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SUCCESSFUL RESOURCE SEEKING STRATEGIES: AN AGENT BASED MODEL OF BUDGETARY COMPETITION

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ABSTRACT

The strategies that bureaucratic actors employ to secure resources are the result of a complex interplay between motivational states and environmental conditions. The strategies employed by bureaucrats to secure resources are now best understood as heuristics. Heuristics that may be adaptive in securing resources under some conditions may be maladaptive under different environmental circumstances (Gigerenzer 2000; 2008). This study reviews the various strategies employed by bureaucrats to secure financial resources through the lens of Downs' typology of bureaucrats to determine the fundamental heuristics the successful strategies employ. We sought inspiration from both the extant literature and models of bureaucratic behaviour within organizations beginning with Downs (1967) and continuing with the work of Bowling, Cho, and Wright (2004), and the methodological innovations afforded by agent-based modelling. By making certain basic assumptions regarding decision-making heuristics, we show a remarkable consistency between Downs, Bowling and her colleagues, and our own findings.

KEYWORDS

Budgetary heuristics, Resource constraints, Taxonomy of Bureaucrats, Decision-making

1. INTRODUCTION

For more than 50 years public administration scholars have attempted to examine the strategies and attitudes of bureaucrats regarding the acquisition of budgetary resources (Wildavsky, 1964). Early public choice theorists (Downs, 1967; Niskanen, 1971) claimed that bureaucrats were motivated significantly by self-interest and were budget maximizers seeking to always increase their budgetary allocations. These theorists assumed that bureaucratic agents act in a manner analogous to firms in a competitive market place, where profit maximization is the goal.

More recent examinations of the attitudes of public managers toward budget increases do not support the single-minded budget maximizing claims of the public choice theorists. Dolan's (2000, p. 42) sample of Senior Executive Service members found that these senior managers preferred less government spending than the public in general and preferred less spending "...even on issues that fall within their own department's jurisdictions." Bowling, Cho, and Wright's (2004) longitudinal study of state-level agency heads revealed a spectrum of attitudes regarding budget increases. These agency heads revealed attitudes toward budget increases ranging from no increase to increases to 15 percent or more. In a recent experiment, Moynihan (2013) found that individuals scoring high in public service motivation did not advocate for significantly higher increases in budgets relative to others.

These divergent views on the budget seeking behavior and attitudes of public managers result in very different views of the motivational sets of bureaucrats. The public choice perspective sees bureaucrats as fundamentally self-interested in the pursuit of budgetary resources. The more recent literature offers a more complex view of the motivations of bureaucrats with regard to budget seeking behavior. This literature suggests that there is a wide spectrum of attitudes concerning budget seeking behavior among bureaucrats. Bureaucracy is not seen as a monolith of selfish actors pursuing their economic self-interest but rather as a mixture of attitudes toward seeking financial resources.

The debate over whether bureaucrats are budget utility maximizers or display a spectrum of attitudes with regard to increasing budgets does not inform us, however, as to which resource seeking strategies are most effective in obtaining resources. Budget allocations remain as signals as to not only what an agency can accomplish but also signal the preferences of government itself. The strategies that government managers use to receive budgetary allocations must also be viewed within the light of environmental factors. The context of a strategy is critical if a strategy is to succeed (Bryson, 2004).

A major, if not the predominant context, for public administration in the last 40 years is the public sector's economic and institutional reality of declining resources. The reality of resource constrained environments should thus serve as one primary context for examining how bureaucrats' strategies for acquiring resources interact with such environs. Perhaps more importantly, it is important to understand if resource constraints serve to change the mix of bureaucratic actor types and thus the mix of strategies toward resource seeking.

This paper seeks to answer two primary questions. First, which bureaucratic types, defined by their resource seeking strategies, are most effective in capturing financial resources under conditions of resource constraints? Second, does the initial mix of bureaucratic types change, over time, as more

successful resource capture strategies replace less successful strategies in a resource constrained environment?

We present the results of an experiment embedded in an agent-based model. This model imbues agents with differing strategies, enacted through heuristics that guide the agents toward resource acquisition. The agents are placed in an environment of constrained resources as a means to examine which bureaucratic type, as defined by its basic strategy and its associated heuristics is most effective in acquiring resources. The model thus provides a determination of which bureaucratic types and their associated heuristics are likely to thrive in and inhabit a resource constrained environment.

While the strategies of public administrators may vary in the details of their origin, Gigerenzer (2008) has detailed why simple rules of thumb often outperform complex decision-making models. In many complex scenarios, “simple rules give concrete guidance without being overly prescriptive” (Sull and Eisenhardt 2015, p. 25). The approach embodied in the model presented in this work is premised on the decision-making literature (Gigerenzer, 2008; Sull and Eisenhardt, 2015) that reveals that simple heuristics are both more effective and more typical of actual decision-maker behavior relative to more complex strategies, especially under conditions of uncertainty and numerous alternatives (Gigerenzer, 2014).

Downs’ classic model (1967) of bureaucratic types provides a foundational template for selecting the fundamental bureaucratic types that populate the simulation. These fundamental types each present distinct strategies for navigating a landscape of reduced resources. Bowling, Cho, and Wright’s (2004) (BCW henceforth) more recent application of Downs’ typology provides an empirical foundation for the strategies each bureaucratic type employs toward budget increases. We apply a model combining Downs’ view of the expected resource seeking behavior of each type toward budgetary acquisition with BCW (2004) longitudinal data of the attitudes of state agency heads toward budget increases. BCW (2004) study results thus serve as an empirical foundation for determining the initial proportion of bureaucratic types that populate the simulation and their associated strategies for resource acquisition in the simulated environment.

This paper is comprised of six sections. The first section reviews the literature examining the motivations of public managers with the particular contextual relevance to budgetary behavior and dynamics. The second section details the typologies of bureaucrats produced by Downs (1967) and BCW (2004). The third section details the general elements of agent-based models. We next provide a description of our model in the ODD (Overview, Design concepts, and Details) protocol format (Railsback & Grimm, 2012). The fifth section reports the results of the simulation and the final section provides a discussion of the simulation results.

2. THE DYNAMICS OF BUREAUCRATIC MOTIVATION

Early research on the budgetary motivations of public managers viewed them as devoted to budget maximization. Wildavsky’s work (1964) created the assumption that public managers attempt to maximize budgets by using the various strategies he detailed. In later works, public choice theory served as foundation for some of the early research on the topic. Downs’ (1967) saw bureaucrats as budget maximizers. He saw this as especially true for agencies in the early years of their existence that were likely dominated by (Downs, 1967, p. 4) “Climbers” seeking to attain status and power

through budget expansion. Niskanen's (1971) early theoretical work was also premised on a public choice assumption that public managers are rational utility maximizers (Conybeare, 1984) who are consistently devoted to securing larger budgets for their agencies or units.

