Small-World
Networks of Corruption*

La corrupción en redes
de mundo pequeño

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Abstract

Collective behavior forms and spreads through social contact. This thesis introduces a framework for understanding how the structure of social ties may impact the evolution of bribery. We represent relationships as highly clustered networks with small characteristic path lengths (i.e., small-world models which have 'local' and 'long-range' contacts). Based on a principal-agent-client formulation, our model focuses on the effects of clustering on an equilibrium of persistent bribery. Collective outcomes depend on decision-making mechanisms that rely on sensitivity functions, which capture the level of influence between local contacts. Moreover, we represent the evolution of the network

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as a system of differential equations and identify its region of parameters for which the equilibrium of persistent bribery is stable. Our results show that an increase in clustering tends to decrease the levels of bribery. A more sensitive response to the behavior of neighbors, on the other hand, tends to increase bribery, but only up to a certain point. Beyond this threshold, the expected level of bribery remains constant, despite variations in the structural properties of the network.

Keywords: Corruption, local decision-making, small-world networks.

Classification JEL: C02, D7, D73, D85

Resumen

El comportamiento colectivo se forma y se propaga a través de contactos sociales. Esta tesis introduce un marco teórico para comprender cómo la estructuración de los lazos sociales puede impactar la evolución del soborno. Se representa las relaciones como redes altamente agrupadas y caracterizadas por pequeñas longitudes de paso (es decir, los modelos de mundo pequeño, que contienen contactos 'locales' y de 'largo alcance'). Basándose en una formulación del tipo principal-agente-cliente, el modelo presentado se centra en los efectos del agrupamiento en un equilibrio de soborno persistente. Los resultados colectivos dependen de los mecanismos de toma de decisiones, que a su vez, se basan en funciones de sensibilidad que captan el nivel de influencia entre los contactos locales. Por otra parte, se representa la evolución de la red como un sistema de ecuaciones diferenciales y se identifica una región paramétrica, dentro de la cual el equilibrio de soborno persistente es estable. Los resultados muestran que un aumento en la agrupación tiende a disminuir los niveles de soborno. Por otro lado, una respuesta más sensible al comportamiento de los vecinos tiende a aumentarlo, pero sólo hasta cierto punto. Más allá de este umbral, el nivel esperado de soborno permanece constante, a pesar de las variaciones en las propiedades estructurales de la red.

Palabras clave: corrupción, toma de decisiones locales, redes de mundo pequeño..

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1. Introduction

Network representations provide analytical frameworks to study the relationships between individual decision-making and group behavior at higher levels of abstraction (i.e., macro-outcomes). When data collection is costly (either in terms of time or money (Louie & Carley, 2008;Armantier & Boly, 2008)), it is useful to design experiments based on the implications of analytical results (Hammond, 2000;Guerrero, 2011; Epstein, 1999; Abbink, 2004; Wang & Zhang, 2008; Lambert, Majumdar & Radner, 2007; Blanchard, Krueger, & Martin, 2005). In particular, in evaluating anti-corruption strategies it is of interest to characterize the economy of influences underlying the offer and acceptance of bribes in contact networks. Efforts to understand what factors influence these networks have focused on two properties[1]: (i) the proportion of links grouped into local neighborhoods (clustering); and (ii) the expected number of links that separates any two individuals (average path length)[2]. Understanding the impact of both properties on the collective behavior of bribery is a first step in moving from theoretical concepts to field experiments that attempt to validate and take into account the effects of social structures. Our aim is to illustrate how macro-outcomes resulting from similar local incentives strongly depend on the underlying network structure.

The principal-agent-client formulation is a useful representation of an economy of influences, e.g., among shareholders, investors, or government officials (Busquets, 2003). It illustrates the interaction between a third party (the client) and an individual (the agent), who is responsible for advancing the purpose of an institution (the principal)[3]. A conflict of interest represents an improper dependence between clients and agents. It can be viewed as a condition of asymmetric information, which distinguishes between how the principal expects an agent to service a client and the actual intentions and interactions between them (Ross, 1973; Nyberg, Fulmer, Gerhart, & Carpenter, 2010) (see Figure 1)[4]. An event where conflicts of interest induce an agent to behave in ways that go against the interest of the principal is considered an act of corruption (e.g., bribery).

