The impact of corruption on procurement performance.
An assessment of Italian public work contracts and suppliers

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Key words: Corruption, Governance, Public Infrastructure, Risk Assessment

Abstract

This study develops an original corruption risk indicator at the Italian procurement level – analysing Italian public infrastructures from 2007 to 2013 – and estimates the correlation between the profile of contract suppliers and the corruption risk indicator in question. The methodology builds on a three stage semi-parametric procedure and relies on a residual approach in which the unexplained part of an inefficiency equation provides the estimates of the potential risk of corruption. The results from an updated Italian public procurement dataset suggest that the risk of corruption prevails in larger urban, especially in Lazio, Tuscany and Lombardy. Then, a risk-based assessment exercise is performed to profile suppliers. The risk indicator is regressed on suppliers' financial and ownership data to identify patterns among firms winning risky contracts. Suppliers associated with high levels of corruption risk in public contracting are more profit-seeking, hold low levels of debts and need on average more days to pay their customers. Finally, suppliers involved in public work contracts at high risk of corruption are more likely to have legal and/or financial connections with opaque jurisdictions.

[1] I am grateful to Maurizio Lisciandra and Emanuele Millemaci for the continuous support, the precious suggestions and their insightful point of view on this working paper. I also thank my former colleagues at Transcrime, especially Francesco Calderoni, the participants of XIV ISLE conference held in Lecce on the 13–15 of December 2018, and the participants of 2018 Annual Congress of the European Society of Criminology held in Sarajevo on the 29 August – 01 September 2018. They all contributed by providing inputs, discussion and feedback. Finally, my sincere thanks go to Marco Piepoli from the General State Accounting Department of the Ministry of Economy and Finance, who gave me access to the Italian procurement data.

This paper was submitted as part of a competitive call for papers on integrity and anti-corruption in the context of the 2019 OECD Global Anti-Corruption & Integrity Forum.

1. Introduction

This study proposes an innovative methodology to develop a new corruption risk indicator at a procurement level (1) to assess the impact of corruption on procurement outcomes, and (2) to explore the correlation between high risk contracts and suppliers involved in procurement transactions.

Most of the available indices of corruption in public procurement face severe methodological shortcomings (context-dependency, poor comparability and replicability, lack of time-variation) and they measure first-hand experience of corruption, which usually refers to bribery (Heywood and Rose 2014).

To overcome the limitations of existing measures, the first section of this paper uses a big data approach to derive a new fitting estimate of corruption risk at the contract level in the Italian context. The proposed measure derives from objective open procurement data to allow for multi-level aggregation, comparisons and replicability. The new risk indicator allows comparing public contracts to determine more precisely which of them are more likely to experience corruption upon execution.

In the second part, a risk-based assessment exercise is performed to profile suppliers. Suppliers are analysed by linking financial and corporate data to contract-level information in order to raise new, substantiated hypotheses on corruption-related red flags at the firm level. The risk indicators at the firm-level might flag how firms exploit legal mechanisms to weaken audits and to ensure that corrupt rents are extracted from procurement contracts.

The paper is organized as follows. Section 2 describes the analytical and empirical strategy used to develop a new measure of corruption risk at the contract-level in Italy and presents the results of the adopted approach; section 3 focuses on suppliers, by identifying red flags at the firm level; section 4 discusses the methodological strengths of the adopted empirical strategy, together with some policy implications.

2. A new corruption risk indicator at the contract level

2.1 The measurement strategy

This section proposes an innovative methodology to measure the risk of corruption at the contract level by adopting a residual approach, in which the unexplained part of an inefficiency equation provides the estimates of the potential risk of corruption. Corruption in public procurement is here defined as one of the sources of inefficiency in contract execution, intended as the additional time and costs entailed by the actual realization of the public infrastructure.

According to Bandiera et al. (2009), cost overrun and time delay in contracts execution can be the result of *passive waste* (pure inefficiency) and *active waste* (corrupt transactions). For example, at the Expo event in Milan in 2015, the realization of the main infrastructure, also known as “la Piastra”, experienced an increase in costs for over €60 million due to corrupt agreements between the awarding body and the winning bidder (Milani et al. 2018). Besides corruption, there are several sources of passive waste in contracts management and execution (Ganuza 2007; Cantarelli et al. 2010): private interests of firms acting opportunistically, contract complexity, underinvestment in design specification, inaccurate cost forecasting as well as changes in political agenda. Since Bandiera et al. (2009) suggest there is no

trade-off between the two forms of waste, it derives that corruption can be identified by inefficiency and not as a complementary phenomenon.

Therefore, the strategy adopted to measure the risk of corruption consists in three stages:

1. Cost overrun and time delay are combined to estimate inefficiency at the contract level using a non-parametric technique called Data Envelopment Analysis (DEA). DEA is used to benchmark each public work contract in terms of its relative performance. In other words, for a given input of time and cost, best performers are those that minimize the actual time and costs of implementation. Considering that DEA represents a deterministic approach, inefficiency levels are measured as the distance between each observation unit and the defined best performer;

2. The single indicator of inefficiency is explained by means of factors that only denote the presence of pure inefficiency in contract execution, while factors encompassing corruption (in any of its manifestations) are excluded from the specification, in order to identify corruption using the residual approach.

