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COVID-19 emergency public procurement in Romania: Corruption risks and market behavior

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The Integrity Pacts – Civil Control Mechanism for Safeguarding EU Funds project has brought together government agencies, civil society and the private sector in 11 EU countries, to ensure that 18 major public contracts were designed and implemented to the highest possible standards of transparency and accountability.

Abstract

The aim of this research is to track corruption risks affecting the Romanian public procurement system during the COVID-19 emergency. We develop a composite Corruption Risk Index (CRI) to track public procurement contracting risks in Romania in the period from 2015 to 2021. We find that the emergency context exposed the procurement process to more corruption risk which may have been directly related to the relaxed regulatory framework adopted by the Romanian authorities to address supply shortages. Furthermore, we document that the CRI scores for COVID-19-related products increased especially during the emergency period. However, other health-care products and products entirely unrelated to the pandemic also increased their risks to a comparable level which raises concerns of corruption risk spillovers on the market. We also extend our CRI methodology to investigate the contracts and public buyers participating in the Integrity Pact program. While the sample is small, results show that Integrity Pacts may help to decrease specific corruption risks such as single bidding.

Keywords

Public procurement, Corruption, COVID-19, Romania, Integrity Pacts

Introduction

Public procurement as a key area of government spending is heavily regulated in order to ensure value for money, fair competition, and transparency. However, public procurement is exposed to corruption risks due to the large amount of money spent, technical and legal complexity, and the public discretion with which the details of spending decisions are set. These risks may become even higher under extraordinary circumstances which make hiding corruption easier while also necessitating the spending of exceptionally large amounts in a short period of time. Efficiency, fairness, and transparency may be overshadowed temporarily during a crisis, such as the COVID-19 pandemic, when rapid response is needed to protect citizens' health and lives. In this special situation, it is particularly important to test how integrity initiatives, such as Integrity Pacts, can play their role to control this pressure.

With the increased availability of detailed and comprehensive administrative datasets, containing information on the different phases of public tendering, data-driven risk assessment methodologies are getting better in detecting corruption risks and institutional vulnerabilities, and supporting the mitigation of key risks. Such data and methods enable us to look at the novel COVID-19 emergency in Romania shortly after contract awards have taken place. Romania is particularly interesting to look at from the perspective of emergency procurement risks because it is subject to a stringent regulatory regime while also maintaining a high level of corruption risks. Hence, the relaxation of rules coming with the COVID-19 emergency period offers a unique insight into how regulations and specific institutions such as Integrity Pacts may constrain corruption and how risks evolve in the wake of a nation-wide, in fact global, crisis.

Accordingly, this analysis aims to answer the following research questions:

- How have public procurement corruption risks changed during the state of emergency time period compared to the 5 prior years?
- Do contracting authorities participating in an Integrity Pact display different corruption risks compared to other organisations?

The data used to build a specific corruption risk assessment for the pandemic-induced emergency period in Romania was collected from three publicly available official data sources: the Romanian government portal (Data.gov), from Romania's Electronic Public Procurement System (SEAP) and the EU Tenders Electronic Daily (TED). A key methodological aspect is that the collected dataset provides us with information on contracts 5 years prior to the emergency period. This enables us to build an adequate framework to statistically measure the risk of corruption in Romanian public procurement before and during the emergency period by calculating several corruption risks proxies that indicate the overall health of the public procurement system. The validity of selected indicators was tested by looking at the input-output relationships between process biases (inputs) and single bidding and supplier income share (outputs) and whether they contribute to outputs in line with the theoretical expectations of the corruption definition. The steps are outlined in the methods section.

The present research is structured in the following manner. First, we present details on the data collection process from the 3 official sources and the steps we undertook to build a comprehensive dataset. Then we proceed with explaining our methodology and the reasoning behind choosing each corruption proxy. After presenting the overall state of corruption in Romania, we dive deeper into analyzing the state of corruption of COVID related products within the healthcare market. We chose a reasonable group of contracts that resemble the COVID related contracts but that are not directly impacted by the emergency period in order to statistically test if the effects we observe in our analysis group are significant – these represent the control group in our analysis. The final section is primarily concerned with assessing the performance of Integrity Pact programs over several corruption proxies. Due to the low number of contracts, it is not directly possible to statistically test the observed differences. However, a means comparison could offer us a picture on how these contracts are generally performing in comparison to similar contracts that were not part of the Integrity Pact program. Finally, we conclude the paper with policy recommendations stemming from our analysis using the composite CRI and other corruption proxies.

Policy Context

The COVID 19 emergency: regulatory changes

Based on the recent estimates by (Bosio et al. 2020) public procurement in Romania is estimated to make up around 7.75% of GDP. Since the Government Emergency Ordinance No. 13 of May 20, 2015[4], the National Authority for Regulating and Monitoring Public Procurement (ANRMAP), the Unit for Coordination and Verification of Public Procurement (UCVAP) have been merged into a single National Public Procurement Agency (ANAP) within the Ministry of Finance. This centralization was regarded as a positive step in the institutional framework of the Romanian public procurement system. The ANAP was further strengthened by shielding it from the Ministry of Finance by eliminating the political appointment of its leadership. Its enforcement powers were also strengthened by several actions such as its ability to halt procurement procedures. As of currently, the ANAP is the public procurement entity responsible for legislative and policy making, executive and oversight functions (European Commission. Directorate General for Regional and Urban Policy. and PWC. 2016).

Although there were previous attempts to designate specific institutions to procure medical goods through the “negotiated without publication” procedure type in accordance with the provisions of Law no. 98/2016 regarding public procurement, Romania still experienced supply shortages especially in essential medical products due to the recent COVID-19 emergency (Preda and Simion 2020). On March 16, 2020, the Romanian president issued Decree no. 195/2020 which declared the state of emergency in Romania. Establishing a state of emergency has made it easier to procure emergency goods by using simplified procurement procedures. Therefore, the ANAP issued a notification allowing contracting authorities to directly procure materials and equipment necessary to combat the COVID-19 epidemic. Although relaxing the regulatory framework and granting greater autonomy to contracting authorities is seen as more efficient during emergency periods, it poses a significant risk of increasing corrupt transactions (Preda and Simion 2020).

Integrity Pacts in Romania

Our report is also concerned with a second set of policies, namely the Integrity Pact program. The Romanian National Anti-Corruption Strategy (2016-2020) piloted the IP program to monitor the public procurement process. It takes the form of a contract between contracting authorities, bidders and third parties (mostly NGOs) to comply with best practices and ensure maximum transparency. The parties involved undertake fully transparent monitoring and commit themselves not to offer or to demand a bribe, not to reach secret agreements to influence the award of

[4] Government Emergency Ordinance no. 13/2015.

contracts and not to encourage acts of corruption either prior to the conclusion of the contract or during the execution of the contract. The main aim of the IP is to increase transparency and reduce the risk of corruption in public procurement. The program was implemented in the context of four projects by the Ministry of National Education, The National Agency for Cadastre and Land Registration, the Ministry of Culture, and the Ministry of Public Works, Development and Administration. The main innovative aspect is that the IP also introduces civil society organizations to safeguard those commitments and monitor four EU-funded projects.

Conceptual Framework

Measuring corruption risks: measurement framework

Corruption in public procurement is the process of deliberate allocation of public contracts by distorting principles of open and fair competition to benefit specific participants, often at the expense of others. In other words, *the aim of such corruption is to steer the contract to the favoured bidder without detection in an institutionalised and recurrent fashion* (World Bank 2013) by 1) avoiding or biasing competition in order to 2) favour a certain, connected bidder. By shifting our attention on unfair access to public resources, we have a clearer focus on the measurement framework. Such corruption may involve bribery and transfers of large cash amounts as kickbacks, but it is more typically conducted through broker firms, subcontracts, offshore companies, and bogus consultancy contracts. By implication, not everything designated as corruption under this definition represents illegal activity as defined by the law in a given country (Fazekas and Kocsis 2020; Fazekas, Tóth, and King 2016).

This definition implies that, for measuring corruption, its underlying logic must be contrasted with a competitive market logic. Institutionalized grand corruption's primary aim is extracting corruption rents, which can be obtained in public procurement when the winning contractor is a pre-selected company that then receives extra profit by charging higher than the average market price for the delivered quantity and/or quality. In order to measure extra profit, the price, delivered quantity, and quality of deliveries must be known with high precision, yet none of these three can adequately be measured in most public procurement administrative datasets. Price and quantity of procured deliveries are usually publicly available but not comparable across time and space, while quality cannot be reliably observed in official records. Therefore, it is proposed to alternatively proxy corruption risks by analyzing the process of awarding contracts and key outputs such as number of bidders and market concentration. Crucially, lack of bidders for government contracts (single bidder) is an outcome whereas the means to introduce certain procedural rules for limiting competition (manipulating procedure types and shortening advertising period, etc.) are inputs. The relationship between inputs and outcomes forms the measurement model and can serve as a test for validity when selecting proxy indicators for constructing the composite Corruption Risk Indicator (CRI). We go further in outlining the indicators (and justifications) for each of our indicators that we use as inputs for our measurement model in the "Methods" section below.

We use publicly available micro data on public procurement in Romania from three sources to construct a dataset that documents the procurement activity before and during the emergency period. We use the dataset to calculate several corruption proxies and then use a difference-in-differences identification method to find an unbiased correlation between the emergency period and our composite CRI scores. The report primarily tracks the corruption risk indicators for COVID-products and the healthcare market at large that can be seen as direct effects of the emergency period. We also track the correlation of the emergency period on non-COVID products and the rest of the markets that can be seen as non-direct effects of the emergency period.

To answer the second question of the report, we locate IP contracts in our dataset and pair them with similar contracts over several characteristics such as size, location, buyer type. A simple comparison of means between those pairs will allow us to understand how IP contracts specifically have been performing.

Expectations

During the COVID-19 emergency period, public organizations faced a double challenge. On the one hand, public organizations participating in the delivery of specific healthcare services, such as intensive care, were required to drastically increase spending to cover supply shortages in crisis related items such as masks. On the other hand, regulatory bodies at the European as well as national levels relaxed the set of controls, especially ex ante controls, of corruption in public procurement to allow for quicker transactions. Although these steps were likely to contribute to a quicker supply system, they may also create opportunities for exploiting the system to extract corruption rents. As a result, it is to be expected the relaxed regulatory framework during emergencies will negatively impact the integrity of public procurement (Gallego, Prem, and Vargas 2020; Schultz and Søreide 2008). As the relaxed rules and spending pressures specifically applied to COVID-19 related goods and services, we expect the emergency period to increase corruption risks in specific markets only.

