An Agent-Based Model of Corruption as a Cellular Automaton

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Declaration of Compliance

I declare that all material in this dissertation is my own work except where there is a clear acknowledgement and reference to the work of others.

Signed ______________ Date: 2018-06-26

Abstract:

As a collective action problem, understanding the dynamics of corruption is a difficult task to undertake utilizing traditional approaches to economic analysis. This issue only compounds if one wishes to look at the problem at a micro-level, especially in relation to the role of neighbors and communities when exploring petty corruption. Therefore this paper utilizes an agent-based computational economics methodology in order to explore significant agent parameters' association to corruption prevalence and distribution at a micro-level. By adding a spatial element to a corruption agent-based model created by Ross A. Hammond, I find two key endogenous parameters linked to corruption. First is a lack of behavioral individualism; societies more prone to influence by neighbors and friends increase the likelihood of corruption within that society. Second, limiting individual's knowledge on local corruption reduces peoples' exposure to the risks of corruption, thereby propagating the behavior.

Keywords: corruption, cellular automata, agent-based modeling, agent-based computational economics, neighborhood effect

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List of Abbreviations

ABM	Agent-Based Model
ACE	Agent-Based Computational Economics
CA	Cellular Automata
ODD	Overview, Design Concepts, and Details
UML	Unified Modeling Language

1. Introduction

As corruption has steadily come to the forefront of international attention as one of the primary inhibitors to economic development, both academics and policymakers have increasingly placed efforts into better understanding corruption's determinants as well as researching methods to better mitigate its prevalence (Anthony et al. 2018, 1). Unfortunately, by looking at corruption from a typical institutional level, research into certain aspects of the concept is limited (ex. nonlinear behavior) (Phillips 2004, p. C28-C40). By instead studying corruption as a byproduct of individual-level decision-making, a better understanding of independent social interactions' involvement in corruption arises (Bonabeau 2014, 7281). This study of macro-level economic consequences as a dynamic network of individual interactions is known as agent-based computational economics, or ACE; this is the primary methodology upon which this paper is based.

One of the facets of corruption that has not been deeply studied is its spatial dynamics. Although existing literature concerning corruption is vast, most current empirical models of corruption's determinants ignore its spatial aspects, instead focusing on the internal consequences of corruption that result from policies or cultural norms from within each society (e.g. Khan 2006, 1-35; Andrei et al. 2009. 11-25). Studies that have looked at the effect of adjacency on corruption do prove its existence and relevancy to the spread of corruption but have cited that limitations of institutional-level econometric analysis as a common inability to better understand its specific influences (Becker et al 2008, 2009; Cihan 2014, 391-401). Standard methodology is reliant on macro-level determinants or aggregatable characteristics, both of which are difficult to successfully integrate into the study of endogenous and emergent behavior, which is often more than the sum of its parts. This limitation is only further enhanced by standard econometric methodology's reliance on existing real-world data. Direct measurement of corruption is often nigh impossible, and most current corruption indexes rely on questionnaires that often lack a lot of potentially useful micro-data (e.g. the geographical composition of corruption, identifiable individuals engaged in corruption, etc.).

Therefore in order to understand corruption's still only vaguely understood spatial characteristics, this paper relies on the aforementioned agent-based computational economics perspective by building upon an agent-based model (ABM) by Ross A. Hammond (2000, 1-18), one of the few existing computational models built to study corruption as a product of micro-level behavior. ABMs are computational models designed to study emergent behavior by autonomous agents and are the primary tool used within ACE methodology. By applying spatial characteristics to Hammond's existing ABM, my paper attempts to answer the questions: What effects do neighborhoods and local social networks have on the endogenous dynamics and prevalence of corruption? Additionally, how do these model alterations affects the findings first presented by Hammond? In order to answer these questions, my paper explores both the level of corruption as well as its distribution under various parameters.

Specifically, I expand Hammond's model so that agents' networks are composed of overlapping 'neighborhoods', dependent on agent-type and location rather than a series of isolated same agent-type networks that are randomly composed. Additionally, I allow for agents to alter their own individual attitudes towards honesty, which remained static within Hammond's models. I have also decreased the ratio of bureaucrats-to-citizens for increased realism as well made a series of model changes for better data exploration (e.g. allowance for changes in starting model honesty, individual attributes for bureaucrats and citizens, etc.) and model efficiency (e.g. streamlined coding).

The overall goal of this paper is to provide further illumination on the spatial effects of corruption by substituting the normal approach of looking at corruption as an unintended byproduct of macro-level policies and institutions, and instead view the phenomenon as a consequence of individual-level behavior. By making these alterations, my model aims to provide new insights into the individual rationality for corrupt behavior, its macro-level consequences, and possible methods to mitigate the behavior's prevalence. By utilizing the young but growing ACE methodology, my paper delves into the unexplored territory of local neighborhood interaction and influences on corruption, which has thus far been largely overlooked within the academic community.

In order to explore these questions, the rest of the paper is organized as follows: Section 2 helps clarify the definition of corruption, and explores current literature that attempts to explain the societal effects and individual motives for corruption, including Hammond's own theory on the matter. Section 2.3 further reviews current empirical literature that quantifies corruption's consequences and factors. Section 3 contains an ODD (Overview, Design Concepts, and Details) protocol-based description of the agent-based model used in this paper. This section additionally presents the experimental design in order to systematically elucidate on how my model is used to test the significance of neighborhood influences in relation to corruption's dynamics and distribution. Section 4 contains a regression analysis of my results and their possible implications. Lastly, Section 5 provides a discussion of findings, model limitations, and possibilities for further research.

2. Literature Review:

2.1 Definition of Corruption

UN's Anti-Corruption Toolkit (2004) describes (political) corruption as "an abuse of public power for private gain that hampers the public interest." (2) Yet on more specific actions, there is no global consensus on what constitutes corruption due to the differing perceptions among various nations/ cultures (Transparency International 2004, 30). As an example, while many nations are beginning to place tighter stipulations on gift-giving, the act, itself, has often considered an acceptable practice for currying favor in many nations (Steidlmeier 1999, 121-32). Beyond cultural differences, corruption may not always be an illegal practice, and thus difficult to identify. Especially in many industrial countries, lobbyists utilize legislative influence to create legal barriers or operable limits as a way to favor themselves at the expense of all other parties (Kaufman and Vicente 2005, 2-4). Some academics even consider behavior like networking as a legal form of corruption that seeks to undermine equal opportunity and employment efficiency (Dobos 2017, 467-78).

Corruption can be further divided on the scale on which it occurs (Nystrand 2014, 821-22). Routine or petty corruption is corruption that occurs on a smaller scale and often at the end of some public service, such as a citizen bribing a local tax officer. Petty corruption is most often harmful when it becomes systematic: widespread petty corruption distorts economic decision-making, producing benefits for a few individuals at a small cost to society as a whole, which aggregates into large system-level consequences as petty corruption becomes normalized within a society, creating an additional inherent cost to typical government interactions. Conversely, grand corruption occurs at higher levels of authority, so that even one individual may bring about dire consequences from legal subversion, economic distortion, or the active propagation of petty corruption.

While the understanding of the dynamics that bring about grand corruption is, itself, important to societal welfare, the scope of this paper is limited to petty corruption. Petty corruption provides a clearer view of corruption as an endogenous behavior that spawns from a series of multiple corrupt interactions and thus lends itself as an overall better use of the ACE methodology, as compared to grand corruption.

2.2 Theoretical Literature Review

2.2.1 Societal Effects of Corruption

While there maybe a lack of delineative cohesiveness on the precise composition of corruption, there is a general agreement that it is harmful to society in many debilitating ways. Corruption adds direct costs for individuals when engaging with the public sector, whereby provisions that are normally guaranteed to an individual from the payment of taxes – such as the ability to obtain a license or usage of a road- may come with the added cost of a bribe or necessary association with a specific entity (OECD 2015, 45-51). More dangerous is the complete distortion of public institutions, whereby money dedicated to schools, hospitals, or other publicly funded institutes is instead funneled into the pockets of bureaucrats responsible for these institutions. The World Bank (2017) lists the long-term economic consequences of this misaligned behavior as including: weakening of public infrastructure, rising cost of doing business, discouragement of investment/ innovation, and general societal inefficiency (16-17).

Corruption can thus hinder economic development and exacerbate income inequality. Furthermore, standard attempts to mitigate petty corruption through legal watchdogs or tighter regulation can dampen bureaucratic efficiency, discourage economic activity, as well as carry its own monetary costs for implementation and maintenance (Quah 2007, 87-88).

2.2.2 Individual Motivation for Corruption

In regards as to why individuals engage in corruption, Klitgaard (1998) noted that corruption is a "crime of calculation, not of passion." (6) He regarded corruption as a natural behavior that will grow whenever its benefits outweigh its costs. Klitgaard thus argued that the prevalence of corruption is dependent upon three main factors: a public official's degree of monopolistic power, discretion in terms of decision-making, and degree of accountability (1998, 52-98). In other words, the level of jurisdiction possessed by a bureaucrat needs to be balanced with an equal level of accountability if prevention of corruption is to be achieved. While Klitgaard's view of corruption has sometimes been seen as trite, his framing of societal corruption as a product of misaligned incentives and ineffective institutions resulted in viewing the behavior as something that could be tackled through multiple routes, beyond the typical governmental tendency to use oversight as a primary corruption inhibitor. Klitgaard especially promoted the use of decentralization as a way to reduce bureaucrats' monopolistic power.

