Journal of Business Research 129 (2021) 757–773

Contents lists available at ScienceDirect

Journal of Business Research

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

Understanding and managing complexity through Bayesian network approach: The case of bribery in business transactions

Ahmet Ekici [a,*], Şule Önsel Ekici [b]

[a] Bilkent University, Faculty of Business Administration, 06800 Ankara, Turkey
[b] Doğuş University, Istanbul, Turkey

ARTICLE INFO

Keywords:
Bribery
Complexity
Bayesian networks
Research methods
Economic development
Corruption

ABSTRACT

Managing complex business problems requires decision makers to take a systemic perspective and utilize tools that can generate knowledge from the interdependencies of the system's complex properties. As such, the current research focuses on an important yet ambiguous business problem–bribery. Using the Global Competitiveness Index data provided by the World Economic Forum, the authors constructed and analysed a Bayesian network to delineate a 'system' of bribery in business transactions. In this context, they first determined the factors related to bribery activities and then developed a structural model (the Bayesian network). Through scenario and sensitivity analyses performed over the constructed model, the authors identified the factors that have the greatest impact on bribery activities. They further analysed the resulting model based on the countries' stage of economic development in order to provide the manager and policy maker with a more informative diagnostic tool to understand and deal with bribery activities locally and globally.

1. Introduction

Among the most challenging tasks of business is understanding and dealing with complexity (e.g. Braun & Hadwich, 2016; Kirman, 2013). Approaching complex problems through proper tools, however, can provide decision-makers with invaluable insights as to how to take advantage of the opportunities as well as deal with the adverse effects that are introduced by the complexity (Cherrier, Paromita, & Subhasis, 2018; Ferraro & Iovanella, 2016; Ahrweiler, Schilperoord, Pyka, & Gilbert, 2015). We aim to contribute to the literature on complexity by illustrating a research methodology that is particularly useful in understanding complex business phenomena. To this end, using of one the most complex business problems –bribery–this paper aims to introduce the Bayesian networks (BN) methodology and demonstrate its value in understanding and managing the negative impact of this complex business problem.

As we know from the extant literature on business, economics, and law, a variety of micro, mezzo, and macro level factors may drive bribery in business transactions. These factors include, but are not limited to, economics, culture (e.g., ethics diversity), politics, legislation (e.g., tax rates and tax regime), organizations, professional-work environments, ownership structures, personal characteristics of decision makers, competition, and internalization (e.g., Cerqueti & Coppier, 2011, Cerqueti, Coppier, & Piga, 2012; McKinney & Moore, 2008; Theobald, 2002). These studies rely on theories such as the stakeholder theory, residual control theory, institutional theory, integrative social contract theory, general theory of marketing ethics, as well as normative ethical decision models to understand the relationships between bribery and the various forms of internal and external environmental drivers. Nevertheless, despite the extensive research conducted in this area and the measures taken to control the phenomenon, the problem of bribery still persists.

The conceptual and empirical understanding of bribery has been mostly based on linear models. However, it has been argued that understanding and dealing with complex business problems such as bribery requires research methods that take system perspective (e.g., Ryan, 2000) because decision making in complex social systems is not always "a clear cut cause-effect process but is characterized by contingency and uncertainty" (Ahrweiler et al., 2015, p.1). Bribery occurs in a complex business eco-system in which a host of structural and market based factors interact. We argue in this paper that such complex market conditions call for approaches that can enable decision makers to consider uncertainties and map the interactions that are related to bribery. To this end, we propose BN methodology as a proper tool for decision makers in

* Corresponding author.
E-mail addresses: ekici@bilkent.edu.tr (A. Ekici), sonsel@dogus.edu.tr (Ş. Önsel Ekici).

https://doi.org/10.1016/j.jbusres.2019.10.024
Received 15 March 2019; Received in revised form 16 October 2019; Accepted 17 October 2019
Available online 15 November 2019

their attempts to map connections and interactions (Ferraro & Iovanella, 2016) and "to identify areas that need intervention, [and] to specify the desired state of the system" (Ahrweiler et al., 2015, p.1). Decision makers can then be better equipped to understand and manage the complexities surrounding bribery activities.

2. Complex nature and systematic understanding of bribery in business transactions

There are various factors that impact the level of bribery activity in a given country. Those most often studied are the economic, political, and cultural factors. For example, there are arguments that corruption in a nation is a function of its economic development (e.g., Husted, 1999; Theobald, 2002). In addition, as Nwabuzor (2005) and Olaya & Wiehen (2006) argue, more developed economies have well-established institutions and policies to deal with corruption. In poorer countries (where government officials are usually underpaid), bribery may be viewed as a form of salary supplementation (a natural way of ensuring one's standard of living). The level of literacy, education, freedom of press (media), property rights, ethnic diversity, taxing, political rights, and economic freedom may also be linked to higher/lower levels of corruption (e.g., Husted, 1999). These articles conceptually point out the possible links between the institutions/structural factors and the bribery activities. Some research demonstrates an empirical link between a particular factor (e.g., ethnic diversity, tax rates, level of competition, etc.) and bribery (Cerqueti & Coppier, 2011; Cerqueti et al., 2012; Wu, 2009). However, most research is limited in demonstrating empirical evidence of how various structural factors interact and explain bribery in countries of different economic developmental stages.

Scholars have also come to the conclusion that bribery is a systematic problem and can be better understood and possibly better addressed through studies that take a systems approach. As Ryan (2000) points out, combatting corruption/bribery would require a shift in our approaches to the problem. That is, instead of blaming a single factor (such as culture or education), a more comprehensive understanding of the interplay among a host of factors (including economic development and the political and competitive environments) would yield more fruitful insights for managers and policy makers alike. With a few notable exceptions (e.g., O'Higgins, 2006; Riley, 1998), the current understanding of the relationship between bribery and various structural factors lacks a comprehensive perspective.

Moreover, as noted before, the discussion surrounding the systemic nature of bribery often lacks a data-driven empirical evaluation (Emerson, 2006). The current empirical understanding of bribery is almost exclusively based on econometric modelling, in which the dependent variable (i.e., bribery) is explained through a host of independent variables in a linear (regression) fashion (e.g., Ades & Di Tella, 1999; Wu, 2009). Such an approach, although quite informative about the link between bribery and a particular set of (independent) variables, cannot effectively lay out the concurrent interactions among the variables and thus may limit the understanding of the phenomenon from a systemic perspective.

To fill these gaps in the literature, the current research takes a systemic approach. Through the use of Bayesian Networks it empirically investigates the linkages between development and bribery through a host of political, economic, administrative, competitive, and other structural factors (e.g., market structure, crime and violence, financial system). Using World Economic Forum (WEF) data collected from over 14,000 business executives in more than 140 countries over an eight-year period, the objective of this research is to delineate a 'system' of bribery in business transactions for various economic development stages. In summary, this research (1) identifies factors related to bribery activities; (2) empirically identifies a structural model that delineates the probabilistic dependency relationships between bribery activities and other structural factors; (3) specifies the factors that have the greatest explanatory power on bribery activities; and (4) interprets findings based on a country's development stage.

As such, our aim goes beyond merely identifying factors and delineating the relations among them; we also aim to quantify the relationships of the complex system properties so that researchers and policy makers can run 'what-if' scenario analyses to determine the effect of a change in one (or more) factors on others in the network for various development stages. In other words, the model we develop can be used as a diagnostic tool for researchers and policy makers in their attempts to understand and reduce bribery activities across the world.

The next section of the paper (Section 3) explains the advantages of studying complex business problems through the BN methodology. We provide information about the method and explain the steps of the proposed methodology in Sections 4 and 5. Section 6 presents the results and the interpretations of the sensitivity and scenario analyses in detail. Section 7 discusses the implications of the findings.

3. Advantages of BN methodology in understanding/dealing with complex business problems

In recent years, to increase the quality of decision making and to transform strategic objectives into effective policies and decisions, managers and policy makers have been forced to deal with increasingly complex issues related to economic, technological, environmental, and social developments in all kinds of organizations and systems (Wu, 2010). The success of decision making in such environments is strongly related to the decision makers' ability to analyse complex cause– and effect relationships. However, to capture the cause and effect relationship in a system or to predict the possible results of different courses of action is not an easy task due to the complexity and uncertainty embedded in such macro environments.

A causal map that uses causal knowledge and analyses the cause and effect relation in a system is a very important and useful tool to generate new ideas, promote creativity, and understand complex systems. In the literature there are a number of methodologies that are used to analyse causal knowledge. Techniques such as influence diagrams, fishbone diagrams, or cognitive maps are based entirely on expert knowledge and do not model the uncertainty associated with decision variables. BNs, on the other hand, use the advantage of data in order to produce complex causal diagrams, and as a result, enable decision makes to analyse the interrelations between variables in an efficient way. The BN method can transform the relations between variables into a visible structural model that makes the complex system easier to analyse. In a macro environment it is obvious that the decisions made at the end of an analysis will have a great deal of uncertainty due to the complexity level of the system (Cain, 2001). BNs help decision makers analyse the results of a possible action and then investigate the consequences of its uncertainty.

Moreover, BNs are powerful and efficient explanatory tools. They make analysing complex causal relationships between variables easier and simpler. Therefore, as a type of probabilistic model, BNs are used frequently for understanding and simulating complex systems with high uncertainties in many different decision making environments, such as health care, climate changes, ethical issues, transportation, and so on (e.g., Daniel, Zapata-Rivere, & McCalla, 2007). With the help of probability, BNs can deal with uncertainty in an efficient manner. This makes them useful for data mining as well as for determining and clearly interpreting the relationship between variables that are based on expert knowledge and empirical data (Bruce, Marcot, & Penman, 2019). BNs are highly useful tools for representing and modelling current knowledge in order to gain a better understanding and perspective on uncertainties and complexities so as to help advise managers and decision makers.

Bayesian networks use Bayesian theorem while identifying possible mutual relations between variables and representing the joint probability distribution of these variables (Horny, 2014). BNs are especially useful in complex problems where there are many interrelated variables and one needs to calculate the probability of an uncertain event (with the observed evidence that is given). BNs combine a graph with the conditional probabilities of the variables to discover the effects of various variables on each other (Jaitha, 2017). Their ability to deal with relations among a set of random variables makes them efficient for coping with not only uncertainty but complexity (Horny, 2014). With the help of the Bayes theorem, a dense representation of a joint probability distribution becomes available in a graphical model. This graphical model in turn helps us to analyse a system consisting of variables that have many direct and indirect interrelationships. Moreover, BNs make it possible to see the effects of a change in one variable on any other remaining variables. This gives us a more realistic perspective when trying to analyse complex systems. The next section provides details of this methodology and our study.

4. Constructing models through Bayesian networks

As noted, BNs are used for understanding and simulating complex systems with high uncertainties (Daniel et al., 2007). They are especially useful for describing a problem to gain a better understanding and modelling it with a perspective on uncertainties and complexities (Bruce et al., 2019). With the help of BNs it becomes more effective to update and revise beliefs based on probabilistic inference.

There are a number of steps that must be taken when constructing a BN (Korb & Nicholson, 2011). Initially, one must identify the variables of the problem domain. Then one establishes the graphical structure to determine the qualitative relationships between variables. After the specification of the structure, the last step requires quantifying the relationships between the variables using a conditional probability distribution for each node.

There are two different methods to construct the graphical structure of a BN: In the *data-based method*, the parameters as well as the structure of the BN is learned directly from data. In the *knowledge-based method,* only human expert knowledge is used (Nadkarni & Shenoy, 2004; Onisko, 2008). The data-based method, which is used in this study, uses the conditional independence theory to extract models from data. The knowledge-based approach, on the other hand, uses causal knowledge of domain experts in constructing networks. Ekici and Onsel (2013) offer an example of the knowledge-based approach in the context of business ethics.

A BN is a directed acyclic graph in which variables are linked by conditional probabilities and where model outputs are expressed as probabilities of various states calculated using Bayes' Theorem (Bruce et al., 2019). In a BN, the variables of the domain that is being analysed are represented by nodes and the conditional dependencies between the variables are represented by links.