Later empirical analyses of the public choice assumptions concerning bureaucratic behavior questioned Niskanen's view that bureaucrats' budget preferences are singularly devoted to increasing budgets. Conybeare's (1984) work exploring inter-agency competition showed that competition between agencies reduces the monopoly power that necessarily expedites budget maximization. Dolan's (2000) study of members of the U.S. Federal Senior Executive Service (SES) also did not support Niskanen's budget maximization theory. Dolan (2000) found that SES members did not demand budget increases even for their own agencies.

BCW (2004) examined data gathered over four decades from the American State Administrators Project (ASAP) in an effort to determine the budget preferences of state level managers. These data reveal considerable variation in the sampled managers' views regarding the expansion of their own agency's program and their views of increases in overall state budget expenditures. In particular, the decade of the 1990s showed distinct increases in the number of administrators who showed no desire for overall State budget expansions. The decade of the 1990s also showed a clear decline in the proportion of sampled administrators seeking large budget increases, in this case 15 percent or more, for their own agencies (BCW, 2004). Thus, the empirical literature reveals that public managers are more than singularly motivated automatons with a preference set dominated only by those seeking increased budgets. However, BCW (2004, p. 495) did find that the majority of the administrators in the ASAP samples, ranging from 62 percent in 1964 to 56 percent in 1998, favored both the expansion of their own agencies and state-level budgets. Thus, while many public managers may be budget maximizers, the public choice perspective presents only a partial picture of the actual heterogeneity revealed in government managers' budget preferences (Dolan 2000; BCW, 2004).

2.1. Typologies of Heterogeneous Administrators

Downs' study of bureaucratic decision-making provided a classic taxonomy of bureaucratic behaviors that provides a model that is still useful today (Kiel, 2005). Although Downs describes nine different motivations within the "bureaucrat's utility function" he identifies "five ideal types" of behavioral abstractions that "provide insights into the way bureaus actually behave" (1967, p. 88). The characteristics described by Downs break down into two primary groups: those that are driven by personal self-interest and those with mixed motives. The self-interested group includes the two subtypes of Climbers and Conservers. Climbers are interested in ascending the organizational hierarchy to increase their own power, prestige, and resources to the almost complete exclusion of other goals. Conservers, on the other hand, are interested in securing their current position of power, prestige, and resources and are not interested in taking risks to accumulate more resources.

Mixed-motive officials constitute the second of the primary groups. The mixed-motive officials possess goals that contain elements of both self-interest and altruism. Within this group are three of Downs' subtypes: Advocates, Zealots, and Statesmen. Advocates are loyal to a modestly broad set of functions and in particular to the segment or department of the bureau to which they identify with or belong. They seek power to further the policies and wellbeing of their current organization,

unit or function. Zealots are similar to Advocates but have a narrower agenda. They seek power to effect policies, considered sacrosanct, to which they are fiercely loyal as well as seeking power for its own sake. Zealots have an almost single minded focus on the furtherance of these policies. Statesmen, however, are the antithesis of the Zealots in that their loyalties lie with society. They seek power to improve the general welfare and in doing so “closely resemble the theoretical bureaucrats of public administration textbooks” (Downs, 1967, p. 89).

A more recent typology of administrators’ motivations was developed by BCW (2004). Their review of survey data from the American State Administrators Project resulted in their typology of administrators’ motivations based on administrators’ preferences for or against budget increases. The BCW (2004) typology also reveals heterogeneous motivations among administrators and their preferences toward budget increases. In particular, these motivations are based on administrators’ preferences for increasing or decreasing their own agency budgets and for increasing or decreasing the entire State level budget. The typology consists of four administrator types beginning with Abiders who prefer no increases in either their own agency’s or the State’s budget. A second group, the Altruists, prefer expanding the State budget but not their own agency’s funding. A third group, the Advocates, favor increasing their own agency level funding but not increased state level funding. Finally, BCW (2004) view Aggrandizers of varying intensity who prefer both their agency level and State level budget increases. Thus, BCW (2004) identify a continuum of administrator preferences ranging from “minimizers” willing to accept no increase to their own budgets to “maximizers” who consistently seek increased budgets.

3. AGENT BASED MODELING

Axelrod (1997) offers a rationale for the use of computer simulation in the social sciences. One of his basic premises concerning agent-based modelling is that such simulation “is a way of doing thought experiments” (Axelrod, 1997, p. 4). Holland (1995) describes the idea that agent-based models could be used in a manner similar to flight simulators allowing the possible outcomes of a process change or intervention to be explored in the benign environment of a computer model prior to implementation in the real world. One of the chief aims is to achieve parsimony, while also faithfully capturing the essence of the phenomena in question.

Agent based modelling (ABM) is a simulation tool for uncovering the connections between the micro-motives and macro-outcomes in a complex environment. One form of agent-based modelling is participatory modelling. Participatory modelling is essentially a role-play exercise with highly defined behavioural characteristics for the players. The players or agents can characterize actors in a scenario or they can represent more abstract types of agents such as parts or warehouses in a supply chain (North & Macal, 2007). The main assumption is that the behavioural attributes for the agents are determined a priori to the simulation and tested for their ability to emulate historical outcomes. Once these attributes have been established and tested via a simple participatory or desktop simulation, more elaborate models can be developed in a modular fashion.

Agent-based models are comprised of two essential elements. First, agents exist that are imbued with various attributes for navigating their environments. Second, the agents inhabit and traverse a landscape. The landscape may represent human organizations, cultural innovations such as markets or the virtual representation of the topography of a geographic region. It is this combination of the

heuristics that drive the behaviour of agents and the composition and characteristics of the landscape that produce the dynamics and the outcomes of the simulation.

4. THE AGENT BASED MODEL PRESENTED IN THE ODD PROTOCOL

4.1. Purpose

It is not possible to test directly the psychological state of bureaucratic agents which for the purposes of our study represent agency or bureau heads. Rather, we assume that the fundamental postures agents enact are based on heuristics toward resource acquisition. Faced with the need to make decisions about which strategies to follow, bureaucratic agents employ heuristics consistent with their basic postures, with what they have learned over time, or which they develop by mimicking others they believe are successful. Such heuristics, or “cognitive maps” (Gigerenzer, 2000; Gigerenzer, 2008, pp. 3-45), provide a means for bureaucratic agents to navigate the uncertainty of bureaucratic politics.