Aidt (2003) largely echoed Klitgaard in terms of what promotes the emergence and persistence of corruption but instead labeled the necessary conditions that promote corruption as being: discretionary power, economic rents, and weak institutions (p. F633). Aidt postulated that discretionary power is important only in the way it is able to produce economic rent for a public official and argued that both accountability and healthy governmental incentive structures were necessary to substantially mitigate corruption. Specifically, this means that in addition to an efficient monitoring system/ sufficient legal recourse, an introduction of an efficiency wage that indirectly raises the cost of dismissal could further reduce corruption by public officials (p. F637). Overall, Aidt's paper was important due its expansion upon how corruption could be mitigated through a more positive incentive structure, something that had only been touched upon by Klitgaard.

Recently, many authors have gone beyond looking at corruption as more than just a product of poor policy. Larmour and Wolanin (1999, p. xii) posited that a government-led ‘managerial-style’ of corruption control possesses a multitude of limitations that could frustrate governmental interventionist efforts to dissuade misconduct. As corruption is a reciprocated crime between two parties, investigation into corruption often requires a massive amount of resources in order to ensure effective supervision and punishment. Especially for countries deeply engaged in multiple forms of corruption, the issue’s embeddedness often mean that anti-corruption efforts include expensive and draconian methods (p. xvii). The authors thus argued that a larger focus should be placed into exploring human element of corruption by looking beyond government policies and institutions and instead examine individuals’ incentives’ for misconduct (128). By taking this approach, governments might be able to introduce more nuanced tools to combat corruption: such as fostering community awareness or developing policies that more precisely combat certain strands of corruption.

In line with this approach, Vannucci (2015, 10-18) provided deeper insight into the relationship between corruption and regular citizens by exploring how social pressures may influence corruption. Vannucci noted the moral costs of corruption are as much a product of the endogenous dynamics between individuals within a society as it is a consequence of good policy implementation. Porta and Vannucci (2016, p. 32-37) argued that the “moral costs” of corruption are heightened when that individual’s peers do not share the same internalized norms. However, if an individual’s neighbors and peers believe corruption is systematic, the costs of corruption become lower simply due to its inevitability. Even if there are multiple explicit laws that actively denounce it, corruption as an internalized norm among neighbors results in it itself becoming a kind of institution. In this way, both corruption and anti-corruption behavior are self-enforcing, enhanced by the accepted norms of that society (2016, 74-76).

While not specifically exploring corruption within societies, Ashforth and Vikas (2003, 1-52) provide an explanation of how the corruption as a norm could spread within a work environment. The authors broke down the process of organizational corruption dissemination into three main processes 1) institutionalization, the system of routinizing corrupt decisions; 2) rationalization, or the justification of corruption decisions to align with personal ideologies; and 3) socialization, where newcomers are introduced to corruption as being permissible (2003, 4-15). Ashforth and Vikas argued that corruption proliferation often begins when an entity within an organization noticeably gains from corrupt behavior, which then signals to others within the system to also act similarly in order to maximize either their own or their organization's goals (6). Those from outside the organization might also act similarly if they view corruption as a necessity to compete in the relevant market (11). The authors postulated that once this corruption is normalized, its reduction or eradication must come from an outside shock if amelioration is to be achieved. Ashforth and Vika's paper clearly highlights the importance of corruption as an often-natural act brought about by an individual's incentive to maximize personal welfare, one that most often arises from small beginnings.

Attila (2008, 1-33) continued this exploration of corruption as a social norm by using econometric analysis to see how it might spread between countries. Attila posited that while there is little overlap in terms of interactions between citizens and public officials of neighboring countries, corruption as a social norm could still spread indirectly through cross-country business dealings, cooperation on political issues, and an overlapping of social networks. Attila's results support the idea that corruption will often 'spillover' between neighbors, even between those engaged in different governmental systems. While there is a lack of quantitative studies that look at this issue within the same country, this study, as well as Vanucci's and Ashforth and Vika's, indicate that corruption may often be more than a result of individual decision-making, instead being a byproduct of what is known as the 'neighborhood effect.'

This 'neighborhood effect' is an economic theory that posits that individual decision-making is strongly influenced by relational interactions between individuals and their daily contacts. While the term 'neighborhood' itself is a vague one, within the theory it is normally assumed to be a social unit that shares a similar spatial abode with continuous direct and indirect interaction among its members e.g. an office, school, or town. This concept, popularized by Julius Wilson in his book *The Truly Disadvantaged* (1987), states that local social environments often strongly influence behaviors of individuals. While this theory can be easily applied to an individual's social norms like voting ideologies or religion, the theory is often expanded to include rational decision-making (Bisgaard et al. 2016, 719-32; Ionnides and Topa 2009, 1-29). Dependent upon the assumption that individuals adhere to the idea of bounded rationality, or limitation to information available, people will often use their general observations of the behavior of neighbors, friends, and families when making rational decisions, even if that rationality may not be reflective of what is considered rational for an individual with unrestricted access to systematic data. Thus, in accordance with this theory, corruption can be endemic even to regions with strong anti-corruption efforts or good democratic practice, and, furthermore, it may exist in different capacities amongst various communities, even when controlling for other social factors.

2.2.3 Hammond's Game-Theoretic Approach

Hammond (2000, 1-18) is one of the few academics to try to empirically explore the dynamics of corruption between individuals from an ACE approach. Hammond's model utilizes a simple game-theoretic framework whereby an equal proportion of citizens and bureaucrats continually interact with each other while deciding to either pursue a corrupt or non-corrupt strategy during each time step based on the payoff matrix found below (Table 1).

Table 1: Hammond's Payoff Matrix

		Bureaucrats: Corrupt	Bureaucrats: Non-corrupt
Citizens	Corrupt	x	y
	Non-corrupt	y	y

Source: Hammond 2000, 3.

Here, corruption only pays off if both a citizen and the corresponding bureaucrat decide to collude. However, perceived personal gain from corruption is not universal but is instead but upon a 0 to 1 decimal value representing the individual's inherent propensity for honesty (i) (which is assigned at model initialization). Agents with a perfect level of honesty, 1, perceive the moral cost of corruption to be unthinkable while an i of 0 signifies that agent assumes no moral cost. Thus the personal benefit of successful collusion changes from x to $x_i = (1-i)x$. Hammond also includes a social aspect into the model, whereby each agent is rationally bounded; agents' only access to information comes from an exclusionary "social network" of same-type agents randomly determined at the beginning of each run. Information gained from this social network includes knowledge of who has pursued corrupt actions and how many of their social network have been caught being corrupt.

From this model, Hammond discovered corruption could endogenously transition to honesty even if no new anti-corruption policies were implemented (in contrast to Ashford and Vika's findings). A few individuals' decision to not comply with corruption often promotes a cascade of non-corruption compliant behavior throughout the entire model, while the reverse was far less likely. From this, Hammond suggested that the societal dynamics of social norms and values within a society might be critical towards effectively eliminating corruption.

Hammond further concluded that limited local information and sufficient moral heterogeneity are two agent features vital to this endogenous transition to honesty. Limited local information is important because the less information garnered by an individual, the higher consideration that individual attaches to any negative event that happens to his social network. Conversely, differences in moral values creates skepticism amongst a social network, so that one is hesitant to suggest a collusive act that is not guaranteed (or highly likely) to be reciprocated.

2.3 Empirical Literature Review

Even given the difficulty regarding the empirical measurement of corruption, academics have undertaken a multitude of different methods in an attempt to better quantify the behavior's overall real-world presence, consequences, and primary determinants. Even given the impossibility of measuring corruption with complete accuracy, these studies provide estimates that give a more complete image of the nature of corruption as it relates to the world economy.

In order to better explore the standard macro-level determinants of corruption, Saha and Gounder (2009, 70-9) used a panel data estimation of 100 countries from 1995 to 2004 in order to test some of the most commonly proposed economic, institutional, and social variables linked with higher corruption (using Transparency International's Perceived Corruption Index). The authors found that increases in per capita income, expansion of tertiary education, and economic freedom all led to lower levels of corruption. Conversely, increases in income inequality and unemployment worsened corruption. While the authors did not go very far into the effect of regional variables on corruption, the authors did find a strong positive relationship between all regional dummy variables (Asia, Latin America, Africa, Middle East, East Europe) and corruption (except for Africa).

Becker et al. (2008, 300-10) took a deeper look into corruption's spatial effects by seeing how one country's level of (perceived) corruption depends on others by utilizing a cross-sectional spatial econometric model for 123 countries for the year 2000. Here a spatial lag and a spatially-autoregressive residual (SAR) were added to the equation in order to see how adjacency and distance impacted corruption. The authors' results suggest a high level of positive spillover from corruption to nearby countries, which declined with geographical distance. Unfortunately, the model did not allow them to test the method through which corruption travels between nations (e.g. migration, peer group learning, criminal activity) but still highlighted the real-world existence of the spatial significance in relation to corruption.

Barr and Serra (2009, 488-503) provide one of the more significant real-world depictions of individual decision-making with their formulation of two controlled 'bribery game' experiments that simulated the interactions between private citizens and public officials. For their experiments, Barr and Serra gathered students from 34 countries (for the 2005 experiment) and 22 countries (for the 2007 experiment) in order to test if corruption in each participant's home country affected whether or not the participant would engage in corruption. Similar to Hammond's ABM, the 2005 experiment divided participants into private citizens and public officials that randomly interacted with each other each round.

The authors found that values and norms from the participants' country accounted for some but not all individual propensities towards corruption, leading them to conclude that corruption is at least partially a cultural phenomenon (502). Additionally, those who came from corrupt countries would show fewer tendencies towards corruption as they spent more time in the UK (where the experiment was conducted). From this experiment, it is fairly easy to see how corruption can be seen as something more than just a product of policy and rather a mix between institutional efficiency as well as socialization.