In addition, as pre-pandemic corruption controls also considerably vary between buyers with some achieving high integrity while others only very low integrity. As the relaxation of corruption controls in public procurement rules apply across the board, we can expect organizations to adapt differently to the new rules. Given the pre-pandemic propensity to corrupt contracting, it is expected that those buyers which have a high pre-pandemic risk level will take advantage of the relaxed rules to contract more corruptly than those which display high integrity scores.

Furthermore, IP programs imply the participation of various stakeholders to mutually monitor public procurement contracts to ensure that procurement is performed at high levels of integrity in order to safeguard public interest. Therefore, we expect that IP contracts and participating public entities, to display an overall lower corruption risk in relation to several corruption risk proxies when compared to similar contracts and entities.

Data & Methods

Data

Romanian public procurement data was gathered from two publicly accessible official government sources: periodic procurement data dumps from the Romanian open data government portal (Data.gov) and from Romania's Electronic Public Procurement System (SEAP). We also supplement our dataset by collecting notices published on the EU Tenders Electronic Daily (TED) which covers public procurement from the Europe Economic Area. The combined dataset of more than 3.4 million notices went through a mastering process that removed duplicate records and standardized buyer and bidder names, locations, etc. in order to create a standardized dataset.

After the standardization process, the data was manually validated against records from the multiple sources to ensure the scraping process was successful. The data are then pre-processed, supplemented, and prepared for analysis. Some of the adjustments made to the data include further location improvement using the location APIs, combining supplier country secrecy scores values, filtering data from bad calendar dates due to data errors, adjusting bid prices by the purchasing power parity. After filtering the dataset to contract awards, we worked with 1,737,248 records from 2007 to 2021. Therefore, 66.04% of the data comes from the SEAP, while 28.23% & 5.73% are from TED and Data.gov respectively. Table 1 shows the number of records, buyer and suppliers in each data source.[5]

Table 1: Dataset by source

Source	Observations	Buyers	Suppliers
DATA.GOV	99,465	7,010	20,151
E-LICITATIE.RO	1,147,332	13,665	38,968
TED	490,451	2,706	13,415
Overall	**1,737,248**	**23,380**	**72,534**

Medical equipment is the main CPV sector in the dataset by frequency (57%) followed by Construction work (6.25%) and Food & beverages (5.66%). However, Construction work (59.8B EUR) is the highest sector by contract volume followed by Medical equipment (14.9B EUR) and Transport equipment (4.86B EUR) as shown in Figure 1. The majority of contracts are supplies (76%) while works and services account for 13.1% and 10.9% respectively.

[5] Annex figure A.1 shows the distribution of the CRI for each source.

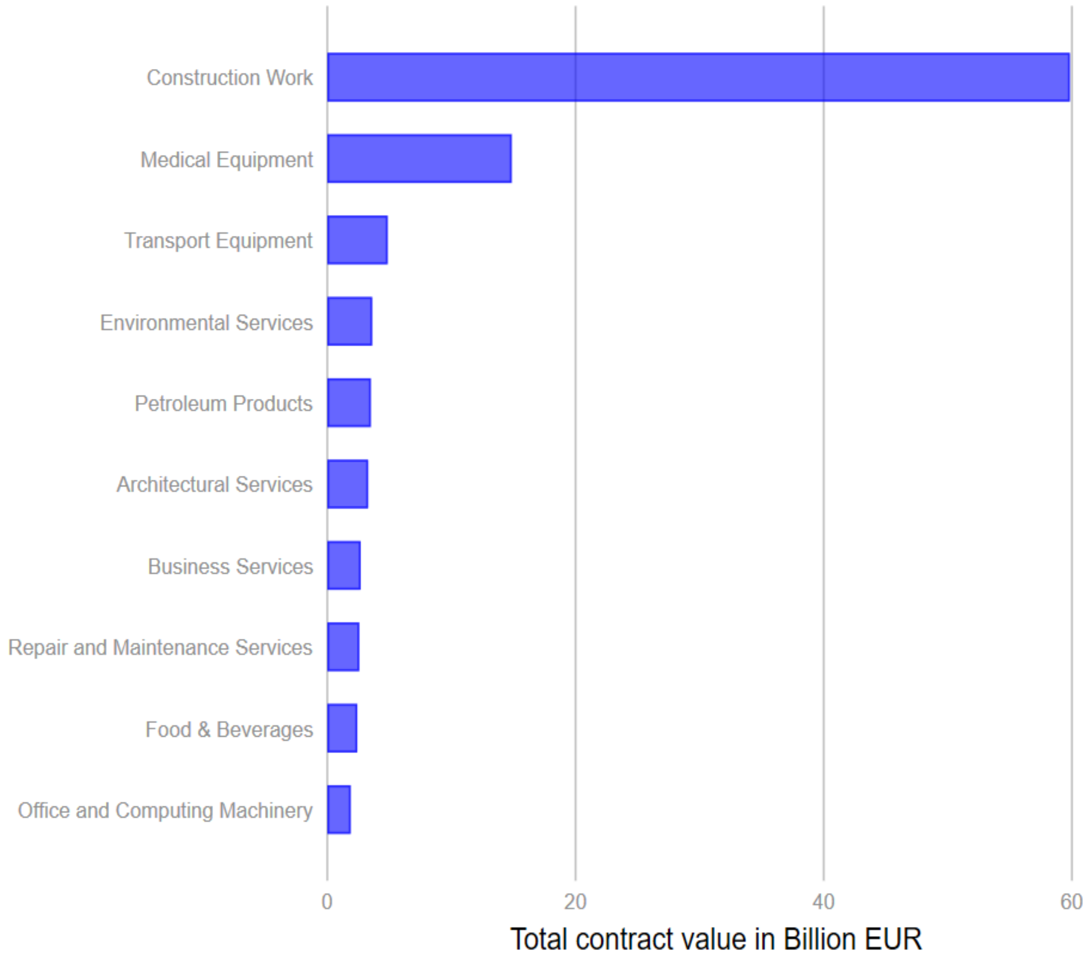
We supplement the bidder information in our data using the Confidas company registry.[6] The portal offers detailed information on Romanian suppliers such as the number of employees and the company's main activity domain through the registered NACE code.[7] This information enables us to develop new indicators such as identifying market switching patterns and helps us to further analyse the relationship between size and procurement risk, as will be outlined below.

Our two main sub-analysis groups are the COVID product list and healthcare suppliers.[8] We identify COVID products through two main lists:
1) COVID related products used by TED[9] and
2) regulated COVID products published by the Romanian authorities in Ordinance nr 11/2020.[10]
From a tendering perspective, the product list varies from more complex purchases such as Oxygenators and Respiratory monitors to less complex ones such as Disposable gloves. A contract is regarded as a COVID product contract if at least one of the contracted products is COVID related.

To identify healthcare bidders, we use a list of NACE codes that show the company's main activity through the registration forms. Companies that are registered under "Manufacture of medical and dental instruments and supplies" and "Hospital activities" are included in the list as well as companies operating in the "Wholesale of clothing and footwear" to account for companies selling masks and other protective clothing.[11]

[6] https://www.confidas.ro/
[7] We use the company's tax ID to identify bidders on the Confidas portal.
[8] We list the CPV codes and a description of each product and the NACE codes used to identify healthcare suppliers in Table A.1 & Table A.2 in the Annex respectively.
[9] https://simap.ted.europa.eu/web/simap/covid-related-tenders
[10] Ordonanța de urgență nr. 11/2020 privind stocurile de urgență medicală, precum și unele măsuri aferente instituirii carantinei
[11] We also search for keywords in the names of suppliers such as "pharm|medical|medi|diabetes" to expand on the healthcare bidders list to account for suppliers with missing NACE codes.

Figure 1: Distribution of CPV sectors in the dataset



**All other sectors combined have a total value of 16.87 Billion EUR
Contract with missing product codes have a total value of 10.56 Billion EUR

Methods: measuring corruption risks over the emergency period

The domain-specific definition of risk in public procurement is operationalized as restricted and unfair access to public resources (Mungiu 2006; Rothstein and Teorell 2008). Objective procurement risk indicators have been defined and measured using administrative data. Based on the methodology developed by (Fazekas and Kocsis 2020), the criterion for the selection of procurement risk indicators is the **degree of unjustified restriction of competition**. All risk indicators are calculated at the contract level.

We identify 11 indicators that could contribute to the restriction of competition.

- **Single bidding**. The most straightforward indicator of the restricted competition included in the dataset is single bidding. This is a public procurement outcome when only one bid is submitted in a tendering process on an otherwise competitive market.
- **Procurement procedure type**. While open tenders are by default competitive procedures, some other procedure types such as direct purchases or negotiated procedures with no announcement could contribute to the limitation of competition.
- **Lack of publicity**. The lack of a tender announcement is defined as a standalone risk indicator. The reason is that it could be seen as a deliberate attempt to prevent the spread of information related to a procurement process.
- **Tax haven**. A contract is flagged if a supplier is registered in a tax haven. Participation of suppliers registered in tax havens in a tendering process poses a risk to project completion as bidders may be less accountable than a non-tax haven registered bidder.
- **Winner contract share**. It is defined as the share of contract value won by a supplier from a buyer within that buyer's total procurement spending, annually. Higher contract share values are unlikely in competitive markets.
- **Length of bid submission and of the award decision periods**. While the length of these phases could be largely defined by a procedure type, such outliers as extremely short or long submission and/or decision periods could signal either collusion between a buyer and a supplier or legal challenges associated with a process. During emergencies shorter periods of procurement are usually preferred to cover immediate needs. However, because some of the COVID products are more complicated to procure, they might require a longer period of time to complete the process. Therefore, we assume that shorter time periods may still pose a significant risk to competition.

In addition, we developed the following indicators that are specific to the COVID-19 emergency:

- **Market switching**. Non-healthcare suppliers were identified through the NACE code list and flagged when the majority of their contracts were in the medical products CPV sector during the emergency. Suppliers exhibiting this kind of behaviour may be risky from a tendering perspective because one way to exploit the changing regulatory framework during the emergency is by switching the domain of activity. We denote this behaviour as market switching.
- **COVID-19 products experience**. Suppliers who are primarily providing medical products during the emergency but had no experience in selling COVID products prior to the emergency are identified as risky.[12]
- **Newly established companies**. Since our database covers 14 years of public procurement activity in Romania (limited to 7 years for our analysis purposes), we identify companies that entered our public procurement database during the emergency period as

[12] If more than half of a supplier's post-emergency contracts start with the CPV sector code 33 they are considered to be primarily providing for the medical products sector during the emergency.

newly established companies. Newly established companies are less likely to win contracts in highly competitive markets and, in particular, during emergency periods as they do not have the necessary experience and qualifications.

- **Company size**. We define micro-companies as a company where the median number of employees is less than 50 employees as per the European Commission recommendation.[13]
- **Geographical proximity**. We include local suppliers as a risk category as the close geographical proximity between the supplier and buyer may be indicative of procurement collusion.

