the indicator calculation and measurement logics are generic, their country-specific realisations are highly diverse and context-dependent. This also includes great differences across countries in terms of data quality. Given that missing information can serve as a reliable risk indicator on its own, the relationship between the usefulness of BO datasets and their quality is by no means straightforward. We hope that these results will increase the trust in BO datasets for systematic risk assessment purposes and will inspire further research validity testing and optimally parametrising BO data-based risk indicators.

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Annexes

Annex A. Linear correlations between BO indicators and public procurement risk indicators

Table A1 Correlation table: CRIs vs indicators

	cri_dk	cri_lv	cri_sk	cri_ua	cri_uk	cri_ee
variables						
bo_freq	0.008612	-0.018036	0.004758	0.066039	0.013776	-0.002855
bochanges_freq	0.015948	NaN	NaN	NaN	NaN	0.043085
bo_age	NaN	0.027873	-0.020753	NaN	-0.129931	NaN
bo_foreigner_risk	0.006014	-0.009311	-0.008182	-0.030110	-0.001221	0.004793
bo_foreigner_china	0.005050	0.007630	0.002700	-0.008378	-0.002403	-0.010553
bo_foreigner_sanctions	NaN	-0.008490	-0.008639	-0.024627	-0.000260	0.007789
bo_foreigner_offshore	0.004247	-0.006341	0.013021	-0.015455	0.018025	0.004297
bo_pep	NaN	NaN	NaN	0.030142	NaN	NaN
no_bo	0.000005	0.063704	0.048072	0.212816	0.082947	-0.070431

Table A2. Correlation table: Single bid vs. BO risk indicators

	corr_singleb_dk	corr_singleb_lv	corr_singleb_sk	corr_singleb_ua	corr_singleb_uk	corr_singleb_ee
variables						
bo_freq	-0.004670	0.014973	-0.071546	0.073647	0.023274	-0.033122
bochanges_freq	0.047447	NaN	NaN	NaN	NaN	0.049900
bo_age	NaN	0.015758	0.014920	NaN	-0.060871	NaN
bo_foreigner_risk	0.008219	-0.007208	-0.031819	-0.028919	-0.006883	0.007344
bo_foreigner_china	-0.012949	0.001015	-0.001364	-0.008057	0.004008	NaN
bo_foreigner_sanctions	NaN	-0.010986	-0.031950	-0.023802	-0.009549	0.004749
bo_foreigner_offshore	0.021181	0.003001	0.079887	-0.014645	0.013952	0.006342
bo_pep	NaN	NaN	NaN	0.033700	NaN	NaN
no_bo	0.070892	0.010175	-0.043303	0.207076	0.082589	0.046310



Annex B. Description of the matched dataset used in the analysis

Table B1.

