Physica A 658 (2025) 130288

Contents lists available at ScienceDirect

Physica A: Statistical Mechanics and its Applications

journal homepage: www.elsevier.com/locate/physa

Dynamics of corruption: Theoretical explanatory model and empirical results

Domenico Marino [1]

Digies Department, Mediterranea University of Reggio Calabria, Via dell'Università, Reggio Calabria 89126, Italy

ARTICLE INFO

JEL classifications:
K42
K14
R58

Keywords:
Corruption
dynamical models
data mining

ABSTRACT

Corruption silently distorts markets and diverts resources from the public good. This paper explores the cyclical nature of corruption, analyzing corruption from a microeconomic perspective and identifying a relationship between the intensity of state repressive action and the level of corruption. This research offers new insights into the cyclical behavior of corruption, addressing issues relevant to economic policy. An important aspect for understanding corruption dynamics lies in its cyclical behavior. The concept of the corruption cycle has been sufficiently explored at the theoretical level, but empirical evidence remains limited. This paper attempts to fill this gap by constructing a robust theoretical model that elucidates the interaction between sanctions and bribes and between the level of corruption and state intervention as a cause of corruption cyclicality and validating the theoretical findings through empirical analysis using spectral analysis and data mining techniques. The empirical verification of the theoretical hypothesis of cyclicality of corruption opens up interesting scenarios for developing anti-corruption policies.

1. Introduction

Corruption is a pervasive yet hazy phenomenon that, to a greater or lesser extent, affects every country around the world. It is a type of illegal behavior that causes little social alarm and can become a system known to and accepted by all. Corruption has a very high social cost that is manifested in many spheres. First, corruption distorts market competition because the selection of contractors is not made on the basis of merit but on the basis of corrupt agreements. Merit and quality take a back seat because competitions and contests lead not to the selection of the best candidates but of those who are closest to power or the powerful or are simply more adept at the mechanisms of corruption [7].

The cost of corruption is also represented by the misappropriation of resources that are diverted from their intended use for the collective good and instead transformed into unlawful private benefits. This inefficiency generates broader social harm that is not limited to the waste of resources but also negatively affects economic freedom by distorting the mechanisms of free competition and meritocracy that form the basis of any economic democracy. Eliminating and/or reducing the cost of corruption is a goal of society, as well as a means of balancing public budgets and improving the quality of public spending. The World Bank in 2004 estimated the amount of bribes worldwide to be 3 percent of GDP.

By analyzing corruption from a microeconomic perspective, it is observed that there is a correlation between the intensity of the state's repressive action and the level of corruption, as it is also intuitively clear that bribes are the price to remove the repressive effect

E-mail address: dmarino@unirc.it.

[1] ORCID: 0000-0003-3491-2625

https://doi.org/10.1016/j.physa.2024.130288
Received 29 June 2024; Received in revised form 2 November 2024; Accepted 3 December 2024
Available online 6 December 2024

of the state.

Therefore, the change in the level of corruption can be described as a cycle. The cyclicality of corruption is an idea that is quite present in the literature, especially in the theoretical field, while the contributions that have attempted to empirically measure this aspect are rather limited.

This paper aims to build a theoretical model that, starting from the link between penalties and bribes, explains the cyclical behavior of levels of corruption. This relationship will be verified by analyzing empirical data with the use of spectral analysis and data mining techniques. The originality of the work presented in the paper lies in the attempt to theoretically explain the cyclical behavior of corruption and to empirically prove this dynamic with a technique, spectral analysis, which is widely used in the exact sciences but very little used in the economic sciences. In the next second section, the theoretical background within which the work is situated is outlined, and in the third section, the theoretical model is described and analyzed. The fourth section is devoted to empirical analysis using spectral analysis and classification using machine learning techniques. The fifth section will be devoted to the discussion of the results and will contain some concluding remarks.

2. Background

To construct a functional literature survey for the contents of the paper, it is necessary to focus on two theoretical aspects. The first is certainly the definition of the traditional concept of corruption and traditional attempts to measure the phenomenon. The second aspect concerns more specifically those studies that attempt to investigate the cyclicality of corruption with different tools and different methodologies. Starting from the link between penalties and bribes, we attempted to explain the levels and the differential rate of corruption between various countries.

One of the earliest major works on corruption is that by Cressey [13], which focuses on the capital of influence exerted externally through public relations, lobbying, or bribery for the purpose of nullifying government action, which today means a complex and constant work of activating a vast set of regulatory practices. Another seminal contribution to corruption is that made by Rose-Ackerman [33,34], who gave a first definition of corruption, relating it to the public function carried out by a certain agent to obtain an unlawful advantage.

The microeconomic foundation of this paper is Becker's [10] theory, developed in the context of the economic analysis of crime, which shows that illegal activity is subject to a rational cost—benefit calculation. More recently, Aidt [3], referring to Becker's theory, identified corruption as a phenomenon persisting in time and space, focusing on the determinants of corruption by identifying them as discretionary power, the economic advantage derived from it, and the relationship between the penalty and the probability of being caught.

Vannucchi [38] emphasized three paradigms for studying corruption: the principal-agent model approach, the cultural traditions and social norms approach, and the neo-institutional approach. Treisman's [37] approach focused on the dissonance between law and moral norms, explaining that a lower degree of legitimacy of the legal system corresponds to a higher level of corruption.

Andvig [6], on the other hand, focused on the evolutionary path of the corruption phenomenon, explaining the persistence of the phenomenon as a function of its historical evolution.

Another interesting line of enquiry on corruption focuses on the relationship between electoral rules and the corruption phenomenon. An important contribution to this approach is the work by Persson et al. [31], while Tanzi [36] explored the relationship between corruption and the decentralization of public decisions, which led to a more direct relationship between politicians and citizens, thereby increasing the risk of cronyism.

A very interesting approach was proposed by Hirschman [24], who emphasized that the incidence of corruption depends not only on institutional opportunities but also on public morality, i.e., the degree of social aversion to corruption. This approach is extremely useful for understanding the persistence of corruption in certain contexts and formulating policy proposals.

However, corruption has specific characteristics that involve psychological, sociological, and cultural aspects in addition to economic aspects. Therefore, a multidisciplinary analysis is necessary, and to fully understand the dynamics of this phenomenon, it is useful to apply the theory of complex systems [27,39,41].

In relation to the second aspect, the literature is not very numerous and is generally related to the relationship between politicians and voters. The first contribution is that of Feichtinger, Wirl [17], who considers the widespread phenomenon of political corruption and analyses some of its political, economic, and dynamic properties, assuming that a rational politician derives benefits from popularity and corruption.

Bicchieri, Duffy [11] analyze corruption as a cyclical phenomenon. In this case, the pattern of corruption is the exchange of bribes for public contracts, although this pattern can easily be extended to other types of corrupt exchanges. In this work, corruption cycles occur for two different reasons. One is the inability of corrupt politicians to compensate contractors for their Pareto inferior performance. The other reason is that politicians offer too much excess compensation to corrupt contractors, thus depleting their accumulated resources. Alesina et al. [5] conclude that the procyclicality of fiscal policy is more pronounced in more corrupt democracies.

Potrafke [32] examines whether elections influence perceived corruption in the public sector, where perceived corruption in the public sector is measured by the reversed Transparency International's Perception of Corruption Index (CPI). He found that cyclical dynamics in corruption may be related to political business cycles.

Accinelli et al., [2] propose an evolutionary dynamical model for corruption in a democratic state describing the interactions between citizens, government, and officials, where the voting power of citizens is the main mechanism to control. Abbas et al. [1] developed a predator—prey model to understand the relationship between criminal and noncriminal populations. Initially, a basic predator—prey model was applied, which was later improved with the consideration of logistic growth for the noncriminal group. The results reveal that the criminal population persists unless the law enforcement coefficient exceeds a specific limit, beyond which criminals decrease.