1 Here we focus on small-world networks (Watts & Strogatz, 1998; Wan & Chen, 2008; Newman, 2003). The property of small-world, introduced by (Milgram, 1967), implies that the average number of intermediate steps between a pair of nodes is relatively small compared to the size of the network. Examples of small-world social networks can be found in (Girvan & Newman, 2005; San Miguel, Toral, & Eguiluz, 2005; Bjrneborn, 2004).

2 Clustering, also known as transitivity, is a topological property of the network, which represents the probability that two nodes who are connected to a third node are connected to each other, as in the saying, that friend of your friend is likely as well to be one's friend. Clustering captures the presence of a heightened number of triangles in the network. Average path length is a measure of the average shortest number of links among nodes at a network. Short paths imply quicker flows (Newman, 2003).

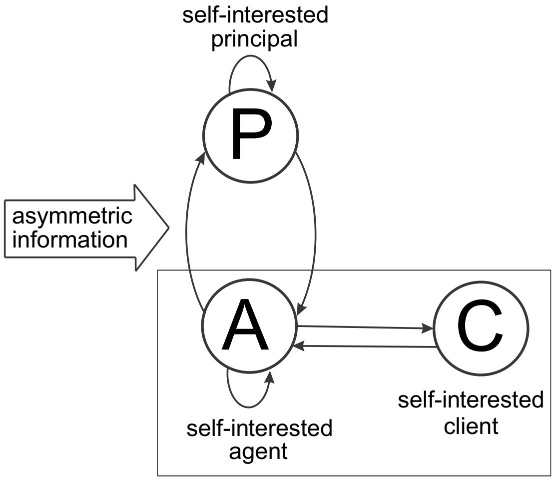
3 For example, the model introduce by Klitgaard (1988) considers a scenario where the principal is a regulator, the agent is an inspector, and the client is a firm.

4 Various mechanisms can be used to try to align the interests of the principal with the agent, for example, commissions, profit sharing, generous wages. Such problems are generally divided into three categories, depending on the imperfection of information: adverse selection, moral risk, and signaling (Eisenhardt, 1989; Brickley, Dark, & Weisbach, 1991).

REVISTA
CIFE 26
ISSN: 0124-3551 / Año 17, No 26 / enero-junio / pp. 19-35

The following scenario views the interaction dynamics between agents and clients as a network in which nodes represent individuals (either agents or clients) and links connect any two acquaintances.

Figure 1: The principal-agent-client formulation



Let the probability that any two individuals interact (e.g., engage in a transaction) be random, but constrained according to the topology of this contact network. An individual (the client) may offer a bribe to a neighbor (the agent), who in turn may accept or reject it. Under what conditions will there be a constant offering and acceptance of bribes (i.e., an equilibrium of persistent bribery)? Does the structure of the network affect the incentives of agents or clients? What type of enforcement mechanisms seems to minimize bribery?

To try to address these questions, we characterize four possible state transitions for the clients. First, as long as a client does not make an offer, he is considered a law-abiding individual. Second, trying to bribe an agent turns a client into a proposer. Third, if the agent accepts the offer, then the client becomes an offender. Finally, if the bribe is uncovered (according to a random process), the client becomes a detected offender. This simple scenario allows us to theorize about bribery, but perhaps more importantly, it will facilitate the characterization of the evolution of the contact network as a linear time-invariant model. As we will see below, the equation-based representation is useful to identify conditions, which enable state transitions that favor persistent bribery (Lerman & Galstyan, 2004).

To evaluate how incentives may vary depending on the local contact structure of individuals, we introduce two subjective parameters. These parameters represent the probability of a bribe being uncovered and the probability of a successful getaway after agreeing to an offer. They underlie the local mechanisms of decision-making and capture an individual's perception of a deal based on his relative position within the network. The different mechanisms try to capture indifferent, moderate, and extreme micro-behavior.

The proposed *network model* serves, on the one hand, as a tool to model the local interaction between individuals (i.e., the presumed relationships between agents and clients). The equation-based model, on the other hand, allows us to explore different values in its parameter region. Specifically, it identifies domains of stability for certain parameters. Combined, the proposed analytical framework takes advantage of both perspectives to quantify of the effects of network structure on the dynamics of bribery.

2. Methodology

2.1. Theorizing bribery as a social game

This section describes two models that aim to capture the set of incentives underlying the dynamics of bribery between clients and agents at different levels. While the network model describes the collective behavior of clients based on a game theoretic framework, the equation based model focuses on the dynamics around an equilibrium point of persistent bribery. The payoff associated to an interaction depends on the actions of both players. Figure 2, shows the possible actions of each player and its payoffs.

