Fighting Corruption in Emergency Procurement through Big Data

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1. Crises, emergency procurement and corruption risks

by *Michela Gnaldi*[*]

Abstract

This introductory chapter delves into the multifaceted challenges posed by corruption to global progress and stability, with a particular emphasis on its heightened prevalence during crises. Public procurement systems, which play a crucial role in emergencies, become more vulnerable under emergency circumstances. The interconnected nature of contemporary crises, exemplified by the Covid-19 pandemic, underscores the necessity to shift from a mere responsive stance to a comprehensive approach. This approach should center around proactive preparedness, effective prevention, and mitigation strategies.

The chapter highlights the impact of emergency shocks on anti-corruption enforcement and emphasizes the need for adaptive corruption risk assessment systems during crises. While common red flags remain foundational to such systems, their interpretation and use during non-competitive situations or crises require caution. Contextually, measures to mitigate false positives need reinforcement.

Furthermore, the chapter addresses the challenges faced by researchers and policymakers in measuring corruption and advocates for a balanced measurement approach. It underscores the transformative potential of big data and data analytics in comprehending, detecting, and mitigating corrupt practices.

The discussion introduces the CO.R.E. project (CO.R.E. - Grant agreement n. 101038790), an EU-funded initiative under the Internal Security Fund Police (ISF-P) program. This project aims to adapt corruption risk assessment systems to emergency contexts. Aligned with previous and concurrent projects, the CO.R.E. project capitalizes on big data potentials for corruption risk assessment, and further introduces a crisis-specific methodology and a general measurement framework for red flag computation during crises. The project provides a mapping of corruption risks over emergencies through the CO.R.E.-CI (Composite Indicator), which aggregates individual red flags. Leveraging public procurement big data, the CO.R.E.-CI

[*] This contribution is a product of the research from the CO.R.E. project: COrruption Risk indicators in Emergency, co-financed by the European Union, Grant Agreement No. 101038790 – Core – Isfp-2020-AG-Corrupt.

facilitates prioritizing high-risk cases and guides focused audits and preventive measures.

The chapter closes with a description of the structure of the present book.

1. Corruption risks in public procurement: challenges, adaptations and mitigations during crises

Corruption poses formidable challenges to the progress and stability of nations across the globe. As societies grapple with the multifaceted nature of corruption, the imperative to employ innovative and effective strategies to tackle it becomes increasingly apparent. During times of crisis, the conditions become conducive to corruption due to relaxed regulatory frameworks, diminished oversight, and a surge in financial activities. Among the sectors, public procurement systems are especially vulnerable to corruption risks during emergency periods, given their frontline role in many countries' responses to crises.

The interconnected nature of our world heightens the vulnerability of communities to challenges of varying types and entity. From environmental crises to health crises like the COVID-19 pandemic, the impact of these events reverberates across borders, affecting individuals, communities, and entire nations. The pervasiveness and inevitability of crises underscores the imperative for proactive preparedness and effective mitigation strategies. Preparedness involves anticipating potential crises, developing robust response plans, and ensuring that resources and infrastructure are in place to manage the immediate aftermath. Concurrently, mitigation strategies reduce the severity and long-term consequences of crises by addressing underlying vulnerabilities, enhancing resilience, and implementing preventive measures.

As the frequency and magnitude of crises continue to escalate, it becomes increasingly evident that fostering a culture of preparedness, investing in mitigation measures and devising proactive strategies to contain their harmful impacts through new and realistic models of interacting risks are all critical components of societal resilience. Similarly, corruption risk assessment systems designed to identify corruption risks in public procurement during ordinary periods need to undergo adaptation to be effective in devising solutions for mitigating corruption risk during emergency situations.

At the peak of the Covid-19 crisis, the European Commission issued a guidance for Member States aimed at assisting public authorities in ensuring rapid and efficient procurement of necessary equipment (European Commission, 2020). This guidance outlined three main options for public purchasers in response to the Covid-19 emergency: i. contractors' direct contacts, enabling contracting authorities to hire agents with direct market knowledge; ii. accelerated procedures, allowing authorities to reduce minimum time limits; iii. negotiated procedures without tender publication, permitting authorities to use this procedure at any time when, for reasons of extreme urgency, the time limits for open or competitive procedures could not be met.

During the height of the Covid-19 crisis, the surge in demand for specific medicines and personal protective products (e.g., medical equipment, ventilators, masks, etc.) and the scarcity of supply for the same products and services heightened competition among public buyers and created a fundamentally different purchasing environment. In this new environment, the dynamics and bargaining powers of the public and private sectors were completely overturned (OECD, 2020). The demand-driven approach, typical of procurement systems under ordinary competitive circumstances, where public buyers can choose among many competing suppliers, shifted to a supplier-driven approach. Here, thousands of contracting authorities competed for the supply of the same specific supplies produced by a few companies.

The OECD highlights three primary effects of emergency shocks on anti-corruption enforcement (UNODC, 2021). The first revolves around threats to accountability, control, and oversight, stemming from the relaxation of constraints to quickly spend funds in an effort to address crisis-induced economic downturns. The second major effect of emergency events pertains to risks of integrity violations in public organizations. Instances of workplace fraud, embezzlement, bribery of public officials, and other integrity violations within public entities tend to increase during crises. The internal control and audit systems of organizations may become less effective due to widespread mass layoffs, making them more vulnerable to internal fraud and misconduct. Thirdly, global emergencies like the Covid-19 crisis give rise to new integrity risks in the public procurement process.

Overall, relaxed regulatory measures, increased spending, and the transformed purchasing environments brought about by crises create new opportunities for fraud and intensify the likelihood of corruption in the public procurement process (Gallego *et al.*, 2020). This underscores the importance of measuring the risk of corruption during crisis periods, adjusting the risk assessment systems to new conditions. Such a readaptation involves a focus on red flags, which form the basis of corruption risk assessment systems. Red flags are proxy indicators for corruption, indicating potential risks rather than actual instances of corruption. They are indirect measures of corruption centered on the context where corruption might take place and providing insights into the conditions that heighten (or reduce) the risk of corruption. While red flags remain foundational to risk assessment systems, common red flags employed during ordinary circumstances – such as the use of exceptional procedure types, direct awards, short advertisement time-periods – may not effectively highlight corruption during non-competitive situations or crises. In these scenarios, relying solely on these indicators might result in an overestimation of corruption risks as high values assumed by such indicators might mirror the legitimate adaptive response to a relaxed regulatory framework rather than an actual high level of corruption. Indeed, red flag indicators can yield false positives (OECD, 2019), signaling risk even in non-corrupt instances. In exceptional situations, measures to mitigate false positives should be reinforced to accommodate unexpected disruptions, extraordinary market fluctuations and relaxed regulatory frameworks.

Additionally, as acknowledged in the literature (UNODC, 2023), red flags should not be used in isolation and the identification of units at risk of corruption in public procurement should rely on an array of red flags, rather than just a few of them. In this regard, composite indicators (CIs) that aggregate a collection of red flags for corruption risk can serve as valuable tools to assist government agencies and oversight bodies in prioritizing high-risk cases. Indeed, through public procurement big data, CIs can synthetically highlight processes, contracts, or entities (such as contracting authorities and/or winning companies) that face corruption risks, guiding oversight organizations in conducting focused audits, implementing risk mitigation strategies, and formulating preventive measures.

2. Combatting corruption: integrating repression and prevention into effective measurement strategies

Corruption is a persistent issue in societies worldwide. It undermines the foundations of governance, erodes public trust, and impedes socio-economic development. Controlling corruption is a multifaceted challenge that goes beyond mere repression. It necessitates a comprehensive approach that encompasses both repression and prevention strategies. Repression entails the investigation and prosecution of corrupt practices, holding individuals accountable for their actions. While essential, repressive measures alone are insufficient to tackle the root causes of corruption. Prevention, on the other hand, involves implementing systemic changes, promoting transparency, fostering ethical behavior, and creating an environment that discourages corrupt practices.

Integrating prevention strategies alongside repressive measures not only addresses immediate concerns but also cultivates a culture of integrity and accountability within institutions. Not only controlling corruption demands a balance between punitive actions to deter wrongdoing and proactive measures to build a resilient and transparent framework that minimizes opportunities for corruption to thrive. Additionally, it necessitates the implementation of a diverse set of measurement instruments that quantify corruption (once corrupt activities have already occurred) and identify in advance risks of corruption, focusing on the context rather than corruption occurrence itself. Indeed, understanding under which conditions corruption risks get higher or lower is pivotal for policymakers, as it strengthens a State capacity to prevent corruption among public officials, private sector entities, and individuals.

Measuring corruption poses complex challenges. Corruption is a multidimensional phenomenon and proves difficult to define due to its diverse manifestations impacting various sectors of society. Thus, the initial hurdle in corruption measurement lies in establishing a clear definition for the term corruption and delineating the conceptual and analytical frameworks that effectively capture its dimensions and impacts across society. A further challenge in measuring corruption arises from its secretive nature and inherent complexity. Indeed, corruption, by its very nature, is a latent phenomenon. It cannot be directly observed or analyzed as individuals engaged in corrupt activities for illicit gains have a vested interest in concealing them. Corruption is also inherently complex, as it covers a spectrum of activities ranging from trivial to more severe instances, such as a bribe to evade prosecution for a traffic violation to the falsification of public decisions for unlawful private interests. Additionally, various types of corruption exist, influenced by the sectors in which they occur (public or private, political or administrative), the actors involved (public officials, private citizens, politicians), and the degree to which they are formalized (systemic or occasional) (Andersson and Heywood 2009).

Moreover, unlike other crimes, detecting corruption proves more challenging due to factors such as the absence of immediate victims willing to report, fear of retaliation against whistleblowers, and limited investigative and prosecutorial capacities in certain jurisdictions. The dark figure of corruption, representing incidents not reported to authorities, is arguably higher than that of most other crimes, owing to a reluctance to report arising from fear, potential complicity, or direct gains from corrupt behavior.

In spite of these premises, the circumstance that corruption is not directly observable does not equate to the impossibility of measuring it (Gnaldi and Del Sarto, 2022). Indeed, within the realm of applied sciences, researchers often grapple with the challenge of measuring phenomena that are not directly observable. Examples of these include emotions, consumer confidence, student skills, quality of life, etc. In all these instances, since it is not possible to directly observe and measure the phenomenon of interest, indirect measures – the so-called proxy variables or indicators – are employed to approximate the unobservable phenomenon.

Overall, a broad spectrum of approaches can be employed to measure corruption. Direct measures, often derived from population and business surveys, specifically target forms of corruption, like bribery. These indicators provide robust and representative insights when survey designs effectively represent the entire population. Still, employing these measures has limitations due to high costs and the difficulty of repeated survey administration. What is more, measuring corruption directly encounters challenges in sectors shielded from public scrutiny, like defense or privacy-related areas, where survey assessments may inadequately capture the true extent due to a lack of firsthand experiences to report.

Indirect measures of corruption include perception-based indicators, risk indicators and response indicators (UNODC, 2023). They evaluate not corruption directly but rather factors that can either support or impede corrupt practices. Perception-based indicators encompass diverse attitudes toward corruption, shaped by subjective elements like culture and mass communication. On a different perspective, risk indicators concentrate on the presence or absence of structures and processes affecting corruption risk and may play a crucial role in policymaking, enhancing a State ability to prevent corruption. Response indicators include legislative measures and practical actions addressing those involved in corruption (*de facto* response) and offer insights into a State capability and willingness to combat corruption.

As it will be further discussed in Chapter 2, among indirect measures of corruption, red flag indicators are considered to be more accurate and effective than other measures, as devised by Mungiu-Pippidi (2016). These metrics prioritize the proactive identification of situations susceptible to corruption and are fundamental to corruption risk assessment systems, playing a crucial role in identifying and preventing potential corruption risks. Particularly significant in public sector activities, corruption risk assessment enables the identification of vulnerabilities and weaknesses in systems, offering valuable insights for strategic decision-making. This process empowers public sector officials to prioritize interventions, strategically allocate resources, and address the most critical vulnerabilities efficiently.

3. Harnessing big data potential into anti-corruption strategies

In the era of digital transformation, big data and big data analytics emerge as powerful tools with substantial promise for reshaping anti-corruption efforts. The accessibility of vast and complex data originating from diverse sources – comprising administrative documents and unstructured data from previously unexplored sources, such as crowdsourcing and web scraping –

presents an unprecedented opportunity to enhance the understanding, detection, and mitigation of corrupt practices. In parallel, the processing of massive datasets and big data analytics act as lens to scrutinize patterns, relationships, and anomalies that may indicate corrupt behaviors.

Data sources may encompass a wide array of information, including administrative records pertaining to public finances and various procedures within the public administration, such as records related to public procurement, asset declarations and audits. Sources may also involve sample surveys on corruption targeting households and businesses, as well as other surveys focusing on public services, expert-based interviews, anonymized records detailing individual corruption offenses, court case files with anonymized information, whistle-blowing data, administrative records originating from the criminal justice system and civil procedures throughout their respective stages. Further, the web serves as a prolific source of diverse and accessible material that can be collected, aggregated, and analyzed. While web platforms may implement protection mechanisms to restrict data extraction, data scraped from web sources may provide invaluable information.

Effectively addressing corruption through access to big data sources demands the establishment of a well-defined data architecture. In this context, the term data architecture refers to the systematic organization and structuring of data, encompassing the methods for data collection, storage, retrieval, and analysis. A well-designed data architecture ensures the efficient flow of information, enabling the processing of massive datasets generated at a very high speed from various sources. This structured framework is essential to handle the volume of data and facilitate the seamless processing, integration, and analysis of vast and diverse datasets. A robust data architecture serves as the cornerstone for deriving accurate insights and, consequently, formulating evidence-based anti-corruption strategies.

Data pipelines are vital components within data architectures. They represent the operational feature of how data moves and transforms within the architecture. Indeed, data pipelines serve as the mechanism for implementing data movement and transformation strategies outlined in the data architecture. They enable the execution of the planned processes for data ingestion, transformation, and delivery to end destinations. Effective data pipelines align with the goals and principles set by the data architecture so that, for example, if the data architecture emphasizes real-time data processing, the data pipelines should be designed to support and implement real-time data movement and processing.

In summary, well-defined data architecture and data pipelines play a key instrumental role in the fight against corruption. By ensuring that data are well organized and accessible, anti-corruption efforts can benefit from a deeper understanding of corruption mechanisms, identifying root causes, and unveiling secreted relationships within societal and institutional frameworks.

4. The CO.R.E. project: exploiting big data for corruption risk assessment in emergency procurement

The CO.R.E. project – COrruption Risk indicators in Emergency (CO.R.E. - Grant agreement n. 101038790) – whose main results are described in this volume, was launched with the dual objective of adapting corruption risk assessment systems to emergency contexts and provide a mapping of corruption risks over emergencies through a composite indicator (CI) of corruption risks called CO.R.E.-CI. The project, funded under the EU Internal Security Fund Police (ISF-P) program in 2019 and lasting two years, aimed at both enhancing earlier detection of corruption risk through big data techniques, and at fostering a stronger evidence base for policy reform in emergency scenarios, by serving anti-corruption authorities, law enforcement agencies, journalists and the general public/citizenship for accountability objectives.

CO.R.E. is a highly technological project leveraging advanced data-driven approaches and harnessing the power of big data to effectively address and counteract corruption in the public procurement cycle in time of crises. In the CO.R.E. project, we refer to two main data sources: the *Banca Dati Nazionale dei Contratti Pubblici* (BDNCP) managed by the Italian Anticorruption Authority (ANAC) and the Opentender data, developed with the support of Digiwhist, a project funded by the EU Horizon 2020 initiative.

The BDNCP is an open data portal that provides access to information contained into over a hundred datasets. A data architecture and a big data pipeline have been developed and employed for the ingestion, cleansing, transformation, and storage of these extensive data. Purposely, the CO.R.E. pipeline was responsible for extracting data from open data portals, parsing data extracted by the web scraper, transforming parsed data into a suitable format and storing the aggregated data in an extensive file with over 10 million public contracts over a time span of ten years (2013-2022).

By harnessing the informational wealth contained in these two big data sources, within the CO.R.E. project we propose a replicable procedure to compute a CI of corruption risk in public procurement over emergencies, called CO.R.E.-CI (Corruption Risk in Emergency-Composite Indicator). As it will be further detailed in Chapter 2 and Chapter 4, the CO.R.E.-CI normalizes, weights and aggregates a curated selection of red flag indicators specifically developed to measure the risk of corruption in the public procurement process over emergencies. The red flags employed to ingest the CO.R.E.-CI are developed within a proposed new methodology, which capitalizes on the time discontinuity introduced by a crisis and allow to evaluate the behaviors of companies and/or contracting authorities after a crisis outbreak in comparison to their historical (pre-crisis) behaviors. The risk of corruption is subsequently assessed through statistical testing, where hypotheses are set according to the observed market trends during a crisis. Finally, based on the CO.R.E.-CI, a mapping of corruption risks over emergencies is provided.

Contextually, recognizing the imperative to foster a culture of integrity within the public service and among businesses, the project aimed to enhance data collection and analysis through an exploration of the legal frameworks of procurement data and delineating the role of data in maintaining public procurement integrity. This activity involved identifying quality requirements for procurement data, analyzing legal regulations regarding the reusability of data, examining the technical and legal framework for data interoperability, and assessing limitations in data and their impact on public procurement integrity.

The CO.R.E. project provides support to any users interested in assessing and computing corruption risk in public procurement over emergencies through the coresoi R-package. The coresoi R-package is the primary tool for transferring the computation of the red flags of corruption risk in emergency and the CO.R.E.-CI to additional stakeholders – such as anti-corruption authorities, journalists, researchers – and new geographies and future emergencies that were not included in the original project, nor foreseeable at the time of its development. R packages play a crucial role for data analysts and statisticians using the R programming language. These packages comprise organized functions, data, and documentation tailored to address specific challenges in data analysis. Purposely, the aim of the coresoi R-package[1] is to allow researchers and anti-corruption analysts to use the CO.R.E. indicators of corruption risk in public procurement over emergencies for their own purposes. In order to fully enable stakeholders to apply the indicators to their own datasets and to adapt them to their needs, the package establishes that permission is granted free of charge and without restrictions.

While the use of the coresoi R package by external beneficiaries requires some level of familiarity with the R coding language, the package contains guides, tools and other documents that are meant to facilitate its effective adoption and to share the necessary know-how. Specifically, the coresoi R package includes: i. guidelines on how to calculate the indicators, which serve as a tutorial for utilizing the package; ii. example codes on how to

[1] Available at https://core-forge.github.io/coresoi/

compute the red flags and the CO.R.E.-CI; iii. tips for utilization, advising on how to effectively install, load and use the package, avoiding common mistakes; iv. technical support on how users can seek help if they encounter problems with the package.

The CO.R.E. project also develops a dashboard[2] for the visualization of the main risk indicators resulting from the data analysis through maps and infographics. Data visualizations tools are helpful for several purposes, including i. understanding complex data, as representing them in a visual format makes it easier to grasp patterns and relationships within the data; ii. exploration and analysis, by enabling users to zoom in for details and zoom out for a broader perspective; iii. communication, by allowing to convey findings to audiences with different level of technical expertise; iv. decision making, by providing a quick and intuitive understanding that enable informed choices; v. storytelling, by making it easier to present a compelling argument based on the visualized data.

The CO.R.E. data visualization dashboard allows citizens, journalists, activists and other interested actors to navigate the results of the calculation of the CO.R.E. elementary indicators and the CO.R.E.-CI for a selected list of emergencies (Covid-19, Forest fires and Earthquakes) in the four Countries involved in the project, that is, Ireland, Italy, Portugal and Spain. As such, it represents the main tool to foster the transferability of the CO.R.E. results, showcasing the effectiveness of the developed methodology to external users.

The CO.R.E. dashboard allows users to interact and filter data by selecting the emergency they are interested in, the country, the specific indicators, the geographic entities (regions or provinces), and the data visualization mode (table, map, or bar chart). Through an intuitive and easy-to-use navigation system, users can visualise the results of the individual red flags (elementary indicators) and the CO.R.E.-CI for each individual contracting authority and awarded company. All software components are released with open licenses and accessible also from different repositories (e.g. Github).

The CO.R.E. project was carried out thanks to the collaboration of an international network of academic and non-academic partners, who also contributed as Authors to the writing and editing of this book. The CO.R.E. international network involved the University of Perugia (Italy) as leader and the following partners: Universitat Obierta Catalunya (Spain), Dublin City University (Ireland), Oficina Antifrau de Catalunya (Spain), Infonodes (Italy), Transparency International (Portugal), Villa Montesca Foundation (Italy).

[2] Available at https://www.core-anticorruption.eu/dashboard

5. Current global practices and projects exploring big data and AI potential for enhanced anti-corruption measurement

The potential of big data and artificial intelligence systems is currently being explored in public organizations as well as at the academic level on an experimental basis. Numerous national control authorities have begun to employ big data and new technology in practical ways to target and enhance the effectiveness of their control actions for the purpose of thwarting and preventing corruption. In this direction should be seen, for instance, the experiences of the Central Procurement Office of the German Federal Ministry of the Interior (Beschaffungsamt des Bundesministeriums des Innern - BMI); the engagement of the Observatório da Despesa Pública (ODP) of the Ministério da Transparência e Controladoria-Geral da União (CGU) in Brazil; the monitoring activities of the Korea Fair Trade Commission; the commitment of the Italian Autorità Nazionale Anticorruzione (ANAC) in identifying corruption risks in public procurement and the contextual factors affecting them at the territorial level.

Besides the CO.R.E. project, whose main results are described in this book, there are currently several instances of good practices exploiting big data potentials. Scholars of the Corruption Research Center in Budapest have developed the Corruption Risk Index (CRI), a composite index based on the collection and cross-processing of public procurement data with other data of public administrations, signaling anomalies in individual tender procedures, political connections between party representatives and economic operators, anomalies in the economic characteristics of companies, other than regulatory, organizational and procedural weaknesses in public tenders.

The Opentender platform is a further initiative, funded by the European Union and bringing together six European research institutes. It was launched in January 2018 by Digiwhist with the aim of facilitating societal scrutiny of corruption. It pursued this key objective through the systematic collection, structuring, analysis, and wide dissemination of information on 17.5 million public procurements executed within the European Union since 2003. The platform includes a filter function to evaluate the integrity of bids, which enables identifying those at risk of corruption through the computational work of an algorithm that routinely scans websites with open data on public procurement, downloads and stores the data contained therein, and compares them with data from other useful datasets[3].

Another such is the Dozorro public procurements monitoring system from Transparency International Ukraine, which employs a machine learning

[3] See: https://opentender.eu/start

algorithm to enhance the detection of violations in public tendering procedures. The programmers themselves trained the machine learning system by sending approximately 3,500 tender bids to 20 experts, contextually asking, “Do you see any risk in these procedures?” and then entering the experts’ responses into the AI algorithm. Based on the learning process, the system assesses the probability of corruption risks in tenders and shares the results to civil society organisations in the Dozorro community[4].

Further, a team of Spanish researchers (López-Iturriaga & Sanz, 2017) developed a warning system based on neural networks, with the aim of estimating the likelihood of public corruption occurring in a given territory, by analysing the presence or absence of certain economic factors (property taxation, economic growth, property prices, number of depository institutions and non-financial companies) as well as political factors (permanence in power of the same political party). Actual examples of corruption that were reported in the media between 2000 and 2012 were utilized as data for the model design. Depending on how the economic or political elements indicated previously changed, the study gave short, medium and long-term predicted scenarios of corruption over a period of three years.

Without claiming to be exhaustive, the mentioned initiatives and research endeavors underscore the growing role of big data and artificial intelligence as invaluable tools in the global fight against corruption, with each project contributing unique insights and methodologies to enhance control actions, promote transparency, and prevent corruption at various levels of governance.

6. The structure of this book

The book is organized as follows. Chapter 2 initially provides an examination of classical corruption measures, encompassing direct and indirect methods and clarifying their potential and limitations. In the chapter, Michela Gnaldi further underscores the centrality of corruption risk assessment through red flags, emphasizing their pivotal role in identifying potential risks and promoting integrity within the public sector. Shifting focus to corruption risk assessment systems during emergencies, the chapter advocates for adaptive systems, drawing insights from the CO.R.E. project, which introduces a crisis-specific methodology and a general measurement framework for red flag computation. The discussed approach utilizes time discontinuity and

[4] See: https://ti-ukraine.org/en/news/dozorro-artificial-intelligence-to-find-violations-in-prozorro-how-it-works/

statistical testing to compute a set of nine red flags and assess corruption risks during crises while mitigating false positives. The presented framework covers aspects such as referencing relevant literature justifying red flag selection, adjustments made for emergency contexts, rationale behind each red flag choice, required quantities for indicator calculation from available data, and the process of raising red flags, including statistical test. Finally, the chapter underscores the need to validate red flags, recognizing the challenges in obtaining evidence from final judgments and media reports and discussing potential of statistical tools based on the minimum validity criterion.

The matter of the effectiveness of red flags in identifying corruption risks in emergency procurement is addressed and further explored in Chapter 3 by Davide Del Monte, Lorenzo Segato, and Simone Del Sarto. This chapter seeks to address this by empirically applying the CO.R.E. red flags to contracts awarded during emergency situations where corruption incidents have been identified. The study identified six cases of corruption during the Covid-19 emergency in Italy, running the indicators on the involved contractors and contracting authorities. Red flag scores were analyzed not so much to validate the indicators, but rather to explore potential practical applications by various stakeholders in corruption prevention and control strategies during emergency procurement. The chapter concludes with recommendations for enhanced collaboration between academics and practitioners in the development of anti-corruption tools for future endeavors.

In Chapter 4, Simone Del Sarto, Michela Gnaldi, Niccolò Salvini and Maria Giovanna Ranalli clarify the substantive and methodological choices made in the CO.R.E. project to develop a composite indicator (CI) for corruption risk in public procurement during emergencies, the CO.R.E.-CI (Corruption Risk in Emergency-Composite Indicator). Unlike existing CIs that aggregate red flags developed for ordinary times, the CO.R.E.-CI normalizes, weights, and aggregates a curated selection of red flag indicators specifically designed to measure corruption risk in public procurement during emergencies. This selection is entirely based on the methodology outlined in Chapter 2 of this volume. The chapter then presents the territorial distribution of corruption risk in the public procurement cycle over a ten-year period (2013-2022) based on the computation of the CO.R.E.-CI and using the Covid-19 crisis as an illustrative example of an emergency. While for illustrative purposes the primary focus is on the Covid-19 pandemic, and the analysis pertains to Italy's public procurement, the proposed method is adaptable to different crisis scenarios, can be applied to other national contexts, and customized to align with prevailing market trends during various crises.

Chapter 5 is devoted to a discussion on public procurement transparency over emergencies and to the presentation of the SCO.R.E. index. The authors, Agustí Cerrillo i Martínez and Wellington Migliari, stress that transparency in public procurement is essential for accountability and citizen trust, with digitalization aiding accessibility to information. In line with these premises, the authors present the SCO.R.E. index, a measurement tool aimed at assessing transparency and focused on data availability and interoperability. Through quantifying the extent of digitalization and by defining precise constructs and variables, the SCO.R.E. model generates evidence aimed at bolstering transparency in public affairs thereby enhancing the effectiveness of anti-corruption efforts.