Sooknanan et al. [35] propose a modified predator—prey model in which both predator (police) and prey (gang members) can contract a communicable disease. Infected prey are more susceptible to predation, while sick predators hunt less effectively. The research explores the possibility of police control of gangs using stability analysis and simulations. The model identifies five steady states: four without gang members and one in which all gangs coexist. Ekblom [16], starting from the consideration that crime prevention is constantly evolving to address emerging criminal opportunities, studies the lessons that crime prevention can learn from the struggles between technologies, innovative prevention methods and strategic concepts. To remain relevant, prevention methods must also be adaptive. This ongoing challenge mirrors other 'evolutionary struggles', such as the biological coevolution typical of predator—prey models or arms races. The evolution of criminal activity is characterized by continuous adaptations on both sides, influenced by accidental changes such as new technologies. Marino et al. [28]. Using a predator—prey model to explain the dynamics between legal and illegal enterprises, they identify two states of specialization in which the market becomes totally illegal or totally legal and a situation of coexistence between illegal and illegal enterprises. Through an empirical analysis, they then verify the results of the theoretical model.

Galbraith [18] asserts that during the Great Depression (Great Crash1929) (1997), the higher the transitory income is, the higher the corruption. Following this reasoning, Gokcekus & Suzuki [19] studied a panel of 39 countries over 13 years, 1995–2007 proving that Galbraith's assumption is correct. Of note are the contributions of Blackburn et al. [12], who develop a model to study the interaction between crime and corruption in which they explain the coexistence of legal and illegal firms in the market, with illegal firms using corruption to compete.

Bai et al. [9] studied the relationship between business growth and corruption in the case of Vietnam and found that firm growth reduces bribes as a share of revenues.

In Marino and Tebala [29], a taxonomy of corruption across Italian regions is constructed using a synthetic indicator.

3. The corruption feedback model

Understanding the microeconomic behavior of agents in relation to corruption must begin with an understanding of the state's action. This intervention is perceived by agents as being related to their cost configurations. The role of the state is to guarantee the legality of the system by punishing corrupt behavior. One assumption is that the larger the market and the more widespread the corruption, the stronger and more decisive the state's intervention will be. This assumption introduces a feedback mechanism that explains the presence of cycles in the level of corruption that are linked to different intensities in the fight against corruption.

Let us consider, therefore, that the state imposes a penalty σ, understood as a monetary measure of the cost of being caught, and which also depends on the speed and effectiveness of the state's action, on the illegal enterprise that is "caught", and that the probability of being caught is π, which is a function of the agent's effectiveness in escaping justice ϑ. The probability π increases in dimension ϑ. The expected value of the penalty σ is given by:

$$V\sigma)= (\vartheta)\sigma \tag{1}$$

In addition, it is given that:

$$\frac{d\pi}{d\theta} > 0, \quad \frac{d^2\pi}{d\theta^2} < 0 \tag{2}$$

The fight against corruption has its cost, consisting of the public resources that must be used to combat this phenomenon. Agents defend themselves against the state's action by attempting to thwart the penalty by way of Eqs. (1) and (2), set out above. With this premise on microeconomic behavior, one can try to construct a model explaining the relationship between corruption, the price of the penalty and state intervention. Growth in the level of corruption triggers a stronger response by the state, thereby raising the price of offsetting the penalty.

In mathematical terms:

$$S = S(C) \tag{3}$$

$$\frac{dS}{dC} > 0 \tag{4}$$

where S is the function describing the intensity of the state's intervention and C is the level of corruption. The positive first derivative has the immediate meaning of a correlation between growth in the state's action and growth in corruption. Thus, assuming that the link between intensity of intervention and corruption is linear, the following will be given:

$$S^*_{t+1} = a + bC_t \tag{5}$$

$$\text{with } S_t^* = (S_{t+1} - S_t)/S_t \tag{6}$$

It is possible to define the price of offsetting the state's penalty by assuming that an increase in the state's action increases the price of offsetting the penalty (e.g., the price of the bribe):

$$K\frac{S_{t+1} - S_t}{S_t} = \frac{T_{t+1} - T_t}{T_t} \tag{7}$$

A kind of time elasticity of the amount of illegality in relation to the price of offsetting it can be defined so that if the bribe increases, in the following period, the level of illegality will decrease. Consequently, the following will occur:

$$E_{TI} = -\frac{\Delta C/C}{\Delta T/T} \tag{8}$$

Through simple steps, the feedback relationship can be obtained:

$$C_{t+1} = C_t(1 - wa) - C_t^2 wb, \text{ with } w = KE_{TI} \tag{9}$$

This relationship has a point of equilibrium:

$$C_e = 0, C_e = -a/b \tag{10}$$

The local stability conditions are given by the values of the following expression:

$$dC_{t+1}/dC_t = (1 - wa) - 2wbC_t \tag{11}$$

from which it follows that where a< 0, the first solution is unstable and the second is stable.[2] If a is negative, then C_t(1-wa) represents a form of proportional growth, and a more negative value of aa means faster growth. When b> 0, this could represent a saturation effect or negative feedback.

This explanation can be summarized as follows. A growth in corruption increases the state's action, which in turn raises the price of offsetting the penalty (e.g., increases the amount of the bribe). Increasing the price decreases the demand for offsetting, and the state's intervention pushes down the level of corruption. Pushing down the level of corruption decreases the state's intervention, thus decreasing the price of the bribe and increasing the demand for it. Corruption starts to increase, and the cycle begins again. Future research advances could deal with more explicitly incorporating considerations of the electoral cycle and the role of social disapproval into the theoretical model to be able to analyze the empirical evidence in this light as well.

To highlight the process described by Eq. (9) analytically, it is necessary to solve this equation and work out the phase diagram. The two-phase diagram (Fig. 2, Fig. 3) represents a situation in which the system oscillates with regular cycles or even stable limit cycles for different values of parameters a, b and y.

Fig. 2 shows regular cycles in corruption levels, indicating a stable feedback loop. In this scenario, an increase in corruption triggers a stronger state intervention, which raises the associated costs (such as bribes or penalties). These costs temporarily reduce corruption, leading to a decrease in state action. This cycle then repeats, producing a predictable pattern that maintains a balance between corruption levels and state intervention. Fig. 3 shows chaotic behavior in corruption levels, where fluctuations are irregular and unpredictable. In this phase, the system becomes highly sensitive to changes, so even small shifts in parameters can lead to significant variations in corruption levels. The state's response varies erratically, reflecting a lack of stability and suggesting that the system cannot settle into a regular cycle. This instability can represent situations where the feedback loop intensifies to the point of disrupting any predictable pattern. These results indicate that, as the intensity and effectiveness of anti-corruption policies vary, the system may oscillate between stable phases and chaotic instability. Furthermore, electoral cycles and/or social disapproval could be causes of these behaviors.

4. Empirical analysis and results

Empirical verification of the theoretical model has elements of complexity for two orders of reasoning. The first order concerns the ontological nature of the phenomenon, that is, the fact that it is an illegal behavior that agents attempt to make as little manifest as possible. Measuring corruption is impossible in a direct way and can only be done by indirect methods. The second order of reasons has to do with the fact that awareness of the economic significance of corruption has only recently been raised so that the available descriptive time series are quite limited. The empirical test will obviously have exploratory significance because of the limitations of the data previously highlighted. Taking these considerations into account, to empirically verify the theoretical model described above, a database will be constructed with the temporal evolution of two variables: the Corruption Perceptions Index elaborated by transparency and the World Justice Project Rule of Law Index elaborated by the World Justice Project. By using data from a large number of countries, an attempt was made to limit the problem of the short length of time series.

The Corruption Perceptions Index (CPI) is the world's most widely used global corruption ranking. It measures how corrupt each country's public sector is perceived to be according to experts and businesspeople. The CPI ranks 180 countries and territories worldwide according to their perceived levels of public sector corruption. The results are given on a scale from 0 (completely corrupt) to 100 (no corruption). Each country's score is a combination of at least three data sources drawn from 13 different surveys and assessments of corruption. These data sources are collected from a variety of institutions with a strong reputation for independence, including the World Bank and the World Economic Forum. Potrafke [32] and Gründler, Potrafke [22] use this indicator to compare

[2] There is local stability if $0 < \frac{dC_{t+1}}{dC_t} < 1$, whereas there is instability if $\frac{dC_{t+1}}{dC_t} > 1$.