Country 2016 960 920 1880 3937 207874 568 940 0.238760 0.302 2017 1016 749 1765 4105 251869 670 1216 0.296224 0.373 2018 1118 645 1763 3603 278525 712 1121 0.31130 0.403 2019 1315 615 1930 4271 295713 872 1437 0.336455 0.433 2020 1112 661 1773 4191 305620 779 1441 0.43832 0.433 2021 1015 590 1605 3168 317475 716 1139 0.359533 0.444 2022 1 1 2 2 324299 1 1 0.50000 0.500 Demmark 6537 4181 10718 2327 429513 4318 7295 0.31339 0.402 2017 4622 632 <	28 03 57
2016 960 920 1880 3937 207874 568 940 0.238760 0.303 2017 1016 749 1765 4105 251869 670 1216 0.296224 0.373 2018 1118 645 1763 3603 278525 712 1121 0.311130 0.403 2019 1315 615 1930 4271 295713 872 1437 0.336455 0.457 2020 1112 661 1773 4191 305620 779 1441 0.343832 0.433 2021 1015 590 1605 3168 317475 716 1139 0.359533 0.444 2022 1 1 2 2 324239 1 1 0.50000 0.500 Denmark 6537 4181 10718 23277 429513 4318 7295 0.313399 0.402 2017 4622 632 5254	28 03 57
201710167491765410525186967012160.2962240.374201811186451763360327852571211210.3111300.403201913156151930427129571387211370.3364550.455202011126611773419130562077914410.343820.433202110155901605316831747571611390.359530.44420221122324239110.500000.500Denmark653741811071823277429513431872950.313390.402Countryvisitation of the second o	03 57
2018 1118 645 1763 3603 278525 712 1121 0.311130 0.403 2019 1315 615 1930 4271 295713 872 1437 0.33645 0.455 2020 1112 661 1773 4191 305620 779 1441 0.43832 0.438 2021 1015 590 1605 3168 317475 716 1139 0.359533 0.448 2022 1 1 2 2 324239 1 1 0.50000 0.500 Denmark 6537 4181 10718 23277 429513 4318 726 0.31339 0.442 Country Line Line bider_mark 6537 0.09463 0.004 2017 4622 632 5254 2567 751 46 243 0.00463 0.004 2018 4465 131 4596 26291 15638 740 4791 0.18220 0.662 2019 4050 117	57
2019 1315 615 1930 4271 295713 872 1437 0.336455 0.457 2020 1112 661 1773 4191 305620 779 1441 0.343832 0.438 2021 1015 590 1605 3168 317475 716 1139 0.359533 0.444 2022 1 1 2 2 324239 1 1 0.50000 0.500 Denmark 6537 4181 10718 23277 429513 4318 7295 0.31339 0.402 Country bidder_id bidder_name sum_com bid_id company_bo_counts bidder_matched bids_matched bid_cov bidder_matched bid_cov bidder_matched bid_cov bidder_matched 0.09463 0.00463	
202011126611773419130562077914410.3438320.433202110155901605316831747571611390.3595330.44620221122324239110.5000000.500Denmark653741811071823277429513431872950.3133990.402bidder_idbidder_namesum_combid_idcompany_bo_countsbidder_matchedbids_matchedbid_covbidder_outCountry4622632525425679751462430.0094630.00220174622632525425679751462430.0094630.002201844651314596262911563874047910.1822300.166201940501174167279541064823512174640.6247410.8424202040396884107273101184324018200280.7333580.978202139999734972312791315604236223640.7149840.653Latvia2117519212309613851315441812552648900.4684760.544bidder_idbidder_namesum_combid_idcompany_bo_countsbidder_matchedbids_matchedbid_covbid_cov2009121030115113302062	13
202110155901605316831747571611390.3595330.446202211223242391110.500000.500Denmark653741811071823277429513431872950.3133990.402bidder_idbidder_namesum_combid_idcompany_bo_countsbidder_matchedbids_matchedbid_covbidder_20174622632525425679751462430.0094630.008201844651314596262911563874047910.1822300.166201940501174167279541064823512174640.6247410.84220204039684107273101184324018202280.7333580.978202139999734972312791315604236223640.7149840.857Latvia2117519212309613851315441812552648900.4684760.543bidder_idbidder_namesum_combid_idcompany_bo_countsbidder_matchedbid_matchedbid_matchedbid_matched0.645972bidder_idbidder_namesum_combid_idcompany_bo_countsbidder_matchedbid_matched0.6459720.41166	68
202211223242391110.500000.500Denmark653741811071823277429513431872950.3133990.402bidder_idbidder_namesum_combid_idcompany_bo_countsbidder_matchedbids_matchedbid_covbidder_ov201746226325254256797514662430.0094630.006201844651314596262911563874047910.1822300.166201940501174167279541064823512174640.6247410.84220204039684107273101184324018200280.7333580.978202139999734972312791315604236223640.7149840.857Latvia2117519212309613851315441812552648900.4684760.543bidder_idbidder_namesum_combid_idcompany_bo_countsbidder_matchedbid_covbidder_covbidder_cov2009121030115113302062221330.6459720.41166	06
Denmark 6537 4181 10718 23277 429513 4318 7295 0.313399 0.402 bidder_id bidder_name sum_com bid_id company_bo_counts bidder_matched bids_matched bid_cov bidder_cov 2017 4622 632 5254 25679 751 46 243 0.009463 0.008 2018 4465 131 4596 26291 15638 740 4791 0.182230 0.166 2019 4050 117 4167 27954 106482 3512 17464 0.624741 0.842 2020 4039 68 4107 27310 118432 4018 20028 0.733358 0.978 2021 3999 973 4972 31279 131560 4236 22364 0.71498 0.857 Latvia 21175 1921 23096 138513 154418 12552 64890 0.468476 0.543 bidder_id	00
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2019 4050 117 4167 27954 106482 3512 17464 0.624741 0.842 2020 4039 68 4107 27310 118432 4018 20028 0.733358 0.978 2021 3999 973 4972 31279 131560 4236 22364 0.714984 0.85 Latvia 21175 1921 23096 138513 154418 12552 64890 0.468476 0.543 bidder_id bidder_name sum_com bid_id company_bo_counts bidder_matched bids_matched bid_cov bidder_country 2009 1210 301 1511 3302 0 622 2133 0.645972 0.41164	10
2020 4039 68 4107 27310 118432 4018 20028 0.733358 0.978 2021 3999 973 4972 31279 131560 4236 22364 0.714984 0.85 Latvia 21175 1921 23096 138513 154418 12552 64890 0.468476 0.543 bidder_id bidder_name sum_com bid_id company_bo_counts bidder_matched bids_matched bid_cov bidder_cov Country 2009 1210 301 1511 3302 0 622 2133 0.645972 0.41164	13
2021 3999 973 4972 31279 131560 4236 22364 0.714984 0.85 Latvia 21175 1921 23096 138513 154418 12552 64890 0.468476 0.543 bidder_id bidder_name sum_com bid_id company_bo_counts bidder_matched bids_matched bid_cov bidder_cov 2009 1210 301 1511 3302 0 622 2133 0.645972 0.41164	30
Latvia 21175 1921 23096 138513 154418 12552 64890 0.468476 0.543 bidder_id bidder_name sum_com bid_id company_bo_counts bidder_matched bids_matched bid_cov bidder_co Country 2009 1210 301 1511 3302 0 622 2133 0.645972 0.41164	71
bidder_id bidder_name sum_com bid_id company_bo_counts bidder_matched bids_matched bid_cov bidder_co Country 2009 1210 301 1511 3302 0 622 2133 0.645972 0.41164	71
Country 2009 1210 301 1511 3302 0 622 2133 0.645972 0.41164	
2009 1210 301 1511 3302 0 622 2133 0.645972 0.41164	
2010 1171 290 1461 3560 0 624 2425 0.681180 0.42710	
2011 1082 357 1439 4520 0 638 3224 0.713274 0.44336	
2012 1971 372 2343 6330 0 1196 4756 0.751343 0.51045	
2013 1619 158 1777 5561 0 968 4126 0.741953 0.54473	
2014 1936 13 1949 6611 0 1195 5242 0.792921 0.61313	
2015 2624 307 2931 8358 0 1652 6263 0.749342 0.56363	
2016 2085 114 2199 5823 0 1752 5251 0.901769 0.79672	
2017 1559 33 1592 4339 0 110 232 0.053469 0.06905	
2018 1875 28 1903 4201 0 74 192 0.045703 0.03888	
2019 1781 16 1797 3776 0 712 1753 0.464248 0.3962	
2020 1560 12 1572 3510 0 584 1560 0.444444 0.37150	
2021 1672 8 1680 3808 0 649 1677 0.440389 0.3863	
Slovakia 22145 2009 24154 63699 11052 10776 38834 0.609649 0.44613	



