On Collusion and Coercion: Agent Interconnectedness and In-Group Behaviour

F. Jordan Srour
Lebanese American University, Lebanon
Jordan.Srour@lau.edu.lb

Neil Yorke-Smith*
Delft University of Technology, The Netherlands
and American University of Beirut, Lebanon
n.yorke-smith@tudelft.nl

ABSTRACT

The interconnectedness of actors is an antecedent for collective corruption, which in turn can lead to endemic corruption in a society. As a testbed for studying the effects of social interconnectedness on corrupt behaviours, we examine the domain of maritime customs. We add to our existing agent-based simulation a nuanced model of actor relatedness, consisting of clan, in-group (sect), and place of origin, and encode associated behavioural norms. We examine in simulation the effects of social interconnectedness on domain performance metrics such as container outcomes, delay, revenue, collusion, and coercive demands. Results confirm that, when corruption is widespread, localized punitive- or incentive-based policies are weakened, and that the effect of process re-engineering is frustrated when interconnectedness increases beyond a critical point, for two out of three forms of homophily connections. Our work connects with and provides a complementary methodology to works in the political economy literature.

KEYWORDS

social networks; agent-based simulation; maritime customs; ethics

ACM Reference Format:

F. Jordan Srour and Neil Yorke-Smith. 2018. On Collusion and Coercion: Agent Interconnectedness and In-Group Behaviour. In *Proc. of the 17th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2018), Stockholm, Sweden, July 10–15, 2018,* IFAAMAS, 9 pages.

1 INTRODUCTION

A process with the opportunity or obligation for actors to negotiate gives rise to the possibility of corruption: "the misuse of public office for private gain" [35]. The negative repercussions of corruption upon institutions, societies, and nations include poverty, tax evasion, reduced national competitiveness, political instability, and weakened democracy and rule of law. Further still, corruption—whether *collusive* or *coercive*—reinforces disenfranchisement and hinders development, being "one of the most serious barriers to overcoming poverty" with a strong negative correlation between perceived corruption and income per capita [36].

It is known that the interconnectedness of actors is an antecedent for collective corruption, which in turn can lead to endemic corruption [20, 25] and all of its repercussions. Among case studies, Hungarian researchers noted how government structures can allow for the formation of elite cliques which can design and coordinate entire networks of corruption [18]. Studies in China explored the influence of corrupt in-group networks which, in situations of collective corruption, tend towards rewriting norms and thus legitimizing further corruption [10].

Previous work on social interconnectedness and corruption falls into two broad categories. The first—such as the studies in Hungary and China—examines observed in-practice behaviours, usually in a particular societal context. The second category of work uses mathematical modelling or simulation—sometimes agent-based simulation [31]—to examine in-theory behaviours in a synthetic or stylized setting.

Our work lies at the intersection of these two approaches. We adopt agent-based simulation as a tool to study corrupt behaviours, but in a validated simulation of an actual case study domain: maritime customs, namely the import of sea-based containers. The domain is in itself important, because customs revenue contributes a significant component of public finances, particularly in developing countries, and the Organization for Economic Co-operation and Development (OECD) finds that widespread corruption often hampers customs efficiency, creating a "major disincentive and obstacle to trade expansion" and resulting in "disastrous consequences in terms of national security and public finance" [16].

We build on our extant agent-based simulation of maritime customs imports [33]. The goal of the simulation model is not to simulate precise behaviours or to make quantitative forecasts, but to simulate archetypal process deviations and suggest possible qualitative outcomes of policy and reform measures. To the simulation we add a nuanced model of actor relatedness, consisting of clan, in-group (sect), and town of origin, and encode associated behavioural norms. We examine the effects of social interconnectedness on domain performance metrics, such as container outcomes, delay, revenue collected and revenue diverted, and instances and type of corrupt practices. Simulation results confirm that, when corruption is widespread, localized punitive- or incentive-based policies are further weakened, and that the effect of process re-engineering, which has been found to offer more promise, is frustrated on many metrics when interconnectedness increases beyond a critical point, for two out of three forms of homophily connections.

Section 2 introduces the domain. Section 3 overviews the simulation model. Section 4 reports the results and their analysis. Section 5 offers concluding remarks.

2 BACKGROUND AND RELATED WORK

A port, including its customs processes, is an instance of a complex socio-technical system with multiple stakeholders. The literature

*Corresponding author.

Proc. of the 17th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2018), M. Dastani, G. Sukthankar, E. André, S. Koenig (eds.), July 10–15, 2018, Stockholm, Sweden.

