On Collusion and Coercion:
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. 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:

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
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 Sadani and Gardner [30] study work

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.
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.


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 regulatory 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 makes 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 Officer behave similarly.

**Inspection Officer (IO).** Unless opposed to bribes in principle, accepts any bribe of sufficient amount, to waive or expedite the inspection, to 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).

**Deviation**, 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 deviant 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.

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

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, . . . , 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 1/2 of the towns; clan 2 has approximately 1/4 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 st 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 st; 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:

\[
\frac{1}{6}(3 \times \text{sameClan} + 2 \times \text{sameSect} + \text{sameOrigin}) \quad (1)
\]

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...
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 chance 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>
<thead>
<tr>
<th>Table 2: Main simulation parameters [33].</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>-----------------------------------------</td>
</tr>
<tr>
<td>Illicit container %</td>
</tr>
<tr>
<td>Standard tariff rate</td>
</tr>
<tr>
<td>VAT rate</td>
</tr>
<tr>
<td>Fine penalty</td>
</tr>
<tr>
<td>Chance of inspection</td>
</tr>
<tr>
<td>Inspection success</td>
</tr>
<tr>
<td>Work-slow ratio</td>
</tr>
<tr>
<td>CO collusive propensity</td>
</tr>
<tr>
<td>CO coercive propensity</td>
</tr>
<tr>
<td>Chance of audit</td>
</tr>
<tr>
<td>Audit penalty</td>
</tr>
<tr>
<td>Number of clans</td>
</tr>
<tr>
<td>Number of in-groups (sects)</td>
</tr>
<tr>
<td>Number of towns of origin</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Time (hrs)</th>
<th>Delay (hrs)</th>
<th>Cost ($)</th>
<th>Deviations</th>
<th>Iterations</th>
<th>% Not caught</th>
<th>Deviant</th>
<th>Revenue ($)</th>
<th>Bribe ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>baseline</td>
<td>2703</td>
<td>14345</td>
<td>34191</td>
<td>48.20</td>
<td>6.38</td>
<td>10.08</td>
<td>97.04</td>
<td>22286</td>
<td>3282</td>
</tr>
<tr>
<td>owner honesty</td>
<td>2470</td>
<td>13439</td>
<td>35266</td>
<td>47.28</td>
<td>6.24</td>
<td>9.88</td>
<td>96.88</td>
<td>25743</td>
<td>3282</td>
</tr>
<tr>
<td>lower collusion</td>
<td>715</td>
<td>270</td>
<td>28782</td>
<td>49.36</td>
<td>6.55</td>
<td>9.98</td>
<td>97.87</td>
<td>20767</td>
<td>756</td>
</tr>
<tr>
<td>lower coercion</td>
<td>1498</td>
<td>5390</td>
<td>38483</td>
<td>43.80</td>
<td>4.42</td>
<td>9.93</td>
<td>97.70</td>
<td>25743</td>
<td>2128</td>
</tr>
<tr>
<td>higher tariff</td>
<td>2935</td>
<td>15513</td>
<td>93666</td>
<td>49.76</td>
<td>6.55</td>
<td>9.98</td>
<td>97.77</td>
<td>80312</td>
<td>3376</td>
</tr>
<tr>
<td>punitive fines</td>
<td>2958</td>
<td>15864</td>
<td>71506</td>
<td>49.21</td>
<td>6.55</td>
<td>9.99</td>
<td>97.81</td>
<td>59158</td>
<td>3371</td>
</tr>
<tr>
<td>more inspection</td>
<td>5713</td>
<td>57286</td>
<td>34277</td>
<td>83.02</td>
<td>11.43</td>
<td>9.93</td>
<td>97.82</td>
<td>20767</td>
<td>1268</td>
</tr>
<tr>
<td>perfect inspection</td>
<td>2928</td>
<td>20712</td>
<td>36462</td>
<td>57.71</td>
<td>7.78</td>
<td>9.92</td>
<td>96.73</td>
<td>23502</td>
<td>4025</td>
</tr>
<tr>
<td>more staff</td>
<td>601</td>
<td>853</td>
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Table 4: Correlation between independent variables (rows) and dependent variables (columns). Significance codes: *** < 0.001, ** < 0.01, * < 0.05, . < 0.1

<table>
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<tr>
<th>input</th>
<th>% Not caught</th>
<th>Tariff + Fine</th>
<th>Bribe</th>
<th>Revenue</th>
<th>% Divert.</th>
<th>Time</th>
<th>Delay</th>
<th>Iter.</th>
<th>CO–FF linkage</th>
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</table>

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.
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 in-
put 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 enforce-
ment 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 2: Effect of parameter clans on four KPIs, factored by process. Shaded areas depict errors of the fitted lines.](image-url)
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].

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

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