Using beneficial ownership data for large-scale risk assessment in public procurement.

	bidder_id	bidder_name	sum_com	compa	ny_bo_counts	bidder_	matched	bid_id	l bids_matche	d bid_cov	bidder_cov
Country											
2016.0	24571	24550	24571		0		13061	163638	9922	0 0.606338	0.531562
2017.0	45031	45067	45031		0		23428	460864	28062	4 0.608908	0.520264
2018.0	50261	50385	50261		0		27731	548050) 34985	1 0.638356	0.551740
2019.0	51817	51888	51817		0		30635	573969	37989	0 0.661865	0.591215
2020.0	54179	54286	54179		0		33532	688434	47649	7 0.692146	0.618911
2021.0	55341	55440	55341		0		35241	828953	3 55684	7 0.671747	0.636797
2022.0	41480	41427	41480		2045940		26881	537883	36299	3 0.674855	0.648047
Ukraine	645360	646086	645360		2045940		381018	7603582	2 501184	4 0.659142	0.590396
0	bidder_id	bidder_name	sum_com	bid_id	company_bo_	_counts	bidder_n	natched	bids_matched	bid_cov	bidder_cov
Country	1400	45450	40500	01001		007400		4440	0700	0.070004	0.047075
2016	1439	15150	16589	31284	2	907429		4112	8/22	0.278801	0.247875
2017	1549	9933	11482	23375	3	3933191		3680	/4/8	0.319914	0.320502
2018	1642	9132	10774	25857	4	704740		3542	7755	0.299919	0.328754
2019	1793	8759	10552	23813	5	516679		3663	7255	0.304666	0.347138
2020	1833	6434	8267	12234	6	6448112		3348	5070	0.414419	0.404984
2021	1510	4130	5640	9719	7	370504		2490	3765	0.387386	0.441489
UK	9766	53538	63304	126282	8	317840		20835	40045	0.317108	0.329126
	bidder_id	bidder_name	sum_com	bid_id	company_bo_	counts	bidder_m	atched	bids_matched	bid_cov	bidder_cov
Country											
2018	2254	1	2255	6680		123205		1624	4496	0.673054	0.720177
2019	2474	1	2475	7716		156018		1962	5992	0.776568	0.792727
2020	3143	1	3144	8470		186726		1432	4350	0.513577	0.455471
2021	2488	0	2488	9457	2	219000		2141	8149	0.861690	0.860531
2022	2774	1	2775	10053	2	245427		2494	9233	0.918432	0.898739
Estonia	13133	4	13137	42376	2	275985		9653	32220	0.760336	0.734795





Annex C. Full regression results underpinning Table 10

Denmark

Table C1. BO	Frequency.	Denmark	ζ.			
predictor of interest	$\operatorname{coefficient}$	stand e	rror p	o-values	t	-test
BO frequency from 1 to 5	0					
BO frequency from 6 to 20	0.002390	0.004	1790 0	.617160	0.499	9880
BO frequency from 21 to 30	0.009720	0.007	780 0	.211520	1.249	9430
BO frequency from 31 to 202	0.020120	0.006	6980 O	.003960	2.881	1700
BO frequency NaN	0.002350	0.002	2080 0	.260020	1.12	6380
Number of observations $= 23134$ R-squared $= 0.794785$						
*Control variables are Main CPV, Ten	der price, B	uyer's type	e, and N	UTS num	ber.	
Table C2. Compa	any age in y	years. De	nmark			
predictor of interest	coefficien	t stand	error	p-value	s	t-test
Company age from 0 to 4	0.018860	0.0	08330	0.023500) 2.	265400
Company age from 5 to 30	-0.002240	0.0	05420	0.678910) -0.	413960
Company age from 31 to 90	0					
Company age NaN	0.000660	0.0	02720	0.808090) 0.	242890
Number of observations $= 23134$ R-squared $= 0.794778$						
*Control variables are Main CPV, Te	ender price,	Buyer's ty	pe, and	NUTS nu	mber.	
Table C3. BO information	change frequ	ency. Dem	mark			
predictor of interest	C	oefficient	stand e	rror p-v	values	t-test
BO information change frequency from	m 1 to 2 ()				
BO information change frequency from	n 3 to 3 (0.006360	0.011	300 0.5	73270	0.563250
BO information change frequency from	m 4 to 11 (0.076400	0.024	200 0.00	01590	3.157310
Number of observations $= 23134$ R-squared $= 0.794792$		1.000890	0.001	.020 0.58	80370	0.552850



Using beneficial ownership data for large-scale risk assessment in public procurement.