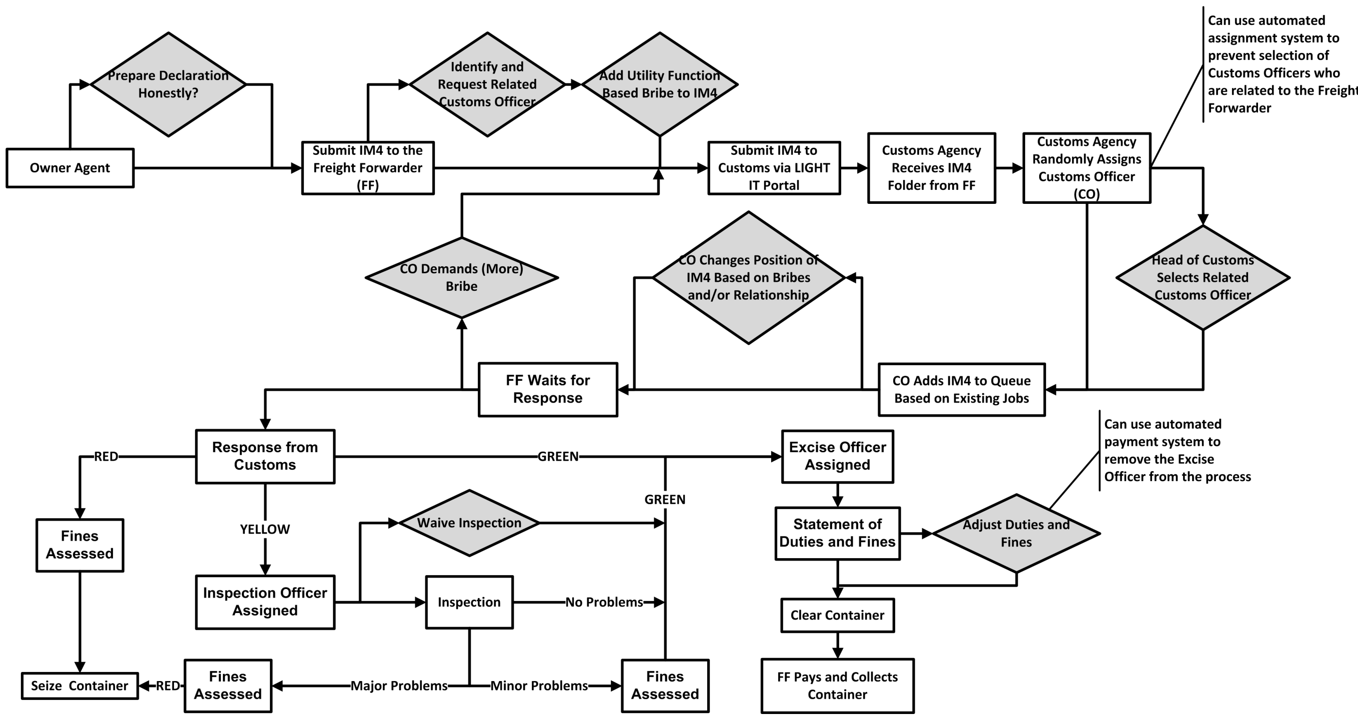

Figure 1: Flowchart of archetypal import process as implemented in the MABS [33]. Decisions are highlighted in grey; two possible process re-engineering measures are marked by the callouts.

concludes that customs corruption not only has serious implications, but that it is not easily tackled by policy changes, that reform policies can have unexpected side-effects, and that a broadly-based, systemic approach is required [19, 23, 28]. In order to counter established, widespread corrupt practices, a deeper understanding is required of the processes in which corruption features, together with a deeper understanding of the corrupt practices that occur, within the broader socio-political, socio-economic, governmental and cultural situation [1, 16, 19, 25].

A crucial role in the process of moving a container through customs is played by the *freight forwarder* (FF), an intermediary which manages and organizes shipments for others. The process is primarily based on a match between shipping documents and customs documents. If this match is made and the involved actors are considered trustworthy, then the container may proceed following payment of standard duties. Otherwise, or if the container should be randomly selected, then the container is subject to search and may see additional duties or fines. The import of each container can be construed as one round in a repeated game between a mostly fixed set of agents, who have specified and fixed roles in the typical situation [6, 11].

Possible *deviations* from an archetypal customs import process (see Figure 1) include incomplete, inaccurate, or fictitious documentation; waived or additional inspection; inaccurate value estimation; waiving true fines or imposing additional fines; and delaying or expediting certain containers. Although outside our scope, in some situations a whole grey 'parallel customs' system evolves [17, 25].

Policy efforts led by trans-national organizations such as the OCED focuses on reducing trade barriers, reforming trade procedures, and building 'cultures of integrity'. However, as the contemporary political economy literature concludes, such policy engineering has, more often than not, proved ineffective [19, 23, 28, 29].

Agent-based models and multi-agent-based simulation (MABS) have been successful in maritime container logistics (e.g., [21]) and port management (e.g., [13, 14]). Agent-based simulation has also been used to study corruption. Hammond [11] develops an agent-based population model in an effort to explain shifts in corruption levels. Corruption is modelled as a simple, game-theoretic repeated interaction on the micro level. Endogenous shifts in tax evasion levels are observed as emerging from the micro-behaviour.

Situngkir [31] is interested in the link between corrupt behaviours in individual agents and the normative societal and cultural environment in which they interact. He builds a MABS inspired by corrupt bureaucrats in Indonesia and obtains system-wide results. However the model is highly stylized and does not capture a real process in any detail.

Our previous work adopted MABS to study customs process and corruption of a Mediterranean container port [33]. Although the model featured a simple construct of agent interconnectedness, it did not study the effects of this aspect of the organization on the performance metrics.

From an anthropological perspective, Makhoul and Harrison [22] study interconnectedness and in-group effects in a Mediterranean Arab context, while Sidani and Gardner [30] study work practices, including corruption. Roman and Miller [27] find that status in social hierarchy and familial connections are "precursors" for corruption. Ferreira et al. [8] show the importance of in/out-group agent behaviour. Abdallah et al. [1], among studies of social behaviour, demonstrate that peerpunishment is more effective than an overly strong centralized punishment in promoting cooperation, if actors are able to bribe centralized authorities.

Bloomquist and Koehler [2] simulate individuals' compliance to tax regulations, while Elsenbroicha and Badham [7] develop a simulation of extortion, noting the importance of social factors beyond game-theoretic models. Lauchs et al. [20] apply social network simulation for the case of a real corrupt police network.

Besides MABS focused on illicit or corrupt behaviour, the literature is extensive on simulation studies of norms, social networks, and organizational effects. We mention just Villatoro et al. [37], who highlight how agents' norm internalization can provide an alternative regulation mechanism when external regulation is difficult, such as when the regulative agents are themselves corrupt.

3 SIMULATION MODEL

Our work focuses on ports in high-corruption Mediterranean countries. In this section we outline the simulation model with emphasis on the developments in the model in this paper, which concern agent interconnectedness in an Arab cultural milieu. Our earlier papers [12, 32, 33] give background on the domain, describe the basic model, and report the data used.

The simulation models collusive and coercive corruption, in-group relationships, and agents' adaptive behaviours in negotiation. At the heart of the MABS are the actors' progression through the documented processes for each shipment, the points of possible deviation, the decisions whether to engage in (or how to respond to) non-standard practices, and the negotiation that may ensue.

The nine types of **agents** are summarized in Table 1. We describe the role of the main agents, then the process in which they interact. Each agent make its decisions aiming to maximize its expected utility. At the port there is a known schedule of bribes [17].

Owner's Agent (OA). Decides what to declare based on the tariff for the actual container contents, and estimates of the cost of bribes necessary and probability of inspection.