Isaksson and Kotsadam (2018) offer further empirical evidence affirming the importance of norms in relation to corrupt behavior by studying the influence of Chinese aid on local corruption (146-159). By comparing spatial data concerning 227 local Chinese aid projects over the period of 2000-2012 in 29 African countries against a survey of 98,449 respondents detailing their experiences with local corruption, the authors supply evidence that indicates that these aid projects, in comparison to World Bank aid projects, were more likely to fuel local corruption through the transmission of norms (158). The lack of evidence suggesting active bribery payments by Chinese aid donors, further suggested that these areas' attitude towards corruption stemmed from the Chinese own standard non-interference attitude towards the behavior rather than from any active engagement in corruption. This paper thus shows how important corruption is as an endogenous behavior, heavily reliant on the attitudes of the interactions between individuals. As the World Bank actively discouraged corruption while Chinese donors normally did not, local areas additionally altered their own attitudes towards the behavior.

Reinikka and Svensson (2001; 2002) provide some of the best empirical evidence concerning micro-level corruption in a game-theoretic context through a data collection project carried out in Uganda during the late 1990s. The authors first compared budget allocation to actual spending for local school grants, yielding results suggesting that 87% of the allocated school grants never reached their target schools (2002, 8). The money received, however, varied widely from school to school ranging from between 5% to over 50%. By regressing each school's various characteristics against the amount of fund leakage experienced, the authors discover three main variables that minimized leakage: school size, income per student, and level of teacher qualification (15). The authors posited that the significance of these variables directly related to each schools bargaining power when receiving school grants; richer and/or more powerful schools were able to more easily argue for a larger release of funds from local officials, while smaller, poorer schools had a more difficult time at successful negotiation attempts. The authors further stressed the importance of knowledge, and noted that interviewed headmasters with the most knowledge of the local political economy were often the most successful at securing funds. Here, it is easy to see how corruption, at its most basic level, can be regarded as a bargaining process that is highly dependent on the negotiation between bureaucrats and end-users when determining monetary consequences. Corruption here is also depicted as being somewhat emergent, highly dependent on the ongoing dynamics between schools and governments.

In order to further expand on the significance of citizens' local knowledge from their last project, Reinikka and Svensson undertook a follow-up project in Uganda that again focused on leakage of funds. However, this time the authors focused on how school grant leakage related to a newspaper campaign aimed at providing parents with better knowledge of local officials' handling of school grant money. The authors discovered that this campaign resulted in significantly more enrollment and better standardized test scores in school districts with higher newspaper penetration, citing that these positive enrollment and test figures were due to the higher amount of grant money received from schools in these districts. Both of Reinkka and Svensson's studies provide some counterevidence to Hammond's original findings. While it might indeed might be the case that a more secret law enforcement entity emphasize the significance of each corruption action, increased informational access also gives citizens a better ability to identify the corrupt actions of local officials which instead minimizes corrupt behavior.

3. Methodology

3.1 Agent-Based Modeling

The current limitation of systemic econometric models to properly explain endogenous mechanisms is one of the primary reasons why agent-based models (ABMs) are often utilized in their stead. Standard econometric techniques are dependent on the assumption that what is seen at the macro-level is an aggregation of the effects at the micro-level. However, for heterogeneous agents or changing behavior, this may not always be true. Seemingly inconsequential changes in attributes often lead a cascade of changes in macro-level results and dynamics that may not be fully caputred by a static model. Thus, ABMs have especially been useful at modeling economic concepts that involve continually interaction-dependent phenomenona such as technical analysis of the stock market or collective action theory, where individual optimal decision-making results in a total suboptimal solution for everyone, which includes corruption (Bruch and Atwell 2015, 186-221; Marquette and Peiffer 2014, 1-13).

Of course, this approach to economics is still a relatively new methodology and contains drawbacks. ABMs rely on the internal conditions of the model, such as agent characteristics and strategies, which are often difficult to observe empirically (Manzo 2014, 653-688). This also includes details and endogenous parameter interactions not included within the model, something that is reflected in systematic economic analyses as noise, but will go unnoticed by computer simulations. In other words, ABM’s numerical accuracy is linked to the general model complexity, which explains the common utilization of supercomputer technologies in ABMs when attempting to make precise numerical predictions. However, even given these issues, even relatively simplistic ACEs are still highly useful at looking at the general relationships between individual behaviors and their effect on the system, even if these relationships cannot always be reduced to precise quantifications when compared to the real world.

Within an ABM context, the dynamics of individual corrupt behavior can be best visualized utilizing a cellular automaton (CA) (also known as a tessellation automaton or iterative array). First discovered by John Neumann and Stanislaw Ulam, the CA model was first designed to study the phenomenon of self-replication utilizing a discrete model (Schiff 2011, 40). At its core, CA modeling consists of looking at how entities react to local entities around them, with the goal of extrapolating information about this system as a whole. Thus, CAs have been most often used when studying interactive behavior dependent on the spatiality between entities. Thomas Schelling (1969) utilized a CA framework in order to study how relatively weak individual preferences for racially similar neighborhoods resulted in the observation of strong self-segregation within cities. More recently, Bartolozzi and Thomas (2008, 1-17) used a cellular automaton in order to better illustrate how individual stock decisions by traders often results in bubbles and crashes through the bandwagon effect. Within a corruption context, Osipian (2013, 1-24) applied a cellular automaton in order to explore the relationship between school environments and the corruption of educators.

It is important to note that beyond the rule that cellular automata must consist of agents who react to those around them, the model also generally consists of a certain set of other rules, including:

- Models are composed of a discrete grid of cells
- Each cell possesses a state among a finite number of states
- Each cell possesses a neighborhood, normally composed of directly adjacent cells
- Each cell's state is in some way contingent upon the composition of its neighborhood
- Simulations occur in discrete steps

Overall, the model's rather simplistic design makes it especially useful for observing how macro-level consequences emerge from micro-level decision-making, thus making it a commonly used framework within ACE.

3.2 Model Description

The following model description utilizes ODD (Overview, Design Concepts, and Details) protocol as is commonly used for ABM model documentation (Railsback et al., 2005). The base model and code (excluding the spatially related components) are based upon Hammond's corruption ABM (1999) as interpreted by Dzutsati (2015).

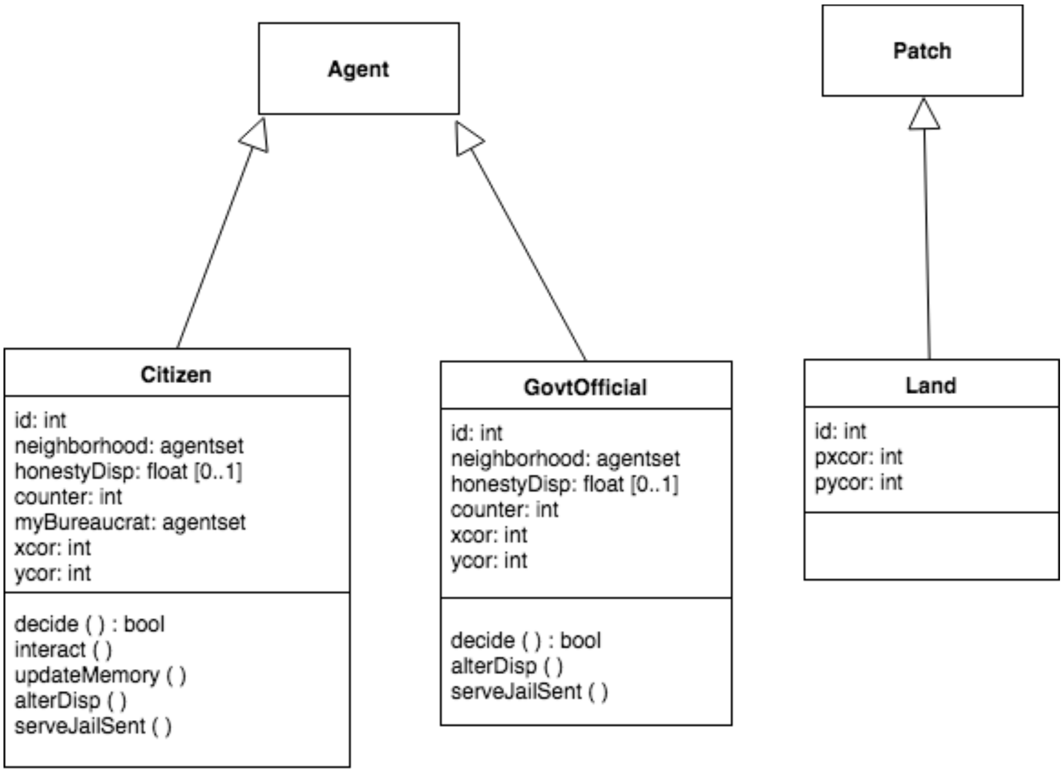
3.2.1 Purpose

This model is designed to explore how corruption endogenously spreads within a spatial context using the multi-agent programming language and modeling environment Netlogo (Wilensky 1999).

3.2.2 Entities, State variables, and Scales

Figure 1 below provides an overview of the entity types utilized in my model categorized by their class, attributes, and associated procedures.

Figure 1: UML Class Diagram



As seen in Figure 1, this model contains two types of agents (bureaucrats, citizens) and one type of patch (square piece of land). The model's world is composed of a non-toroidal square lattice grid of 35 x 35 patches. Citizens and bureaucrats are characterized by their disposition towards honesty (*honestyDisp*), times they've been reported for trying to collude (*counter*), and location (*xcor*/ *ycor*). Additionally, each step, citizens choose one local bureaucrat from the nearest government office with which to interact (*myBureaucrat*). Unlike Hammond's original model where bureaucrats and citizens exist in equal proportion, I have altered the model parameters so that the proportion of bureaucrats is more similar to the US case, using information from the U.S. Census Bureau 2014 Annual Survey of Public Employment and Payroll data.