In Chapter 6 Alessio Cornia and Dimitri Bettoni examines lessons learned from the collaboration fostered within the CO.R.E. project between investigative journalists and institutional actors to develop corruption-risk indicators for public procurement during emergencies. This cross-field collaboration provided mutual learning opportunities and synergies among diverse partners sharing common goals. Journalists shared techniques, approaches, and examples of corruption triggers in public procurement during emergencies, contributing to the development of CO.R.E. indicators. Their input also informed the design of the CO.R.E. data visualization dashboard and suggested improvements for enhancing investigative activities. By exploring the cross-field nature of the project, this chapter aims to enhance dialogue and leverage the untapped potential of synergies between institutional and civil society sectors. It offers recommendations to optimize collaboration and maximize the project's impact, aligning with journalists' perspectives on the need for improved cooperation in combating corruption.

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2. Measuring corruption risks in ordinary and emergency times

by *Michela Gnaldi, Simone Del Sarto*[*]

Abstract

This chapter begins with an overview of classical corruption measures, delving into direct and indirect methods along with their potential and limitations. It emphasizes corruption risk assessment through red flags, highlighting their key role in identifying potential risks and fostering integrity within the public sector.

The chapter then shifts its focus to corruption risk assessment during emergencies, where vulnerability to corruption intensifies due to relaxed regulatory frameworks, diminished oversight, and increased financial flows. It advocates for adapting corruption risk assessment systems to crisis contexts, drawing insights from the CO.R.E. project, which introduces a crisis-specific methodology and a general measurement framework for red flag computation over crises. This methodology leverages time discontinuity and statistical testing to assess corruption risks over crises while mitigating false positives. Overall, the nine proposed red flags and the whole proposed methodology are intended to accommodate the changing and far-reaching corruption risks induced by crises.

The chapter also underscores the importance of validating red flags for accurate corruption risk assessments, noting the challenges in obtaining such evidence through final judgments for bribery offenses and media reports. Finally, we discuss the "minimum validity" criterion, suggesting an evaluation of red flag internal coherence through statistical criteria, and explore the potential in this direction of models framed within the Item Response Theory approach.

1. An overview of classical measures of corruption

A variety of methods are currently employed to measure corruption, encompassing a broad spectrum of approaches (UNODC, 2023). Direct

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measures focus on the prevalence of specific forms of corruption, such as bribery, and are typically derived from population and business surveys. These indicators offer robust, accurate, and representative insights when the statistical designs of the surveys adequately mirror the entire population. However, their implementation presents challenges due to the often high cost and the difficulty of conducting surveys repeatedly. Direct measurement of corruption is further hindered by contextual factors and the nature of certain sectors, such as those inherently shielded from the public eye, like financial transactions, defense, or areas involving privacy, where survey-based assessments may fail to uncover the true extent of corruption due to a lack of direct experiences to report.

In response to the challenges in directly measuring corruption, indirect measures are employed as well. While these measures do not gauge corruption itself, they assess factors that may either facilitate or hinder corrupt practices. Perception-based indicators are a kind of indirect measures and capture a broad range of attitudes and beliefs related to corruption, albeit influenced by subjective factors such as culture and mass communication. Risk indicators, another set of indirect measures, offer insights into existing or absent infrastructures and procedures that heighten or reduce the risk of corruption, focusing on the context rather than corruption occurrence itself. Risk indicators play a pivotal role in policymaking, as they can be employed to support state's capacity to prevent corruption among public officials, private sector entities, and individuals.

Response indicators – the third category of indirect measures – gauge how states react to corruption, encompassing legislative initiatives (*de jure*) and criminal justice or other actions targeting corruption perpetrators (*de facto* response). These indicators, while indirect, provide valuable insights into a state's capacity and political will to combat corruption.

Composite indicators relying on the perception of corruption, such as the Corruption Perception Index released by Transparency International, exhibit various critical aspects. First, perception-based measures are subjective, relying on the opinions and experiences of respondents. Different individuals may have varying perceptions of corruption based on their personal experiences and cultural backgrounds. Besides, perceptions may be influenced by cultural norms and expectations, as what may be considered corrupt in one culture may be viewed differently in another.

Further, drawbacks arise from the uncertainties inherent in every composite indicator (CI) construction process. Indeed, any CI can be viewed as a statistical model, where the dependent variable is the composite indicator influenced by independent variables representing judgments made during its development (Munda *et al.*, 2009; Saisana *et al.*, 2005). These judgments encompass choices like selecting the single red flags, choosing the aggregation systems, the criteria for standardization, normalization, etc. These decisions introduce uncertainty into the model, leading to variations in the composite indicator value based on the choices made during its construction. For instance, opting for a specific criterion for aggregating simple indices or a particular weighting system impacts the final value of the composite and any ranking of individual units based on CI values.

Furthermore, the aggregation of diverse simple indices often results in a composite indicator that lacks comprehensive insights into the nature of the phenomenon. This limitation narrows the scope of answerable questions and reduces the informative potential of these measures in supporting policymakers (Rose-Ackerman, 1983). Further, Heywood and Rose (2014) note that such measures struggle to capture different types of corruption and fail to distinguish between various forms of corruption in different sectors.

Others (Rose and Peiffer, 2012; Heywood and Rose, 2014) emphasize that perceptions may not correlate with direct experiences of corruption and can be influenced by general sentiments about past economic growth (Kurtz and Schrank, 2007) or media coverage of corruption incidents or scandals (Mancini *et al.*, 2017). Donchev and Ujhelyi (2014) add that, although perceptions and direct experiences of corruption may be strongly correlated, the relationship is not linear: perception-based measures can differentiate well between countries where the perceived level of corruption is generally low but struggle to distinguish those where the perception of corruption is high.

Despite representing an advancement in some respects over perception-based measures, direct measures of corruption, such as those relying on the World Bank Enterprise Surveys (WBES) and the Business Enterprise Economic Surveys (BEES), also have some limitations. The first, common to all surveys that employ standardized questionnaires administered cross-nationally, is related to the accuracy and reliability of data, which depend largely on the quality and consistency of the questions posed to the interviewed subjects. The same question can be interpreted very differently by individuals from national and cultural contexts that are widely different.

The most significant limitation, however, concerns the degree of accuracy with which respondents report the occurrence of corrupt events. On one side, fear of legal persecution can clearly lead to non-disclosure or underreporting of corrupt activities, resulting in an underestimation of the phenomenon. Conversely, the wish to influence political-institutional action can lead to an overestimation of corruption. The direction of this social desirability, leading to underestimation and overestimation of corruption, is difficult to evaluate because it depends on the respondent's interest, which, in turn, may be linked to the willingness to facilitate or prevent corrupt practices (Sequeira, 2012).

Judicial measures are primarily punitive measures, focused on addressing past corrupt acts through legal consequences. They often involve legal proceedings and convictions, which can take a considerable amount of time. This time lag means that corrupt activities may be detected and punished long after they have occurred, making it challenging to address corruption in real-time or to use such measures for timely preventive action (Carloni, 2017).

Furthermore, it is observed (Fisman and Golden, 2017) that the effectiveness of judicial measures assumes a trustworthy and independent legal system capable of identifying, prosecuting, and convicting individuals involved in corruption. However, in countries where the legal system is compromised or lacks independence, reliance on judicial measures may not accurately reflect the extent of corruption. In environments where corruption is systemic, the absence of convictions does not necessarily indicate the absence of corruption. It could, instead, suggest that the legal system is unable or unwilling to address corruption, leading to underreporting. On the other hand, a high number of judgments and legal cases could be the result of genuine efforts against corruption and generally reflect an efficient judicial system. However, it would not rule out the possibility that those cases are manipulated for political or public relations purposes, for instance to give the public a false image of a state addressing the problem. Finally, cross-national investigations based on these measures can be complex because legal rules and judicial systems can vary significantly from country to country (Carloni, 2017).

2. Corruption risk assessment through red flags

Red flag indicators form the cornerstone of corruption risk assessment systems, designed to pinpoint potential corruption risks, and devise effective strategies for their prevention. Corruption prevention encompasses a broad spectrum of measures, ranging from educational initiatives and public awareness campaigns to the implementation of comprehensive national anti-corruption programs and corruption risk assessments. Among these strategies, corruption risk assessment stands out as a pivotal component in public sector activities. Corruption risk assessment allows public sector entities to identify potential vulnerabilities and weaknesses in their systems and operations. It provides valuable insights that support strategic decision-making. Public sector officials and managers can prioritize and plan interventions based on the identified risks. Further, corruption risk assessment helps in efficient resource allocation by directing attention and resources toward areas identified as having a higher risk of corruption. This ensures that limited resources are strategically deployed to address the most critical vulnerabilities. Moreover, corruption risk assessment safeguards public resources from mismanagement, embezzlement, or other forms of corruption. This is essential for maintaining the financial integrity of public institutions and ensuring that resources are allocated for the benefit of the public. Finally, regular corruption risk assessments contribute to the establishment of a culture of integrity within the public sector as well. By promoting awareness and accountability, organizations can foster a work environment where corrupt practices are less likely to occur.

In recent years, advancements in technology, particularly in the collection and cross-referencing of public procurement data with other administrative data sources, have revolutionized corruption risk assessment (Gnaldi *et al.*, 2021). This technological evolution has not only empowered the assessment process but has also directed the focus of researchers and policymakers towards red flags. These indicators, serving as the bedrock of corruption risk assessment systems, have gained increased attention due to their crucial role in identifying and addressing corruption risks proactively.

Red flags serve as markers for corruption risk and are commonly derived by assessing the extent of unjustified limitations on competition within the public procurement process, as highlighted by previous studies (Fazekas *et al.*, 2016a; Fazekas *et al.*, 2016b; Fazekas *et al.*, 2018). These indicators operationalize the definition of corruption, which posits that corruption occurs when public officials systematically bypass the principles of open and fair competition, leading to the repeated awarding of public contracts to affiliated companies (Fazekas and Kocsis, 2020). As already discussed in previous studies (Fazekas and Kocsis, 2020; OECD, 2019), corruption red flags serve as proxy measures indicating the potential presence of corruption risks, rather than direct evidence of actual corruption. It is anticipated that red flags will exhibit correlation with corrupt practices, but they are not expected to align perfectly with them.

Usually, corruption in public procurement involves manipulating the contract allocation process to favor a preferred bidder while avoiding detection. Grand corruption at an institutional level primarily seeks to extract rents, and in the context of public procurement, rents may be acquired by favoring preselected companies that, in turn, charge prices for contract deliveries higher than the average market rates (Abdou *et al.,* 2021). Therefore, assessing corruption risks by quantifying extra profit necessitates data on both the price and quantity of procured deliveries, typically available in public procurement administrative datasets but often incomparable across different periods and regions. As a result, additional proxies for corruption risk are proposed. For example, instances where a procurement procedure receives a single offer from a sole bidder and the number of bids, especially when only one bid is submitted (Klasnja, 2015), are widely adopted in the literature as corruption proxies. Other recurrent indicators of corruption risk include (Fazekas and Kocsis, 2020): absence of the publication of the call for tenders (when the call publication is voluntary); non-open or exceptional procedures (e.g., direct awards) that stifle competition and direct contracts to selected bidders; extremely short advertisement time periods, hindering non-connected bidders from preparing comprehensive bids in time; insufficient time intervals to award contracts, suggesting snap decisions that may involve premeditated assessments; subjective and challenging-to-quantify evaluation criteria (instead of price-related criteria), implying discretionary margins and potentially limiting accountability and control mechanisms.

The extensive body of literature on corruption risk can be organized into four distinct categories, as proposed by Fazekas and colleagues (Fazekas *et al*., 2016b). The first block includes the Tendering Risk Indicators. These indicators focus on the potential for corrupt manipulation during the tendering process, aiming to generate profits and distribute them among affiliated businesses. The second groups Political Connections Indicators. Indicators included in this group examine direct or indirect political ties between the contracting authority and companies, exploring how such connections might corruptly influence the public procurement process. The Supplier Risk Indicators is the third category of corruption indicators. It assesses the use of contract winners as tools to illicitly distribute benefits, rewarding all parties involved in the unlawful arrangement. The fourth group includes Contracting Body Risk Indicators, that is, indicators that evaluate vulnerabilities within the formal contracting bodies.

Tendering risk indicators proposed in the literature include using missing procurement outputs in infrastructure as a proxy for corruption, calculated as the difference between the stock of infrastructure and cumulative public spending on it (Golden and Picci, 2015). Recurrently awarding contracts to the same companies and employing exceptional procedural types, such as direct awards (Coviello and Gagliarducci, 2010) are also considered warning signs for corruption risk in public procurement (Fazekas *et al*., 2016b). Additional key indicators within this group include instances where a procurement bid receives only one offer (single bidding) and extremely short contract advertisement periods (Fazekas *et al*., 2016b)

Political Connections Indicators primarily focus on personal political connections and political influence gained through donations to political parties. Research in this area often explores specific countries and findings are only partially comparable across different contexts (Fazekas *et al*., 2016b). For instance, Amore and Bennedsen (2013) demonstrate that direct familial relationships between Danish businesses and country politicians enhance business profitability, particularly in industries dependent on public demand, such as public procurement.

Supplier characteristics, including headquarters location, incorporation date, and size, may serve as indicators of suppliers' involvement in corrupt transactions. Red flags in this category may include multiple businesses being established at the same address (Caneppele *et al.*, 2009) and proximity between the procurement body and winning firm, especially in environments of long-term political stability (Coviello and Gagliarducci, 2010). The incorporation date is considered a potential sign of corruption, particularly when paired with other data (Fazekas *et al.*, 2015). For instance, businesses formed during or shortly before a change in government and winning significant contracts are more likely to be exploited for rent extraction than for genuine company operations. Changes in a firm's corporate structure, particularly those linked to increases in company profits (Caneppele *et al.*, 2009) and the socioeconomic status of business owners are additional warning signs identified in the literature.

Papers addressing company financial information, such as those by Cheung *et al.*, (2012), David-Barrett and Fazekas (2016), and Cingano and Pinotti (2013), consistently demonstrate that indicators based on the growth of profits of companies awarded public contracts are closely linked to corruption risks, particularly when the company economic growth takes on extraordinary dimensions. Concurrently, the literature recommends validating these indicators by combining them with other proxies to minimize false positives. In other words, caution is advised when interpreting cases where companies exhibit an exceptional increase in profits due to genuine high levels of efficiency and growth.

Research focused on company ownership and management structures suggests that missing or concealed ownership can signal corruption. For instance, van der Does de Willebois *et al.* (2011) reveals that grand corruption is often associated with unknown owners who are deliberately kept hidden, either by registering the company in "opaque" jurisdictions, such as tax havens, or by failing to accurately disclose the company owners. Another method to conceal proprietary information is through the use of intricate ownership structures, such as "Chinese box" structures (Riccardi and Savona, 2013). Additionally, besides lacking data on company ownership structures, other factors identified as red flags in the literature include changes in the corporate structure, particularly when linked to increases in company profits, as asserted by Caneppele *et al.* (2009).

Another risk factor is the socio-economic profile of company owners, with studies showing that owners in the same sector tend to share similar profiles in terms of age, gender, and educational level (Caneppele *et al.*, 2009; Riccardi *et al.*, 2016). Consequently, any deviation from the typical profile of a company owner in a specific sector can be considered a red flag.

The corporate governance literature concentrates on how responsibility and discretion are allocated within a company and their connections with company performance. Despite the limited number of studies exploring the relationships between corporate governance and corruption, the literature generally suggest that external supervision and monitoring can decrease corruption risks.

The literature on Contracting Body Risk Indicators seeks to capture corruption risks at the organizational or agency level. It focuses on characteristics related to corruption risks, such as organizational capacity, integrity, transparency, and accountability. Initiatives in this direction include the Supreme Audit Institution's independence measure suggested by a 2016 poll conducted by the Public Expenditure Financial Accountability program. Other initiatives include the Sustainable Governance Indicators, which rate the Auditor General's level of accountability; the Tax Administration Diagnostic Assessment Tool, combining several sub-dimensions to determine corruption risk assessment; and the Global Integrity Report survey, capturing corruption-related features of various special agency kinds through expert evaluations.

3. Measuring corruption risks over emergencies: the CO.R.E. methodology

3.1. Premises

In times of crisis, the conducive environment for corruption is fueled by relaxed regulatory frameworks, diminished oversight, and a surge in financial activities. Public procurement systems, vital to many countries' crisis responses, are particularly vulnerable to corruption risks during emergency periods (European Commission, 2020; OECD, 2020; UNODC, 2021). As highlighted in Chapter 1, loosened regulatory measures, increased spending, and transformed purchasing environments point to the need for adapting corruption risk assessment systems to crisis contexts.

The adaptation of corruption risk assessment systems to crisis contexts involves a specific focus on red flags, serving as the foundation of such assessment systems. Indeed, red flags commonly utilized during ordinary circumstances may not effectively highlight corruption during non-competitive situations or crises. The reliance solely on these indicators, especially in scenarios with numerous bids resulting in a single offer through expedited procedures, may lead to an overestimation of corruption risks. Addressing this, measures to mitigate false positives should be reinforced in exceptional situations, considering unexpected disruptions and extraordinary market fluctuations (OECD, 2019).

In the CO.R.E. project, we propose an approach to measure corruption risk during crises by adapting previously developed red flags to the specific emergency context and implementing controls to address false positives (Gnaldi and Del Sarto, 2023b). This approach capitalizes on the time discontinuity introduced by a crisis, distinguishing between a pre-crisis period (period 1) and a post-crisis period (period 2). The methodology involves comparing the behaviors of companies and/or contracting authorities (our target units) after the crisis outbreak with their historical (pre-crisis) behavior, by means of various relevant red flags extracted from contracts within sectors or markets pertinent to the specific emergency being considered. The identification of these pertinent contracts can be achieved by scrutinizing the contract subject, particularly by classifying it using the Common Procurement Vocabulary (CPV). Specifically, contracts with CPV codes deemed relevant to the specific emergency are isolated through a difference-in-difference method, which allows us to identify the markets most involved in the crisis at issue.

Subsequently, the approach assesses the risk of corruption through statistical testing, allowing for hypotheses that can be set according to observed market trends during the crisis. The proposed approach therefore mitigates false positives by controlling for market trends and assumes that any statistically significant deviation in the behaviors of target units during the crisis – compared to what is expected based on observed marketplace tendencies – may indicate a corruption risk.

3.2. Statistical testing procedure

Hypotheses in the statistical testing procedure described above should be formulated in line with observed market trends. For instance, consider a red flag that compares a quantity or parameter of interest (e.g., a mean or proportion) denoted by θ and related to a specific target unit. Let θ_1 and θ_2 denote its values before and after the crisis, respectively. When there is no substantial difference in the overall market trend observed during the crisis outbreak, the hypotheses for the statistical test comparing θ_1 and θ_2 need to be formulated accordingly, as follows:

$$H_0: \theta_2 - \theta_1 \leq 0$$
$$H_1: \theta_2 - \theta_1 > 0.$$

Therefore, any significant positive difference in the observed behavior of the target unit during the crisis (i.e., between θ_2 and θ_1) can be interpreted as a corruption risk. Conversely, in the case of a different trend observed during a crisis, denoted as θ^*, the set of hypotheses must be adjusted as indicated below:

$$H_0: \theta_2 - \theta_1 \leq \theta^*$$
$$H_1: \theta_2 - \theta_1 > \theta^*.$$

Anytime a red flag is based on a statistical test, its raising rule takes the following form: if the test is significant, the target unit is considered as at risk, otherwise it is not.

Furthermore, target units identified as at risk through a red flag and relying on a statistical test may not be uniformly treated, as each may carry a different level of associated risk. To elaborate, at-risk target units can be differentiated based on (i) the degree of deviation from historical behavior (potentially adjusted for the overall observed trend), implying that a higher degree of deviation corresponds to a higher risk of corruption for that specific target unit, and (ii) the quantitative evidence provided by the statistical test associated with the red flag, relying on the traditional *p*-value. These two metrics can be jointly employed to effectively profile and differentiate target units according to varying degrees of risk.

3.3. The set of CO.R.E. red flags

In the following paragraphs, we present our curated selection of nine red flag indicators of corruption risk over crises and discuss the general measurement framework for their computation, as developed in the CO.R.E. project. The choice of the red flag criteria put forth in the project has been predominantly guided by substantive considerations to ensure their efficacy in addressing corruption risks during crises. In addition to substantive assessment, practical factors related to data accessibility in various national and international settings have also been taken into account, aiming to make our proposal viable for implementation by any interested parties.

When discussing the new formulation for each red flag, the framework provided below encompasses the following aspects: referencing pertinent literature that justifies the selection of specific red flags; detailing the adjustments made to existing indicators to accommodate emergency contexts; explaining the reasons behind the selection of each red flag; elucidating the specific quantities or information necessary for obtaining the indicator from available data; describing the process by which the red flag is raised, be it through statistical tests or other preliminary evaluation steps on the available data.

3.3.1. Winning rate across the crisis

A key aspect in measuring corruption risk in public procurement is the frequency with which contracts are awarded to the same companies. In this context, Coviello and Gagliarducci (2010) propose using the recurrence of awarding contracts to the same companies as a proxy for corruption risk in public procurement.

In crisis situations, the adapted version of the red flag, labelled *Winning rate across the crisis,* targets companies that, following an emergency outbreak, experience a significantly higher frequency of winning public contracts in the relevant economic market associated with the crisis, compared to the period before the emergency.

The rationale behind this indicator is to identify companies at risk that exceptionally enhance their competitive power during the emergency, as reflected in the proportion of awarded contracts within the relevant economic market(s). The approach involves assessing the behavior of companies that, post-emergency, secure public contracts in the relevant economic sector(s) much more frequently than in the pre-emergency period. This examination is conducted by comparing the proportions of awarded public contracts based on the contract main object/sector for each company before and after the crisis, utilizing an appropriate statistical test.

For the red flag to be computed, the necessary information includes the proportion of awarded contracts in the relevant economic market out of all awarded contracts for each company before and after the emergency outbreak. The red flag is raised when the proportion of awarded contracts after the crisis is found to be significantly greater than that before, considering the general market trend. Various statistical tests, such as the asymptotic z-test, Fisher exact test, or small-sample unconditional tests of independence, can be employed for this purpose (Agresti, 2003; Fleiss *et al.*, 2013).

3.3.2. Awarded economic value across the crisis

The red flag titled *Awarded economic value across the crisis* draws from the literature emphasizing the significance of exceptional profit or value growth in companies when assessing corruption risk in public procurement. Studies, such as Fazekas *et al*., (2015) and Cheung *et al*. (2012), suggest that companies established around a government change and winning large contract values are potential vehicles for rent extraction, linking profit growth to corruption risks.

In its adapted version for crisis scenarios, this red flag identifies companies that, post-emergency outbreak, have been granted public contracts within the relevant economic market(s) with higher economic value than before the crisis. The red flag considers these companies at risk, focusing on their exceptional increase in competitive power during the crisis.

To investigate this, the approach involves monitoring the behavior of companies over time, comparing two distributions of economic values of awarded contracts before and after the crisis, using suitable statistical tests such as the Mann-Whitney U test or the Kolmogorov-Smirnov test for two samples.

3.3.3. Contract economic deviation across the crisis

Red Flag 3, labelled *Contract economic deviation across the crisis*, addresses the potential connivance between companies and contracting authorities to artificially increase contract costs, as highlighted in the literature by sources such as ANAC (2017), Fazekas *et al*. (2022), OLAF (2013), and OLAF (2017).

The original formulation of this red flag measures the relative distance between the actual execution economic value and the initially awarded value of a contract, known as the economic deviation ratio. At the target unit level, this red flag is obtained by averaging the deviations over the involved contracts and provides insights into potential "moral hazard" behaviors during contract execution.

In its adapted version for crisis situations, the red flag assesses whether there is an increase in the economic deviation ratio across the crisis, specifically for contracts within relevant economic markets. The indicator deems companies or contracting authorities at risk if their contracts experience a significant increase in the economic deviation ratio during the crisis. To evaluate this, the red flag compares two distributions of economic deviation ratios (before and after the emergency) for each target unit, utilizing a suitable statistical test to check for a shift toward greater values in the post-emergency distribution.

3.3.4. *Contract length deviation across the crisis*

The *Contract length deviation across the crisis* is a further red flag addressing the potential opportunistic behaviors of companies influenced by contracting authorities, as deviations in the actual execution duration from the stated or expected one may hide such behaviors. Literature from sources like ANAC (2017), Decarolis *et al*. (2019), and Fazekas *et al*. (2022) suggests that time deviations, while sometimes justified by legitimate suspensions, can also signal corruption.

The original formulation of this red flag measures, at the single contract level, the deviation of actual execution times as a relative distance from those expected by the contract, known as the length deviation ratio. At the target unit level, this red flag is obtained by averaging the deviations over the unit's contracts.

In its adapted version for crisis situations, the red flag evaluates whether there is an increase in the deviation of the contract actual execution duration from its stated or expected duration, specifically for contracts within the relevant economic market. The indicator identifies companies or contracting authorities as at risk if their contracts exhibit a significant increase in the length deviation ratio during the crisis. To assess this, the red flag compares two distributions of length deviation ratios (before and after the emergency) for each target unit using a suitable statistical test, aiming to detect any shift towards higher values in the post-emergency distribution.

3.3.5. *Excess of concentration of the winners' distribution*

The red flag titled *Excess of concentration of the winners' distribution* is grounded in the indicator known as the "Winner's share of issuer contracts". In its original form, as discussed in literature by Fazekas (2020), Fazekas *et al*. (2022), and Abdou *et al.* (2021), this indicator assesses the proportion of contract value allocated to a winning company by a contracting authority, focusing on the count of procedures rather than economic value. The adapted version considers a concentration index, such as one based on the Gini heterogeneity index, on the winners' distribution of a contracting authority.

This red flag evaluates the frequency with which a contracting authority awards its contracts to the same company(ies), with a heightened risk associated with repeatedly awarding contracts to the same firms. In crisis situations, the red flag compares the concentration degree of the winners' distribution based on contracts issued after the emergency with that before the emergency, specifically for contracts within the relevant market.

The red flag identifies contracting bodies at risk if they exhibit an increase in the concentration of the winners' distribution across the crisis, indicating a higher frequency of awarding contracts to a diminishing number of firms. To assess this, the red flag requires the winners' frequency distribution for each contracting authority, both pre- and post-emergency. While no specific statistical test is available for testing two-sample differences based on the Gini heterogeneity index, the proposal involves discretizing the distribution of the computed concentration index into categories and labeling an administration as at risk if its concentration category increases across the emergency.

3.3.6. Award communication default across the crisis

The red flag labelled as *Award communication default across the crisis* is based on the acknowledgment that failure to adhere to reporting requirements is indicative of potential government misconduct and a risk of corruption.

This indicator, in its original form, focuses on the award communication default rate, representing the fraction of contracts for which award details have not been reported to anti-corruption authorities. In emergency situations, the adapted red flag specifically examines contracting authorities that exhibit an increase in the award communication default rate after the emergency, compared to the period before the crisis, with reference to contracts within the relevant economic market.