Freight Forwarder (FF). Offers bribe to the Customs Officer (CO), part of which will be passed on to other actors in customs, to expedite container if its due date is close. Offer a bribe to the Head Customs Officer (HCO) to obtain assignment to a preferred CO, i.e., a CO to whom the FF has a relationship. Offers bribe to CO obtain a GREEN decision if the expected cost of doing so is less than the cost of fines and fees; assumes that all COs will accept a bribe of sufficient amount [17] (a warranted assumption when corruption is endemic). If the CO demands, will increase bribe amount up to the maximum amount where expected cost would exceed expected value. Routinely offers tips. We include the role of the customs broker [17] into the FF.

Customs Officer (CO). Unless opposed to bribes in principle, accepts any bribe of sufficient amount, to either expedite the container, waive inspection, or change decision outcome. May demand a bribe if none offered or if its amount is too low. May impose an unnecessary inspection unless bribed. Works slowly on a container unless given a tip. Always declares GREEN a container whose owner or consignee is related closely enough.

Head Customs Officer (HCO). Supportive of the COs, turns blind eye to non-standard practices [17]. Does not overrule a CO's decision, except for RED decisions for a sufficient bribe. Will override the departmental IT system's assignment of container to a CO, for a sufficient bribe. Head Inspection Officer and Head Excise Office behave similarly.

Inspection Officer (IO). Unless opposed to bribes in principle, accepts any bribe of sufficient amount, to waive or expedite the inspection, to or report a different contents than the actual found. Works slowly unless given a tip.

Excise Officer (EO). Unless opposed to bribes in principle, accepts any bribe of sufficient amount, to set lower duty than the published tariff rules. Works slowly unless given a tip.

We simulate the main, documented customs **process** as follows (Figure 1): (1) owner's agent submits documents to the freight forwarder company, which assigns a specific FF agent; (2) FF submits documents to customs agency via the *LIGHT* electronic portal; (3) *LIGHT* assigns the case to a specific customs officer (CO); (4) the CO sees output of the *STAR* computer (IT) system and can override: the decision is RED (fines imposed, seize container), YELLOW (inspect container), or GREEN (approve container, duty imposed); (5) if inspection is required, *LIGHT* assigns a specific inspection officer (IO); (6) the IO inspects the container and sends the report to the CO via *STAR*; (7) the CO revises a YELLOW decision to RED or GREEN and informs the FF; (8) approved GREEN containers proceed to the Excise Department and are assigned by *LIGHT* to a specific excise officer (EO); (9) the EO computes the final duty, fines (if any), and other costs (handling, storage, etc.) and informs the FF; (10) the FF pays the due amount (plus applicable interest); and (11) the CO approves the release of the container. The heads of the respective departments can override both the assignment of officers (by *LIGHT*) and the decisions of officers (in *STAR*).

Deviations, depicted in grey in Figure 1, can occur from the documented process in various ways, as follows. First, the FF can offer bribes (to the HCO) to attempt to obtain its preferred CO, (to the HCO or CO) to expedite the container, (to the CO) to have duties reduced, or (to the CO) to have a *deviant* container (i.e., illegal or misdeclared) pass through as GREEN. Second, the HCO can accept a bribe and assign the preferred CO. Third, the CO can accept a bribe (collusive), or it can demand (more) bribe (coercive). Fourth, the IO can waive, expedite, or report differently the inspection. Fifth, the EO can change the amount due.

Audits occur, randomly, at two points in the process. We assume that audits are effective, and will find the actual container contents and value. The first audit point is after IO's inspection. The second audit point is after the CO's decision. The audits constitute a learning opportunity: the deviational behaviour of all customs actors are reinforced if they are not caught by audit, but the behaviour is reduced if caught. For example, a CO that accepted a bribe and was not caught is more likely to accept bribes in future, but one that was caught is less likely. For the FF, whether a deviant container made it through as GREEN or was stopped as RED (whether by a customs employee or by audit) is a learning opportunity about bribe success and amounts, and CO characteristics.

Table 1: Agents in the simulation: their key attributes and roles.

Agent class	Attributes	Key actions
Owner's Agent	Knows true contents	Prepares declaration (contents, value)
Freight Forwarder	Knows true contents	Submit container, bribe
Customs Officer	Relationship status	Decide container outcome
Head Customs Officer	Relationship status	Assign CO to container
Inspection Officer	Relationship status	Inspect container
Head Inspection Officer	Relationship status	Assign IO to container
Excise Officer	Relationship status	Receives payment of tariff and fines
Head Excise Office	Relationship status	Assign EO to container
Audit Officer	Knows agent actions	Audit any part of customs dept.

3.1 In-group relationships

The degree to which two agents share an affinity, and the obligations that come from such an in-group relationship, is a cornerstone of business and society in all Arab and many other Mediterranean countries [15, 19, 30]. As noted earlier, interconnectedness of actors is an antecedent for various forms of corruption. We capture such relationships by a three-part profile of each agent's clan (family relationship), in-group (e.g., sect), and ancestral place of origin (village, town, or city quarter). The form of relationship modelled is the same as in our previous work [33], but the instantiation of the profiles is richer and the behavioural accommodation of agents in the simulation according to their relationship with other agents is now implemented, rather than comprising a token effect. In fact, although we previously identified their potential relevance, the effect of interconnectedness on the simulation results was unexplored.

An agent's profile is instantiated as follows. First, the clan is chosen randomly among the set of clans, labelled $1, \ldots, C$. Second, the agent's origin ('town') is set based on the clan. Towns are divided logarithmically from largest clan (1) to smallest (C): clan 1, the largest, has approximately $\frac{1}{2}$ of the towns; clan 2 has approximately $\frac{1}{2}$ of the remainder, etc, with the constraint that every clan has at least one town. If the agent is to live in one of its clan's towns (based on chance), the town is assigned randomly among them; otherwise the town is assigned randomly from all the other clans' towns. Third, the agent's sect is set based on the town. Note this means that not every agent from a given clan will have the same sect. Let s_t be the sect of the majority clan of town t. If the agent is to have the sect of the town it is living in, it is assigned sect s_t; otherwise it is assigned a sect randomly from all the other sects.

Based on the relationship between two agents, the propensity to offer, accept, and demand bribes, the bribe amounts, and customs actor behaviours (e.g., cooperation with requests, speed of work, inspection decisions, assessed tariff levels, fines raised/waived), may all change. An agent quantifies its relationship with another agent as two parts: static relationship (closeness between profiles) and dynamic trustworthiness (based on interactions to date with the other agent). These two parts capture respectively pedigree and performance. They are combined linearly, with equal weight.