Such heuristic devices for guiding organizational behaviour are based upon what agents have concluded are their preferred strategies for adapting to an uncertain environment. Over time, as the environment changes, agents may evolve different heuristic strategies. But humans are also cognitive misers; they tend to conserve cognitive energy (Fiske & Taylor, 1984). To change heuristics requires a significant expenditure of cognitive energy. Of course, in the real world, bureaucratic types may play multiple strategies simultaneously, or may alternate strategies over short periods of time. We make no such assumptions here, since we seek to make the analysis more tractable. With these aspects in mind, we utilize a model design very similar to the NetLogo Wealth Distribution Model (Wilensky, 1998), to determine whether agents operating under a small set of relatively simple attributes can accurately simulate empirical findings regarding the preferences of bureaucrats in budget environments. Our model is built in NetLogo with its familiar landscape, patch, and turtle protocols (Wilensky, 1999).

One important point is that the agents in this model retain their initial heuristics throughout the simulation. In other words, the agents maintain a stable set of simple heuristics toward resource acquisition. Moreover, we assume, for the purposes of this study, all the agents are of equal authority within the organization. We assume the bureaucratic agents, the agency heads, operate in an environment of rough equality. While this assumption may not be strictly realistic at any one point in time where the political winds may temporarily favour one agency over another, we think that over time, shifting political fortunes result in a rough balance. The assumptions made regarding the agents’ decision making assumes, consistent with Gigerenzer (2008), that the agents are boundedly rational, a common assumption in such situations. Importantly, however, here we assume, again, consistent with Gigerenzer, that the decision-making strategies, the agents’ heuristics in this case, are adaptive and efficient. Indeed, Gigerenzer’s “fast and frugal” heuristics produce efficient behaviors while requiring agents to ignore certain kinds of information. As defined by Gigerenzer (2008, p. 22) “A fast and frugal heuristic is a strategy, conscious or unconscious, that searches for minimal information and consists of building blocks that exploit evolved capacities and environmental structures.” This contrasts with Kahneman and Tversky (1979; 1996) who assumed that such reliance on shortcuts can be maladaptive and produce decisions that result in poor outcomes.

In our model, we operationalize the heuristic Gigerenzer and Brighton (2009) describe as “take-the-best.” According to Gigerenzer and Brighton:

Take-the-best is a member of the one-good-reason family of heuristics because of its stopping heuristics: The search is stopped after finding the first cue that enables an inference to be made. Take-the-best simplifies decision-making by both stopping after the first cue and by ordering cues unconditionally by validity. Both these simplifications have been observed in the behaviour of humans and other animals but routinely interpreted as signs of irrationality rather than adaptive behaviour (Gigerenzer & Brighton 2009, p.113).

This assumption in our model that our simulated agents’ use “heuristics” for navigating budgetary acquires is also supported by research examining how managers employ strategy. Davis, Eisenhardt and Bingham (2009) found that simple heuristics for strategy are efficacious in dynamic environments. Bingham and Eisenhardt (2011, p. 1437) discovered that private sector managers apply heuristics to acquire business opportunities in a manner that, “... results in a deliberately small, yet increasingly strategic, portfolio of heuristics.” Furthermore, given the extent of the cognitive demands placed on managers it is reasonable to assume that relatively simple heuristics are employed when attempting to acquire resources.

4.2. Entities, State Variables, and Scales

There are five types of entities in this model: four bureaucratic subtypes of mobile agents, and immobile patches containing varying amounts of resources. The simulation environments the mobile agents navigate are made up of the patches in a square grid measuring 150 by 150 patches. Each of the patches has one state variable: its amount of resources. The simulations last for 30-time steps (ticks) with each time step simulating one budgetary year. The total number of each agent type is captured at the end of the simulation run (30-time steps). Simulations should rely on valid empirical data when such data are available. The survey data presented by BCW (2004) identified the relative percentage of each bureaucratic type over a 30-year time frame. Our goal was to set the initial proportion of the agents in the model to those identified by BCW. This approach provides an initial condition, or starting point, for the simulation based on the starting point of the existing data. The data shows that there were fluctuations in the relative percentages of agents over time and so we chose an ending point coincident with the lowest percentage of Aggrandizers to allow for a stable, downward trend in budgetary resources. These starting, and end points were chosen to provide a clear break in the resource rich environments and the resource poor environments. This allowed the model to run in a constant resource poor environment, providing the conditions we wished to observe the agents interact. The timeframe also coincides with an historic aggregate slowdown in state government revenue growth (BCW, 2004).

We varied the settings for agent vision and resource needs through multiple experimental runs until the outcomes mirrored the changes of relative agent percentages of the ASAP data set over time. The Altruists had their resource needs set to the highest value. Altruists, with their goals aligned with the overall wellbeing of the organization as a whole, have the highest rate of resource needs and thus engage the simple heuristic of requesting more resources out of concern that others may not get the resources they need to help the organization achieve its goals. The Altruists’ resource need rate was followed in descending order by the low Aggrandizers, the Abiders, and the high Aggrandizers. Although the motivations of the groups are disparate in orientation, all these types

require relatively moderate levels of resources to reach the budget goals associated with their resource seeking behaviour. Advocates had the lowest relative resource need rate. To reproduce these changes within the model, the resource need variable proved to be the strongest indicator of agent relative success.

With the agent attributes and environmental variables established, the simulation was run in the following manner. To remain true to the findings of BCW (2004), the model's initial populations of agent types were set to mirror the proportions of the ASAP data from 1964, the initial year of the study, and the agent attributes were adjusted until the model outcomes coincided with the proportions of the 1978 year of the study. These points were chosen to examine the impact of public preference for agency growth reductions beginning in 1964—the ending of a period of relative high resource availability—to 1978, the year California's Proposition 1 was enacted by voters (BCW 2004). This approach resulted in initial starting proportions for the simulation of 200 low Aggrandizers, 190 Abiders, 120 Advocates, 400 high Aggrandizers, and 60 Altruists. Budget reduction was set at zero. We ran this simulation 1,000 times to ensure consistent and stable outcomes for the agent subtypes. All of the following run series were conducted with up to a 35 percent budget reduction from the initial baseline. The absolute reduction amount of the budget amounts is not as germane to the functioning of the model as is the more subjective terminology of modest, or severe budget reductions.