The red flag identifies companies at risk if there is a deterioration in their communication behavior regarding award details during the crisis. To assess this, the red flag requires the proportion of contracts without award notices out of all contracts issued, both before and after the emergency. The comparison is made using a suitable statistical test, similarly to what discussed for *Winning rate across the crisis* (red flag 1).

3.3.7. One-shot opportunistic companies across the crisis

The *One-shot opportunistic companies across the crisis* indicator is a unique red flag that does not have a specific reference in the current literature on corruption risk in public procurement, and it is not an adaptation of an existing red flag to emergency contexts.

This red flag is designed to identify companies that, after the emergency outbreak, are awarded one or more public contracts without having won any contracts in the years before the emergency (e.g., in the preceding five years), with a focus on contracts awarded within relevant economic markets.

The rationale behind this indicator is to flag companies exhibiting a "one-shot opportunistic behavior". It identifies companies at risk if they secure one or more public contracts after the crisis without demonstrating any competitive activity in the years leading up to the emergency.

To implement this red flag, information on a company's history of awarded contracts in the market(s) of interest over time is needed. Unlike other red flags, no statistical test is applied here. Instead, the red flag raises a warning if a company is awarded at least one contract after the crisis while having been absent from the relevant public procurement market (i.e., no awarded contracts) for a specified number of years before the emergency outbreak (e.g., five years, depending on the characteristics of the emergency). The absence of the company in the market during the specified period indicates a potential risk according to this red flag.

3.3.8. Pre-existing contracts modified after the crisis

The *Pre-existing contracts modified after the crisis* red flag addresses the concern that modifications to awarded contracts during the execution phase may signal irregularities, as indicated in the literature by ANAC (2017), OLAF (2013), and OLAF (2017). At the single contract level, the original formulation is a binary variable indicating whether at least one variant has occurred. At the contracting body or company level, the red flag is expressed as the proportion of modified contracts out of all concluded contracts.

In its adapted version for crisis situations, this red flag assesses whether a contracting authority or company has at least one pre-existing contract, initiated with a call before the emergency outbreak, that has been modified after the emergency. The rationale behind this red flag is to identify as at risk those entities with contracts published before the emergency and subsequently modified via amendments after the emergency began. Notably, the assessment excludes modifications made immediately thereafter, introducing a parametric time window. The duration of this window can be adjusted based on the specific characteristics of each crisis.

To implement this red flag, the necessary information involves the dates of publication for calls for tenders and the occurrence of contract variants for the contracts managed by a contracting authority or company. Unlike other red flags, no statistical test is applied here. Instead, the assessment involves determining, for each target unit (company or contracting authority), the presence of at least one contract meeting the criteria: (i) call published before the emergency and (ii) occurrence of at least one variant after the emergency outbreak (excluding those within the parametric time window). If these conditions are met, the target unit is labeled as at risk according to this red flag.

3.3.9. Lengthy contracts

The *Lengthy contracts* red flag lacks a specific reference in the literature on corruption risk in public procurement. While existing literature suggests red flags monitoring time extensions during the procurement process, such as extensions in the tender publication period or in the tender evaluation phase, the present red flag focuses on extensions to the contract duration itself. This extension refers to the time span between the start and end dates of the contract and is evaluated exclusively in the post-emergency period.

In its version for emergency situations, the red flag aims to identify contracting authorities or companies as at risk if they are awarded post-emergency contracts with durations significantly longer than the overall average post-emergency duration. The rationale is rooted in the detection of excessive contract durations that cannot be justified by the nature of the crisis.

To compute this red flag, the necessary information involves the distribution of durations for contracts issued or won after the emergency outbreak, belonging to the relevant economic market. The red flag employs statistical tests, such as the classic t-test or non-parametric tests like the Wilcoxon signed-rank test (Wilcoxon, 1945) to compare the distribution of post-emergency contract durations with the overall average duration. If the distribution is significantly greater than the overall value, the red flag raises concerns about the contracting authority or company being at risk.

3.4. Summary

The theoretical foundation of the suggested set of red flags largely relies on exploiting the temporal discontinuity introduced by the initiation of a crisis. This approach enables the distinction between two separate time periods: one preceding the crisis and one following it. In many instances, it involves a comparison of the behaviors of companies and/or contracting authorities after the crisis outbreak in relation to their past patterns.

The proposed methodology can be adapted to various crisis scenarios by: (i) aligning the time spans with the enactment date of legislative acts recognizing the commencement of the emergency period; (ii) choosing pertinent contract categories based on the markets most impacted by the specific crisis.

The discussed risk assessment strategy relies on a set of red flag indicators derived exclusively from contracts within sectors or markets relevant to the particular emergency under consideration (using their CPV classification).

Finally, the approach described above is applicable to various national contexts where the required data for red flag calculation are available, and it can be fine-tuned to accommodate market trends across crises by adjusting the hypotheses of the statistical tests accordingly.

4. The validity issue of red flags of corruption risk

The validity of red flags in assessing corruption risk is a critical aspect that demands careful consideration in the field of corruption studies. A robust validation process is essential to ensure the accuracy of these measures. Indeed, the reliability of corruption detection hinges on the validity check, which acts as a safeguard against inaccuracies and false positives. By subjecting red flags to validation procedures, researchers and policymakers can enhance the efficacy of corruption risk assessments, thereby contributing to more accurate and targeted anti-corruption measures.

The issue of validating red flag indicators for corruption risk is both strategic and complex, representing a relatively unexplored territory in the international scientific literature. The validity of a measurement tool refers, in essence, to its ability to accurately reflect the intended concept (Adcock & Collier, 2001). Valid corruption measures should detect corruption in cases where it has actually occurred. However, getting evidence of the existence of corruption is inherently challenging due to its hidden and latent nature.

While relying on final judgments for bribery offenses might seem useful, it poses substantial and technical challenges (Gnaldi and Del Sarto, 2023a). Cases resulting in convictions for bribery represent only a portion of the corrupt activities that authorities have identified and taken legal action against. Notably, numerous instances of bribery remain undetected or unprosecuted, introducing a selection bias in the available data. Moreover, the outcomes of bribery cases leading to convictions can be influenced by various factors, including the strength of evidence and the effectiveness of law enforcement. These elements may not necessarily indicate the presence or absence of corruption risks but rather reflect the legal process outcome. It is important to recognize that the absence of legal convictions in bribery cases does not automatically imply the absence of corruption; it could signify limitations within the legal system or challenges in detecting and prosecuting such cases.

Further, judgments are typically expressed in a qualitative manner and are embedded in documents with unstructured formats that may not be easily accessible and directly analyzable. Indeed, qualitative and quantitative analyses of bribe sentences may encounter difficulties when dealing with unstructured or semi-structured data. Unstructured information can overwhelm analysts, making it difficult to efficiently identify and prioritize relevant data related to potential bribe offenses.

Sorting through vast amounts of unstructured data manually can be time-consuming and resource-intensive. A substantial amount of information may be irrelevant or noise, consisting of sentences that have no bearing on corruption risks. Qualitatively distinguishing meaningful signals from the noise becomes a critical challenge, as false positives may result from the inclusion of irrelevant data. Moreover, corruption often involves complex interactions, transactions, and relationships. Analyzing sentences without considering the broader context may lead to misinterpretations and a lack of understanding of the multifaceted web of factors contributing to corruption.

The use of advanced data scraping techniques and text mining methods becomes then essential to access fundamental information embedded in bribe sentences, such as the type of crime, the entities involved (individuals, companies, public officials, contracting authorities, etc.), the timeframe of the offense, and more. However, the human resources and computational power required to sift through and analyze large volumes of qualitative data merged with public procurement data can be substantial. This can pose challenges for organizations with limited resources, hindering their ability to conduct thorough and efficient validation assessments.

What is more, accessing and analyzing a vast amount of qualitative data may raise privacy concerns, particularly if data involve sensitive or personally identifiable information. Besides, language evolves over time, and the use and interpretation of certain expressions may change. Relying on static sets of bribe sentences may become outdated and ineffective as language dynamics shift. Finally, judgments are often rendered many years after the commission of the crime. Given this temporal misalignment, an ex-post evaluation of the validity of corruption measures based on them requires an efficient judicial system capable of maintaining records of crime actors, types of crimes, etc., over time. This necessitates a system that facilitates interested users in accessing judgment contents freely and timely.

Similarly, relying on media reports to validate red flag indicators of corruption risk can offer valuable insights, but it is not without limitations. Media coverage may not offer a comprehensive overview of all bribery cases, with high-profile incidents receiving more attention compared to smaller or less sensational cases. Consequently, the cases highlighted in the media may be limited in number and may not fully represent the entire range of corruption instances, introducing a selection bias in the available data. Additionally, akin to bribe sentences, media reports may not consistently furnish adequate contextual information necessary for correlating those cases with the details required to calculate the red flags.

The scientific literature on corruption measurement seldom addresses the validation of corruption risk indicators, with only a few exceptions. In the work of Fazekas *et al*. (2018), red flags validity is assessed for their predictive power concerning the single bidding indicator, within a logistic regression modeling framework. This approach uses the single offer as the primary criterion to test the validity of a set of red flags. While the method is easily replicable, it assumes that a public contract receiving only one bid unequivocally signifies a corrupt circumstance. An assumption that, like those on which other red flags are based, requires validation. Another notable procedure is outlined in Decarolis *et al*. (2019) and Decarolis and Giorgiantonio (2022), who propose assessing the reliability of red flags in predicting a variable indicating whether a company's owners or top executives have been under police investigation for engaging in corrupt practices. Despite the strength of this latest variable in reflecting corruption risk, the procedure appears limited in replicability, given the confidentiality and restricted access to police investigation data.

Acknowledging the complexity and limitations of validating corruption measures using the aforementioned procedures, the literature (see, for instance, Bello y Villarino, 2021) propose to adopt a "minimum validity" criterion, which involves evaluating the degree of validity of a set of indicators based on their internal coherence, using specific statistical criteria. According to this criterion, corruption measures can be considered valid when they are strongly correlated with the latent phenomenon they intend to measure. The focus is on assessing the extent to which corruption measures capture the higher-level theoretical construct they aim to detect while excluding irrelevant elements.

Consistently with this criterion, Gnaldi and Del Sarto (2023a) suggest an approach for evaluating the validity of red flags, focusing on their internal coherence. This method relies on a procedure rooted in the framework of multidimensional Item Response Theory (Reckase, 2009). This framework is especially suitable as it enables an examination of how well corruption measures encapsulate the higher-level theoretical construct, by assuming that the connections among red flags are depicted by a latent and unobservable trait (corruption). Besides, this methodological framework assumes that the latent trait is multidimensional. Such an assumption is particularly appropriate as it accounts for the possibility that the relational structure among red flag indicators may mirror a complex and multidimensional configuration, rather than a simple and unidimensional one: high correlations are expected to be observed between subgroups or sub-dimensions of red flags. In cases where the focal point is a one-dimensional latent variable, it is anticipated that the proxy indicators employed for corruption measurement must exhibit strong correlations, indicating a singular underlying one-dimensional latent construct. Conversely, in instances where the latent phenomenon is multidimensional, such as the risk of corruption, it is reasonable to anticipate that the red flag indicators may not all exhibit correlations with each other. Instead, they may form sub-groups of indicators, with each sub-group measuring a distinct sub-dimension of the same underlying risk of corruption. According to the method above, the validity of a red flag is assessed with respect to the strength of the relationship between the red flag itself and the other red flags belonging to the same sub-dimension of the underlying latent variable. In this way, the degree of validity of a red flag is expression of the degree of coherence of that corruption risk proxy with the other indicators included in the sub-dimension.

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3. *Validation of red flags of corruption risks through actual cases occurred over the Covid-19 emergency*

by *Davide Del Monte, Lorenzo Segato, Simone Del Sarto*[*]

Abstract

This work takes inspiration from the efforts conducted by statistical research to confirm the validity of corruption risk indicators (red flags) in emergency, whose limits were highlighted in the paragraph 'Validity issue of red flags of corruption risk' of the previous chapter. Red flags are based on retrospective analysis of data on ordinary public procurement, exploiting the statistical ability to identify anomalies that might be relevant for corruption risk, and tend to be less applicable – or useful – to public procurement in emergency. This gap has suggested researchers to develop red flags for emergencies within the CO.R.E. project.

From the point of view of practitioners, red flags can help in corruption preventive strategies for public procurement. A question is if – and how – CO.R.E. red flags can be used in preventing corruption in emergency.

The chapter aims to contribute to the answer, applying empirically CO.R.E. red flags to a group of contracts, awarded during and for emergency situations, in which corruption episodes have occurred and later emerged from press reports.

The choice to conduct this type of research is motivated by the difficulties encountered in testing red flags using public procurement databases, which do not contain information on any adverse events manifested in individual contracts. The application of red flags to contracts that have shown, over time, to have been affected by the phenomenon of corruption can indeed serve as a litmus test.

Researchers have identified 6 cases of corruption occurred during the Covid-19 emergency in Italy, then have calculated the indicators with the CO.R.E. dashboard, scoring the red flags by contractor and contracting authority involved in the cases. Furthermore, researchers have selected other contracts than those affected by corruption, with the same contractors, running indicators to see if any difference occurred.

Red flags scores have been analyzed. The result of the test does not mean to validate the indicators, rather looking for possible practical application of the indicators by contracting authorities, law enforcement, citizens, or even other contrac-

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tors, in preventive or control strategies to avoid corruption in public procurement during emergencies.

The chapter ends up with some conclusions and recommendations for the future, suggesting more synergies between academics and practitioners in the development of anti-corruption tools.

Introduction

This chapter stems from the idea of developing an empirical verification system for the reliability of corruption risk indicators, built using statistical techniques, concerning contracts awarded in emergency contexts.

The previous chapters describe how statistics have been involved in the development of corruption risk indicators in public procurement, aiming to identify higher probabilities of a crime occurring, through theoretical study and the measurement of available parameters related to the contracts themselves. The indicators have a preventive function because they are generally applied to databases on public contracts, contracting authorities, or contractors to identify anomalies that could indicate possible corruption during the contractor selection or the contract execution phases. Statistical science has made significant progress in this regard, also thanks to the increasing availability of information for individual contracts aggregated in large databases accessible for free (cf. infra).

Corruption risk indicators in procurement (also called "red flags") present numerous aspects that can limit their usefulness from a preventive perspective. Partly, this uncertainty is linked to the nature of the phenomenon under analysis, partly it is linked to the quantity and quality of data available on contracts, partly it is linked to the concept of risk itself. Furthermore, corruption risk indicators cannot be applied and interpreted in the same way in ordinary procedures or in extraordinary procedures, such as those used in emergency situations (Schultz and Søreide, 2008). In such contexts, some relevant parameters for corruption risk indicators change, for example, those related to the contractor selection method, publicity, or contract award times. This causes corruption risk indicators to rise significantly during emergencies, justifying and partly legitimizing higher levels of corruptive risks.

For example, most contracting authorities that need to speed up the approval of contracts in emergency situations proceed by direct award, as is understandable in a critical phase. This raises the values of the associated risk indicator. It is therefore important to question the usefulness of indicators that report a high level of risk related to a choice (direct award) that instead appears legitimate and even reasonable in an emergency. The same can be said of other indicators, such as the participation of a single contractor or the extension of existing contracts.

Indicators are not able to distinguish between ordinary and extraordinary situations. For this reason, the CO.R.E. project was born, to develop risk indicators applied in emergency contexts, to be validated both through statistics and through empirical verification.

The underlying idea of this contribution is to empirically verify corruption risk indicators in emergencies, testing them on some contracts concluded during Covid-19 which retrospectively have been subject to corruption. The objective of this activity is not to validate the indicators, but to verify their possible uses during the emergency. The results of this experimentation can be useful for designing corruption prevention strategies in emergencies (Segato, 2021) for the benefit of contracting authorities who are in the critical situation of managing contracts to respond to emergencies.

1. Empirical evaluation and the scientific method

The idea of validating abstract elaborations with empirical tests is not new but belongs to the scientific method, developed by Galileo Galilei in the XII century to achieve a knowledge of reality based on mathematical rules but confirmed by empirical data. The method is based on the construction of models, based on data collected with inductive or deductive methods, which must then be verified with other empirical data, which obviously cannot be the same as those on which the model was built. The abstract model works when comparison with empirical data confirms its functioning.

The scientific method finds application in many fields, and it is intended to apply it in support of statistical science that deals with the development of corruption risk indicators.

The statistical activity of developing indicators focuses on the first part – the construction of the theoretical model on collected data – thanks to which it becomes possible to predict with sufficient reliability the probability of a certain future event occurring.

As one can understand, the subject matter is complex because it deals with measuring an event that is not certain, but uncertain (risk). Risk can be defined as the probability of an adverse, future, and uncertain event to occur. Think for example of hail, a fire, or theft. We are not able to know when our home will be affected by one of these events, but we can assess the possibility and probability of this happening. Therefore, risk, by its nature, contains an element of uncertainty that is difficult to measure. The issue becomes more complicated when considering the object of risk. Compared to the previous example, hail is a natural phenomenon, which occurs when certain atmospheric conditions occur; the fire can be of natural or human origin, in turn, it can be negligent (throwing a cigarette butt into a forest) or intentional (pouring fuel on the floor and setting it on fire); theft is a human and intentional phenomenon. The ability to predict when and if these three events will occur will be very variable, and it must be built based on elements that can be observed and measured at the time of assessment.

For example, by measuring barometric pressure and temperature, we can predict where hail might occur, by analyzing data on rainfall and the type of terrain, we can try to determine the risk of a fire, or finally, by evaluating the characteristics of our assets (value, accessibility, transportability, marketability) we can determine the risk of theft.

With respect to this last typology, the object of risk assessment, regarding the present contribution, is corruption. This further complicates the possibility of calculating the indicators. Corruption is a criminal phenomenon with characteristics that make its detection particularly difficult. Corruption is defined as an invisible crime because it is an illicit agreement of a consensual nature. Now when the crime of corruption occurs, neither of the two parties involved (simplifying, the public official, and the private individual) has an interest in reporting the fact. Unlike other crimes, such as murder, where there is an evident victim, for corruption, the victims are not directly involved in the negative event. When a businessman agrees with a public official regarding a tender to be favored in exchange for a sum of money, no complaint is lodged. The victims of the illicit agreement, namely the beneficiaries of what is provided in the tender, may remain unaware of the criminal phenomenon indefinitely. It is indeed said that corruption is a crime without victims or better without direct victims.

The nature of this crime therefore makes it extremely difficult to recognize the occurrence of the negative event, unlike the hail, fire, or theft. Consequently, the mechanisms for calculating the probabilities of the event do not work with corruption cases.

If the risk of corruption can be defined as the probability of a future and uncertain corrupt event occurring, the measurement of this risk remains one of the most complex challenges in criminology.

2. Methodology for empirical analysis

The comparative analysis started with the research and collection of information on cases of corruption or fraud related to public contracts signed during the COVID-19 pandemic and linked to emergency management. The research therefore excluded all contracts, signed during the emergency phase, that were not related to pandemic management. The research focused on contracts for the purchase of special cleaning services, the purchase of personal protective equipment, and the establishment of COVID-19 patient management units.

As this is an experimental analysis, the team did not develop a proper cases selection system for analysis, but significant episodes emerged from the research among the press reports. The reference time frame for the selection of contracts is determined by the ministerial decrees declaring the beginning or the end of the emergency period. The contracts subject to analysis must have a date of award falling within the emergency period.

Fig. 1 – A case identified in the media

Once the case was identified in the media, the first step was to retrieve the data of the entities involved. Newspapers usually report the news with the names of the main entities involved, and sometimes of the individuals under investigation, but without unique identifying details. To retrieve information on the contract, researchers first searched for the contractor's identifying data in the national companies register (www.registroimprese.it), searching in the example case for the name of the individual under investigation and the city where the company is based. The search generated a list of entities, which were sifted through to identify the most plausible one.

The company register system does not make all identifying data available for free (for example, the VAT number). Therefore, other free platforms were used to complete the contractor's profiling, cross-referencing data such as the headquarters address and the ATECO code.

Fig. 2 – Contractor identified in the national companies registry

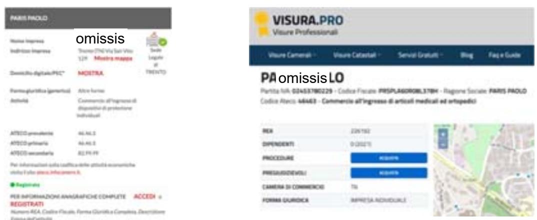

Fig. 3 – Information on company are completed from other sources

Once the contractor was correctly identified, the tender identifying codes (CIG) were searched for to verify the presence of contracts in the national public contracts database (BDNCP), to ensure that the contract data falls within the databases on which the risk indicators are run.

In the example case, a query was launched in the ANAC Public database for contracts, using the contractor's VAT code. The response was 2 contracting authorities, 6 contracts, 6.24 million Euros awarded.

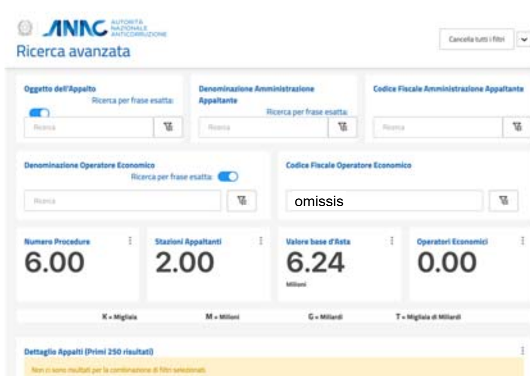

Fig. 4 – Search in tender database via VAT Code

The database provided no details on the contracts, so researchers went through the transparency section of the websites of the two contracting authorities. Data published in the Contracting authority website – public procurement (Amministrazione Trasparente – Bandi e Contratti) includes all contracts, and there is no search engine by VAT code of the contractor. This can make the search complex and time-consuming. But the transparency section of the websites has a special section on emergency acts (Interventi straordinari e di emergenza).

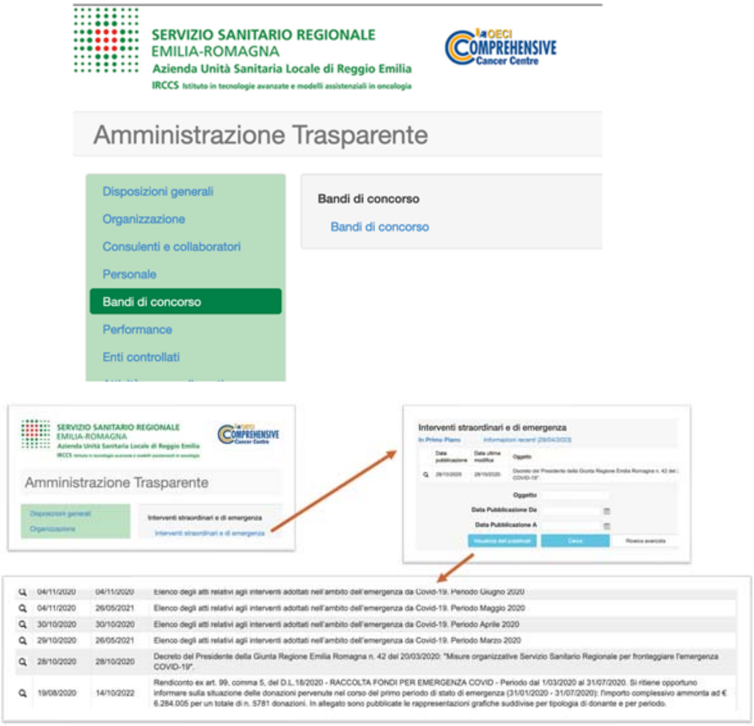

Fig. 5 – Searching contract details through special section on emergency acts

Thanks to this research, it was possible to identify the contracts involved in the investigations emerged in the media, with their respective GIC (Tender Identification Code) and CPV codes. CPV codes are related to the purchased product and are necessary to filter the public contracts database on which corruption risk indicators are run.

In this way, indeed, it is possible to empirically verify the reliability of corruption risk indicators for that specific CPV. Otherwise, comparing contracts with very different objects could invalidate the behavior of the indicators.

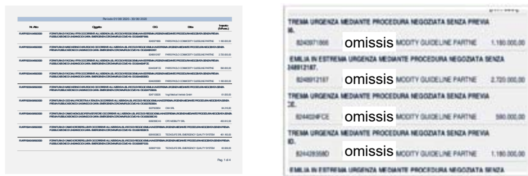

Fig. 6 – Four contracts details were found

The research also allowed retrieving individual contracts to carry out further analyses on the awards and identify the anomalies indicated in the contract text. This further analysis is not part of this contribution.

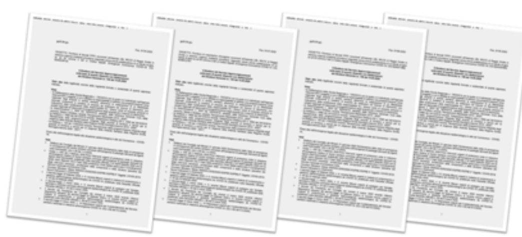

Fig. 7 – Single contracts awarded to the contractor

3. Cases of corruption in Covid-19 emergency contracts

The research on cases emerged in the press allowed the selection of six cases. In this section, the data of contracts concluded during the Covid-19 emergency, which have been affected by corrupt phenomena, are reported. It should be noted that all the information reported in this paragraph has been retrieved from press sources and verified by multiple sources, but it has not been possible to verify the status of the proceedings or to access investigation documents. The cases of corruption have not yet been judicially ascertained, so we are dealing with cases in which corrupt activities have been hypothesized, characterized by a series of elements such that judicial referral can proceed. The fact that corruption is later judicially ascertained is of little relevance because the contracts still exhibit characteristics of anomaly that should be intercepted by risk indicators. Indicators are meant to identify contract anomalies, not cases of corruption. For each contract, there is a brief description of the case, the source, the identification code of the tender, the contracting authority, and the economic operator involved, as well as the type of accusation for which there has been a judicial referral. Each case is described with the code name of the Police operation that distinguished it.

CASE 1 | "The Mask"

Six individuals are under investigation without detention for a major contract involving the supply of five million masks for a total of 5.6 million euros. The contract was directly awarded by the Local Health Authority of (omissis) to an individual company in Trento. Among the individuals under investigation is the entrepreneur (omissis). Charges including corruption, aggravated fraud, fraud in public procurement, issuance, and use of invoices for nonexistent operations.

RELATED PROCUREMENT – CASE 1

Between March and April 2020, the same company implicated in case 1 was awarded three similar contracts by the province of (omissis).

*CASE 2 | Operation "(*omissis*)"*

The Financial Police of Bari carried out searches against seven individuals, including entrepreneurs and a public officer of the Puglia Region, (omissis). They have been investigated for collusion with the head of the regional Civil Protection, (omissis), who was arrested. The charges being variously alleged include corruption, bid rigging, and forgery. The investigation pertains to the construction and setup of a facility for large-scale Covid emergencies, which was established at the (omissis).

RELATED PROCUREMENT – CASE 2

The same company implicated in case 2 (omissis) was awarded with other similar contracts by different contracting authorities during the Covid-19 emergency.