Following Makhoul and Harrison [22], we model static relationship as the weighted mean of the three factors:

$$\frac{1}{6}(3 * \mathit{sameClan?} + 2 * \mathit{sameSect?} + \mathit{sameOrigin?}) \qquad (1)$$

Dynamic relationship depends on the agent type (CO, IO, etc) and the agent's memorized history of interactions with the other agent. For example, for a FF agent assessing its relationship with a CO agent, factors include: percentage of bribes accepted, percentage of containers approved, percentage of favours done, and number of interactions. This can be seen a computation of one agent's emergent trust in another; social trust in illicit networks is necessary for their function [20]. The FF considers all the COs it knows about, and—assuming the net expected utility is favourable, after accounting for expected cost including fines if caught—offers a bribe to the HCO to have its preferred CO selected.

Notwithstanding the computed interconnectedness, the strongest component of relationship in Arab culture is familial. If two agents hail from the same clan, then cultural norms require that they act selflessly for the welfare of the other [22]. Hence, a CO will accept a bribe from a family member even if the expected value of the bribe is negative. The Head Customs Officer will, for a family member in the customs department, assign more lucrative work, and for a related FF, readily assign a container to the FF's preferred CO.

The final major development in the model is the role of the assigned Customs Office as 'corrupt ambassador' of the containers assigned to him by the HCO, should the CO accept a bribe. In effect, having accepted a bribe for a container, it is in the CO's interest to ensure that the container receives favourable treatment from the subsequent customs actors; it is the CO who decides how much of the bribe to allocate to the latter agents. Here, we model behaviour in the studied port customs system, but also effectively encode a norm that might emerge in a repeated game setting: COs who accept a bribe, but fail to deliver on their side of the implied bargain, will in the long term be 'punished' by the FFs who learn that the CO is not trustworthy.

4 EXPERIMENTS ON AGENT INTERCONNECTEDNESS

We implemented the simulation using the Java-based agent toolkit Jadex [3]. The development, calibration, and validation and verification (V&V) of the basic MABS (prior to our extensions here) are treated in previous papers [33]; we continued the same methodology. Briefly, V&V consisted of data validity (triangulation between data sources), conceptual model validation (by domain experts), implementation verification (longitudinal tracing of agent behaviour

Table 2: Main simulation parameters [33].

Parameter	Baseline value
Illicit container %	10%
Standard tariff rate	5–10%
VAT rate	10%
Fine penalty	10x tariff
Chance of inspection	25%
Inspection success	80%
Work-slow ratio	3 times
CO collusive propensity	75%
CO coercive propensity	60%
Chance of audit	2%
Audit penalty	6x salary
Number of clans	50
Number of in-groups (sects)	16
Number of towns of origin	6

through runs, code review, extreme parameter values), and operational validity as far as possible (qualitative comparison of model outputs with reported outcomes). Results reported here cannot be compared directly with those of [33], due to the developments in the model outlined in the previous section, and to minor changes in how the metrics are computed.

We ground our simulation in the instance of the Port of Beirut, Lebanon. This port is a major container terminal in the eastern Mediterranean [5, 17], located in a high-corruption country. Table 2 gives the baseline parameter values extrapolated from the modelled customs system. Note that the baseline number of clans yields a 2% chance of the FF and CO being related. The baseline value of the number of places of origin ('towns') is small, reflecting the six main regions of the country of the modelled port.

Hypotheses. The approach we adopt is exploratory, examining emergent phenomena from the MABS. At a high level, however, we can conjecture two hypotheses. The first is that the amount of deviant behaviour will increase as the interconnectedness of actors increases. The second hypothesis is that reform measures will be less effective as the interconnectedness increases.

Results. The baseline parameters produced the Key Performance Indicators (KPIs) of Table 3. Results reported are averaged over 100 runs of 1,600 containers each. Metrics are reported as the average per container, with the exception of the percentage columns, which reflect the total proportion of all containers. Column *Time* is total elapsed time between submission of a container to the customs department and its release (or seizure) from customs; it does not include the time that the container waits with the FF prior to its submission to the CO.

In the second section of rows of Table 3, we report the effects of a range of localized policy measures; and in the third section, characteristic process re-engineering measures identified in the literature as promising. The former localized measures are: moral reform campaigns (leading to greater honesty by the owner (50% less willing to permit bribe), or less (by 50%) collusive or coercive behaviour by customs staff), higher tariffs (x4), punitive fines on owners (x4), more inspection (x2), perfect inspection (a deviant container will always be revealed, if inspected), more customs staff (x2), higher customs salaries (x5), more audits (x3, x10, or 100%), and higher penalties on caught customs staff (x10).

The latter process re-engineering measures are (1) strengthening the *LIGHT* IT system, so that allocations of containers to Customs Officers cannot be overridden by the HCO, (2) streamlining payment sub-process so that the EOs no longer have an intermediary role, and (3) both measures together.

In the final row of Table 3, we report the effect of regressing the model to purely static (profile-based) relationship computation. The most interesting observation is that the number of CO–FF iterations and the number of deviations both increase, along with the average bribe value. We attribute this to the FF not taking into account dynamically which COs are more conducive and which will accept lower bribes for the same action. A similar effect occurs if agents' adaptive (learning) behaviour is disabled.

Sensitivity analysis. To understand the importance of specific parameter values (Table 2), we perform an initial analysis of the sensitivity of the KPIs to variation in the input parameters. Sampling points in the parameter space of non-structural parameters, we observe that the simulation converged to qualitatively similar behaviours; the value of the equilibria depending on the combination of parameter values ('nature') and the effect of learning on system dynamics ('nurture'). For reasons of space we do not go into detail here. We next study systematically the parameter space, focusing on the variables affecting inter-agent relatedness.