3. The estimate residuals from the second-stage regression are extracted and treated to be considered as a proxy measure of corruption at the contract-level. By doing so, the aim is to identify corruption by ruling rule out all sources of passive waste from the indicators of cost overrun and time delay. The residual scores obtained are normalized (0-1) and indicate the relative risk of corruption for each work contract, from low corruption risk (closer to 0) to high corruption risk (closer to 1).

2.2 Italian procurement data

The data used to develop a new risk measure of corruption are retrieved from the website of the Italian Ministry of Economy and Finance (MEF) and refer to public works awarded from 2007 to 2015.[2] Roughly 60,000 tenders were awarded during the sample period (2007-2015), although only for 9,691 tenders, the information on the final date of completion and the final costs is available. The period of time considered excludes the tenders notified before the reform 163/2006, and those notified after the reform 50/2016, in order to include only contracts governed under the same procurement code.

To mitigate sample biases, a range of selection procedures is adopted. It has been noted that the contracts awarded between 2007 and 2015 differ in terms of contract length. To reduce this bias, only contracts with a maximum length of three years are considered, reducing the sample to contracts between 2007 and 2013. In this way, it is possible to compare public works contracts of similar lengths. Moreover, to reduce the effect of delays (which influence the calculation of the inefficiency scores in the first stage), work contracts must have been completed within a specific delay of a maximum of one

[2] MEF data on public works are available at http://www.bdap.tesoro.it. Data downloaded on 15th March, 2018

year. Therefore, all the contracts in the sample have a maximum length of three years and must have been completed by the end of 2017.[3]

The final sample consists of 4,940 public tenders that were awarded in Italy between 2007 and 2013. Contracts are distributed across all Italian regions. Tuscany (10%), Lazio, Lombardy, and Sardinia (9%) are the most represented regions, while Molise, Valle d'Aosta, and Basilicata are the least represented regions (1-2%).[4] The largest share of contracts in the final sample has an initial tender value between 40,000 euros and 500,000 euros (82.1%). Only 23 public work contracts have an initial value higher than € 5 million, thus published at European level. The majority of the contracts has been procured by municipalities (about 65%), followed by provinces (9.2%) and state-owned firms (9.1%), and refers mainly to social infrastructures (40%), transportation infrastructures (32%), and environmental infrastructures (15%).

2.3 Results of the three-stages procedure

2.3.1 Results from DEA analysis

To evaluate the efficiency of a contract, it is necessary to determine the actual length and the actual costs for the realization of the public work. Efficient contracts fulfill contractual terms. Inefficient contracts may encounter delays and require additional financial resources. The volume of contracts that experience an increase in cost (88%) and time (15%) in the sample used is relevant.

To perform DEA, the planned time (days) and the costs envisioned for infrastructure completion (thousands of euros) are the inputs, while the actual time (days) and the actual costs of infrastructure completion (thousands of euros) are the outputs. The DEA identifies only three fully efficient units. This indicates that public works are not usually performed at optimal efficiency. The average efficiency is 0.8, while the minimum value is 0.58 (Table 1).

Public contracts tendered at higher values tend to be more efficient, especially when they are procured at the European level (0.86 out of 1). Furthermore, public work contracts tendered locally – either by municipalities (0.78) and local entities (0.79) – perform worst with respect to central agencies (especially Ministries – 0.83) and State-owned firms (0.95).

Table 1. Main statistics from DEA

Variable	Obs.	Mean	Std. Dev.	Min	Max
DEA Score	4940	0.798	0.121	0.575	1.000
Bias	4940	0.000	0.004	0.000	0.271
Bias-corrected DEA Score	4940	0.798	0.121	0.573	1.000

Notes: 500 bootstrap replications.

Source: Author's own elaboration of MEF data

[3] As the choice to limit the sample including contracts with a maximum length of three years and delay up to one year is arbitrary, the analysis is carried out on several samples of contracts to check for robustness (see the result section)

[4] The correlation between the number of contracts per region included in the final sample (N=4,940) and the regional distribution of the sample of contracts (with information on the final date of completion and the final costs) awarded from 2007 to 2015 (N=9,691) is verified to check for consistency after the selection procedure (r=0.95). Moreover, the number of contracts per region included in the final sample also correlates to the regional distribution of public work contracts presented by the National Anti-Corruption Authority (ANAC 2018) in the annual statistics (r=0.68).

Inefficiency scores derived from DEA scores and calculated as the distance between each observation and the best performer. The inefficiency scores range from 0 (full efficiency) to 0.45, with a mean of 0.20, according to the DEA specification. DEA reveals the existence of relevant differences in the performance of public contracts, which can be determined by territorial drivers or contractual conditions.