*CASE 3 | Covid Center at (*omissis*)*

According to an investigation by Fanpage, the work for the preparation of the area where the Covid Modular Hospital of the hospital (omissis) was established allegedly began days before the submission of the bid by the French multinational company (omissis), which later won the tender. A key figure involved in the projects undertaken in Campania was (omissis), a former manager at (omissis), who was arrested by the Palermo Prosecutor's Office regarding bribes in the Sicilian healthcare system, in which he is implicated.

CASE 4 | Shining

The case relates to bribery for the cleaning services awarded by the Municipality of (omissis) to the Apulian company (omissis). The town official (omissis) received an envelope with 8,000 euros by (omissis), partner in the Apulian company along with his brother. Alongside them, (omissis) has been arrested – a former employee who transported the envelope from Bari to Turin, and (omissis), the owner of a cleaning company who had advanced the money. (omissis) had claimed that the money was a loan but couldn't explain why it was delivered in cash and a shoebox, nor why an intermediary was involved.

RELATED PROCUREMENT – CASE 4

During the Covid-19 emergency the same company (omissis) was awarded by the city of (omissis) for cleaning services of the municipality offices.

*CASE 5 | Chinese masks in (*omissis*)*

A former Lega Party parliamentarian was arrested for an alleged mask scam from China to a Local Health Authority (omissis). (omissis) is accused of aggravated fraud, money laundering, commercial and public procurement fraud, and two instances of corruption.

According to a city counsellor, "how it was possible to establish a framework agreement with (omissis), a company which, as indicated earlier, primarily engages in wholesale trade of beverages and general food products, while its secondary activities include "other business consulting activities and administrative-managerial consultancy and business planning"?

CASE 6 | Bad masks in Tuscany

A former President of the national assembly is accused of fraud in public procurement for the purchase of 1.3 million FFP2 and KN95 masks with a commercial value of over 3.2 million euros, manufactured in China, reportedly with a lower filtering capacity than declared. A portion of the masks was intended to be delivered to the Civil Protection Department, while the other part was for the Technical Administrative Support Entity for the Tuscany Region.

RELATED PROCUREMENT – CASE 6

The same company won a supply contract for the same material with another public company (omissis) only a few days before being awarded the contract for CASE 6.

4. Red Flags in emergency to test

The CO.R.E. project has developed specific risk indicators for corruption, which can be applied to analyze risk levels for both the contracting authorities and the private contractors assigned to the contract. In previous chapters, the indicators were introduced, and here we revisit those applied to the contractor and the contracting authority.

	Red flag	*Main target unit*
1	Winning rate across the crisis	Company
2	Awarded economic value across the crisis	Company
3	Contract economic deviation across the crisis	Company/contracting authority
4	Contract length deviation across the crisis	Company/contracting authority
5	Excess of concentration in the winners' distribution	Contracting authority
6	Award communication default across the crisis	Contracting authority
7	One-shot opportunistic companies across the crisis	Company
8	Pre-existing contracts modified after the crisis	Company/contracting authority
9	Lengthy contracts	Company/contracting authority

Two macro indicators have been developed, one for the contracting authority and one for the contractor. These composite indicators are constructed based on individual indicators applicable to either party in the contract.

To measure the average risk level for each case, the indicators were run on the public contract database, limited to the emergency period. Each indicator can filter contracts for analysis based on a set of CPV codes relevant to the type of emergency. The indicators provide an average risk value for all contracts with the same CPV codes signed during the emergency period. The higher the indicator value (ranging from 0 to 1), the greater the detected anomaly, and consequently, the risk level. Not all indicators yield positive results.

5. Scoring red flags

In the context of emergency risk assessment for Covid-19 contracts involved in corruption incidents, the goal is to compare the synthetic risk indicator and the single indicators attributed to the contracting authority or the contracting party with the risk level for all contracts with the same CPV codes during the same period.

Furthermore, the results of the indicators have also been extracted in relation to other contracting authorities that have entered into contracts with the economic entities involved in corruption cases during the same period. This operation allows for a simple comparison between the behavior of the indicators concerning the contracting authorities involved in corruption cases and those not involved. The objective of this activity is to verify whether the behavior of the indicators changes consistently. The results of this application are reported in **Table 1** for the contracts affected by corruption reports, and in **Table 2** for other contracts connected to the same contractor. Table 2, of course, does not include indicators for the contractor; only the synthetic indicator, which is the same as in Table 1, is indicated.

Tab. 1 – Corruption risk indicators for contracting authority e contractor

	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
COMPANY						
1 Winning rate across the crisis	1	1	NA	NA	NA	1
2 Awarded economic value across the crisis	1	1	NA	NA	NA	1
3 Contract economic deviation across the crisis	NA	NA	NA	NA	NA	NA
4 Contract length deviation across the crisis	NA	NA	NA	NA	NA	NA
7 One-shot opportunistic companies across the crisis	1	1	NA	NA	NA	1
8 Pre-existing contracts modified after the crisis	0	0	NA	NA	NA	0
9 Lengthy contracts	0	NA	NA	NA	NA	0
COMPOSITE INDICATOR	*0.506*	*0.506*	*NA*	*NA*	*NA*	*0.506*
CONTRACTING AUTHORITY						
3 Contract economic deviation across the crisis	NA	0.158	NA	NA	0.947	0.701
4 Contract length deviation across the crisis	NA	0.954	0.141	NA	0.993	0.614
5 Excess of concentration in the winners' distribution	1	1	1	NA	1	1
6 Award communication default across the crisis	1	0.456	1	NA	0.888	0
8 Pre-existing contracts modified after the crisis	1	0	0	0	1	0
9 Lengthy contracts	NA	0.048	0	NA	0.1	1
COMPOSITE INDICATOR	*0.488*	*0.341*	*0.366*	*0*	*0.463*	*0.370*

As said, the scores are related to six cases that have reported episodes of corruption, the upper part of the table includes the red flags related to the contractor, the lower part can be referred to the contracting authority. The cases have involved six different companies and six different public administrations.

Related procurement cases

Tab. 2 – Corruption risk indicators for contracting authority in related contracts

CONTRACTING AUTHORITY	Case 1-1	Case 2-1	Case 2-2	Case 4-1	Case 6-1
3 Contract economic deviation across the crisis	0.593	0.601	NA	NA	NA
4 Contract length deviation across the crisis	0.154	0.497	0.833	0.814	NA
5 Excess of concentration in the winners' distribution	0	0	1	0	NA
6 Award communication default across the crisis	0	0	0	0.024	0
8 Pre-existing contracts modified after the crisis	0	0	0	0	0
9 Lengthy contracts	0	0.004	1	0	NA
COMPOSITE INDICATOR	*0*	*0*	*0.175*	*0*	*0*

Table 2 shows the results of the indicators for five contracting authorities that have awarded contracts to four companies involved in the cases of corruption above described.

6. Test results

As mentioned, the data in the tables presents the corruption risk indicator values for both the contracting authority and the contractor that have been involved in actual corruption cases. In this section, we analyze the results of these indicators to understand whether they have reliably highlighted the risk level concerning the occurrence of corrupt events, as indeed they have.

It is essential to reiterate that the effectiveness of indicators concerning individual cases is inherently limited. Therefore, the analysis of results does not aim to question the scientific work on the indicators but rather to empirically verify the usability of these indicators for individuals who must manage, oversee, or participate in individual contracts during emergency situations.

At first glance, it becomes evident that not all indicators yield useful results for risk assessment.

The indicators provide a result equal to 0 or 1, without any gradation allowing for the evaluation of potential differences between the analyzed entities, or they do not provide any result at all. Risk indicators 3 and 4 for companies do not provide any result compared to the six companies involved. These indicators relate to the modification of the duration or amount of an existing contract during the crisis, which may not be applicable in all cases where a company enters a new contract during the pandemic. Indicator 8 is not applicable for the same reason. Indicator 9, relating to the length of contracts, did not detect any anomalies, while the first two indicators report a maximum risk level (equal to 1), linked to the fact that the company won a contract for the first time during the emergency. Analyzing the situation case by case, it is evident that the indicators only work when information regarding the contracts of the involved company is available in the database. For three cases, it was not possible to obtain any result from the indicators. The lack of transparency regarding public contracts, which is a legal obligation, could represent a risk factor, but the malfunctioning of the indicators also depends on the failure to upload contract data. This constitutes an insurmountable limitation for these type of indicators, which is partly mitigated by the elaboration of a composite indicator, which for three out of six cases reports a value of 0.506. The data should be compared with the distribution of the composite over about 10,000 companies analyzed in the CO.R.E. Project. According to the elaborations produced by statisticians, about 90% of the analyzed companies have a composite risk value lower than 0.506, with an average value of 0.096. Since the maximum value is 0.672, the three companies analyzed with an indicator equal to 0.506 show a high level of risk. Where data is complete, the composite indicator seems to highlight a rather marked anomaly situation for the entities under observation, corresponding to companies that have been involved in corruption cases.

Risk indicators for contracting authorities present a better picture, probably because the initial data is more complete. In general, the results are distributed on a scale from 0 to 1, which allows for identifying entities with a higher level of anomaly. For example, indicator 4 (Contract length deviation across the crisis) indicates that the contracting station of case 5 has a higher risk index than the entity of case 2 or case 6. This could facilitate the control system to focus inspections among entities with higher risk levels. Also, in the case of contracting stations, some indicators have returned a result of 0 or 1 or have not returned any data.

For the contracting station involved in one of the six corruption cases (case 4), all indicators except one did not produce results. It should be noted that for this specific case, the indicators did not produce results even for the contractor.

The processing of the composite indicator reports different values ranging from 0 (case 4) to 0.488 (case 1) on a scale from 0 to 1, but for case 4, the composite indicator does not seem reliable, as it provides a value of zero in the face of a situation of alleged corruption. The composite data for the other 5 cases should be compared with the distribution of the composite over about

3,100 contracting authorities analyzed in the CO.R.E. Project. Almost all the contracting stations analyzed have a composite risk value lower than that measured for the involved contracting stations. The average value of the composite indicator is 0.030, the maximum value is 0.809, therefore the composite indicator seems to highlight a rather marked anomaly situation for the entities under observation (except one), corresponding to contracting stations that have been involved in cases of corruption.

7. Conclusions

The effort to create a corruption risk analysis tool in procurement during emergencies is certainly commendable. Traditional risk indicators indeed detect anomalies compared to ordinary procurement procedures that are perfectly understandable - and even justifiable - in an emergency context. The high use of direct procurement, for example, is a significant anomaly indicator compared to a tender, especially if of significant value according to community norms. In fact, the direct choice of the contractor entails a greater risk of abuse of power. However, in an emergency, direct procurement probably represents the best choice to ensure a prompt response to the critical situation. In these cases, the traditional indicator is probably not very significant because all contracting authorities proceed with that type of procedure.

Hence the opportunity to work with innovative risk indicators based on the large amount of data on public contracts, which has the great advantage of continuously feeding itself and providing updated information for analysis. This obviously requires that the information flows feeding the databases are as constant, timely, and complete as possible. The PNRR also represents an interesting opportunity from this point of view, since the reporting rules imposed by Europe oblige entities to upload data into computer systems to obtain the settlement of European funding.

An additional added value of corruption risk indicators in emergencies comes from the ability to understand, ex post, the characteristics of contracts during emergencies that have then revealed fraud problems. Anomaly characteristics can be kept under observation in the subsequent emergency, thus designing an effective risk prevention strategy even during the emergency.

At present, the indicators of the CO.R.E. project still have room for improvement and potential development of great interest. The developed indicators require complete and coomprehensive databases to provide useful data for analysis, and therefore encounter a largely incomplete state of the art in databases. For example, the national database of public contracts does not contain data on sub-threshold awards, contains little data on the phase following the award (e.g., contract variations), and is not linked to data on the liquidation of amounts. Furthermore, the developed indicators are difficult to apply to individual entities or contracts, so it is necessary to understand how these indicators can be useful to anticorruption managers or compliance managers of the different entities involved in procurement.

There are some interesting development areas: one is Comparing Emergency Risks Across European Countries. This is feasible in the case of a global emergency (such as a war or a pandemic), or by precisely identifying the recurring patterns of similar emergencies in different countries (e.g., flooding or earthquakes). Another development theme concerns Analyzing Red Flags for Individual CPVs: Selecting and analyzing red flags specific to each Common Procurement Vocabulary (CPV) code could allow more precise analysis of the risks of corruption related to specific works, goods, or services.

Finally, the indicators can be profitably used to monitor projects of the National Recovery and Resilience Plan (PNRR) financed with the Recovery and Resilience Fund (RRF), which have updated and detailed databases. In this sense, the intersection between statistical development of indicators on procurement databases and criminological analysis of cases of (presumed) corruption that are gradually identified by the judiciary and law enforcement agencies remains of interest. The intersection of the different information, comparing contracts that have shown criticality with the totality of PNRR contracts, can provide further relevant insights for the development of indicators.

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4. The CO.R.E. Composite Indicator (CO.R.E.-CI): territorial distribution of corruption risks across the Covid-19 crisis in Italy

by *Simone Del Sarto, Michela Gnaldi, Niccolò Salvini, Maria Giovanna Ranalli*[*]

Abstract

The chapter emphasizes the versatility of Composite Indicators (CIs) in policy analysis and public communication. While discussing the key role of CIs in supporting the decision-making process, it acknowledges the challenges associated with developing robust CIs, highlighting a limited focus on creating a CI specifically addressing corruption risk in emergency procurement in the existing literature. To address this gap, this chapter describes the application of a CI of corruption risk to the Italian public procurement process. The CI is named CO.R.E.-CI (Corruption Risk in Emergency-Composite Indicator) and is settled according to the overall methodology developed within the CO.R.E. project. In contrast to existing CIs that aggregate red flags designed for normal times, the CO.R.E.-CI normalizes, weights, and aggregates a carefully selected set of red flag indicators specifically tailored to measure corruption risk in public procurement during emergencies. This selection is entirely based on the methodology outlined in Chapter 2 of this volume. After detailing the methodological steps undertaken to build CIs, the chapter presents the territorial distribution of corruption risk in the public procurement cycle over a ten-year period (2013-2022) through the computation of the CO.R.E.-CI. The Covid-19 crisis is used as an illustrative example of an emergency. While the primary focus is on the Covid-19 pandemic, and the analysis pertains to Italy's public procurement, the proposed method is adaptable to different crisis scenarios, can be applied to other national contexts, and customized to align with prevailing market trends during various crises.

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1. Composite indicators as suitable tools for measuring corruption risk

The measurement of complex phenomena like corruption and corruption risks encounters a major challenge in summarizing the information derived from a set of individual indicators, often referred to as red flags, into a single metrics, such as a Composite Indicator (CI) of corruption risk. This challenge stems from the multifaceted nature of corruption, which involves several interrelated factors and behaviors that can vary across contexts and environments. Single red flags provide specific insights into certain aspects associated with corruption or corruption risks. However, relying solely on individual indicators can present limitations in capturing the holistic picture of corruption, as they often highlight isolated aspects without considering the broader context.

Composite indicators can be therefore employed to convey summary information in a relatively simple way. Indeed, they are used widely in various sectors in public services as tools in policy analysis and public communication to compare units of analysis (Countries, regions, contracting bodies etc.). The policy potentials of composite indicators extend across numerous sectors, offering decision-makers a view of complex phenomena. Their potential lies in their capacity to distill multifaceted data into actionable insights, fostering evidence-based policymaking. In the context of governance and public administration, composite indicators provide a nuanced understanding of institutional effectiveness. By incorporating metrics related to transparency, accountability, and service delivery, these tools assist policymakers in identifying areas for improvement, enhancing public services, and strengthening democratic governance structures. In areas such as economic governance, composite indicators serve as tools for crafting policies that foster sustainable economic growth or resource allocation, and for identifying areas in need of targeted interventions. Within the realm of social development, composite indicators contribute to understanding complex societal dynamics – such as social inclusion, poverty alleviation, equitable resource distribution, societal well-being – and to support policymakers to identify areas requiring attention and intervention.

Developing a composite indicator is a complex undertaking fraught with challenges, ranging from issues related to data availability and the selection of individual indicators to the choices of normalization, aggregation, weighting schemes (Munda *et al.*, 2009; Saisana *et al.*, 2005). Presently, there has been a limited focus on developing a composite indicator of corruption risk in public procurement, as an aggregated measure derived from individual red flags. Notably, the proposal by Fazekas and colleagues (Fazekas *et al.*, 2016) stands out. Their work involves creating a composite score, the Corruption Risk Index (CRI), which serves as a proxy for high-level corruption in public procurement. This index is derived from public procurement data spanning 28 European countries for the period 2009-2014. A similar endeavor is undertaken by Troìa (Troìa, 2020) using data and red flag indicators developed from the Italian National Database of Public Contracts (*Banca Dati Nazionale dei Contratti Pubblici,* BDNCP). Additionally, within the Single Market Scoreboard Initiative, individual indicators (red flags) are aggregated through summation to depict the performance of various EU countries concerning key aspects of public procurement.

Composite indicators of corruption risk in public procurement are currently based on elementary indicators or red flags developed for ordinary times. In the present chapter, we deal with emergency scenarios and propose a CI of corruption risk in public procurement over emergencies, called CO.R.E.-CI, standing for Corruption Risk in Emergency-Composite Indicator. The CO.R.E.-CI normalizes, weights, and aggregates a curated selection of red flag indicators specifically developed to measure the risk of corruption in the public procurement process over emergencies. The selection of the red flags used to feed the CO.R.E.-CI procedure is fully based on the methodology described in the Chapter 2 of the present volume.

The present Chapter is organized as follows. In paragraph 2 (and subparagraphs therein), we describe the main methodological steps needed to develop a composite indicator, while in paragraph 3 we describe the procedure to build the CO.R.E.-CI. Based on the CO.R.E.-CI, in paragraph 4 we show the territorial distribution of the risk of corruption in the public procurement cycle in emergency, across a ten-year period (2013-2022). For illustration purposes, we consider the Covid-19 crisis as emergency at stake. While the primary emphasis of the analysis is on the pandemic, and the specific analytical context pertains to Italy's public procurement, the proposed method is adaptable to various crisis scenarios. Besides, it can be extended to other national contexts and customized to align with market trends prevalent during different crises.

2. Building a composite indicator

Developing a composite indicator is a complex process, with several substantive and methodological alternatives and possibilities influencing the quality and reliability of the outcomes (OECD, 2008). In the following, we briefly revise the main steps implied for CI's construction.

2.1. Choice of elementary indicators

The effectiveness and limitations of composite indicators largely stem from the quality of the underlying variables and the dataset they come from. During this stage, it is essential to define both the size and characteristics of the elementary indicators fueling the CI procedure. They should be quantitative (discrete or continuous) and possess a clearly defined polarity (i.e., the positive/negative relationship with the underlying construct they measure). Typically, the selection process is guided by theory, empirical analysis, pragmatism, or intuitive appeal. Ideally, indicators should be chosen based on their relevance, analytical soundness, timeliness, accessibility, and other relevant criteria (OECD, 2008).

2.2. Normalization, weighting and aggregation schemes

Normalization is necessary to ensure comparability among individual indicators, especially when they possess different measurement units or exhibit a skewed distribution. Additionally, normalization becomes crucial when indicators exhibit different polarities, in view of their aggregation. In such cases, it is customary to normalize indicators with a negative correlation to the latent phenomenon being measured (negative polarity). This normalization transforms them into positively correlated indicators with the latent phenomenon (positive polarity). Consequently, larger values of the normalized indicator correspond to larger values of the composite.

There are various normalization methods, such as ranking, standardization (or z-scores), re-scaling (or min-max transformation), indexing (index number transformation or "distance" to a reference), and categorization. A complete review and a thorough discussion of possible normalization methods are provided in OECD (2008), Munda *et al*. (2009), Saisana *et al*. (2005), and Terzi *et al.* (2021). In the following we will sketch only three among the most widely used normalization methods.

Let x_{qc} be the q-th elementary indicator of the c-th unit, $q = 1, \ldots, Q$, and $c = 1, \ldots, C$, where Q is the overall number of elementary indicators and C is the overall number of target units. Moreover, let I_{qc} be the standardized version of indicator x_{qc}.

Standardization (z-scores) is based on the following formula:

$$I_{qc} = \frac{x_{qc} - \mu_q}{\sigma_q},$$

where μ_q and σ_q are the mean and standard deviation of the q-th elementary indicator, respectively. Hence, for each indicator, the difference between the original values and the mean over the target units is divided by the standard deviation. In this way, indicators have a common scale with mean 0 and standard deviation 1. If an indicator has negative polarity, standardized values can be multiplied by -1.

Rescaling (Min-Max transformation) can be carried out as follows:

$$I_{qc} = \frac{x_{qc} - min_c(x_{qc})}{max_c(x_{qc}) - min_c(x_{qc})}.$$

Then, the difference between the original values and the minimum is divided by the range of an indicator. Consequently, transformed indicators have a common scale ranging between 0 and 1. Therefore, this transformation should be applied only to non-binary red flags. If an indicator has negative polarity, the complement of rescaled values with respect to 1 can be calculated.

Categorization (or discretization) assigns a score for each indicator according to a specific rule, such as through threshold values. At this regard, let k be the number of categories to use for normalizing an indicator and let s_1, s_2, …, s_k be the scores to be assigned (generally, contiguous integers). Hence $k - 1$ thresholds need to be specified, t_1, t_2, t_{k-1}, generally defined using the percentiles of the observed indicator distribution. Then,

$$I_{qc} = \begin{cases} s_1, & x_{qc} < t_1, \\ s_2, & t_1 \leq x_{qc} < t_2, \\ s_3, & t_2 \leq x_{qc} < t_3, \\ & \dots \\ s_k, & x_{qc} \geq t_{k-1}. \end{cases}$$

In order to obtain a single CI from a set of individual indicators, two other important choices are at stake: the weighting system and the aggregation scheme. The former implies the scale of importance of each individual indicator, while the latter identifies the technique (compensatory, partially compensatory or non-compensatory) for summarizing the individual indicator values into a single number.

Weights should reflect the relative importance of the individual indicators and heavily influence the outcomes of the CI. The most widely used techniques for weighting individual indicators are the following (Munda *et al.*, 2009; Saisana *et al.*, 2005; Terzi *et al.*, 2021): *i.* no weighting, that implies that equal weights are applied to all individual indicators; *ii.* subjective or expert weighting, where a group of specialists defines a weight for each indicator; and *iii.* objective or "data-driven" weighting, as, for example, when the coefficients of the first factor of Principal Component Analysis are used as weights (this is the set of weights that explains the largest variation in the original indicators). The choice of the weighting system is usually by far the most influential among the others on the final CI value and related rankings (as an example, see results in Gnaldi and Ranalli, 2016).

The choice of the aggregation scheme, on the other hand, heavily depends on the degree of compensability or substitutability of the individual indicators. A compensatory approach involves the use of linear functions, such as a linear combination of the normalized individual indicators, whereas a partially compensatory or non-compensatory approach requires the use of non-linear functions, such as with a multiplicative approach. In the first case, the CI for unit c (CI_c) can be obtained as follows:

$$CI_c = \sum_{q=1}^{Q} w_q I_{qc},$$

where $0 \leq w_q \leq 1$ is the weight given to indicator q, and it is such that $\sum_{q=1}^{Q} w_q = 1$. When using a geometric aggregation rule, like the following:

$$CI_c = \prod_{q=1}^{Q} I_{qc}^{w_q},$$

partial compensability is allowed. The additive and the multiplicative aggregation functions can be seen as special cases of a generalized mean or power mean of order *r*, where $r = 1$ for the arithmetic mean and $r \to 0$ for the geometric mean. Alternative aggregation methods are, among others, the Wroclaw Taxonomic Method, the Mean-Min Function, and the Mazziotta-Pareto Index (for details see Munda *et al.*, 2009; Saisana *et al.*, 2005; Terzi *et al.*, 2021).

3. The development of CO.R.E.-CI

The objective of this paragraph is to describe and clarify the methodological choices (see paragraph 2) taken for the application of the CO.R.E.-CI presented in this Chapter. The procedure involves several stages, as reported in the previous paragraph (choice of elementary indicators, normalization, weighting, and aggregation schemes). Before clarifying the details of these procedural steps, we describe the data sources, that is, the Italian National Database of Public Contracts (BDNCP) and Opentender, devoting special attention to the former and the data architecture built to manage it, given its magnitude and complexity.

3.1. The data sources and architecture

In the CO.R.E. project we rely on two main data sources: the Italian National Database of Public Contracts (BDNCP) and Opentender data.

The former, managed by the Italian Anticorruption Authority (ANAC), is an open data portal[1] that provides access to information related to anti-corruption, transparency, and public contracts as part of ANAC's institutional functions. The portal allows users to search for information on public procurement using keywords and offers various filters for refining results, which can be visualized through a dashboard. The data is also accessible in a machine-readable format, enabling further analysis and distribution through API using OCDS, a shared standard data model designed to support organizations in promoting international transparency.

The portal is organized into five subsections: RPCT (list of individuals in charge of corruption prevention and transparency within each Italian public institution), In-House (list of in-house companies), L190 (register of communications according to article 1 paragraph 32 L.190/2012), register of referees and datasets (the data on public contracts in Italy). The latter is primarily the subject of our analysis and comprises nearly 158 different datasets, containing information released in various formats, such as CSV, JSON, and TILL. The dataset section is also organized into several subsections, mainly related to the stages/actors of the public procurement process, including contracting authorities, economic operators, call for tenders, award notices, economic framework, etc.

The second dataset employed in the CO.R.E. project comes from Opentender, a tool designed to explore, analyze, and retrieve public procurement data linked to the 28 EU member states, Norway, the EU Institutions, Iceland, Switzerland, and Georgia. It is developed with the support of Digiwhist, a project funded by the EU Horizon 2020 initiative. The primary objective of the project is to systematically address public sector corruption by collecting, organizing, analyzing, and sharing information related to public procurement and accountability mechanisms for public officials in the EU and neighboring countries. Opentender has been built using robust data collection and

[1] https://dati.anticorruzione.it

processing software that extracts procurement data from 25 public procurement sources, including but not limited to TED (Tenders Electronic Daily) and national web portals/open data sources.

In paragraph 4 of the present chapter, we will provide a real case application of corruption risk assessment in public procurement during the Covid-19 emergency, applied to the Italian case. For this purpose, the BDNCP is used. Due to the complexity of managing such a massive amount of data, a programmatic approach needs to be considered, particularly through the implementation of a big data pipeline, which can be synthetically visualized in Fig. 1 and described in the following.