4.1 Effect of interconnectedness

We systematically explore the parameter space of clans ($C = [2, 64]$), in-groups ($S = [2, 48]$), and places of origin ($T = [2, 48]$). We performed pairwise type-2 ANOVA tests between the independent variables (*clans*, *sects*, *towns*, *illicit%*, *tariff*, *fine*, *staff*, *audit*, *audit-penalty*) and the dependent variables (all the metrics of Table 3, together with additional variables, including internal variables such as the relationship between CO and FF). The analysis is factored by variable *process*, which takes discrete levels $\{0, 1, 2, 3\}$, corresponding respectively to the regular process, empowered IT, streamlined electronic payment, or both, and the values of other variables. Table 4 reports the significance levels of the ANOVA p-values.

We study first the variables that directly affect the interconnectedness of actors: *clans*, *sects*, and *towns*.

Relatedness input variables. All three relatedness variables have a strong effect on the total relatedness between CO and FF, although for *clans* and *towns* the effect is manifest via the 'dynamic' relationship, perhaps because *sects* dominates in terms of the 'static' relationship. Indeed, *sects* is the most significant relatedness variable. As the number of sects decrease, the change of any two agents being statically linked, i.e., solely through a common sect, increases. The number of sects has a highly significant effect on almost all of the KPIs. Second, as with sects, when the number of *towns* decrease, the chance of agents' sharing homophily increases. The effect is slightly weaker than that of *sects*, but still with significant effect on more than half of the KPIs. The third parameter, *clans* has effect on *cost* to the owner (higher), *tariff* paid (higher), *% diverted* revenue (higher), and enforcement cost (also higher).

Table 3: Snapshot KPI results for baseline scenario, localized policy changes, and process re-engineering.

Experiment	Time (hrs)	Delay (hrs)	Cost ($)	Deviations	Iterations	% Illicit	% Not caught Deviant	Revenue ($)	Bribe ($)
baseline	2703	14345	34191	48.20	6.38	10.08	97.04	22286	3282
owner honesty	2470	13439	35266	47.28	6.24	9.88	96.88	24179	3052
lower collusion	715	270	28782	14.79	1.57	9.91	97.82	20767	756
lower coercion	1498	5390	35843	34.80	4.42	10.06	96.69	25743	2128
higher tariff	2935	15513	93666	49.36	6.55	9.98	96.77	80312	3376
punitive fines	2958	15864	71506	49.35	6.55	9.99	96.81	59158	3371
more inspection	3713	37286	34277	83.02	11.43	9.93	97.10	18180	6168
perfect inspection	2928	20712	36462	57.71	7.78	9.92	96.73	23502	4025
more staff	601	853	32674	41.95	5.46	9.98	97.35	21147	2931
higher salary	2565	14625	49330	49.89	6.63	10.03	97.28	21822	15656
more audits	1885	5367	31990	34.17	4.33	9.89	96.95	21040	2469
many more audits	433	147	36817	15.92	2.31	10.13	94.10	25075	1311
100% audits	386	67	44841	9.01	1.11	10.06	82.02	33757	1708
higher penalties	2096	10385	47189	35.70	6.23	10.17	96.49	33467	848
empowered IT system	2153	11724	31965	37.52	6.52	10.14	96.61	23360	803
electronic payment	2646	16338	34510	49.76	6.89	10.06	97.14	22260	3520
IT & electronic	1935	9787	31374	33.91	6.20	9.87	96.71	22846	786
static relationships	2409	21014	33156	57.40	7.73	10.10	97.55	20340	3962

Table 4: Correlation between independent variables (rows) and dependent variables (columns). Significance codes: $^{***} < 0.001$, $^{**} < 0.01$, $^{*} < 0.05$, $\cdot < 0.1$

input	% Not caught Illicit	% Not caught All deviant	Cost	Fee	Tariff + Fine	Bribe	Revenue	% Divert.	Time	Delay	Iter.	CO–FF linkage Static	CO–FF linkage Total	Devi-ations	% Audited	Cost of Enforce.
clans	*		**		**		**	***		·			***			**
sects	***	***		***	***	***	***	**	***	***	***	***	***	***	***	***
towns	***			***		***	***	***		***	***		***	*	***	***
adaptive	*		*	***	*		*	*		**	***			***		
process			*	·	·	***		*						·		
illicit	**	***							***							
tariff			***	*	***	**	***				*	·	*	*		
fine			***		***		***	***								
staff		*								·						***
audit	***										·			·	***	
penalty			***		***	**	***	***								

To further examine the effect of interconnectedness on process re-engineering, we plot *bribe*, *delay*, *revenue*, and *iterations* versus *clans*, for each of the four values of *process*. (*Deviations* closely follow the pattern of *iterations*.)

Figure 2 plots locally weighted regressions (shaded areas). A commonality across the four graphs is that the first process re-engineering measure (IT system)—and by extension the combined measures—is markedly more effective than the second measure in reducing corruption. This effect is most easily seen in the graph of *clans* versus *bribe* (top-left in Figure 2), where it results in an average bribe amount below $1,000 compared to $3,500. Interestingly, there is little variation with the number of clans: only a slight increase when *clans* is very small. The graphs for the other variables show some more variation, and in particular *delay* and *iterations* start to vary when the clans are few or many.

The second process re-engineering measure (streamlined payments) in fact proves slightly worse than the original process—as also seen in Table 3 in the case of the baseline scenario—although the difference is not significant. Lastly, we observe that the second measure causes worse KPI values when the number of clans is large, in contrast to the original process and the first measure; we do not have an immediate explanation for this phenomena.

Figure 3 gives sets of graphs for variable *sects*; we omit the graphs for variable *towns* for reasons of space. In both, however, a critical point emerges, below which there is greater corruption whatever the process variation, except in one case. This critical point is below approximately $S = 8$ and $T = 12$ respectively; the effect is more pronounced for *sects* than for *towns*. Again the first process measure (IT system) is much more resilient in holding down the average bribe level when the number of in-groups is small, i.e., when the