Each variable in the BN has a group of disjoint events and the union of all these events constitutes the universal event. (Baclawski, 2004). For instance, the Irregular Payments and Bribes (IPAB) variable in our net has five states: very low, low, medium, high, and very high. The related probabilities that define the probability distribution of IPAB for the whole data are: P(IPAB = very low) = 14.5%, P(IPAB = low) = 34.7%, P(IPAB = medium) = 22.7%, P(IPAB = high) = 13.8%, and P(IPAB = very high) = 14.3%, equalling 100% in total. These probabilities define the probability distribution of the random variable such that the intersection is empty and the union is universal.

In a BN, each variable is dependent to each other in some way. That is why BNs require joint probability distributions of each variable in order to make necessary inferences about the system. Let's assume that the Intensity of Local Competition (IOLC) is dependent to IPAB, which means that IPAB is the parent of IOLC. Here one has to calculate the term P(IOLC\IPBAB). This term is called 'posterior probability' and takes into account the probability of the evidence.

If there is a directed link from a variable X_1 to a variable X_2, then X_1 is called the parent of X_2 and X_2 the child of X_1. As evident in Formula 1, where $Pa(X_i)$ denotes the set of parents of X_i, the joint probability distribution of the network can be calculated simply by multiplying the conditional probability distribution of each variable $X_1, \ldots, X_N$ given its parents.

$$P(X_1, ..., X_N) = \prod_{i=1}^{N} P(X_i|Pa(X_i)) \tag{1}$$

From a mathematical point of view, the basic property of a BN is the chain rule: a BN is a compact representation of the joint probability table over its universe (Jensen, 2002). In a simple BN, where A affects B and B affects C, it is assumed that

$$\mathrm{P(A,B,C) = P(A) \otimes P(B|A) \otimes P(C|B)},$$

where $\otimes$ denotes pointwise multiplication of tables. In fact, the rule of total probability tells us that:

$$\mathrm{P(A,B,C) = P(A) \otimes P(B|A) \otimes P(C|A,B)}.$$

The difference between these two expressions depends on the assumption that P(C|A,B) = P(C | B), hence C is conditionally independent of A given B. In other words, in BNs one can assume that a variable is conditionally independent of its predecessors in the sequence given its parents, meaning that missing links (from a node to its successors in the sequence) signify conditional independence assumptions. If any evidence about B is known in a BN, then the occurrence or non-occurrence of A provides no information about the occurrence or non-occurrence of C. The fundamental assumption of a BN is that when the conditional probabilities for each variable are multiplied, the joint probability distribution for all variables in the network is obtained (Mishra, Kemmerer, & Shenoy, 2001). Conditional probability is very useful in examining a number of real world applications (Jaitha, 2017). One can determine the probabilities of various events using the observed events and their probable effects; this makes the BN extremely useful. In practice, the calculation of the posterior probabilities of each variable is computationally intractable when there are an extensive number of variables because the joint distribution will have an exponential number of states and values. That is why software programs are used to calculate the huge number of conditional probability values of the system.

Fig. 1 shows a very simple BN consisting of four variables: Public Trust in Politicians (PTIP), Favouritism in Decisions of Government Officials (FIDOGO), Irregular Payments and Bribes (IPAB), and Burden of Government Regulations (BOGR). The dependence relations are expressed in terms of conditional probability distributions for each variable. Each variable has a set of five possible values for a specific state: very low, 1; low, 2; medium, 3; high, 4; and very high, 5. In Fig. 1 the PTIP node has no parents and is defined through its prior probability distributions. The remaining three nodes have parents and are defined through conditional probability distributions. For child nodes, these conditional probability distributions are defined through the deterministic functions of their parents (such as the FIDOGO node). In this small example, FIDOGO and BOGR are the children of the same parent (PTIP) and IPAB is the only child of its parent (FIDOGO).

Fig. 1 also shows the conditional probability tables of P(PTIP), P(FIDOGO\PTIP), P(IPAB\FIDOGO), and P(BOGR\PTIP). From these tables, one can easily analyse the relationships among the variables. For example, if we assume that the state of PTIP is known to be medium (3), then the probability of FIDOGO being very low (1) is 0.44%, of being medium (3) is 73.128%, and of being very high (5) is 0.44%.

One of a BN's most important properties is that conditional independence relationships are implicit in the directed acyclic graph (Fenton, Hearty, Neil, & Radlinski, 2010). This property means that all nodes are conditionally independent of their ancestors given their parents, which makes it unnecessary to list conditional independence relationships explicitly. In other words, if an analysis is being done on Irregular Payments and Bribes (IPAB), for example, and the state of FIDOGO is known, then there is no use trying to find the state of Public Trust in Politicians (PTIP) because IPAB is conditionally independent of PTIP

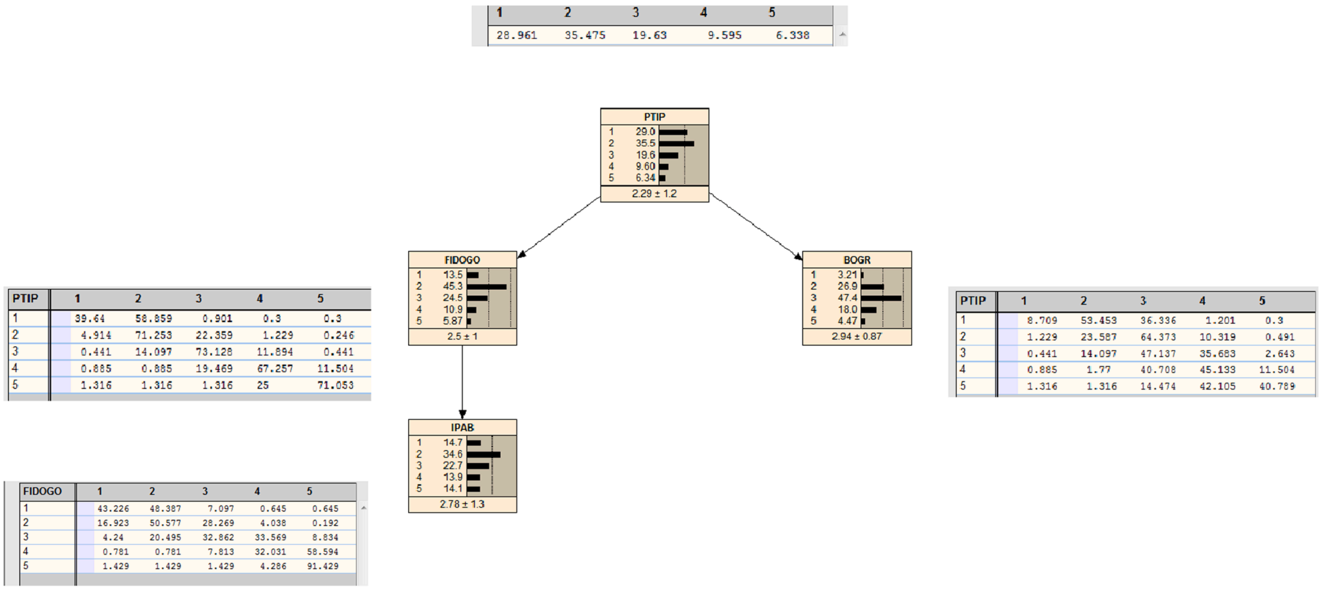


Fig. 1. A small BN example with four variables.

given FIDOGO.

5. Proposed methodology

Fig. 2 summarizes the framework of the proposed methodology. Recall that first the factors must be determined. In our case, a panel of business ethics experts determined the factors they felt were most related to Irregular Payments and Bribes (IPAB). Next, we developed a BN through (1) structural learning using GeNIe (developed by Bayes Fusion, LCC), and (2) parameter learning using Netica (developed by Norsys Software Corp). In the last step, we conducted a number of 'what if' scenario and sensitivity analyses to help managers and policy makers understand and, hopefully, reduce bribery activities.

5.1. Identifying the variables

To determine the factors related to the Irregular Payments and Bribes (IPAB) variable, we gave seven academic experts (of business ethics) the list of variables used in the WEF's Global Competitiveness Index (GCI) and asked them to choose the concepts that they thought were most related to IPAB in a given country. The expert panel members share a common characteristic: they either teach undergraduate and/or graduate levels of business ethics courses and/or publish regularly on business ethics topics in major business journals (e.g., *Journal of Business Ethics, Journal of Macromarketing, Journal of Public Policy and Marketing, Journal of Business Research, Business Ethics Quarterly*).

The majority of the expert group (six of seven) determined that the following seven variables are related (affected by it or affects it) to IPAB in a given country. Table 1 provides details as to how each of the eight variables (including Irregular Payments and Bribes) is measured in the WEF-Executive Opinion Survey.

- Diversion of public funds (DOPF)
- Public trust of politicians (PTIP)
- Favoritism in decisions of government officials (FIDOGO)
- Burden of government regulation (BOGR)
- Business costs of organized crime (OC)
- Reliability of police services (ROPS)
- Intensity of local competition (IOLC)

The data related to these nine variables were gathered from the Global Competitiveness Index (GCI) for 2010 to 2017. The countries analysed by the WEF differ each year; the total number of countries analysed in this study changed from 139 to 148 over these eight years.

To identify the effect of the cluster (i.e., economic development stage) that a country is in, we also included a variable called 'Cluster' in

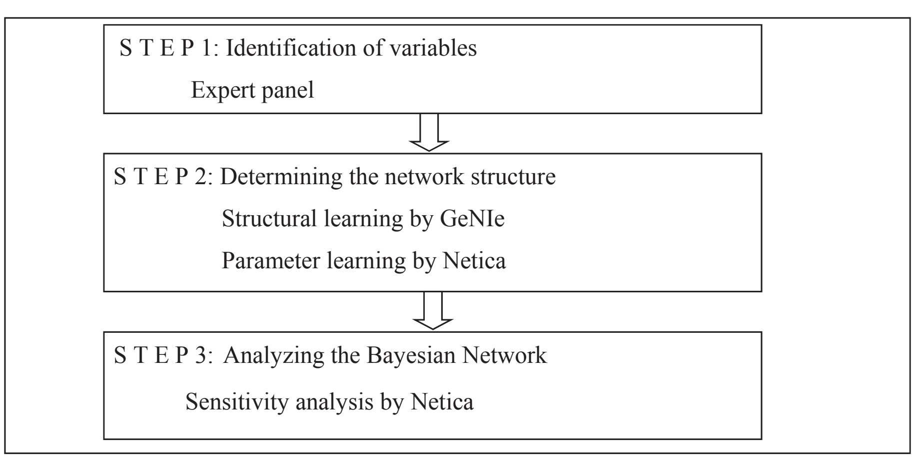


Fig. 2. Framework of the proposed solution methodology.

Table 1
List of variables (concepts) and their measurements in the WEF-executive opinion survey.

Variables	Related questions
01 Diversion of public funds	In your country, how common is diversion of public funds to companies, individuals, or groups due to corruption? [1 = very common; 7 = never occurs]
02 Public trust in politicians	How would you rate the level of public trust in the ethical standards of politicians in your country? [1 = very low; 7 = very high]
03 Irregular payments and bribes	Average score across the five components of the following Executive Opinion Survey question: In your country, how common is it for firms to make undocumented extra payments or bribes connected with (a) imports and exports; (b) public utilities; (c) annual tax payments; (d) awarding of public contracts and licenses; (e) obtaining favorable judicial decisions? In each case, the answer ranges from 1 (very common) to 7 (never occurs)
04 Favoritism in decisions of government officials	To what extent do government officials in your country show favoritism to well-connected firms and individuals when deciding upon policies and contracts? [1 = always show favoritism; 7 = never show favoritism]
05 Burden of government regulation	How burdensome is it for businesses in your country to comply with governmental administrative requirements? (1 = extremely burdensome; 7 = not burdensome at all]
06 Business cost of organized crime	To what extent does organized crime (mafia-oriented racketeering, extortion) impose costs on businesses in your country? [1 = to a great extent; 7 = not at all]
07 Reliability of police services	To what extent can police services be relied upon to enforce law and order in your country? [1 = cannot be relied upon at all; 7 = can be completely relied upon]
08 Intensity of local competition	How would you assess the intensity of competition in the local markets in your country? [1 = limited in most industries; 7 = intense in most industries] |

the analysis. In each year, WEF clusters the countries into three stages of development (Stage 1, Stage 2, and Stage 3) and two transition stages, leading to five groups as given in Table 2 (Sala-i Martin et al., 2012). The stages of development are mainly based on Gross Domestic Product (GDP) per capita. (It is noted that for economies highly dependent on mineral resources GDP is not the sole criterion for determining development stage, but this is a relatively small percentage of countries involved).