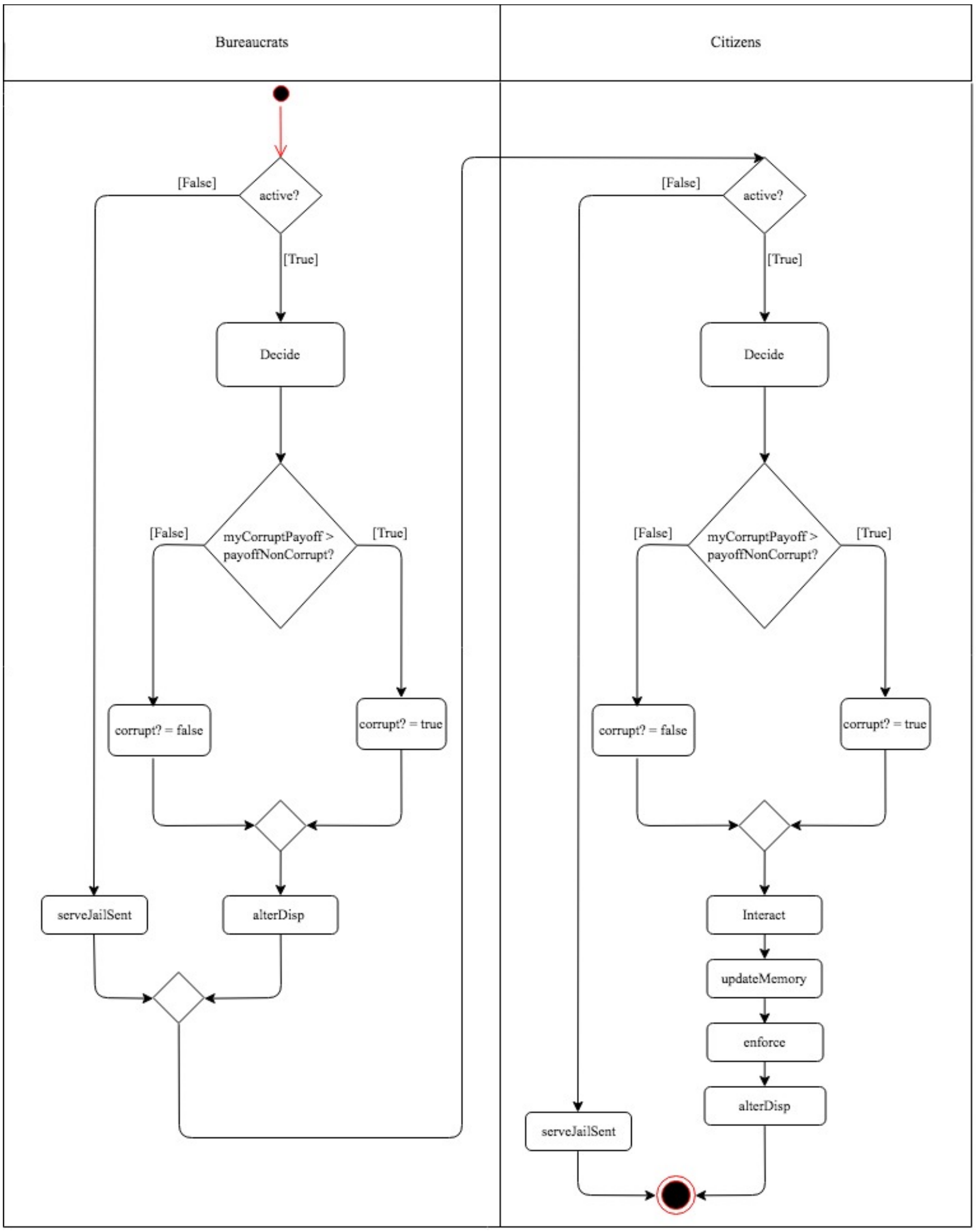
Additionally, each agent possesses a neighborhood of same-type agents, analogous to the 'social networks' found in Hammond's original model. However, whereas Hammond's social networks consisted of isolated groups of agents of a user-defined size, ‘neighborhoods’ in my model are formed differently. For bureaucrats, neighborhoods consist of all bureaucrats on the same patch as that agent, the patch itself representing a government office. The sizes of government officials’ neighborhoods are then based on the number of government offices for a fixed number of government officials i.e. more government offices mean smaller ‘neighborhoods’ of bureaucrats. For citizens, neighborhoods are depicted of the surrounding same-type agents. Within the model neighborhoods are thus composed of a Moore neighborhood composition, being all agents on patches surrounding the interested agent. Therefore, given radius, r, an agent possessing an r=1 neighborhood can have up to eight neighbors, while any larger user-defined radius can have a maximum number of $(2r+1)^2 - 1$ neighbors. Within the model a neighborhood’s radius is determined by the variable, *neighborhoodSize.*

Each simulation lasts for up to 100 time steps but will end prematurely if no decision changes occur for 10 steps. Each time step represents approximately one year, assuming that this is enough time for incremental agent behavioral change and only one major bureaucrat-citizen interaction occurs per year. Additionally, the total world size within real terms can be equated to a large-scale community (such as a city or province) where influence/communication is somewhat limited by distance and multiple duplicate bureaucratic offices exist.

3.2.3 Process Overview and Scheduling

Below is a process overview describing the processes that occur within the model in sequential order. Table 3 is a United Modeling Language (UML) Activity Diagram for visualization of the same process overview. (A detailed description of the mechanics for each procedure is further elucidated within the 3.2.6 *Submodels* section.)

Figure 2: UML Activity Diagram



- Bureaucrats independently choose to pursue either a corrupt or non-corrupt strategy.
- If the *neighborhoodInfluence?* switch is activated within the simulation, agents (both citizens and bureaucrats) may incrementally alter their own disposition towards honesty by the variable *honestyChange* between (0% and 100% change in honesty) in order to better reflect the average disposition towards honesty within that agent's neighborhood[2]. Agents with a difference in honesty between themselves and their neighborhood that is less than *rateChange* alter personal disposition towards honesty to the neighborhood average.
- If in jail, bureaucrats serve one time step of their total user-defined jail sentence (defined by the variable, *jailTerm*).
- Similar to bureaucrats, citizens make their own behavioral strategy.
- Each citizen initiates interaction with a random bureaucrat at the nearest government office.
- Agents update their memory account from their most recent interaction. The length of this memory bank is user-determined by the variable *memoryLength*.
- If either agent type chooses to be corrupt when the interacting agent is not, the non-corrupt agent reports him to a central authority by increasing that agent's *counter* variable by 1. (The central authority, itself, implicitly exists outside the model.)
- If the *lawEnforcement?* switch is activated, an exogenous law enforcement agency imprisons agents who have been reported enough times.
- If the *neighborhoodInfluence?* switch is activated, citizens alter their own honesty disposition by the variable *honestyChange*.

[2] Previous corruption focused ABMs have kept each individual's propensity for honesty static. However, literature into corruption shows that norms and values are highly relevant and thus previous behavior by that individual's social network may affect an individual's perceptions regarding honesty.

- Citizens in jail serve one part of their jail sentence.

3.2.4 Design Concepts

Basic Principles: Like Hammond's original model, my model attempts to depict the endogenous dynamics of corruption, however adds in a spatial element to observe the significance of agent 'neighborhoods'. This model additionally attempts to answer the questions: Do systems tend toward complete corruption and non-corruption as in the original model or do stable systems of mixed decision-making form? For systems that tend towards a mixed decision-making equilibrium, can agents' corrupt or non-corrupt tendencies be divided spatially? What are the relevancies of certain agent parameters (especially those concerning neighborhood influences)?

Emergence: There are two primary emergent results depicted in this simulation. The first looks at how agents' personal observations about the strategies and arrests of other local agents affect the strategies within different areas of the model. The second is how the composition of honesty (including the allowance of neighbor influences) affects the distribution and prevalence of corruption.

Adaptation: Agents will adjust their strategy based on personal observations of neighbors' behavior and interactions with opposite-type agents. Agents also have the option to alter their honesty disposition based on their neighborhoods' attitudes towards corruption.

Interaction: Every time step, each citizen interacts with a bureaucrat at the nearest government office. Before this interaction, each of the agents will independently decide whether or not to try to bribe the opposite agent before this interaction.

Motivation: Each agent's main goal is to maximize expected payoff from each bureaucrat-citizen interaction. While corrupt and non-corrupt strategies have explicit numerical payoffs, agents also consider their neighbors' influence, individual disposition towards honesty, and perceived risk of jail time. The model assumes that the numerical payoff for corruption is at least as high as the numerical payoff for honesty (i.e. not considering other factors).

Sensing: Citizens and bureaucrats are able to perceive the level of corruption found within their neighborhood, which itself is composed of nearby same-type agents. Agents' also perceive the risk of engaging in corruption based on the number of neighbors serving jail time in relation to how many of them are corrupt. My model adds onto the original model by building upon the bounded rationality aspect of the original model; this new model transforms isolated networks into spatially determined neighborhoods and allows for agents' to alter their propensity towards honesty based on neighbors' attitude towards corruption.

Stochasticity:

Randomized elements found within the model include:

i. The individual placement of each agent every run (100-step simulation)
ii. The initial corruption level of an individual at the beginning of each run (although the mean and standard deviation of agents and bureaucrats is user-determined)
iii. The starting strategy of bureaucrats and citizens (again, the total proportion of each agent-types' strategy is user-determined)
iv. The starting memory of past interactions for each agent

Observation: The primary observable here is the total level of model corruption at the end of each run. Secondary observables utilize cluster analysis measures in order to explore the average similarity of neighborhoods and the concentration of corruption within the model.

3.2.5 Input Data

As of now the environment is assumed to be a constant closed system, so no input data is used.