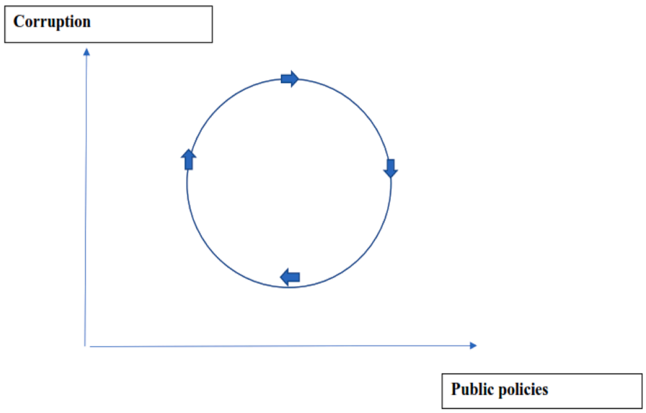

Fig. 1. Corruption vs public policies.

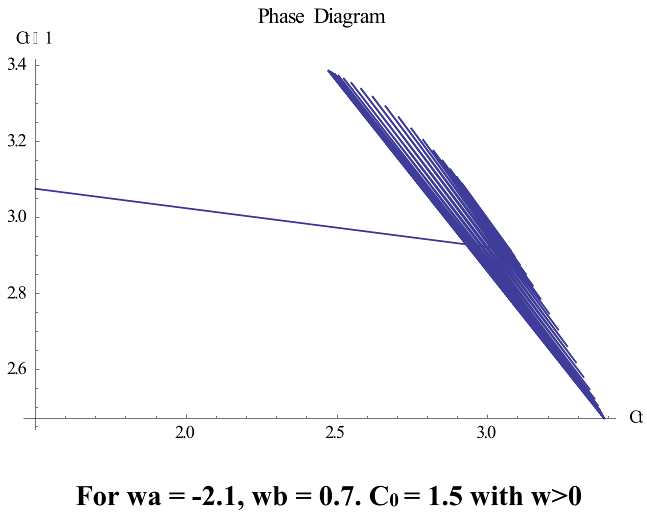

Fig. 2. Phase diagram representing cycles.

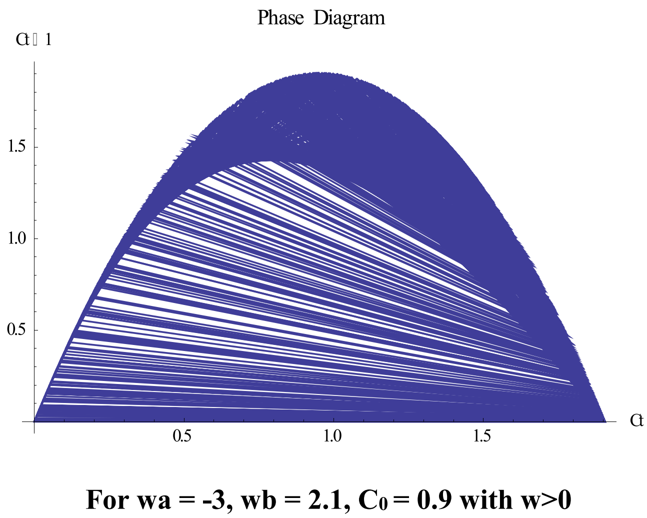

Fig. 3. Phase diagram representing chaos.

differences in perceived corruption in an international context.

The World Justice Project Rule of Law Index is the world's leading source of original, independent data on the rule of law. Covering 139 countries and jurisdictions, the index draws on national surveys of more than 138,000 households and 4200 legal professionals and experts to measure how the rule of law is experienced and perceived around the world.

The result that emerges from the theoretical model (Fig. 1) is a cyclical pattern of the value of perceived corruption in response to the level of law enforcement policies implemented by the state. The CPI is an indicator describing perceived corruption, while the Law Index is an indicator of the efficiency of the justice system, which can be a good proxy for the effectiveness of law enforcement policies, as it is directly correlated with the subjective probability of being caught in the case of adherence to a bribery pact. Spectral analysis is an excellent tool to verify the existence of cyclical behavior of time series, even with little data.

Original data from the two sources were homogenized and compiled into a database containing CPI data from 2012 to 2021 and Law Index data from 2014 to 2021 for 112 countries. Countries that did not have time series for both indicators and some countries that had time series with very little data were eliminated. The dynamics of the two indicators should empirically describe the theoretical considerations developed in the previous section.

A first analysis can be made by studying the correlation diagrams between the two indicators for each of the years 2019–2021.

As can easily be seen from the graphs, the trends are strongly correlated, with few outliers. This does not reassure us as to the causal link between the data, of course, but it does show a close correlation between the two indicators in the different countries. The possibility of finding a spatial correlation between two data series is a good starting point to study the dynamics of the time series in more depth.

4.1. Spectral analysis

Spectral analysis is a very powerful research methodology that aims to identify harmonic components within a time series. Time series can be analyzed on the basis of two dimensions: dynamics and frequency. Frequency is related to cycles. Spectral analysis breaks data down into frequencies. The first systematic work on spectral analysis in the study of economic variables can be traced back to the studies by Cunnyngham [14], Granger and Hatanaka [20], Granger and Morgenstern [21], Hatanaka [23] and Nerlove [30]. One of the reasons that recommended the use of spectral analysis is the possibility of obtaining robust results through this methodology even with little data. The basic idea of spectral analysis is the decomposition of a time series into its orthogonal components, which are related to a particular frequency that determines the total variance of the series. The concentration in a particular frequency indicates that frequency explains the dynamics of the series. In our case, the objective of the spectral analysis was to identify cyclical components within the time series of the CPI and the Law Index. A first exploratory test to verify the cyclicality hypothesis consists of rejecting the hypothesis that this is white noise. This consideration is important because if the data were representable by white noise, no causal periodic relationship could be found between the two series. Conversely, rejection of the white noise hypothesis and the identification of a specific frequency of oscillation make explicit the existence of a causal link between the two variables that interact, following the results of the theoretical model.

The results of the Fisher's Kappa and Bartlett's Kolmogorov—Smirnov tests are very important to verify the rejection of the white noise hypothesis. Looking at the test values and the significance level p, it can be seen that in all the examples presented, the white noise hypothesis for the data can be safely rejected, as the p values are all in the order of 10^-3 or lower, with the one exception being

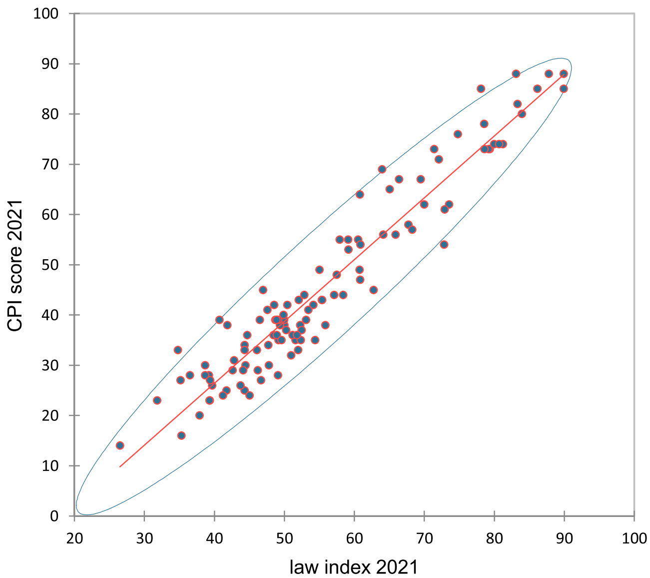

Fig. 4. Correlation diagrams for 2019.

