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On Collusion and Coercion: A Study of Agent Interconnectedness and In-Group Behaviour

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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. Taking an extant agent-based simulation, we add to the simulation 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 revenue, container outcomes, time, coercive demands, and collusion. Initial results confirm that as actor interconnectedness increases, established policies to combat corruption, such as process re-engineering, become less effective. Our work connects with and provides a complementary methodology to works in the political economy literature.

1 Introduction

Whenever a process has the opportunity or obligation for actors to negotiate, the possibility of corruption arises. The World Bank frames corruption as "the misuse of public office for private gain" [24]. The negative repercussions of corruption upon institutions, societies, and nations include poverty, tax evasion, political instability, weakened democracy and rule of law, and reduced national competitiveness. Further, corruption—whether *collusive* or *coercive*—reinforces disenfranchisement and hinders development, being "one of the most serious barriers to overcoming poverty" with a strong correlation between perceived corruption and income per capita [25].

It is known that the interconnectedness of actors is an antecedent for collective corruption, which in turn can lead to endemic corruption [13,16] 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 [11]. 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 [6].

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Previous work on social interconnectedness and corruption falls into two broad categories. The first—exemplified by 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 [22]—to examine in-theory behaviours in a synthetic or stylized setting.

Our work provides a blend 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 leading to "disastrous consequences in terms of national security and public finance" [9].

After necessary background (Section 2), we build on our extant agent-based simulation of maritime customs imports [23]. 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. We add a nuanced model of actor relatedness, consisting of clan, in-group (sect), and town of origin, and encode associated behavioural norms (Section 3). We examine the effects of social interconnectedness on domain performance metrics, such as revenue collected and revenue diverted, container outcomes, time, and instances and type of corrupt practices (Section 4). Initial 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 as interconnectedness increases beyond a critical point.

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 concludes that customs corruption not only has serious implications, but that it is not easily combated by policy changes, that reform policies can have unexpected side-effects, and that a broadly-based, systemic approach is required [12,19,15]. 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 [9,12,1,16].

A crucial role in the process of moving a container through customs is played by the *freight forwarder* (FF), a company that manages and organizes shipments for others. The process is 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 it should be randomly selected, the container then is subject to search and may see additional duties or fines. The import of each container can be seen as one round in a repeated game between a mostly fixed set of agents, who have specified and fixed roles.

Possible *deviations* from an archetypal customs import process (see Fig. 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 [10,16].

Policy efforts led by the International Monetary Fund, OECD, World Customs Organization, and World Bank have focused on reducing trade barriers, reforming trade procedures, and building 'cultures of integrity'. As the contemporary political economy literature concludes, such policy engineering has, more than not, proved ineffective [12,19,15,20].

Agent-based models and multi-agent-based simulation (MABS) have been successful in maritime container logistics, port management, and transport policy analysis. Agent-based simulation has also been used to study corruption. Hammond [7] 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. In a tax-evasion domain, endogenous shifts in global corruption levels are observed as emerging from the micro-behaviour.

Situngkir [22] 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 [23]. Although the model featured a simple construct of agent interconnectedness, we did not study the effects of this aspect of the organization on the performance metrics.

From an anthropological perspective, Makhoul [14] study interconnectedness and in-group effects in a Mediterranean Arab context, while Sidani and Gardner [21] study work practices, including corruption. Roman and Miller [18] find that status in social hierarchy and familial connections are "precursors" for corruption. Ferreira et al. [5] show the importance of in/out-group agent behaviour.

Abdallah et al. [1], among studies of social behaviour, demonstrate that peer-punishment 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. Elsenbroicha and Badham [4] develop a simulation of extortion, noting the importance of social factors beyond game-theoretic models. Lauchs et al. [13] 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. [26], 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.

Generalizing from the literature, empirical study of corruption by means of simulation—and, we argue, MABS in particular—offers a lens into otherwise obtuse and difficult-to-study behaviours.

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 the present work, which concern agent interconnectedness. For background on the domain and description of the basic model, we refer to [23].

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, and then describe the process in which they interact.

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 (a warranted assumption when corruption is endemic). If the CO demands, will increase bribe amount up to the maximum amount where expected cost would

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.