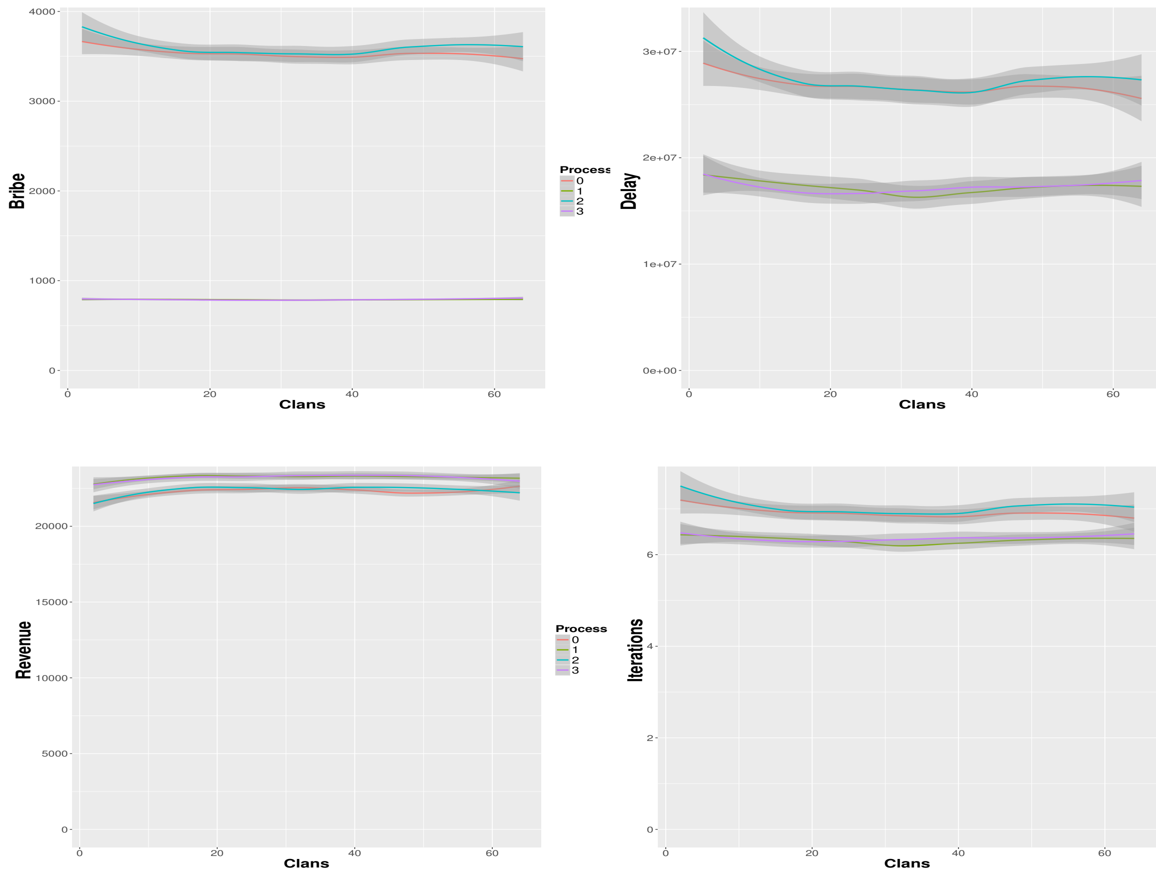

Figure 2: Effect of parameter *clans* on four KPIs, factored by *process*. Shaded areas depict errors of the fitted lines.

likelihood is high that two agents are in the same in-group. The graph of *bribe* versus *towns* also agrees with Figure 2 that it is the first re-engineering measure that is most effective, even though it makes a significant difference only to *bribe*, when compared to the second measure.

For the latter two relatedness variables, *sects* and *towns*, there is a much clear difference than for *clans*, between the 'critical' region when the number of sects (etc) is small, versus an intermediate region, and indication of a region of variation when the number is large. In the former, the social network is tightly knit, while in the latter and especially for large numbers of sects (etc), the society is fragmented and agents can be described a priori as strangers in terms of static relationship factors [9]. It is an interesting open question why any effect from *clans* is very much more modest.

Process input variables. Whether the agents are adaptive or not has little effect on bribe levels, but significant effect on the percentage uncaught deviant containers, *fee*, *iterations*, and *deviations*. It has some effect on most other KPI variables, notably *delay*.

By contrast, the process re-engineering has significant impact on bribe level, as we also saw in the graphs, because the empowered IT system reduces the incidence of preferred COs. This observation agrees with studies of task assignment to bureaucrats in China's public sector [10, 38]; the concept of 'guanxi' in Chinese society is similar to that of 'wasta' in Arab society [22]. However, the effect on CO–FF linkage overall is not significant. We attribute this to the static agent linkages (which process changes do not directly address) and to the continuation of dynamic linkages between those agents who interact in non-automated steps of the customs process.

Non-relatedness input variables. The effect of changing other input variables such as *illicit%* has the expected effects, given the literature. Namely, only a system-wide decrease in propensity to corruption across all agents, or external (i.e., outside the system, and hence not corruptible) audits, are really effective on corruption-related KPIs. As examples, increasing the number of customs staff increases system capacity and also increases the cost of enforcement through the additional staffing cost—labour cost is the greatest component of enforcement cost—while increasing the number of audits increases the percentage of containers audited and hence reduces deviations. Increasing penalties (to customs staff) is more effective than increasing fines (to owners).

Hypotheses. The first hypothesis, that deviant behaviour increases as interconnectedness increases, is supported in the case of *sects* and *towns*, but, contrary to our expectation, not for *clans*. The second hypothesis, that greater interconnectedness hampers reform measures, is likewise evidenced in part from the simulation results: a critical point is seen for *sects* and *towns*, but only weakly for *clans*.