Sala-i Martin et al. (2012) state that countries in the first stage (i.e., Stage 1 countries) are mainly factor driven and compete based on their factor endowments, primarily low-skilled labour and natural resources. Companies acting in such countries compete on the basis of price, and sell basic, low-quality products or commodities. Their low productivity is reflected in low wages. Companies in efficiency-driven countries (i.e., Stage 2 countries), on the other hand, develop more efficient production processes and increase product quality. Companies in innovation-driven countries (i.e., Stage 3 countries) compete by producing new and different goods through new technologies and/or the most sophisticated production processes or business models. Wages are high in such countries, and companies are only able to sustain them and the associated standard of living if their businesses are able to compete with new and/or unique products, services, models, and processes.

5.2. Determining the network structure

In the second stage of the proposed methodology we construct a network model using a BN to determine and analyse the relationships between bribery activities and other factors (e.g., political, legislative, and competitive). To identify the BN from the data we first transformed the data such that the ratings of each of the nine variables were classified into five main probability states: very low, low, medium, high, and very high. Because each state has a different width of range (each variable has different minimum and maximum values), we calculated the difference between the maximum and minimum values for each variable. This data transformation (also called discretising) resulted in five states of the discrete version of the variable (Table 3).

After determining the possible states for each variable, we used GeNIe (developed by Bayes Fusion, LCC) to identify a BN that represents the dependency relations among the fundamental factors of Irregular Payments and Bribes (IPAB). In order to construct the model, two types of structure learning algorithm can be used: (1) constraint based algorithms that learn the structure by using conditional independence tests and (2) score based algorithms that assign a score to each candidate BN and try to maximize it with some heuristic search algorithm (Hesar, Tabatabaee, & Jalali, 2012). The basic aim of the methods is to search for network structures that maximize the probability of observing the given data set (Darwiche, 2009). As a score based method, which is also used in this study, the best way to find the highest score for the BN is to try every possible combination of dependence relations for the variables that maximizes the probability (Kent, 2008). However, this is not feasible due to the complexity issues. That is why a heuristic method is needed. One of the known heuristics methods is the Greedy Thick Thinning approach.

The structure of the net is modified with a number of iterations and the result is calculated in order to optimize the structure of the BN by the Greedy Thick Thinning Algorithm. This algorithm starts with an empty graph and repeatedly adds the link that maximally increases the marginal likelihood until no link addition will result in a positive increase. This phase is known as 'thickening'. In the second phase, known as 'thinning', it removes the links until no link deletion will result in a positive increase in the marginal likelihood. Moreover, in order to get the best scored net, a number of different combinations of link additions and deletions are used to ensure that the best scoring network is produced and the net structure is optimized. The related BN is given in Fig. 3.

After the structure learning of the BN, software parameter learning was conducted using Netica. Once a BN is constructed it can be used to make inferences about the variables in the model (Nadkarni & Shenoy, 2004). Thus, the BN was ready for a series of 'what if' scenario and sensitivity analyses by observing the resulting changes in the system after giving evidence to different variables.

The BN created using Netica and the marginal probabilities of the variables in the network are shown in Fig. 4. The model consists of three components: a set of nodes, representing the variables of the bribery system; a set of links, representing the dependency relationship (conditional dependence) between the nodes; and a set of probabilities, representing the belief that a node will be in a certain state given the states of the connecting nodes. The model has 15 conditional relations and 905 conditional probabilities among the nine variables.

In Fig. 4, the numbers are given in the left section for each state along with a number expressing the belief (probability) of that state as a

Table 2
Set of stages used in the study (adopted from WEF, 2017).

	Stages of development				
	Factor Driven Stage 1	Transition from Stage 1 to 2	Efficiency Driven Stage 2	Transition from Stage 2 to 3	Innovation Driven Stage 3
GDP per capita Thresholds (USD)	<2000	2000–2999	3000–8999	9000–17000	>17000

Table 3
State intervals of variables.

	Diversion of Public Funds DOPF	Public Trust in Politicians PTIP	Irregular Payments and Bribes IPAB	Favoritism in Decisions of Government Officials FIDOGO	Burden of Government Regulation BOGR	Business Cost of Organized Crime BCOC	Reliability of Police Services ROPS	Intensity of Local Competition IOLC	Country Cluster Cluster
Very low	1.21–2.30	1.27–2.30	1.94–2.91	1,40–2,32	1.32–2.17	1.53–2.58	1.73–2.75	2.60–3.36	1
Low	2.30–3.38	2.30–3.33	2.91–3.87	2,32–3,23	2.17–3.03	2.58–3.64	2.75–3.76	3.36–4.11	2
Medium	3.38–4.47	3.33–4.36	3.87–4.83	3,23–4.14	3.03–3.89	3.64–4.69	3.76–4.78	4.11–4.86	3
High	4.47–5.55	4.36–5.39	4.83–5.80	4.14–5.06	3.89–4.75	4.69–5.75	4.78–5.79	4.86–5.62	4
Very high	5.55–6.63	5.39–6.42	5.80–6.76	5.06–5.97	4.75–5.61	5.75–6.80	5.79–6.82	5.62–6.37	5

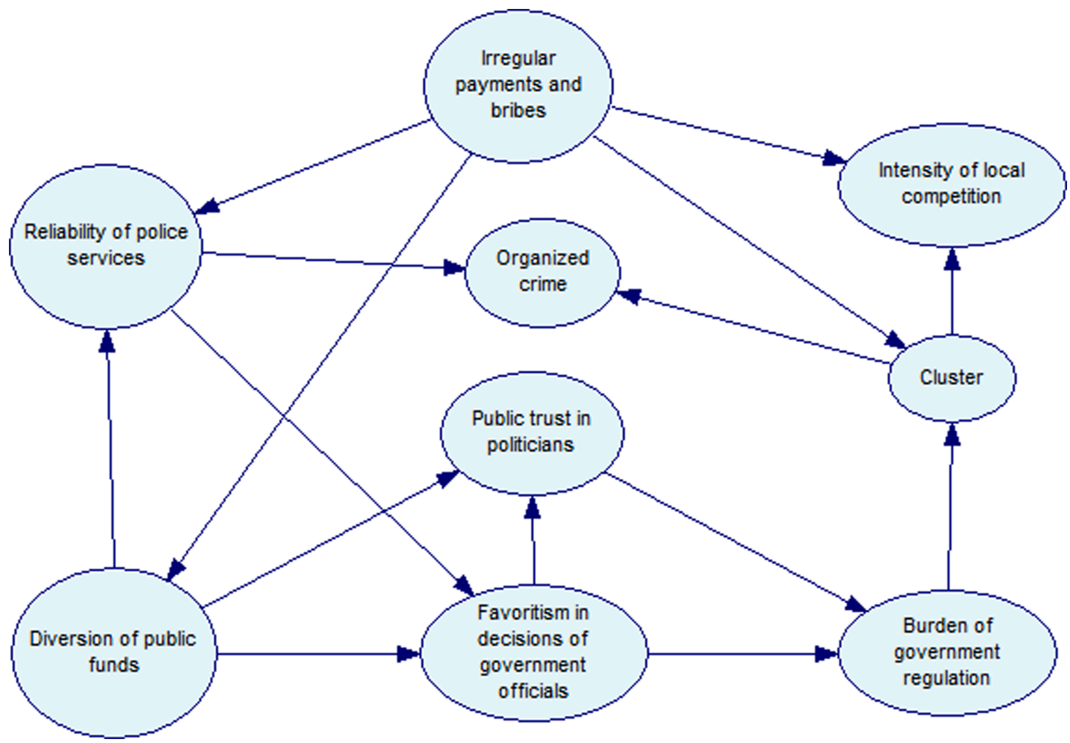


Fig. 3. BN of the system after structural learning phase.

percentage. In the right section of the boxes, bar graphs show the belief amounts. The mean and standard deviation values are shown at the bottom of each box. In addition to various scenario analyses, the BN model created using Netica allows us to perform a sensitivity analysis. This analysis identifies the (parent) variables with the most explanatory power on another (child) variable. A detailed investigation of the child variables is crucial because positive or negative changes in them have substantial impacts on the parent variables. In the following sections we report the results of the scenario and sensitivity analyses.

6. Results and interpretations

The overall model (i.e., based on the WEF's dataset of 139–148 countries over the eight-year period) depicted in Fig. 4 shows that, globally, executives generally believe that (with no specified posterior probabilities) Irregular Payments and Bribes (mean+/- standard deviation) is in the low state (2.79+/1.3), with a 34.7% probability. This indicates that *firms making undocumented extra payments or bribes is a very common behaviour.* More specifically, based on the existing variables and the BN relationships, managers around the world believe that there is a 49.4% (low: 34.7% + very low: 14.5%) probability that IPAB are common practices in the world. The managers that were surveyed believe that issues related to Diversions of Public Funds (DOPF), Favouritism in Decisions of Government Officials (FIDOGO), Public Trust in Politicians (PTIP), and Reliability of Police Services (ROPS) are all problematic aspects of the bribery system, that is, they all receive low probabilities (a low probability for negative concepts such as favouritism and nepotism indicates poor performance). Managers draw a relatively more optimistic picture with respect to Business Cost of Organized Crime (OC), believing that there is only about a 20% (6.11%+14.6%) probability that business costs are high due to the presence of mafia type groups.

6.1. Scenario analysis

Various scenario analyses can be provided for each of the variables included in the system (Fig. 4) depending on the conditional probability values. However, because the focus of this manuscript is on bribery, in this section we provide scenario analyses for the IPAB variable only. The interpretation of Fig. 4 can be done in two main ways: the bottom-up and top-down approaches. Each type of analysis offers decision makers distinct perspectives as to how to improve a complex system. The

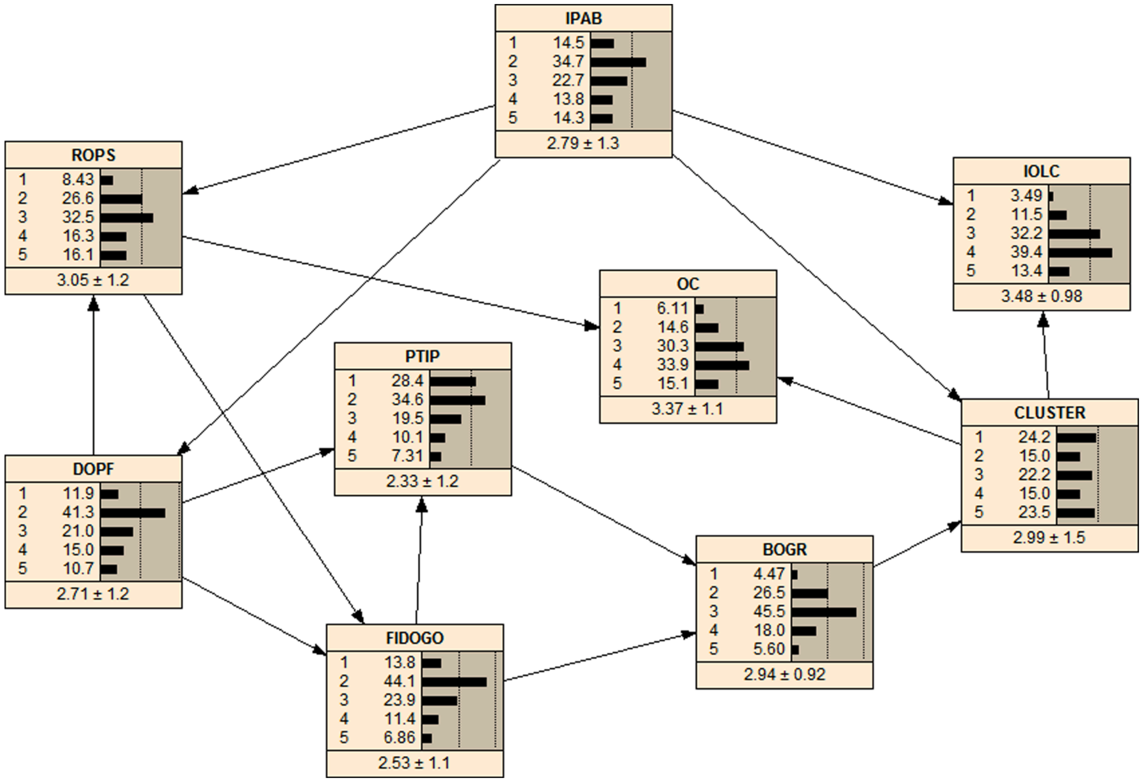
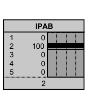
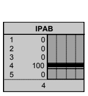