Suppose that a client decides to offer an agent a bribe. If the agent accepts and the bribe goes undetected both offenders receive a payoff of $a > 0$. There is, however, a probability $\pi > 0$ that the bribe is uncovered, in which case the detected offenders receive a payoff of zero. In any other way, both offenders receive a payoff of b, where $b < a$. All payoffs are summarized in Table 1, where the payoff is always the same for agents and clients.

Table 1: The payoff matrix shows the possible decisions of individuals and their payoffs. If $(1-\pi)\,a > b$, then engaging in bribery represents a Nash equilibrium. At the Nash neither the client nor the agent benefit by unilaterally adopting another strategy (Holt &Roth, 2004).

	Client	
Agent	approves bribery	refuses bribery
approves bribery	$((1-\pi)a,(1-\pi)a)$	(b,b)
refuses bribery	(b,b)	(b,b)

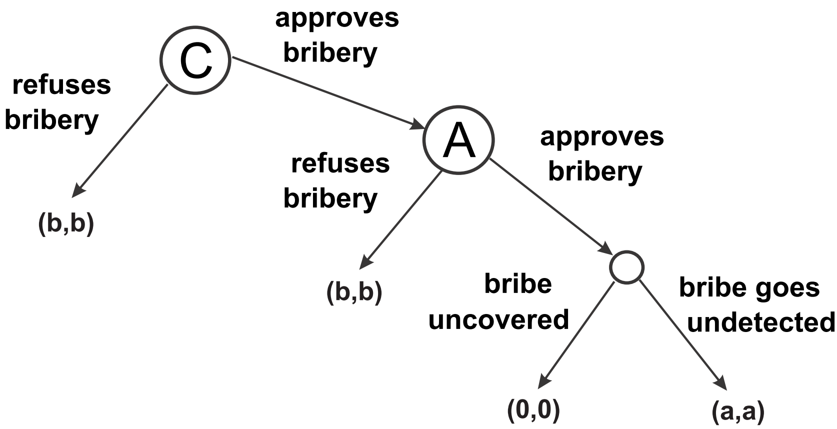
REVISTA CIFE 26
ISSN: 0124-3551 / Año 17, No 26 / enero-junio / pp. 19-35

2.2. A network model of the evolution of bribery

Let $\mathcal{N} = (H, W)$ represent the contact network, where $H = \{1,\ldots,n\}$ denotes a set of agents and clients. Acquaintanceship is represented by the set of undirected edges $W = \{\{i,j\}: i,j \in H\}$. An edge $\{i,j\}$ indicates that individuals i and j may interact at some point in time. Formally, the finite game is defined by $(\mathcal{N}, S, U)$. The set $S = S_C \times S_A$ represents the action profiles (for clients and agents), with $S_C = S_A = \{$*approves bribery,refuses bribery*$\}$. Finally, $U = \{a,b\}$ is the set of payoffs for both agents and clients.

Clients and agents make decisions based on the utility function defined by Equation 2.1[5]. Utility captures the motivation (incentive) to engage in bribery and depends on the payoffs in Figure 2, and two locally-assessed variables. The variable m_f is a subjective parameter that represents

Figure 2: A game-theoretic framework. The arrows represent the possible decisions by the agents and clients or that bribe is uncovered (with probability π). The values in parentheses represents the payoffs (when (1-π)a>b>0 bribing represents a Nash).



an individual's fear of being discovered based on the number of bribes detected in his neighborhood in the previous time instant. The variable m_c represents an individual's desire to engage in bribery based on the number of neighbors who offered a bribe in the previous time-step without being detected.