Table 1. Agent Types, Postures Toward Budgetary Growth and Heuristics

Downs' Types	Associated Bowling et al. Type	Bowling Types Postures toward Budgetary growth	Propensity Toward Strategic Maneuvering (Very Low to Low = take-the-best)	The Agent's Need for Resources (Operationalized posture toward budgetary growth)	Take Resources from Other Agents
Climber	Low Aggrandizer	Agency Expansion – Yes; State Expansion-Yes	Very Low	Moderate	Yes
Climber	High Aggrandizer	Agency Expansion – Yes; State Expansion-Yes	Moderate	Moderate	Yes
Conservator	Abider	Agency Expansion- No; State Expansion - No	Low	Moderate	No
Advocate	Advocate	Agency Expansion – Yes State Expansion - No	Very Low	Low	No
Statesman	Altruist	Agency Expansion – No; State Expansion - Yes	High	High	No

4.3. Process Overview and Scheduling

There are four processes that occur for turtles (the mobile agents representing the bureaucrats) in the model: the agents look for resources, they move to the resources, they consume the resources, and if they do not find enough resources for their needs, they die. When death occurs, the agent is removed from further iterations of the simulation. The patches, the stationary locations that hold the resources needed by the mobile agents, hold varying amounts of resources that are randomly distributed and diffused around the simulation. The turtles can move one space and the patches resources recharge to their initial state during each iteration (or tick) of the simulation.

4.4. Design Concepts

The basic attributes of the agents consist of the three elements of vision, resource needs, and willingness to take resources from another agent (See Table 1). Vision is the relative distance within the landscape that an agent can see resources. This attribute represents the sweep of the perspective the agent types have regarding their environment as well as adding a temporal aspect to the agents' heuristics. An agent with greater vision can see across a larger scope of the landscape to identify resource pools, but since an agent can only move one unit (patch) per time increment, it allows the agent with greater vision to have a longer-term view. This agent attribute allows the model to simulate the take-the-best approach by limiting the number of choices an agent can see. Altruists who seek only to increase total State spending, presumably for the betterment of all agencies, are thus imbued with the highest vision valued at six; a long-term perspective. This means Altruists can see as far as six patches in all directions on the landscape from their current location to identify resources and therefore utilize a more complex decision-making process. Advocates and low Aggrandizers have the lowest vision due to their immediate need to acquire resources for their own agency and thus can see only one patch, or increment, from their current location that equates with them using the take-the-best heuristic. The concepts of objectives and prediction are not explicitly considered because organizational survival is presumed a priori to be the objective of the bureaucratic agents.

Sensing: Agent vision enables the movement of the agents on the landscape. At the beginning of each simulation run, agents are randomly located on patches, or grids, of space on the landscape. Agents navigate the landscape by turning on their initial patch, identifying the closest pool of resources based on the extent of their vision and moving toward that pool of resources. Agents with greater vision can then identify resource pools further away from their current location. This gives these agents a larger view of the resource pools available as opposed to their less "visionary" counterparts. This vision constraint provides a proxy for the heuristic the agent uses to implement its budgetary strategy. Lower vision equates with the "take the best" heuristic in the battle for scarce resources. If an agent 'sees' distant resources but is unable to get to them before exhausting its on-hand metabolic resources, it dies and is removed from the simulation.

Resource need refers to the amount of resources desired and varies between agent types on a graduated scale from high to low (See Table 1). The resource need of the agent is sustained by "harvesting" resources necessary to maintain the desired expenditure level of its agency. Thus, agent types with high resource needs must acquire equally high levels of budgetary resources. For example, an Altruist has a high level of desire for resources to ensure that all agencies have their needs met while the Advocate's resource needs are lower due to this agent's narrower interest in its

own agency's budget increases. Resource needs in this case is a proxy for the simple desire of whether to have a lower or higher budget need relative to the budgetary process.

Interaction: The willingness of an agent type to take resources from another is represented by the agent attribute of either avoiding a resource containing patch on the landscape where another agent is already harvesting resources or competing with them on the same patch. According to Downs (1967), the agent type of Climbers, low and high Aggrandizers in this case, are more willing to risk agitating others to gain the resources they need to accomplish their goals than are the other agent types. The agent attributes are then reinforced such that these two Aggrandizing types will clash with other agent subtypes and compete for resources on a patch, causing the Abiders, Advocates and Altruists to move to a new patch without an agent on it. Abiders and Altruists will also avoid patches that are already populated with low Aggrandizers or high Aggrandizers. If a low Aggrandizer and a high Aggrandizer both find themselves in the same resource space, they will consume resources at equal speed until the resources are exhausted.

Stochasticity: The environment or landscape designed for this simulation has the following characteristics. The allocation of resources through the organization (the environment for the simulation) is randomly situated on the landscape at each iteration (time step) of the simulation. This provides adequate variation in the relative success of the agents in capturing resources to determine a stable range of agent behaviour even when the budgetary environment is altered.

The next environmental variable is the 'total resource allocation replenishment' for the organization. The simulation control allows for a reduction in the number of resources that are replenished within the next fiscal cycle which, in this model, simulates an overall decrease in the funding available for all organizations. Finally, the number of 'ticks' or cycles each represent one year. The 'ticks' within the simulation are limited to thirty, simulating an abstract bureaucratic career life. The logic diagram for the simulation is presented in appendix (1).

4.5. Initialization

When the model is initialized, the mobile agents are randomly distributed around the landscape as are the levels of resources contained on each of the patches or grid squares that the mobile agents occupy. The available, budgetary resources are constrained, and these decreased resources become more concentrated in certain areas leaving other areas on the landscape bare. If an agent spends too much time in a resource barren area, the individual agent of that type (dies) is removed from the simulation, thus reducing the number of agents of that type in the simulation. Agents are thus either relatively successful or unsuccessful at gathering resources adequate to sustain their metabolic needs.

Since individual agents that cannot harvest resources adequate to maintain their resource needs are eliminated from that iteration of the simulation, each following simulation run then uses the remaining sum of the number of each agent type. Since the simulation has a stochastic element in the initial positioning of the agents as well as the distribution of resources, we ran the simulation 1,000 times from start to finish, ensuring we do not allow outlier events to skew the resulting averages. We then take the average of each agent type of the 1,000 simulation runs to accumulate a final average of the agent types that survive. Since agents leave, but do not join during a simulation run, the total number of each agent type is either retained or decreases during those

runs. In short, the agent type capturing the resources to stay in the simulation has the best fitness strategy.

Input data: the environment is assumed to be constant (resource constrained) throughout the simulated timeframe, so the model has no input data other than the initial parameters and attributes for resource provision.

4.6. Sub-models

The vision sub-model defines how the agents decide to move. The agents can look horizontally and vertically up to vision patches but cannot look diagonally at all. The agents choose their direction of travel based upon the grids containing the most assets within their allotted vision range. The movement sub-model then has the agents move one grid and harvest the resources contained on that grid. If the agents do not receive enough resources on that grid to satisfy their resource need, they die. Two of the agent subtypes will move away from another agent if both land on the same grid, without taking resources from it.