Validated indicators are combined to build a composite CRI where each indicator informs us about one aspect of potentially corrupt behaviors. The composite CRI score only indicates the risk of corruption, meaning that they are proxy indicators indirectly pointing at potential underlying corrupt exchanges.

Table 2 presents the exact definitions and thresholds used for each indicator. It also flags the indicators which are valid during the emergency period. We use single bidding and winner's contracts share as the main competition restricting proxies to validate the indicators. We use regression models to test each individual corruption indicator's fit with the corruption proxies while controlling for other alternative explanations. Table A.3 in the annex presents the validation regression of individual indicators during the emergency period. We find that all indicators are valid during the emergency period except for the "no call for tenders" indicator. This means that this indicator had no correlation with any of our corruption outcome variables such as single bidding during the emergency period. The ratio of the contract's final price (Relative price) is another corruption proxy that could be used to validate our composite CRI. As the aim of procurement corruption is steering contracts to favored bidders through hindering open competition, higher final prices are to be expected as one of the results.

Please note that not all indicators turn out to be valid on these validity tests tailored to the COVID 19 emergency period. In particular, the lack of publishing the call for tenders was not associated with higher single bidder probability and higher share of the winner. This most likely reflects the fact that many non-corrupt contracts in the emergency period was not advertised. As a result of these validity tests, this indicator is not part of the specific emergency CRI.

[13] Commission Recommendation (2003/361/EC) https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32003H0361&from=EN

Table 2: Corruption risk indicator definitions and valid indicators

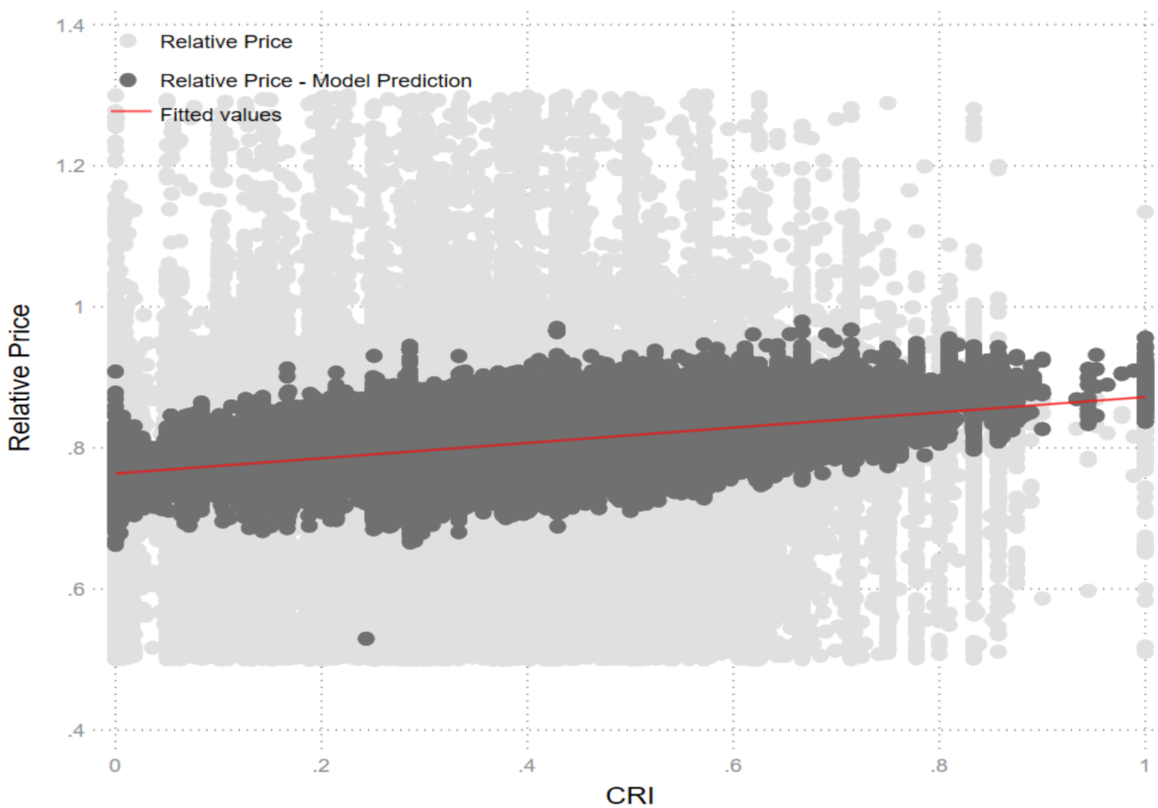
Component	Risk category type 1	Risk category type 2	Not a risk category	CRI (Valid during emergency period)
Single Bidding	Only one bid submitted		More than one bid submitted	✔
Procedure type	Approaching bidders Negotiated Negotiated with publication	Negotiated-without publication. Missing *Negotiated without publication for non-regulated COVID products added as a risk category type 3	Competitive dialog Open Restricted	✔
Submission period	2 to 33 days		34 to 365 days Missing	✔
Decision period	32 to 60 days	0 to 31 days Missing	61 to 365 days	✔
Call for tender	Call for tender not published		Call for tender is published	
Tax haven	Supplier registered in a tax haven		Supplier not registered in a tax haven Local suppliers Missing supplier reg.	✔
Winner contract share	Share of buyer's annual procurement spending captured by a single supplier.			✔
Market Switching[14]	Current Healthcare supplier switched market during emergency		Current healthcare Supplier did not switch markets during emergency	✔
COVID products Experience[15]	Healthcare suppliers without prior experience in selling COVID products		Healthcare suppliers with prior experience in selling COVID products)	✔
Newly created company	Supplier only appears in dataset after emergency		Supplier appears in dataset before and after emergency	✔
Supplier location	Local supplier		Foreign supplier	✔
Micro Supplier	Supplier has less than 50 employees		Supplier has more than 50 employees	✔

[14] A healthcare supplier is identified using its NACE code (see annex). The most common market during the emergency period is identified using a contract's CPV code. Non-healthcare suppliers (identified using NACE codes) mainly supplying the healthcare market (CPV sector 33) are identified as market switchers.

[15] COVID products are identified using the TED COVID related tenders product list and the products regulated for the COVID emergency based on the Romanian Ordinance nr 11/2020. A supplier that has no experience in supplying COVID products prior to the emergency and is currently mainly supplying the healthcare market (identified by CPV sector 33) is regarded as risky.

Figure 2 shows a linear fit between the composite CRI and a contract's relative price (ratio between the contract value and the estimated price) indicating that high CRI is associated with higher prices. This relationship between prices and corruption risks lends support to the validity of the CRI indicator as generally we expect corrupt contracts to cost more.

Figure 2: CRI and Relative price linear correlation.



State of corruption risks in Romania - General Description

The analysis shows that the *length of both submission and decision periods* occupy the largest share out of the 11 valid corruption indicators. Contracts with submission periods of around a month and/or decision periods of less than two months are positively correlated with at least one of our corrupt behaviour proxies (Single bidding/ Supplier contract share).

Micro suppliers also significantly contribute to the composite CRI demonstrating that contracts from smaller suppliers are positively correlated with our corruption proxies compared to their larger counterparts. Figure 3 (b) breaks the composite CRI to its components and shows the share by which each individual risk indicator contributes to the fuller picture.

A further breakdown of the change in share of each component across time (as it will be presented below) can help us to identify how the corruption risk patterns change during an emergency period. Figure 3 (a) shows an overview of the distribution of the composite CRI score for all contracts in our dataset. The score takes values between 0 and 1 and we see that the majority of contracts are below 0.6 CRI score. The distribution is slightly skewed to the left indicating corrupt behaviour makes use of one or more of the indicator's strategies to hinder competition rather than heavily combining all strategies to extract corruption gains.

Figure 3a: Component share and Histogram of Corruption Risk indicators

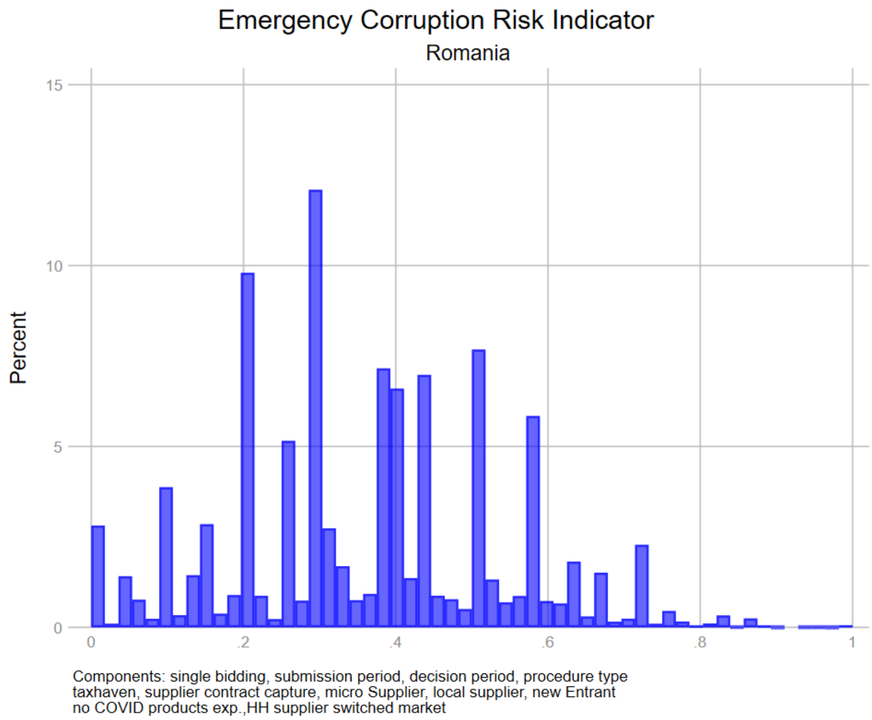
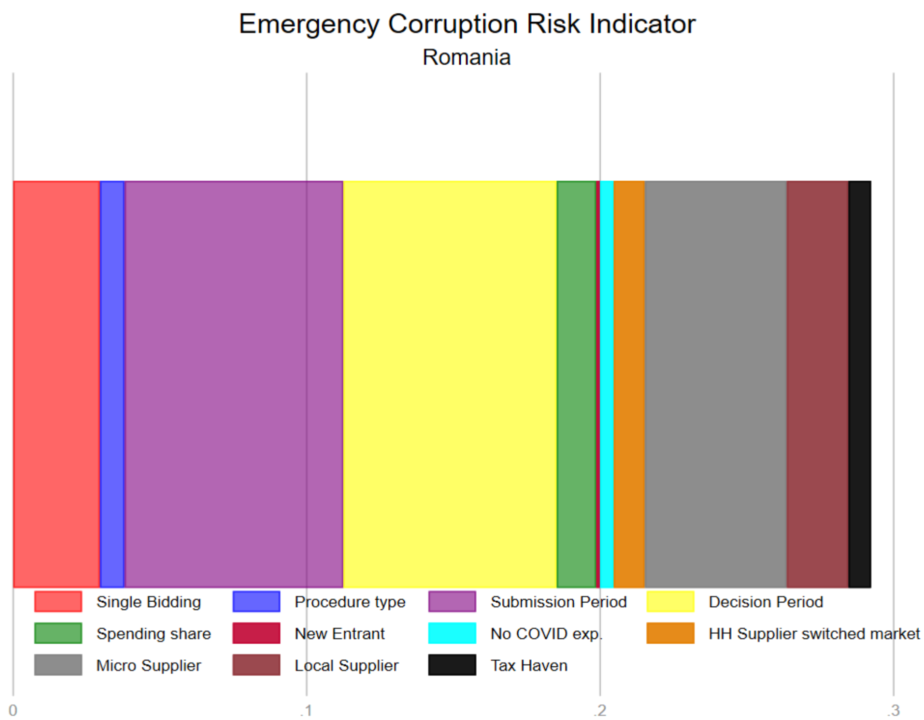