predictor of interest	coefficient	stand error	p-values	t-test	R-squared		
BO foreigner risk dummy	0.022050	0.023504	0.348230	0.938044	0.794709		
No BO data	0.000580	0.001608	0.719020	0.359776	0.794701		
Number of observations $= 23134$							
*Control variables are Main CPV, Tend	der price, Buy	er's type, a	nd NUTS nur	mber.			
Table C5	5. Foreigner	rs. Denma	ark				
Table C5 predictor of interest	5. Foreigner	rs. Denma	ark nd error	p-values	t-test		
Table C5 predictor of interest	coeffici	rs. Denma ient sta	ark nd error	p-values	t-test		
Table C5 predictor of interest Domestic	6. Foreigner coeffici 0	rs. Denma ient sta	ark nd error	p-values	t-test		
Table C5 predictor of interest Domestic Developed	coeffici 0 0.0011	rs. Denma ient stat 20 (nd error 0.021300	p-values 0.958030	t-test 0.052630		
Table C5 predictor of interest Domestic Developed Offshores	5. Foreigner coeffici 0 0.0011 0.0213	rs. Denma ient sta 20 (90 (ark nd error 0.021300 0.025810	p-values 0.958030 0.407350	t-test 0.052630 0.828580		
Table C5 predictor of interest Domestic Developed Offshores China	5. Foreigner coeffici 0 0.00111 0.02131 0.0239	rs. Denma ient sta 20 (90 (80 (nd error 0.021300 0.025810 0.058910	p-values 0.958030 0.407350 0.684020	t-test 0.052630 0.828580 0.406990		
Table C5 predictor of interest Domestic Developed Offshores China No data	5. Foreigner coeffici 0 0.0011: 0.0213: 0.0239: 0.0006	rs. Denma ient stat 20 (90 (80 (80 (nd error 0.021300 0.025810 0.058910 0.001610	p-values 0.958030 0.407350 0.684020 0.675250	t-test 0.052630 0.828580 0.406990 0.418960		
Table C5 predictor of interest Domestic Developed Offshores China No data Number of observations = 2313	5. Foreigner coeffici 0 0.0011 0.0213 0.0239 0.0006 34	rs. Denma ient stat 20 (90 (80 (80 (ark nd error 0.021300 0.025810 0.058910 0.001610	p-values 0.958030 0.407350 0.684020 0.675250	t-test 0.052630 0.828580 0.406990 0.418960		

Estonia

predictor of interest	coeffici	ent stand	error	p-values	t-test
BO frequency from 1 to 3	0				
BO frequency from 4 to 7	-0.0039	0.0	02590	0.132700	-1.503560
BO frequency from 8 to 311	0.00989	0.00	02900	0.000660	3.407880
BO frequency NaN	0.00801	LO 0.00	03370	0.017390	2.378550
Number of observations $= 4137$	'3				
R-squared = 0.821050					
Control variables are Main CPV, Table	Tender price	e, Buyer's ty	pe, and	NUTS num	nber.
Control variables are Main CPV, Table predictor of interest	Tender price C7. Estonia coefficient	e, Buyer's ty	pe, and	NUTS num	ıber. test R-squared
Control variables are Main CPV, Table predictor of interest BO foreigner risk dummy	Tender price C7. Estonia coefficient -0.098430	e, Buyer's ty stand error 0.006269	pe, and p-valu 0.0000	NUTS num es t- 00 -15.702	ber. test R-squared
Control variables are Main CPV, Table predictor of interest BO foreigner risk dummy No BO data	Tender price C7. Estonia coefficient -0.098430 -0.098540	e, Buyer's ty stand error 0.006269 0.006268	pe, and p-valu 0.00000 0.00000	NUTS num es t- 00 -15.702 00 -15.720	ber. test R-squared 2061 0.820950 368 0.820942



Table C8. BO information change frequency. Estonia

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
BO information change frequency from 1 to 2 BO information change frequency from 3 to 7 BO information change frequency NaN Number of observations = 41373 R-squared = 0.821257	0 0.045050 -0.000670	0.005290 0.001090	0.000000 0.537050	8.524150 -0.617290

Latvia

redictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
30 frequency from 1 to 4	0			
BO frequency from 5 to 6	-0.020560	0.003640	0.000000	-5.646950
BO frequency from 7 to 122	0.015860	0.002570	0.000000	6.166940
BO frequency NaN	0.017870	0.001530	0.000000	11.704040
Number of observations $= 138345$				
3-squared = 0.615810				
Control variables are Main CPV, Tend	ler price, Buy	er's type, and	NUTS numb	per.
Control variables are Main CPV, Tend Table C10. BO ag	der price, Buy e in years (m	er's type, and nax). Latvia	NUTS numb	per.
Control variables are Main CPV, Tend Table C10. BO ag predictor of interest	ler price, Buy e in years (n coefficient	er's type, and nax). Latvia stand error	NUTS numb	ber. t-test
Control variables are Main CPV, Tend Table C10. BO ag predictor of interest BO age from 26 to 38	der price, Buy e in years (m coefficient -0.045120	er's type, and nax). Latvia stand error 0.014250	NUTS numb	t-test -3.165940
Control variables are Main CPV, Tend Table C10. BO ag predictor of interest BO age from 26 to 38 BO age from 39 to 70	ler price, Buy e in years (m coefficient -0.045120 0	er's type, and nax). Latvia stand error 0.014250	NUTS numb	t-test -3.165940
Control variables are Main CPV, Tend Table C10. BO ag predictor of interest BO age from 26 to 38 BO age from 39 to 70 BO age from 71 to 86	ler price, Buy e in years (m coefficient -0.045120 0 0.052930	er's type, and nax). Latvia stand error 0.014250 0.007640	NUTS numb p-values 0.001550 0.000000	t-test -3.165940 6.926640
Control variables are Main CPV, Tend Table C10. BO ag predictor of interest BO age from 26 to 38 BO age from 39 to 70 BO age from 71 to 86 BO age NaN	der price, Buy e in years (m coefficient -0.045120 0 0.052930 0.000790	rer's type, and hax). Latvia stand error 0.014250 0.007640 0.002660	NUTS numb p-values 0.001550 0.000000 0.766290	t-test -3.165940 6.926640 0.297230
Control variables are Main CPV, Tend Table C10. BO ag predictor of interest BO age from 26 to 38 BO age from 39 to 70 BO age from 71 to 86 BO age NaN Number of observations = 138345	der price, Buy e in years (m coefficient -0.045120 0 0.052930 0.000790	rer's type, and hax). Latvia stand error 0.014250 0.007640 0.002660	NUTS numb p-values 0.001550 0.000000 0.766290	t-test -3.165940 6.926640 0.297230