2.3.2 Results from truncated regression analysis

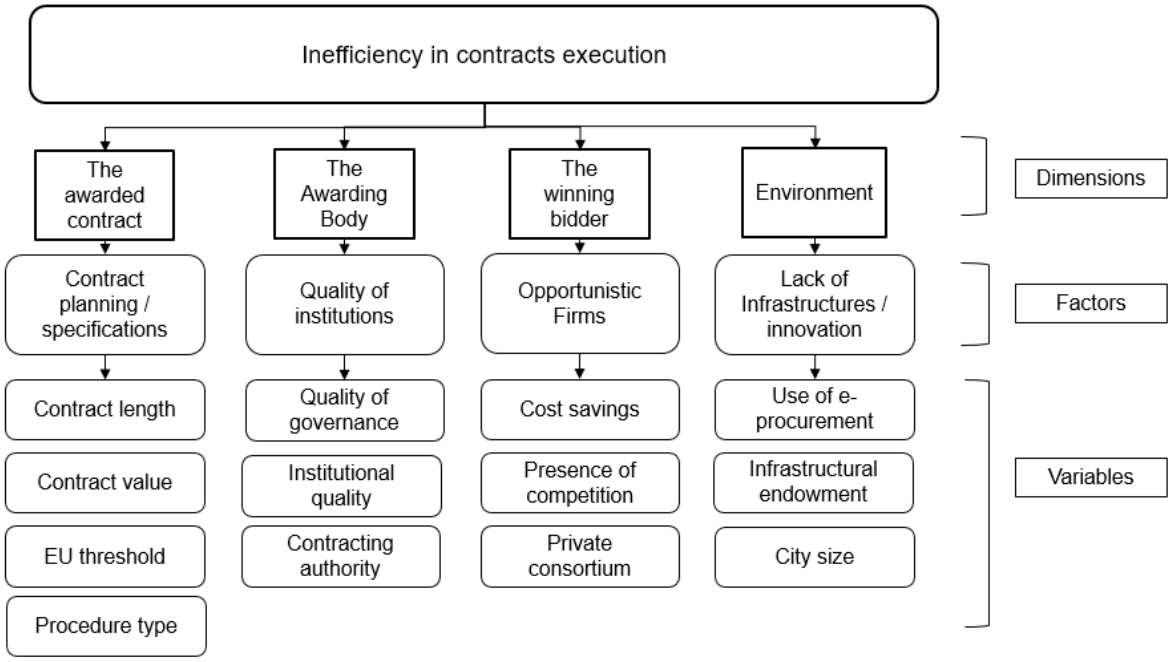
To explain performance differences, the inefficiency scores are regressed on environmental and contract-level predictors in the second-stage truncated regression. A truncated regression is performed in order to exclude from the second stage analysis those observations whose distance from the optimal frontier is equal to 0. To facilitate the identification and measurement of several of the main factors identified within the literature, inefficiency factors are grouped into four categories, each of which refers to a different 'contract dimension' (Figure 1):[5]

- **the contract award**: there is empirical evidence that a high level of complexity in design specification affects tender outcomes and that large projects regularly spend more than originally agreed upon in the contract focus on the complexity of the contract and the awarding procedures (Cantarelli et al. 2010). Moreover, awarding procedures can have an impact. Greater discretion has been found to be associated with decreased efficiency, especially among contracting entities with lower administrative quality (Baltrunaite et al. 2018);
- **the awarding body**: inefficient contracting authorities produce poorly designed and managed tenders, i.e., by underestimating the economic resources needed to execute infrastructural projects (Charron et al. 2014; Baltrunaite et al. 2018);
- **the winning bidder**: firms can act opportunistically to increase profits, extract rents from the contract and influence the political agenda. The use of underbidding is a means to secure the win of the bid and, subsequently, to exploit the opportunity of a renegotiation with incomplete contracts (Decarolis and Palumbo 2015)
- **the environment**: a lack of physical and economic infrastructures is correlated with poor results in contract implementation, which entails waste of financial resources (Golden and Picci 2005). Social and industrial innovation is also key to improving efficiency in procurement (Mungiu-Pippidi 2015).

For robustness check, alternative specifications are conducted (1) to compare the findings using a different estimator (OLS regression); (2) to verify the extent to which the results are driven by the selected sample by performing the second-stage truncated regression on different samples; (3) to control for potential multicollinearity in the second-stage truncated regression considering normalized variables through the so-called centering technique.

[5] The full set of variables included in the second-stage truncated regression is listed in Table 2.