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

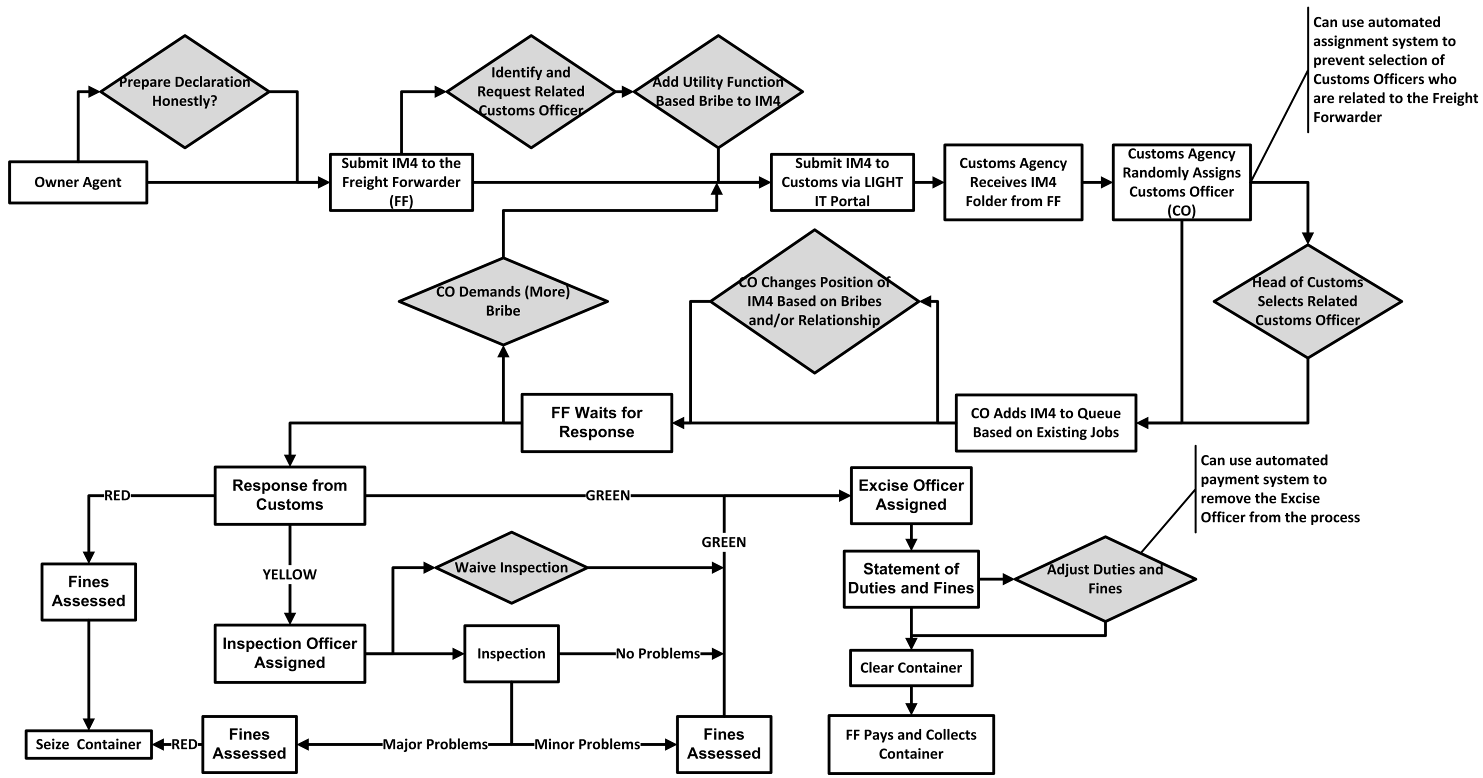

Fig. 1. Flowchart of archetypal import process as implemented in the MABS [23].

exceed expected value. Routinely offers tips. We include the role of the customs broker [10] 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 [10]. 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. HIO and HEO 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 (Fig. 1): (1) owner's agent submits documents ('IM4') 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 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 Fig. 1, can occur from the documented process 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.

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 [21,8,12]. 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 our previous work, 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 in our previous work.

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 clan, has approximately $\frac{1}{2}$ of the towns; clan 2 has approximately $\frac{1}{2}$ of the remainder, and so on, 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 that 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.