3.2.6 Submodels

Below is a description of the various model processes within the model.

decide:

Each agent decides a strategy (corrupt or non-corrupt) by weighing personal perceived payout for corruption, x_p, against the payout for being non-corrupt, y. The agent decides to engage in corruption if:

$$x_p > y$$

$$where$$

$$x_p = (1 - B)[Ax_i + (1 - A)y] + B[y - ky]$$

Here, x_p represents the perceived payout for pursuing a corrupt strategy. Agents will pursue a corrupt strategy that term whenever x_p is greater than the standard non-corrupt payout, y. B is the perceived probability of being caught for corruption; A is the perceived probability of being matched with a corrupt agent; x_i is the perceived payoff for engaging in corruption; and k is the length of a prison sentence. Consequently, x_p is directly correlated with higher perceived probability of engaging with a corrupt agent, A. It is, however, inversely correlated with higher perceived risk of being caught, B, and higher personal tendencies towards honesty, i. The cost of going to jail, ky, is determined by the length of the jail sentence, k, multiplied by the lost (lower-bound) payout for each time step spent in jail, y.[3]

interact:

During each time step, each citizen chooses to engage with a random bureaucrat at the nearest government office. It is during this process that mismatched agents who have proposed corruption are reported to an exogenous authority figure.

[3] Before going to jail, it is assumed each agent is able to collect a non-corrupt payoff, y.

(This results in an increase to corruption proposing agent's *counter* attribute by 1).

agentPayoff (reporter):

While the payoff, x, is user-determined at the beginning of each run, agents measure this payoff against their personal propensity for honesty, i, so that $x_i = (1 - i)x$. Thus higher levels of honesty are inversely proportionally to an agent's personal perceived rewards for being corrupt, x_i.

encounterCorruptAgent (reporter):

The agent estimates the probability of encountering a corrupt agent, A, based on the number of corrupt interactions, n, that agent has made over total N number of total interactions, i.e. $A = n/N$, N representing that agent's user-determined short-term memory length.

chanceOfJail (reporter):

Agents determine their risk of going to prison by looking at the perceived probability of a corruption conviction, B, which is measured as the total number of neighbors in jail, m, divided by total number of corrupt interactions made by neighbors in the last time step, M. Thus $B = m/M$.

enforce:

Law enforcement entities outside of the model imprison any agents who have been reported for crimes in equal or excess of the *crimeReports* variable (*counter* ≥ *crimeReports*). Agents that are indicted collect a final non-corrupt payoff, y, before heading to prison.[4]

[4] Because it is not necessary to the goals of this model, total agent payoff is not measured.

updateMemory:

After the interaction is concluded, agents update their memory to include the decision made by the opposite agent of that interaction.

alterDisp:

At the end of each step, if the *neighborhoodinfluence?* switch is activated, agents and bureaucrats alter their honesty disposition (*honestyDisp*) by within *honestyChange* to better reflect their neighbors' average honesty disposition. If the agent's honesty disposition already reflects his neighbors, then no alterations are made this step.

serveJailSent:

Inactive agents (those current in jail) serve one time unit of their jail time. If they have completed their jail term, they are released, reset their current strategy to *non-corrupt* (so that neighbors perceive them to be 'reformed' for at least that time step), and are free to interact in future time steps.

3.3 Experimental Design

3.3.1 Research question and hypotheses

At the heart of this model and experiment lies the question: What effects do neighbors or local networks have on the endogenous dynamics of corruption?

In an attempt to answer this research question, the model presents the following five hypotheses:

i. Due to the expanded bounded rationality aspect (so that interaction and influences occur on a local basis), unlike Hammond's base model, few instances of complete corruption or non-corruption will occur beyond a few extreme cases.

ii. As in Hammond's model, where limiting local information was an important aspect of the mitigation of model corruption, my model should also display a significant positive relationship between *neighborhoodSize* and model-level corruption.

iii. Hammond's conclusion that diversity is key to the elimination of corruption should also be present within my model. Specifically, the ability for agents to influence neighbors' level of honesty (*neighborhoodInfluence*) should have a strong positive relationship with corruption as this attribute indirectly lowers the total level of diversity in terms of honesty dispositions within the model.

iv. Decision-making will occur in spatial clusters that are highly correlated with both the size of an agent's neighborhood (*neighborhoodSize*) as well as the ability for agents to share moral values (*neighborhoodInfluence*). Spatial decentralization of government decision-making should further reduce instances of exposure to corruption by bureacurats thus reducing overall corruption, as posited by Klitgaard (1998) and Aidt (2003).

v. Decentralization of government (*govtOffice*) will increase governmental diversity and will thus lead to lower system corruption as well a lower concentration of similar behavior among neighborhoods (including corrupt behavior).

In order to test these hypotheses, the experiment utilizes the following parameters found below (Table 2, 3). Each iteration (run with same parameters) is ran over n = 5 iterations to minimize the already minimal amount of variance found between runs, while the seed of each iteration is stored by initializing the *random-seed = BehaviorSpace run* inside Netlogo to allow for future replicability.

3.3.2 Outcome Measures

In order to test my hypotheses, respectively, I utilize the following three endogenous variables as measurement.

i. *corruption* measures the proportion of corruption behavior against total interactions. This variable measures the basic prevalence of corruption within the model.[5]

ii. *corruptRatio* is one of the two measures of aggregation originally utilized within Schelling's segregation model (1971, 1978). This dependent variable is a ratio of unlike to like neighbors alternatively known as the [u/ l]-measure. Unlike in the original model, agents here take no consideration for vacant space so is not considered within the ratio measured here.

Furthermore, in order to optimize for regression-use, I then convert the ratio into a decimal whereby I divide the number of similar neighbors by the total number of neighbors (like and unlike neighbors) found within the model. Afterwards, I convert this decimal into a percentage. Therefore 100 represents a completely homogenous system while 0 represents a completely heterogeneous one.

iii. *corruptionDensity (dense and sparse)* is an alternative density measurement that was used by Schelling that better elucidates the phenomenon of clustering, or the grouping of similar entities within an area, which my model utilizes in order to focus solely on pockets of corruption. Since citizens are the only agent who can experience clustering, this measurement applies only to them. Given a Moore neighborhood of eight possible neighbors, $N=8$, a sparse cluster within a cellular automaton is defined as being any citizen with at least 3 neighbors that are corrupt ($T = 3$) while a compact cluster requires $T \geq 4$ corrupt neighbors.[6] This number is then divided by the total number of citizens found within the model for standardization purposes.

[5] As the second and third measurements may be dependent upon the proportion of corrupt to non-corrupt decision makers found within the model, corruption is used as an independent variable for measurements ii. and iii.

3.3.3 Experiment Parameters

Table 2 below presents a baseline scenario used to compare my model against Hammond's own base case. Table 3 presents my own fixed and treatment parameters used for the simulation experiment. In an effort for computational efficiency, treatment parameters and their ranges are limited to those most relevant for the purposes of this paper.

Table 2: Baseline Scenario[7]

Parameter	Description	Type	Baseline Scenario Value	Hammond's Base Case[8]
payoffCorrupt	payoff to be corrupt	int	20	20
payoffNonCorrupt	payoff to be honest	int	1	1
avgHonestyDisp	average agent attitude towards corruption	float	0.5	N/A (uniform distribution)
stdDevHonestyDisp	standard deviation of above average model honesty	float	0.5	N/A
memoryLength	size of memory	int	5	5
neighborhoodSize	radius of neighborhood (Moore type)	int	1 (up to 8 agents)	10 agents
jailTerm	length of jail term	int	2	2
crimeReports	decision mismatches	int	2	2

---

[7] Baseline scenario uses parameters found in Hammond's original model. While not explicit within Hammond's model, the baseline values here for *corruptCitizens,* and *corruptBureaucrats* reflect the implicit values that can be found there. However, variables *density, neighborhoodInfluence?, govtOffice* and *govtPerCapita* do not possess analogs within the original model so that the values are of my own determination. Since cellular automata (Moore neighborhood) do not typically allow for a social network to exist outside of 2^n integers, *neighborhoodSize* is kept at the closest baseline size of 8 possible neighbors (r = 1). Lastly, while the original model possessed a uniform distribution for honesty, the values found here follow a truncated normal distribution similar to what could be found in a typical uniform distribution function.

[8] Values used in Hammond's Base Case Model (2000, Table 2).

	to get caught			
corruptCitizens	proportion of corrupt citizens	float	0.9	0.917
corruptBureaucrats	proportion of corrupt bureaucrats	float	0.9	0.917
density	% of land occupied by a household	int	75	N/A
neighborhoodInfluence?	existence of social influence on personal norms	bool	True[9]	N/A
govtOffice	# of bureaucratic offices	int	15	N/A
govtPerCapita	bureaucrats per 1000 citizens	int	51	1
lawEnforcement?	existence of an effective police force	bool	True	True
honestyChange	rate at which agents alter attitude towards corruption	float	0.2	N/A

Table 3: Experimental Parameters

Exogenous Constants

Parameter	Description	Type	Value
density	% of land occupied by a household	int	75
crimeReports	decision mismatches to get caught	int	5
stdDevHonestyDisp	standard deviation of above average model honesty	float	0.2
govtPerCapita	bureaucrats per 1000 citizens	int	51

[9] Another baseline scenario is ran with *neighborhoodInfluence? = false* to facilitate better comparability to Hammond's model by testing both scenarios.

corruptCitizens	starting proportion of corrupt citizens	float	0.5
corruptBureaucrats	starting proportion of corrupt bureaucrats	float	0.5
memoryLength	size of memory	int	5
honestyChange	rate at which agents alter attitude towards corruption	float	0.2

Treatment Parameters

Parameter	Description	Type	Range
payoffCorruption	payoff to be corrupt	int	10, 15, 20
payoffNonCorrupt	payoff to be honest	int	1, , 10
avgHonestyDisp	average model honesty	float	0.0, 0.25….1.00
neighborhoodSize	radius of neighborhood size	int	1, 2, 3
jailTerm	length of jail term	int	1,2…..5
govtOffice	# of bureaucratic offices	int	5,10,…20
neighborhoodInfluence	existence of social influence on personal norms	bool	True/False
lawEnforcement?	existence of a law enforcement body	bool	True/False

3.3.4 Measurement Tools and Data Analysis Methods

Various scenarios are run through Netlogo's integrated software tool for experiments, BehaviorSpace. BehaviorSpace also allows for data to be collected, which I then coalesce into a single spreadsheet inside Microsoft Excel (v14.0). I then run cross-sectional linear regressions using Stata (StataCorp 2013). When measuring corruption and corruption ratio, I utilize a Tobit censored regression model due to the high volume of corner solutions. Because these dependent variables are measured as a percentage of the system as a whole, many of the dependent variable figures are limited to above 0% or below 100%. Therefore, the Tobit model minimizes bias by estimates true y-values whenever the measured variable appears latent. For *clusterDensity*, I utilize a standard linear-regression methodology, as my other dependent variables are uncensored.