Figure 1. Dimensions, factors and selected variables of passive waste in contracts execution



Source: Author's own elaboration

Table 2. Main statistics of the determinants of the inefficiency scores

Variable	Source	Type	Level/Detail	Obs.	Mean	Std. Dev.	Min	Max
Inefficiency	DEA	continuous	Contract	4940	0.202	0.121	0.000	0.425
Rebate	MEF	continuous	Contract	4940	0.175	0.111	0.000	0.890
Rebate_null	MEF	dummy	Contract	4940	0.041	0.199	0.000	1.000
Consortium	MEF	dummy	Contract	4940	0.043	0.203	0.000	1.000
Other	MEF	dummy	Contract	4940	0.005	0.072	0.000	1.000
Direct_contracting	MEF	dummy	Contract	4940	0.040	0.197	0.000	1.000
"Cottimo_Fiduciario"	MEF	dummy	Contract	4940	0.099	0.298	0.000	1.000
Open_procedure	MEF	dummy	Contract	4940	0.340	0.474	0.000	1.000
Negotiated	MEF	dummy	Contract	4940	0.040	0.197	0.000	1.000
Negotiated_woCall	MEF	dummy	Contract	4940	0.449	0.497	0.000	1.000
Restricted	MEF	dummy	Contract	4940	0.026	0.158	0.000	1.000
Institutional_quality	Nifo & Vecchione 2014	index	Regional	4940	0.654	0.255	0.000	1.000
Quality_governance	Charron et al. 2014	index	Regional	4940	0.343	0.227	0.000	1.000
E-procurement	OpenCoesione	index	Regional	4940	25.363	18.016	0.000	100.000
Infrastractural_index	Tagliacarne	index	Regional	4940	104.469	52.340	21.200	266.380
Stateowned_firms	MEF	dummy	Contract	4940	0.091	0.288	0.000	1.000
Local_health	MEF	dummy	Contract	4940	0.032	0.176	0.000	1.000
Central_authority	MEF	dummy	Contract	4940	0.130	0.336	0.000	1.000
Municipality	MEF	dummy	Contract	4940	0.644	0.479	0.000	1.000
Inhabitants_log	Istat	log	Municipality	4940	10.023	2.317	4.673	14.871
Length_contract	MEF	log	Contract	4940	5.835	0.833	2.197	6.999
Lot_value	MEF	log	Contract	4940	12.281	1.007	10.597	18.975
EU_threshold	MEF	dummy	Contract	4940	0.005	0.068	0.000	1.000

Source: Author's own elaboration

Table 3. Truncated regression second stage estimation results

Variables	Coeff. (SE) (1)	Coeff. (SE) (6)	Coeff. (SE) (7)	Coeff. (SE) (8)	Coeff. (SE) (9)
Inefficiency (dependent variable)					
Rebate	0.061 **	0.048 **	0.092 ***	0.087 ***	0.061 **
	(0.023)	(0.017)	(0.017)	(0.019)	(0.021)
Rebate_null	-0.088 ***	-0.059 ***	-0.074 ***	-0.071 ***	-0.089 ***
	(0.014)	(0.007)	(0.010)	(0.011)	(0.013)
Consortium	-0.007	-0.005	-0.003	-0.006	-0.006
	(0.011)	(0.008)	(0.009)	(0.009)	(0.010)
Infrastructural_index	-2E-04 **	-1E-04 **	-2E-04 ***	-2E-04 ***	-2E-04 **
	(7E-05)	(5E-05)	(5E-05)	(6E-05)	(6E-05)
E-procurement	5E-04	5E-04	2E-04	2E-04	4E-04
	(5E-04)	(4E-05)	(4E-04)	(5E-04)	(5E-04)
Inhabitants_log	-0.006 ***	-0.005 ***	-0.008 ***	-0.007 ***	-0.006 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Institutional_quality	-1.239 *	-1.094 *	-0.639	-1.223 *	-1.172 *
	(0.509)	(0.429)	(0.308)	(0.503)	(0.523)
Quality_governance	-0.079 *	-0.068 **	-0.068 **	-0.078 **	-0.080 **
	(0.034)	(0.025)	(0.023)	(0.026)	(0.030)
Stateowned_firms	-0.338 ***	-0.117 ***	-0.306 ***	-0.292 ***	-0.339 ***
	(0.036)	(0.010)	(0.024)	(0.020)	(0.021)
Local_health	0.025	0.019	0.004	0.028 *	0.024
	(0.016)	(0.011)	(0.012)	(0.013)	(0.015)
Central_authority	0.029 **	0.018 **	0.025 ***	0.027 ***	0.028 **
	(0.009)	(0.007)	(0.006)	(0.008)	(0.009)
Municipality	0.016 *	0.012 *	0.014 *	0.021 **	0.015 *
	(0.008)	(0.006)	(0.005)	(0.006)	(0.007)
Length_contract	0.009 **	0.008 **	0.005 *	0.011 ***	2E-05 **
	(0.003)	(0.002)	(0.002)	(0.003)	(8E-06)
Lot_value	0.007 *	0.004 *	0.006 **	0.005	6E-09
	(0.003)	(0.002)	(0.002)	(0.003)	(4E-09)
EU_threshold	-0.082 *	-0.055 *	-0.084 **	-0.085	-0.114 **
	(0.049)	(0.026)	(0.028)	(0.046)	(0.047)
Procedures	YES	YES	YES	YES	YES
Years	YES	YES	YES	YES	YES
Sectors	YES	YES	YES	YES	YES
Regions	YES	YES	YES	YES	YES
_cons	1.191 **	1.093 **	0.796**	1.162 **	0.409 ***
	(0.395)	(0.328)	(0.291)	(0.389)	(0.080)
SEs of regression	0.122	0.106	0.127	0.122	0.122
Obs.	4937	4940	9678	5870	4937
Adj. R-squared	0.173	0.230	0.185	0.183	0.168
Wald (Prob. > chi2)	0.000	0.000	0.000	0.000	0.000