Fig. 4. BN of the system after parameter learning phase. Sample of key findings from Fig. 4: Irregular Payments and Bribes (IPAB): managers around the world believe that there is a 49.4% (low: 34.7%+ very low: 14.5%) probability that IPAB are rather common practices in the world. More problematic components of the bribery system: Diversions of Public Funds (DOPF), Favouritism in Decisions of Government Officials (FIDOGO), Public Trust in Politicians (PTIP), and Reliability of Police Services (ROPS). The least problematic component of the bribery system: Business Cost of Organized Crime (OC) - only about 20% (6.11%+14.6%) probability that business costs are high due to the presence of mafia-type groups.

bottom-up approach can demonstrate how parent variables are shaped by the changes in child variables. That is, the bottom-up approach can illustrate how the probability of each stage change results in changes in the whole system. The top-down approach, on the other hand, informs decision makers about what is needed (what improvements need to be made) in each of the critical variables so that they can achieve their desired level of the focal variable (i.e., IPAB). An illustration of the top-down approach is shown in Table 4. We have noted that bribery is generally perceived in the low state (i.e., very common) around the world, and a top-down 'what if' scenario analysis can provide more information about this belief. As can be seen in Table 4, improvements on IPAB are closely linked to the improvements that can be made in other critical variables. More specifically, a change from low to high state in IPAB can be possible when the perceptions related to Diversion

Table 4
Top-down scenario analysis for IPAB.

IPAB	DOPF	FIDGO	PTIP	ROPS
Low 	DOPF 1 13.8 2 73.6 3 12.1 4 0.25 5 0.25 1.99 ± 0.54	FIDOGO 1 18.4 2 65.9 3 12.9 4 1.50 5 1.24 2.01 ± 0.7	PTIP 1 42.6 2 43.1 3 11.3 4 1.63 5 1.41 1.76 ± 0.82	ROPS 1 8.27 2 44.9 3 43.0 4 3.00 5 0.81 2.43 ± 0.72
High 	DOPF 1 0.62 2 1.24 3 28.0 4 68.9 5 1.24 3.69 ± 0.55	FIDOGO 1 2.57 2 13.2 3 53.8 4 27.2 5 3.26 3.15 ± 0.78	PTIP 1 4.27 2 24.7 3 41.3 4 23.5 5 6.26 3.03 ± 0.95	ROPS 1 1.71 2 1.71 3 19.2 4 56.4 5 21.0 3.93 ± 0.79

of Public Funds (DOPF) and Reliability of Police Services (ROPS) improve from low to high (two state improvement), and the posterior probabilities of Favouritism in Decisions of Government Officials (FIDOGO) and Public Trust in Politicians (PTIP) also improve from low to medium state (i.e., fewer probabilities will be observed in the low and very low categories). Please note that because of the reverse scaling used in the Executive Opinion Survey (EOS), higher numbers in FIDOGO and DOPF indicate a perception about fewer occurrences of these phenomena.

The BN methodology allows one to examine changes in all system variables, regardless of whether these variables are directly linked to the focal variable (the IPAB variable in this case). As can be seen in Fig. 4, BOGR, PTIP, FIDOGO, and OC do not have a direct link to IPAB, yet the influences of these variables on IPAB can still be observed through the dynamic interactions that take place within the system.

6.2. Sensitivity analysis

A sensitivity analysis investigates how the outputs of a system depend upon its input parameters. In a BN, each variable may not be equally important and they may have different effects on the network's performance (Wang, Rish, & Ma, 2002). Sensitivity analysis can identify the most important variables by analysing the conditional probabilities of the variables. The conditional probabilities of each variable in the system change due to small changes in the evidence values. Investigating these changes (their magnitudes) can give important information about the variable of interest in a BN. In this study, as explained earlier, sensitivity analysis reveals factors that have the highest explanatory power on the chosen focal variable (e.g., IPAB) within the system.

This analysis is done through the observed variance reduction of the output variable (O) due to the value of an input variable (I). Variance reduction is the difference between the variance of the output node (var (O)) and the variance of the output node given the input node (Var(O|I)). The variable with the greatest variance reduction rate is expected to be the one that would most change the beliefs of the observed variable, and hence has the highest explanatory power over the output variable.

The results of the sensitivity analysis (Table 5) suggest that Diversion of Public Funds (DOPF) has the highest explanatory power over IPAB, followed by Reliability of Police Services (ROPS) and Favouritism in Decisions of Government Officials (FIDOGO). Interestingly, the other important variable is the Cluster variable, indicating that country cluster also has explanatory power in a country's level of IPAB. More specifically, changes in IPAB are explained by DOPF by about 74%, by ROPS by about 62%, and by FIDOGO by about 48%. As one can see in Fig. 4, variance in IPAB is 1.3 (see the bottom of the IPAB variable box). Further, when specific evidence (a value) of Diversion of Public Funds is entered into the system, the variance of IPAB drops dramatically. For example, when a value of 1 is entered (i.e., DOPF is very low), then the variance of IPAB drops from 1.2 to 0.63; when a value of 5 is entered (i.e., DOPF is very high), then the variance of IPAB drops to 0.49. For all value levels of DOPF the variance of IPAB drops greatly, allowing for a more precise estimation of IPAB. In a nutshell, the analysis reveals DOPF as the most critical variable to explain IPAB.

One of the main advantages of using BN as a tool to investigate a complex system is the method's capability of analysing the whole system depending on the network's probabilistic dependency structure and the observed evidences. The result of any change in any variable in the system can easily be analysed by a BN. To produce more information about the bribery system depicted in Fig. 4 (i.e., to examine the interdependency relations in more detail) we conducted a similar sensitivity analysis. The results of the sensitivity analysis for each variable, along with the top three variables influencing each one, are given in Table 6.

Table 6 suggests that for three variables in the system (namely Cluster, Diversion of Public Funds, and Reliability of Police Services), IPAB is particularly important. More specifically, the sensitivity results given in Table 6 indicate that the cluster that a country belongs to is mostly explained by the level of IPAB. That is, if we have an observation about the bribery level in a country, we can easily predict the cluster to which this country belongs. Irregular Payments and Bribes is not the only variable that explains the Cluster variable, but, as the sensitivity analysis reveals, it clearly has great influence. A deeper understanding of the interactive relationships between economic development and bribery perceptions would provide invaluable insights into the problem of bribery across the world. The rest of this section will be devoted to the cluster level (economic development) analysis of the bribery system.

6.3. Bribery in Stage 3 (innovation-driven, advanced) economies

As one can see in Fig. 5, IPAB in innovation-driven countries is generally perceived as high. As suggested by Fig. 5, there is a 73.5% (24% high; and 49.5% very high) probability that business people working in advanced economies believe that *firms making undocumented extra payments or bribes* is NOT a common behavior in these economies. Moreover, there seems to be a common belief that most of the factors that are in relation to IPAB are also perceived positively. Nevertheless, an overall review of the model reveals that the perceptions regarding

Table 5
Results of the sensitivity analysis for IPAB.

Indicator	Variance reduction (%)
DPF	74.1
RPS	61.8
FDGO	47.9
PTIP	41.4
Cluster	41.3
OC	24.4
IOLC	19.5
BOGR	17.8

Table 6
Results of the sensitivity analysis performed for each variable in the network.

Target variable	Top variable influencing the target variable	Variance reduction (%)
Cluster	IPAB	37.7
	IOLC	26.6
	DOPF	25.8
Intensity of Local Competition (IOLC)	Cluster	23.5
	IPAB	17.3
	DOPF	11.5
Burden of Government Regulation (BOGR)	PTIP	27.7
	FIDOGO	25.6
	DOPF	19.9
Irregular Payments and Bribes (IPAB)	DPF	74.1
	RPS	61.8
	FIDOGO	47.9
Favoritism in Decisions of Government officials (FIDGO)	DOPF	58
	PTIP	55.9
	IPAB	48.2
Diversion of Public Funds (DPF)	IPAB	75.4
	ROPS	61.4
	FIDOGO	59.2
Public trust in politicians (PTIP)	FIDOGO	57.4
	DOPF	53.4
	IPAB	43.5
Reliability of Police Services (ROPS)	IPAB	59.4
	DOPF	58.9
	FIDOGO	44.9
Business Cost of Organized Crime (OC)	ROPS	31.2
	IPAB	20.5
	DOPF	19.6

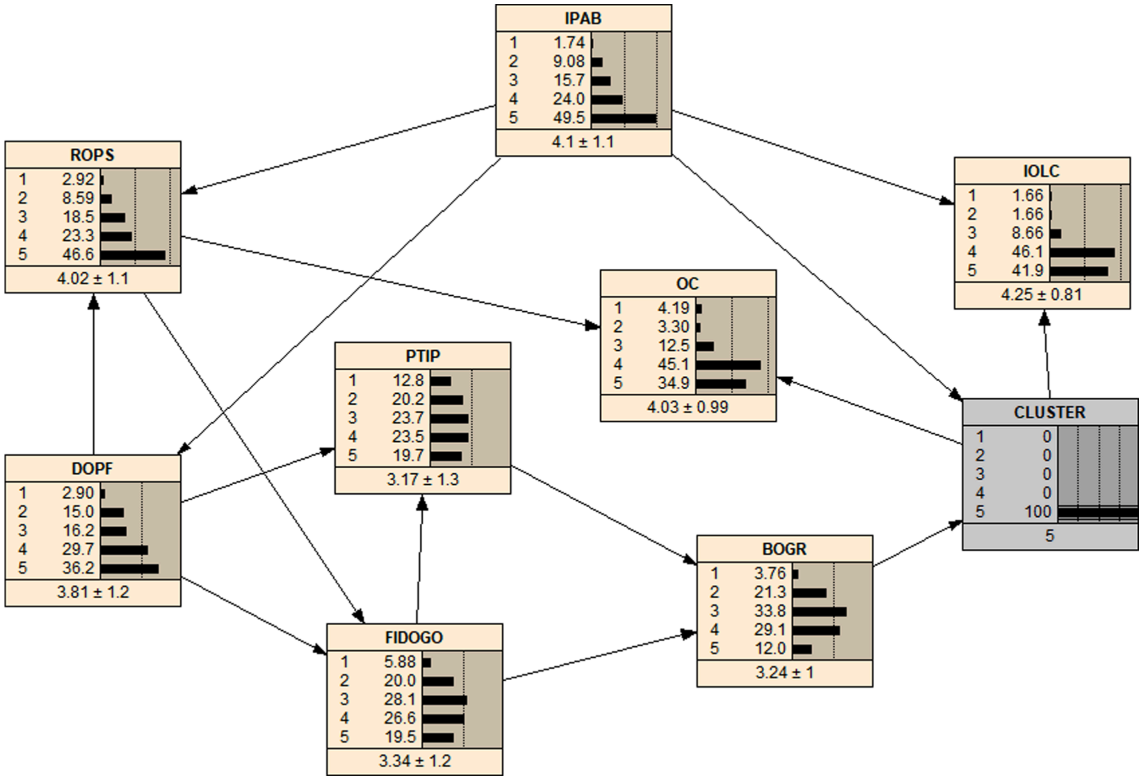


Fig. 5. Bribery in Stage 3 countries (Innovation-Driven, Advanced Economies). Sample of key findings from Fig. 5: Irregular Payments and Bribes (IPAB): 73.5% (24% high and 49.5% very high) probability that business people working in advanced economies believe that IPAB is NOT a common behavior in these economies. More problematic components of the system: Burden of Government Regulations (BOGR)—BOGR as medium or low is 68.9% (33.8% medium; 21.3% low; and 3.3% very low). Public Trust in Politicians (PTIP) and Favoritism in Decision of Government Officials (FIDOGO) are also relatively low (percentages of perception being medium or lower in these two factors are 56.7 and 54 respectively). The least problematic component of the bribery system: Intensity of Local Competition (IOLC)—These markets are chracterized with a high level of competition (80% probability that competiton is perceived to high (46.1%) or very high (41.9%).