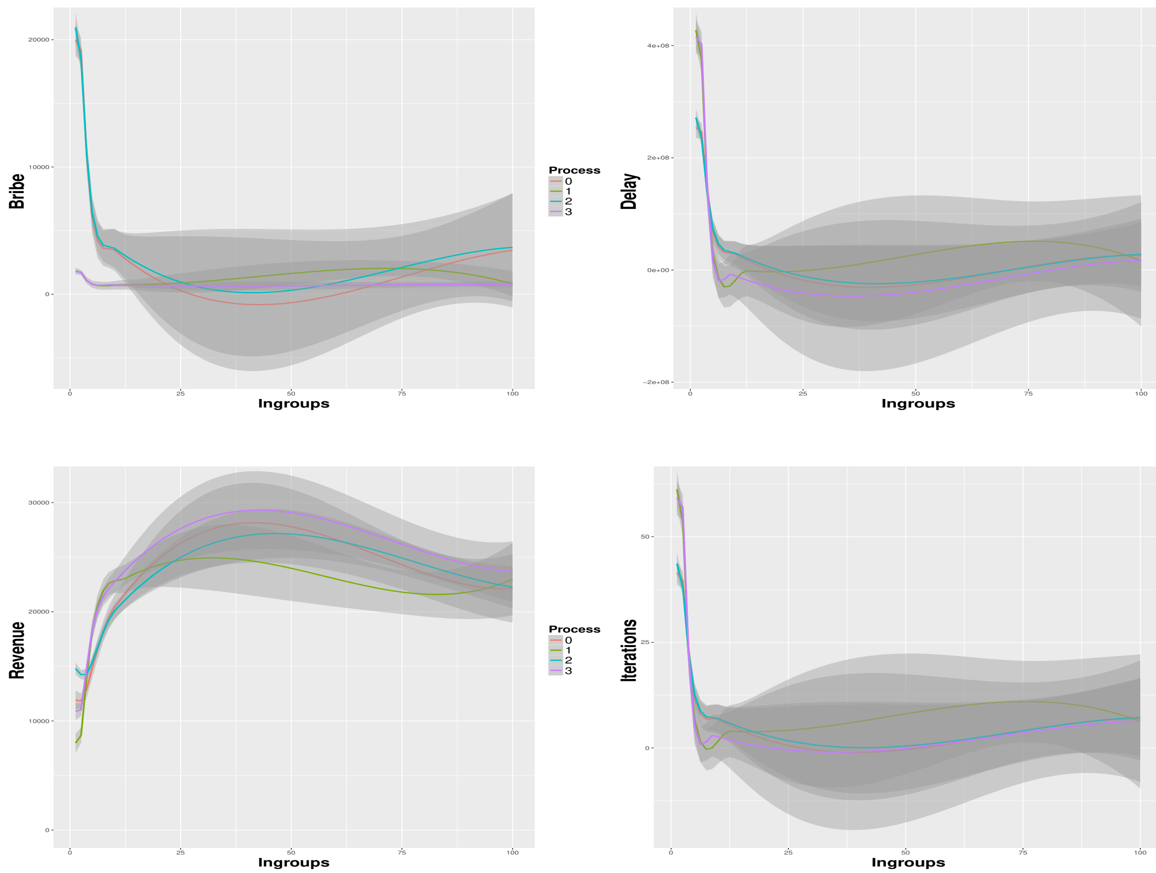

Figure 3: Effect of parameter *sects* on four KPIs (*bribe, delay, revenue, iterations*), factored by *process*. Shaded areas depict errors of the fitted lines.

5 CONCLUSION

This paper adopts agent-based simulation to examine the effects of social interconnectedness on corruption. The domain of study is customs imports, based on the processes—and the deviations from them—at an archetypal Mediterranean port in a context of widespread corruption. The domain is in itself important due to its contribution to public finances in developing countries.

While the literature identifies the potential relevance of interconnectedness, our work is the first to study its effect using MABS in this domain. A strength of a MABS approach is to explore what-if scenarios and policy measures (e.g., process changes) which are costly or infeasible to experiment with in the real world. Our ultimate goal is to understand the potential effectiveness of reform measures in their social and organizational context.

Mungiu-Pippidi finds that "so few success stories exist" of national-level reduction in corruption and that "typical internationally assisted anti-corruption strategies focused on the civil service and the judiciary" do not engender success [23, pp. 211–212]. Rather, as our results support, social factors—especially agent interconnectedness—mean that reform measures tend to lead to a displacement rather than a reduction in overall corruption [29].

Our work is exploratory and ripe for further development. First, we can analyze the data from the simulation using structural methods, to further explore latent connections. Second, our simulation model supposes that the auditors are diligent and are not open to corruption (contrary to [37]). More generally, our model can be expanded in scope by including additional actors (including auditor agents) and enhancing individual agent negotiation behaviours. Third, while we have begun to examine the effect of agent interconnectedness on policy efficacy, we have not examined specific social network structures [26]. Finally, in light of the existing case studies on tackling endemic corruption, there are connections with norm change mechanisms [4], norm internalization [37], and evolution of norms in a social network [24].

Acknowledgements. We thank the anonymous reviewers for their suggestions. Thanks to A. Komashie, B. Reinsberg, and M. de Weerdt. A preliminary version of this work was presented at the AAMAS'17 Workshop on Multi-Agent-Based Simulation (MABS) [34], and we thank the workshop participants for discussions. This work was partially supported by University Research Board grant numbers A88813 and 288810 from the American University of Beirut. NYS thanks the fellowship at St Edmund's College, Cambridge.

REFERENCES

[1] Sherief Abdallah, Rasha Sayed, Iyad Rahwan, Brad L. LeVeck, Manuel Cebrian, Alex Rutherford, and James H. Fowler. 2014. Corruption drives the emergence of civil society. *J. Royal Society Interface* 11, 93 (2014), 20131044.

[2] Kim M. Bloomquist and Matt Koehler. 2015. A large-scale agent-based model of taxpayer reporting compliance. *J. Artificial Societies and Social Simulation* 18, 2 (2015), 20.

[3] Lars Braubach and Alexander Pokahr. 2013. The Jadex project: Simulation. In *Multiagent Systems and Applications*. Springer, 107–128.

[4] Soham De, Dana S. Nau, and Michele J. Gelfand. 2017. Understanding norm change: An evolutionary game-theoretic approach. In *Proc. of AAMAS'17*. 1433–1441.

[5] William Diab, Nicolas Jarrouj, and Georges B. Melki. 2014. Corruption on the Port of Beirut. American University of Beirut, PSPA 202, Spring 2013–14. (2014).

[6] Elena Duggar and Madhur Duggar. 2004. *Corruption, Culture and Organizational Form.* Working paper. Social Science Research Network.

[7] Corinna Elsenbroich and Jennifer Badham. 2016. The extortion relationship: A computational analysis. *J. Artificial Societies and Social Simulation* 19, 4 (2016), 8.

[8] Nuno Ferreira, Samuel Mascarenhas, Ana Paiva, Gennaro di Tosto, Frank Dignum, John McBreen, Nick Degens, Gert Jan Hofstede, Giulia Andrighetto, and Rosaria Conte. 2013. An agent model for the appraisal of normative events based in in-group and out-group relations. In *Proc. of AAAI'13*. 1220–1226.