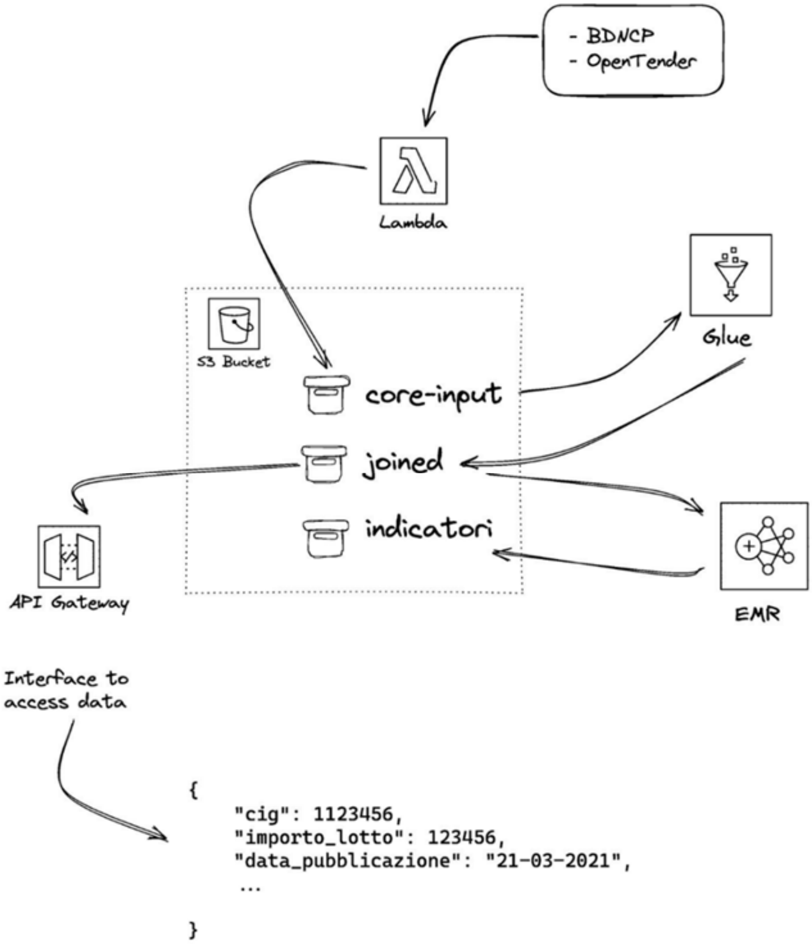

Fig. 1 – Sketched overall software architecture of CO.R.E. indicators

A data pipeline comprises processes for ingesting, cleaning, transforming, and storing data. Pipelines are crucial for data-driven applications, facilitating the reliable and efficient movement of data. Depending on application needs, data pipelines can be either batch or real-time. Batch pipelines, commonly used for Extract, Transform, Load (ETL) processes, extract data from sources, transform them for analysis, and load them into a target data store. Real-time pipelines are systems designed to process and analyze data as they are generated or received, providing immediate and continuous insights. Unlike batch processing, which deals with data in chunks or batches at scheduled intervals, real-time pipelines handle data on the fly, allowing for near-instantaneous analysis and response.

The CO.R.E. data pipeline comprises several essential components: a web scraper, a data parser, a data transformer, and a data store (see Tab. 1).

Tab. 1 – Main components of the CO.R.E. big data pipeline

Component	*Description*
Web Scraper	Responsible for extracting data from the BDNCP open data portal.
Data Parser	Parses data extracted by the web scraper, written using the Apache Arrow open-source framework.
Data Transformer	Transforms parsed data into a suitable format, run on Amazon Elastic MapReduce (EMR) for large-scale data processing.
Data Store	Chooses Amazon Simple Storage Service (S3) as the final storage for transformed data.

The web scraper extracts data from the BDNCP open data portal, adhering to a schedule synchronized with the source's update frequency. Specifically, data is scraped from the official BDNCP datasets related to the several public procurement stages (call for tenders, award notice, contracting authorities, winner companies, contract economic framework, etc.).

The data parser is responsible for parsing the information extracted by the web scraper and managing the file extensions employed by the organization for data replication across the infrastructure.

The third component, the data transformer, is tasked with converting the parsed data into a format suitable for loading into the final data store. Given the substantial volume of data being processed, this transformation step is executed in cloud infrastructures rather than on local machines. Specifically, transformation is executed on AWS (Amazon Web Services), using either AWS Glue or a combination of AWS managed services such as Elastic Container Registry (ECR) and Elastic Container Service (ECS) Elastic Beanstalk for containerized data transformation. The transformed data is then stored in Amazon S3, an object storage service known for scalability, availability, security, and performance.

Once the data undergo transformation, they are loaded into the ultimate data store. The data store serves as the concluding element of the data pipeline, housing the aggregated data in an extensive file with over 10 million contracts and 150 columns of variables. Additionally, sizable indicator files are computed, including those resulting from the CO.R.E.-CI, generating an equivalent number of additional files. For each indicator, distinct files are produced, addressing specific target units of measurement such as contracting authorities and winner companies, identified by their tax code or geographical aggregation units, such as regions (NUTS-2 level), and provinces (NUTS-3 level).

3.2. Elementary indicators for the CO.R.E.-CI

As described in Chapter 2, the red flags employed to ingest the CO.R.E.-CI are developed by capitalizing on the time discontinuity introduced by a crisis and allow us to evaluate the behaviors of companies and/or contracting authorities after a crisis outbreak in comparison to their historical (pre-crisis) behaviors.

The risk of corruption is subsequently assessed through statistical testing, where hypotheses are set according to the observed market trends during a crisis. The list of individual red flags considered for building the CO.R.E.-CI is reported in Tab. 2, which also includes, for each indicator, the involved target unit and whether it relies on a statistical test. In cases where a statistical test is applied, the red flag yields a numerical value between 0 and 1, calculated as one minus the p-value of the relevant test. Conversely, if the red flag is not based on a statistical test, it is binary, taking the value of 1 if the risk situation is detected for a specific target unit and 0 otherwise.

3.3. Computing the CO.R.E.-CI

Considering the data sources described in paragraph 3.1 and the elementary red flags recalled in paragraph 3.2, the application of the CO.R.E.-CI presented in this Chapter is built through the following methodological choices.

As far as normalization is concerned, categorization is considered, in particular by dichotomizing (i.e., using two categories and one threshold) the red flags by means of statistical testing. In fact, since we have two red flags that are binary by construction, it becomes necessary to adapt the scale of the remining indicators. Specifically, since the red flags based on a statistical test return one minus the p-value (as measure of the statistical evidence against the null hypothesis of no risk), a threshold equal to 0.95 can be used (corresponding to the usual significance level of 0.05), as follows:

$$I_{qc} = \begin{cases} 0, & x_{qc} < 0.95, \\ 1, & x_{qc} \geq 0.95. \end{cases}$$

for $q = \{1, 2, \ldots, 9\} \setminus \{5, 7\}$.

Tab. 2 – Selection of elementary red flags involved in the computation of the CO.R.E.-CI (Gnaldi and Del Sarto, 2023)

	Red flag	*Main target unit*	*Statistical test*
1	Winning rate across the crisis	Company	Yes
2	Awarded economic value across the crisis	Company	Yes
3	Contract economic deviation across the crisis	Company/contracting authority	Yes
4	Contract length deviation across the crisis	Company/contracting authority	Yes
5	Excess of concentration in the winners' distribution	Contracting authority	No
6	Award communication default across the crisis	Contracting authority	Yes
7	One-shot opportunistic companies across the crisis	Company	No
8	Pre-existing contracts modified after the crisis	Company/contracting authority	Yes
9	Lengthy contracts	Company/contracting authority	Yes

Afterwards, the single red flags are weighted according to expert opinions. Specifically, seven experts in the field of anticorruption and corruption risk assessment in public procurement have been interviewed and asked to score the nine red flags (separately on the basis of the target unit). Subsequently, by averaging the scores over the experts and scaling them so that they sum up to one, we obtain the weights reported in Tab. 3.

Finally, normalized and weighted red flags are aggregated through a linear function, so that the CO.R.E.-CI results in a weighted average of binary indicators, where the weights reflect expert opinions.

Tab. 3 – Expert weights of each elementary red flags, separately for those concerning winner companies (a) and contracting authorities (b)

a) Company

	Red flag	*Weight*
1	Winning rate across the crisis	0.170
2	Awarded economic value across the crisis	0.151
3	Contract economic deviation across the crisis	0.114
4	Contract length deviation across the crisis	0.093
7	One-shot opportunistic companies across the crisis	0.185
8	Pre-existing contracts modified after the crisis	0.120
9	Lengthy contracts	0.166

b) Contracting authority

	Red flag	*Weight*
3	Contract economic deviation across the crisis	0.191
4	Contract length deviation across the crisis	0.146
5	Excess of concentration in the winners' distribution	0.195
6	Award communication default across the crisis	0.171
8	Pre-existing contracts modified after the crisis	0.122
9	Lengthy contracts	0.175

4. The CO.R.E.-CI over the Covid-19 emergency: an application to the Italian case

For illustrative purposes, in this paragraph we show an application of the CO.R.E.-CI to the Italian case and the Covid-19 emergency. To this aim, the data architecture introduced in paragraph 3.1 is utilized to access the BDNCP data, identify the public procurement sectors most significantly impacted by the Covid-19 emergency, and compute the elementary red flags employed for obtaining the CO.R.E.-CI.

These indicators (refer to Tab. 2) evaluate the corruption risk of companies and/or contracting authorities by comparing their behavior after the crisis with their historical (pre-crisis) conduct. Accordingly, we designate January 31st, 2020, as the date to distinguish between post-crisis and pre-crisis contracts, based on the publication date of the call for tenders. This date aligns with the official start of the state of emergency in Italy due to the pandemic, as declared by the Italian government[2].

To identify the public procurement sector(s) primarily affected by the Covid-19 emergency, we rely on the Common Procurement Vocabulary (CPV), a unified classification system for public procurement that standardizes

[2] https://www.gazzettaufficiale.it/eli/id/2020/02/01/20A00737/sg

references used by contracting authorities to describe the subject matter of procurement contracts. Specifically, we select public contracts with a call for tenders published across the beginning of the emergency (six months before/after), categorized by the first two digits of the CPV code (i.e., the CPV division). The same analysis is conducted for procedures published one year before the outbreak. Subsequently, a methodology akin to Difference-In-Difference is applied to identify the CPV divisions experiencing a significant increase during the emergency, while accounting for inherent spontaneous dynamics. This approach leads us to pinpoint three CPV divisions as the main sectors affected by the Covid-19 crisis, as follows: 33 ("Medical equipments, pharmaceuticals, and personal care products"), 35 ("Security, fire-fighting, police, and defense equipment"), and 18 ("Clothing, footwear, luggage articles, and accessories").

In analyzing the territorial distribution of the CO.R.E.-CI in Italy, we focus on provinces (NUTS-3) as the aggregation level and consider red flags 3, 4, 5, 6, 8, and 9 (Tab. 2) due to their applicability and relevance to contracting authorities, for which a geographic variable is available. Referring to Fig. 2, we can provide comments on each indicator. When examining the elementary indicators at the provincial level, we can discern more granular patterns of potential corruption risk that mirror the local administrative and socio-economic landscapes.

Red flag 3 (Contract economic deviation across the crisis) reveals varying levels of contract economic deviations across provinces. Some provinces exhibit particularly dark shades, suggesting a higher risk or occurrence of financial irregularities in contract management. These areas might have complex procurement systems or faced severe impacts from the crisis, potentially increasing the chance of deviations from established financial norms. High values are present in some northern provinces and in the center (i.e., Tuscany), which could be reflective of their industrial and economic complexity.

Red flag 4 (Contract length deviation across the crisis) highlights provinces with deviations in contract lengths. Higer values are more prevalent again in central provinces and the northeast. This could suggest a reaction to the intensity of the pandemic impact in these areas, requiring adjustments to contract terms to accommodate unforeseen needs.

Red flag 5 (Excess of concentration in the winners' distribution) shows higher concentrations in the northeast, in Emilia-Romagna, and in some central and southern provinces (especially in Sicily). This indicates that in these provinces there might be fewer companies able to meet the procurement demands, leading to a smaller group of firms repeatedly winning contracts.

As regards red flag 6 (Award communication default across the crisis), results indicate that the risk is high throughout Italy, and there is no clear prevalence in specific areas. This could be the result of low attention to formal issues during the emergency and a priority for the practical provision of essential goods for survival.

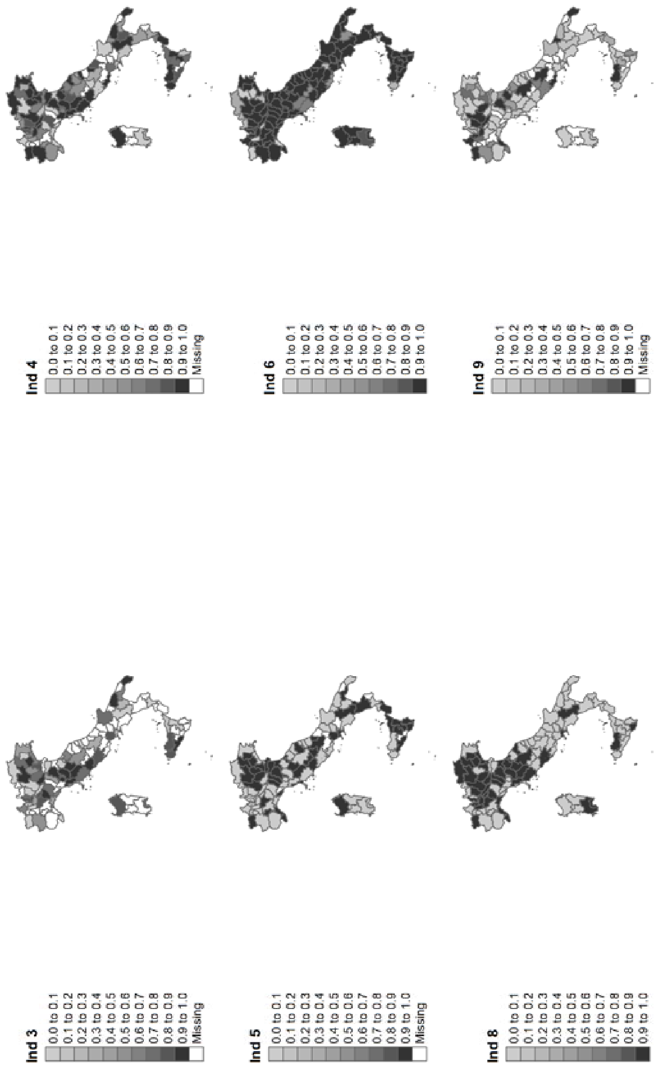

Fig. 2 – Provincial (NUTS-3) distribution of corruption risk indicators in Italy for Covid-19 emergency. The maps show gradations of risk as per indicators 3, 4, 5, 6, 8, and 9, from low (light grey) to high (dark grey), with white spaces representing missing data

As far as red flag 8 (Pre-existing contracts modified after the crisis) is concerned, we can notice high values among provinces located in the North and in some provinces of the Centre (especially in Tuscany and Emilia-Romagna). The reason could be due to the dynamic economic environment where contracts are more frequently revised to respond to changing conditions.

Lastly, as regards red flag 9 (Lengthy contracts) no clear and consistent pattern is shown. The risk associated with this indicator appears to be lower overall compared to the other red flags, with some peaks observed throughout the entire territory of Italy. This suggests that the strategy for long-term contracts during the crisis did not follow a clear north-south gradient but was rather influenced by local needs and administrative decisions.

Across all the six red flags, the distribution of darker shades (i.e., high red flag values) suggests a varied risk landscape, possibly influenced by regional administrative capacities, the resilience of local economies to the crisis, and existing governance structures. Lighter shaded provinces may indicate more robust systems in place to mitigate the risk of corruption. These insights can inform targeted, province-specific anti-corruption strategies to strengthen the integrity of public procurement processes.

The provincial-level insights are indeed vital for understanding the nuances of corruption risk within smaller administrative units. They enable localized anti-corruption interventions and the creation of tailored solutions that consider the unique characteristics of each province.

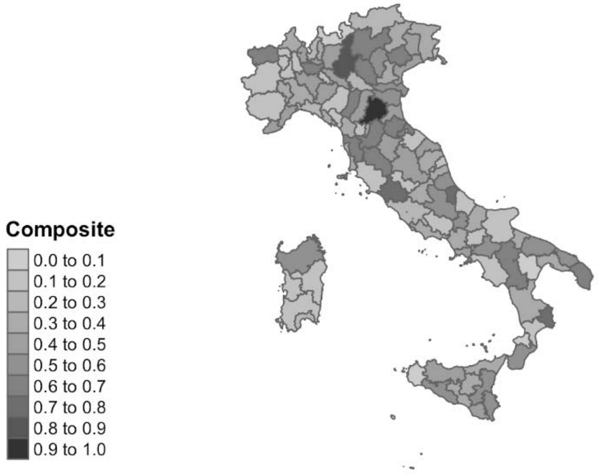

Fig. 3 – Provincial (NUTS-3) distribution of the CO.R.E.-CI in Italy during Covid-19. Darker shades represent higher risk levels

With respect of the composite indicator, the C.O.R.E.-CI, as represented in Fig. 3, provinces with darker shades may be experiencing a confluence of factors that contribute to a higher risk of corruption. These factors could include, but are not limited to, economic deviations in contracts, abnormalities in contract lengths, a high concentration of contract awards within a small number of companies, a lack of transparency in award communications, frequent modifications to pre-existing contracts, and a tendency towards longer contracts. The darker shades in some provinces could indicate areas where the emergency state may have exacerbated pre-existing vulnerabilities or inefficiencies in the public procurement process.

Conversely, provinces with lighter shades suggest a lower composite risk. These areas may have more robust and transparent procurement systems, effective checks and balances, and a competitive market with a larger pool of businesses capable of meeting procurement needs. The lighter shades could also suggest that these provinces were less affected by the pandemic in terms of public procurement or that they were more successful in managing the crisis in a way that mitigated potential corruption risks.

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5. *Public procurement transparency over emergencies: the SCO.R.E. index*

by *Agustí Cerrillo i Martínez, Wellington Migliari*[*]

Abstract

The concept of transparency in public procurement is crucial for fostering accountability, integrity, and citizen trust in governmental processes. In recent years, digitalization has played a pivotal role in enhancing transparency by facilitating access to information and preventing conflicts of interest. This is why the need for objective indicators to measure transparency, particularly in public procurement, has led to proposals like the SCO.R.E. index, which evaluates the digitalization of public procurement information across European Union member states to improve public integrity. The index aims to provide a standardized measure of transparency based on factors like data availability, interoperability, and re-usability. Particularly in emergency situations like the COVID-19 pandemic, transparency proved to be even more critical as public administrations navigate urgent contracting procedures through official web sites for public procurement as well as open data web pages. By quantifying the degree of digitalization and establishing clear constructs and variables, evidence has been produced by the SCO.R.E. model to strengthen transparency in public affairs and, consequently, combat corruption more effectively.

Introduction

Transparency of public affairs facilitates accountability and control of public administration. It is also an effective means of preventing conflicts of interest as well as fighting corruption. Digital information tends to reach more easily the public opinion and, consequently, people. In addition, the availability, interoperability, and re-usability of data can make the asses-

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sment of public officials stronger. As it has been indicated, transparency that contributes to public integrity (Kaufmann, 2005).

Different empirical studies have concluded that higher levels of information about what happens inside the public sector result in lower levels of corruption in the public sector (Rose-Ackerman and Palifka, 2004). On the other hand, Kaufmann (2005) discusses how a low level or an absolute lack of transparency is one of the main triggers for the emergence of corruption.

Nowadays, common sense around the principle of transparency as an instrument to mitigate corruption by preventing it from occurring has prevailed, but its development in public sector is still waiting for more objective indicators to gauge acts in public procurement.

The goal of this chapter is to show how higher levels of digitalized information can improve transparency in public procurement, particularly during emergency situations. To complete the task, we scanned and analysed the open data portals and public procurement websites of the 27 EU member states in order to gauge the degree of transparency using more objective standards. We categorised the web pages' features and functions in our study according to factors like data quality and accessibility, which allowed us to group the pages in three dimensions, i.e., availability, interoperability, and re-usability. Relying on the outcomes, it was possible to create an index, which was named the SCO.R.E. (Scores of the Corruption Risk Indicators in Emergency).

This chapter is divided into five parts. The first delves into the idea that data quality is one of the foundations for combating opacity in the public sector. In the second section, we explain how the constructs and variables proposed were developed, emphasising the syntactic and semantic aspects of a high-quality data set. The third section presents the findings of our study, which proposes a three-level scale for good practices in public procurement based on the degree of digitalization of public procurement and open data web pages in each European Union country. It also describes the methodology used to generate the data collected. In the fourth section, a statistical model is developed and tested to determine how the SCO.R.E. performs compared with other transparency indicators. The final section of our chapter outlines how increased levels of digitalization in public procurement can reinforce the principle of transparency.

1. Towards digitalization measurement in public procurement

We quantify the degree of digitization of public procurement information to objectively measure transparency in the public sector. The first dimension to be examined is data availability, which denotes the accessibility of the information. In this regard, Soylu mentions that "transparency and accountability require giving citizens and companies much more data with the possibility of easily connecting relevant data sets (e.g., spending and company data), both within and beyond national borders and languages, allowing extended and deeper analyses'' (Soylu *et al.*, 2022).

Interoperability is another point worth mentioning. According to Prier, McCue, and Boykin (2018), reducing opaqueness in public contracting and public administration requires the harmonisation of standards. As the quantity and quality of data available increases, all information is expected to be integrated and shared. Contract objects, contract prices, and other variables are closely related to data quality, as the literature (Fazekas, 2017; Villamil, Kertész and Wachs, 2022) has demonstrated. All public contract phases appear simultaneously on various portals thanks to interoperable information of public procurement, which raises the degree of data availability.

The third dimension is re-usability. In fact, if the level of re-used information decreases, the opacity increases because the re-usability dimension is responsible for connecting what is happening in the public sector to the public eye.

2. Constructs and variables

This section introduces the syntactic and semantic definitions used to classify the SCO.R.E. outputs. Availability, interoperability, and reusability are settled on eighty variables (in white), with fifty-two variables applied to public procurement web pages and twenty-eight to government open data portals (in grey).

Tab. 1 shows three columns, i.e., constructs with their respective subconstructs, variables, and the semantic and syntactic definitions used to categorize the SCO.R.E. outputs.

The rows in white weigh 0,945, corresponding, therefore, to non-emergency variables, while the ones in grey weigh 1,815, referring to emergency variables. Since we assume a probability of 50-50, representing approximately 50% of the chance of finding or not finding the functions and features that may serve the best practices to prevent and fight corruption, the 28 emergency variables have a heavier weigh representing emergency contracts[1].

Being *non-emergency variables* represented by wi and *emergency variables* by vi, we have that the SCO.R.E. index is $SCO.R.E.Index = \left[\left(\sum_{i=1}^{52} f(wi)\right) \times 0{,}945\right] + \left\lfloor\left(\sum_{i=1}^{28} f(vi)\right) \times 1{,}815 \right\rfloor$. Therefore, the mathematical function as follows: $[(w1 + w2 + \cdots + w52) \times 0{,}945] + [(v1 + v2 + \cdots + v28) \times 1{,}815]$.

[1] 0, 945x 52 ≈ 50 points; 1, 815x 28 ≈ 50 points being the total score 100.

Tab. 1 – SCO.R.E.: syntactic and semantic definitions

Construct	*Variable*	*Semantic and Syntactic Definitions*	*Construct*	*Variable*	*Semantic and Syntactic Definitions*
AAC-01:	Territorial Level (info)	If the contracts available on the e-public procurement platforms bring information about territorial level, the country scores 1. If not, 0.	AO-01:	Data Format	If the e-public procurement platforms bring information through different data format (reports, numbers, basic statistics, graphs etc), the country scores 1. If not, 0.
AAC-02:	Contracting Authority ID	If the contracts available on the e-public procurement platforms identify the contracting authorities, the country scores 1. If not, 0.	AO-02:	Open Data Standard	If the data is open and contributes to a higher quality of information (especially on emergency times), the country scores 1. If not, 0.
AAC-03:	Contract Object	If the contracts available on the e-public procurement platforms have information of what is being bought (goods or services), the country scores 1. If not, 0.	Inter-01:	Different Government Levels	If the e-public procurement platforms have information/data on contracts making references to different levels of the public administration/authorities, the country scores 1. If not, 0.
AAC-04:	Contract Amount	If the contracts available on the e-public procurement platforms have information related to prices, the country scores 1. If not, 0.	Inter-02:	Interoperability Standards	If the information is shared and integrated (different platforms related to e-procurement have the same information found on e-procurement platforms using the same format, especially on emergency times), the country scores 1. If not, 0.
AAC-05:	Contract ID/CPV/ Case File	If the contracts available on the e-public procurement platforms identifies the public authorities and/or the contracts by a code/case file, the country scores 1. If not, 0.	Inter-03:	Hyperlinks to other Gov. Levels	If the e-public procurement platforms facilitate hyperlinks to different levels of the public administration/authorities (especially on emergency times), the country scores 1. If not, 0.

(Following Tab. 1)

Construct	*Variable*	*Semantic and Syntactic Definitions*	*Construct*	*Variable*	*Semantic and Syntactic Definitions*
AAC-06:	Contract Duration	If the contracts available on the e-public procurement platforms have information of the contract duration, the country scores 1. If not, 0.	Re-Use-01:	API	If the e-public procurement platforms present information or conduct public contracting through applications, the country scores 1. If not, 0.
AAC-07:	Contract Type	If the contracts available on the e-public procurement platforms have information of the type of contract (fixed-priced contract, cost reimbursable contract or time and materials contract), the country scores 1. If not, 0.	Re-Use-02:	Metadata	If the e-public procurement platforms have clear documentation explaining technical information (E.g., CPV), the country scores 1. If not, 0.
AAC-08:	Contract Updates	If the contracts available on the e-public procurement platforms inform on updates (day, month and year), the country scores 1. If not, 0.	Re-Use-03:	Information on Fees	If the e-public procurement platforms have information about fees (sometimes fees are charged based on specific demands from users, i.e., especially data on emergency contracting), the country scores 1. If not, 0.
AAC-09:	How many tenders?	If the contracts available on the e-public procurement platforms have information related to the number of suppliers participating in the call, the country scores 1. If not, 0.	Re-Use-04:	Free Re-Use/Data Re-Use Licence	If the e-public procurement platforms offer the possibility of using the data on contracts freely and stating clearly licences, the country scores 1. If not, 0.
AAC-10:	Contracting Procedure	If the contracts available on the e-public procurement platforms have information of procedure (open, negotiated etc), the country scores 1. If not, 0.	Re-Use-05:	Machine Readable Data	If the e-public procurement platforms have data easily readable by machines (operating systems from the most to the least common like Windows, Mac, Linux etc), the country scores 1. If not, 0.