Burden of Government Regulations (BOGR) are somewhat problematic as the probability that managers perceive BOGR as medium or low is 68.9% (33.8% medium; 21.3% low; and 3.3% very low). Similarly, perceptions of Public Trust in Politicians (PTIP) and Favoritism in Decision of Government Officials (FIDOGO) are also relatively low (percentages of perception being medium or lower in these two factors are 56.7 and 54 respectively).

We can further investigate the relationships depicted in Fig. 5 through the sensitivity analysis. In this way we can identify the factors that have the highest explanatory power on the IPAB variable. The results of the sensitivity analysis for Stage 3 countries reveal that Diversion of Public Funds (DOPF) has the highest explanatory power on IPAB, followed by Reliability of Police Services (ROPS) and Favoritism in Decision of Government Officials (FIGODO).

6.4. *Bribery in Stage 2 (efficiency-driven, developing) economies*

As suggested by Fig. 6, managers working in Stage 2 countries believe that IPAB (*firms making undocumented extra payments or bribes*) is a common behavior in these economies. More specifically, there is a 53.2% probability that IPAB in these countries are perceived to be below the medium threshold level (48.1% low; and 5.1% very low). In line with this perception, almost all the factors that are related to the IBAP variables are also in low or very low states. Managers draw a relatively more optimistic picture with respect to Business Cost of Organized Crime and Burden of Government Regulations, believing that there is about 30% probably that business costs are high due to the existence of mafia type groups and government red tape.

The sensitivity analysis of the relationships depicted in Fig. 6 resulted in almost the same outcomes as the Stage 3 countries. More specifically, the order of the factors having the greatest explanatory power on IPAB is exactly the same: DOPF, ROPS, and FIDOGO. The variance reduction properties of each variable, however, are smaller than the output observed in Stage 3 countries. Nevertheless, these three factors have important explanatory power over IPAB in Stage 2 countries.

6.5. *Bribery in Stage 1 (factor-driven, underdeveloped) economies*

Based on the existing variables and the BN relationships (Fig. 7), one can conclude that managers in factor-driven economies believe that there is 85.4% (48.2% low; and 37.3% very low) probability that IPAB is a common practice in these countries. Similar to the results in Stage 2 economies, except for the perceptions of OC and BOGR, all the other variables are problematic aspects of the bribery system in Stage 1 countries. Issues such as PTIP, FIDOGO, and DOPF are particularly problematic as there is more than 75% probability that these factors are perceived to be low or very low.

In line with these perceptions, the sensitivity analysis reveals DOPF, ROPS, and FIDOGO are the factors that have the greatest explanatory power over IPAB in Stage 1 countries. Please note that these are the same variables (and in the same order) that we identified through the sensitivity analyses in Stage 2 and Stage 3 countries. However, since variance reduction properties of these factors are quite high (0.71, 0.54, and 0.41 respectively), we can conclude that, as compared to the countries in other stages, the changes in these three factors would result in the highest change in the bribery perceptions in Stage 1 countries. Regardless of where business is conducted in the world, DOPF, ROPS, and FIDOGO will be the most critical factors in understanding and managing bribery activities; however, any positive (negative)

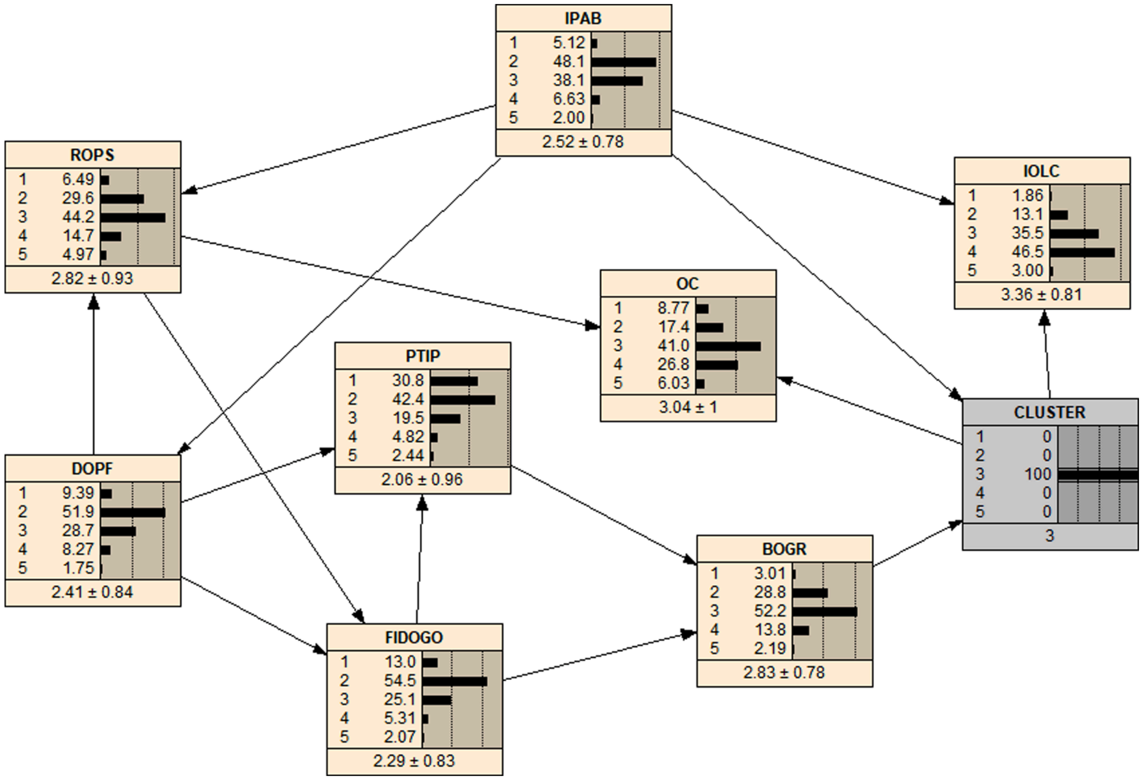


Fig. 6. Bribery in Stage 2 countries (Efficiency-Driven, Developing Economies). Sample of key findings from Fig. 6: Irregular Payments and Bribes (IPAB): Managers working in Stage 2 countries believe that IPAB is rather a common behavior in these economies. There is a 53.2% probability that IPAB in these countries are perceived to be below the medium threshold level (48.1% low and 5.1% very low). More problematic components of the system: Almost all the factors that are related to the IBAP variables are in low or very low states. Nevertheless, Diversion of Public Funds (DOPF)-with 63.3% probability of being low (51.9%) or very low (9.39%); Favoritism in Decisions of Government Officials (FIDOGO)-with 67.5% probability of being low (54.5%) or very low (13%); and Public Trust in Politicians (PTIP)-with 73.2% probability of being low (42.4%) or very low (30.8%) appears to be the most problematic. The least problematic components of the bribery system: Managers draw a relatively more optimistic picture with respect to Business Cost of Organized Crime and Burden of Government Regulations, believing that there is about 30% probably that business costs are high due to the existence of mafia-type groups and government red-tape.

development on these variables will have more positive (negative) implications on the occurrence of bribery in Stage 1 (underdeveloped) economies.

6.6. Detailed analyses of Stage 2 and Stage 1 economies

A comparison among the three figures (Figs. 5–7) clearly demonstrates the link between economic development and the perceptions of corruption/bribery. Moreover, Fig. 5 reveals a relatively 'ideal' (very low occurrence of bribery) environment for conducting business. In other words, the business environment in Stage 3 economies may be viewed as benchmarks for countries that are classified in other stages.

We will now provide a more detailed analysis and discussion of Stage 2 and Stage 1 economies in order to produce practical implications for managers and policy makers to improve the business ethics environment in these markets. Despite the marked differences between Stage 2 and Stage 1 economies with respect to distribution of our main (IPAB) variable (i.e., very low state is 37.3% in Stage 1 versus only 5.1% in Stage 2; medium state is only 9.2% in Stage 1 versus 38.1% in Stage 2), the overall distribution pictures of most variables of the system are similar. Even though these two groups of countries differ significantly in terms of their economic development levels, this difference is not quite reflected in executives' perceptions in the areas of BOGR, PTIP, FIDOGO, and OC.

In other words, managers view both types of markets similarly with respect to the above four factors. Despite significant economic development level differences, managers in Stage 2 economies still perceive their business environment as involving red tape, nepotism, shady politicians, and high business costs due to organized crime. The main difference in the perceptions of managers working in these two types of markets is in their perceptions of bribery activities: managers in Stage 2 economies perceive bribery as a less common behaviour in their markets. We observe a more positive (i.e., less bribery) environment in Stage 2 economies as well as the perception of a greater (more intense) competitive environment and more reliable law enforcement services in these markets. It becomes important to understand the roles that these two variables (i.e., competition and law enforcement) play in shaping bribery perceptions in these two type of economies. Although there is a slight difference in the distribution of DOPF in these two types of economies, since DOPF has emerged as the factor having the greatest explanatory power over IPAB in Stage 2 and Stage 1 countries we will provide a detailed analysis around this 'key' variable as well.

Table 7 demonstrates the most common state for the perception probability of each variable. For example, as one can see in Figs. 6 and 7, the most common state of IPAB in Stage 1 countries is '2′ (i.e., 'low state' with 48.1%). Similarly, the most common state of ROPS in Stage 2 countries is '3′ (i.e., 'medium state' with 44.2%). A review of Table 7 suggests once again that these two groups of economies differ from each other mainly in the areas of Reliability of Police Services (ROPS) and Intensity of Local Competition (IOLC). Even though the most common state of the DOPF variable is the same (i.e., '2′) in both economies, because of its pivotal role that we discovered earlier, this variable also deserves a further analysis. We believe that a detailed analysis along the lines of these three variables would yield valuable insights for the managers and policy makers of Stage 1 and Stage 2 economies.