4.7. Simulation Results

The results of the simulation run shown in Table 2. After 1,000 model runs there are definitive changes in the proportion of four of the five bureaucratic types. Table 2 shows that the combined sum of low and high-Aggrandizers / Climbers decreased from an initial state of 61.8 percent of the total population to 45 percent. Aggrandizers were thus reduced from a majority position on the landscape to that of a distinct plurality of types. Low-Aggrandizers seeking overall budget increases were reduced by more than 50 percent and high-Aggrandizers, seeking overall budget increases of more than 10 percent were reduced by 14 percent.

On the other hand, Abiders reveal only a very slight increase in relative numbers under the simulated conditions. The heuristics of the Abider appear to retain a stable proportion of Abider agent types over the 1000 runs.

Table 2. Simulation Results

	Aggrandizer low	Aggrandizer high	Abiders	Advocates	Altruists
Initial Count as Percent of Total (converted from Bowling et al. 1964 data)	20.6%	41.2%	19.6%	12.4%	6.2%
Average as percent of total after 1000 model runs	10.06%*	35.14%*	20.83%*	32.02%*	1.95%
Confidence Interval @ 0.95	9.96% to 10.15%	35.01% to 35.26%	20.72% to 20.92%	31.91% to 32.13%	1.90% to 1.99%
Change in Proportion of Agent Type from Initial Count	51.15%	-14.71%	6.26%	158.25%	-68.54%

* $p < .05$

The simulation results show a 19.6 percent increase in Advocates increasing this type from an initial state of 12.4 percent to finally comprising 32 percent of the total population of bureaucratic types. The Advocates' heuristics of "take the best," minimize the need for resources, and do not fight with other agents over resources resulted in a 158 percent increase in this type.

We calculated confidence intervals using the distribution of the means for each run around the total mean for each type. The simulation results had the Advocates make not only significant, but also consistent gains relative to the other types. In Table 2, the confidence interval for the Advocates demonstrated that through the 1,000 simulation runs, the gains relative to the other subtypes varied in a very narrow range ($\pm 0.2\%$) over the runs.

The Altruists were the opposite. Their small initial numbers frequently led to the elimination of the subtype as well as a great deal of volatility in their outcomes. The one consistent result was an overall decrease in the relative numbers of Altruists. The relative number of Altruists never increased throughout the multiple simulation runs. The heuristics of the Altruists' revealed a very limited ability to capture resources.

The agent heuristic that had the greatest moderating effect on resource need was the take-the-best attribute. The relative rate of success at gathering resources, and therefore surviving, was directly proportional to the strength of the take-the-best approach of an agent. The more an agent used the take-the-best approach in a resource poor environment, the more successful the agent was in acquiring resources. The Advocates showed the greatest increase in their proportions and maximized their use of the take-the-best approach while the Altruists decreased markedly with their use of the take-the-best attribute minimized.

The simple attribute to minimize resource needs provided the most influence in determining agent type success in a resource poor environment, which was an expected outcome. The surprising result was the effect the take-the-best heuristic had on agent subtype success. Having the ability to engage in more strategic resource acquisition approaches turned out to be a detriment rather than a benefit in a resource poor environment. Regardless of the agent's resource need setting (evidenced by multiple simulation runs with alternate settings) because while this simple attribute was one of the secondary influences on success, it was a necessary influence in recreating the BCW results.

Table 3. Sensitivity Test

	Initial Model	Vision Plus (+.5)	Vision Minus (-.5)	Metabolism Plus (+.5)	Metabolism Minus (-.5)
Average as percent of total after 1000 model runs					
Aggrandizer low	10.06%	10.11%	13.20%	16.19%	21.21%
Aggrandizer high	35.14%	35.11%	35.72%	21.48%	34.02%
Abiders	20.83%	20.79%	23.42%	13.43%	17.85%
Advocates	32.02%	32.02%	25.11%	29.21%	24.02%
Altruists	1.95%	1.96%	2.55%	19.69%	2.89%
Confidence Interval @ 0.95					
Aggrandizer low	9.96 to 10.15	10.01 to 10.20	13.10 to 13.28	16.06 to 16.32	21.13 to 21.29
Aggrandizer high	35.01 to 35.26	34.98 to 35.24	35.61 to 35.82	21.33 to 21.62	33.92 to 34.12
Abiders	20.72 to 20.92	20.68 to 20.89	23.33 to 23.49	13.31 to 13.54	17.76 to 17.92
Advocates	31.91 to 32.13	31.90 to 32.14	25.01 to 25.20	29.07 to 29.34	23.96 to 24.08
Altruists	1.90 to 1.99	1.91 to 1.99	2.51 to 2.59	19.59 to 19.77	2.84 to 2.93
Change in Proportion of Agent Type from Initial Count					
Aggrandizer low	51.15%	-50.91%	-35.94%	-21.39%	2.98%
Aggrandizer high	-14.71%	-14.77%	-13.30%	-47.87%	-17.42%
Abiders	6.26%	6.09%	19.47%	-31.47%	-8.95%
Advocates	158.25%	158.26%	102.53%	135.55%	93.75%

To test the robustness of the results, we run multiple sensitivity tests by varying vision and metabolism in the simulations. Particularly, we increase and decrease these attributes by .5 to examine the differences it creates. See Table 3. As we increase vision by .5, we find that results remain largely unchanged compared to our initial model. Decreasing vision by .5 creates some noticeable differences by slightly increasing the percentage of aggrandizer and abiders and decreasing the percentage of advocates. Overall, these results remain robust and similar to the initial model.

On the other hand, we find that the metabolism assumption has a larger impact on the results. After reducing metabolism, we find that the percentage of aggrandizers increases from 10% to 21% at the expense of abiders and advocates. While this model differs from the initial model, the other factors remain robust and stable. However, we find that increasing metabolism by .5 dramatically increases the percentage of altruists from 2% to 20% at the expense of aggrandizer high and abiders. Additionally, we find the percentage of aggrandizers increases from 10% to 16%.

Overall, we find that increasing metabolism by .5 leads to differing results, while the other models remain fairly stable and robust.