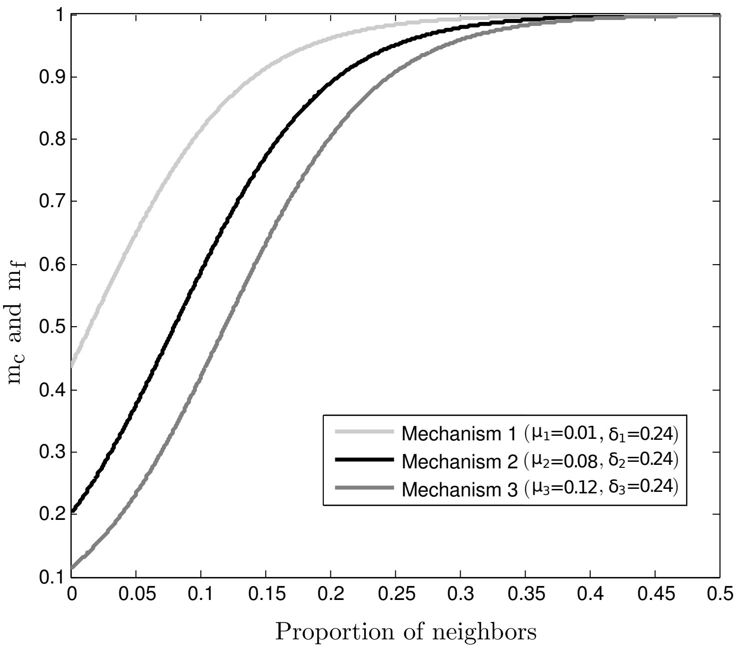
If a bribe is uncovered, detected offenders refrain from further illegal activity for k time steps. Whether to propose or agree to a bribe depends on satisfying the condition r > b, where

5 This equation is introduced by Hammond (2000) as part of a game-theoretic framework of corruption that focuses on the analysis of endogenous social transition from a high-corruption to a low-corruption state.

$$r = (1 - m_c)\,(m_f\,(1 - h)\,a + (1 - m_f)\,b) + m_c\,(b - kb) \quad [2.1]$$

In particular, for a client, the utility value r captures the benefit of offering a bribe. For an agent, it captures the value of accepting the proposal. The values of m_c and m_f are determined by a sensitivity function that captures the local interaction, which is influenced by individuals within a neighborhood of radius two. In other words, each agent can sense the actions of his neighbors and the ones of the neighbors of his neighbors. Figure 3, illustrates the general form of these functions (the mean μ displaces the function horizontally, while δ changes its threshold). Finally, the constant h is an index of honesty (characterizing an inherent propensity for honesty), similar to the one introduced by Hammond (2000), and it takes values between 0 (perfect corruption) and 1 (perfect honesty). The utility function described in Equation 2.1 is appropriate for the theoretical game because, in addition to considering the payoffs of the strategies, it relates limited network information of contacts of an individual with subjective factors, for and against bribery, as well as an intrinsic valuation of honesty.

Figure 3: Local decision-making mechanisms. The general form of the local mechanisms are defined as $m = \frac{1}{1+e^{\frac{-1(x-\mu)}{\delta^2}}}$. Here, x can be the proportion of neighbors offenders or detected offenders (depending if is m_c or m_f), and $\delta = 0.24$ for all cases. Mechanism 1 has $\mu_1 = 0.01$, mechanism 2 has $\mu_2 = 0.08$, and mechanism 3 has $\mu_3 = 0.12$. The values of μ and $\delta = 0.24$ allows us to generate three sensitivity functions, which will be useful to analyze different ways of influence of neighbors on the decisions of individuals.