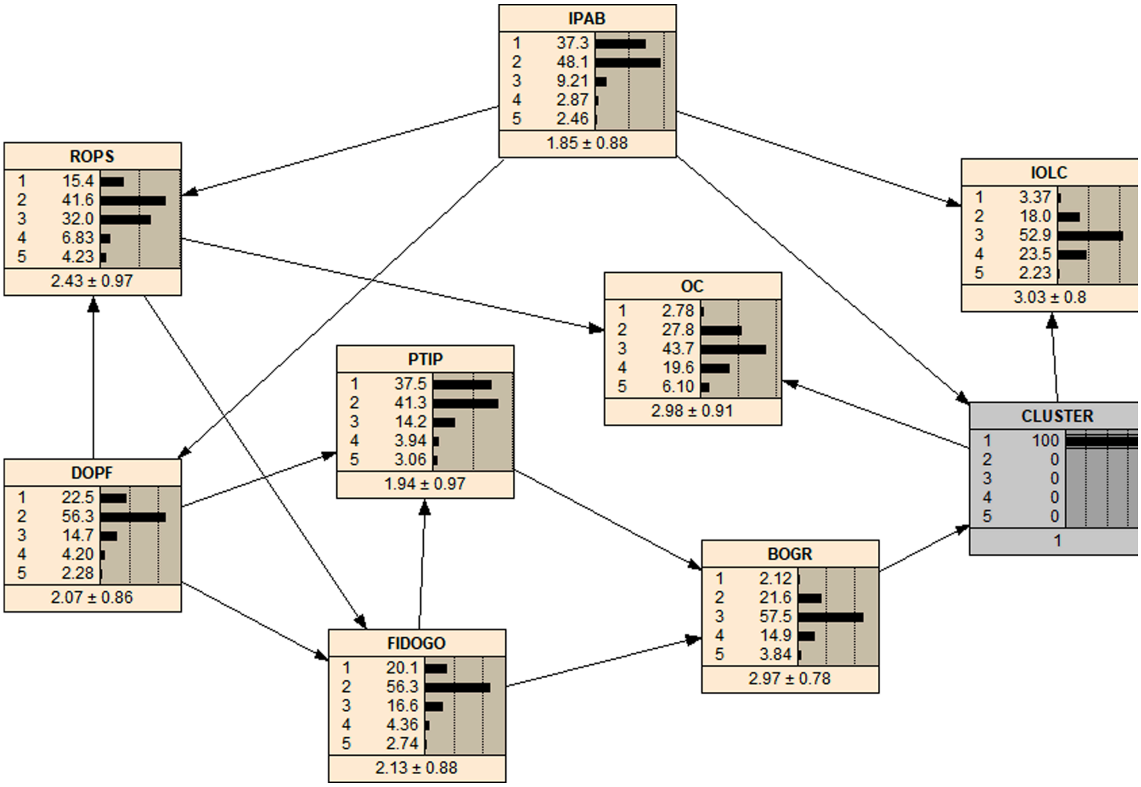


Fig. 7. Bribery in Stage 1 countries (Factor-Driven, Underdeveloped Economies). Sample of key findings from Fig. 7: Irregular Payments and Bribes (IPAB): Managers in factor-driven economies believe that there is 85.4% (48.2% low and 37.3% very low) probability that IPAB is a common practice in these countries. More problematic components of the system: Almost all the factors that are related to the IBAP variables are in low or very low states. However, issues such as PTIP, FIDOGO, and DOPF are particularly problematic as there is more than 75% probability that these factors are perceived to be low or very low. The least problematic components of the bribery system: There are only two factors (Business Cost of Organized Crime and Burden of Government Regulations) that are perceived to have less than 50% probability of being low or very low. However, it should be noted that these factors are only (by comparison to other factors) are less problematic.

Table 7
The most common state of each factor for Stage 1 and Stage 2 Countries.

	Stage 1 (Factor Driven) Countries	Stage 2 (Efficiency Driven) Countries
IPAB	2	2
DOPF	2	2
ROPS	2	3
FIDOGO	2	2
PTIP	2	2
OC	3	3
IOLC	3	4
BOGR	3	3

6.6.1. The role of Diversion of Public Funds (DOPF)

Table 8 clearly demonstrates the crucial role that DOPF plays in bribery perception in both types of economies. With respect to Stage 1 economies, improvement by one 'state' in DOPF perceptions (from its current low state to a medium state) results in important changes in IPAB perceptions. More specifically, the probability of IPAB being medium or higher improves from only 5.05% (4.17 + 0.47 + 0.41) to 42.65% (38.8 + 3.74 + 0.11). As suggested by Table 8, the observed improvement in Stage 2 economies will be much more significant: The probability of IPAB being medium or higher will improve from 26.9% (26.3 + 0.12 + 0.48) to 80.62% (74.7 + 5.86 + 0.06). Please also note that improvement by one 'state' in DOPF will results in one 'state' improvement in bribery perceptions in Stage 2 economies. While it is currently in the 'low' state with 68.9%, it is expected to be overwhelmingly in the 'medium' state with 74.7%.

6.6.2. The role of competition (IOLC)

As stated in Table 7, the current state of IOLC in Stage 1 economies is 'medium'. Table 9 demonstrates how much improvement we can observe in IPAB perceptions if IOLC perceptions can be increased even one state. Whereas currently there is only 3.31% (1.98 + 1.33) probability that perceptions regarding bribery activities are above the medium state, when the markets become slightly more competitive (i.e., when IOLC perceptions move from medium '3′ state to high '4′ state), the perceptions regarding the occurrence of 'bribery' probability improves more than two times to 7.44% (4.45 + 2.99). However, the overall picture/distribution of the IPAB variable does not change much: IPAB is still generally viewed to be in the low state.

Similarly, for Stage 2 economies, the current state of IOLC is '4: high state.' When managers' perceptions regarding the intensity of competition increase even minimally from state 4 to state 5, the perceptions regarding the occurrence of bribery improves significantly. More specifically, as can be seen from Table 9, whereas the current probability of IPAB perceptions being above the 'medium' is only 6.41% (5.55 + 0.86), an improvement in the competitive environment increases the same perception by almost four times to 25.6% (12.3 + 13.3).

6.6.3. The role of law enforcement/police services (ROPS)

As suggested by Table 7, perceptions regarding the Reliability of Police Services (ROPS) are in low state in Stage 1 economies and in medium state in Stage 2 economies. Table 10 shows that when/if perceptions of police services can be improved even one state, there will be significant improvements in the bribery perceptions in both economies. More specifically, in Stage 1 economies, bribery perceptions being medium or above will improve from 2.54% (2.28 + 0.14 + 0.12) to 17.65% (16.1 + 1.37 + 0.18). The improvement in Stage 2 economies, however,

Table 8
The role of diversion of public funds-DOPF in Stage 1 and Stage 2 countries.

	DOPF-Low State	DOPF-Medium State
Stage 1 Economies	IPAB 1 32.9 2 62.8 3 4.17 4 .047 5 .041 1.71 ± 0.54	IPAB 1 11.4 2 46.0 3 38.8 4 3.74 5 0.11 2.35 ± 0.73
Stage 2 Economies	IPAB 1 4.63 2 68.9 3 26.3 4 0.12 5 .048 2.22 ± 0.52	IPAB 1 0.81 2 18.6 3 74.7 4 5.86 5 .059 2.86 ± 0.51

Table 9
The role of competition-IOLC in Stage 1 and Stage 2 countries.

	IOLC-Medium State	IOLC-High State	IOLC-Very High State
Stage 1 Economies	IPAB 1 36.4 2 46.5 3 13.8 4 1.98 5 1.33 1.85 ± 0.82	IPAB 1 33.3 2 56.5 3 2.70 4 4.45 5 2.99 1.87 ± 0.89	IPAB 1 13.5 2 44.7 3 14.3 4 11.7 5 15.8 2.72 ± 1.3
Stage 2 Economies	IPAB 1 5.76 2 52.5 3 35.4 4 5.19 5 1.13 2.43 ± 0.73	IPAB 1 4.41 2 48.1 3 41.0 4 5.55 5 0.86 2.5 ± 0.71	IPAB 1 11.4 2 24.9 3 38.1 4 12.3 5 13.3 2.91 ± 1.2

will be much higher: when perceptions of police services improve even one state (from its current ‘3: medium state’ to ‘4: high state’), the perceptions regarding the absence of bribery will improve from 52.36% (49.5 + 2.73 + 0.13) to 89.91% (62.2 + 25.6 + 1.81).

Reliability of Police Services (ROPS) also has an important explanatory power on perceptions of the Cost of Organized Crime (OC). Our analysis reveals that in all country groups OC is best explained by ROPS. The interactive effects that are presented in Table 11 clearly demonstrate how improvements in the perceptions of law enforcement would result in significant positive changes in the perceptions of business costs due to mafia, and as a result, in the perceptions of occurrence of bribery.

7. Discussion and implications

Corruption has been identified as one of the most important barriers to worldwide economic development, growth, and ultimately, societal well-being (e.g., Di Guardo, Marruco, & Paci, 2016; Emerson, 2006; Gray & Kaufmann, 1988; Hotchkiss, 1998; Ryan, 2000). Bribery, as one of the most common forms of corruption, is the focus of this paper. The expansive literature in international business, management, public policy, economics, business ethics, and law has offered detailed accounts of definitions, types, antecedents, and consequences/costs of global bribery activity (e.g., Argandona, 2007; Clarke & Xu, 2004; Rabl & Kuhlmann, 2008). Our intention was not to repeat this vast and established literature but to focus on delineating a ‘system’ of bribery and discussing its relationships with various critical structural factors.

Through the substantive domain of bribery, we aim to introduce a unique methodology to business research that is particularly useful in understanding complex phenomena. To the best of our knowledge, this study is the first application of the BN methodology to delineate and understand the complexities surrounding bribery activities around the world. Despite inherent limitations (see Ekici & Ekici, 2016 and Gupta & Kim, 2008 for a discussion on the weaknesses of BN), this methodology is very powerful in capturing the dynamics and interactions among the variables of a complex phenomenon such as bribery. In the previous section, we provided our results along with their interpretations; this

Table 10
The role of police services-ROPS in Stage 1 and Stage 2 countries.

	ROPS-Low State	ROPS-Medium State	ROPS-High State
Stage 1 Economies	IPAB 1 46.8 2 50.7 3 2.28 4 0.14 5 0.12 1.56 ± 0.56	IPAB 1 14.9 2 67.4 3 16.1 4 1.37 5 0.18 2.04 ± 0.62	IPAB 1 14.1 2 22.2 3 36.5 4 22.9 5 4.29 2.81 ± 1.1
Stage 2 Economies	IPAB 1 8.77 2 74.0 3 16.7 4 0.35 5 0.17 2.09 ± 0.53	IPAB 1 1.43 2 46.2 3 49.5 4 2.73 5 0.13 2.54 ± 0.58	IPAB 1 0.96 2 9.44 3 62.2 4 25.6 5 1.81 3.18 ± 0.66

section will focus on some of the important implications of our findings for business and public policy.

First, through the use of completely new methodology, the findings confirm the notion that bribery is a very common practice across the globe and that the problem deepens as we move from more (economically) developed countries to less developed ones. The link between economic development and bribery is not a novel finding; however, our detailed analyses help determine the priorities when dealing with the complexities of the bribery system in various economic development levels. For example, Diversion of Public Funds (DOPF) appears as the key 'policy' variable across the world. However, detailed analyses reveal that minimal improvements on this variable would result in the greatest improvement in the occurrence of bribery in Stage 1 (underdeveloped) economies.

Diversion of Public Funds is at the centre of the complex bribery system depicted in our study. This is a critical finding and an important contribution of our study. The main societal cost of DOPF comes from nurturing inefficient individuals and organizations as well as directing skills, money, and technology/know how away from more productive uses (Murphy, Shleifer, & Vishny, 1991, 1993). Our analysis reveals that the current global perception of DOPF is in a low state (Fig. 4). However, as indicated by our additional scenario analysis (see Figs. 8a–8c), one can attain a more positive business environment across the globe when managers' DOPF perceptions are improved by even one state (from low to medium).

An important implication for policy makers, then, is to establish mechanisms to improve DOPF perception. One such mechanism is the G20 Anti-Corruption Action Plan, which was prepared by the organization's Anti-Corruption Working Group (ACWG) and announced in 2014. One of the plan's six main action topics involves *public sector transparency and integrity*, and includes specific deliverables in the areas of open data (to help businesses assess risk and opportunities in different markets in order to make more informed decisions and to provide increased transparency regarding the flow of public money); procurement (preparing a practical toolkit for G20 governments on integrity in public procurement and identifying the best practices of public procurement systems globally); whistle-blower protections (to increase government effectiveness in identifying cases of DOPF); removing prosecution immunities, such as policies to undermine corruption-control efforts; fiscal and budget transparency (to deter DOPF and to promote good governance); and guidelines for public officials to regulate conflicts of interest and establish standards of conduct (ACWG, 2014). These collaborative efforts are certainly steps in the right direction and are likely to have a positive influence on managers' perceptions about the diversion of public funds. These more positive perceptions, as depicted in our findings (see Table 4, Table 8, and Figs. 8a–8c), will have a tremendous impact on the bribery activities in the world.

With respect to the role of competition in understanding bribery activities, our study makes two main contributions: First, the findings provide much-needed empirical support for the relationship between competition and the level of bribery activities in a particular market; research to date has been inconclusive about the relation between these two variables. Even though, intuitively, more competition should reduce corruption, Ades & Di Tella (1999) and Emerson (2006) explain that the theoretical link between the two concepts is ambiguous: Ades & Di Tella (1999) argue (and through a regression model demonstrate) that corruption is higher in markets where local firms are protected from foreign competition (i.e., less competition breeds bribery). Others (e.g., Emerson, 2006; Waller, Verdier, & Gardner, 2002) also report that competition and corruption are negatively related, with the understanding that the relationship between the two factors may not be one-directional.