Table 4. Sensitivity Test

	Model 1 % Aggrandizer low	Model 2 % Aggrandizer High	Model 3 % Abiders	Model 4 % Advocates	Model 5 % Altruists
Vision Minus (-.5)	0.031** (43.65)	0.006** (6.76)	0.026** (36.60)	-0.069** (90.89)	0.006** (15.08)
Vision Plus (+.5)	0.001 (0.71)	-0.000 (0.27)	-0.000 (0.48)	0.000 (0.02)	0.000 (0.12)
Metabolism Minus (-.5)	0.112** (155.30)	-0.011** (12.95)	-0.030** (42.14)	-0.080** (105.22)	0.009** (23.55)
Metabolism Plus (+.5)	0.061** (85.39)	-0.137** (158.71)	-0.074** (104.53)	-0.028** (37.03)	0.177** (443.35)
Constant	0.101** (198.16)	0.351** (577.41)	0.208** (416.29)	0.320** (595.79)	0.020** (68.96)
R^2	0.87	0.89	0.82	0.80	0.98
N	5,000	5,000	5,000	5,000	5,000

* $p < 0.05$; ** $p < 0.01$ Omitted Group for Comparison is the Initial Model

To further test the sensitivity of our results, we run an OLS regression model to compare the different specifications. In the model, we include results from our five simulations: (1) initial model, (2) vision reduced by .5, (3) vision increased by .5, (4) metabolism reduced by .5, and (5) metabolism increased by .5. For each specification, we generate 1,000 simulation runs, so our OLS model includes 5,000 observations. See Table 4. In the OLS model, we exclude the initial model to serve as our omitted group for comparison. Based on our regression results, we find that increasing vision by .5 does not statistically affect the results compared to the initial model. While as we reduce vision by .5, we find all coefficients are statistically significant; however, all the coefficients are small which indicates the differences are relatively minimal compared to the initial model. While as noted in our descriptive statistics, we find that increase metabolism creates differences that are more noticeable. Particularly, increasing metabolism by .5 has a statistically significant impact on the percent of altruists ($\beta = .177$) and on percent of aggrandizer high ($\beta = -.137$). Additionally, decreasing metabolism by .5 has a statistically significant impact on the percent of aggrandizer low ($\beta = .112$) and on the percent of advocates ($\beta = -.080$). Overall, from this sensitivity test, we find robust and stable results as we increase and decrease vision; however, we find some noticeable differences as we modify metabolism.

5. DISCUSSION

This experiment sought to answer the question, “Which bureaucratic strategies or heuristics for capturing resources are most successful under conditions of resource constraints?” The results of the simulation showed that the relative mix of bureaucratic types and thus their associated heuristics were altered in a resource constrained environment. There were definitive decreases in the proportion of Aggrandizing types (Climbers) in our resource constrained landscape. Abiders remained as a relatively consistent proportion of bureaucratic types while Advocates who seek only minimal increases in their own agency’s budget increased at a rate of 167 percent.

While Downs’ (1967) and other public choice theorists (Niskanen, 1971) views of public bureaucracy peopled by predominantly self-interested agents holds true to some extent under conditions of resource constraints, it does not tell the entire story. Altruists did not show a significant change in proportion. Altruists did show great variation in proportion during the simulation runs and, at times, were almost eliminated from the landscape. The combination of high resource needs and more complex strategic resource acquisition approaches did not succeed in engendering more agents to take on these heuristics. Demanding more and engaging in strategic manoeuvring is not a bureaucratic type “growth strategy” in this simulated environment.

The more than doubling of the number of Advocates is the most salient finding from the simulation. Advocates’ heuristics maintained a take-the-best approach when seeking out resources across the organizational landscape. Advocates also have a low need for resources. And, Advocates avoid conflict in the sense that they do not engage in taking resources from other agents. Advocates increased their proportion to an extent that they constitute almost one-third of the bureaucratic types under conditions of resource constraints.

Advocates, from Downs’s initial incarnation, do want to influence public policies but lack the level of self-aggrandizement typical of Aggrandizers. In our simulation, Advocates seem to succeed and increase in numbers by reducing the extent of their search for resource acquisition to the immediate environment. This apparently sub-optimal behaviour appears to increase under conditions of resource constraints. This understanding raises further questions concerning whether the conditions of resource constraints actually enhance the behaviours we would hope for in bureaucrats. It may be that resource constraints serve to engender a level of passivity evidenced by a reduction in aggrandizement and an increase in Advocates with a take-the-best approach. Resource constraints may thus undermine the managerial energy and enthusiasm necessary to achieve the high-performance organizations so often touted by practitioners. In a broader sense, these results diminish Deming’s (1994) call for all organizational actors to be concerned with the system and larger organizational values because conditions of resource constraints appear to produce a greater focus on agency or unit level concerns.

Economists have attempted to examine how individuals behave under conditions of resource scarcity. Some studies suggest that resource scarcity increases competition (Grossman and Mendoza, 2008) implying that in our simulation Aggrandizers should increase in numbers. In short, in the case of Aggrandizers their willingness to take resources from others should be an effective strategy. Our results showed that such strategies did not result in increasing numbers of this competitive type.

Another body of literature examining behaviour under conditions of resource scarcity suggests that people will attenuate their expectations in concert with the perceived level of resources in the environment (Ostrom, 1999). Osés-Eraso and Viladriçj-Grau (2007) found that under the expectation of resource scarcity actors will restrain their desired appropriations from the resource pool. This accommodation strategy, in which actors appear to adjust their desires for resources based on their expectations of resource scarcity, may be a key to understanding the findings from our simulation.

The behavioural economics literature exploring how individuals respond to resource scarcity may also offer insight into our findings. Shah, Mullainathan and Shafir (2012) show that conditions of resource scarcity tend to increase an individual's focus on salient and immediate challenges. Shah, Mullainathan and Shafir (2012, p. 683) also discovered that as increased focus occurs under conditions of scarcity an opposing "attentional neglect" results as other matters of import receive less attention. This insight adds credibility to our finding that Advocates may increase in numbers, under resource constraints, in part, because of their low tendency toward strategic manoeuvring. Strategic manoeuvring may simply be less likely when resources are constrained as decision-makers focus on their own unit's resources to the neglect of other, perhaps, more important strategic concerns. For Advocates, simple attributes involving a very low sense of strategic manoeuvring (exemplified by the take-the-best approach), a low need for resources and the avoidance of conflict appear as a growth strategy for that bureaucratic type under conditions of scarce resources.

The mix of agents in our simulation, using relatively simple attributes, changed in a manner typical of what we view as an "accommodationist" strategy. The reduction of the number of self-serving Aggrandizers suggests a reduction in the efficacy of strictly self-aggrandizing budgetary strategies under conditions of resource constraints. Even the most "climbing" Aggrandizers seem to accommodate to an environment of resource constraints. Strategic and high resource need Altruists have a highly variable, "bumpy ride" over time and continue as a small proportion of the total agent population.