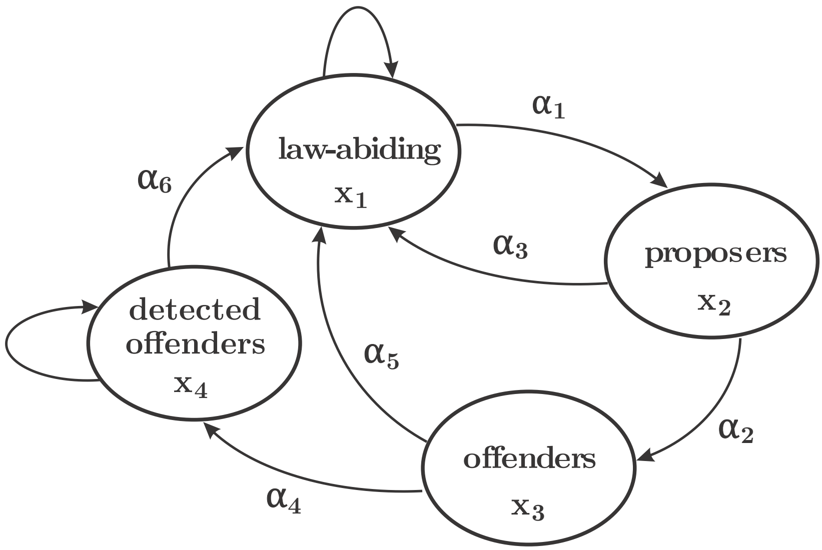


REVISTA
CIFE 26
ISSN: 0124-3551 / Año 17, No 26 / enero-junio / pp. 19-35

Our analysis focuses on the dynamic evolution of the game (*N, S, U*) over time. Broadly speaking, the persistency of bribery can be seen as a macro-outcome resulting from individual decision-making based on Equation 2.1. As the game evolves, bribery levels may increase, decrease or turn stationary. The state vector x = $[x_1, x_2, x_3, x_4]^T$ captures the proportion of clients that are law-abiding, proposers, offenders, and detected offenders. Moreover, let the parameters α_i in Figure 4 describe the transition rates between these states. Note that $\alpha_4 = \pi$.

We considered the proportion of clients that are offenders (i.e., x_3) as the indicator of the level of corruption. Such indicators are very simple in its definition, but in reality difficult to obtain because of the illegal nature involving , hence the importance of a network representation to provide an analytical framework for studying (Del Castillo, 2003; Busquets, 2003). The proportion of clients that are proposers, offenders, and detected offenders indicate the perception of corruption across the population (represented by the variable $p = 1 - x_1$). The state diagram will allows us to quantify the effect of the network structure on the rate of transition between states (i.e., α_i where $0 < \alpha_i < 1$).

Figure 4: State diagram of the state dynamics of clients. The alpha parameters represent the transition rates between states and depend, in general, on both the clustering and the local mechanisms of decision-making.



2.3. An equation-based model of the collective behavior

This section introduces a system of differential equations that allows us to abstract patterns (i.e., the aggregate dynamics of corruption) found in the network model. Most importantly, the macro-outcome across the network can be captured by a time-invariant model of coupled linear equations. Here we focus on the stability properties on an equilibrium of persistent bribery and determine stability domains for the parameters of this model.

Following similar ideas as analyzed by Lerman and Galstyan (2004), the dynamics on the network can be represented as a finite state machine (i.e., a Markov process). In particular, the evolution of the average fraction of clients in each state can be represented by the incoming and outgoing flow of clients[6]. The equation-based model is defined by:

$$\frac{dx_1}{dt} = -\alpha_1 x_1 + \alpha_3 x_2 + \alpha_5 x_3 + \alpha_6 x_4$$

$$\frac{dx_2}{dt} = \alpha_1 x_1 - (\alpha_2 + \alpha_3) x_2$$

$$\frac{dx_3}{dt} = \alpha_2 x_2 - (\alpha_4 + \alpha_5) x_3$$

$$\frac{dx_4}{dt} = \alpha_4 x_3 - \alpha_6 x_4 \qquad [2.2]$$

The constant α_1 represents the average transition rate of individuals from the state of law-abiding to proposers, α_2 from proposers to offender, α_3 from proposers to law-abiding, α_4 from offenders to detected offenders, α_5 from offenders to law-abiding, and finally α_6 from detected offenders to law-abiding individuals.

3. Results

3.1. Simulations

This section illustrates the impact of the topology of the contact network on the dynamics of bribery. Note that individuals do not interact uniformly with each other, their interactions are constrained by network N, which resembles small-world properties of human interaction (Newman, 2003). Based on the work described by Wan and Chen (2008), we assume that the average path length correlates to global clustering coefficient of the network (in particular, the higher the clustering coefficient, the lower the average path length). As a consequence, the network substrates described below are characterized solely by their clustering coefficient, which we denote by c.

At time t = 0, consider all clients to be law-abiding individuals (i.e., $x(0) = [1,0,0,0]^T$). Clients randomly engage in transactions with neighboring agents and may offer bribes

6 Following similar ideas as examinedby Lerman (2003;2004), we derive the Rate Equation, which describes how the average number of individuals at a state s changes over time: $(dQ_s)/dt = \sum_{s'} [T(s|s') Q_{s'}) - T(s'|s) Q_s]$. The transition rate $T(s|s')$ gives the rate at which agents go from performing action s' to action s.

ISSN: 0124-3551 / Año 17, No 26 / enero-junio / pp. 19-35

according to the game (N, S, U) described above. A time-step represent the average period for an individual to make decisions and perceive the ones made by others. A time-step may represent days, weeks, or months.