Notes: Bootstrap SEs are reported in parentheses. Specification (1) refers to the final sample; specification (6) is performed using the OLS estimator; specification (7) includes the contracts awarded between 2007 and 2015 with post-award information; specification (8) includes contracts awarded between 2007 and 2014 with a maximum length of 2 years; specification (9) refers to the final sample but with centered variables.

**** Significant at the 0.5 percent level.*

*** Significant at the 1 percent level.*

** Significant at the 5 percent level.*

Source: Author's own elaboration of MEF data

The results are in accordance with previous studies and consistent across the different specifications. Two of the three proxies for firms' bidding behavior are significant, but in differing ways. Rebates are likely to be higher when inefficiency is higher. Underbidding opens the path to renegotiation due to budget constraints during contract execution (Milani et al. 2018). The latter study empirically supports the inverse relationship between the absence of cost savings in contract awarding and inefficiency.

Infrastructural endowment is negatively associated with inefficiency. Lack of infrastructure entails the waste of financial resources in contract implementation. Contract complexity is instead positively associated with inefficiency. Long and expensive public works are more likely to suffer delays or budget increases during the contract implementation phase (Baldi et al. 2016). Nevertheless, public infrastructures noticed at the European level decrease the risk of inefficiency in contract execution. Exposure to foreign investments and foreign competitors increases the overall efficiency in procurement, as some territories may lack the technical capacity to complete complex development projects and may require foreign exchange and foreign expertise to compensate for these shortcomings (Kenny and Crisman 2016).

High levels of inefficiency are related to poor institutional quality (Charron et aI. 2014; Nifo and Vecchione 2014). Regions characterized by high levels of civic and political engagement and high administrative capacity have the ability to manage contracts more efficiently. Furthermore, results indicate that the involvement of central authorities and municipalities increases the probability of inefficient contracts, while state-owned firms are more efficient. Previous research shows that local governments do not seem to be under sufficient and effective pressure to behave efficiently in the execution of public works (Finocchiaro Castro et al. 2014).

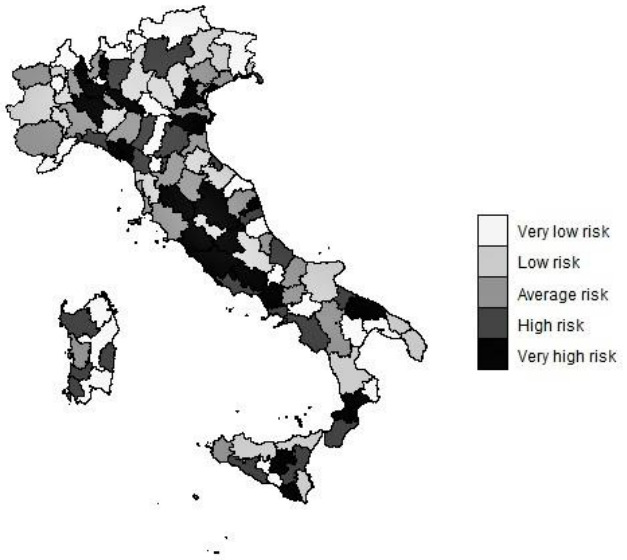
2.3.3 A new corruption risk indicator

Estimate residuals from specification (1) are transformed into a score of corruption risk at the contract level, hereinafter referred to as "Corruption Risk Indicator". The Corruption Risk Indicator establishes the level of corruption risk of each public contract. Using these new risk scores, public contracts are compared to determine which ones are more likely to experience corruption in contract execution. Risk scores are also aggregated into different indices at different disaggregation levels: by region, province and municipality.

For the sake of brevity, results are presented at the provincial level. In Figure 2, provinces are classified according to the level of associated corruption risk. The map shows that Rome, Rieti and Frosinone (all provinces in Lazio) exhibit high levels of corruption risk. Provinces such as Siena (Tuscany), Milan (Lombardy), Bari (Apulia) and Vibo Valentia (Calabria) are also near the top of the ranking.

At the bottom of the two rankings, the presence of some Southern provinces is surprising, namely Caltanissetta (Sicily), and Avellino (Campania), especially in relation to the regional average score of the regions to which they belong, which are typically influenced by the rooted presence of mafia groups particularly interested in extracting rents from procurement contracts (Caneppele 2014). Moreover, the presence of Bolzano is to be expected. The autonomous province of Bolzano is usually characterized by high levels of quality of life and good efficiency in the management of public resources.