The decrease in the proportion of Aggrandizers also suggests that the level of conflict may be reduced under resource constraints as fewer agents engage in "taking" resources from others. This understanding further suggests that rather than the self-seeking, utility maximizing bureaucracy described by public choice theorists, that under conditions of resource constraints accommodationist dynamics dominate. Aggrandizers remain the largest proportion of actors, but conflict is reduced via less "taking" behaviour. In the accommodationist agency, a moderate to low need for resources and engagement attributes emphasizing very low to moderate strategic manoeuvring results in significant proportions of Aggrandizers, Abiders and Advocates. The combined proportion of Abiders and Advocates is now larger than that of the Aggrandizers. Since neither Abiders nor Advocates are "takers" such potential conflict is reduced throughout the bureau. Under conditions of resource scarcity taking from others loses its dominance.

We do not envision the decline in Aggrandizing behaviour as signalling a stagnant or declining bureaucracy as suggested by Downs (1967, p. 13). Accommodationist strategies appear to expand under resource constraints as bureaucrats adapt to their financial environs. We may be living in an historical era in which boundedly rational actors have accommodated themselves to a resource

constrained environment in which relatively narrow boundaries of concern dominate bureaucratic strategies.

In his classic study of the evolution of cooperation Axelrod (1997, p. 6) noted that “models that aim to explore fundamental processes should be judged by their fruitfulness, not by their accuracy.” The simulation presented here cannot present a complete picture of the dynamics of budgetary acquisition, but it does provide a readily accessible and, we think fruitful, window into the dynamics of the individual-environment interaction and the simple attributes that may be employed. It is not a novel insight to suggest that humans attempt to adapt, or to accommodate, to their environments. Our results more than validate this point. Yet, if we are to fully grasp bureaucratic behaviour we must understand that the individual-interaction is an essential piece of that puzzle. Whether we view bureaucratic behaviour from the lens of the public choice approach or that of public service motivation the behaviour of bureaucratic actors must be seen with regard to how the motivational sets of individuals interact with environmental circumstances to drive organizational dynamics.

From the practitioners’ perspective, such simulation methods may serve as means to anticipate the dynamics of organizational initiatives based on assumptions of bureaucratic types and the heuristics managers apply to navigate their environs. Such agent-based models may also begin to fulfil Holland’s (1995) recommendation for organizational flight simulators by providing a means to examine the parameters of expected organizational behaviours (Lewin, Parker & Regine, 1998). Thus, agent-based modelling would in Downs’ words (1967, p. 4) “...enable us to make forecasts about the behaviour of officials and bureaus that will hopefully prove more accurate than forecasts made with alternative forms.”

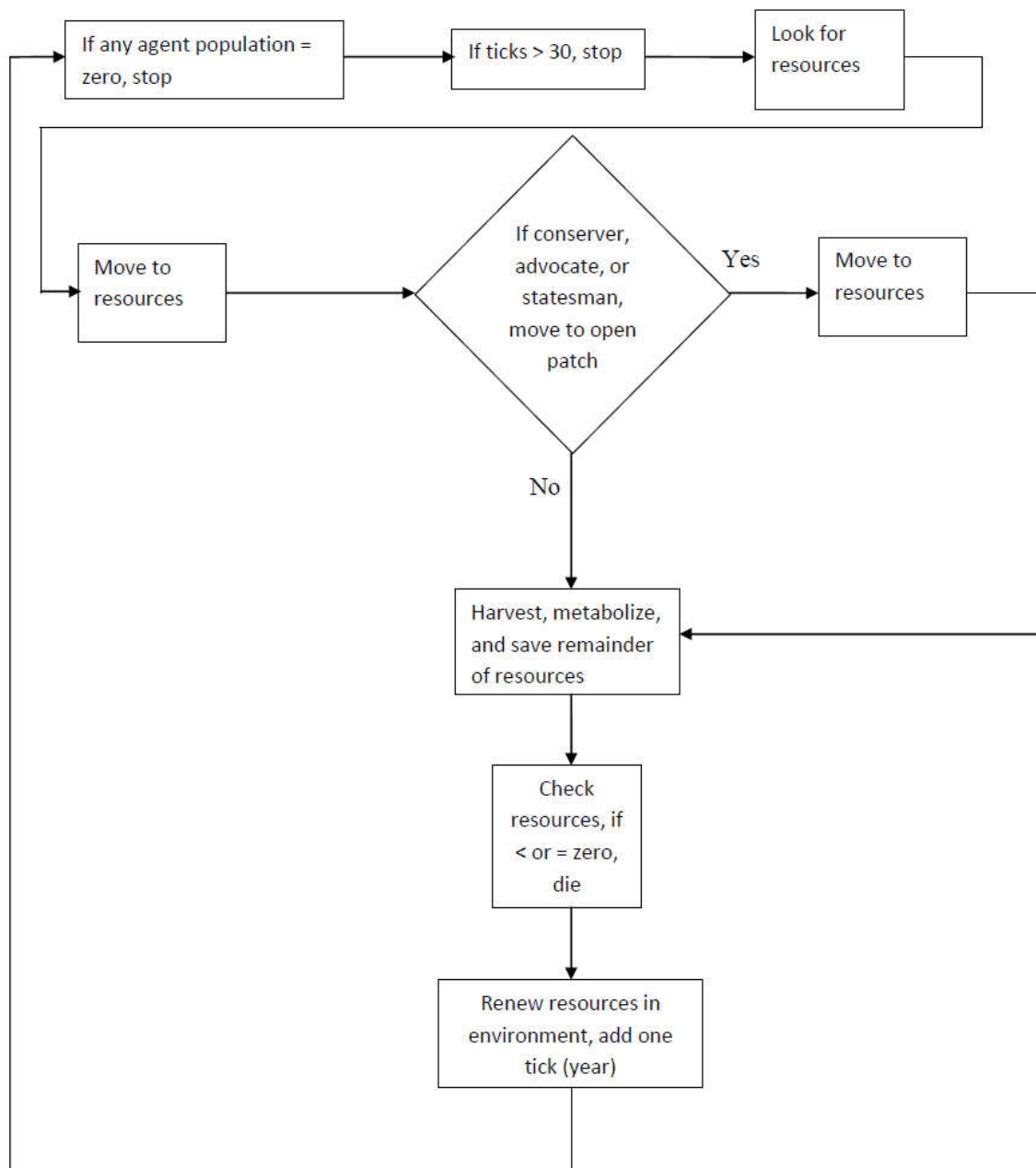
6. CONCLUSIONS

Public administration and public choice theorists have sought for decades to understand the motivations of bureaucratic agents regarding the acquisition of budgetary resources. Public choice theorists have tended to assume classic microeconomic utility maximization models, as exemplified by Downs (1967) and Niskanen (1971). Bureaucrats, in other words, behaved in a manner consistent with firms in the competitive marketplace. Other scholars, however (Dolan, 2000; Bowling, Cho, and Wright 2004; Moynihan 2013) have found that bureaucratic strategies are more heterogeneous and varied than what one would expect under traditional public choice assumptions. Based upon the work of Bowling, Cho, and Wright, we have created an agent-based model that tests the efficacy of different budgetary strategies in resource constrained environments. We choose this particular context given the fact that budgetary constraints have tended to be the dominant fact of life for public managers for the last several decades.