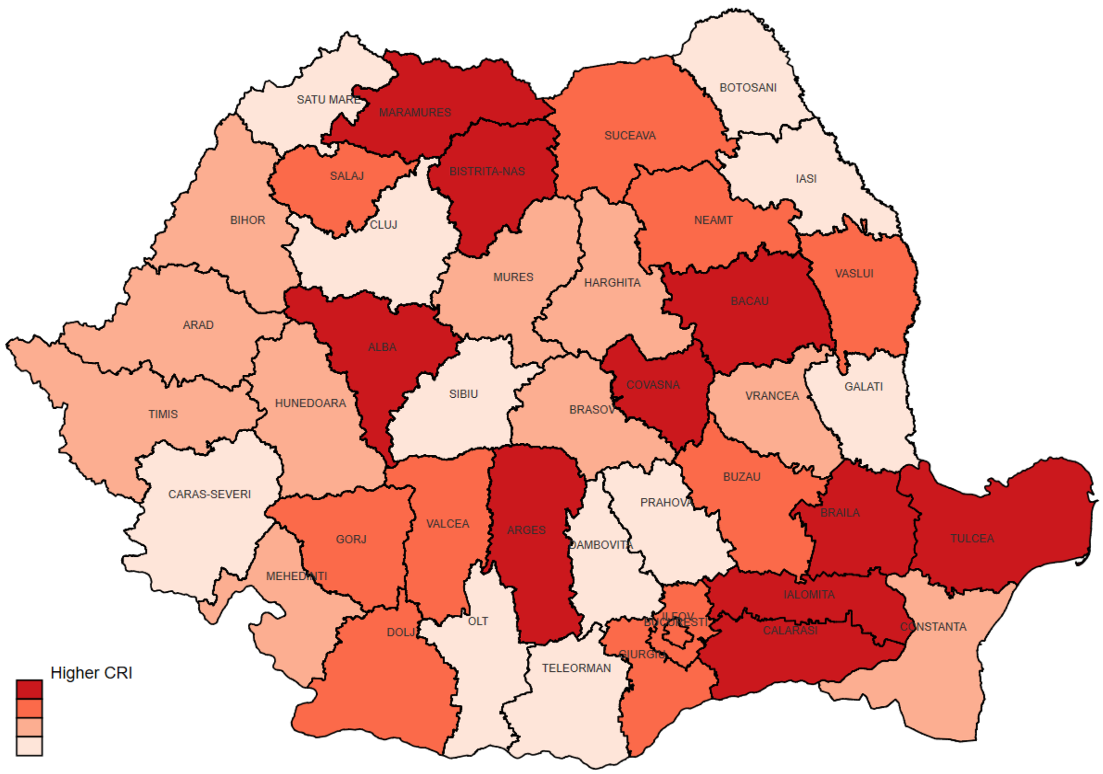
Figure 3b: Component share and Histogram of Corruption Risk indicators



The main advantage of the composite indicator approach resides in the fact that it offers a more comprehensive assessment of contracting processes that are potentially affected by corruption risks to capture the underlying corruption techniques. It allows for 'red flag' definitions to change from context to context in order to capture similar levels of risk irrespective of the detailed forms of corruption techniques used.

This flexibility in corruption indices aims to ensure that the same level of risk is associated with a similar level of actual corruption risk in a comparative perspective. As corruption techniques are likely to change over time, tracking multiple corruption strategies in one composite score is most likely to remain consistent. Both characteristics underpin its usefulness for cross-regional comparisons. In Figure 4, we show the regional distribution of the CRI over Romanian counties (NUTS 3 administrative classification of Romania).

Figure 4: Regional comparison of Corruption Risk Indicator in Romania



The Impacts of the COVID-19 Emergency Period

Emergency CRI

We perform our analysis on two main subsets of the data. The COVID products subset refers to all COVID -related products denoted by the European Commission, along with emergency regulated products by the Romanian Ordinance nr 11/2020 (See Table A.2 in Annex). The second subset is the healthcare market identified through the first two digits of a contract's CPV code; all contracts that begin with the CPV code 33 (Medical equipment, pharmaceuticals and personal care products) make up the healthcare market subset. We first examine the CRI components in each subset over time to identify changes in the underlying patterns of corruption during the emergency period.

Table 3 presents the means (standard deviation in parentheses) of the composite CRI and sample sizes in the full sample and for each of our analysis subsets before and during the emergency period. Our data covers 7 years of public procurement activity and amounts to 1,735,635 records split between 1,477,177 records before the emergency and 258,458 records during the emergency period. We observe that the means of the CRI increase during the emergency period for all our analysis groups.

As expected, corruption risks increase during emergency periods when procurement stakeholders are more concerned with procuring goods in shorter periods of time and less concerned about the integrity of the whole process. In our dataset, we observe increases in CRI scores across all analysis subsets. More importantly, the Increases in the CRI scores for the analysis subsets (Healthcare market 0.19, COVID products 0.20) are more pronounced relative to the CRI increase in the full sample (0.14) during the emergency period. This shows that although most markets have been compromised during the emergency, Healthcare markets and covid products have been particularly vulnerable.

Table 3: Comparison of CRI means (standard deviation) over analysis groups.

		Pre-emergency (2015-2020)	**Emergency period (2020-2021)** [16]	**Overall (2015-2021)**
Full sample	**Sample size**	1,477,177	258,458	1,735,635
	Mean (std.dev.)	0.41 (0.21)	0.55 (0.21)	0.43 (0.22)
Healthcare market	**Sample size**	842,789	147,358	990,147
	Mean (std.dev.)	0.36 (0.22)	0.54 (0.22)	0.39 (0.23)
COVID products	**Sample size**	51,551	12,707	64,258
	Mean (std.dev.)	0.35 (0.21)	0.55 (0.23)	0.39 (0.23)

To understand the underlying patterns contributing to the increase in the composite CRI, we break down the CRI scores by individual corruption components in each of our analysis subsets (Figure 5). The left panel presents the CRI component changes for the COVID products and the right panel tracks changes within the Healthcare market subset.

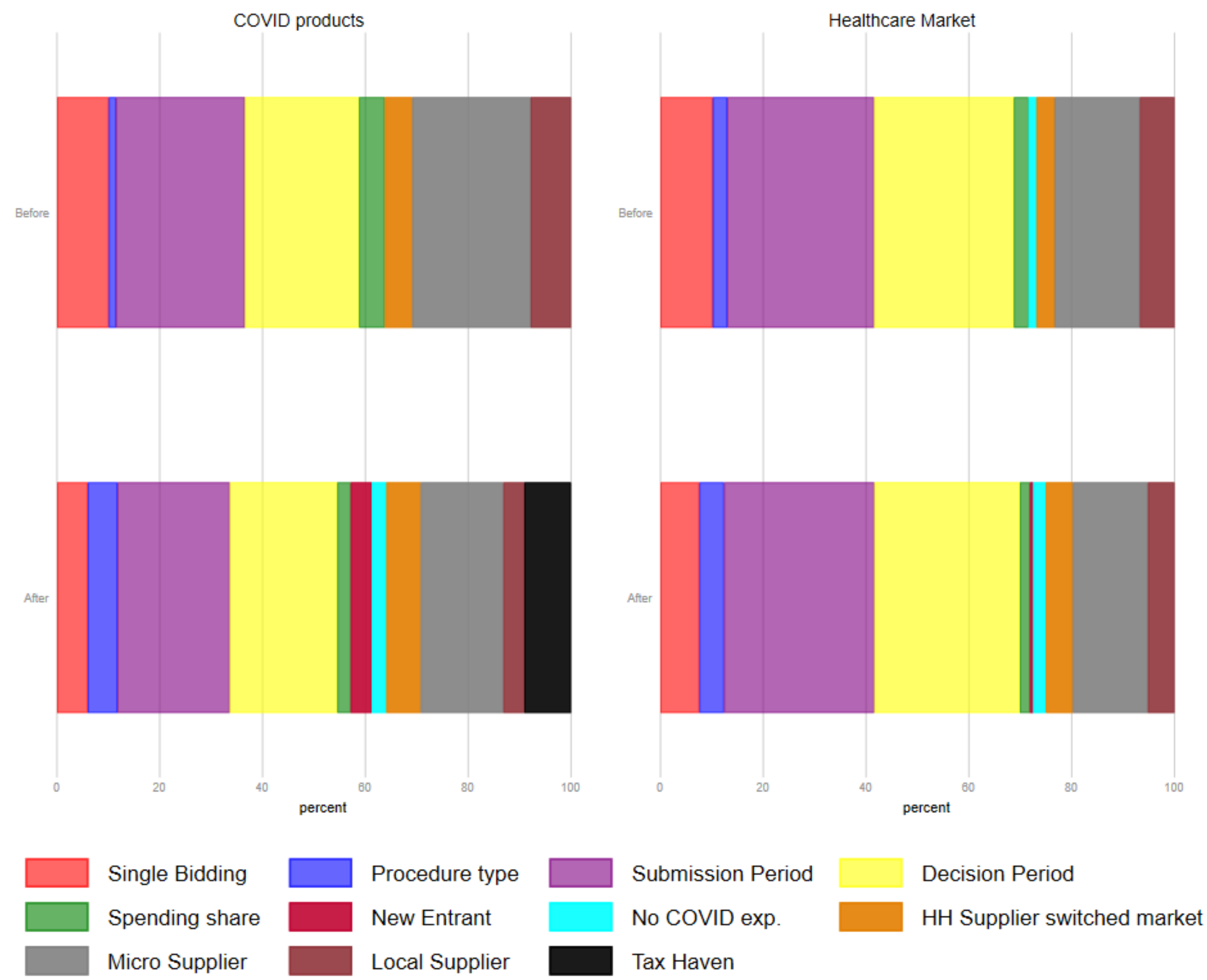
A range of interesting, detailed patterns emerge. First, contrary to expectations, we observe that single bidding goes down during the emergency period in both subsets compared to the pre-emergency rates. This is surprising, as urgent spending and the widely reported supply bottlenecks suggested that there will be more limited competition for each COVID-19 related contract during the emergency period. However, quite in line with our expectations, the share of dominant suppliers have gone down considerably from before to after the institution of the emergency period. Second, consistent with our expectations, a wide range of market entrants

[16] The emergency period begins on the 16th of March 2020

arrived during the emergency period. We observe that suppliers without experience selling COVID products have increased by around 9 percentage points during the emergency period within the COVID products subset which resemble an increase of 214 suppliers and/or 548 contracts flagged during the emergency. Similarly, we can see more than 350 suppliers during the emergency that had no prior history in our dataset selling products. In addition, market switching patterns have also increased in both of the subsets. It increased by around 12 percentage points for the COVID products sample and by 9 percentage points for the healthcare products sample. Third, quite concerningly, we observe that the tax haven indicator appears in the COVID products subset during the emergency while absent prior and during the emergency in the Healthcare market. Along with information on new entities entering the COVID products market during the emergency, this uncovers a new phenomenon in the COVID products market where suppliers registered in tax havens (e.g. Switzerland)[17] have increased their participation prior to the emergency period.