Using beneficial ownership data for large-scale risk assessment in public procurement.

Table	C11.	Latvia

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test	R-squared
BO for eigner risk dummy No BO data Number of observations $= 138345$	-0.012050 0.015940	$0.013345 \\ 0.001492$	$0.366450 \\ 0.000000$	-0.903138 10.682006	$0.615216 \\ 0.615531$

*Control variables are Main CPV, Tender price, Buyer's type, and NUTS number.

10000012, $1000000000000000000000000000000000000$	Table	C12.	Foreigners.	Nationality.	Latvia
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predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
Domestic	0			
Developed	0.006850	0.002150	0.001420	3.189800
Developing	-0.025410	0.017360	0.143150	-1.464150
Offshores	-0.029960	0.021510	0.163710	-1.392710
China	0.208740	0.076820	0.006580	2.717310
Sanctions	-0.005240	0.012360	0.671790	-0.423690
No data	0.016820	0.001460	0.000000	11.489990
Number of observations $= 162029$				
R-squared = 0.610987				

*Control variables are Main CPV, Tender price, Buyer's type, and NUTS number.

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
Domestic	0			
Developed	0.004780	0.002130	0.024910	2.242760
Developing	-0.019150	0.018060	0.288920	-1.060500
Offshores	0.041370	0.012190	0.000690	3.395060
China	0.007330	0.035770	0.837600	0.204970
Sanctions	-0.041670	0.025290	0.099320	-1.648150
No data	0.016680	0.001460	0.000000	11.393440
Number of observations $= 162029$				
R-squared = 0.610981				



Slovakia

predictor of interest	coefficient	stand error	p-values	t-test
BO age from 15 to 37	-0.008120	0.005260	0.122710	-1.543520
BO age from 39 to 70	0			
BO age from 71 to 77	0.002360	0.005710	0.679990	0.412480
BO age from 78 to 92	0.022500	0.009930	0.023460	2.265890
BO age NaN	0.018820	0.002800	0.000000	6.721090
Number of observations $= 6369$ R-squared $= 0.609517$	99			
Control variables are Main CPV,	Tender price, B	uyer's type, and	d NUTS nun	nber.
Table C15. Co	ompany age in y	years. Slovakia		
predictor of interest	coefficient	stand error	p-values	t-test
Company age from 0 to 2	0.019620	0.006580	0.002860	2.982000
Company age from 3 to 16	-0.002240	0.005420	0.678910	-0.413960
Company age from 16 to 19	0.002740	0.002460	0.265130	1.114360
Company age from 20 to 62	0			
Company age NaN	0.007340	0.004480	0.101350	1.638380
Number of observations $= 636$ R accurred $= 0.600516$	99			
n-squared = 0.009510				
*Control variables are Main CPV	, Tender price, B	Buyer's type, and	l NUTS num	ber.
Table C	16. Slovakia			
predictor of interest	coefficient star	nd error p-val	ues t-t	est R-squared
3O foreigner risk dummy	0.013450 0	.003552 0.0001	150 3.7878	0.609266
<u> </u>	0.010010	000964 0.0000	10 5175	769 0 600179

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
Domestic	0			
Developed	-0.001630	0.002620	0.533730	-0.622330
Offshores	0.020810	0.003970	0.000000	5.243200
China	-0.025670	0.046060	0.577310	-0.557320
Sanctions	-0.042560	0.007580	0.000000	-5.617820
No data	-0.012400	0.007760	0.110340	-1.596700
Number of observations $= 63699$				
R-squared = 0.609456				
*Control variables are Main CPV, Te	nder price, Bu	yer's type, and	NUTS num	ıber.

Ukraine

Table C18. BO frequency. Ukraine								
predictor of interest		$\operatorname{coefficient}$	stand error	p-values	s t-te	est		
BO frequency from 0 to 0 BO frequency from 1 to 7	BO frequency from 0 to 0 BO frequency from 1 to 7		0.000690	0.000000	212.0582	90		
BO frequency from 8 to 4	BO frequency from 8 to 495		0.000910	0.000000	44.0046	80		
BO frequency NaN		0.298390	0.002320	0.000000	128.7734	30		
Number of observations = 1144564 R-squared = 0.550012 *Control variables are Main CPV, Tender price, Buyer's type, and NUTS number.								
	Table C19.	Ukraine						
predictor of interest	No of obs	coefficient	stand error	p-values	t-test	R-squared		
BO foreigner risk dummy	1144564	-0.054840	0.003568	0.000000	-15.370517	0.528156		
No BO data	1126248	0.132590	0.000661	0.000000	200.610503	0.534419		
BO PEP	1144564	0.017640	0.003496	0.000000	5.045262	0.528069		
*Control variables are Main C	CPV, Tender	price, Buyer's	type, and NUT	S number.				