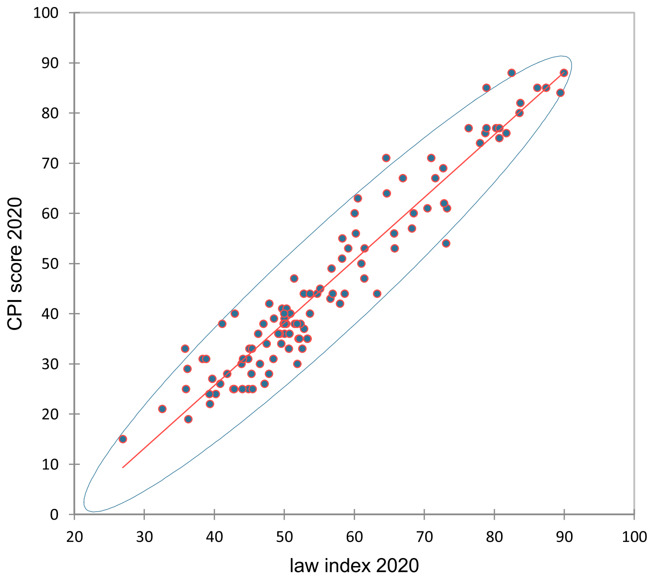

Fig. 5. Correlation diagrams for 2020.

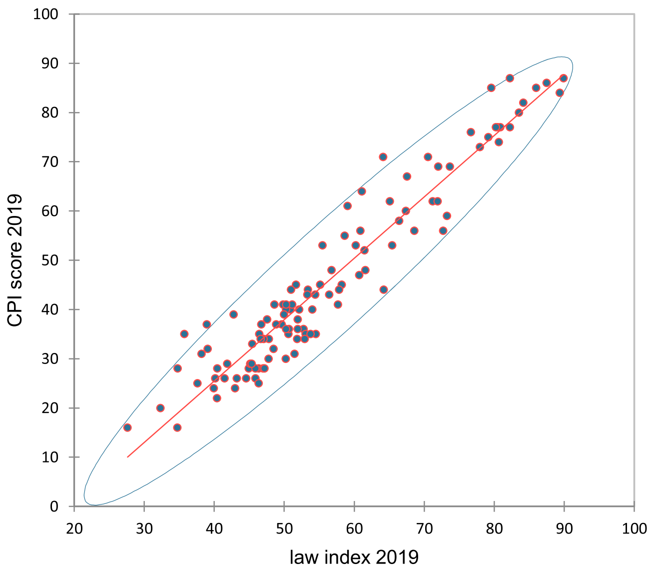

Fig. 6. Correlation diagrams for 2021.

Finland (p value = 0.017). Passing the tests shows that despite the short length of the time interval studied, a cyclical behavior emerges from the data, which is further highlighted by the fact that similar dynamics are found in different countries.

After this initial exploratory analysis, we can move on to a detailed analysis of the data obtained from the application of spectral analysis. Below are graphs and statistical analyses for periodograms, spectral density, phase spectra and cospectral density for two time series.

From the analysis of Figs. 7 and 8, the following evidence emerges. We focus more specifically on the spectral density graph for the Rule of Law variable, which is simply a smoothed version of the periodogram. The presence of nine distinct peaks suggests that there

Table 1
White noise tests (Corruption Perceptions Index).

Statistic	Value	p value
Fisher's kappa	36,871	< 0,0001
Bartlett's Kolmogorov—Smirnov	0784	< 0,0001

Table 2
White noise tests (Rule of law index).

Statistic	Value	p value
Fisher's kappa	38,814	< 0,0001
Bartlett's Kolmogorov—Smirnov	0782	< 0,0001

Table 3
Granger test.

Granger Test		Min lag	p-value	Series 1		Series 2
Confidence	Max lag	20	0.001	Rule of Law Index	→	Corruption Perception Index
99 %	20	1	0.002	Corruption Perception Index	→	Rule of Law Index

are nine dominant frequency components in the signal. We also note that the distance between the peaks is quite regular, and this regularity signals the presence of harmonics of a fundamental frequency. This is common in many signals, particularly those describing periodic phenomena. Since the low-frequency peaks have the highest values, this suggests that the low-frequency components are the most dominant or significant in the signal, indicating the presence of long-term trends in the data.

Figs. 9 and 10 for the variable Corruption Perception Index show a similar pattern. Again, we note that the presence of nine distinct peaks suggests that there are nine dominant frequency components in the signal. The fact that these peaks have a decreasing value with increasing frequency indicates that the low-frequency components have greater power or amplitude than the high-frequency components and are the most significant. As in the previous case, this highlights the presence of long-term trends. Again, the distance between the peaks is quite regular, indicating the presence of harmonics of a fundamental frequency.

Fig. 11 represents the cospectral density between two time series over a set of frequencies. These values are ordered according to frequencies, probably starting from the lowest frequencies (long-term trends) to the highest frequencies (short-term fluctuations). The highest values indicate a strong correlation between the two time series at the corresponding frequency. These values then tend to decrease, suggesting that the series may be more strongly correlated at lower frequencies than at higher frequencies. All values are positive, indicating that the components of the two time series are generally in phase at all frequencies analyzed. This means that the two series are interdependent and could be related by a causal relationship, which will be better explained and highlighted in the following graphs. The higher initial values suggest a strong correlation between the long-term trends of the two series. As the values decrease as the frequency increases, the correlations between the short-term fluctuations of the two series seem to become less strong. Although the values generally decrease, there are some fluctuations (i.e., some frequencies may have relatively high values compared to their neighbors). These fluctuations could indicate particular cycles or periodicities in the time series that are strongly correlated. Based on the values provided, it appears that the two time series are strongly correlated at the level of long-term trends, with the correlation generally decreasing for short-term fluctuations.

The quadrature spectrum (Fig. 12) represents the phase between the time series as a function of frequency. Positive values indicate that the first series precedes the second, while negative values indicate that the first series lags behind the second. At the beginning, the cospectral density is high and positive, and the quadrature spectrum is very close to zero, suggesting that the series are strongly phase-correlated at low frequencies. As the frequencies advance, the cospectral density remains positive but decreases in intensity, while the quadrature spectrum becomes negative. This suggests that the series become less correlated and begin to diverge in phase. Series 1 may lag behind series 2. Toward the end of the series, the cospectral density becomes lower and fluctuates, while the quadrature spectrum shows more variability. This could indicate that the phase relationships between the series become less clear at higher frequencies.

Fig. 13 represents the phase spectrum between two time series. The phase spectrum provides information on the time difference (or phase) between the two series as a function of frequency. Phase spectrum values close to 0 indicate that the two time series are aligned

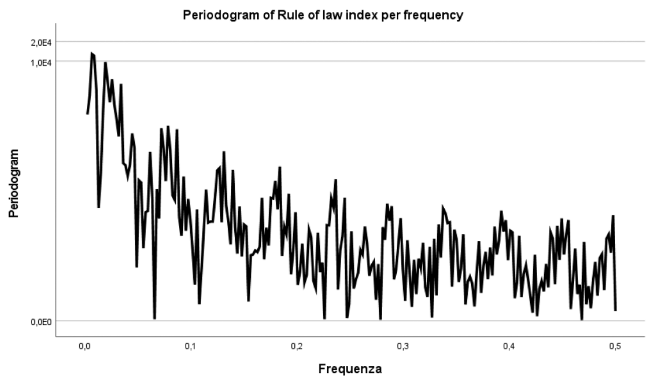

Fig. 7. Periodogram of rule of law index per frequency.

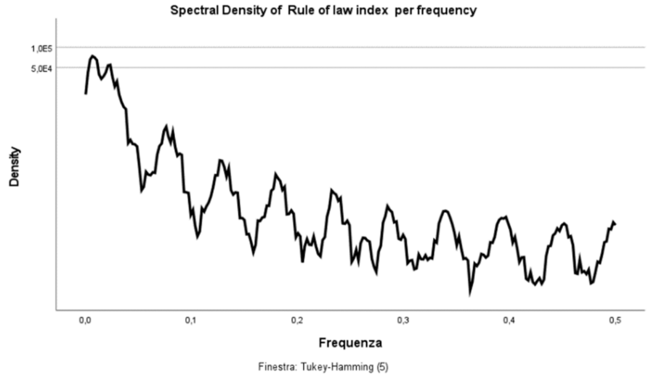

Fig. 8. Spectral density of the rule of law index per frequency.