[17] We use data from the Tax Justice Network (https://www.taxjustice.net/) to supplement our dataset with secrecy scores to identify the tax haven status of a country. The score is updated bi-annually to reflect any changing status for a country.

Figure 5: Comparison of change in CRI components by analysis subsets

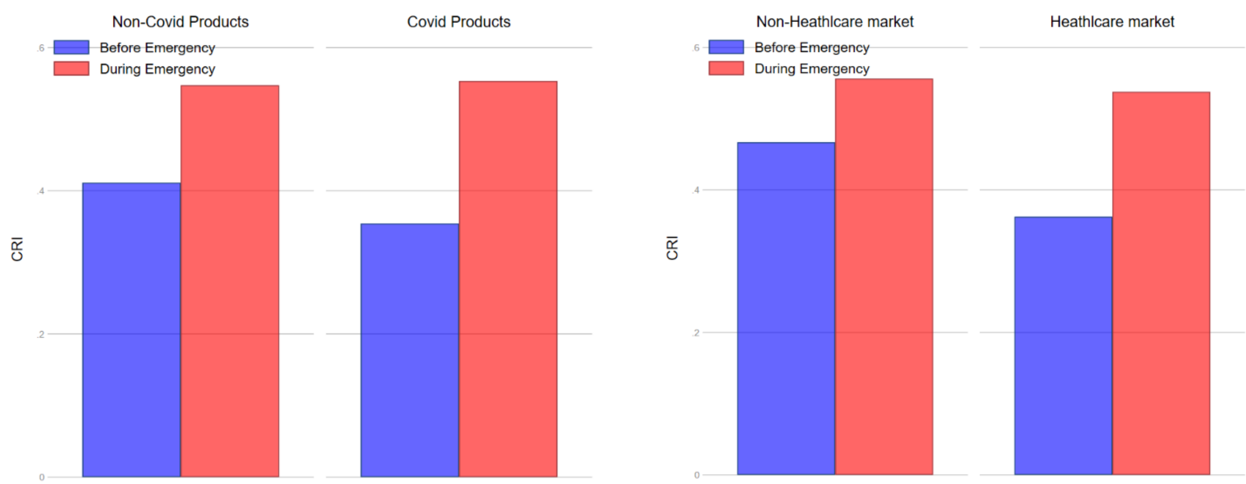


Direct and Indirect Effects of the Emergency Period

Emergencies are often associated with an increase in the risk of corrupt behaviour. In this section, we explore the relationship between the emergency period and the composite CRI. We run regression models that aim to isolate the relationship between the emergency period and the CRI from alternative scenarios. In each of the regression models, we control for different attributes such as the contract value quantiles, buyer type, buyer location, tender year, and month (to capture the temporal dimension of the procurement process). The regression models contrast 4 sets of products[18] COVID products and non-COVID products (Figure 6 - Left panel) and the Healthcare market and the non-Healthcare market (Figure 6 - Right panel).

In line with our expectations, the emergency period is associated with higher CRI in each of the four subsets signaling an increased corruption risk during the emergency period. However, there are differences in the extent to which the emergency period impacts on corruption risks in each sub-group. After controlling for several characteristics that might influence the contract's CRI score, we find that contracts awarded during the emergency period are associated with a 0.28 point increase in CRI (about 3 red flags) for both COVID and the Healthcare products when compared to similar contracts in the pre-emergency period. We regard this increase as the direct impact of the emergency period. Moreover, we are also interested in tracking changes in CRI within the rest of the public procurement market during the emergency period to understand potential spillovers. We run the same regression models on samples of non-COVID products and non-Healthcare markets. The contracts for the non-COVID products subset are associated with an increase in CRI of 0.21 points (a little over 2 red flags) during the emergency while contracts in the non-Healthcare market are only associated with a 0.12 points increase in CRI (a little over 1 red flag) during the emergency. The increases we observe within our samples of COVID products and Healthcare products are higher than the changes observed in the broader public procurement market.

Figure 6: Mean Corruption Risk Indicator over time
[Left: by COVID product Right: by Healthcare market]



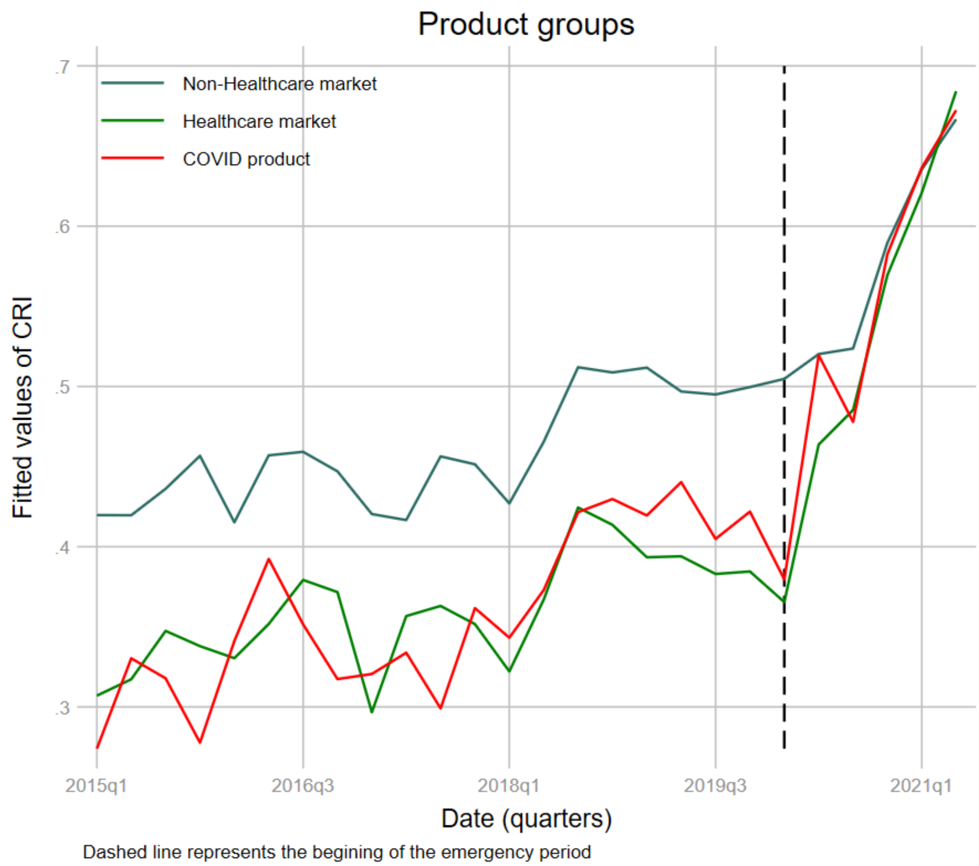
[18] For the full regression results see Table A.5 and A.6 in the Annex.

Further exploring the time trends around the introduction of the emergency rules, Figure 7 below shows CRI trend lines for three product groups: non-healthcare products, healthcare products, and COVID products. It indicates that the CRI for COVID products dramatically shoots up, from around 0.4 to about 0.6; about 50% increase in risks. The pattern is very similar for the broader market for healthcare products where it is conceivable to assume similar spending pressures as for the specific COVID products. Interestingly, non-healthcare products where we did not expect particular spending pressures, and where more relaxed rules did not apply, have seen almost as much increase in CRI as COVID-19 products. This parallel development across the whole economy suggests that increased risks may have spilled over from COVID-19 related markets to the rest of the economy. In addition, there is no decrease in corruption risks after the initial surge of spending pressures during the be beginning of the emergency period.

We further test these CRI differences between COVID products and Healthcare products on the one hand and the rest of the public procurement market on the other using advanced regression methods (Difference in Differences).[19] Relying on a set of carefully constructed comparisons over time as well as across product groups, we find that indeed the main changes across all markets have happened after the emergency rules were introduced. In addition to this, we also detect a small additional uptick in CRI specifically for COVID products and also for healthcare products, in both cases compared to the rest of the public procurement market. This further strengthens the argument that there was a significant spillover from COVID and healthcare products to the rest of the procurement market.