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
Domestic	0			
Developed	0.062290	0.002720	0.000000	22.896640
Developing	-0.024860	0.002420	0.000000	-10.281390
Offshores	-0.024390	0.005530	0.000010	-4.413570
China	-0.200430	0.012830	0.000000	-15.620300
Sanctions	-0.059060	0.004960	0.000000	-11.912850
No data	0.225000	0.002290	0.000000	98.298050
Number of observations $= 1144564$				
R-squared = 0.532431				

The UK

Table C21. BO frequency. The UK							
predictor of interest	coefficient	stand error	p-values	t-test			
BO frequency from 1 to 4	0						
BO frequency from 5 to 8	-0.004740	0.003780	0.209910	-1.253830			
BO frequency from 9 to 1324	0.032610	0.004260	0.000000	7.662460			
BO frequency NaN	0.004510	0.002170	0.037320	2.082310			
Number of observations $= 126282$ R-squared $= 0.826749$							
*Control variables are Main CPV, Tender price, Buyer's type, and NUTS number.							
Table C22. BO age in years (max). The UK							
predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test			
BO age from 0 to 37	0.008160	0.004350	0.060480	1.877330			
BO age from 38 to 75	0						
BO age from 76 to 85	-0.016780	0.006040	0.005450	-2.778960			
BO age from 86 to 93	-0.025380	0.017040	0.136340	-1.489560			
BO age NaN	0.003260	0.002170	0.134060	1.498300			
Number of observations $= 126282$							
R-squared = 0.826680							
*Control variables are Main CPV, Tend	der price, Buy	ver's type, and	NUTS num	ber.			



Using beneficial ownership data for large-scale risk assessment in public procurement.

Table C23. The UK						
predictor of interest	coefficient	stand error	p-values	t-test	R-squared	
BO foreigner risk dummy	0.023770	0.012453	0.056290	1.908810	0.826664	
No BO data	0.007840	0.000638	0.000000	12.285339	0.826659	
Number of observations $= 126282$						
*Control variables are Main CPV, Tender price, Buver's type, and NUTS number.						

Table C24. For eigners. Nationality. The UK

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
Domestic	0			
Developed	-0.005840	0.004490	0.193260	-1.301000
Offshores	0.013130	0.012820	0.306010	1.023630
China	0.074870	0.030330	0.013570	2.468460
Sanctions	0.018550	0.013680	0.174950	1.356470
No data	0.011610	0.001980	0.000000	5.855690
Number of observations $= 126282$				
R-squared = 0.826722				

*Control variables are Main CPV, Tender price, Buyer's type, and NUTS number.

predictor of interest	coefficient	stand error	p-values	t-test
Domestic	0			
Developed	-0.017920	0.007350	0.014700	-2.439830
Offshores	0.030610	0.010310	0.002980	2.969450
China	0.066390	0.039340	0.091530	1.687390
Sanctions	0.028470	0.011430	0.012770	2.490270
No data	0.011950	0.001960	0.000000	6.103020
Number of observations $= 126282$				
R-squared = 0.826739				



Annex D. Robustness tests: Bo-procurement risk indicator regressions using single bidding as DV

Denmark

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
BO frequency from 1 to 5	0			
BO frequency from 6 to 20	-0.300990	0.114980	0.008850	-2.617770
BO frequency from 21 to 30	-0.242710	0.177490	0.171480	-1.367470
BO frequency from 31 to 202	0.045160	0.169020	0.789320	0.267200
BO frequency NaN	-0.034510	NaN	NaN	NaN
Number of observations $= 12336$				
R-squared = 0.101539				

ompany age from 0 to 4				
	0.133700	0.254970	0.600020	0.524370
ompany age from 5 to 30	0.125440	0.124370	0.313180	1.008560
ompany age from 31 to 90	0			
ompany age NaN	0.074160	2486546.592870	1.000000	0.000000

Table D3. BO information change frequency. Denmark

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
BO information change frequency from 1 to 2	0			
BO information change frequency from 3 to 3	0.436030	0.246640	0.077080	1.767910
BO information change frequency from 4 to 11	1.931200	0.444790	0.000010	4.341820
BO information change frequency NaN	0.056200	4194304	1.000000	0.000000
Number of observations $= 12336$				
R-squared = 0.102500				

 $^{*}\mathrm{Control}$ variables are Main CPV, Tender price, Buyer's type, and NUTS number.



Table	D4. Denmar	'k			
predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test	R-squared
BO foreigner risk dummy	0.895650	0.544066	0.099720	1.646209	0.100965
No BO data	0.038630	NaN	NaN	NaN	0.10074
Number of observations $= 12336$					

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
Domestic	0			
Developed	-0.389520	0.517680	0.451790	-0.752430
Offshores	1.278400	0.587190	0.029470	2.177130
China	-15.188770	2703.568200	0.995520	-0.005620
No data	0.042950	NaN	NaN	NaN
Number of observations $= 12336$				
R-squared = 0.101311				

Estonia

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
BO frequency from 1 to 3	0			
BO frequency from 4 to 7	-0.092630	0.044190	0.036070	-2.096180
BO frequency from 8 to 311	-0.121400	0.050690	0.016620	-2.395120
BO frequency NaN	-0.056760	0.054070	0.293890	-1.049620
Number of observations $= 30130$				
R-squared = 0.138063				



Using beneficial ownership data for large-scale risk assessment in public procurement.