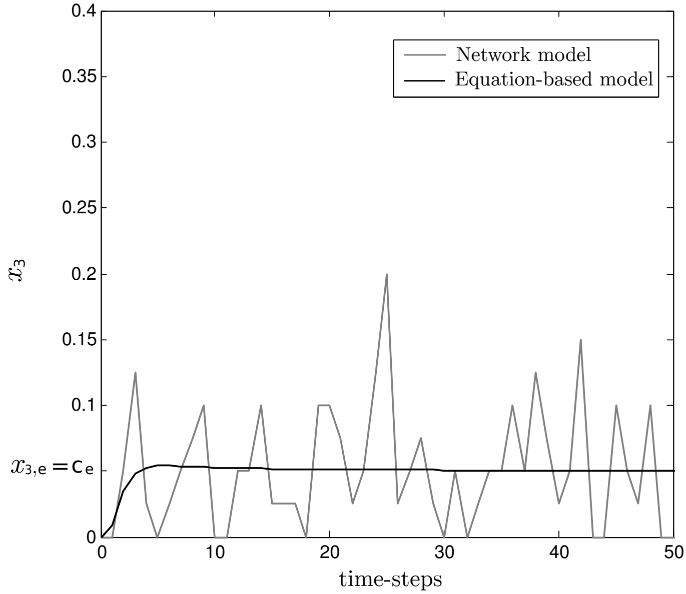
The parameters m_f and m_c specify the utility function r, indicating the particular sensitivity of individuals to their surroundings. An increase in the proportion of detected offenders (or offenders who have not been uncovered) generates a greater response, represented by a greater value of m_c (or m_f). Table 2 summarizes the parameters used for our simulations.

Simulation results take into account networks models, with different values of r and c, and are consistent with the equation-based models. Both types of models show that, from the initial state $x(0) = [1,0,0,0]^T$, the system converges to an equilibrium. Figure 5 shows the simulations of the dynamics on the network. Note that the evolution of bribery has an oscillatory but bounded behavior. The solution to the set of differential equations, based on the average value of the transition rates (i.e., the average value for each α_i for the network model), are also shown on the same plot.

Table 2: Simulation parameters

	Parameter	Value
1	Total number of individuals (n)	100
2	Proportion of clients	0.4
3	Total number of time-steps	50
4	Corruption payoff	20 units
5	Honesty payoff	1 unit
6	Time-out period (k)	8 time-steps
7	Neighborhood radius	2
8	Honesty index	[0.2,0.8] Randomly assigned
9	Parameters m_c, m_f	See Figure 3
10	Differentiable degrees of clustering	152
11	Networks with same clustering	20
12	Total network substrates	3040

Figure 5: Simulations of the network dynamics with a global clustering coefficient of 0.4 and a decision-making mechanism with μ = 0.08.



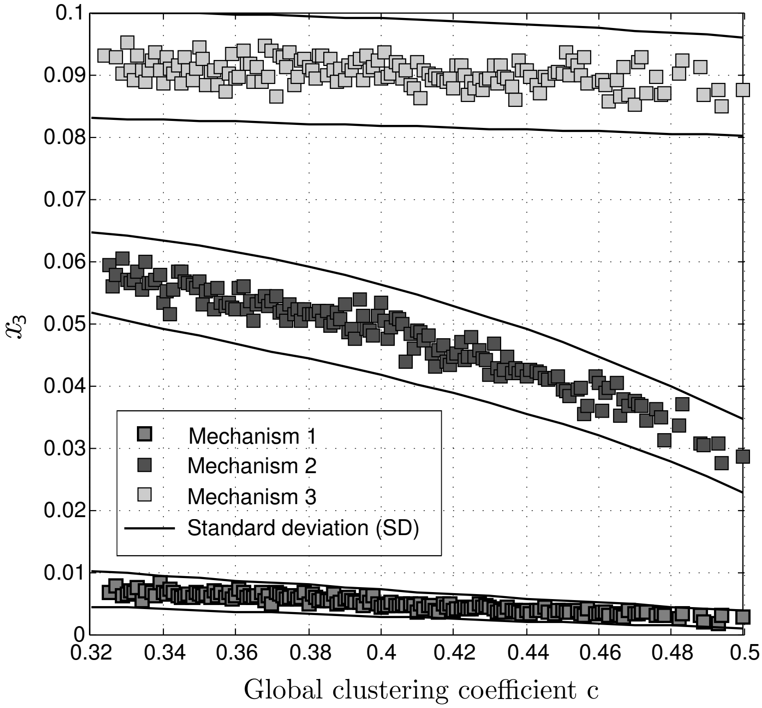
Next, Figure 6 shows the evolution of the level of bribery (x_3) as a function of the clustering coefficient of the network. In general, the network model suggests that greater sensitivity to the actions of neighbors increases the levels of bribery. Note that for mechanism 1, corruption decreases only slightly with increasing clustering, whereas for mechanism 2, corruption is significantly influenced by the structure of the network. Furthermore, for mechanism 3, the value of the sensitivity again overrides the effects of clustering, generating stationary levels of bribery which are independent of the structure. In other words, the expected level of bribery is not significantly affected by clustering. This behavior suggests the existence of a threshold beyond, which clustering ceases to impact the dynamics of bribery.