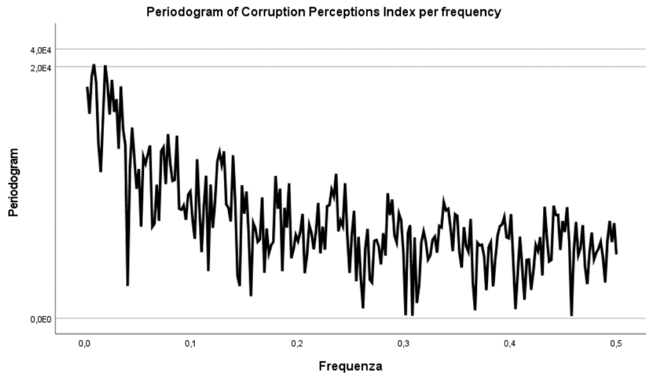

Fig. 9. Periodogram of the corruption perception index per frequency.

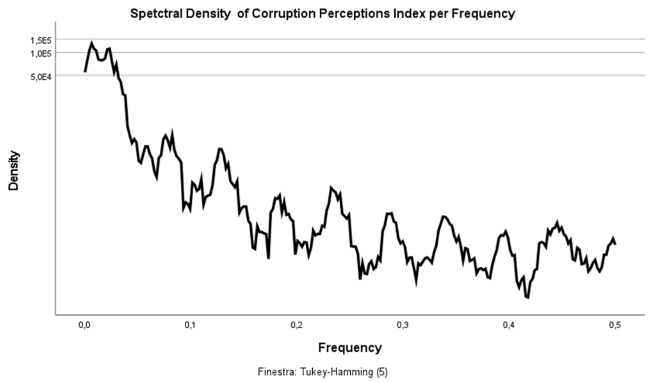

Fig. 10. Spectral density of the corruption perception index per frequency.

in the same phase, i.e., are synchronized at that specific frequency. Positive phase spectrum values indicate that the first series precedes the second at that specific frequency. Negative phase spectrum values indicate that the first time series follows (or lags behind) the second at that specific frequency. Analyzing the graph, one finds that initially, the phase spectrum is close to 0, indicating that the two series are almost in phase. As one progresses, there are both positive and negative variations, indicating changes in the phase relationship between the two series at different frequencies. At some frequencies, the value of the phase spectrum becomes significantly negative (such as −.801 or −.909), suggesting that there is considerable lag between the two series at those frequencies. At other frequencies, the phase spectrum becomes significantly positive (such as 1.122), indicating that the first series significantly precedes the second.

Since the two time series represent 'state intervention' and 'level of corruption', we can try to interpret the data in that context. Here is some evidence: there seems to be an inverse trend between the two series (Fig. 14). That is, when state intervention is high, the

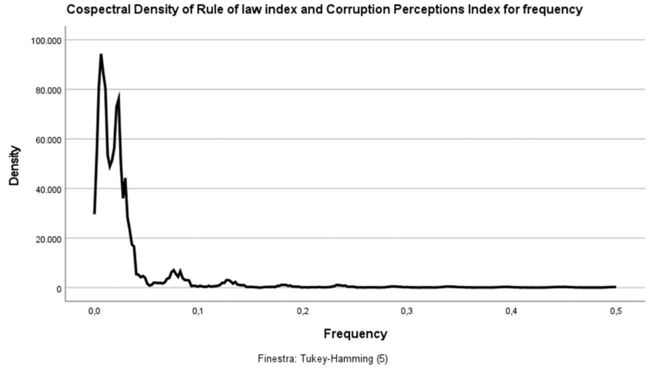

Fig. 11. Cospectral density of the rule of law index and corruption perception index per frequency.

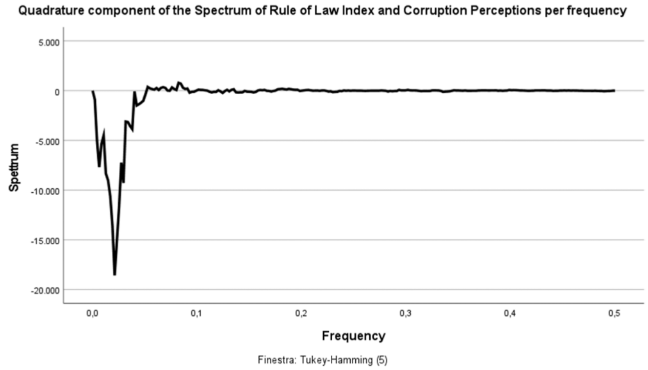

Fig. 12. Quadrature component of the rule of law index and corruption perception index per frequency.

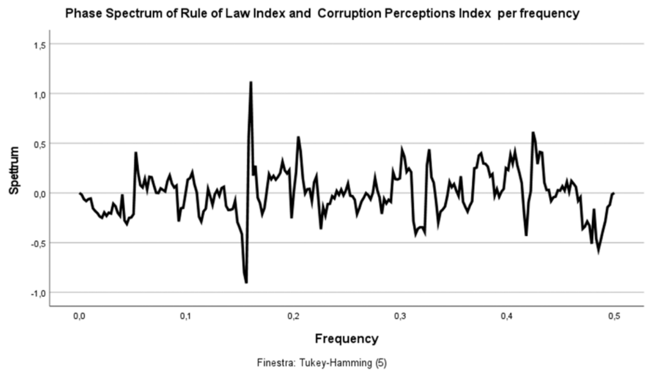

Fig. 13. Phase spectrum of rule of law index and corruption perceptions index per frequency.

level of corruption tends to be low and vice versa. This might suggest that greater state intervention might have a reducing effect on corruption. However, correlation does not necessarily imply causation, so further investigation would be necessary to establish a causal relationship.

a) Both series show variations over time. This indicates that neither state intervention nor the level of corruption has been constant over the time period represented by the data. These fluctuations could be influenced by various external factors, political, economic, social or other significant events.
b) If there are particular periods in which peaks or troughs in both state intervention and the level of corruption are observed, it might be useful to correlate them with specific historical or political events. This could provide a better understanding of the reasons for such variations.

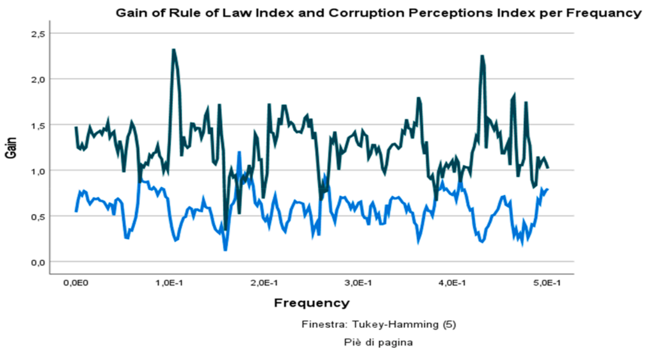

Fig. 14. Gain of rule of rule of law index and corruption perceptions index per frequency (Independent series (Rule of Law) on dependent series (Corruption perceptions index) in green, dependent series (Corruption perceptions index) on independent series (Rule of Law) in azure).