Our model assumes that boundedly rational bureaucratic agents possess heterogeneous strategies that rely upon simple heuristic “cognitive maps.” These heuristics tend to be relatively stable; moreover, their actions are governed by simple attribute sets consisting of the three elements (a) “taking the best” versus strategic manoeuvring, (b) agents’ relative resource needs and (c) the willingness to take resources from other agents. These results suggest strategies focused on a preference for short-term goals, a low need for resources and a lack of willingness to expropriate resources from other agents dominate other strategies. These heuristics for acquiring resources lead to what we label accommodationist strategies. To be sure, our model may not apply in other

circumstances, and indeed, an important element of future research is to examine the efficacy of our model in other resource contexts. Moreover, future research should allow for learning to take place so that individual agents can adapt their behaviour. While we believe a good case can be made in this first effort to explore the dynamics of resource constrained agents, it is also clear that incorporating learning will provide additional insights. In fact, it would be useful to explore models in which heterogeneous agents learn and adapt at different rates. Nonetheless, we believe this study has demonstrated the useful and important role of agent-based modelling in providing new insights into bureaucratic behaviour

APPENDIX (1)



REFERENCES

1. Axelrod, Robert. (1997). *The complexity of cooperation: Agent-based models of competition and collaboration*. Princeton, NJ: Princeton University Press.
2. Bingham, C. & Eisenhardt, K. (2011). Rational heuristics: the ‘simple rules’ that strategists learn from process experience. *Strategic Management Journal*, 32, 1437-1464.
3. Blom-Hansen, J., Morton, R. & Serritzlew, S. (2015). Experiments in Public Management Research. *International Public Management Journal*, 18, 151-170.
4. Bowling, C., Cho, C. and Wright, D. (2004). Establishing a Continuum from Minimizing to Maximizing Bureaucrats: State Agency Head Preferences for Government Expansion - A Typology of Administrator Growth Postures, 1964-1998. *Public Administration Review*, 64, 489-499.
5. Bryson, J. (2004). *Strategic Planning for Public and Nonprofit Organizations: a guide to strengthening and sustain organizational achievement*, 3rd ed. San Francisco: Jossey-Bass.
6. Conybeare, J. (1984). Bureaucracy, Monopoly and Competition: A Critical Analysis of the Budget-Maximizing Model of Bureaucracy. *American Journal of Political Science*, 28, 479-502.
7. Davis, J., Eisenhardt, K., & Bingham, C. (2009). Optimal Structure, Market Dynamics, and the Strategy of Simple Rules. *Administrative Science Quarterly*, 54, 413-452.
8. Deming, W.E. (1994). *The New Economics: For industry, government, education*, 2nd ed. Cambridge, MA: MIT Press.
9. Dolan, J. (2000). The Budget-Minimizing Bureaucrat? Empirical Evidence from the Senior Executive Service. *Public Administration Review*, 61, 42-50.
10. Downs, A. (1967). *Inside Bureaucracy*. Boston: Little, Brown and Company.
11. Fiske, S. & Taylor, S. (1984). *Social Cognition*. New York: Random House.
12. Gigerenzer, G. (2000). *Adaptive Thinking: Rationality in the New World*. New York: Oxford University Press.
13. Gigerenzer, G. (2008). *Rationality for Mortals*. New York: Oxford University Press.
14. Gigerenzer, G. (2014). *Risk Savvy: How to Make Good Decisions*. New York: Viking Penguin.
15. Gigerenzer, G. & Brighton, H. (2009). Homo Heuristicus: Why Biased Minds Make Better Inferences. *Topics in Cognitive Science*, 107-143.
16. Grossman, H. & Mendoza, J. (2003). Scarcity and Appropriative Competition. *European Journal of Political Economy*, 19, 747-758.
17. Holland, J. (1995). *Hidden order: How adaptation builds complexity*. Reading, MA: Helix Books.

18. Kahneman, D. & Tversky, A. (1979). Prospect Theory: An Analysis of Decisions Under Risk. *Econometrics*, 47, 263-291.
19. Kahneman, D. & Tversky, A. (1996). On the Reality of Cognitive Illusions. *Psychological Review*, 103, 582-591.
20. Kiel, L. D. (2005). A primer for agent-based modeling in public administration: Exploring complexity in “would-be” administrative worlds. *Public Administration Quarterly*, 29, 268-296.
21. Langton, C. (1989). Artificial life. In *Artificial life, the proceedings of an interdisciplinary workshop on the synthesis and simulation of living systems*, held September, 1987 in Los Alamos, ed. C.G. Langton, 1-47. Redwood City, CA: Addison Wesley.
22. Lewin, R., Parker, T. & Regine, B. (1998). Complexity Theory and the Organization: Beyond the Metaphor. *Complexity*, 3, 36-40.
23. Moynihan, D. (2013). Does Public Service Motivation Lead to Budget Maximization? Evidence from an Experiment. *International Public Management Journal*, 16, 179-196.
24. Niskanen, W. (1971). *Bureaucracy and Representative Government*. Chicago: Aldine.
25. North, M. & Macal, C. (2007). *Managing Business Complexity: Discovering Strategic Solutions with Agent-Based Modeling*. New York: Oxford University Press.
26. Oses-Eraso, N. & Vildrich-Grau, M. (2006). Appropriation and concern for resource scarcity in the commons: An experimental study. *Ecological Economics*, 63, 435-445.
27. Ostrom, E. (1999). Self-governance and forest resources. Occasional Paper, vol. 20. Center for
28. International Forestry Research, CIFOR.
29. Railsback, S. & Grimm, V. (2012). Agent-based and individual-based modeling: A practical introduction. Princeton University Press. New Jersey.
30. Shah, A., Mullainathan, S., & Shafir, E. (2012). Some Consequences of Having Too Little. *Science*, 338, 682-685.
31. Sull, D. & Eisenhardt, K. (2015). *Simple Rules: How to Thrive in a Complex World*. Boston: Houghton Mifflin Harcourt.
32. Wildavsky, A. (1964). *The Politics of the Budgetary Process*. Boston: Little, Brown.
33. Wilensky, U. (1998). NetLogo Wealth Distribution model. <http://ccl.northwestern.edu/netlogo/models/WealthDistribution>. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.
34. Wilensky, U. (1999). NetLogo. <http://ccl.northwestern.edu/netlogo/>. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.



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