(Following Tab. 1)

Construct	*Variable*	*Semantic and Syntactic Definitions*	*Construct*	*Variable*	*Semantic and Syntactic Definitions*
AAC-11:	Emergency Justification	If the contracts available on the e-public procurement platforms have information concerning emergency (Covid.19, war etc), the country scores 1. If not, 0.	ODP--01-AAEA:	Open Data Webpage	If the country has an open data webpage, it scores 1. If not, 0.
AAC-12:	Open Tender Notice	If the e-public procurement platform has a channel for suppliers to publish their offers, the country scores 1. If not, 0.	ODP-02-AAEA:	data.europa.eu	If the country has a section for open data on data.europa.eu, it scores 1. If not, 0.
AAC-13:	Tender Name	If the e-public procurement platforms disclose tender's name, the country scores 1. If not, 0.	ODP-03-AAEA:	Contact Channels	If the Open data Portal have contact channels (e-mail, chat, traditional address etc) to solve general doubts, the country scores 1. If not, 0.
AAC-14:	Tender ID	If the e-public procurement platforms disclose the name of the tenders (suppliers), the country scores 1. If not, 0.	ODP-04-AAEA:	FOIA/Transparency Act	If the Open data Portal have information about transparency (legislation, compliances etc), the country scores 1. If not, 0.
AAC-15:	Other Documents (Gov)	If the e-public procurement platforms make other documents available (legislation, instructions, FAQ etc), the country scores 1. If not, 0.	ODP-05-AAEA:	Search Engine for the Data	If the Open data Portal have search engine bars to make easier for the user the access to information, the country scores 1. If not, 0.

(Following Tab. 1)

Construct	*Variable*	*Semantic and Syntactic Definitions*	*Construct*	*Variable*	*Semantic and Syntactic Definitions*
AAC-16:	Aggregated Info (Contract Copy)	If the e-public procurement platforms make a contract copy available, the country scores 1. If not, 0.	ODP-06-AAEA:	Information Structure	If the Open data Portal have a design about open data organized with a navigation bar on top of the webpage, graphic icons to facilitate the user finding the information etc (enhancing the user experience), the country scores 1. If not, 0.
AAEA-01:	Public Contracting Web	If the e-public procurement platforms conduct contracting through a web (electronically), the country scores 1. If not, 0.	ODP-07-AAEA:	Site Map	If the Open data Portal show a link for a site map at the bottom of the page, the country scores 1. If not, 0.
AAEA-02:	Emergency Contract (Internal/ External Web)	If the e-public procurement platforms give the option of using a specific webpage for emergency contracts (Covid-19, war etc) to suppliers, the country scores 1. If not, 0. The emergency portal be an internal link (inside the public procurement webpage) or external (another address indicated on the e-procurement portal).	ODP-08-AAEA:	Data Protection	If the Open data Portal bring information (legislation, legal grounds, national law and European directives on data protection for suppliers), the country scores 1. If not, 0.
AAEA-03:	Emergency Contracts (info)	If the e-public procurement platforms have information on how a supplier can make an offer under emergency time, the country scores 1. If not, 0.	ODP-09-AAEA:	Intellectual Property	If the Open data Portal have information about the use of information how to use it and if there is any intellectual property condition, the country scores 1. If not, 0.
AAEA-04:	Info about Web/ e-procurement	If the e-public procurement platforms have information related to e-procurement process (how to apply, which criteria are taken into consideration, legislation etc), the country scores 1. If not, 0.	ODP-10-AAEA:	Help	If the Open data Portal have a help desk for users (different from contact channels), the country scores 1. If not, 0.

(Following Tab. 1)

Construct	*Variable*	*Semantic and Syntactic Definitions*	*Construct*	*Variable*	*Semantic and Syntactic Definitions*
AAEA-05:	Contact Channels	If the e-public procurement platforms have contact channels (e-mail, chat, traditional address etc) to solve general doubts, the country scores 1. If not, 0.	ODP-11-A-Q:	Last Updates	If the certified information can be traced according to the last updates (especially on emergency times), the country scores 1. If not, 0.
AAEA-06:	FOIA/ Transparency Act	If the e-public procurement platforms have information about transparency (legislation, compliances etc), the country scores 1. If not, 0.	ODP-12-A-Q:	Updates Frequency	If the certified information has a list of the last updates (especially on emergency times), the country scores 1. If not, 0.
AAEA-07:	Hyper-links/Icon Emergency Contracting	If the e-public procurement platforms have visible icons and hyperlinks for emergency contracting, the country scores 1. If not, 0.	ODP-13-A-O:	Data Format	If the e-public procurement platforms bring information through different data format (reports, numbers, basic statistics, graphs etc), the country scores 1. If not, 0.
AAEA-08:	Search Engine for the Contracts	If the e-public procurement platforms have search engine bars to make easier for the user the access to information, the country scores 1. If not, 0.	ODP-14-A-O:	Open Data Standard	If the data is open and contributes to a higher quality of information (especially on emergency times), the country scores 1. If not, 0.
AAEA-09:	Information Structure	If the e-public procurement platforms have a design about public procurement organized with a navigation bar on top of the webpage, graphic icons to facilitate the user finding the information etc (enhancing the user experience), the country scores 1. If not, 0.	ODP-15-A-O:	Data Efficiency	If the country publishes data on public procurement on its open data webpage in an efficient fashion, the country scores 1. If not, 0.

(Following Tab. 1)

Construct	*Variable*	*Semantic and Syntactic Definitions*	*Construct*	*Variable*	*Semantic and Syntactic Definitions*
AAEA-10:	Site Map	If the e-public procurement platforms show a link for a site map at the bottom of the page, the country scores 1. If not, 0.	ODP-16-A-O:	Data on Emergency Contracts	If the country publishes data on public procurement (emergency contracts), it scores 1. If not, 0.
AAEA-11:	Complaint Channel	If the e-public procurement platforms have a link for complaints, the country scores 1. If not, 0.	ODP-17-A-O:	Data at Different Administrative Levels (Regions/ Municipalities)	If the country publishes data on public procurement identifying all administrative levels, it scores 1. If not, 0.
AAEA-12:	Anonymous Disclosure	If the e-public procurement platform gives the possibility to the user of communicating anonymously with the authorities responsible for public procurement, the country scores 1. If not, 0.	ODP-18-Inter:	Sharing	If the country shares the same information on public contracts using the same format on its open data webpage and data.europa.eu, it scores 1. If not, 0.
AAEA-13:	Whistleblowers Protection	If the e-public procurement platforms have a mechanism of protection (anonymity and person's data protection), the country scores 1. If not, 0.	ODP-19-Inter:	Integrated	If the country integrates the same information on public contracts using the same format on its open data webpage and data.europa.eu, it scores 1. If not, 0.
AAEA-14:	Data Protection	If the e-public procurement platforms bring information (legislation, legal grounds, national law and European directives on data protection for suppliers), the country scores 1. If not, 0.	ODP-20-Inter:	Different Government Levels	If the e-public procurement platforms have information/data on contracts making references to different levels of the public administration/authorities, the country scores 1. If not, 0.

(Following Tab. 1)

Construct	*Variable*	*Semantic and Syntactic Definitions*	*Construct*	*Variable*	*Semantic and Syntactic Definitions*
AAEA-15:	Intellectual Property	If the e-public procurement platforms have information about the use of information how to use it and if there is any intellectual property condition, the country scores 1. If not, 0.	ODP-21-Inter:	Interoperability Standards	If the information is shared and integrated (different platforms related to e-procurement have the same information found on e-procurement platforms using the same format, especially on emergency times), the country scores 1. If not, 0.
AAEA-16:	Help	If the e-public procurement platforms have a help desk for users (different from contact channels), the country scores 1. If not, 0.	ODP-22-Inter:	Hyperlinks to other Gov. Levels	If the e-public procurement platforms facilitate hyperlinks to different levels of the public administration/authorities (especially on emergency times), the country scores 1. If not, 0.
AAU-01:	Graphics	If the e-public procurement platforms present information about public procurement using graphics (charts, infographics, tables etc), the country scores 1. If not, 0.	ODP-23-Re-Use:	Downloadable and Easy to Mine	If the data and information can be easily downloaded, the country scores 1. If not, 0.
AAU-02:	Info based on Directive (UE) 2016/2102	If the e-public procurement platforms have information about public procurement and accessibility, the country scores 1. If not, 0.	ODP-24-Re-Use:	eInvoicing Verified	If the country has contributed to the implementation of eInvoicing mechanisms (verifying the information about public procurements systematized by the European Commission), it scores 1. If not, 0.
AAU-03:	Information Levels	If the e-public procurement platforms have legal information on different levels about public procurement (local, intermediate and state level especially on emergency times), the country scores 1. If not, 0.	ODP-25-Re-Use:	Administrative Capacity	If the country has contributed to the analysis of the administrative capacity conducted by the European Commission, the country scores 1. If not, 0.

(Following Tab. 1)

Construct	*Variable*	*Semantic and Syntactic Definitions*	*Construct*	*Variable*	*Semantic and Syntactic Definitions*
AAU-04:	Information Complexity	If the e-public procurement platforms have information complexity on public procurement made accessible simplifying the language, explaining contracting processes, diversifying tools such as video tutorials or apps (especially on emergency times), the country scores 1. If not, 0.	ODP-26-Re-Use:	API	If the e-public procurement platforms present information or conduct public contracting through applications, the country scores 1. If not, 0.
AAU-05:	FAQs	If the e-public procurement platforms have a section or at least a document with FAQs, the country scores 1. If not, 0.	ODP-27-Re-Use:	Information on Fees	If the e-public procurement platforms have information about fees (sometimes fees are charged based on specific demands from users, i.e., especially data on emergency contracting), the country scores 1. If not, 0.
AQ-01:	Precise/ Certified Data	If the e-public procurement platforms have mechanisms to certify the information, the country scores 1. If not, 0.	ODP-28-Re-Use:	Free Re-Use/Data Re-Use Licence	If the e-public procurement platforms offer the possibility of using the data on contracts freely and stating clearly licences, the country scores 1. If not, 0.
AQ-02:	Last Updates	If the certified information can be traced according to the last updates (especially on emergency times), the country scores 1. If not, 0.	ODP-29-Re-Use:	Re-use conditions	If the Open data Portal have information about the conditions to re-use information, the country scores 1. If not, 0.
AQ-03:	Updates Frequency	If the certified information has a list of the last updates (especially on emergency times), the country scores 1. If not, 0.	ODP-30-Re-Use:	Machine Readable Data	If the e-public procurement platforms have data easily readable by machines (operating systems from the most to the least common like Windows, Mac, Linux etc), the country scores 1. If not, 0.

AAC: Availability-Accessibility Completeness; AAEA: Availability-Accessibility Easy Access; AAU Availability-Accessibility; Understandability; AQ: Availability Quality; AO: Availability Openness; ODP: Open Data Portals

The SCO.R.E. indicator collects the data based on what is found and can be accessed.

3. Three levels of good practices

The results of the SCO.R.E. are represented in fig, 1. The EU average for the SCO.R.E. is 71.5. With the purpose of reflecting these differences, we created an intermediate level between more and less appropriate good practices, suggesting three levels of good practices.

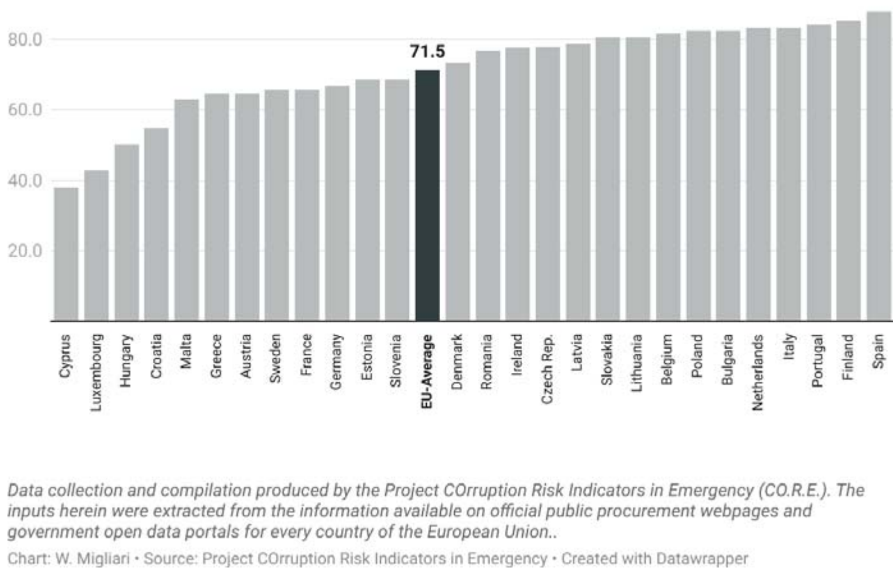

Fig. 1 – Public and good practices in the EU

The first one brings those countries ranking from 0 to 60, the second between 60 and 80, and the third highest level for those scoring above 80, as shown in fig. 2.

All the 27 countries of the European Union were analysed. The index is made of 12 constructs and 80 variables, as tab. 6 categorises. The construct AA Completeness refers to the Availability-Accessibility of information particularly related to contracts; AA Easy Access to functions such as hyperlinks and buttons, among other web functions on public procurement; and AA Understandability concerning graphic, legal, and contact features.

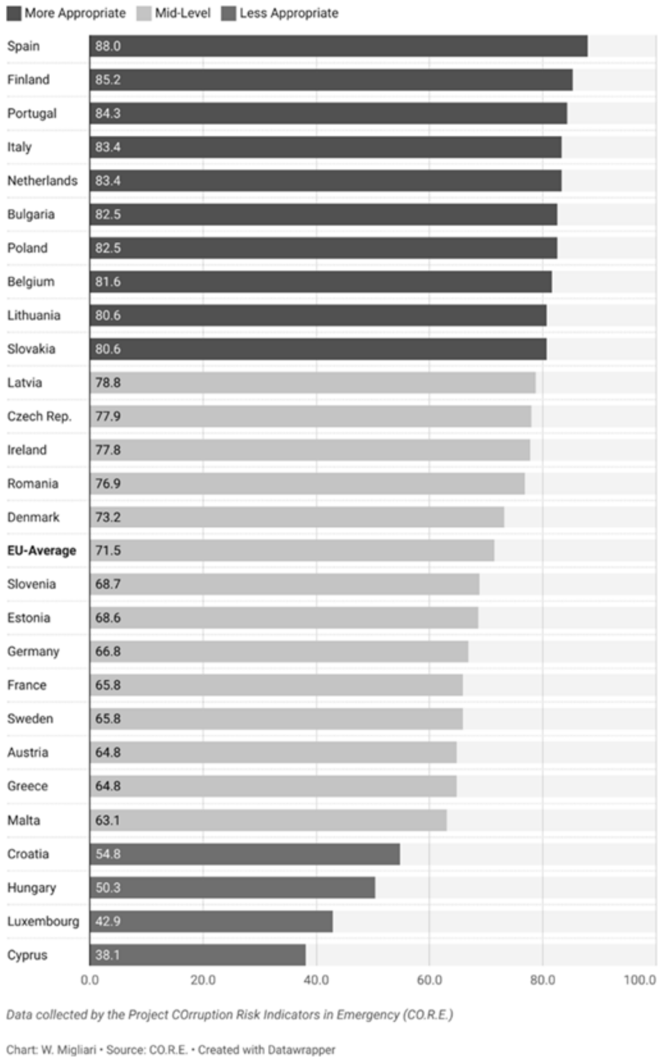

Fig. 2 – More, mid-level and less appropriate good practices

Tab. 2 – The SCO.R.E.: constructs and variables

	Construct	*Variable*
1	AA - Completeness	Territorial Level (info)
	AA - Completeness	Contracting Authority ID
	AA - Completeness	Contract Object
	AA - Completeness	Contract Amount
	AA - Completeness	Contract ID/CPV/Case File
	AA - Completeness	Contract Duration
	AA - Completeness	Contract Type
	AA - Completeness	Contract Updates
	AA - Completeness	How many tenders?
	AA - Completeness	Contracting Procedure
	AA - Completeness	Emergency Justification
	AA - Completeness	Open Tender Notice
	AA - Completeness	Tender Name
	AA - Completeness	Tender ID
	AA - Completeness	Other Documents (Gov)
	AA - Completeness	Aggregated Info (Contract Copy)
2	AA - Easy Access	Public Contracting Web
	AA - Easy Access	Emergency Contract (Internal/External Web)
	AA - Easy Access	Emergency Contracts (info)
	AA - Easy Access	Info about Web/e-procurement*
	AA - Easy Access	Contact Channels
	AA - Easy Access	FOIA/Transparency Act
	AA - Easy Access	Hyperlinks/Icon Emergency Contracting
	AA - Easy Access	Search Engine for the Contracts
	AA - Easy Access	Information Structure
	AA - Easy Access	Site Map
	AA - Easy Access	Complaint Channel
	AA - Easy Access	Anonymous Disclosure
	AA - Easy Access	Whistleblowers Protection
	AA - Easy Access	Data Protection
	AA - Easy Access	Intellectual Property
	AA - Easy Access	Help

	AA - Understandability	Graphics
	AA - Understandability	Info based on Directive (UE) 2016/2102
3	AA - Understandability	Information Levels
	AA - Understandability	Information Complexity
	AA - Understandability	FAQs
	A - Quality	Precise/Certified Data
4	A - Quality	Last Updates
	A - Quality	Update Frequency
5	A - Openness	Data Format
	A - Openness	Open Data Standard
	Interoperability	Different Government Levels
6	Interoperability	Interoperability Standards
	Interoperability	Hyperlinks to other Gov. Levels
	Re-Usability	API
	Re-Usability	Metadata
7	Re-Usability	Information on Fees
	Re-Usability	Free Re-Use/Data Re-Use Licence
	Re-Usability	Machine Readable Data
	ODP-AA-Easy Access	Open Data Webpage
	ODP-AA-Easy Access	data.europa.eu (EU)
	ODP-AA-Easy Access	Contact Channels
	ODP-AA-Easy Access	FOIA/Transparency Act
8	ODP-AA-Easy Access	Search Engine for the Data
	ODP-AA-Easy Access	Information Structure
	ODP-AA-Easy Access	Site Map
	ODP-AA-Easy Access	Data Protection
	ODP-AA-Easy Access	Intellectual Property
	ODP-AA-Easy Access	Help
9	ODP-A-Quality	Last Updates
	ODP-A-Quality	Updates Frequency
	ODP-A-Openness	Data Format
10	ODP-A-Openness	Open Data Standard
	ODP-A-Openness	Data Efficiency
	ODP-A-Openness	Data on Emergency Contracts

	ODP-A-Openness	Data at Different Administrative Levels (Regions/Municipalities)
11	ODP-Inter	Sharing
	ODP-Inter	Integrated
	ODP-Inter	Different Government Levels
	ODP-Inter	Interoperability Standards
	ODP-Inter	Hyperlinks to other Gov. Levels
12	ODP-Re-Usability	Downloadable and Easy to Mine
	ODP-Re-Usability	eInvoicing Verified (EU)
	ODP-Re-Usability	Administrative Capacity (EU)
	ODP-Re-Usability	API
	ODP-Re-Usability	Information on Fees
	ODP-Re-Usability	Free Re-Use/Data Re-Use Licence
	ODP-Re-Usability	Re-use conditions
	ODP-Re-Usability	Machine Readable Data

Regarding the availability and quality of information for the public, outputs on certified data, updates, and data format conform to the A Quality and A Openness constructs. Interoperability and re-usability are, respectively, connected to the ubiquity of data on public tenders at different levels of public administration and to Application Programming Interfaces (APIs), metadata, and machine-readable data. ODP-AA-Easy Access stands for the Availability-Accessibility of information regarding the compiled data on public procurement available on the government open data web pages, checking whether public tenders and adjudicated contracts, for example, are reflected on open data platforms such as data.europa.eu as well as national web pages. Similar to the other constructs applied to public procurement web pages, ODPA-Quality and ODP-A-Openness display information on updates, data frequency, data format, and so on. ODP Interoperability and ODP Re-usability identify whether the data on public procurement is shared, integrated, and downloadable easily from catalogues or repositories on government open data web pages concomitantly. In the case of re-usability, different from the construct applied to public procurement online portals, we included the variable eInvoicing Verified (EU) to establish an extra objective criterion linked to the verification of data on public procurement at the European level.

4. Statistically testing the SCO.R.E.

To test its validity, the SCO.R.E. is compared to six other indicators using similar or totally different scales covering interconnected topics with our data set, such as corruption risk, internet access, and the number of hours per year required to pay taxes. In order to test statistically the accuracy of our data on public procurement and government open data portals, we have attributed z-scores to every index used in our model[2].

Tab. 3 – Comparison of the SCO.R.E. with Indexes on Corruption and Other Indicators

SCO.R.E. Index	Institutional Support	What is Measured	Scale
Scores of the COrruption Risk indicators in Emergency	Universitat Oberta de Catalunya and co-funded by the European Union	Risk of Corruption in Emergency Times, Public Procurement	0-100
Indexes Compared	**Institutional Support**	**What is Measured**	**Scale**
Corruption Perception Index	Transparency International	Perception of corruption levels	0-100
Open Data Maturity	European Commission	Development of the European countries in the field of data	0-100
Budget Transparency	International Budget Partnership	How public funds are raised and spent	0-100
Fixed Broadband Subscribers	World Bank	Number of fixed broadband subscribers per 100 inhabitants	per hundred
Individuals Using Internet	World Bank	Number of Individuals Using Internet per 100 inhabitants	per hundred
Administrative Burden	European Research Centre for Anti-Corruption and State-Building (ERCAS)	Time required to pay taxes (hours per year)	per annum

The most adequate workaround we could come up with to solve the numerical incompatibility of the other indexes with the SCO.R.E.'s was through the normalization of all indicators before building up our model. The result then is a z-score for every index, including the SCO.R.E., covering all countries of the EU until 2021.

[2] For model, we mean the SCO.R.E.'s z-scores and the z-scores of the other indicators. See tab. 10.

Tab. 4 – Multiple linear regression: SCO.R.E. and indexes for the EU

call: lm(formula = CO.R.E. TI + ODM + BT + FixBbU + IUI + AB)

Residuals for all the 27 countries of the EU:

1	2	3	4	5	6	7	8	9	10
-0.64723076	0.77145236	0.07666998	-0.97192476	-0.55798344	0.73017699	0.24611796	0.12940357	-0.06660312	0.06838992
11	12	13	14	15	16	17	18	19	20
-0.68909313	-0.22548061	-0.84297137	0.06536566	-0.44474912	0.81899621	0.56544120	-1.65799407	0.10220989	1.17556784
21	22	23	24	25	26	27			
0.18541864	0.09306916	-0.50592687	0.97290667	-0.28424865	1.56945838	-0.67643851			

Coefficients:

	Estimate	**Std. Error**	**t value**	**Pr(>|t|)**
(Intercept)	1.299e-16	1.594e-01	0.000	1.00000
Transparency International (TI)	1.104e+00	3.315e-01	3.332	0.00332**
Maturity (ODM)	-1.256e-01	1.786e-01	-0.703	0.49018
Budget Transparency (BT)	8.374e-02	1.861e-01	0.450	0.65749
Fixed Broadband Users (FIxBbU)	-2.026e-01	2.671e-01	-0.759	0.45692
Individuals Using Internet (IUI)	-9.792e-01	3.643e-01	-2.688	0.01414*
Administrative Burden (AB)	1.024e-01	2.350e-01	0.436	0.66768

Mean: 1.027181e-17 **Standard Deviation:** 0.726234 **Signif. codes:** 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.828 on 20 degrees of freedom
Multiple R-squared: 0.4726, Adjusted R-squared: 0.3144
F-statistic: 2.987 on 6 and 20 DF, *p-value*: 0.02999

Tab. 5 – Multiple linear regression: SCO.R.E. and indexes for the EU without Luxembourg, Netherlands and Spain

call: lm(formula = CO.R.E. TI + ODM + BT + FixBbU + IUI + AB)

Residuals for overall countries of the EU except Luxembourg, Netherlands and Spain:

1	2	3	4	5	6	7	8	9	10
-0.76243295	0.37945389	0.32210658	-0.87153194	-0.24800052	0.84000237	0.45370569	0.16474509	-0.17411485	0.62665552
11	12	13	14	15	16	17	18	19	20
-0.56396946	0.03670902	-1.09654946	0.08644317	-0.08856154	0.74627708	0.70020248	-0.10531781	0.30259070	-0.04618137
21	22	23	24						
-0.40256333	0.56977916	0.03802677	-0.90747428						

Coefficients:

	Estimate	**Std.Error**	**t value**	**Pr(>|t|)**
(Intercept)	6.618e-16	1.311e-01	0.000	1.00000
Transparency International (TI)	1.388e+00	2.615e-01	5.310	5.76e-05***
Maturity (ODM)	-3.956e-01	1.498e-01	-2.641	0.01714 *
Budget Transparency (BT)	2.604e-02	1.540e-01	0.169	0.86775
Fixed Broadband Users (FIxBbU)	-4.273e-01	2.121e-01	-2.014	0.06007
Individuals Using Internet (IUI)	-9.229e-01	2.800e-01	-3.296	0.00427 **
Administrative Burden (AB)	1.168e-01	1.861e-01	0.628	0.53852

Mean: -6.995815e-17 **Standard Deviation:** 0.5521707 **Signif. codes:** 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ‘ 1

Residual standard error: 0.6423 on 17 degrees of freedom
Multiple R-squared: 0.6951, Adjusted R-squared: 0.5875
F-statistic: 6.46 on 6 and 17 DF, *p-value*: 0.001089

We have also done a multiple linear regression to check the correlation between the SCO.R.E. and the other indexes. When compared to other indexes, the SCO.R.E. captures the perception of corruption from the other indicators in part because its methodology only includes objective elements from the public procurement and open data web pages. We test the correlation between the objectivity of our indicator comparing it with other indexes. In short, the results of our first test with a *p-value* of 0.02999, or a value < 0.05, mean the alternative hypothesis can be rejected or that there is no variation in our model.

The multiple R-squared is 0.4726, or 47%, accompanied by the adjusted R-squared of 0.3144, or 31%. Bearing in mind that this statistic reflects the percentage of the variance in the dependent variable, which is in our case the SCO.R.E. with normalized values. Therefore, the R-squared of the test is measuring the strength of the relationship between the SCO.R.E. and the other indexes on a 0–100% scale.

After removing Luxembourg, the Netherlands, and Spain as outliers, the R-squared increases to 0.6951 and the adjusted R-squared to 0.5875. The *p-value* drops to 0.001089, which is a very significant result to prove the linearity of the model and to attest to the accuracy of the data collected. When we compare tab. 4 and 5, the level of significance for the Transparency International indicator relying on perception increases considerably in contrast with the World Bank's indicator on the number of individuals using the internet. This output reveals that the exclusion of the countries strengthens the hypothesis of perception more than the predictors indicating our model works better with objective information. The same happens to the coefficient for the Open Data Maturity Index, which starts becoming significant with the exclusion of the outliers[3].

About the specifics of our index, it must be clear that the SCO.R.E. is related to digital contracting platforms designed to be operated by public tenders and bidders. It aggregates knowledge about the risk of corruption in emergency situations and measures the availability, interoperability, and reusability of information on public procurement and government open data portals. It also helps us assess how far the functions and features of the web portals constituting the SCO.R.E. can prevent and fight corruption in emergency times. Moreover, it will support the documentation of good practices about public procurement and government open data. It is indispensable to stress that the R-squared linked to these indicators herein is not used to

[3] We recall that the presence of human factors in indexes measuring corruption can diminish the correlations between the SCO.R.E. index and other indicators. The Open Data Maturity Index, for instance, includes in its methodology the category of strategic awareness, focusing on four areas (Data.europa.edu, 2021, p. 9 orig. ed.).

determine whether our coefficient estimates and predictions are inadequate. For that, we have to check in what fashion the residuals of the model behave and, eventually, the distribution of them.