Table	e D7. Estonia	a.			
predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test	R-squared
BO foreigner risk dummy No BO data	-1.143630 -1.042950	0.162620 NaN	0.000000 NaN	-7.032544 NaN	$0.130846 \\ 0.129670$
Number of observations $= 30130$					

Table D8. BO information change frequency. Estonia

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
BO information change frequency from 1 to 2	0			
BO information change frequency from 3 to 7	0.305420	0.084610	0.000310	3.609670
BO information change frequency NaN	0.071070	3160089	1.000000	0.000000
Number of observations $= 30130$				
R-squared = 0.138210				
*Control variables are Main CPV, Tender price, Bu	yer's type, an	d NUTS numb	er.	

Latvia

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
BO frequency from 1 to 4	0			
BO frequency from 5 to 6	-0.008260	0.040610	0.838730	-0.203510
BO frequency from 7 to 122	0.373060	0.028070	0.000000	13.289320
BO frequency NaN	0.145960	0.017390	0.000000	8.394450
Number of observations $= 116472$				
R-squared = 0.104033				



Table D10. BO age in years (max). Latvia

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
BO age from 26 to 38 BO age from 39 to 70	$0.006220 \\ 0$	0.142110	0.965080	0.043780
BO age from 71 to 86 BO age NaN Number of observations $= 116472$ R-squared $= 0.103180$	0.338180 -0.171060	$0.080450 \\ 0.028590$	0.000030 0.000000	4.203340 -5.984140

*Control variables are Main CPV, Tender price, Buyer's type, and NUTS number.

Table	D11. Latvia				
predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test	R-squared
BO foreigner risk dummy	1.063780	0.058176	0.000000	18.285564	0.102664
No BO data	1.064770	0.058230	0.000000	18.285687	0.102660
Number of observations $= 116472$					
*Control variables are Main CPV Ten	der price Buy	er's type and	NUTS numb	er	

*Control variables are	e Main CPV,	Tender price,	Buyer's type,	and NUTS number.
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predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
Domestic	0			
Developed	0.185170	0.023120	0.000000	8.007680
Developing	0.758660	0.186160	0.000050	4.075350
Offshores	0.280020	0.252940	0.268260	1.1070700
China	-0.453590	0.869220	0.601790	-0.521830
Sanctions	-0.673340	0.203150	0.000920	-3.314440
No data	0.021220	0.016720	0.204540	1.268730
Number of observations $= 136510$	0.01110	0.020.20	0.20.20.20	
R-squared = 0.104993				

*Control variables are Main CPV, Tender price, Buyer's type, and NUTS number.



predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
Domestic	0			
Developed	0.142180	0.022980	0.000000	6.186940
Developing	0.768000	0.190960	0.000060	4.021800
Offshores	0.447970	0.128490	0.000490	3.486480
China	1.066890	0.363670	0.003350	2.933650
Sanctions	-0.276080	0.340410	0.417360	-0.811020
No data	0.018810	0.016730	0.260780	1.124560
Number of observations $= 136510$				
R-squared = 0.104868				

Table D13. Foreigners. Residence. Latvia

IJ ιyμ e,



Slovakia

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
BO age from 15 to 37	0.124920	0.073380	0.088700	1.702290
BO age from 39 to 70	0			
BO age from 71 to 77	0.265440	0.075980	0.000480	3.493520
BO age from 78 to 92	0.274600	0.132910	0.038820	2.066100
BO age NaN	0.505660	0.041730	0.000000	12.118000
Number of observations $= 45210$				
R-squared = 0.121646				

*Control variables are Main CPV, Tender price, Buyer's type, and NUTS number.

Table D15.	Company	age in years.	Slovakia
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predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
Company age from 0 to 2	0.200240	0.093040	0.031390	2.152130
Company age from 3 to 16	0.107780	0.033670	0.001370	3.200920
Company age from 16 to 19	-0.153060	0.040400	0.000150	-3.788520
Company age from 20 to 62	0			
Company age NaN	0.398220	0.082350	0.000000	4.835490
Number of observations $= 45210$				
R-squared = 0.124903				

*Control variables are Main CPV, Tender price, Buyer's type, and NUTS number.

Table	D16. Slovak	ia			
predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test	R-squared
BO foreigner risk dummy	0.393480	0.044355	0.000000	8.871180	0.120219
No BO data	0.142230	0.024038	0.000000	5.917105	0.119019
Number of observations $= 45210$					
*Control variables are Main CPV, Te	nder price, Bu	iyer's type, and	NUTS num	ıber.	

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
Domestic	0			
Developed	-0.030790	0.031820	0.333330	-0.967430
Offshores	0.582740	0.050550	0.000000	11.528210
China	-0.012210	0.585500	0.983370	-0.020850
Sanctions	-0.471010	0.112900	0.000030	-4.171780
No data	0.189980	0.025430	0.000000	7.471650
Number of observations $= 45210$				
R-squared = 0.121680				

Table D17. Foreigners. Nationality. Slovakia

Ukraine

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
BO frequency from 0 to 0	1.017640	0.005440	0.000000	186.944170
BO frequency from 1 to 7	0			
BO frequency from 8 to 495	0.327420	0.007330	0.000000	44.683770
BO frequency NaN	2.485290	0.023360	0.000000	106.376440
Number of observations $= 1144564$				
R-squared = 0.178742				

	Table D19.	Ukraine				
predictor of interest	No of obs	$\operatorname{coefficient}$	stand error	p-values	t-test	R-squared
BO foreigner risk dummy	1144564	-0.298850	0.221947	0.178150	-1.346471	0.147983
No BO data	1126248	-0.144990	0.221778	0.513260	-0.653766	0.164421
BO PEP	1144564	-0.322010	0.222371	0.147600	-1.448063	0.147763
*Control variables are Main C	PV, Tender	orice, Buyer's	type, and NUT	'S number.		