In addition to the argument that the amount of corruption can be determined by the level of competition, these authors argue that the plausibility of the level of corruption itself is a determinant of competition. To make the picture even more complex, some researchers find a positive link between competition and corruption. Wu (2009), for example, reports that the level of competition has positive effects on bribery in Asian firms. In summary, even though theoretically the cause and effect relationship between competition and bribery appears to be nebulous, the empirical findings, to a large extent, support the notion that bribery is antithetical to competition. Our findings offer additional support for those who argue a negative relationship between the level of competition and the level of bribery in a given market.

Second, the detailed economic development level analyses reveal that making improvements in the competitive structure of a market results in greater improvements in the occurrence of bribery in Stage 1 and Stage 2 economies. The analysis suggests that making markets slightly more competitive appears to be the pathway to improve bribery related perceptions by two times in Stage 1 countries, and by four times in Stage 2 economies. Public policies aimed at making markets more competitive would help reduce/control bribery, particularly in Stage 1 and Stage 2 countries.

According to the US Department of Justice, there are still countries (about 50) in the world without antitrust laws and/or regulations

Table 11
Interactive relationships among ROPS, OC, and IPAB in Stage 1 and Stage 2 countries.

	Node	State			
Stage 1 Economies	IPAB	1	46.8	14.9	14.1
		2	50.7	67.4	22.2
		3	2.28	16.1	36.5
		4	0.14	1.37	22.9
		5	0.12	0.18	4.29
			1.56 ± 0.56	2.04 ± 0.62	2.81 ± 1.1
	OC	1	0.74	0.93	4.76
		2	34.8	13.1	4.76
		3	47.4	55.1	23.8
		4	16.3	26.2	42.9
		5	0.74	4.67	23.8
			2.81 ± 0.73	3.21 ± 0.76	3.76 ± 1
	ROPS	1	0	0	0
		2	100	0	0
		3	0	100	0
		4	0	0	100
		5	0	0	0
			2	3	4
Stage 2 Economies	IPAB	1	8.77	1.43	0.96
		2	74.0	46.2	9.44
		3	16.7	49.5	62.2
		4	0.35	2.73	25.6
		5	0.17	0.13	1.81
			2.09 ± 0.53	2.54 ± 0.58	3.18 ± 0.66
	OC	1	20.5	1.77	3.13
		2	26.5	10.6	3.13
		3	39.8	54.0	21.9
		4	12.0	31.0	46.9
		5	1.20	2.65	25.0
			2.47 ± 0.99	3.22 ± 0.74	3.88 ± 0.93
	ROPS	1	0	0	0
		2	100	0	0
		3	0	100	0
		4	0	0	100
		5	0	0	0
			2	3	4

(Morton, 2016). These countries are largely classified as Stage 1 countries in our study. Therefore, increasing the number of countries with some type of competition regulations – perhaps through the WTO and bilateral agreements – would likely decrease the overall bribery problem. In addition, the antitrust laws that do exist (as in many Stage 2 countries) may not be as effective as they could be in preventing anti-competitive practices, therefore, constant monitoring of their implementation may also help create less corrupt business environments. Other measures policy makers could take to foster the intensity of local competition include developing policies to reduce barriers to trade, avoiding overprotection of domestic firms, and creating incentives to attract foreign direct investment. These efforts may not only help by increasing competition but also improve accountability in markets.

Reliability of Police Service (ROPS) appears as the second key/policy variable. This is truly a unique contribution of our findings. Although the role of law enforcement in understanding corruption may be recognized conceptually in the business literature, its role in this complex system had not been empirically demonstrated. Our study not only demonstrates its role, but through its BN methodology, prioritizes its impact for various economic development levels across the world. The results suggest that successful interventions to improve the law enforcement perceptions would have the greatest interactive effects among the system properties, and as a result, the biggest improvement in bribery perceptions in Stage 2 (developing) economies.

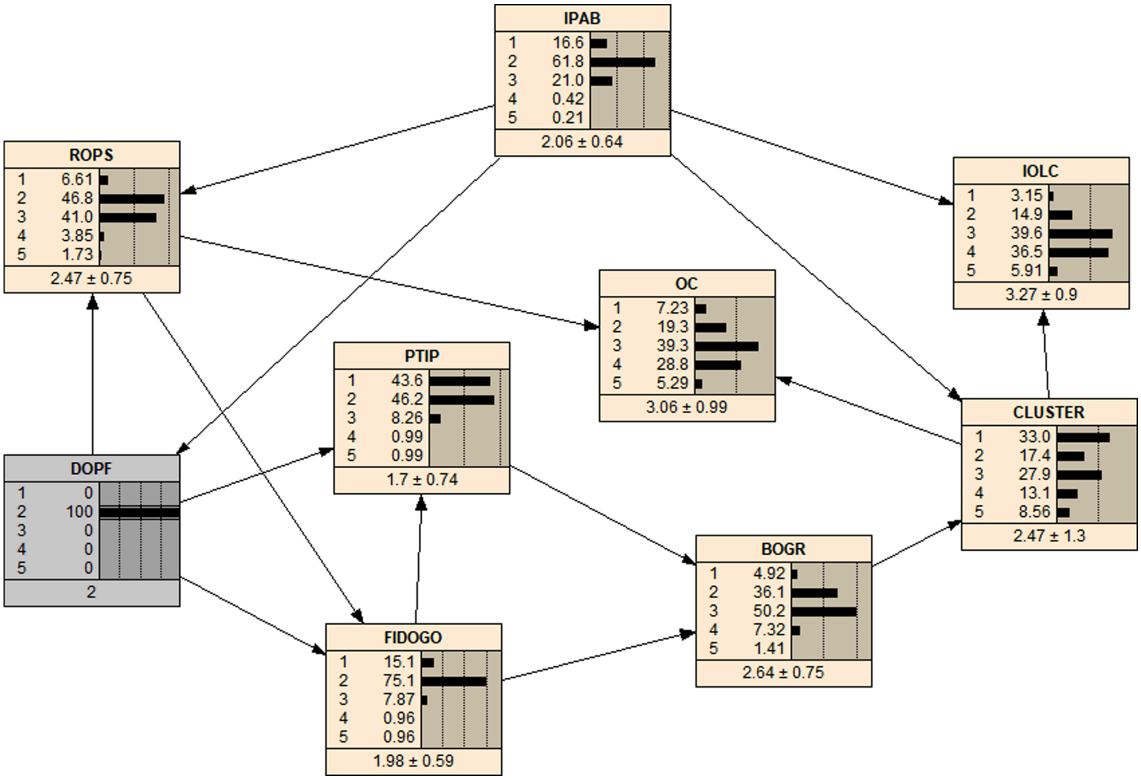


Fig. 8a. The overall network given that the observed level of DOPF is ‘low’.

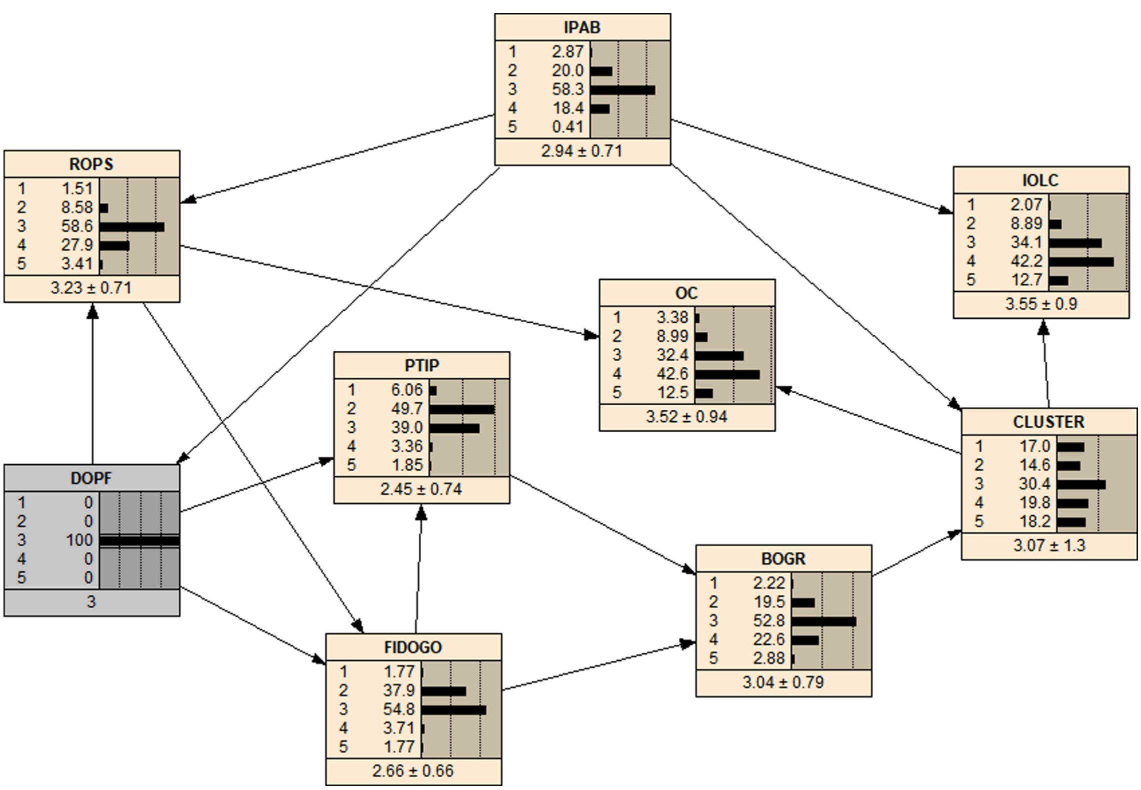


Fig. 8b. The overall network given that the observed level of DOPF is ‘medium’.

To date, studies have generally focused on law enforcement perceptions from the citizen (public administration) point of view, but our study indicates that the way managers perceive the quality of these services may have important business (cost) ramifications, which, in turn, affect their bribery perceptions. The findings detailed in Table 11 clearly demonstrate the interactive linkages among the perceptions of

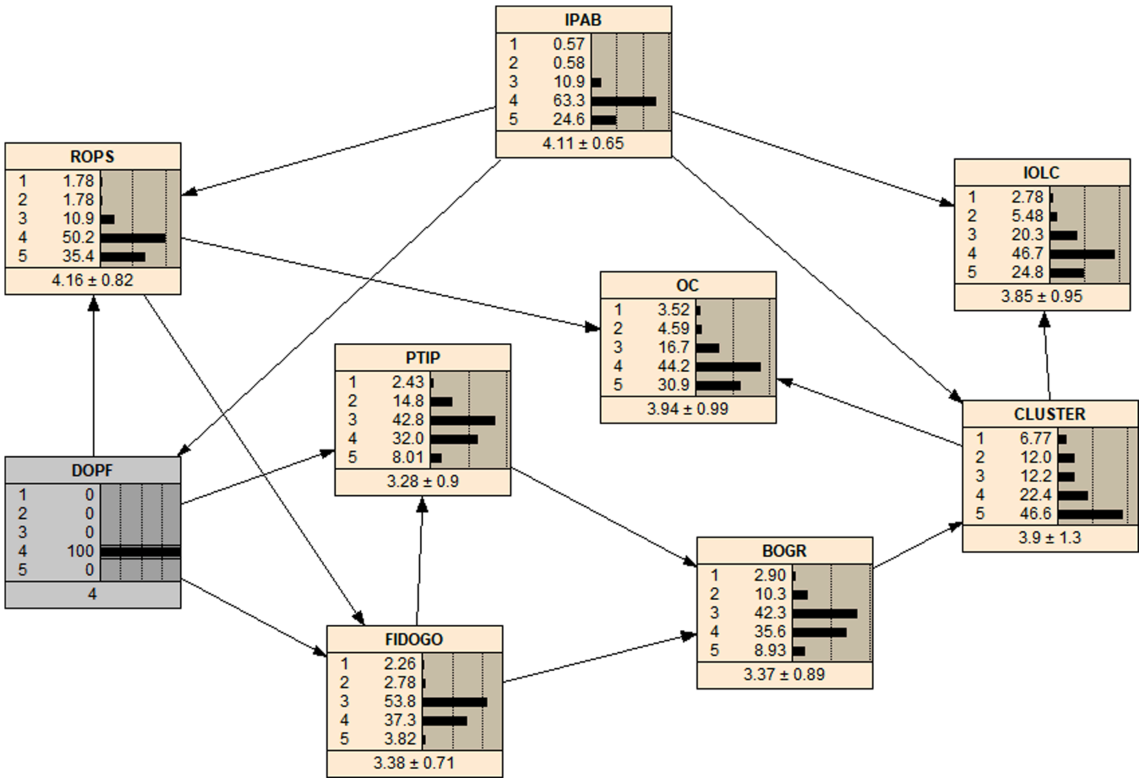


Fig. 8c. The overall network given that the observed level of DOPF is 'high'.

police services, business cost, and bribery for Stage 1 and Stage 2 economies.