[19] Results from this analysis can be found in the Annex in Table A.8 and A.9

Figure 7: CRI trend line by different product groups



Convergence of risks - The effect of the emergency period on buyers[20] with different levels of pre-COVID risks

Buyers with varying levels of CRI may respond differently to the emergency period. For instance, reduced monitoring during the emergency may incentivize buyers differently to make use of the lax regulatory framework. In this section, we test if buyers with different levels of pre-emergency CRI react differently to changes to the tendering environment brought about by the emergency period. For each buyer, we introduce the average base CRI, i.e. we calculate the average of the CRI for their contracts prior to the emergency. By using the base level of CRI for each buyer as a

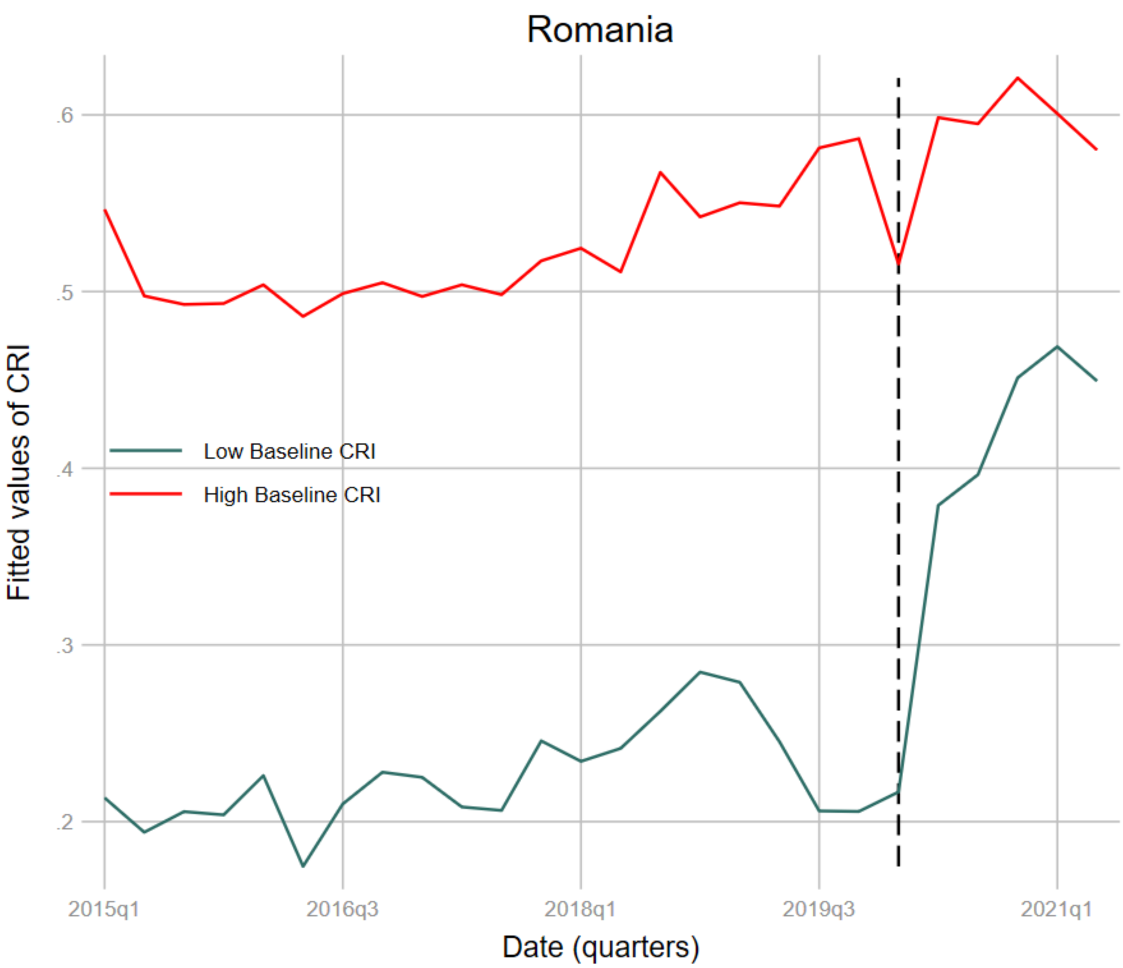
[20] We present a similar analysis on contracts in the Annex.

control variable, we can observe how buyers with dis-similar levels of CRI react to the emergency rules.[21]

As expected, buyers with high levels of baseline CRI carry their risks forward, thus exhibiting a pattern of path dependency. However, during the emergency period, buyers with lower levels of baseline CRI experienced an increase in CRI. Figure 8 demonstrates this pattern, namely that buyers with a baseline CRI in the bottom 2 quantiles display a clear increase in their CRI score during the emergency period compared to a buyer with a baseline CRI in the top 2 quantiles. In other words, it seems that the CRI scores for varying buyers are converging. A possible explanation for this pattern of convergence to the highest risk profiles could be twofold: 1) buyers with high pre-COVID risks were constrained by regulatory and institutional controls only to a limited degree, hence the relaxation of controls impacted them only marginally. 2) While buyers with low pre-COVID risks were effectively constrained by institutional and regulatory controls, so the relaxation of these significantly pushed up their risk levels. Nevertheless, it is important to note that a range of impactful changes happened during the institution of the emergency period: not only did the regulatory environment change, market conditions, such as the expected supply and demand structures have also dramatically shifted during the emergency period.

[21] We input each buyer's base CRI as a control variable and interacted with the emergency period dummy along with controls for contract values, contract type, buyer type, buyer location, market, tender year and month. See Table A.10 in the Annex for the full specification of the regression model.

Figure 8: How buyers with varying baseline CRI responded to the emergency period.



Dashed line represents the begining of the emergency period

Integrity Pacts

In this section, we analyse the relationship between the IP program and our corruption proxies. In order to see how IP contracts and the public entities managing these contracts perform, we needed to find comparable contracts and buyers. In other words, we try to find contracts that are similar but are not part of an IP. We did this by roughly matching contracts based on several characteristics such as:

1. approximately similar contract sizes,
2. similar CPV codes,
3. the buyers have a similar type of function and are located in the same location,
4. similar contract type,
5. tendered around the same time.[22]

Table 10 presents the contracts tracked in our dataset from the public entities that are participating in the IP program: the National Agency for Cadastre and Land Registration, the Ministry of Culture and the Ministry of Public Works, Development and Administration.

[22] In other words, we implement the Coarsened Exact Matching method to reduce the imbalance of covariates between the control and the treatment samples. In brief, the covariates are initially temporarily coarsened and a balance is found between the covariates. We can then run our analysis on the un-coarsened matched data. The advantages of CEM is that it requires fewer assumptions than other matching methods such that it does not need a separate procedure to restrict data to common support. For an extended discussion of CEM see (Blackwell et al. 2009).

Table 10: Integrity pact contracts in dataset

Buyer Name	Notice Number	Supplier Name
Ministerul Culturii	CN1009659	SC TRENCADIS CORP SRL
	CN1009661	Net Brinel
	CN1009660	S & T ROMANIA
	SCN1033901	ANAIDRO COMPANY S.R.L.
	CN1021190	A.F. MARCOTEC BUCURESTI-CONSULTING, ENGINEERING, MARKETING
Agentia Nationala de Cadastru si Publicitate Imobiliara	CN1005022 *2 records	S.C. GEOSILVA S.R.L.
	CN1010660	GAUSS
	CN1010659	GEOTER PROIECT S.R.L.
	CN1012622	TOPOGEOTEHNICS
	CN1015932	CORNEL & CORNEL TOPOEXIM S.R.L
Ministry of Public Works, Development and Administration	CN1003743	CIVITTA STRATEGY & CONSULTING
	CN1008302	MAGNUM S.R.L.

For example for the tender with the notice number “CN1010659” by Agentia Nationala de Cadastru si Publicitate Imobiliara we found a second service contract by the same buyer, and awarded the same product “71354300-7 Cadastral surveying services” with comparable logarithmic price values and both were awarded in February 2020. Another example, we match the tender with notice number “CN1009661” by “Ministerul Culturii” to another contract by “Ministerul Afacerilor Externe” which are both National authorities in the same location. Both contracts also have comparable prices 2.4 mil. RON (488k EUR) and 2.3 mil. RON (467k EUR). Although the products are not identical - one is a tender for Network infrastructure supplies while the other is a tender for Information system servers - on average these slight differences would be compensated to provide us with a rough estimate on our different corruption proxies. We first analyze the performance of IP contracts relative to similar contracts that are not part of the IP. We then perform a similar analysis on all contracts by IP buyers and compare them to a similar set of contracts that are not part of the IP. We do this to test if IP buyers are generally different from non-IP buyers. We assume that public buyers that rank lower on corruption indicators are the ones that participate in IP procurement procedures.

We compare the IP contract with the matched contracts over four main corruption proxies. It is important to note that due to the small sample size, it is not feasible to perform a statistical assessment of the difference in means, hence our results remain tentative. Figure A.4 shows the difference in the distribution of IP contracts and non-IP contracts over the four main corruption proxies. While the samples are too small to draw any statistically meaningful conclusions, it is worth noting the main differences between IP and matched non-IP contracts. Overall, we find a mixed picture with some risk factors being higher for IP contracts (e.g. suppliers' contract share) while others being lower (e.g. single bidding is lower). Hence, based on the limited evidence we have, there is no clear indication that IP contracts would considerably outperform similar non-IP contracts.

Table 11: Integrity pact Contracts - Mean Comparison by matched sample

	Non-Integrity pact	Integrity pact
Observations	13	13
CRI	0.392	0.419
Relative Price[23]	0.835	0.747
Single bidding	0.500	0.462
Contract share	0.499	0.545
Decision period	214.75 days	294 days
Submission period	38.8 days	45 days
Micro supplier	0.500	0.462

We perform a similar analysis on all contracts from buyers that participated in the IP program to test the broader beneficial effects of the IP program. In total, we are able to match 3,923 contracts from IP buyers with contracts from buyers that did not participate in the IP program. Table 12 presents the point estimates and Figure A.5 shows the distribution of the matched pair over our main corruption proxies[24]. This case, we have a sufficiently large number of observations to statistically test the differences between the 2 groups. Overall, we find that IP buyers have a

[23] Restricted Relative price to be between 0.5 and 1.3

[24] Results for CRI, Relative price are statistically significant from the 95% confidence interval. While the mean difference for the contract share indicator is less significant with a p-value = 0.0114. Finally, the mean difference for the Single bidding indicator is not significant p-value =0.1694.

significantly lower risk of corruption than non-IP buyers. For example, their average CRI is lower: 0.42 versus 0.46 (about half a red flag on average). These results while encouraging for the performance of the IP program, should not be interpreted as definitive evidence for effectiveness. It may well be that those buyers apply for the IP program which have had lower risks to start with, rather than joining the IP program making them lower risk entities.

Table 12: Integrity pact Buyers- Mean Comparison (95% CI) by matched sample

	Non-Integrity pact	Integrity pact
Observations	3,923	3,923
CRI	0.463 [0.456-0.470]	0.421 [0.414-0.429]
Relative Price[25]	0.810 [0.800-0.820]	0.779 [0.768-0.790]
Single bidding	0.364 [0.338-0.390]	0.337 [0.307-0.366]
Contract share	0.358 [0.341-0.375]	0.391 [0.372-0.410]

Conclusions

In this report, we used publicly available data to test the overall health of the Romanian public procurement system during the emergency period with a special focus on its effects on COVID related products and the Healthcare market as a whole. Although lax procurement conditions may be beneficial for a faster delivery of emergency products, important policy discussions must be held to discuss how those new emergency regulations could be abused for corrupt gains. IP programs are one of the initiatives adopted by some of the Romanian contracting authorities, civil society organizations and other stakeholders to ensure the integrity of the public procurement system.

Our analysis of individual corruption indicators over the emergency period indicates that the misuse of procedure types in non-crises related products has contributed to the increase of the CRI. It is crucial to monitor the use of emergency procedure types as they display a higher mismanagement risk. Cases of tax haven supplier registration were also raised as a red flag by our measurement framework. However, our indicator only captures the suppliers' country of registration without consideration towards their beneficial owners or the whole ownership network.