Table D20.	Foreigners.	Nationality.	Ukraine
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predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
Domestic	0			
Developed	0.477640	0.022410	0.000000	21.315310
Developing	-0.237920	0.020700	0.000000	-11.494330
Offshores	-0.379330	0.052630	0.000000	-7.206950
China	-1.949420	0.154260	0.000000	-12.637370
Sanctions	-0.649670	0.051630	0.000000	-12.584380
No data	1.909600	0.021720	0.000000	87.907830
Number of observations $= 1144564$				
R-squared = 0.154698				

The UK

iculator of mitorost	coentcient	stand error	p-values	t-test
3O frequency from 1 to 4	0			
30 frequency from 5 to 8	-0.120410	0.062250	0.053050	-1.934480
BO frequency from 9 to 1324	0.464500	0.066150	0.000000	7.021430
BO frequency NaN	0.195490	0.035620	0.000000	5.488640

*Control variables are Main CPV, Tender price, Buyer's type, and NUTS number.

predictor of interest	coefficient	stand error	p-values	t-test
BO age from 0 to 37	-0.228870	0.063820	0.000340	-3.586300
BO age from 38 to 75	0			
BO age from 76 to 85	-0.054510	0.112410	0.627720	-0.484930
BO age from 86 to 93	0.019910	0.303570	0.947710	0.065580
BO age NaN	0.136980	0.035920	0.000140	3.814000
Number of observations $= 80867$				
R-squared = 0.125983				



Table	D23. The U	K			
predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test	R-squared
BO foreigner risk dummy	0.234360	0.229303	0.306760	1.022041	0.130820
No BO data	0.133500	NaN	NaN	NaN	0.130810
Number of observations $= 80867$					
*Control variables are Main CPV, Te	nder price, Bu	iyer's type, and	NUTS num	ber.	

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
Domestic	0			
Developed	0.179980	0.072860	0.013500	2.470390
Offshores	0.148070	0.149150	0.320850	0.992710
China	1.538530	0.446980	0.000580	3.442010
Sanctions	-0.127870	0.274200	0.640980	-0.466330
No data	0.278680	0.032700	0.000000	8.523590
Number of observations $= 80867$				
R-squared = 0.131616				

Control variables are Main CPV, Tender price, Buyer's type, and NUTS number.

predictor of interest	$\operatorname{coefficient}$	stand error	p-values	t-test
Domestic	0			
Developed	0.039880	0.135060	0.767760	0.295310
Offshores	1.403960	0.146570	0.000000	9.578790
China	1.644990	0.563120	0.003490	2.921190
Sanctions	-0.042010	0.217500	0.846850	-0.193140
No data	0.288050	0.032110	0.000000	8.971900
Number of observations $= 80867$				
R-squared = 0.131590				

^kControl variables are Main CPV, Tender price, Buyer's type, and NUTS number.



Annex E. Frequency tables

Denmark

Denmark
frequency
2514
3168
683
930
15839
23134

Company age in years	frequency
From 0 to 4	702
From 5 to 30	5187
From 31 to 90	1406
Missing (NaN)	15839
Number of observations	23134

BO information change frequency	frequency
From 1 to 2	6984
From 3 to 3	256
From 4 to 11	55
Missing (NaN)	15839
Number of observations	23134



Estonia

Table E4. BO Frequency.Estonia

BO frequency	frequency
From 1 to 3	14014
From 4 to 7	7602
From 8 to 311	5700
Missing (NaN)	14057
Number of observations	41373

ble E5. BO information change free	quency.Esto
BO information change frequency	frequency
From 1 to 2	29910
From 3 to 7	1307
Missing (NaN)	10156
Number of observations	41373

Latvia

Table E6. BO Frequency.Latvia

BO frequency	frequency
From 1 to 4	44090
From 5 to 6	3981
From 7 to 122	8986
Missing (NaN)	81288
Number of observations	138345



Using beneficial ownership data for large-scale risk assessment in public procurement.

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frequency
244
7612
936
129553
138345

Slovakia

BO age in years (max)	frequency
From 15 to 37	1473
From 39 to 70	28975
From 71 to 77	1226
From 78 to 92	393
Missing (NaN)	31632
Number of observations	63699

Company age in years	frequency
From 0 to 2	979
From 3 to 16	16918
From 17 to 19	7064
From 20 to 62	10953
Aissing (NaN)	27785
Number of observations	63699



Using beneficial ownership data for large-scale risk assessment in public procurement.

Ukraine

Table	E10.	во	Frequency.Ukraine
rabio	L 10.	$\mathbf{D}\mathbf{O}$	riequency. e maine

BO frequency	frequency
From 0 to 0	300463
From 1 to 7	793585
From 8 to 495	140918
Missing (NaN)	19435
Number of observations	1254401

The UK

Table E11. BO Frequenc	y. The UK
BO frequency	frequency
From 1 to 4	16414
From 5 to 8	2790
From 9 to 1324	2177
Missing (NaN)	104901
Number of observations	126282

Table E12. BO age in years (max). The UK

BO age in years (max)	frequency
From 0 to 37	2098
From 38 to 75	18155
From 76 to 85	1009
From 86 to 93	119
Missing (NaN)	104901
Number of observations	126282