Spectral coherence (Fig. 15) is a statistically normalized measure that indicates how consistent two time series are in frequency. Values vary between 0 and 1, where 1 indicates perfect consistency (or linearity) between the two series for a specific frequency, while 0 indicates no consistency. Values closer to 1 suggest a strong consistency between the two time series at that specific frequency. This means that there is a consistent linear relationship between the two series for that frequency. Average values, approximately 0.5 or slightly higher, indicate moderate consistency between the series. There may be other factors influencing the series, or the relationship may not be perfectly linear. Low values, close to 0, indicate low consistency, suggesting that the two time series are not linearly related at that frequency. An analysis of the data shows that there are periods where the coherence is high (close to 1), indicating that the two time series are strongly correlated at those frequencies. There are also periods with medium and low values, suggesting that the two series may not be strongly correlated in those frequencies or that other variables may interfere with the relationship. From an economic point of view, a strong consistency between two time series could indicate a cause—effect relationship or a common dependence on external factors. However, it must be said that the notion of 'causality' in this context is specific and does not imply a causal relationship in the traditional sense. Instead, it refers to the ability of one set to 'predict' or 'precede' another set. Granger causality, which describes the concept expressed above, is a statistical technique used to determine whether one time series can predict another time series. It is important to note that even if one variable 'causes' another in the Granger sense, this does not necessarily imply a causal relationship in the traditional sense. Granger causality is only a measure of temporal precedence and predictive ability. By subjecting the data of the two time series to the Granger causality test, we obtain the following results:

Analyzing them in detail, it can be seen that:

1. Series L→C

o Min lag: 20

- You used a minimum delay of 20 periods in the test for the L series, indicating that you are considering variations in the L series up to 20 periods ago to see if they affect the predictions of the C series in the present.

o **p value:** 0,0001

- This value is very low and indicates that the past information of the L series contains useful information for predicting the C series in the sense of Granger.

o Series **C→L**:
o **Min lag:** 1

- Here, you have used a minimum delay of 1 period in the test for the C series, which indicates that you are considering changes in the C series 1 period ago to see if they affect the L series predictions in the present.

o **p value:** 0,0002

- This value is also very low, suggesting that the past information of the C series contains useful information for predicting the L series in the sense of Granger.

The results show a two-way relationship between the L- and C-series in Granger's sense. Past variations in the L series help predict the C series, and vice versa, past variations in the C series help predict the L series. However, it is important to note the differences in the delays. While the L-series seems to have an influence on the C-series predictions with a lag of 20 periods, the C-series affects the L-

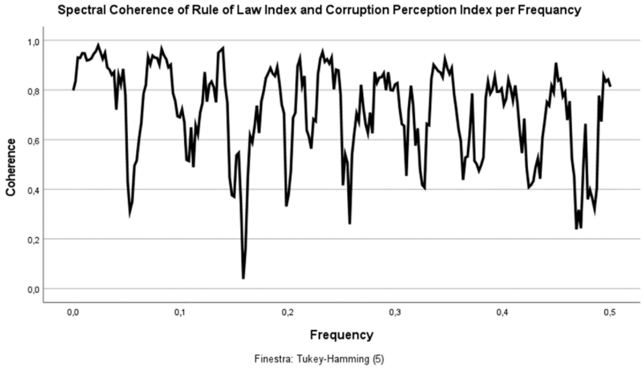

Fig. 15. Spectral coherence of the rule of law index and corruption perception index per frequency.

series predictions with a lag of only 1 period. This asymmetry could have interesting implications depending on the context of the series. This means that changes in state intervention against corruption take 20 periods to influence the level of corruption, but an increase in corruption has an almost immediate impact on state intervention. The spectral analysis as a whole thus confirms the periodic and cyclical nature of the relationship between perceived corruption and the intensity of state repressive action. The spectral analysis confirms, therefore, the results of the theoretical model with reference to the interdependence of the two variables. In fact, while the increase in state intervention as corruption increases is almost immediate, the return to a lower level of corruption following intervention needs a longer time interval. In the former case, in fact, we have a decision that stems only from the observation of a high level of perceived corruption, whereas even stronger anti-corruption policies need a certain time lag to bring corruption back to a lower level.

4.2. A Machine learning experiment

Only recently have machine learning techniques been developed to address aspects of the economics of crime and corruption. These methods are very useful and generate interesting results both in terms of explanatory capacity and robustness. De Blasio et al. [15] tried to predict corruption-related crimes in Italian municipalities in the period 2012–2014 and succeeded in predicting crimes with an accuracy ranging between 70 and 80 percent. López-Iturriaga, Sanz [26] developed an early warning system based on a neural network approach to predict public corruption in Spain based on economic and political factors. This prediction is important because, from a policy point of view, corruption must be detected as soon as possible so that corrective and preventive measures can be implemented. The paper by Lima, Delen [25] presented a predictive analysis to discover the most important corruption perception predictors. Aldana et al. [4] studied a machine learning model to understand and predict corruption in the public sector in Mexico. Ash et al. [8] applied machine learning tools to detect local-government corruption using budget accounts data in the context of Brazilian municipalities. Walczak [40] used neural networks for forecasting crime and other police decision-making problem solving.

In this paper, it seemed appropriate to reinforce the results obtained from the spectral analysis by developing a classification of the level of corruption between different countries using machine learning techniques to identify whether there are evolutionary paths of corruption between countries.

Table 4
Contribution (analysis of variance).

Variable	DF (Model)	Mean squares (Model)	DF (Error)	Mean squares (Error)	F	Pr > F
Law Index 2021	3	6752.706	108	27.162	248.609	**< 0.0001**
Law Index 2020	3	6589.159	108	25.250	260.957	**< 0.0001**
Law Index 2019	3	6627.672	108	24.782	267.439	**< 0.0001**
Law Index 2017/18	3	6603.620	108	24.597	268.474	**< 0.0001**
Law Index 2016	3	6828.769	108	23.080	295.877	**< 0.0001**
Law Index 2015	3	6213.746	108	18.934	328.184	**< 0.0001**
Law Index 2014	3	6270.402	108	19.053	329.101	**< 0.0001**
CPI 2021	3	11,766.268	108	27.259	431.647	**< 0.0001**
CPI 2020	3	11,723.485	108	28.205	415.657	**< 0.0001**
CPI 2019	3	11,833.938	108	26.949	439.128	**< 0.0001**
CPI 2018	3	12,159.442	108	23.888	509.015	**< 0.0001**
CPI 2017	3	12,158.938	108	25.610	474.770	**< 0.0001**
CPI 2016	3	12,488.775	108	27.640	451.830	**< 0.0001**
CPI 2015	3	13,172.046	108	37.109	354.951	**< 0.0001**
CPI 2014	3	12,582.112	108	40.310	312.136	**< 0.0001**
CPI 2013	3	12,882.540	108	43.179	298.349	**< 0.0001**
CPI 2012	3	12,804.713	108	45.416	281.940	**< 0.0001**

Therefore, a further step in the empirical analysis can be achieved by applying machine learning techniques to the data. In particular, an unsupervised algorithm, the K-means, will be used. In this case, homogeneous clusters can be built from the data set for the individual states.

Unsupervised clustering algorithms of the K-means type calculate centroids and iterate the process until the optimal centroid is found. The optimal solution is found when classes are assigned to the cluster at a minimum value of the centroid and the sum of the squared distances.

The results are shown in Table 4, Table 5, Fig. 16, Fig. 17, Fig. 18.

The silhouette score analysis shows that almost all the data are in the positive quadrant and are close to 1, a sign that the country assignments are correct. The profile plot shows that the number of clusters represents a good description of the empirical evidence. Analysis of the variance of the data shows us that the data are quite robust.

Looking at the details of the clustering, it is possible to characterize the four clusters as follows.

Cluster 1. This is the cluster of countries with low values of judicial efficiency and high values of corruption. This is the cluster of countries with high corruption.

Cluster 2. This is the cluster of countries with medium-high levels of corruption and medium-low levels of judicial efficiency. This is the cluster of countries with emerging corruption.

Cluster 3. This is the cluster of countries with high levels of judicial efficiency and low levels of corruption. This is the cluster of

Table 5
Results by cluster.