The Pearson correlation between the actual and predicted z-scores is considerably significant for all 27 EU countries. As fig. 3 displays, the result is a correlation of 0.69 and a *p-value* of 7.4e-05.

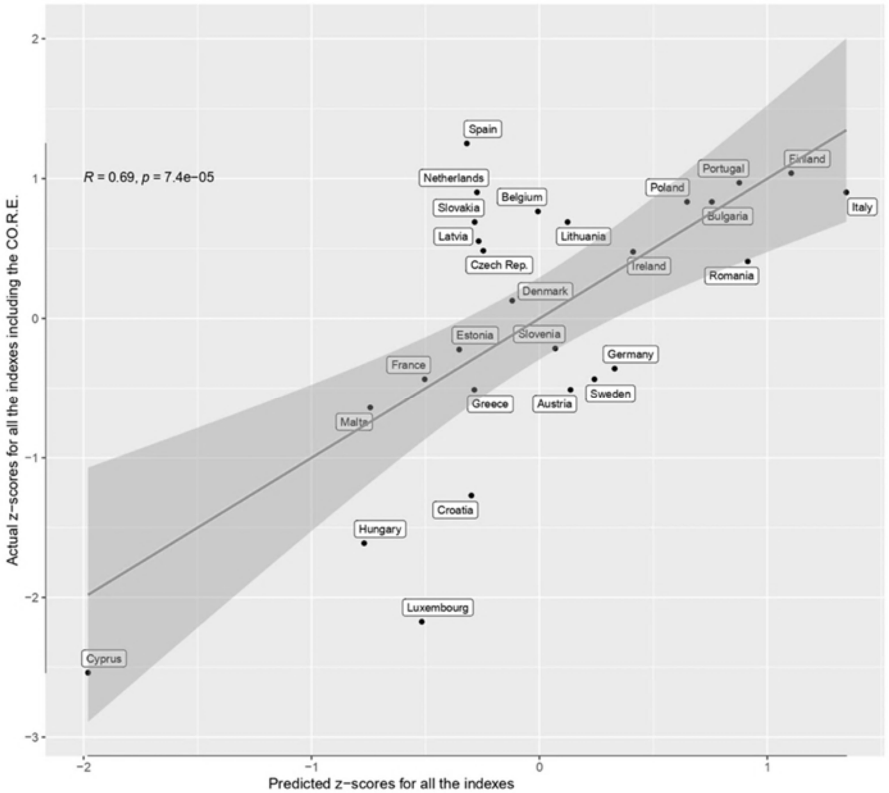

Fig. 3 – Z-score correlation of actual and predicted values for the EU

After removing the outliers Luxembourg, the Netherlands, and Spain, the coefficient is strongly significant. The removal of the outliers from the model also makes the attraction between the actual values – the data collected, and the predicted values – estimated values in a future collection of data, stronger. Since Luxembourg, the Netherlands, and Spain were more distant from the adjusted line in fig. 3, they ended up influencing the correlations returning a lower *p-value*. In this case, the *p-value* obtained expresses more the objectivity of our model, but still capturing the aspect of perception from the other indexes. Another test was conducted to determine whether the removal of the outliers would lead to a higher *p-value* indicating that, in reality, we measure the digitalization of public procurement information more than the perception of the other indicators. After the outliers were eliminated, the model produced a more significant Pearson correlation, or 0.83, with a *p-value* of 4.2e07. Based on the evidence, we can see that removing the outliers reveals how digitalization works in the majority of EU countries as an objective measure of transparency.

Fig. 4 indicates that the Pearson correlation after removing the outliers proves the linearity of our model. That means the SCO.R.E. is a variable that can be explained by the other indexes and the evidence collected is comparable with the other indicators.

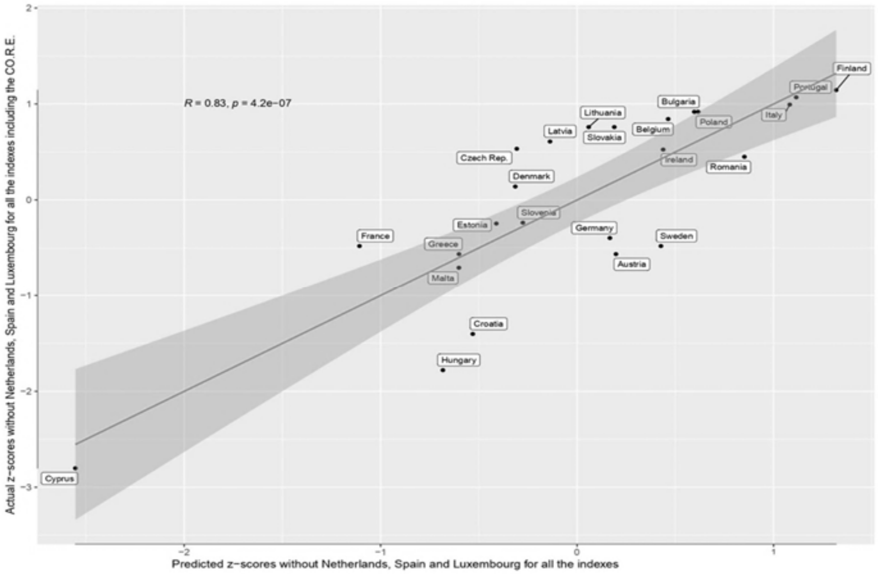

Fig. 4 – Z-score correlation of actual and predicted values for the EU except Luxembourg, the Netherlands and Spain

5. Conclusion

The SCO.R.E. methodology employs a rigorous approach to quantify transparency and assess good practices in public procurement and government open data web pages, particularly during emergency situations. With 52 non-emergency variables and 28 emergency variables, the index provides a comprehensive evaluation framework. The distinction between non-emergency and emergency variables allows for a nuanced understanding of the digital functions and features necessary to prevent and combat corruption. By assigning weights to these variables based on their relevance, the SCO.R.E. model calculates a composite index, facilitating comparisons between countries and identifying areas for improvement. Through this approach, the SCO.R.E. index not only highlights current practices but also offers actionable insights for enhancing transparency and integrity in public procurement processes. The subsequent classification of countries into three levels of good practices further elucidated the strengths and weaknesses of their digital mechanisms, paving the way for targeted interventions and improvements. Overall, the SCO.R.E. index represents a significant step forward in the ongoing efforts to promote transparency and accountability in public administration across the European Union.

Another brief conclusive note is that the statistical tests applied to the SCO.R.E. involving multiple linear regression and Pearson correlation coefficient were able to assess its relationship with other indicators. The multiple linear regression examined the correlation between the SCO.R.E. and various indexes, including Transparency International, Open Data Maturity, broadband subscribers, internet usage, and administrative burden being the three last ones from the World Bank. The outcomes pointed out a significant correlation among them, demonstrating the strength of the relationship between the SCO.R.E. and the other indexes. After removing outliers, the correlation strengthens further, emphasizing the model's accuracy in capturing objective data related to corruption risk in public procurement and government open data portals. Additionally, the Pearson correlation coefficient analysis confirms a significant correlation between actual and predicted z-scores, highlighting the effectiveness of the SCO.R.E. as an objective measure of transparency and corruption risk across EU countries. Overall, these statistical tests validate the SCO.R.E.'s utility in evaluating and addressing corruption risk in emergency situations while emphasizing its objectivity and reliability as a transparency indicator.

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6. From practices to formulas: investigative and data journalism's contribution to combatting corruption in public procurement

by *Alessio Cornia, Dimitri Bettoni*[*]

Abstract

This chapter delves into the pivotal role of journalism in combating corruption. Journalists employ a diverse array of investigative techniques, and the increasing accessibility of public procurement (PP) data can significantly enhance investigative and data journalism. In turn, institutions, anti-corruption professionals, academia, and civil society can benefit from the unique expertise of investigative and data journalists.

The CO.R.E. project exemplifies this synergy by engaging investigative and data journalists in crafting corruption-risk indicators. The chapter explores how journalists' input and feedback has contributed to the design, testing, and improvement of the CO.R.E. indicators of corruption-risk in PP. Based on interviews with Italian, Spanish, and Irish journalists, we provide a comprehensive overview of the methods, tools, and challenges faced by investigative and data journalists. These insights not only contribute to the scholarly discourse but also offer practical guidance for anti-corruption experts, facilitating the ongoing development of red flags and indicators.

Embracing a "from practices to formulas" approach, we advocate for a seamless transition from practical experiences to structured methodologies. Within this framework, the chapter suggests specific red flags that could be further developed through future research. Additionally, targeted recommendations are presented for policy makers, academics, and anti-corruption practitioners, enhancing the overall impact and effectiveness of corruption prevention efforts.

Introduction

Journalism is a powerful actor in the fight against corruption. Investigative, data, and cross-border collaborative journalism are some of the most successful forms of journalism that proved to be particularly effective in

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tackling corruption. Journalism not only uncovers wrongdoings through its investigations. It also plays a key role in raising public awareness on corruption, its causes, and implications, contributing to expose individuals involved in corruption stories and to bring potential remedies and good practices to the attention of the public opinion and other relevant stakeholders.

While journalism already takes advantage of a wide range of investigative techniques and methodologies that are specific of the profession and part of journalists' toolkits, investigative and data journalism can further benefit from the increasing accessibility of data on public procurement (PP). When properly managed, PP data and red flags (RFs) can guide journalists in their investigations and improve the quality of their reporting. Providing journalists with new ways and tools to better harness and exploit the potential of this increasing amount of data can empower journalism's fight against corruption.

At the same time, institutions, law enforcement agencies (LEAs), the academia, civil society and other actors working with PP data to curb corruption can benefit from the collaboration with journalists. The expertise and know-how of investigative journalists, the creativity demonstrated in cross-border collaborative initiatives, such as the Panama Papers investigation, and journalism ability to quickly react to unexpected events such as the Covid-19 crisis can represent an invaluable font of inspiration for other actors involved in the fight against corruption.

To leverage and benefit from the synergy between journalistic and institutional experiences, the CO.R.E. project engaged professionals of the investigative and data-journalism communities in the design, development, and testing of its corruption-risk indicators. This chapter addresses how journalists' input has been taken into consideration in the development of the CO.R.E. indicators. Additionally, by adopting a "from practices to formulas" approach aimed at transforming journalistic practical knowledge into statistical formulas, this chapter offers insights that can be further used by scholars and anti-corruption practitioners to further develop red flags to assess the risk of corruption in PP. It also addresses the challenges faced by journalists investigating corruptions and the obstacles that prevent a fruitful collaboration among actors such as institutions, LEAs, and journalists, actors that are diverse in their nature, scope, and structure, but which often share the common goal of exposing and preventing corruptive behaviours.

After a brief review of the academic literature on journalism and anti-corruption, the first part of this chapter will detail how the CO.R.E. project has drawn from journalistic professional expertise to develop corruption-risk indicators and increase their sustainability. Then, we delve into journalists' perspective and toolkits, detailing how they investigate cases of corruption, their suggestions on possible red flags of corruption risk, and the challenges they encounter when they use PP data. Insights and recommendations on possible red flags that can be further developed are offered with the aim of enhancing collaboration among different actors and unlocking a synergy potential which, according to the interviewed journalists, is still largely untapped and underutilized. The chapter concludes with recommendations for policy makers, academics, and anti-corruption practitioners, with the aim of enhancing the impact and effectiveness of corruption prevention endeavours.

1. Journalism and anti-corruption: a review of the literature

Previous research on journalism and corruption has focused on three key thematic areas: the relationship between free press and corruption (see e.g. Brunetti and Weder, 2003; Stapenhurst, 2000), how corruption stories are covered in news media (see e.g. Berti, 2019; Hajdu *et al.*, 2018; Mancini *et al.*, 2017), and how investigative and data journalism can be particularly effective in exposing corruption when it is based on cross-field and international collaborations (see e.g. Carson and Farhall, 2018; Howard and Constantaras, 2019; Moene and Søreide, 2019).

First, the relationship between free press and corruption. Comparative studies that took into consideration a large number of countries have demonstrated a very sharp relationship between freedom of the press and perceived corruption, meaning that the more press freedom we have in a country, the less perceived corruption we find. One of the most influential studies within this literature stream has been conducted Brunetti and Weder (2003), who also demonstrate that there is a direct negative causal relationship between the two variables, meaning that it is the level of press freedom that affect the level of perceived corruption, and not the other way around. Therefore, existing studies suggests that a free press can act as a check on corruption and contribute to lower levels of corruption in a society.

Why does a free press determine lower levels of corruption? The literature suggests that independent journalism is a very powerful tool to curb corruption, and this is mainly because by reporting on politicians and businessmen being charged with corruption, news media create a sentiment of shame and indignation that affects the reputation of these actors, and this constitutes an incentive to avoid engaging in corruption (Mancini *et al.*, 2017). Second, by exposing corruption practices and highlighting good practices, independent news media strongly contribute to create public awareness on corruption and its possible solutions, keeping the issue at the centre of public agendas and political debates. Finally, a free press is “bad news” for corruption also because of the watchdog role of journalists: news professionals, among other things, sometimes also investigate and disclose corruption stories, and this further enable public opinion to control the behaviour of power holders (Stapenhurst, 2000).

A second aspect addressed by existing studies relates to how corruption stories are covered by news media. Comparative cross-national studies demonstrate how the level of press freedom in a given country is not the only factor affecting how news media report on corruption. Instead, other factors such as the level of political partisanships of news media and their degree of commercialisation contribute to shape how corruption is covered. In their study on the coverage of corruption in the British, Italian, and French press, for example, Mancini and colleagues (2017) found that corruption is much more covered in Italy than in the other two countries, and this is not because the Italian press enjoys greater levels of freedom than the French or British news media, nor because there is more corruption in Italy. The authors rather point at the higher levels of political partisanships and instrumentalization of Italian media, for which covering stories of corruption where local or national politicians are involved is an opportunity to attack the political camps the individual newspapers oppose. In countries marked by high levels of political polarization, indeed, the media are used as instruments to fight political battels, and news media and journalists are genuinely willing to take part in these struggles, often because of ideological reasons.

The fact that the coverage of corruption stories can be also driven by political or commercial logics, and not only by higher principles such as informing the public and keeping power holders into account, has clear negative implications for journalism's role in the fight against corruption. Mancini and colleagues (2017) conclude their study by emphasising how the different representations of corruption offered by news media in different countries (or by different news outlets within the same country) can be problematic. Market and political segmentation contribute to a lack of a collective sense of outrage necessary for preventing, controlling, and condemning corrupt practices. When each news outlet presents corruption differently based on political affiliations, audiences form different views influenced by their chosen "media bubble". This variance can lead to the dismissal of corruption charges against specific political figures, viewed as products of partisan coverage. Such dynamics erode journalism's ability to instil moral shame associated with corruption, fostering polarization and escalating distrust among political factions and toward institutions.

Third, the literature also addresses how collaboration among different actors can make journalism more effective in combatting corruption. Two forms of journalism have proved to be particularly relevant in investigating financial crimes and fostering transparency in the PP domain: investigative journalism and data journalism (Moene and Søreide, 2019; Moyo, 2019; Vrushi and Hodess, 2017). Investigative journalism is a frontliner in combating corruption, animated by reporters that uncover and expose abuses of power and misuses of economic resources through in-depth reporting activities (Hamilton, 2016; Moene and Søreide, 2019). Although investigative journalism is central in the way the profession is publicly understood and appreciated, reporters in most cases cover corruption by working on information made public by LEAs and the judiciary system. Investigative reporting is underprovided in the news market because investigations require high resources, as teams of journalists need to devote significant amount of time for each investigation. However, as suggested by Hamilton (2016), recent developments with the employment of data and algorithms in journalistic reporting may make it easier for news media to discover corruption stories. Other studies have suggested that investigative journalism produces relevant results also by benefitting from the collaboration of whistle-blowers (Gottschalk and Smith, 2016) or through Freedom of Information (FOI) requests (Mabillard and Zumofen, 2021).

An exemplary yet disconcerting illustration of how the impact a journalistic inquiry into corruptive conduct can rise public awareness on the subject, simultaneously subjecting the journalist to repercussions for probing the sensitivities of influential figures, is epitomized in the case of Greek journalist Thanasis Koukakis. Koukakis, who is a financial reporter for CNN Greece and other national and international media, wrote two stories in 2019: an investigation into alleged wrongdoings by the banking Greek giant Piraeus Bank and a *Financial Times* article on how the Mitsotakis government amended the Greek penal code in a move that, according to the journalist, appeared to overturn Greece's commitment to international standards on combating corruption and money laundering. For his investigations, Koukakis was unlawfully put under surveillance by the Greek secret services, who breached into his phones using a spyware, an intrusive technology that governments claim to use to combat terrorism and other serious crimes[1].

Data journalism instead involves the collection, analysis, and presentation of big amounts of data to uncover and communicate new stories. Data journalists have a key role to play as public interest watchdogs, as they can turn the raw data contained in repositories into insightful stories that improve the quality of the democratic life, provide consumers with useful information, and increase the accountability of the institutions (Howard and Constantaras, 2019). Data journalism benefited from the processes of datafication and

1 https://govwatch.gr/en/sovares-apokalypseis-kai-diethneis-antidraseis-gia-tin-parakoloythisi-dimosiografoy-apo-tin-eyp-kai-to-logismiko-ypoklopon-predator/

digitalisation of society that have followed the development of Web 2.0, and is now and increasingly important part of journalism education programmes and newsroom activities (Porlezza, 2023). In 2017, the European Data Journalism Network (EDJNet), a network comprising media organizations from across Europe that advocates for the practice of data journalism, was established. Data journalism greatly benefitted also from the European open data policies, and, in return, it helped increasing transparency and oversight in public procurement (Duguay *et al.*, 2023).

In journalism, collaborative projects take advantage from the participation of multiple actors that bring together expertise and resources to overcome the difficulties that would otherwise overwhelm a single individual or entity by sharing costs and information, tackling more complex reporting on a global scale, increasing the outreach of stories reach, and strengthening their ability to define the news agenda (Carson and Farhall, 2018). Collaborative projects are particularly important when it comes to investigate corruption, as it enables news organisations to share the high costs associated with their investigations with other media outlets, to increase the societal impact of their outcomes, and to avail of the expertise of professionals that are not available within the organisation (Alfter, 2019; Carson and Farhall, 2018; Heft, 2021; Stonbely and Siemazko, 2022). A noteworthy example of collaborative journalism is the Investigative Reporting Project Italy (IRPI), who dedicated a specific series of investigations to cases of corruption all over the world thanks to its participation in several international journalistic networks[2].

Cross-border collaborative journalism (Alfter, 2019) covers transnational and cross-continental issues (Berglez, 2013) and addresses the specific challenges derived by geographical diversity such as language barriers, cultural diversity, and national structures (Hellmueller and Berglez, 2022), and in recent years brought to the light very successful investigations, such as the Luxemburg Leaks (Guevara, 2014). The Luxemburg Leaks are a cross-border investigation lead by the International Consortium of Investigative Journalism in 2016[3], which denounced the role of Luxemburg as a fiscal paradise within Europe that allowed practices of tax avoidance by hundreds of multinationals, with the complicity of national authorities that also pushed back efforts on behalf of the European Commission to put remedy to practices that greatly damage the European democracies, European market and fiscal justice.

Instead, the term "cross-field collaborations" refers to partnerships that involve actors that belong to different social domains, such as journalism, institutions, LEAs, academia, or civil society. Stonbely and Siemazko (2022)

[2] https://irpimedia.irpi.eu/tema/corruzione/
[3] https://www.icij.org/investigations/luxembourg-leaks/

for instance define a cross-field collaboration one that comprises “at least one journalism organization and one civil society organization in which they work together to produce content in the service of an explicit ideal or outcome” (Stonbely and Siemazko, 2022, p. 3). As mentioned, we share the conviction that the cross-field collaboration between journalists and other actors can strengthen the fight against corruption. In the remaining part of this chapter, we will address how the CO.R.E. project has contributed to enhance the dialogue between these diverse actors, how journalists can benefit from the project results, how anti-corruption experts can benefit from a deeper understanding of investigative and data journalists methodologies, and what are the main challenges that may undermine fruitful cross-field collaborative initiatives.

2. The involvement of journalism within the CO.R.E. project

The CO.R.E. project is aimed at establishing a method to assess the risk of corruption in public tendering during emergency periods, when the usual national governments’ regulations are relaxed. This objective has been achieved through the development of a composite indicator (CI) of corruption risk in PP in time of emergencies. The CI aggregates and summarises a set of elementary indicators (i.e. red flags) into a single metrics. The red flags are developed by focusing on the time discontinuity introduced by a crisis outbreak and the possibility to distinguish two timespans, a pre-crisis and a post-crisis period, and compare the behaviours of companies and contracting authorities after the crisis outbreak to their historical conduct.

The CO.R.E. consortium is based on the cross-field collaboration among partners from four countries and with diverse backgrounds, ranging from statisticians (in charge of the development of the CI and red flags), anti-corruption authorities (supporting the CI development and focusing on validating it with their internal data), and NGOs, civil-society organisations, and activists focusing on anti-corruption (supporting dissemination activities and the development of the project technological tools). Although the CI and the red-flags of corruption-risk in emergency times have been primarily developed based on the expertise of social statisticians, legal scholars, and anti-corruption experts, journalism has also played a relevant role within the project. Journalists have been involved in the project with two main roles: as beneficiaries of the project outputs and as source of inspiration and feedback for the development of the project results and tools.

First, journalists as beneficiaries. Indeed, the CO.R.E. methodology and its outputs are meant to be used by investigative and data journalists in their investigation and reporting activities, as well as by other stakeholders such as LEAs and civil society organisations. Ensuring that the project outputs are widely used by journalists and other actors involved in anti-corruption activities is key to ensure the long-term sustainability of the project results. Two primary tools have been created to facilitate the effective and user-friendly application of the indicators by journalists and other stakeholders with varying levels of technical expertise: the data visualization dashboard and the coresoi R package.

The data visualization dashboard is a web platform that enables journalists, activists, citizens and other stakeholders to analyse PP data, to apply the statistical procedures at the foundation of the indicators, and to produce interactive visualisations of the results. Users can interact and filter data previously analysed by the CO.R.E. team by selecting the emergency they are interested in, the country, the specific red flags (as an alternative to the CI that summarises them), the geographic entities (specific regions or provinces), and the data visualization mode (table, map, or bar chart). Through an intuitive and easy-to-use navigation system, users have the ability to discover the results of the CO.R.E. methodology for each individual contracting authority and awarded company.

The coresoi R package comprises software codes, a user guide, and additional tools designed to empower journalists, researchers, LEAs, and anti-corruption authorities in the application of the CI and red flags to their own datasets. Compared to the dashboard, the coresoi R package requires higher technical skills from the user, but it provides more flexibility as it can be applied any datasets that interested users need to use in their future analyses and investigations. To facilitate and promote its use, the coresoi R package is supplemented by guidelines, sample datasets to help beneficiaries to familiarise with the indicators and procedures, specific guidelines on how the R codes can be applied to new datasets, and details on how to get technical support from the developers.

Journalists have also been involved in the project as a source of inspiration and feedback for the development of the CO.R.E. indicators and tools. Involving journalists since the early phases of the project was aimed at ensuring that the tools developed within the project meet the real needs of the target beneficiaries and will be taken up by potential users. Interviews with data and investigative journalists based in Italy, Spain, and Ireland were conducted to benefit from their experience in investigating corruption stories related to the COVID-19 emergency and to better understand the techniques they employ when investigating corruption in PP. The findings informed the development of the CI and red flags. Journalists have finally been consulted in the final months of the project to test how the newly developed method can be applied in journalistic work and to collect feedback that can further improve the indicators, the coresoi R package and the data visualization dashboard. The insights collected from journalists and the main challenges they face when investigating corruption in PP are discussed in the following part of this chapter.

3. Journalism know-how and methods for investigating corruption

As previously noted, the cross-field collaborative nature of the CO.R.E. project has been enhanced by engaging investigative and data journalists. This strategic involvement aims at leveraging their specialised expertise, soliciting valuable input and recommendations for the development of novel corruption-risk indicators. To achieve this objective, the DCU unit of the CO.R.E. project conducted seven in-depth semi-structured interviews with individual journalists, media organisations, and NGOs in Italy, Spain, and Ireland. They specialize in reporting on corruption and other financial wrongdoings, providing meaningful insights into the multifaceted aspects of their investigative activities. Interviewees have been first identified by drawing from a list drafted thanks to the aggregated knowledge of the members of the CO.R.E. consortium and their personal contacts. Participants were then recruited depending on their expertise in using data and/or reporting on corruption and other financial crimes, their country of origin, and professional role.

3.1. Key investigative approaches and practices

The interviews sought to delve into the investigative methods employed by journalists when addressing corruption, with a focus on their utilization of indicators and data related to PP. We gathered examples of effective practices and specific investigations in this domain to inform the theoretical formulation of CO.R.E. indicators. The underlying notion was that understanding journalistic practices, including what they seek during corruption investigations, where they find evidence, and how they analyse information, could serve as a valuable source of inspiration. This information could later be transformed by statisticians, anti-corruption experts, and IT developers, both within and outside the CORE team, into statistical tools, following a "from practices to formulas" approach.

Several themes were explored during the interviews to tackle all the relevant aspects of journalistic work when investigating cases of corruption in public tendering. These include:

1. Journalistic investigations: examples of investigations and collection of typical patterns of corruptive behaviours in public tendering during emergency periods.
2. Archives and databases created and/or used during investigations.
3. Data protection, terms of service, and related constraints.
4. Cross-border investigations: main challenges and opportunities.
5. Red flags: recommendations inspired by journalistic methods and expertise.

The themes to be explored in the interviews were defined together with our consortium partners, most of which have academic and anti-corruption backgrounds and expressed the need to gain a comprehensive understanding of journalistic practices and, notably, insights from real cases derived from existing investigations.

An example of these cases is the investigation conducted the *Irish Examiner* on the purchase of ventilators during the Covid-19 emergency in Ireland[4]. The newspaper obtained documents used by public officials to evaluate a tender application. These documents revealed that, despite the officials' acknowledgment of evident and serious risks inherent in the tender application, they nonetheless granted approval, irrespective of the activation of numerous red flags. From a methodological standpoint, the investigative acumen demonstrated by journalism can serve as a stress test, scrutinizing the efficacy of theoretically well-constructed risk alerts.

In terms of the sources of data used by the interviewed journalists, we found that they mainly work with official datasets provided in open data format by relevant institutions such as the national or regional anticorruption authorities in the selected countries. Journalists work on these by connecting official data with granular information coming from the investigations. As a result, they produce enriched datasets that can potentially integrate the data already available to the academic and public institutions. In other words, journalists produce their own datasets, as it emerges from the following interview quote:

> In general, crossing different datasets is very much part of my job. It is something that I tend to do often while looking for correlations, to find things. […] [It is a matter of] enrich[ing] the single dataset that was provided … I don't know … by Eurostat, Istat, and so on (Interview, Italian journalist).