Figure 2. Provincial Corruption Risk Scores. 0-1



Source: Author's elaboration of MEF data

The external robustness of the Corruption Risk Indicator is validated by adopting two different strategies. First, the Corruption Risk Indicator is compared at the regional and provincial levels, considering different environmental measures of corruption. Environmental measures of corruption are collected from different sources (police data, administrative statistics, victimization survey and corruption estimates) to encompass the many facets of corruption.[6] The correlation matrix (Table 4) presents the Pearson's r for the Corruption Indicator and alternative environmental measures of corruption. The average Pearson's r is 0.6. It should be noted that correlations are all significant at the 99.9%.

Table 4. Correlation among the Corruption Indicator and environmental measures of corruption. Regional values.

Environmental Measures of Corruption	**1**
Victimization survey (2017)	0.69
Regional Court (TAR) – administrative procedures (2009-2014)	0.69
Criminal proceeding - Emblezzement (2014)	0.50
Criminal proceeding – Malfeasance (2014)	0.37
Estimate of Corruption Crimes committed in Italy (2009-2015)	0.76*

*Notes: All significant p<0.001; *at provincial level, r=0.60.*

Source: Author's own elaboration

Furthermore, an 'evidence-based methodology' is applied to counter-check the indicator (ranked from top to bottom) with open-source information. If the Corruption Risk Indicator is indeed robust, then it

[6] An estimate of corruption crimes is computed based on the ratio between the corruption acts experienced over the last three years by each family in a given region (reported in the ISTAT victimization survey) and the reported number of crimes associated with corruption (from police SDI data) over the period 2013-2015. The obtained estimate is a 'multiplier', i.e. an estimate of the cases of corruption that did not emerge. Therefore, the estimate of 'latent corruption' is multiplied for the number of corruption crimes reported to the police in a given year for each region (or province) for the entire period 2009-2015. Finally, the regional and provincial average is computed to estimate the total number of corruption crimes committed in that period in that specific region (or province).

should capture several cases of real-life corruption, in the right tail of its distribution. This hypothesis is verified by selecting the first 100 and the last 50 contracts, according to the Corruption Risk Indicator, and 50 randomly selected cases around the 50th and 75th percentile. The results of the online research are classified into three corresponding groups:

1. White cases (no online information);
2. Grey cases (presence of a criminal record – e.g., tax crimes, crimes against public administrations - not strictly related to the contract);
3. Black cases (presence of trials, arrest warrant, pre-trial investigation strictly related to the contract).

Table 5 reports the relative distribution. In line with expectations, the black cases are more numerous within the first 100 cases (64%), and residual within the other risk clusters. The share of white cases increases progressively as the Corruption Risk Indicator approaches 0. The presence of false positives is lower than expected, even though white cases are the most represented in all four categories. However, the best confirmation of the model's robustness is the fact that false negatives within the last 50 contracts are exceedingly minimal: about 12% considering both grey and black cases.

Table 5. Validation from Online Evidence

	White cases	Grey cases	Black cases
High corruption risk (n=100)	36%	35%	29%
75% (n=50)	56%	24%	20%
50% (n=50)	78%	14%	8%
Low corruption risk (n=50)	88%	6%	6%

Source: Author's own elaboration

Indeed, it is possible to conclude that the Corruption risk Indicator is robust.

3. Exploring firm-level red flags

3.1 A firm-level analysis of corruption red flags

In this section several firm-level dimensions and indicators are empirically tested and evaluated to raise new hypotheses on the correlation between firms' attributes and corruption risk at the contract level, measured through the Corruption Risk Indicator developed in the previous section.

The assumption is that private firms involved in corruption differ from their peers in their financial performance and corporate structure, because of the different goals in respect to procurement. Corrupt firms are often established and managed strategically to participate in the execution of corrupt contracts, with the goal of reallocating procurement rents among the actors involved in the fraudulent scheme. Accordingly, this section deals with the identification of some risky patterns that might have direct observable effects.

To explore supplier-level red flags, procurement data are combined with the firm-level information gathered from Bureau Van Dijk (BvD). Despite the database on public contracts contains information on 4,940 public works, the sample used in this analysis is reduced to 2,877 observations and about 1605 suppliers due to missing information.

The analysis proposed relies on simple measures based on financial (firm profitability, firm liquidity and firm indebtedness) and corporate ownership information:[7]

- **Firm profitability**: is measured by the profit margin, calculated as the average growth index of the firm's profits on firm turnover;
- **Firm indebtedness**: is measured by the leverage ratio calculated as the average growth of total debts over total assets for the years prior to the tender. It indicates how firms finance their assets;
- **Firm liquidity: is** measured by (a) the current ratio which indicates the ease with which firm assets can be turned into cash; (b) trade debtors which measure the average number of days to be paid by customers for goods or services provided; and (c) trade creditors which measure the number of days to pay a firm's customers;
- **Firm opacity (Risk Shareholders)**: is measured by considering the average number of shareholders links with opaque jurisdictions (Riccardi et al. 2018);
- **Firm complexity**: is measured by the beneficial owner distance indicator which represents the number of 'steps' which separate a company from its beneficial owner(s) (Riccardi et al. 2018);
- **Firm change of name:** observed using a dummy variable for firms who have changed their name during the tender period.