Cluster	1	2	3	4
Number of objects by cluster	34	42	19	17
Sum of weights	34	42	19	17
Within-cluster variance	477.341	381.299	646.209	608.280
Minimum distance to centroid	7.420	7.627	7.667	6.821
Average distance to centroid	18.938	17.451	22.527	22.442
Maximum distance to centroid	50.389	34.442	39.049	38.733
	Afghanistan	Albania	Australia	Bahamas
	Bangladesh	Argentina	Austria	Barbados
	Bolivia	Belarus	Belgium	Botswana
	Cambodia	Benin	Canada	Chile
	Cameroon	Bosnia and Herzegovina	Denmark	Costa Rica
	Cote d'Ivoire	Brazil	Estonia	Czechia
	Dominican Republic	Bulgaria	Finland	Dominica
	Ecuador	Burkina Faso	France	Georgia
	Egypt	China	Germany	Grenada
	Ethiopia	Colombia	Hong Kong	Italy
	Guatemala	Croatia	Japan	South Korea
	Honduras	El Salvador	Netherlands	Mauritius
	Iran	Ghana	New Zealand	Poland
	Kazakhstan	Greece	Norway	Portugal
	Kenya	Guyana	Singapore	Slovenia
	Kyrgyzstan	Hungary	Sweden	Spain
	Lebanon	India	United Kingdom	United Arab Emirates
	Liberia	Indonesia	United States of America	
	Madagascar	Jamaica	Uruguay	
	Mali	Jordan		
	Mauritania	Malawi		
	Mexico	Malaysia		
	Myanmar	Moldova		
	Nepal	Mongolia		
	Nicaragua	Morocco		
	Nigeria	North Macedonia		
	Pakistan	Panama		
	Russia	Peru		
	Sierra Leone	Philippines		
	Uganda	Romania		
	Ukraine	Senegal		
	Uzbekistan	Serbia		
	Venezuela	South Africa		
	Zimbabwe	Sri Lanka		
		Suriname		
		Tanzania		
		Thailand		
		Trinidad and Tobago		
		Tunisia		
		Turkey		
		Vietnam		
		Zambia		

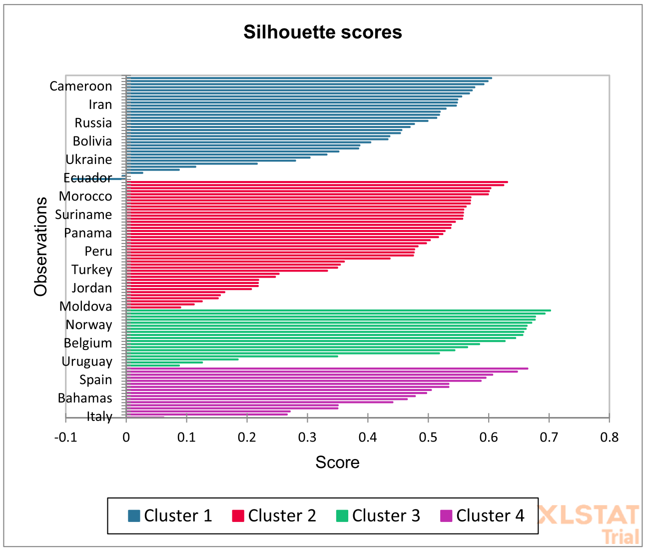

Fig. 16. Silhouette score.

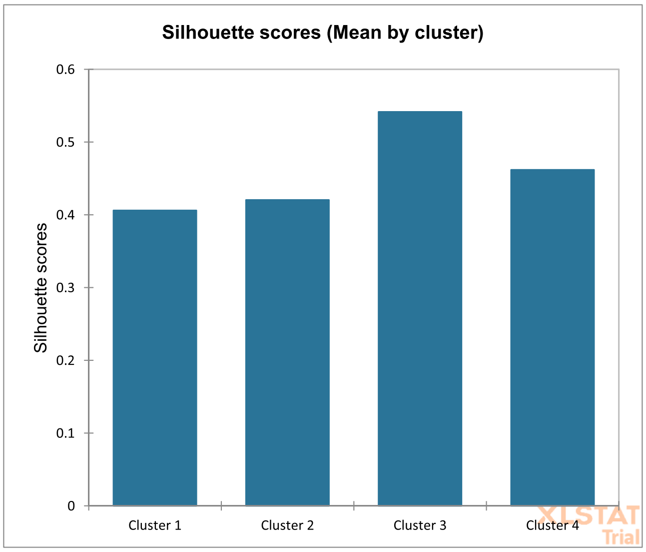

Fig. 17. Silhouette score (mean by cluster).

virtuous countries.

Cluster 4. This is the cluster of countries with medium levels of corruption and medium levels of judicial efficiency. This is the cluster of countries with transition corruption, in the sense that they are in a situation where they can take a virtuous path and become virtuous countries or make the transition to become countries with emerging corruption.

5. Discussion and conclusions

The theoretical model outlined is intended to constitute a kind of microeconomic foundation for explaining the cycle of corruption. The empirical analysis makes use of two quite innovative tools, even though they are still relatively little used within empirical studies with an economic slant, albeit they have been widely used in other fields of research.

The empirical tests aim to analyze cyclicality from two different perspectives. The spectral analysis aims to identify short-term dynamics, that is, those that relate corruption levels to point changes in law enforcement policies. The classification performed with machine learning, on the other hand, tends to highlight the structural elements of corruption levels that generally have a longer-term perspective. Combining these two aspects makes it possible to capture the dynamics of corruption more comprehensively. While it is true that corruption exhibits a short-term cyclical behavior that depends mainly on the variation of the country's level of

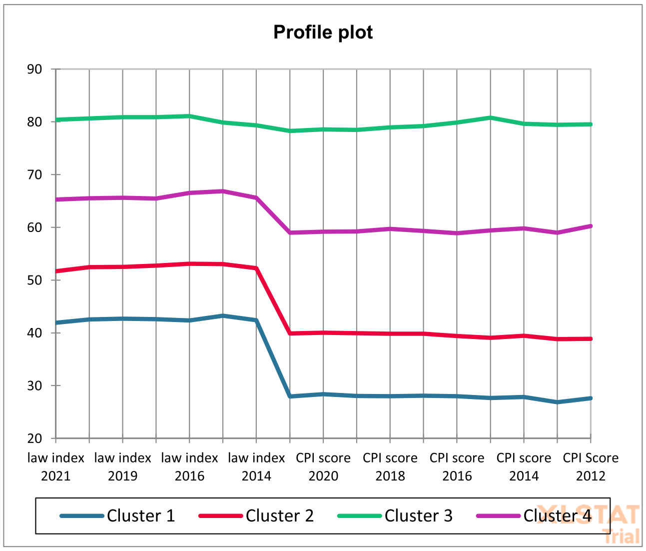

Fig. 18. Profile plot.

corruption and on the policies, while it is quite independent of the levels, nevertheless this cyclical behavior can exhibit an upward or downward trend, and it is this upward or downward path in the level of corruption that determines the placement of countries in the clusters highlighted in the previous paragraph.

From the point of view of the robustness of the data, it should be noted that the values of Fisher's Kappa and Bartlett's Kolmogorov—Smirnov tests show that the results are quite robust. Granger's causality test reinforces the previous conclusions by identifying a relationship between the level of perceived corruption and state intervention. The classification made through the machine learning tool also proves to be quite robust, as one can easily deduce from the silhouette score and highlights how alongside a cyclical behavior of corruption, one can also glimpse a path of historical evolution that leads countries from situations where there are high levels of corruption to situations where the level of corruption remains lower, a sign that the real dynamic is not trivially that of a closed cycle but rather of a cycle that varies within an evolutionary path to reach different states characterized by different levels of corruption. The election cycle may also play a significant role. If we consider corruption as a phenomenon influenced by political decisions, it is plausible that the phases of the election cycle influence corruption levels. For example, in preelection periods, there may be an increase in corruption activities if the incumbent government seeks to secure support through favors, procurement, or other forms of bribery. Similarly, once elected, new administrations might undertake rigorous anti-corruption measures to demonstrate their commitment to integrity and transparency, especially if fighting corruption was one of their election promises. Alesina et al., [32,5,31,36]. However, it must be emphasized that the perceived cost of illegal behavior also contains a component related to the fear of social disapproval, so to achieve a substantial decrease in corruption, it is necessary to work with different policies that are not only restrictive. It is necessary to create a mechanism that generates social disapproval of corruption because, at first glance, it would seem that when corruption levels are high, corruption is accepted almost as a necessary evil. Focusing only on the stiffening of penalties may be unproductive because unless solid and shared social disapproval mechanisms are introduced, targeting bribe givers and bribe receivers, tangible results will not be achieved. This finding has profound implications for the design of anti-corruption policies. Since corruption is both cyclical and evolutionary in nature, law enforcement strategies must not only recognize and adapt to these cycles but also facilitate the transition from high to lower levels of corruption. In other words, it is crucial that policies not only counterbalance the cycle of corruption but also actively guide society toward a state of less corruption. Future research advances could deal with more explicitly incorporating considerations of the electoral cycle and the role of social disapproval into the theoretical model to be able to analyze the empirical evidence in this light as well.

Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

I sincerely thank the referees for their helpful suggestions, which have improved the quality of this paper.

Data Availability

Data will be made available on request.

References

[1] S. Abbas, J.P. Tripathi, A.A. Neha, Dynamical analysis of a model of social behavior: criminal vs non-criminal population, Chaos Solitons Fractals 98 (2017) 121–129.
[2] E. Accinelli, et al., The power of voting and corruption cycles, J. Math. Sociol. 46 (2022) 1. ISSN: 0022-250X.
[3] T.S. Aidt, Economic analysis of corruption: a survey, Econ. J. R. Econ. Soc. 113 (491) (2003) 632–652. ISSN 0013-0133.
[4] A.J. G. Aldana, A. Falcon-Cortes, H. Larralde, A machine learning model to identify corruption in México's public procurement contracts, arXiv.org (2022), https://doi.org/10.48550/arXiv.2211.01478 abs/2211.01478.
[5] A. Alesina, F.R. Campante, G. Tabellini, Why is Fiscal Policy Often Procyclical?, in: Journal of the European Economic Association, 6 MIT Press, 2008, pp. 1006–1036, 09 ISSN 1542-4766.
[6] J.C. Andvig, How corruption may corrupt, J. Econ. Behav. Organ. 13 (1) (1990) 63–76. ISSN 0167 2681.
[7] Arnone, M. & Iliopulos, E. (2005). La corruzione costa. Vita e Pensiero.
[8] E. Ash, S. Galletta, T. Giommoni, A machine learning approach to analyzing corruption in local public finances, Cent. Law Econ. Work. Pap. Ser. 6 (2020).
[9] J. Bai, et al., Firm growth and corruption: empirical evidence from Viet man, Econ. J. 129 (618) (2019) 651–677. ISSN 0013-0133.
[10] G.S. Becker, Crime and punishment: An economic approach, J. Political Econ. 76 (2) (1968) 169–217. ISSN 0022 3808.
[11] C. Bicchieri, J. Duffy, Corruption cycles, Political Stud. XLV (1997) 477–495. ISSN:1467-9248.
[12] K. Blackburn, K.C. Neanidis, M.A. Rana, A theory of organized crime, corruption and economic growth, Econ. Theory Bull. 5 (2017) 227–245. ISSN 2196-1085.
[13] Cressey, D. (1969). Theft of the nation. Report for the President Commission on Law Enforcement and Administration of Justice.
[14] Cunnyngham, J., (1963), The Spectral analysis of economic time series, US Dep. of Commerce, Bureau of the Census.
[15] G. de Blasio, A. D'Ignazio, M. Letta, Gotham city. Predicting 'corrupted' municipalities with machine learning, Technol. Forecast. Soc. Change 184 (2022) 122016, https://doi.org/10.1016/j.techfore.2022.122016. ISSN 0040-1625.
[16] Paul Ekblom, Can we make crime prevention adaptive by learning from other evolutionary struggles?. Stud. Crime. Crime. Prev. 8 (1999) 27–51.
[17] G. Feichtinger, F. Wirl, On the stability and potential cyclicity of corruption in governments subject to popularity constraints, Math. Soc. Sci. 28 (2) (1994) 113–131. ISSN 0165 4896.
[18] J.K. Galbraith, The Great Crash, Mariner Books, Boston, 1961, p. 1929.
[19] O. Gokcekus, Y. Suzuki, Business cycle and corruption, Econ. Lett. 111 (2) (2011) 138–140. ISSN 0165 1765.
[20] C.W.J. Granger, M. Hatanaka, Spectral Analysis of Economic Time Series. (PSME-1), Princeton University Press, 1964.
[21] C.W.J. Granger, O. Morgenstern, Spectral analysis of New York stock market prices, KYKLOS 16 (1) (1963) 1–27. ISSN 1467 6435.
[22] K. Gründler, N. Potrafke, Corruption and economic growth: new empirical evidence, Eur. J. Political Econ. 60 (C) (2019).
[23] M. Hatanaka, A Spectral Analysis of Business Cycle Indicators: Lead-lag in Terms of All Time Points. Econometric Research Program, Princeton Research Memorandum, Princeton University, US, 1963, p. 53.
[24] A. Hirschman, Shifting Involvements, Princeton University Press, Princeton, 1982.
[25] Marcio Lima, Dursun Delen, Predicting and explaining corruption across countries: a machine learning approach, Gov. Inf. Q. (2019) 37. ISSN 0740 624X.
[26] F.J. López-Iturriaga, I.P. Sanz, Predicting Public Corruption with Neural Networks: An Analysis of Spanish Provinces,, in: Social Indicators Research: An International and Interdisciplinary Journal for Quality-of-Life Measurement, 140, Springer, 2018, pp. 975–998. ISSN 0303 8300.
[27] I. Luna-Pla, J.R. Nicolás-Carlock, Corruption and complexity: a scientific framework for the analysis of corruption networks, Appl. Netw. Sci. 5 (2020) 1–18, https://doi.org/10.1007/s41109-020-00258-2.
[28] Marino D., Gil Lafuente J., Timpano F., (2023), The competition between legal and illegal firms in the market: theoretical model and empirical evidences, European Review of Management and Business Economics, ISSN 2444-8842.
[29] Marino, D., & Tebala, D., (2019), Una misurazione sintetica della corruzione: un'applicazione alle regioni italiane, EyesReg, Vol.9, N.4, ISSN 2239-3110.
[30] Nerlove, Spectral analysis of seasonal adjustment procedures, Econometrica 32 (3) (1964) 241–286. ISSN 0012 9682.
[31] T. Persson, G. Tabellini, F. Trebbi, Electoral rules and corruption, ISSN 1542-4766, J. Eur. Econ. Assoc. 1 (4) (2003) 958–989, https://doi.org/10.1162/154247603322493203.
[32] N. Potrafke, Electoral cycles in perceived corruption: international empirical evidences, J. Comp. Econ. 47 (1) (2019) 215–224.
[33] S. Rose-Ackerman, The economics of corruption, J. Public Econ. 4 (2) (1975) 187–203. ISSN 0047 2727.
[34] S. Rose-Ackerman, Corruption: A Study in Political Economy, Academic Press, 1978.
[35] J. Sooknanan, B. Bhatt, D.M.G. Comissiong, A modified predator–prey model for the interaction of police and gangs, R. Soc. Open Sci. 3 (9) (2016) 160083.
[36] V. Tanzi, Corruption around the world: causes, consequences, scope, and cures, IMF Econ. Rev. 45 (4) (1998) 559–594. ISSN 2041 417X.
[37] D. Treisman, The causes of corruption: a cross-national study, J. Public Econ. 76 (3) (2000) 399–457. ISSN 0047 2727.
[38] A. Vannucchi, Three paradigms for the analysis of corruption, ISSN 2421 2695. Labour Law Issues 1 (2) (2015) https://doi.org/10.6092/issn.2421-2695/5468.
[39] A. Vespignani, Modelling dynamical processes in complex socio-technical systems, Nat. Phys. 8 (1) (2012) 32–39. ISSN 1745 2473.
[40] S. Walczak, Predicting crime and other uses of neural networks in police decision making, Front. Psychol. 12 (2021). ISSN=1664 1078.
[41] K. Wiesner, A. Birdi, T. Eliassi-Rad, H. Farrell, D. Garcia, S. Lewandowsky, P. Palacios, D. Ross, D. Sornette, K.P.Y. Thebault, Stability of democracies: a complex systems perspective, ISSN 0143 0807, Eur. J. Phys. 40 (1) (2018), https://doi.org/10.1088/1361-6404/aaeb4d.