Another Italian journalist explains how he is used to create his own dataset of court documents:

[4] https://www.irishexaminer.com/news/arid-40208102.html

I am a serial accumulator of court papers that I recover. I am a bit addicted to archive and to give them an index and things like that. So the data crossing then goes a bit by luck, because maybe you say this company, this thing, this person I have already identified, let me throw it into the archive and let's see what It comes out (Interview, Italian journalist).

From the interview analysis emerged that a stronger collaboration between journalists and public institutions have indeed an unexploited potential. Indeed, the process of cross-consulting different datasets and producing new enhanced datasets to overcome the limitations of existing official sources of data is a rather complex and time-consuming process. An example of journalists' techniques to overcome limitations in existing datasets is provided below. In the quote, the journalist explains how they found a creative solution to solve issues with omissions in the data managed at the European level:

A trick was used for Italy: starting from a contract made at European level that defines the vaccine quotas for each country, Italy has initiated a fake tender in order to produce a CIG[5] code which, according to Italian law, is essential to make use of public resources. This way, we have managed to collect some information, because to obtain a CIG you have to go through ANAC (the Italian anticorruption authority) and a series of information ends up in their (open) databases of public contracts (Interview, Italian journalist).

It is important to consider the unique role of journalists and the distinct challenges they encounter when investigating cases of corruption in PP, challenges that differ from those faced by law enforcement agencies, prosecutors, or other public authorities. Notably, journalists often lack recognition as interested stakeholders in adjudication procedures, as it is illustrated in the following quote:

Another problem in the legal framework in Spain is that even if we see a contract that looks illegal to us, we cannot do anything about it. We cannot appeal the adjudication because we are not interested parties according to the Spanish law. We can complain, we can shout, but that's it (Interview, Spanish journalist).

Journalists seeking to extend the impact of an investigation beyond the simple act of publishing a story often venture into novel collaborations with non-journalistic entities. While this might stretch the traditional boundaries of journalism towards a form of civic activism, it is viewed as a potential

[5] CIG is the Italian Tender Identification Code, a unique identifier assigned to a specific tender, bidding procedure or public contract.

avenue for tangible wider impact and a catalyst for positive change. This is exemplified in the following quote:

> We are doing some strategic litigation, not so much about procurement yet, but about transparency issues. So, we collaborate with lawyers, that's something we want to explore [more]. Like, if we take a particular contract to court, maybe we would collaborate with lawyers and stuff like that (Interview, Spanish journalist).

Difficulties regarding legislative impediments and others stemming from the transnational nature of many investigations on corruption were also discussed with the interviewees, particularly in terms of data accessibility, usability, and the right to publish. For example:

> On vaccines we faced enormous limitations regarding access to information, because that bargaining was managed at European level and those contracts were then classified. They were published on the European Commission's website, but they are so full of omissions that they are illegible (Interview, Italian journalist).

Far from being an issue only for journalists, limitations to data accessibility and usability deeply affected the potential of the CO.R.E. project and the creation of the indicators, which can only be based on data available for calculations. In fact, several potential red flags that are methodologically possible were excluded from the final CI due to the lack of the necessary data in the public databases available to the researchers. The CORE team published several works on this issue[6].

3.2. Primary tools for investigations

The interviewed journalists highlighted specific practices that hold a crucial position in their professional investigative toolkit. The selection and utilization of these tools are influenced by the distinctive context in which journalists operate. Factors like the national legal framework, the type of journalism undertaken, and the unique requirements of each investigation play a significant role in determining the choice and effective deployment of these tools. These practices are listed in Tab. 1 and briefly discussed thereafter.

[6] https://www.core-anticorruption.eu/publications/

Tab. 1 – Journalists' toolkit for investigating corruption

Freedom of Information (FOI) requests
Access to documents from the judicial system
Whistleblowing
Legwork (non-mediated recording of events)
Open source intelligence (OSINT) instruments and search engines dorks

FOI requests

A Freedom of Information (FOI) request is a formal inquiry made by an individual or organisation to a public body seeking access to specific information or records that may not be publicly available. FOI requests remain one of the most powerful tools in the hands of journalists, civil activists, and citizens, as it was stressed by every single journalist interviewed. The following quote exemplifies how FOI requests are often used in combination with PP data analysis:

> We immediately started a data request activity, both through public pressure and FOI applications, to the government, to the Civil Protection. At the same time, we started a memorandum of understanding with ANAC which by law in Italy holds a database of public contracts, and then we began to query that database through search keys (Interview, Italian journalist).

The interviewees also emphasised several necessary conditions for FOI requests being effective: that individuals within the bureaucratic system are familiar with the relevant FOI regulations (which cannot be assumed to be the case), responses are provided within a reasonable timeframe, and precautions are taken to prevent the misuse of privacy constraints that might otherwise limit the efficacy of FOI requests.

Documents from the judicial system

Obtaining documents or records such as court filings, judgments, and transcripts is one of the primary sources of official information. This presents additional benefit of a high degree of verifiability, as it entails official information coming from certified and authoritative sources. As exemplified by an interviewee:

> This kind of [archive] provides judgments, court dates and so on. So, this could be a really, really useful one… as well to see what litigation companies are involved in or have been involved (Interview, Irish journalist).

Whistleblowing

Whistleblowing refers to the act of individuals within organizations or institutions disclosing confidential information or exposing wrongdoing to selected journalists, often "leaking" insider information on activities such as corruption, misconduct, or unethical practices. As exemplified by a journalist, this allows to go beyond official and publicly available information:

> The common denominator in most of those things in Ireland is a whistle-blower, somebody from within the organization you talked with about kind of procurement and finance and things like that. People within their organization to blow the whistle to, to bring you records, to bring you documentation that you would not be able to get via FOIA or other rules (Interview, Irish journalist).

The interviewees emphasized the invaluable insights gained through whistleblowing, acknowledging the challenge of maintaining source anonymity and the time-intensive nature of the verification process. Furthermore, the precarious state of legal protections for anonymous whistle-blowers hampers the optimal utilization of this practice.

Legwork

Traditional legwork, aka "shoe-leather reporting", involves on-the-ground activities such as interviewing sources, visiting locations relevant to the story, and attending events. As illustrated by a journalist, this can lead to find unexpected information:

> Maybe, if you're lucky, the subcontracting sign inside the construction site indicates the companies that enter and exit, because from the point of view of construction site safety the contractor says: "I want it written there because we need to know who comes in and who goes out" (Interview, Italian journalist).

Open source intelligence (OSINT) and search engine dorking

OSINT techniques encompass technical tools to retrieve information from the internet that is not immediately and easily available. It demands a certain level of technical proficiency on the journalist's part. An example of such a tool is Google dorks, which facilitates a more refined and in-depth search of online materials, as elaborated in the following quote:

> Google's Logical Operators are another incredible tool. Search for one or more names in PDFs and link them to searches, for example, in other PDFs, which are usually the documents in which the information actually exists, especially on the subject of procurement. Even judicial documents, for example. Because many times the Supreme Court search engine is filtered by Google anyway (Interview, Italian journalist).

3.3. From practices to formulas: turning journalistic know-how into red flags

Not all the journalistic practices and techniques discussed in the previous part can be automatically translated into solutions for a project, like CO.R.E., aimed at developing red flags and indicators for analysing the risk of corruption in PP. However, we believe that a better understanding of how journalists retrieve relevant information for their investigations can inform the development of new solutions and indicators in future research. In the next pages, we attempt to summarise the key elements of investigative and data journalism know-how and practices, as they emerge from the interview analysis, which can potentially be used as a source of inspiration for the development of red flags and indicators to assess and alert about the risk of corruption in PP. In some cases, these elements are based on our understanding of the journalistic practices and the examples of investigations discussed during the interviews. In other cases, they are based on more explicit suggestions provided by the interviewed journalists.

The suggested red flags have been elaborated following the "from practices to formulas" approach mentioned earlier on, and try to answer the following research question: *How can we translate journalists' investigative know-how, tools, and techniques into material that can be used by other scholars to create statistical formulas to assess the risk of corruption in public procurement?*

We do not claim to offer here an original contribution to the discovery of new indicators. We rather try to provide other scholars and stakeholders with material and ideas coming from the journalistic perspective that can be used in the development of new red flags and indicators. Certainly, several of the journalistic practices and suggestions listed below correspond to RFs that are already well established in the literature and widely used by the anticorruption community. Likely, other practices and suggestions would require specific type of data which are not available in a structured and open format. In other cases, it could simply not be possible to translate these suggestions into statistical formulas. However, we believe that sharing with the anti-corruption community the following journalists' suggestions on possible RFs (which are based on their investigative work) can enhance the future development of new and improved indicators. Some of these practices and suggestions, for example, offered interesting new perspectives that have been considered by the CO.R.E. statisticians and anti-corruption experts while developing the CO.R.E. indicators.

The suggested RFs were aggregated into thematic categories. Most of them belong to two groups: contract-related, which refers to elements that can be found in the contract, or tender-related, which refers to procedural elements of the tendering process per se. The third group, people-related RFs, refers to the individuals involved in the tendering process in any role. The latter group was considered by the interviewed journalists as the hardest yet the most promising dimension to be analysed/investigated, mainly because of obstacles related to data access and privacy regulations. It is the case, for example, of data linked to beneficial ownership. Each of the potential RFs that follows come from journalistic practices and suggestions collected through the interviews conducted with investigative and data journalists.

Contract-related RFs are shown in Tab. 2, and they refer to the content of the contract and its elements, such as prices, timing, or the company structure of the actors involved (individuals are excluded from this set). The analysis of these elements and variables is the most common in established anti-corruption risk-assessment practices. An example of an interview quote used to operate a transformation "from practices to formulas", i.e. to codify journalistic practices and know-how into material that can be used to elaborate anti-corruption RFs, is provided below:

> It is understandable that, in an emergency situation, the price [of certain goods and services] can skyrocket to like ten times. It is not normal that it stays at the same level for a prolonged time. So, through money and of course different tendering over time, you can understand if this anomaly is somehow sustained by the willingness of… (Interview, Spanish journalist).

Tender-related RFs are shown in Tab. 3. They are linked to the tendering procedure in itself and focus on all sorts of irregularities or anomalies that can emerge from the process of adjudication.

People-related RFs are shown in Tab. 4. They specifically refer to physical persons that may be involved in the tendering process, such as legal representatives, beneficial owners, members of the board. These are the most sensitive ones in terms of privacy constraints, as personal data are strongly protected within the EU. Authorities regularly keep list of names that are considered risky or even blacklisted. Journalists rarely have access to these lists, but get around it through investigative work and cross-data references.

A final potential RF, geospatial reference, is shown in Tab. 5. This RF does not fit into any of the previous categories. The journalist that recommended this red flag suggested that georeferentiation of contracts assigned through a tender could help develop new analytics of corruption risks. This is a promising path to be further explored, but it would require new standards in public procurement in terms of type of digital data collected for each record related to an adjudication, for instance geo-tagging with GPS coordinates contracting authorities and bidding companies.

Tab. 2 – Potential contract-related red flags

Potential red flag	*Description*
Sudden changes in prices of goods or services	It refers to anomaly in pricing compared to a consolidated trend, with a magnitude often superior to a 200%+ increase (less frequently a decrease).
Prices behaviour altered over time	It refers to pricing not following market criteria and/or trends, signalling the potential existence of a "will" behind the anomaly.
Multiple contracts with similar value awarded to the same company	It hints at a potential break of a major contract into smaller ones to bring their individual value below a certain threshold, usually where safeguards are less restrictive or absent.
Awarded contract significantly bigger than the usual revenues of a company	It highlights the unlikeliness of the company to be able to uphold the contract. It therefore questions the rightfulness of the awarding and a breach in the expected due diligence evaluation.
Awarded contract does not match the company size in terms of production or management capacity	Similar to the previous potential RF, but it relates to other parameters that refer to the company structure, such as number of employees.
Area of expertise of a company	It refers to a company that is awarded a contract in a sector that does not match the sectors in which it historically operates.
Structure complexity	It suggests that a company with a very complex structure is more likely to hide grey zones.
Company certificates	It refers to situations in which required certificates appear missing, altered, expired or incomplete and they should represent a reason for disqualification from a tendering process.
Company current financial profile	It refers to situations in which a company participates in a tender or win a contract even if it is engaging in a financial settlement agreement, or it started a bankruptcy procedure (as it is possible in times of emergency and economic crisis).

Tab. 3 – Potential tender-related red flags

Potential red flag	*Description*
Progress indicators	It refers to the absence of clearly established progress indicators, such as payment vs service delivery.
Frequency of winning	It refers to a bidder that consistently wins. This may be related to a consolidated obscure relationship that obstacles fair competition.
Award criteria consistency	It refers to the award criteria, which should be explicit in the tender call and consistently applied over time by the tendering station.
Variations after the awarding	It refers to possible significant changes in key elements of the contract, especially money related. Requires continuous monitoring after the awarding.
Due diligence	It refers to due diligence procedures, which could be somehow altered in comparison to standards.
Temporary adjudications	Temporary adjudications allow to temporarily skip certain requirements due to the urgent nature of the process. They generally come with a request to later normalise the agreement, communicate, or report to relevant offices or institutions. This requires checking if those postponed communications are missing.
Publication-awarding timing	A short notice and a quick adjudication may reveal previous agreements between the bidding station and the awarded company.

Tab. 4 – People-related red flags

Potential red flag	*Description*
Individual's background and professional history	Data gathered from journalistic archives and open or secreted blacklists can return relevant information on the history and background of a certain person, and reveal risks associated to a certain person and potential conflicts of interest.
Network	The analysis of the social network, here included information obtained from social media platforms (LinkedIn as a prime example) on a certain person can reveal informal relationships that elude traditional monitoring tools and may be in conflict with the desired impartiality of a tender award.

Tab. 5 – Geospatial-based red flags

Potential red flag	*Description*
Geospatial references	Obtained by referencing the location of bidders, tender stations, sites of services. Further analysis may reveal patterns of interest, such as undue agreements on dividing and/or sharing certain contracts within or across different locations, and indication of cartel tendencies among competitors.

3.4. Major obstacles hindering investigative journalism

The interviews conducted with journalists did not solely cover "what they do", but also "what they are unable to do" because of restrictions they face. In this section, we focus on the main challenges, limitations, and constraints that frequently obstacle their investigations on corruption in PP. Some of these obstacles are legitimate and reasonable limitations that safeguards other actors' rights, such as privacy considerations and ownership rights on databases that private sector companies have invested in. Others are technical, legal, or cultural obstacles that could be mitigated by the intervention of the legislator or by the management of administrative bodies. Interventions in these areas would make journalistic investigations on corruption in PP more effective, widespread, and impactful, de facto strengthening one of the most evident activities that embodies the public service mission of journalism.

It is important to note that, according to the interviewees, the obstacles discussed below do not always depend on a lack of resources, legal frameworks, or technical opportunities. In some cases, they are the result of widespread malpractices, lack of adherence to existing laws and regulations, ignorance, lack of training among public officials, conflicts of interest or work overload within public administration bodies. Discussing these obstacles is not a stylistic exercise or a way celebrate the value of investigative journalism by emphasising the challenges it faces. Instead, this is a matter of pointing at obstacles that are also faced by other anti-corruption actors, pointing (in some cases) at solutions that have been found by journalists to overcome common problems, and making a call for legislative intervention and policy reform.

Lack of access to public data

As it already emerged in the previous pages, journalists often face problems with accessing PP data that should be made available in open and workable formats by relevant anti-corruption authorities and public institutions. In some cases, for example, datasets are provided but in a fragmented manner, meaning that different administrative bodies and institutions publish their own data on the respective websites, but a centralised dataset that includes data from several administrative bodies within the same country and that uses the same formats and standards is not available. The CO.R.E. consortium faced similar issues when looking for datasets that could be used to test the indicators in the countries covered by the project.

Lack of access to privately-owned data, legal limitations to data access and use (intellectual property, industrial secret, etc.)

Economic constraints and paywalls put useful data beyond journalists' reach, unless they can afford to pay for the datasets they need. Moreover, when it comes to journalistic investigations that apply big data analysis techniques, the private owners do not allow access to their entire datasets or meaningful chunks of them, as they represent their core business, which would be damaged by providing full access to data to other parties and stakeholders. Additionally, as illustrated by an interviewed journalist, legal limitations such as the ones that protect commercially sensitive data prevent the effective use of tools such as FOI requests:

> FOI is particularly weak when it comes to trying to investigate matters around tendering, around procurement, around contracts, because the protections around commercial sensitivity are so strong (Interview, Irish journalist).

FOI requests ignored, denied, or delayed

While we saw how FOI requests are a key tool for journalists, their request can be delayed, ignored, or denied. Sometimes the timing of a journalistic investigation does not match with the timing of the workflows of a public administration. Sometimes administrative bodies do not respect the deadlines provided by laws that regulate access to public data. Officials may also be quite arbitrary in deciding whether certain information should be blackened or readable, circumventing or ignoring existing laws and guidelines.

Unfamiliarity of public officials with current regulations

Sometimes public officials deny data access to journalists out of unfamiliarity with the laws that govern these practices, not knowing when, what, and how a member of the press can request access, due to a combination of ignorance, negligence, and lack of training.

Insufficient digitization of the public administration

Data that is not digitised can be harder to find as it requires in person access to archives or other places where such data is stored and, above all, the knowledge that a certain document exist in the first place. This makes journalistic work on corruption way more expensive and time consuming.

Lack of agreements/collaboration between journalists and other relevant actors

The interviewed journalists have conveyed a keen interest in fostering collaboration with institutions and other public bodies. Concurrently, institutional actors frequently assert their aspirations to enhance dialogue with newsrooms and media organisations. However, this prevailing sentiment often tends to be more aspirational than practical, with only a handful of instances marked by the commendable goodwill of individuals facilitating collaboration and the exchange of data. The following quote exemplifies a noteworthy case of best practices in such collaborations, where a journalist has reported sharing a dataset, enriched through their efforts, with pertinent authorities. Furthermore, there are intentions to delve deeper into potential avenues for collaboration with anti-corruption agencies:

> After we finished the investigation, we gave our data to the anti-corruption agencies, the one in Catalonia, the one in Valencia, and the one in the Balearic Islands, because we wanted them to pick up and maybe continue. Something we want to explore: the anti-corruption agencies can look at our data and say, okay, these contracts look weird, they're a clear fragmentation of a big contract into smaller ones. So they can follow up and they can take that to court. So that would be the type of collaboration that would make sense. We haven't done it properly (Interview, Spanish journalist).

However, journalists and institutional actors are evidently governed by distinct mandates, deontological norms, and operational constraints. As stressed by a representative of an anti-corruption authority in a personal communication we had to further explore the issue, while both journalists and authorities align in their overarching goal of addressing the societal challenge posed by corruption, differences exist in their respective visions and strategies for attaining these objectives:

> We have different values and principles: we (anti-corruption authorities) work under a legal obligation of secrecy and confidentiality, and the final outcome is not to publish anything, but to eventually start criminal proceedings. Journalists want to disclose (to the public) (Quote from a personal communication with a stakeholder).

Consequently, establishing formal collaboration is frequently challenging and, at times, perceived as mutually disadvantageous. Despite the infrequent occurrence of direct collaboration between authorities and news media, the authorities actively monitor journalistic investigations, and channel their institutional focus towards potential instances of corruption in PP brought to light by investigative journalists.

4. Conclusions

This chapter delved into the symbiotic relationship between journalism and the development of CO.R.E. indicators, showcasing the integration of journalists' input and feedback into the project design and implementation. Through a comprehensive examination of investigative journalists' perspectives on the methodologies, tools, and challenges encountered in uncovering corruption in PP, coupled with their recommendations for potential journalistic-inspired red flags, the groundwork has been laid for the formulation of innovative approaches. The intent is to contribute to the development of novel red flags and methodologies, reinforcing the anti-corruption initiatives led by authorities, institutions, civil society organizations, and academics alike.

In light of the insights gleaned from the study, several recommendations emerge for academics and research institutes engaged in research projects exploring the assessment of corruption risk in PP:

- *Integration of journalists, news organizations, and anti-corruption practitioners as collaborative partners:* Research project should prioritize collaborative partnerships with journalists, news organizations, and anti-corruption practitioners. This interdisciplinary collaboration can foster a comprehensive understanding of corruption dynamics, enriching the research endeavour with diverse perspectives and practical insights. This could also pose the basis for future collaborations between institutions, journalists, and academics and further empower their anti-corruption daily activities.
- *Early engagement of journalists and practitioners in project design:* To optimize the efficacy of research projects, it is critical to involve journalists and practitioners from the inception of the initiative. This early engagement ensures that the project design aligns with the nuanced insights and practical knowledge possessed by these professionals. By incorporating their expertise at the outset, researchers can tailor projects to address the real-world challenges faced by investigative journalists and anti-corruption practitioners.
- *Integration of professionals' feedback for sustainable research outputs:* The sustainability of research outputs is contingent upon the integration of constructive feedback from journalists and practitioners. Academics and technicians should actively seek and incorporate professionals' insights on the developed tools and research outputs. This iterative feedback loop not only enhances the applicability of the findings but also ensures that the academic contributions resonate with the practical needs of the journalistic and anti-corruption communities.

Based on our findings, three recommendations are directed towards public institutions and anti-corruption authorities:

- *Adoption of comprehensive open data principles:* Public institutions and anti-corruption authorities should seriously embrace open data principles, ensuring the transparent availability of public procurement data in accessible and standardized formats. Recognizing the prevailing challenge of fragmented datasets disseminated across various administrative bodies, efforts should be directed towards establishing centralized datasets that incorporate information from diverse entities within the same jurisdiction, thereby facilitating a cohesive and unified approach.
- *Strengthening whistle-blower protection laws:* Acknowledging the indispensable role of whistleblowing in uncovering corrupt practices, public institutions and anti-corruption authorities must prioritize the fortification of whistle-blower protection laws.
- *Implementation of training programs on open data and FOI laws for public officials:* Streamlining FOI request processes, minimizing delays, and eliminating instances of ignorance or denial based on inadequate awareness of legal provisions can be achieved through targeted training initiatives in open data principles and FOI regulations for public officials, promoting transparency and facilitating journalists' investigative endeavours.

These recommendations, complemented by the journalistic insights discussed in this chapter, aspire to fortify anti-corruption initiatives rooted in cross-field collaboration among diverse stakeholders united by the common objective of combatting corruption in public procurement.

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The authors

Dimitri Bettoni, PhD, is researcher and editor at Osservatorio Balcani Caucaso Transeuropa (OBCT), and research assistant at the School of Communications, Dublin City University. He previously worked as a correspondent from Turkey for the Italian news outlets *OBCT*, *Il Manifesto* and *Atlante di Treccani*. He is a co-founder of the Foreign Media Association in Turkey.

Agustí Cerrillo-i-Martínez holds a PhD in Law and a Degree in Law and in Political Sciences. He is a Full Professor of Administrative Law at the Universitat Oberta de Catalunya (Spain). He is a member of the Legal Advisory Commission of the Administration of the Generalitat de Catalunya. He has been the Ombudsman, the Dean of the Law and Political Sciences School, and the Programme Director of the Law Degree of the Universitat Oberta de Catalunya. He is the Universitat Oberta de Catalunya team leader within the CO.R.E. project.

Alessio Cornia, PhD, is an assistant professor at the School of Communications, Dublin City University (DCU), and research associate at the Reuters Institute for the Study of Journalism, University of Oxford. He is the DCU research team lead for the CO.R.E. project and Co-PI for the H2020 project "MEDIATIZED EU: Mediatized Discourses on Europeanization and Their Representations in Public Perceptions".

Davide Del Monte is one of the founders of info.nodes, a non-profit organization established in September 2019 by a group of activists, researchers, artists, and journalists who aim to restore a more just and equitable society. He collaborates with several organizations for the promotion and protection of social, climate and digital justice. He served as the president of the Independent Commission for Whistleblowers in the city of Milan (from

April 2018 to April 2021) and as the executive director of Transparency International Italy from 2015 to 2020. He is the info.nodes team leader within the CO.R.E. project.

Simone Del Sarto is assistant professor of Social Statistics at the Department of Political Science of the University of Perugia. He is consultant of the Italian National Anti-Corruption Authority as statistician. His main interests deal with latent variable models and composite indicators construction in the field of education and corruption measurement.

Wellington Migliari holds a PhD in Law and Political Science from the University of Barcelona (Spain), Faculty of Law. He is currently a postdoctoral researcher at the Open University of Catalonia and an assistant professor at the Faculty of Law, University of Barcelona (Spain).

Niccolò Salvini is a data scientist and engineer currently pursuing a PhD in Big Data for Healthcare Systems. He has a Master degree in Statistical and Actuarial Sciences, has worked as a teaching assistant in various institutions and has experience as a freelance data scientist and engineer. He collaborated with the CO.R.E. project as a data scientist. His technical skills include Py-thon, R, SQL, and proficiency in multiple data science toolkits and cloud platforms.

Lorenzo Segato is Director of Research at RE-ACT, with over 20 years of experience on crime prevention and risk assessment. He published several papers and researches on corruption related issues, environmental crimes and water crimes.

In this book of contributed chapters, we delve into the pivotal issue of adapting corruption risk assessment systems to emergency scenarios. Corruption poses formidable challenges to the advancement and stability of nations worldwide. As societies confront the complex nature of corruption, the need to employ innovative and efficient strategies to combat it becomes increasingly evident. During periods of crisis, conditions become ripe for corruption due to relaxed regulatory frameworks, reduced oversight, and a surge in financial activities. Among various sectors, public procurement systems are particularly vulnerable to corruption risks during emergencies, given their frontline role in many countries' crisis responses.

As crises escalate in frequency and magnitude, it becomes increasingly clear that fostering a culture of preparedness, investing in mitigation measures, and devising proactive strategies to contain their detrimental impacts through new and realistic risk interaction models are all critical components of societal resilience. Similarly, corruption risk assessment systems designed to identify corruption risks in public procurement during normal periods must undergo adaptation to effectively devise solutions for mitigating and preventing corruption risks during emergencies.

Throughout the book, the discussion revolves around the CO.R.E. project – COrruption Risk Indicators in Emergencies. This project, funded under the EU Internal Security Fund Police (ISF-P) program in 2019, aimed to enhance early detection of corruption risks through big data techniques and to establish a stronger evidence base for policy reform in emergency scenarios. The project served anti-corruption authorities, law enforcement agencies, journalists, and the general public for accountability objectives. CO.R.E. was a technologically advanced project leveraging sophisticated data-driven approaches and harnessing the power of big data to effectively address and counteract corruption in the public procurement cycle during times of crises.

Michela Gnaldi is Associate professor of Applied Statistics at the Department of Political Sciences of the University of Perugia. She is the Principal Investigator (PI) of the CO.R.E. project, and has been consultant of the Italian National Anti-Corruption Authority and of other national and international agencies (i.e., UNHCR, World Bank). Since 2016, she leads a thematic area within the Italian Association for Quality of Life (AIQUAV) on Contrast to corruption, social integrity and quality of life. She is member of the steering committee of the University of Perugia inter-departmental Centre of studies and advanced education on Legality and Participation (LEPA). She is the official representative of the University of Perugia within the ECPR - European Consortium for Political Research - and its standing group on (Anti) Corruption and Integrity.

FrancoAngeli
La passione per le conoscenze