Static relationship is the weighted mean of three factors:

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

Dynamic relationship depends on the agent type (CO, IO, etc) and the agent's remembered history of interactions with the other agent. For example, for a FF agent assessing its relationship with a CO agent, factors include: % of bribes accepted, % of containers approved, % 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 [13]. 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 [14]. 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]. Compared with dedicated MABS environments (e.g., NetLogo, Repast), Jadex readily allows BDI-style agents, i.e., agents with explicit representations of beliefs, goals, and plans; it also provides simulation support. The development, calibration, and validation and verification of the MABS are treated in [23]. Results reported here cannot be compared directly with those of our earlier model [23], due to the developments in the model outlined in the previous section, and to minor changes in how the metrics are computed.

Table 2 gives the baseline parameter values extrapolated from the modelled 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.

The baseline parameters produced the Key Performance Indicators 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. Note

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

Table 2. Main simulation parameters.

that 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.

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.

Effect of interconnectedness. We systematically explored the parameter space of clans ($C = [1, 100]$), in-groups ($S = [2, 128]$), and places of origin ($T = [2, 48]$). We performed pairwise type-2 ANOVA tests between the inde-

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

input	% Not caught Illicit	All deviant	Cost	Fee	Tariff + Fine	Bribe	Revenue	% Diverted	Time	Delay	Iterations	CO–FF linkage Static	Total	Deviations	% Audited	Cost of Enforcement
clans	***			***	*	***	*			***	***	***	***	***		
ingroups	·			*		·				·	*	**	***	*		·
hometowns	***	*		***		*				*	*	**	***	*		
adaptive	*		*	***	*		*	*		**	***			***		
process			*	·	·	***		*						·		
illicit	**	***							***							
tariff			***	*	***	**	***				*	·	*	*		
fine			***		***		***	***								
staff		*								·						***
audit	***										·			·	***	
penalty			***		***	**	***	***								

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

pendent variables (*clans*, *sects*, *towns*, *process*, *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). Variable *process* takes discrete levels $\{0, \ldots, 3\}$, corresponding respectively to the regular process, empowered IT, electronic payment, or both. Table 4 reports the significance levels of the ANOVA p-values.

Since the form of the process has some effect on the structure on the system, we also performed ANOVA tests for the independent variables other than *process*, and the dependent variables conditioned on *process*. The results for most variables, and in particular the relatedness variables (*clans*, *sects*, *towns*), are similar with and without the conditioning, indicating that the majority of the response is not due to the changes in the process.

Relatedness input variables. **Clans** is the most significant relatedness variable. As the number of clans decrease, the chance of any two agents being 'statically' related, i.e., through the familial linkage, increases. There is a significant effect on the % illicit containers not caught (higher), on the FF's fee (lower), on the bribe amount (lower), on delay (lower), and on the number of FF-CO iterations (fewer); and some effect on other output variables. The number of process deviations increases, because of the increased interconnectedness and with it the reduced risk of the FF's bribe being rejected.

Second, as with clans, when the number of **sects** decrease, the chance of agents' static linkage increases. The effect is weaker than that of clans, but still with some significant effect on fee, # iterations, and # deviations. Third, as the number of **towns** decrease, again the chance of agents' static linkage increases. There is a significant effect on % deviant not caught and on fee, and some effect on bribe, delay, # iterations, and # deviations.

In order to begin to examine the effect of interconnectedness on process reengineering, we plot *bribe*, *delay*, *revenue*, and *iterations* versus *clans*, for each of the four values of *process*. Because the data points correspond to simulation scenarios with many values of other input variables (e.g., *tariff*), Fig. 2 plots locally weighted regressions to smooth misleading variation. Note that we conducted more exploration of the parameter space for values of clans in $[10, 25]$, meaning more data points in this region coming from more values of other variables, and hence more variation. Neither the trends in figure nor the variation should not be attributed excessive significance. Rather, the point indicated is that greater interconnectedness, i.e., fewer clans, beyond a critical point (around $C = 10$) tends to lead to greater corruption, whatever the process variation.