[9] Benjamin Golub and Yair Livne. 2011. Strategic random networks and tipping points in network formation. www.people.fas.harvard.edu/~bgolub/papers/formation.pdf. (2011). [Online; 31-Oct-2017].

[10] Ting Gong. 2002. Dangerous collusion: Corruption as a collective venture in contemporary China. *Communist and Post-Communist Studies* 35, 1 (2002), 85–103.

[11] Ross Hammond. 2000. *Endogenous Transition Dynamics in Corruption: An Agent-Based Computer Model.* Working Paper 19. Brookings Institution.

[12] Hassan Harb, F. Jordan Srour, and N. Yorke-Smith. 2012. A case study in model selection for policy engineering: Simulating maritime customs. In *Advanced Agent Technology*. Vol. LNCS 7068. Springer, New York, NY, 3–18.

[13] Lawrence Henesey, Paul Davidsson, and Jan A. Persson. 2009. Agent based simulation architecture for evaluating operational policies in transshipping containers. *J. Autonomous Agents and Multi-Agent Systems* 18, 2 (2009), 220–238.

[14] Lawrence E. Henesey, Theo E. Notteboom, and Paul Davidsson. 2003. Agent-based simulation of stakeholders relations: An approach to sustainable port and terminal management. In *Proc. of Intl. Association of Maritime Economists Annual Conf.* 314–331.

[15] Peregrine Horden and Nicholas Purcell. 2000. *The Corrupting Sea: A Study of Mediterranean History.* Blackwell, Oxford, UK.

[16] Irène Hors. 2001. *Fighting Corruption in Customs Administration: What Can We Learn from Recent Experiences?* OECD Development Centre Working Paper 175. OECD.

[17] Hassan Illeik. 2012. Port of Beirut: A Sea of Corruption. Al Akhbar. (11 Jan. 2012).

[18] David Jancsics and István Jávor. 2012. Corrupt governmental networks. *International Public Management Journal* 15, 1 (2012), 62–99.

[19] Michael Johnston. 2005. *Syndroms of Corruption: Wealth, Power, and Democracy.* Cambridge University Press, New York, NY.

[20] Mark Lauchs, Robyn Keast, and Nina Yousefpour. 2011. Corrupt police networks: Uncovering hidden relationship patterns, functions and roles. *Policing & Society* 21, 1 (2011), 110–127.

[21] Prasanna Lokuge and Damminda Alahakoon. 2007. Improving the adaptability in automated vessel scheduling in container ports using intelligent software agents. *European J. Operational Research* 177, 3 (2007), 1985–2015.

[22] Jihad Makhoul and Lindsey Harrison. 2004. Intercessory wasta and village development in Lebanon. *Arab Studies Quarterly* 26, 3 (2004), 25–41.

[23] Alina Mungiu-Pippidi. 2015. *The Quest for Good Governance: How Societies Develop Control of Corruption.* Cambridge University Press, Cambridge, UK.

[24] Declan Mungovan, Enda Howley, and Jim Duggan. 2011. The influence of random interactions and decision heuristics on norm evolution in social networks. *Computational & Mathematical Organization Theory* 17, 2 (2011), 152–178.

[25] Luis G. Nardin, Giulia Andrighetto, Rosaria Conte, Áron Székely, David Anzola, Corinna Elsenbroich, Ulf Lotzmann, Martin Neumann, Valentina Punzo, and Klaus G. Troitzsch. 2016. Simulating protection rackets: A case study of the Sicilian Mafia. *Autonomous Agents and Multi-Agent Systems* 30, 6 (2016), 1117–1147.

[26] Davide Nunes and Luis Antunes. 2015. Modelling structured societies: A multi-relational approach to context permeability. *Artificial Intelligence* 229 (2015), 175–199.

[27] Alexandru V. Roman and Hugh T. Miller. 2014. Building social cohesion: Family, friends, and corruption. *Administration & Society* 46, 7 (2014), 775–795.

[28] Susan Rose-Ackerman. 2008. Corruption and government. *International Peacekeeping* 15, 3 (2008), 328–343.

[29] Sandra Sequeira. 2016. Corruption, trade costs, and gains from tariff liberalization: Evidence from Southern Africa. *American Economic Review* 106, 10 (2016), 3029–3062.

[30] Yusuf Sidani and William L. Gardner. 2000. Work values in the Arab culture: The case of Lebanese workers. *J. Social Psychology* 140, 5 (2000), 597–607.

[31] Hokky Situngkir. 2004. *Money-Scape: A generic agent-based model of corruption.* Computational Economics Archive 0405008. EconWP.

[32] F. Jordan Srour and N. Yorke-Smith. 2015. Towards agent-based simulation of maritime customs. In *Proc. of AAMAS'15*. 1637–1638.

[33] F. Jordan Srour and Neil Yorke-Smith. 2016. Assessing maritime customs process re-engineering using agent-based simulation. In *Proc. of AAMAS'16*. 786–795.

[34] F. Jordan Srour and N. Yorke-Smith. 2018. An initial study of agent interconnectedness and in-group behaviour. In *Multiagent Based Simulation XVIII*. Vol. LNCS 10798. Springer, New York, NY. To appear.

[35] The World Bank. 1997. *Helping Countries Combat Corruption: The Role of the World Bank.* www1.worldbank.org/publicsector/anticorrupt/corruptn/coridx.htm. [Online; 31-Oct-2017].

[36] Transparency International. 2004. *The Global Corruption Report 2004: Political Corruption.* www.transparency.org/whatwedo/publication/global_corruption_report_2004_political_corruption. [Online; 31-Oct-2017].

[37] Daniel Villatoro, Giulia Andrighetto, Rosaria Conte, and Jordi Sabater-Mir. 2015. Self-Policing through norm internalization: A cognitive solution to the tragedy of the digital commons in social networks. *J. Artificial Societies and Social Simulation* 18, 2 (2015), 2.

[38] Yongqing Zheng, Han Yu, Lizhen Cui, Chunyan Miao, Cyril Leung, and Qiang Yang. 2018. SmartHS: An AI platform to improve government service provision in China. In *Proc. of IAAI'18*.