As our study suggests (see Table 6), the Business Costs of Organized Crime (OC) is best explained by managers' perceptions about the ROPS offered in a particular market. It has been long established that markets with lower perceived costs are likely to be targets for (multinational) firms (e.g., Kwok & Tadesse, 2006). The literature supports the notion that the perceived cost of organized crime (because it creates economic disincentives) is significantly and negatively correlated with inflow of FDI (e.g., Daniele & Marani, 2010, Manrique, 2006). As Gomez-Soler (2012) points out, the literature on the relationship between crime and FDI is very limited; therefore, "it [the relationship] should also be explored further in future research" (p.29). We believe that our findings linking bribery to ROPS and OC (see Table 11) offer a novel insight into these efforts.

8. Concluding remarks

Bribery in particular and corruption in general are considered prime barriers to development and growth. A lack of understanding of the complex nature of bribery is likely to threaten globalization. This may in turn worsen the economic conditions of the developing and the underdeveloped world. Despite its significance, as scholars in international business and economics point out, there has been limited conceptualization (modelling) and even less empirical analysis of this enduring and complex problem. Two of the main reasons for this void are the lack of a systemic perspective and the dearth of extensive and reliable data (e.g., Emerson, 2006, O'Higgens, 2006). We hope that our Bayesian network analysis, with its extensive and reliable perception data from managers around the world, will enhance the understanding of the complexity of the bribery problem and contribute to global bribery control efforts.

9. Compliance with ethical standards

Funding: This study did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Ethical approval: This article does not contain any studies with human participants or animals performed by any of the authors.

References

ACWG (2014).file:///C:/Users/bilkent/Dropbox/etik/Bribery/G20%20Anti- corruption %20action%20plan_extended.pdf Accessed on March 10, 2019.

Ades, A., & Di Tella, R. (1999). Rents, competition, and corruption. *The American Economic Review, 89*(4), 982–993.

Ahrweiler, P., Schilperoord, M., Pyka, A., & Gilbert, N. (2015). Modeling research policy: Ex-ante evaluation of complex policy instruments. *Journal of Artificial Societies and Social Simulations, 18*(4), 1–26.

Argandona, A. (2007). The United Nations convention against corruption and its impact on international companies. *Journal of Business Ethics, 74*, 481–496.

Baclawski, K. (2004). *Bayesian network development* (pp. 18–48). Tools and Techniques: International Workshop on Software Methodologies.

Braun, C., & Hadwich, K. (2016). Complexity of internal services: Scale development and validation. *Journal of Business Research, 69*(9), 3508–3522.

Bruce, G., Marcot, B. G., & Penman, T. D. (2019). Advances in Bayesian network modelling: Integration of modelling technologies. *Environmental Modelling and Software, 111*, 386–393.

Cain, J. (2001). *Planning improvements in natural resources management*. Wallingford, UK: Centre for Ecology & Hydrology, Centre for Ecology and Hydrology.

Cerqueti, R., & Coppier, R. (2011). Economic growth, corruption, and tax evasion. *Economic Modelling, 28*(1–2), 489–500.

Cerqueti, R., Coppier, R., & Piga, G. (2012). Corruption, growth and ethnic fractionalization: A theoretical model. *Journal of Economics, 106*(2), 153–181.

Cherrier, H., Paromita, G., & Subhasis, R. (2018). Social entrepreneurship: Creating value in the context of institutional complexity. *Journal of Business Research., 86*(May), 245–258.

Clarke, G. R. G., & Xu, L. C. (2004). Privatization, competition and corruption: How characteristics of cribe takers and payers affect bribes to utilities. *Journal of Public Economics, 88*, 2067–2097.

Daniel, B. K., Zapata-Rivere, J. D., & McCalla, G. I. (2007) A Bayesian belief network approach for modeling complex domains. In Mittal A., Kassim A. (Eds.), Bayesian network technologies: Applications and graphical models. IGI Publishing.

Daniele, V., & Marani, U. (2010). Organized crime and foreign direct investment: The Italian case. https://www.cesifo-group.de/portal/pls/portal/!PORTAL.wwpob_page.show?_docname=1053967.PDF, Accessed on March 10, 2019.

Darwiche, A. (2009). *Modeling and reasoning with Bayesian networks*. NY: Cambridge University Press.

Di Guardo, M. C., Marrocu, E., & Paci, R. (2016). The effect of corruption on ownership strategy in cross-border mergers and acquisitions. *Journal of Business Research, 69*, 4225–4241.
Ekici, A., & Ekici, S. (2016). A Bayesian network analysis of ethical behaviour. *Journal of Macromarketing, 36*(1), 96–115.
Ekici, A., & Onsel, S. (2013). How ethical behavior of firms is influenced by the legal and political environments: A Bayesian causal map analysis based on stages of development. *Journal of Business Ethics, 115*(2), 271–290.
Emerson, P. M. (2006). Corruption, competition and democracy. *Journal of Development Economics, 81*, 193–212.
Fenton, N., Hearty, P., Neil, M., & Radlinski, L. (2010). Software project and quality modelling using Bayesian networks. DOI: 10.4018/978-1-60566-758-4.ch001.
Ferraro, G., & Iovanella, A. (2016). Revealing correlations between structure and innovation attitude in inter-organizational innovation networks. *International Journal of Computational Economics and Econometrics, 6*(1), 93–113.
Gomez-Soler, S. (2012). Organized crime, foreign investment, and economic grwoth: The Latin American case. *Economina and Region, 6*(2), 5–32.
Gray, C. W., & Kaufmann, D. (1998). Corruption and development. *Finance and Development, 35*(1), 7–10.
Gupta, S., & Kim, H. W. (2008). Linking structural equation modelling to Bayesian networks: Decision support for customer retention in virtual communities. *European Journal of Operational Research, 190*(3), 818–833.
Hesar, A. S., Tabatabaee, H., & Jalali M. (2012) Structure learning of Bayesian networks using heuristic methods. International conference on information and knowledge management (ICIKM 2012),IPCSIT vol. 45 IACSIT Press, Singapore.
Horny, M. (2014). *Bayesian networks. Technical report*. Boston University, School of Public Health.
Hotchkiss, C. (1998). The sleeping dog stirs: New signs of life in efforts to end corruption in international business. *Journal of Public Policy and Marketing, 17*(1), 108–115.
Husted, B. W. (1999). Wealth, culture, and corruption. *Journal of International Business Studies, 30*(2), 339–359.
Jaitha A. (2017). An Introduction to the theory and applications of Bayesian networks" CMC Senior Theses. 1638. http://scholarship.claremont.edu/cmc_theses/1638.
Jensen, F. V. (2002). *Bayesian networks and decision graphs*. New York: Springer-Verlag.
Kent M. (2008). Weather forecasting with Bayesian networks - causal modelling. Honours project report, Department of Computer Science , University of Cape Town.
Kirman, A. (2013). Complexity: Toward an empirical measure. *Technovation, 33*(4), 111–118.
Korb, K. B., & Nicholson, A. E. (2011). *Bayesian artificial intelligence*. USA: CRC Press Taylor & Francis Group.
Kwok, C. C. Y., & Tadesse, S. (2006). The MNC as an agent of change for host-country institutions: FDI and corruption. *Journal of International Business Studies, 37*, 767–785.
Manrique, L. E. (2006). A parallel power: Organized crime in Latin America. *Real Instituto Elcano, 28*(September), 1–8.
McKinney, J. A., & Moore, C. W. (2008). International bribery: Does a written code of ethics make a difference in perceptions of business professionals. *Journal of Business Ethics, 79*, 103–111.
Mishra, S., Kemmerer, B., & Shenoy P. (2001). Managing venture capital investment decisions: A knowledge-based approach, Working Paper, School of Business, University of Kansas.
Morton, F. M. S. (2016). How do you enforce antitrust law in a global marketplace? http://insights.som.yale.edu/insights/how-do-you-enforce-antitrust-law-in-global-marketplace, Accessed on March 10, 2019.
Murphy, K., Shleifer, A., & Vishny, R. (1991). The allocation of talent: Implications for growth. *Quarterly Journal of Economics, 106*, 503–530.
Murphy, K., Shleifer, A., & Vishny, R. (1993). Why is rent-seeking so costly to growth? *American Economic Review., 83*(2), 409–414.
Nadkarni, S., & Shenoy, P. (2004). A causal mapping approach to constructing Bayesian networks. *Decision Support Systems, 38*(2), 259–281.
Nwabuzor, A. (2005). Corruption and development: New initiatives in economic openness and strengthened rule of law. *Journal of Busiess Ethics, 59*, 121–138.
O'Higgins, E. R. E. (2006). Corruption, underdevelepment, and extractive resourse industries: Addresssing the vicious cycle. *Business Ethics Quarterly, 16*(2), 235–254.
Olaya, J., & Wiehen, M. (2006). *How to reduce corruption in public Rocurement* (pp. 13–105). Transparency International: Handbook for Curbing Corruption in Public Procurement.
Onisko, A. (2008). Medical diagnosis. In Bayesian Networks" Pourret, O., Naim, P. & Marcot, B. (Eds.), Cornwall: John Wiley and Sons, pp. 15–32.
Rabl, T., & Kuhlmann, T. M. (2008). Understanding corruption in organizations –development and empirical assessment of an action model. *Journal of Business Ethics, 82*, 477–495.
Riley, S. P. (1998). The political economy of anti-corruption strategies in Africa. *European Journal of Development Research, 10*(1), 129–159.
Ryan, L. V. (2000). Combatting corruption: The 21st century ethical challenge. *Business Ethics Quarterly, 10*(1), 331–338.
Sala-i Martin, X., Bilbao-Osorio, B., Blanke, J., Crotti, R., Hanouz, M. D., Geiger, T., & Ko, C. (2012). The global competitiveness index 2012–2013: Strengthening recovery by raising productivity. *The global competitiveness report*, 2012–2013.
Theobald, R. (2002). Containing corruption. *New Political Economy, 7*(3), 435–449.
Waller, C. J., Verdier, T., & Gardner, R. (2002). *Corruption: Top down or bottom up? Economic Inquiry, 40*(4), 688–703.
Wang, H., Rish, I., & Ma, S. (2002). Using sensitivity analysis for selective parameter update in Bayesian network learning. AAAI Technical Report. SS-02-03.
WEF (2017). The global competitiveness report.
Wu, X. (2009). Determinants of bribery in Asian firms: Evidence from the world business environment survey. *Journal of Business Ethics, 87*, 75–88.
Wu, W. W. (2010). Linking Bayesian networks and PLS path modeling for causal analysis. *Expert Systems with Applications, 37*, 134–139.

Ahmet Ekici (PhD, University of Nebraska-Lincoln) is an Associate Professor of Marketing at Bilkent University, Ankara. His main research areas are public policy and marketing; macromarketing and relationship marketing. His refereed articles have been published in a variety of journals including *Journal of Macromarketing, Journal of Business Ethics, Industrial Marketing Management, Journal of Business Research, Journal of Public Policy & Marketing, and Social Indicators Research.*

Sule Onsel Ekici (PhD, Istanbul Technical University) is a Professor of Decision Making at Dogus University, Istanbul. Her research topics are scenario analysis, neural networks, cognitive mapping, and Bayesian networks. Her refereed articles have appeared in a variety of journals including *Expert Systems with Applications, Transportation Research Part C, Socio Economic Planning Sciences, European Journal of Operational Research, and International Journal of Production Research.*