The maximum effect of clustering on corruption occurs for an intermediate value of μ. Figure 6 also shows that variations in the parameter values of μ may impact the average levels of bribery by up to 9 % (for a fixed clustering coefficient). Variations in the clustering coefficient c may impact the average level of corruption by up to 3 % (for a fixed sensitivity parameter). The impact of both parameters is relevant when considering the difference in payoffs between honest and corrupt behavior. For example, based on our simulations parameters, a valueof $c = 0.06$ means that an average of 2 to 3 clients (out of 40) engage in bribery at each time-step, which gives a total of 120 cases in a period of 50 time-steps. Since the difference between payoffs is 19, the total payoff difference (2280) represents a large economic incentive favoring bribery. Repeating this calculation

ISSN: 0124-3551 / Año 17, No 26 / enero-junio / pp. 19-35

for $c = 0.03$ yields $0.03 \times 40 \times 50 \times 19 = 1140$, a decrease of 50 %. This difference (which may be regarded as the cost of bribery for a more clustered network) is significant if one takes into account that the total payoff associated to a scenario where all clients are honest is 2000 (see Figure 7). The cost of bribery can be used as a reference to determine an acceptable cost for designing implementing anti-corruption strategies.

Figure 6 Network simulations for different local mechanisms. Each point represents the average level of bribery (x_3) for 20 simulation runs with equal clustering.



Finally, Figure 6 suggests that there is a joint influence of the structure of the network and the sensitivity values. Both parameters influence the average transition rate between states. Based on these observations, it seems that the decision to accept or reject a bribe are the most affected by structural characteristics of the network (for sensitivities below the threshold). Figure 8 shows the simulation result of the set of differential equations based on the average transition rates.

To summarize, note that individuals make decisions based on information closely related to their local perception of corruption (i.e., the number bribe proposals, bribe agreements, and bribes uncovered in a neighborhood of radius two). In general, the perception of corruption across the network ($p = x_2 + x_3 + x_4$) may be viewed as the aggregate of various assessments (see Figure 9).

Figure 7: Cost of corruption for mechanism 2 (normalized with respect to the maximum available payoff difference of 2280 units).