[25] Restricted relative price to be between 0.5 and 1.3.

Case evidence as well as quantitative analysis of large-scale datasets have shown the detrimental effects of tax haven-linked companies in public procurement (Fazekas and Kocsis 2020).

Although data limitations hinder us from statistically testing its effects, we have observed signs that the IP initiative is performing as intended based on our corruption indicators. We also tested the differences between public entities that participate in Integrity Pact agreements and the ones that do not. Specifically, IP participants rank, on average, lower on several corruption proxies compared to others. This finding can have policy relevant consequences in extending the scope of these integrity programs towards other public entities in order to reap the benefits of increased external oversight that may lead to improved procurement results for the public, especially during times of emergency.

In the past several years, Romanian authorities made substantive efforts to improve transparency, integrity and curb corruption in public procurement. A key step in this process was to provide detailed open data on the tendering and award phases of the procurement process, offering free access to data users and other third parties to large administrative files. Such publicly available data allow for real time and systematic monitoring of corruption risks by civil society, intergovernmental actors and different levels of the national government. The ready availability of data allows for spotting notable changes in public procurement market risks, for example as a result of regulatory changes. Government-wide data also allows for comparing across a wide range of organizations and identifying high risk entities and transactions even when average risks are acceptable.

Publishing reliable, high quality data and updating publication and licensing policies that oblige government officials to improve data completeness and accuracy is an essential requirement for carrying out insightful, comprehensive corruption risk analyses in order to derive evidence-based policy recommendations. If data are missing, incomplete, or outright erroneous, the analysis is incomplete at best, and misguided at worst. Importantly, missing or erroneous information may indicate a deliberate attempt to hide evidence, hence directly impairing accurate corruption risk assessments. Data quality can be improved by directly enforcing data quality standards for example by refusing to publish incomplete records or imposing fines on recurrent maladministration. However, these assessments should also take into consideration poor or underdeveloped institutional contexts where data gathering, cleaning and publishing are hindered by weak or missing digital platforms and/ or skills, especially when referring to smaller contracting authorities. Therefore, investments in digitalization, linking platforms, datasets and administrative processes, as well as providing training for public sector employees and strengthening the monitoring of existing integrity risks represent non-penalizing policy interventions aimed at improving data quality.

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Annex

Table A.1: COVID related products

CPV code	CPV Description
Products identified from the TED COVID related tenders list	
45215142	Intensive-care unit construction work
33631600	Antiseptics and disinfectants
33191000	Sterilisation, disinfection and hygiene devices
33191100	Steriliser
33191110	Autoclaves
33192120	Hospital beds
33157000	Gas-therapy and respiratory devices
33157100	Medical gas masks
33157110	Oxygen mask
33157200	Oxygen kits
33157300	Oxygen tents
33157400	Medical breathing devices
33157500	Hyperbaric chambers
33157700	Blow bottle
33157800	Oxygen administration unit
33157810	Oxygen therapy unit
39330000	Disinfection equipment
35113400	Protective and safety clothing
33157110	Oxygen mask
33157400	Medical breathing devices
33694000	Diagnostic agents
33141420	Surgical gloves

33195110	Respiratory monitors
33670000	Medicinal products for the respiratory system
33673000	Medicinal products for obstructive airway diseases
33674000	Cough and cold preparations
33675000	Antihistamines for systemic use
18143000	Protective gear
18424300	Disposable gloves

Products regulated for the COVID emergency based on the Romanian Ordinance nr 11/2020

33192160	Stretchers
33172200	Resuscitation devices
33195000	Patient-monitoring system
33195100	Monitors
33195200	Central monitoring station
33194110	Infusion pumps
18114000	Coveralls
35113410	Garments for biological or chemical protection
18142000	Safety visors
33735100	Protective goggles
33735200	Frames and mountings for goggles
33735000	Goggles
42514310	Air filters
33111640	Thermographs
33186100	Oxygenator
33127000	Immuno-analysis devices
33926000	Autopsy fluid collection vacuum aspirators or tubing
33141310	Syringes
33141320	Medical needles
33124130	Diagnostic supplies

Table A.2: NACE codes used to identify healthcare-related bidders

NACE code	Description
3250	Manufacture of medical and dental instruments and supplies
4774	Retail sale of medical and orthopaedic goods in specialised stores
8623	Dental practice activities
4646	Wholesale of pharmaceutical goods
8621	General medical practice activities
8690	Other human health activities
4642	Wholesale of clothing and footwear
8622	Specialist medical practice activities
2110	Manufacture of basic pharmaceutical products
4690	Non-specialised wholesale trade
8610	Hospital activities
2120	Manufacture of pharmaceutical preparations
2059	Manufacture of other chemical products n.e.c.

Table A.3: Corruption Risk indicator - Validation Regression

		Dependent variable Single bidding	Dependent variable Contract share
CRI components	**Component categories**	**Coefficient (Std. error)**	**Coefficient (Std. error)**
Single bidding	Risk category type 1		0.017*** (0.002)
Submission period	Risk category type 1	0.035 (0.051)	0.013*** (0.005)
Decision period	Risk category type 1	0.279*** (0.055)	0.005 (0.005)
	Risk category type 2	0.946*** (0.071)	0.046*** (0.007)
Call for tender	Not published	-0.939*** (0.063)	-0.043*** (0.007)
Tax haven	Foreign supplier not in tax haven	0.721*** (0.165)	-0.032 (0.033)
	Foreign Supplier in tax haven	0.438 (0.430)	0.294*** (0.053)
Supplier contract capture		0.383*** (0.027)	
Procedure type (base:Open procedure types)	Risk category type1	1.194*** (0.225)	0.364*** (0.026)
	Risk category type2	0.957*** (0.047)	0.108*** (0.005)
	Negotiated w/o publication [non-covid products]	0.956*** (0.026)	0.027*** (0.003)
	Missing Information	0.366 (0.768)	-0.020 (0.106)
Market Switching (base: Healthcare Supplier did not switch markets during emergency)	Healthcare supplier switched market during emergency	-0.267*** (0.030)	0.006** (0.003)
	Missing information	-0.903*** (0.096)	-0.034*** (0.012)
COVID products Experience (base: Healthcare suppliers with prior experience in selling COVID products)	Healthcare suppliers without prior experience in selling COVID products	0.299*** (0.040)	0.118*** (0.004)
	Non-Healthcare suppliers	0.616*** (0.100)	0.133*** (0.013)
Newly created company [base: Supplier appears in dataset before and after emergency]	Supplier only appears in dataset after emergency	-0.183*** (0.038)	0.039*** (0.006)

Supplier location [base: Foreign supplier]	Local supplier	0.195*** (0.021)	0.067*** (0.002)
	Missing information	-0.304 (0.452)	-0.019 (0.081)
Micro Supplier [base: Supplier>50 employees]	Supplier < 50 employees	0.116*** (0.018)	0.053*** (0.002)
	Missing	0.392*** (0.038)	0.131*** (0.005)
Observations		91,118	74,236
Pseudo-R^2 /R^2		0.1039	0.350

Regression includes controls for contract values, contract type, buyer type, buyer location, market, tender year and month.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.4: Indicator Frequency Table

CRI components	Component categories	Percent
Single bidding	Non-Risky	19.91
	Risk category type 1	29.73
	Missing	70.27
Submission period	Non-Risky	14.30
	Risk category type 1	85.70
Decision period	Non-Risky	14.56
	Risk category type 1	6.45
	Risk category type 2	79
Call for tender	Not published	
Tax haven	Foreign supplier not in tax haven	0.13
	Foreign Supplier in tax haven	0.01
	National Suppliers	99.86
Supplier contract capture	Non-Missing	49.17
	Missing	50.83
Procedure type (base:Open procedure types)	Open procedure type	94.03
	Risk category type1	0.47
	Risk category type2	0.76
	Negotiated w/o publication	4.74

	[non-covid products]	
	Missing Information	0.01
Market Switching (base: Healthcare Supplier did not switch markets during emergency)	Healthcare Supplier did not switch markets during emergency	25.38
	Healthcare supplier switched market during emergency	4.06
	Missing information	70.56
COVID products Experience	Healthcare suppliers with prior experience in selling COVID products	28.57
	Healthcare suppliers without prior experience in selling COVID products	0.94
	Non-Healthcare suppliers + Missing	70.49
Newly created company	Supplier appears in dataset before and after emergency	59.58
	Supplier only appears in dataset after emergency	0.5
	Missing	39.92
Supplier location	Not local supplier	43.33
	Local supplier	14.13
	Missing information	42.54
Micro Supplier [base: Supplier>50 employees]	Supplier > 50 employees	25.88
	Supplier < 50 employees	30.23
	Missing	43.89

Figure A.1: Histograms of CRI by source

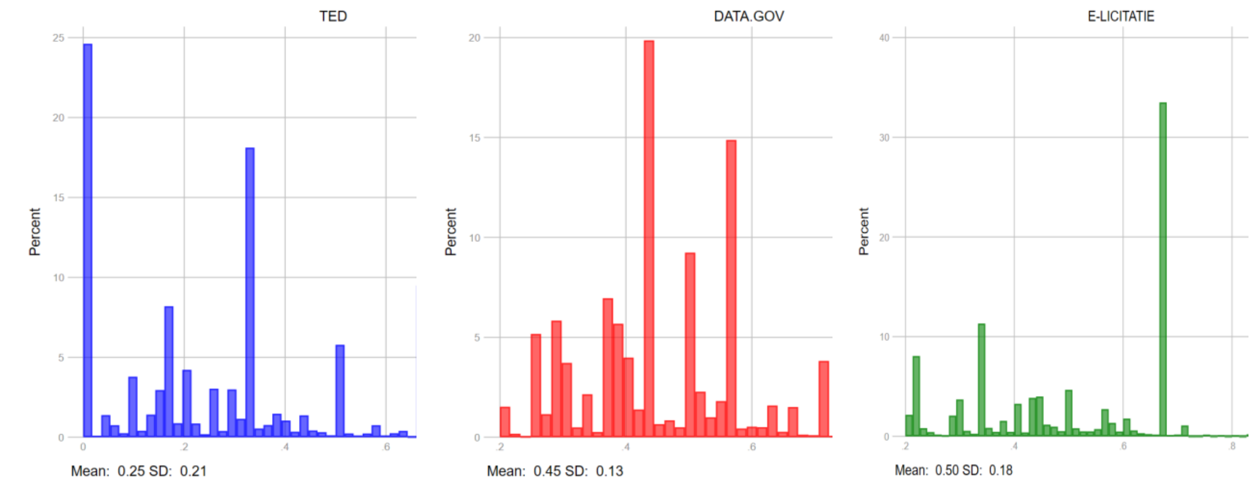


Table A.4: Relative price Regression result

[Sample restricted to relative price from 1.3 to 0.5]