I also make use of a number of interaction variables in order to better observe the relationships between highly related treatment parameters. These include interaction variables between corrupt and non-corrupt payoffs, law enforcement and jail terms, as well as neighborhood influence and neighborhood size.

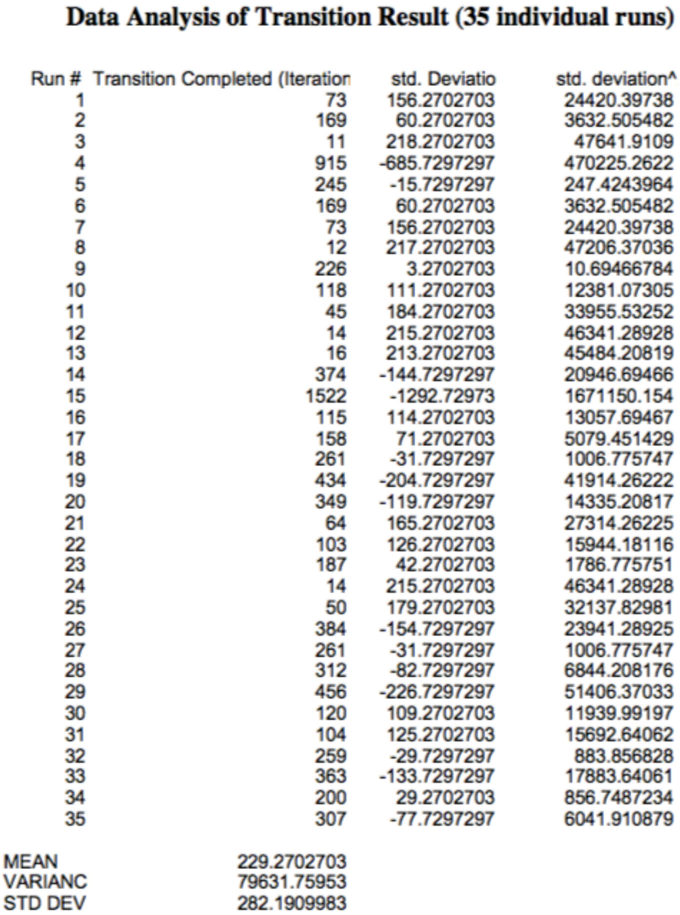
4. Results

4.1 Comparison to Hammond's Model

Table 2, below depicts the baselines parameters used in Hammond and mine's baseline scenarios. Parameters in my baseline scenario are chose as to maxmize comparability to Hammond's own baseline scenario. Each baseline scenario is ran 35 times[10] (each run's results identifiable by *Run Number*).

[10] Hammond justifies this rather large number of identical runs in order to minimize the amount of variance found in his findings (see column "Transition Completed" in Table 4.) While my model experiences significantly less variance, for the base model, I still utilize 35 runs simply toe maximize comparability between the two base scenarios.

Table 4: Hammond's "Base Case"



Data Analysis of Transition Result (35 individual runs)

Run #	Transition Completed (Iteration	std. Deviatio	std. deviation^
1	73	156.2702703	24420.39738
2	169	60.2702703	3632.505482
3	11	218.2702703	47641.9109
4	915	-685.7297297	470225.2622
5	245	-15.7297297	247.4243964
6	169	60.2702703	3632.505482
7	73	156.2702703	24420.39738
8	12	217.2702703	47206.37036
9	226	3.2702703	10.69466784
10	118	111.2702703	12381.07305
11	45	184.2702703	33955.53252
12	14	215.2702703	46341.28928
13	16	213.2702703	45484.20819
14	374	-144.7297297	20946.69466
15	1522	-1292.72973	1671150.154
16	115	114.2702703	13057.69467
17	158	71.2702703	5079.451429
18	261	-31.7297297	1006.775747
19	434	-204.7297297	41914.26222
20	349	-119.7297297	14335.20817
21	64	165.2702703	27314.26225
22	103	126.2702703	15944.18116
23	187	42.2702703	1786.775751
24	14	215.2702703	46341.28928
25	50	179.2702703	32137.82981
26	384	-154.7297297	23941.28925
27	261	-31.7297297	1006.775747
28	312	-82.7297297	6844.208176
29	456	-226.7297297	51406.37033
30	120	109.2702703	11939.99197
31	104	125.2702703	15692.64062
32	259	-29.7297297	883.856828
33	363	-133.7297297	17883.64061
34	200	29.2702703	856.7487234
35	307	-77.7297297	6041.910879
MEAN	229.2702703		
VARIANC	79631.75953		
STD DEV	282.1909983		

Source: Hammond 2000, Table 1.

Table 5: Spatial Model Base Case (w/ and w/o Neighborhood Influence)[11]

	Neighborhood Influence					no Neighborhood Influence				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Run Number	**Step**	**Corruption (%)**	**Std. Dev.**	**Jail Population (%)**	**Std. Dev.**	**Step**	**Corruption (%)**	**Std. Dev.**	**Jail Population (%)**	**Std. Dev.**
1	1000	81.598	3.327	0.000	0.089	1000	45.182	14.494	16.060	7.145
2	1000	82.120	2.805	0.000	0.089	1000	60.526	0.851	9.368	0.454
3	1000	79.895	5.030	0.000	0.089	1000	65.775	6.100	6.952	1.963
4	1000	81.070	3.856	0.000	0.089	1000	48.896	10.780	12.723	3.809
5	1000	94.693	9.768	0.104	0.015	1000	60.236	0.560	9.110	0.196
6	1000	79.850	5.075	0.000	0.089	1000	61.602	1.927	6.348	2.567
7	1000	96.794	11.869	0.310	0.221	1000	72.182	12.506	5.067	3.848
8	1000	79.300	5.625	0.000	0.089	1000	61.792	2.116	7.312	1.603
9	1000	81.263	3.662	0.000	0.089	1000	50.518	9.158	11.077	2.162
10	1000	89.779	4.854	0.000	0.089	1000	63.857	4.181	8.746	0.169
11	1000	80.536	4.390	0.000	0.089	1000	62.925	3.249	7.209	1.706
12	1000	99.266	14.341	0.000	0.089	1000	74.738	15.062	2.830	6.085
13	1000	96.111	11.185	0.307	0.218	1000	66.428	6.752	6.858	2.057
14	1000	81.942	2.984	0.000	0.089	1000	65.762	6.086	7.307	1.608
15	1000	80.862	4.063	0.000	0.089	1000	55.310	4.366	10.936	2.021
16	1000	79.024	5.901	0.000	0.089	1000	51.506	8.170	12.357	3.442
17	1000	94.835	9.910	0.310	0.221	1000	58.805	0.870	9.372	0.457
18	1000	95.572	10.647	0.000	0.089	1000	62.190	2.514	7.955	0.960
19	1000	80.333	4.592	0.728	0.639	1000	57.856	1.819	9.365	0.450
20	1000	81.075	3.850	0.000	0.089	1000	65.054	5.378	6.452	2.463
21	1000	93.700	8.775	0.300	0.211	1000	61.870	2.194	5.672	3.243
22	1000	91.492	6.567	0.315	0.226	1000	59.400	0.276	8.000	0.915
23	1000	80.124	4.801	0.000	0.089	1000	62.822	3.146	7.930	0.985
24	1000	96.908	11.983	0.213	0.124	1000	74.375	14.699	3.438	5.477
25	1000	79.583	5.342	0.000	0.089	1000	58.529	1.147	9.488	0.573
26	1000	84.222	0.703	0.320	0.231	1000	58.209	1.467	6.077	2.838
27	1000	78.287	6.638	0.000	0.089	1000	58.818	0.858	9.582	0.667
28	1000	80.104	4.821	0.000	0.089	1000	53.782	5.893	11.192	2.277
29	1000	79.710	5.215	0.000	0.089	1000	54.517	5.159	11.111	2.196
30	1000	90.654	5.729	0.208	0.119	1000	63.883	4.207	7.933	0.982
31	1000	80.689	4.236	0.000	0.089	1000	63.561	3.885	7.557	1.358
32	1000	79.548	5.377	0.000	0.089	1000	59.849	0.174	9.473	0.558
33	1000	79.430	5.495	0.000	0.089	1000	42.616	17.060	17.194	8.279
34	1000	81.780	3.145	0.000	0.089	1000	48.691	10.985	13.927	5.012
35	1000	80.230	4.695	0.000	0.089	1000	56.590	3.086	10.042	1.127
Mean		84.925	6.036	0.089	0.127		59.676	5.462	8.915	0.000

[11] While later processing of treatment factors limits ticks = 100 in order to try to maximize processing speed, here ticks =1000. Furthermore, no premature stop condition is implemented here.