The full list of variables is summarized in table 6.

Table 6. Main statistics firm-level indicators included in the OLS regression

Variable	Source	Years	Obs.	Mean	Std. Dev.	Min.	Max.
Corruption Risk Indicator	Own elaboration	Contracts year	4940	0.364	0.137	0.000	1.000
ProfitMargin	BvD	Contracts year	2275	0.000	1.000	-46.16	6.013
Leverage	BvD	Contracts year	2595	0.000	1.000	-10.96	37.79
CurrentRatio	BvD	Contracts year	2791	0.157	0.022	0.059	0.186
TradeDebtors	BvD	Contracts year	2791	0.071	0.044	0.054	1.046
TradeCreditors	BvD	Contracts year	2791	0.070	0.038	0.054	0.810
RiskShareholders	BvD	Last Av. Year	2875	0.032	0.063	0.000	1.000
BO_distance	BvD	Last Av. Year	2875	0.129	0.088	0.000	1.000
ChangeName	BvD	Contracts year	2877	0.140	0.347	0.000	1.000

Source: Author's own elaboration

3.2 Preliminary findings

Table 7 presents six different linear regression models. Control variables for company size and the geographical distance between the supplier and the public administration are also included to the

[7] Firm indicators can point in two directions, raising an endogeneity issue. On the one hand, they may favor corrupt agreements; on the other hand, they can simply reflect the outcome of the corrupt transactions. To reduce the reverse-causality bias, firm indicators are developed taking into consideration the years before contract awarding while the Corruption Risk Indicator refers to post-awarding data. For example, if a contract is awarded in 2012, the information at firm-level are collected for the years 2010-2012

specification, together with the following environmental predictors: irregular labor, the degree of meritocracy experienced in the public sector, capital attractiveness and GDP per capita.[8]

Table 7. OLS regression on firm-level red flags

Variables	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)	Coeff. (SE)
	1	2	3	4	5	6
Dependent variable: Corruption Risk Indicator (0-1)						
ProfitMargin	0.003 ***	0.001 *			0.001	0.001
	(0.001)	(0.001)			(0.001)	(0.001)
Leverage	-0.018 ***	-0.009 *			-0.009 *	-0.009 *
	(0.003)	(0.003)			(0.004)	(0.003)
CurrentRatio	0.302 *	0.152			0.177	0.164
	(0.146)	(0.134)			(0.136)	(0.135)
TradeDebtors	-0.357 **	-0.403 **			-0.427 **	-0.441 **
	(0.126)	(0.137)			(0.140)	(0.139)
TradeCreditors	0.310 *	0.297 *			0.289	0.259
	(0.153)	(0.147)			(0.149)	(0.150)
RiskShareholders			0.053 *	0.037	0.053 **	0.066 *
			(0.026)	(0.025)	(0.016)	(0.016)
BO_distance			0.025	0.030	0.205 *	0.174
			(0.067)	(0.075)	(0.091)	(0.093)
ChangeName			-0.010	-0.006	-0.010	-0.01
			(0.007)	(0.007)	(0.007)	(0.008)
TotalAssets	-0.008	-0.007	-0.005	-0.003		-0.006
	(0.006)	(0.006)	(0.005)	(0.005)		(0.006)
Proximity	-0.030 ***	-0.011 *	-0.032 ***	-0.011 *		-0.011
	(0.006)	(0.006)	(0.005)	(0.005)		(0.006)
IrrWorkers		0.154 ***		0.151 ***	0.154 ***	0.153 ***
		(0.016)		(0.015)	(0.016)	(0.016)
Meritocracyindex		-0.111 ***		-0.120 ***	-0.113 ***	-0.108 ***
		(0.018)		(0.017)	(0.018)	(0.018)
CapitalAttractiveness		-0.008 *		-0.009 **	-0.009 **	-0.008 *
		(0.003)		(0.003)	(0.003)	(0.003)
GDPcapita		0.235 ***		0.234 ***	0.235 ***	0.232 ***
		(0.016)		(0.014)	(0.016)	(0.015)
Years	YES	YES	YES	YES	YES	YES
Sectors	YES	YES	YES	YES	YES	YES
_cons	0.372 ***	-1.998 ***	0.364 ***	-2.003 ***	-2.026 ***	-1.984 ***
	(0.065)	(0.168)	(0.067)	(0.148)	(0.166)	(0.168)
Obs.	2275	2275	2789	2789	2274	2274
R-squared	0.072	0.204	0.069	0.207	0.201	0.203
Root MSE	0.133	0.123	0.133	0.123	0.123	0.123
Prob. > F	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Clustered SEs are reported in parentheses.