Process input variables. Whether the agents are adaptive or not has little effect on bribe levels, but significant effect on the % uncaught deviant containers, fee, # iterations, and # deviations. It has some effect on most other KPI variables, notably delay. The process variations through re-engineering have significant impact on bribe level, because the empowered IT system reduces the incidence of preferred COs. However, the effect on CO–FF linkage overall is not significant. We attribute this to the static agent linkages (which process changes do not

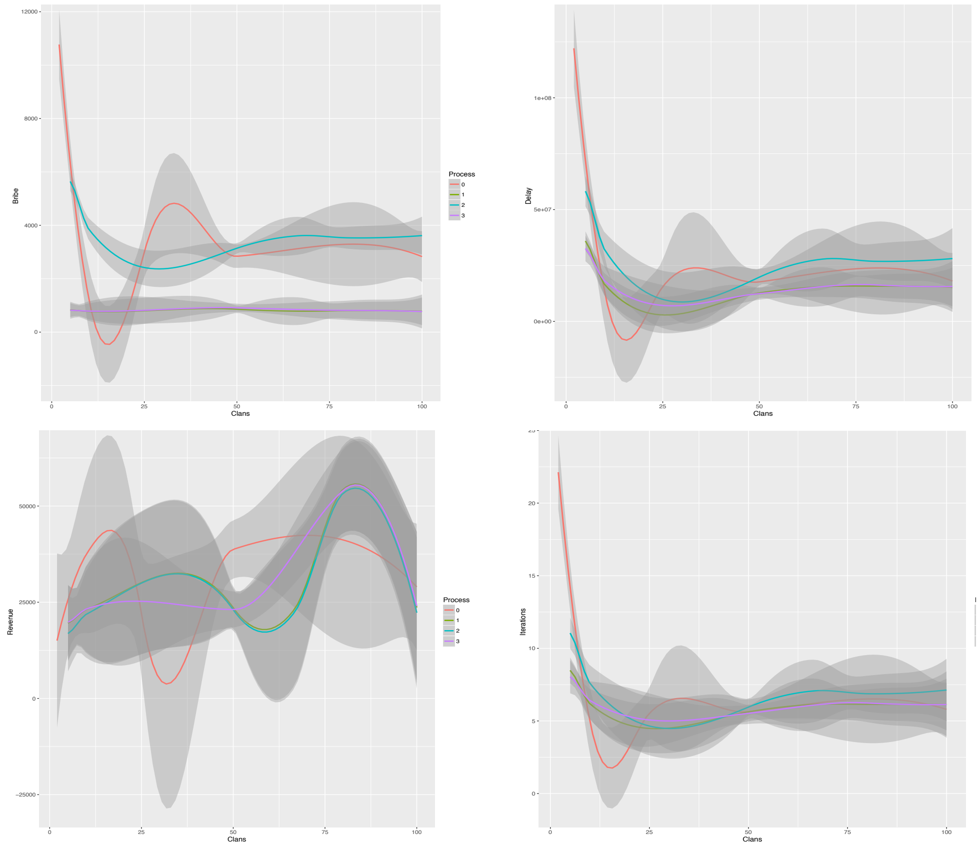

Fig. 2. Effect of *clans* on four KPIs (*bribe*, *delay*, *revenue*, *iterations*), factored by *process*. Shaded areas depict errors of the fitted lines.

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 and our previous work [23]. 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. Increasing penalties (to customs staff) is more effective than increasing fines (to owners).

5 Conclusion and Outlook

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.

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 [15, pp. 211–212]. Rather, as our initial results support, social factors—especially agent interconnectedness—mean that reform measures tend to lead to a displacement rather than a reduction in overall corruption [20,17]. Our ultimate goal is to understand the potential effectiveness of reform measures in their social and organizational context, and to provide a tool to aid policy makers.

Our work is exploratory and ripe for further development. First, our simulation model supposes that the auditors are diligent and are not open to corruption. More generally, our model can be expanded in scope by including additional actors (including auditor agents) and enhancing individual agent negotiation behaviours. Second, while we examine the effect of agent interconnectedness on policy efficacy, we have not examined specific social network structures. Finally, granted the existing case studies on tackling endemic corruption, interesting connections with several MABS topics are norm change mechanisms, norm internalization [26], and evolution of norms in a social network.

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