Since his baseline scenario always results in a complete transition to model honesty, Hammond's base case (Table 4) depicts the numbers of time steps till complete model honesty (as well as the standard deviation and variance) based upon the parameters found in the column titled "Hammond's Base Case" of Table 2. This differs from my model (Table 5) , which instead shows that after an initial spike in corrupt behavior, total model corruption drops off until settling on corruption levels found in Column (2) and (7) of Table 5 (leading me to use the comparable but different measurement variable of end-of-run corruption levels).[12] Furthermore, I additionally allow for both the exclusion and inclusion of the agent ability to alter personal honesty disposition. These results show that model inclusion of neighborhood influence results in a higher overall level of model corruption with a difference in means of 25.249 (p = 0.000).

Hammond posited that a complete transition would always occur after a specific "fault point", a spike in "jailed agents" that promotes a rapid transition into honesty. In contrast, my model sees a spike in jailed agents always occurring at the beginning of the model, before dropping off to levels found in Column (4) and (9). While allowing neighborhood influences results in an overall higher level corruption, the percentage of jailed agents often hovers around 0.00%, implying that when neighbors influence each other almost no mismatched agents interact with each other by the simulation's end.

[12] I furthermore forego including variance from my results, as to try to better increase Table 5 readibility.

4.2 Regression Analysis

Table 6 and 7 found below are the results using the experimental parameters found in Table 3 against the three primary endogenous variables (technically four, since sparse and dense clusters are measured separately.)

Table 6: Summary Statistics

VARIABLES	Variable Description	(1) Mean	(2) SD	(3) Min	(4) Max
Corruption (%)	% of agents who have engaged in corruption this time step	41.547	41.698	0.000	100.000
Corruption Ratio (%)	level of neighborhood homogeneity (in terms of behavior)	88.522	15.349	47.309	100.000
Sparse Cluster	density of corruption (T ≥ 3 corrupt neighbors)	322.476	365.917	0.000	920.000
Dense Cluster	density of corruption (T ≥ 4 corrupt neighbors)	251.611	309.112	0.000	824.000
Average Honesty Disp. (%)	agent attitude towards corruption	0.500	0.354	0.000	1.000
Law Enforcement	existence of a law enforcement body	0.500	0.500	0.000	1.000
Jail Term	length of jail sentence	3.000	1.414	1.000	5.000
Neighborhood Influence	existence of social influence on personal norms	0.500	0.500	0.000	1.000
Neighborhood Size	radius of neighborhood (Moore type)	2.000	0.817	1.000	3.000
No. of Government Offices	# of bureaucratic offices	12.500	5.590	5.000	20.000
PayoffCorrupt	payoff to be corrupt	15.000	4.083	10.000	20.000
PayoffNonCorrupt	payoff to be honest	5.333	3.682	1.000	10.000
Steps till Completion	steps until model end	45.051	41.883	0.000	100.000
Jail Population	% of agents in jail	1.560	4.279	0.000	29.749

Note: Variables descriptions can be found in Section 3.3.3
N = 54,000

Table 7: Regression Analysis of Corruption (% of Model)

Dependent Variable	(1) **Corruption** **TOBIT**	(2) **Corruption** under Law Enforcement **TOBIT**	(3) **Corruption Ratio** **TOBIT**	(4) **Sparse Cluster** **OLS**	(5) **Dense Cluster** **OLS**
Average Honesty Dispostion	-1.038***	-1.037***	0.147***	0.279***	0.434***
	(0.004)	(0.004)	(0.002)	(0.005)	(0.007)
Corruption			-2.859***	2.465***	4.574***
			(0.035)	(0.059)	(0.079)
Corruption^2			0.080***	-0.003	-0.204***
			(0.003)	(0.003)	(0.004)
Corruption^3			-0.001***	0.002***	0.005***
			(0.000)	(0.000)	(0.000)
Corruption^4			0.000***	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)
Corruption^5			-0.000***		
			(0.000)		
Law Enforcement	-11.309***	-15.622***	1.212***	-2.167***	0.491
	(0.650)	(0.9724)	(0.172)	(0.522)	(0.701)
Jail Term	0.094	0.094	0.041	0.175	0.238
	(0.136)	(0.135)	(0.036)	(0.110)	(0.148)
Jail Term * Law Enforcement	-3.967***	-3.996***	-0.408***	-0.582***	-0.781***
	(0.197)	(0.195)	(0.051)	(0.157)	(0.210)
Neighborhood Influence	3.868***	-3.102***	4.588***	5.756***	10.893***
	(0.734)	(0.775)	(0.191)	(0.584)	(0.783)
Neighborhood Size	-1.342***	-0.675**	0.347***	2.431***	1.717***
	(0.240)	(0.286)	(0.061)	(0.192)	(0.257)
Neighborhood Influence (w/ Law Enforcment)		14.543***			
		(0.522)			
Neighborhood Size (w/ Law Enforcement)		-1.431***			
		(0.338)			
Neigbhorhood Size * Neighborhood Influence	0.865**	0.896***	0.061	-1.176***	-0.220
	(0.340)	(0.338)	(0.088)	(0.270)	(0.362)
PayoffCorrupt	-0.224***	-0.224***	0.144***	0.207***	0.372***
	(0.056)	(0.056)	(0.014)	(0.048)	(0.064)
PayoffNonCorrupt	-20.641***	-20.612***	2.492***	3.062***	5.110***
	(0.175)	(0.174)	(0.054)	(0.128)	(0.172)
PayoffCorrupt * PayoffNonCorrupt	0.780***	0.779***	-0.100***	-0.108***	-0.184***
	(0.011)	(0.010)	(0.003)	(0.008)	(0.010)
No. of Government Offices	0.101***	0.100***	0.108***	-0.284***	-0.203***
	(0.025)	(0.025)	(0.006)	(0.020)	(0.026)
Constant	139.947***	140.319***	87.476***	-37.831***	-64.483***
	(1.174)	(1.065)	(0.392)	(1.133)	(1.520)
Observations	53,999	53,999	53,999	53,999	53,999
R-squared				0.995	0.988
Pseudo R-squared	0.167	0.169	0.303		
Uncensored Observations	34801	34801	34798		
Right-censored Observations	913	913	19201		
Left-censored Observations	18285	18285	0		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The treatment parameters chosen for my experiment (Table 3 and Table 6) were chosen discretionarily according their perceived significance to the goals of my model (Section 3.3.1). Treatment parameter values were chosen in a way to maximize the distribution of X_n so as to minimize bias. More treatment parameters and treatment variables values were not included so as to maximize computation efficiency. As to the specific reasoning for each chosen treatment parameter, I include *Average Honesty Disp.* since this is the primary characteristic defining the internal norms of the agents within the model, making it highly important to how corruption operates as an internal norm. *Law Enforcement* is included in order to see how agents behave within a system where corruption goes completely unreported versus one with a healthy legal system. Furthermore, *Jail Term* tests the importance of *risk* and agents decision-making processes. Both *Neighborhood Influence* and *Neighborhood Size* are my interested variables, the two primary agent attributes added to my model in order to explore model spatial significance. *Payoff Corrupt* and *Payoff NonCorrupt* are additionally key as they lie at the heart of all agents decision-making processes. Lastly, *No. of Government Offices* tests how the spatial distribution of *bureaucrats* is important the dynamics of corruption. Since government neighborhoods are simply composed of other bureaucrats within that office, more government offices mean more but smaller isolated neighborhoods, while less government offices lead to an opposite dynamic.

Table 7 measures the various outcome measures listed in Section 3.3.2 against the experiment parameters found in Table 2. While, I utilize a general OLS regression for Coumns (4) and (5), Columns (1) to (3) make use of the Tobit model in order to better estimate my endogenous variable whenever censored, or latent, so that:

$$y_i = \begin{cases} y_i^* \ if \ y_L < y_i^* < y_U \\ y_L \ if \ y_i^* \leq y_L \\ y_U \ if \ y_i^* \geq y_U \end{cases}$$

Here, the endgenous variable, y_i, is equal to the latent variable, y_i^*, whenever not censored by the lower and upper variable limits of y_L and y_U respectively. In Table 7, Columns (1) and (2) have a lower limit of 0 and upper limit of 100 while Column (3) contains an upper limit of 100. As can be seen in the large number of censored observations listed at the bottom of Table 7, disinclusion of these latent variables could there heavily bias my results.

Column (1) displays the general effect of the various parameters on the total level of corruption throughout the whole model, which is measured as the percentage of agents engaged in corrupt behavior by the model's end. My model shows that around one-third (35.55%) of the total scenarios resulted in a complete break down of corruption within the system, fairly conclusively disproving my hypothesis that a wider dissemination of networks across a spatial area would significantly decrease instances of total behavioral transitions. These regressions also seem to highly echo Hammond's posit that corruption is often inherently unstable, as only 1.7% of scenarios resulted in total model corruption, significantly less than the instances of total model honesty.

In terms of parameter significance, as expected, *Average Honesty Disposition* has a near unitary negative elasticity relationship with the level of corruption within the model. Similarly, the presence of law enforcement has a strong negative relationship with corruption that is enhanced as jail terms are elongated (as can be observed in the interaction term, *Law Enforcement * Jail Term*). Furthermore, as hypothesized, the ability for agents to receive influence from neighbors (*Neighborhood Influence*) is associated with an increase in corruption. This supports both Hammond's and my own hypothesis that individuality and behavioral diversity continues to be an important facet for corruption mitigation.