Dependent variable	**Relative Price**
Model	**(1)**
CRI	0.178*** (0.002)
Constant	0.559*** (0.027)
Observations R^2	191,171 0.108

Regression includes controls for contract values, contract type, buyer type, buyer location, market, tender year and month.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.5: Direct/Indirect Effects - By type of product

Dependent variable	**Emergency CRI**	
Model	**(1)**	**(2)**
Sample	COVID products	Non-COVID products
Emergency	0.276*** (0.004)	0.213*** (0.001)
Constant	0.495*** (0.056)	1.072*** (0.017)
Observations R^2	64,258 0.269	1,671,377 0.204

Regression includes controls for contract values, contract type, buyer type, buyer location, market, tender year and month.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A.6: Direct/Indirect Effects - By market

Dependent variable	**Emergency CRI**	
Model	**(1)**	**(2)**
Sample	Healthcare market	Non-healthcare market
Emergency	0.276*** (0.001)	0.124*** (0.001)
Constant	0.872*** (0.064)	0.602*** (0.014)
Observations R^2	990,147 0.197	702,754 0.147

Regression includes controls for contract values, contract type, buyer type, buyer location, market, tender year and month.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Difference in Differences

Throughout the difference in differences analysis, we assume that tenders published after the beginning of the emergency period are treated differently than tenders published prior to the emergency period. We can also construct a control group that we assume not to be directly affected by the emergency regulations. The DID method deducts the average change in time for the control group from the average change in time of the treated group (i.e. COVID products and Healthcare markets). The average change of CRI in time for the control group represents the counterfactual scenario i.e. it is the expected change in the treated group (COVID products or Healthcare market) if they were not subjected to the emergency period. Therefore, after controlling for all other scenarios, the DID method allows us to test if the observed change over time for our analysis groups is statistically relevant and different from non-COVID products and non-Healthcare markets.[26]

For the COVID products subset we use the non-Covid products as the control group. Therefore, we assume that generally non-COVID products behave similarly across time to COVID products. If that was the case, then deducting that expected change from the COVID products observed change should leave us with an unbiased effect of the emergency period on COVID products. Figure A.2 shows how both the COVID products and non-COVID products have been trending similarly across 5 time periods, although at varying levels. We also observe a break in this trend during the emergency period. His pattern is confirmed by the Difference-in-differences regression table (Table A.8). It shows that the emergency period increased the CRI of COVID products by 0.044 than non-COVID products (about half a red flag), in addition to the large increase of CRI for both groups: 0.213 (a little over 2 red flags). As for the Healthcare markets subset, we observe a similar parallel trend between both groups (Table A.9). However, the dip in the CRI for the Healthcare market marks a divergence from the non-Healthcare market and reduces our confidence in the non-Healthcare market being a perfect control group to the Healthcare market. Nonetheless, the model shows that the Healthcare market suffered from a 0.094 increase in CRI (about one extra red flag) relative to the change in the non-Healthcare market. The point estimate may be adjusted to the lower end to compensate for the observed divergence prior to the emergency period. All models include controls for contract values, contract type, buyer type, buyer location, market, tender year and month (See Table A.8 and A.9).

[26] For further reading on the Difference in Differences method see (Abadie and Cattaneo 2018)

Table A.7: Difference in Differences - Time Periods

Time Periods	From	To
Period 1	16/03/2015	15/03/2016
Period 2	16/03/2016	15/03/2017
Period 3	16/03/2017	15/03/2018
Period 4	16/03/2018	15/03/2019
Period 5	16/03/2019	15/03/2020
Period 6 (Emergency period)	16/03/2020	14/04/2021

Table A.8: Difference in Differences - COVID Products

Dependent variable		**Emergency CRI**	
Model	**(1)**	**(2)**	**(3)**
1.COVID_Products	0.003*** (0.001)	-0.003*** (0.001)	-0.011*** (0.001)
Emergency Period		0.215*** (0.001)	0.213*** (0.001)
1.COVID_Products# Emergency			0.044*** (0.002)
Constant	1.239*** (0.016)	1.072*** (0.017)	1.074*** (0.017)
Observations R^2	1,735,635 0.153	1,735,635 0.205	1,735,635 0.205

Regression includes controls for contract values, contract type, buyer type, buyer location, market, and tender year.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.9: Difference in Differences - Healthcare market

Dependent variable		**Emergency CRI**	
Model	**(1)**	**(2)**	**(3)**
1.Heathcare_Market	-0.089*** (0.002)	-0.091*** (0.002)	-0.106*** (0.002)
Missing Market	0.200*** (0.002)	0.187*** (0.002)	0.197*** (0.002)
Emergency		0.215*** (0.001)	0.161*** (0.001)
1.Heathcare_Market# Emergency			0.094*** (0.001)
Constant	1.239*** (0.016)	1.073*** (0.017)	1.046*** (0.016)
Observations	1,735,635	1,735,635	1,735,635
R^2	0.153	0.205	0.210

Regression includes controls for contract values, contract type, buyer type, buyer location, market, tender year and month.
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Figure A.2: Graphical representation of parallel trends

[Left: by Type of product Right: by Type of market]

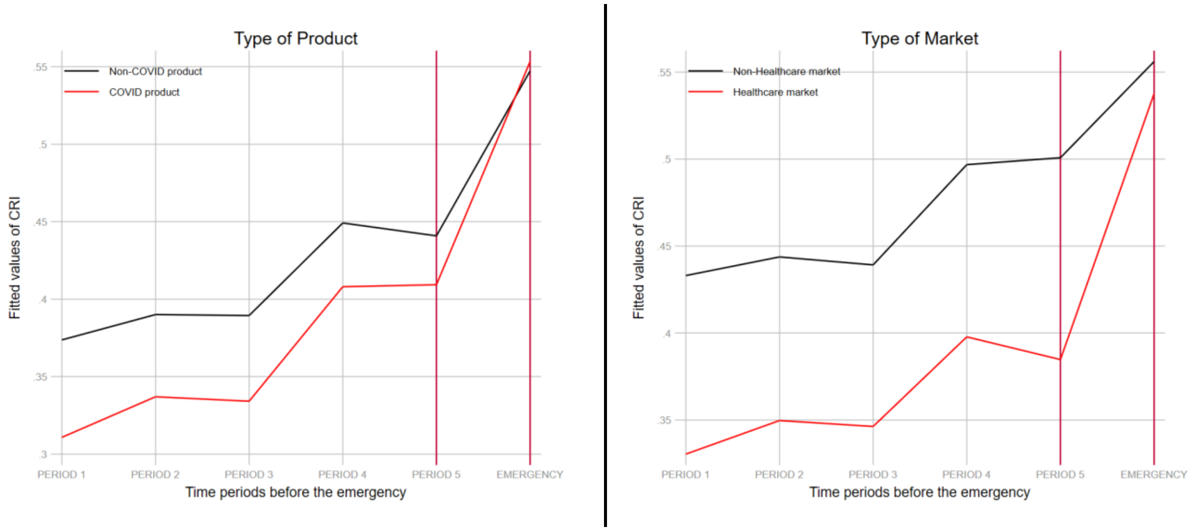


Table A.10: Heterogeneous effects - Average Lagged CRI

Dependent variable	**CRI**
Model	**(1)**
c.Period 0 CRI	0.970*** (0.001)
Emergency Period	0.050*** (0.001)
c.Period 0 CRI#Emergency Period	-0.099*** (0.002)
Constant	0.027*** (0.007)
Observations R^2	1,033,358 0.806

Regression includes controls for contracts per buyer, contract values, contract type, buyer type, buyer location, market, tender year, and month Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Heterogeneous effects on contracts

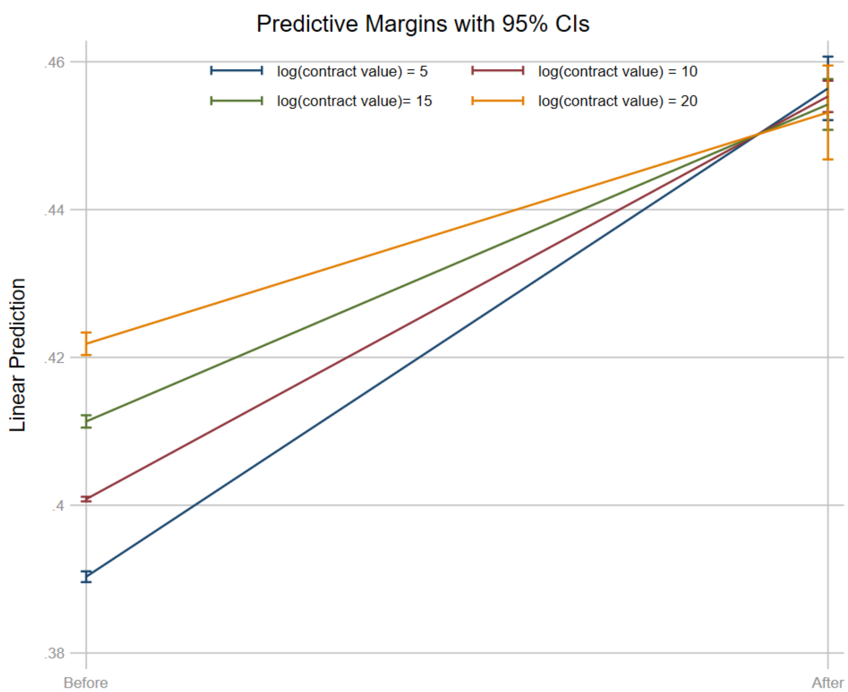
We perform a similar analysis to the one performed on buyers to test how contracts with varying values correlate with a changing regulatory framework due to the emergency period. Contracts on the lower end of the scale experienced a much higher increase in their CRI compared to contracts on the higher end of the contract values scale. This implies that corrupt behaviours have become relatively more prevalent among low-value contracts compared to other contracts. As high value contracts were of much higher risk pre-emergency period, this again suggest a convergence to the highest risk group, similar to our findings related to buyers' pre-pandemic CRI effects. Table A.11 demonstrates the model's full specification and Figure A.3 plots the observed effects for varying values of logarithm of the contract value.

Table A.11: Heterogeneous effects - Contract values

Dependent variable	**Emergency CRI**
log(contract value)	0.002*** (0.000)
Emergency	0.078*** (0.004)
log(contract value)# Emergency	-0.002*** (0.000)
Constant	1.219*** (0.012)
Observations R^2	774,787 0.308

Regression includes controls for contract values, contract type, buyer type, buyer location, market, and tender year.
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure A.3: How contracts with varying contract values respond to the emergency period.



Integrity Pacts

Figure A.4: Integrity pact Contracts - Distribution of corruption indicators by matched sample

+ mean, - standard deviation

Figure A.5: Integrity pact Buyers - Distribution of corruption indicators by matched sample