**** Significant at the 0.5 percent level.*

*** Significant at the 1 percent level.*

** Significant at the 5 percent level.*

Source: Author's own elaboration

[8] It should be noted that the environmental variables cover the years of the tender, when possible. However, the heterogeneity of the time reference should not pose major problems with regards to these variables, as it is reasonable to assume that the processes represented by these variables usually change in the medium to long term.

On a general level, the results highlight the presence of a statistically significant correlation between some of the firm indicators and the Corruption Risk Indicator at the contract level. It is interesting to note that most of the significant red flags preserve their sign, and in most cases their significance as well, even after the introduction of the environmental variables. Environmental variables are also significant, in accordance with previous literature: irregular workers and GDP capita increase as corruption risk increases, while meritocracy and capital attractiveness decrease as the risk of corruption increases.

Firm profit increases significantly in specification (1) and (2), while it loses strength in specification (5) and (6), after the inclusion of the company ownership indicators. Involvement in corruption might lead to an increase in profit margin due to tailor-made public procurement contracts (Cheung et al. 2011). On the one hand, corruption can speed up bureaucratic procedures and promote firms' short-term growth by facilitating transactions in the bureaucratic process. On the other hand, more profitable companies could exploit their strong position in the market to create demand for goods or, in some case, to obtain a de facto monopoly situation to retain business (Søreide 2002).

Firms connected with contracts at high risk of corruption are more capitalized and less indebted (negative and statistically significant in all specifications). The leverage ratio indicator can proxy the probability of personal or political ties that are indicative of corruption in procurement. Indeed, low levels of debt over total assets might suggest that the companies involved in corruption may receive direct funding from the public administrations, which allows maintaining a low level of indebtedness.

Concerning liquidity measures, trade debtors and trade creditors are significant but in differing ways. The results indicate that firms involved in corruption receive customers' payments in a short term with respect to their peers. The results also indicate that these firms take longer to pay their customers. It is interesting to note that suppliers involved in public contracts that are usually executed with delays and additional costs are also those that take longer to pay their customers.

The results also suggest a relationship between the risk of corruption and the level of firm opacity. The use of off-shore countries for corruption purposes is well-documented both in academic research (de Willebois et al. 2011) and from journalistic evidence (i.e. Panama Papers, Paradise Papers). Firms involved in corruption might set up shell companies in opaque jurisdictions to take advantage of laxer anti-corruption and transparency standards. Moreover, being incorporated in a tax haven is also helpful in concealing illicit flows and hiding beneficial ownership (Riccardi and Milani 2018).

Despite the explorative purpose of this analysis, the results seem to profile an 'identikit' of the suppliers involved in corrupt transactions. Firms associated with a high risk of corruption in public procurement appear to be more 'dynamic' than their peers, both from a financial point of view (lower debts, greater profits and fewer trade debtors), and for their ability to establish particularistic ties throughout the country ("proximity" is negatively related with the corruption risk indicator, suggesting that firms are more likely to be involved in corruption outside their province of origin). It is also interesting to note that these firms tend to have a more complex corporate structure, characterized by connections with opaque jurisdictions and tax havens. These connections with opaque jurisdictions could represent the channel through which public funds are diverted.

4. Final discussion

This paper reflects the inherent challenges of developing reliable indicators to support law enforcement agencies and the judiciary authorities in preventing and detecting illegal behaviors in public procurement. To develop a set of corruption risk indicators both with respect to public contracts and to suppliers, this study has provided an applied analytical approach which:

- is solely based on objective indicators derived from open data;
- allows for territorial comparisons within the Italian context;
- allows for the identification of firms that are potentially involved in corrupt transactions;
- can be replicated in other contexts using the same set of pre-existing data.

The results described in section 2 confirm that the applied methodology can provide useful information to understand the level of corruption risk in the Italian procurement context. The findings partially reflect the effort of the judicial authorities and the police forces, as indicated by the robustness analysis carried out to validate the methodology. According to the results, the risk of corruption in Italy has no clear territorial pattern, although larger urban areas presents on average a higher risk of corruption in procurement.

The findings of section 3 have also identified some recurrent firm-level patterns correlated with contracts at high risk of corruption. From a first assessment, firms associated with high risk-contracts act in accordance with their personal interests: they seek profits and are legally and/or financially connected with opaque jurisdictions or tax havens. Further research is required to understand whether these firms' characteristics can hide corruption-related misconducts aiming to divert public funds from procurement contracts on a regular basis.

From a policy perspective, the 'informational power' of these indicators can facilitate the monitoring activities of the overseeing bodies and allow the implementation of a series of initiatives to:

1. assess regions and provinces over time to track the average incidence of public procurement corruption over time and to observe if significant policy changes impact the overall scores;
2. profile public organizations and winning bidders involved in high-corruption risk networks to promote effective corruption countermeasures;
3. support the conduction of risk-based audits of actors and transactions, by guiding the work of auditors and procurement officers in their monitoring activities as well as in the evaluation and selection of bidders through the use of data-driven tools.

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