Surprisingly, a positive relationship between *No. of Government Offices* and corruption exists, indicating that spreading out a static number of government officials across a number of different offices does not necessary lead to a lower system-level of corruption. Similarly, contrary to Hammond's conclusions and my own hypothesis, limiting agent local influence does not mitigate corruption. Instead, any increase in one's neighborhood size is correlated with a decrease in corruption.

Originally, the intuition between the neighborhood effects and corruption was the significance of 'fear'. By increasing the network from which an agent gathered information, each individual arrest held less impact and thus was less likely to inspire any behavioral changes. Therefore, in order to look at the significance of fear of law enforcement, Column (2) looks at both *Neighborhood Size* and *Neighborhood Size* only when the presence of law enforcement exists (designated by the interaction terms *Neighborhood Size (w/ Law Enforcement)* and *Neighborhood Influence (w/ Law Enforcment)*). Still, limiting these variables only increases the absolute value of the coefficients for both *Neighborhood Influence* and *Neighborhood Size*. The significant increase in the *Neighborhood Influence* coefficient suggests as homogeneity increases, agents have significantly less fear of getting caught for corruption. Similarly, whereas Hammond's model suggested that increasing one's information network would decrease the significance of each arrest, the coefficient here suggests that with overlapping networks (i.e. neighborhoods) each arrest has influence over a larger area as *Neighborhood Size* increases, thereby counteracting the mitigating affects found in Hammond.

The same logic can be applied to the disproving of my hypothesis that governmental decentralization would lead to less corruption. While this may indeed increase heterogeneity and thus have some positive influence on government behavior, it is also accompanied by a loss of fear as government officials become less likely to see a colleague imprisoned for any corrupt action.

Columns (3) – (5) [13] explore the effect of various parameters on the concentration of behavior by looking at the fraction of similar neighborhoods (Column (3)) and concentration of corrupt behavior (Column (4), Column (5)). As hypothesized, *Neighborhood Influence* and *Neighborhood Size* both have statistically significant relationships with the similarity of one's immediate neighborhood (Moore neighborhood, *r*=1). However, the weakness of these coefficients is a bit unexpected. Existence of a neighborhood influence on average increases the likelihood of an immediate behaviorally similar neighbor by only around 4.6%, which even as a general estimate is rather weak. Additionally, *neighborhoodSize* only contains a marginal effect on the composition of one's immediate neighborhood, a less than 1% influence for every marginal increase in *neighborhoodSize*. The positive relationship between number of government offices and neighborhood similarity is also an unexpected find that directly contradicts my hypothesis. This seems to suggest the significance of divergent behaviors within a government office may have a stronger influence on nearby neighborhood compositions. Thus, it seems that this internal diversity can be just as important as diversity from decentralization, or as in this model, more important.

Columns (4) and (5) are more in line with model expectations. Here, both *neighborhoodInfluence* and *neighborhoodSize* have a significant positive relationship with instances of corrupt clusters. At the same time, higher bureaucratic dissemination possesses a statistically negative relationship with the occurrence of corrupt clustering; scattered government officials mean a less centralized source of behavioral influence for citizens. When compared with the

[13] Tables 9-11 include different quadratic degrees of corruption as to avoid omitted variable bias. In terms of neighborhood similarity we expect a high level of similarity amongst instances where corruption is very high or very low. Conversely,corrupt clusters possess a positive logarithmic interaction with the total level of corruption found within the model.

results from Column (3), these results suggest that while neighborhood resemblance may increase with the decentralization of government, there is still a stronger tendency towards honesty rather than corruption.

5. Conclusion

5.1 Summary of Findings

Optimistically, this study has found that even when expanding social networks from a series of isolated entities to a series of overlapping ones based on spatiality, many endogenous systems may still transition towards honesty, even if the specific parameters needed to induce this transition may differ from those in Hammond's model. Moreover, under this spatially significant system, while the existence of moral heterogeneity remains significant, less important is the need to localize information to agents. For closed-off networks, limiting informational access maximizes the deterrent effect of every arrest. However for open social networks, more important is the overall scope that information concerning an arrest reaches. Even for individuals not privy to the direct 'fear' from witnessing an arrest, their own proximity to a neighbor who is a witness to some arrest may additionally indirectly influence their own behavior. At the same time behavioral immutability allows for the propagation of a proper 'whistleblower' system, whereby non-corruptible individuals can help mitigate the prevalence of corruption.

Additionally, while networks are still important in terms of behavioral concentration, the less integral neighborhood-dependent rules on agent behavior when compared to more traditional cellular automata mean that larger clusters are less likely to be found within this model, although they are key to the dynamics of behavioral dissemination found here.

Lastly, this model shows that the spatial decentralization of power does not inherently lead to lower corruption, especially if influence between offices is limited or nonexistent, as in this model. While this decentralization might mitigate the likelihood of corruption to spread throughout a central office and the whole system, this wider dissemination of government also means that officials may be less likely to witness the imprisonment of a coworker(s) within their office, and, thus, less likely to experience the 'fear' of law enforcement.

5.2 Recommendations

These findings stress the importance of moral heterogeneity and informational availability. Unlike Hammond's model, in a system of overlapping networks, the best method of corruption deterrence is to maximize people's methods of information acquisition. Although this opening of communication channels may risk persons' access to cases of criminals who 'get away' with corruption or crime, these channels also offer more information on those who get caught, making people less likely to behave corruptly and also indirectly influencing nearby friends and neighbors to act similarly. Politically, this model highlights the importance of governments and other bodies of authority to minimize policies aimed at 'keeping people in the dark.'

Moreover, this model's findings highlight the importance of diversity amongst norms, a finding that enhances Hammond's original conclusions. The dynamics of peer-pressure will often to push people towards being corrupt more often than towards honesty. The mechanisms of this phenomenon seem to lie with agents' perceived risk. Specifically, norm homogeneity provides individuals with local knowledge of instances where corrupt behavior goes unpunished, reducing people's perceived risk of getting caught. Conversely, norm heterogeneity enhances this perceived risk, as people do not receive the positive behavioral reinforcement from their social networks and become less sure of their chances at criminal success. On a policy front, this finding only highlights the importance of community integration between individuals of different values as well as the significance of individualism among those who constitute a system or society.

5.3 Research Limitations and Suggestions for Further Research

While my model attempts to create results that may be applicable to real-life scenarios, it still contains certain limitations that open up possibilities for future research. The rate of influence of neighbors' preferences on an individual's preference is still not completely understood so that the *alterDisp* procedure might be faster or slower than what has been presented in this model. (Indeed, it most likely differs between individuals as well.) Furthermore, by allowing for separate behaviors (i.e. *enforce*, *altDisp*) or attributes (i.e. *jailTerm*, *honestyDisp*, *counter*) for neighbors and citizens, my model would be able to better display the significance of citizens and bureaucrat attributes in relation to corruption. This level of differentiation could even be extended to breeds, or categories, of citizens based on race, political views, or education, which might give better insight into how corruption might distribute itself among various demographics. While not explored in this paper, these possible additions open up many possibilities for further research.

Additionally, as with Hammond's model, the ABM used for this paper depicts law enforcement as an outside and efficient entity. In reality, corruption (especially petty corruption) often flourishes within areas where the authorities responsible for mitigating corruption are often, themselves, part of these corruption networks and neighborhoods and, therefore, may also be corrupt. An inclusion of an endogenous authoritative force could alter the model in many significant ways, such as creating a own personal risk/cost for agents who do the reporting to potentially corrupt authorities.

On a more methodological basis, limitations in computing power mean that further research could consist of a more comprehensive parameter sweep or additional replications in order to acquire more accurate coefficients of the various exogenous parameters.

5.4 Discussion

Petty corruption remains a huge hurdle for hundreds of millions of people around the world, especially in many developing countries and lower-income classes. A system of bribes and nepotism bars many from access to hospitals, public transportation, and jobs. Unlike grand corruption, which can often be amended with the dismissal of a few key individuals, petty corruption often feels ingrained within a society to the point where its eradication often seems to be impossibility. In turn, the elimination of petty corrupt practices may often seem insurmountable. At the same time, corruption's existence in the shadow economy mean that the tools available to better help with our understanding remains highly limited, further encumbering active efforts at its abolition.

Thus, the main ideological goal of this paper is add to the understanding of corruption by taking an alternative approach to the subject. By taking this different approach to studying corruption – utilizing a cellular automaton model and agent-based computation economics methodology – my aim is to better understand how corruption spreads through a system.

As with Hammond's model, the results of this model are rather optimistic. They suggest that it is possible for a society to endogenously transition towards honesty, and, indeed, suggests tendencies towards honesty will occur more often than towards corruption. However, more often than not, systems will reach an equilibrium where full transitions do not occur. In order to stimulate a transition, policies can be implemented, but they can also result from internal societal changes. Specifically, increases in informational access and ideological individualism can spur an internal transition towards a more honest society. Information access provides people with more chances to witness the consequences of corruption, while ideological individualism results in less confidence of the success of a corrupt act.

Empirically, we can see how these parameters are reflected in our real lives. Internet, social media, and mass media are often cited reasons for the discovery and deterrence of crime by public officials (Anderson et al. 2011, 387-417). Technologies such as these have increased the number of 'neighborhoods' we are involved as well as the scope of the networks with which we are currently involved. They have additionally given arise to 'Internet Justice', which while controversial in ways beyond the scope of this paper, has made it so that many individual's immoral actions are witnessed and reacted upon beyond the boundaries with which they would normally be seen. While these technologies have no doubt also led to the proliferation of certain crimes, the overwhelming good they have created cannot be ignored. Furthermore, this paper highlights the importance of independent critical thought in societies and the positive effect this can have on a society as a whole. With further active efforts to spread informational access and stress the importance of independent critical thinking, it may even be possible to make corruption the kind of issue that eventually only effects the smallest percentages of societies in the world.

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