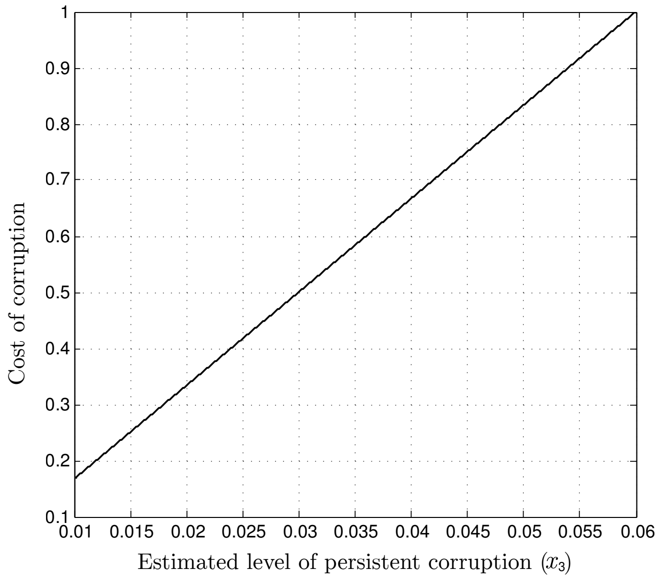
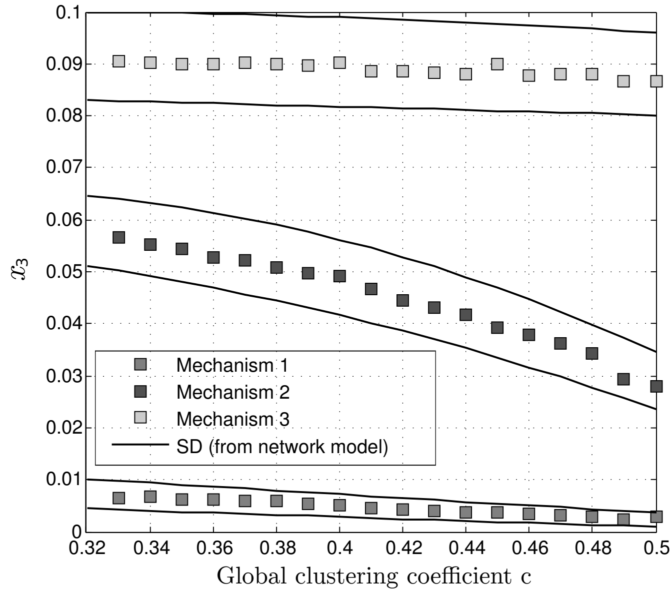
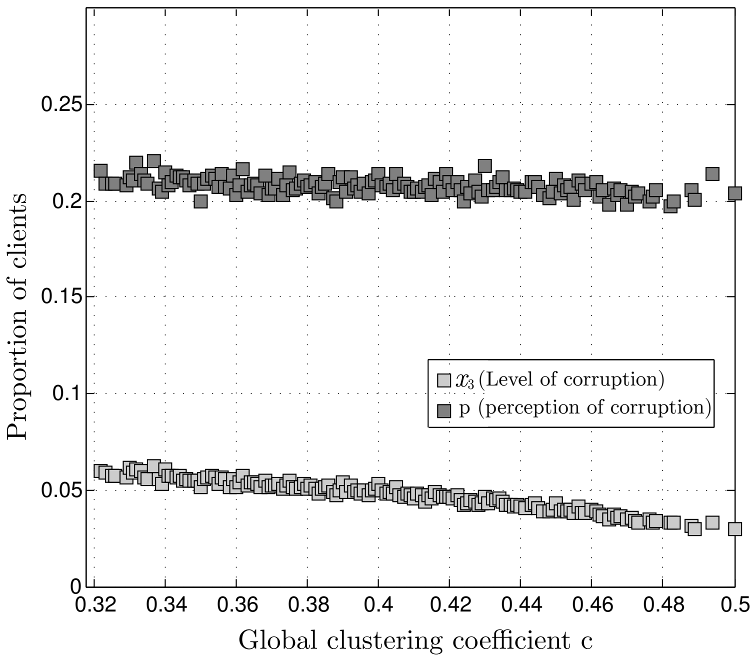


Figure 8: Simulations of the model of differential equations for different local mechanisms.



ISSN: 0124-3551 / Año 17, No 26 / enero-junio / pp. 19-35

Figure 9: Detected offenders and the perception of corruption across the network for a decision-making mechanism with μ = 0.08.



4. Conclusions

The proposed theoretical framework allows us to study relationships, which may underlie the dynamics of bribery. In particular, our work focuses on how the incentives of the individuals are influenced by the structure of contact networks. For networks with small-world properties, increasing the clustering coefficient tends to decrease the level of persistent bribery of the emerging equilibrium point (this is most noticeable for certain decision-making mechanisms).

Our framework suggests that an appropriate institutional policy is to strengthen the interactions, which form triads between employees (in other words, to promote that the friends of an employer are also friends among themselves). Moreover, the framework quantifies the cost of corruption and allows us to estimate an acceptable implementation cost for particular anticorruption strategies.

Broadly speaking, the proposed network model captures how the network affects the incentives of individuals, while the equation-based model is useful for exploring the transition parameters between states, facilitating the stability analysis of the dynamics of bribery.

Finally, simulation results show that a lower sensitivity to the decisions by neighbors generates a significant decrease in the levels of corruption. This implies that, in addition to strengthening triad formation, a policy of discretion (or concealment) of the processes of tolerated (unconvicted) irregular behavior is strongly encouraged.

ISSN: 0124-3551 / Año 17, No 26 / enero-junio / pp. 19-35

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