

**THE COMPLEX PROBLEM OF FOOD SAFETY
APPLYING AGENT-BASED MODELING TO THE POLICY PROCESS**

**A Thesis Submitted to the
College of Graduate Studies and Research
In Partial Fulfillment of the Requirement
For the Degree of Doctor of Philosophy
In the Johnson-Shoyama Graduate School of Public Policy
University of Saskatchewan**

By

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ABSTRACT

Many problems facing policymakers are complex and cannot be understood by reducing them to their component parts. However, many of the policy responses to complex problems continue to be based on simple, reductionist methods. Agent-based modeling (ABM) is one alternative method for informing policy that is well-suited to analyzing complex problems.

ABM has practical implications for different stages of the policy process, such as testing alternatives, assisting with evaluation by setting up a counterfactual, and agenda setting. The objective of the research presented in this dissertation is to explore the opportunity for using ABM to examine complex problems of relevance for policy. To do so, three separate models were developed to investigate different aspects of food safety inspection systems. Complex problems involve interrelated feedback loops, many actors, exponential growth, asymmetric information, and uncertainty in outcomes and data, and food safety exhibits these traits, providing an interesting case study for the use of ABM.

The first model explores three inspection scenarios incorporating access to information. The main finding was that the number of sick consumers is greatly reduced by giving consumers and inspectors more information about whether a retail outlet is contaminated, even if that information may be uncertain. The second model incorporated theories on risk and the role of transparency in encouraging consumer trust by giving consumers access to inspection scores. Overall, the findings were more nuanced: having access to restaurant inspection scores results in a slightly higher mean number of sick consumers, but less variation overall in the number of sick consumers. As well, a greater number of compliant restaurants results in fewer sick consumers. Rather than investigating the structure of the inspection system, the third model examines the potential for mobile technology to crowdsource information about suspected foodborne illness. This model illustrates the potential for health-oriented mobile technologies to improve the surveillance system for foodborne illness.

Overall, the findings from the three models support using stylized ABMs to study various aspects of food safety inspection systems, and show that these models can be used to generate insight for policy choices and evidence-based decision making in this area.

ACKNOWLEDGEMENTS

I would first like to acknowledge the generous financial support I received over the course of my studies from the Social Sciences and Humanities Research Council, the Government of Saskatchewan, the VALGEN and ITraP projects, and the University of Saskatchewan.

I want to express my sincerest gratitude to my supervisor, Peter W.B. Phillips, for his kind mentorship and support since my days as an undergraduate student. Peter, I have learned so much from watching you work, and I really appreciate that you have always encouraged me to take my ideas and run with them. I would also like to thank Nathaniel Osgood for his generous help and for his infectious enthusiasm for complexity science and modeling, his M.Sc student, Wenyi An, for all of her assistance with AnyLogic, and James Nolan, for his words of advice and for teaching me so much about the ins and outs of academia. I further thank my committee members, Jeremy Rayner, Kathy McNutt, David Castle, Keith Walker, and the external examiner, Anil Hira, for their time. Many thanks go to Jason Zorbas for always making time to chat and offer friendly advice when I stopped by to drop off a stack of marking.

Finally, and most especially, I am grateful for my friends and family for offering their support, kind words over beers, and their willingness to listen. I want to thank my mom, for her always spot-on advice and willingness to proofread on short notice, and my dad, for teaching me to never turn down opportunities. Last but not least, I thank my dear husband, Lucas, for his patience, understanding, and excellent sense of humour. Thank you for always being there and encouraging me when I thought it would be easier to quit. Thank you for everything.

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CHAPTER 1

AGENT-BASED MODELING AND THE POLICY CYCLE

1.1 Introduction

Many problems facing policymakers are complex: they cannot be understood by reducing them to their component parts. However, many of the policy responses to complex problems continue to be based on simple, reductionist methods. Agent-based modeling (ABM), a type of computational simulation modeling that focuses on the system-wide effects caused by autonomous agent interaction, is one alternative method for informing policy that is well-suited to managing complex problems.

ABM has practical implications for different stages of the policy process – testing alternatives, assisting with evaluation by setting up a counterfactual and even agenda setting. While these aspects have not been fully explored, the method has been touted as having great potential for policy (Moss, 2008). This dissertation applies ABM to the policy area of food safety, which exhibits many aspects of complex problems, including interrelated feedback loops, many informally and formally organized actors, exponential increases in trade, asymmetric information, and uncertainty in outcomes and data. Chapters two, three and four examine some of these aspects in more detail by applying stylized ABMs to various aspects of food safety inspection systems, with the intent of generating insight for policy choices and evidence-based decision making in this area.

This introductory chapter discusses complex problems, the relevance of ABM to policy problems, some of the advantages or disadvantages of the method, as well as ways ABMs can better be applied to policy and made relevant to policymakers. Finally, some of the aspects of food safety that make it a complex problem will be further explored, and the overall structure of the remainder of the dissertation will be outlined.

1.2 Complex Problems in Public Policy

Many of today's persistent policy issues, such as nuclear power, infrastructure planning, poverty, and food safety, seem to end up back on the agenda fairly frequently – they are settled, but never solved. These problems share the common characteristics of complex or 'wicked' problems.

Wicked problems have a number of important traits; for instance, the information required “to *understand* the problem depends upon one’s idea for *solving* it” (Rittel & Webber, 1973, p. 161). Generally, while trying to define a complex problem, solutions work their way into the problem definition. As such, complex problems are subject to competing problem frames and ‘causal stories’ (Stone, 1989). Additionally, wicked problems are never truly solved; any stopping rule is external to the problem itself (such as a lack of time or money, or changes in risk perception or values). Learning how to solve a wicked problem through trial and error is not feasible since trials cannot be reversed; every decision leaves its mark on the problem (Rittel & Webber, 1973). This also means that the solutions applied to wicked problems often result in unintended consequences.

Wicked problems¹ are interconnected problems: “Problems can be described as discrepancies between the state of affairs as it is and the state as it ought to be. The process of resolving the problem starts with the search for causal explanation of the discrepancy. Removal of that cause poses another problem of which the original problem is a ‘symptom’” (Rittel & Webber, 1973, p. 165). King (1993) clarifies Rittel and Webber’s work through a discussion of a range of problem types, ranging from tame, to ‘messes’ to wicked problems. Tame problems are those that can be solved in “relative isolation from other problems” whereas messes cannot be solved in isolation (King, 1993, p. 106). The need to adopt a broad, cross-cutting view of problems also conflicts with the typical organization of governments into specific departments, and is particularly problematic in federal systems where jurisdiction constrains the actions of different levels of government into specific areas of responsibility.

Policy systems are set up to address well-structured problems and are assumed to deliver clear, well-defined options derived from the application of consistent rules (H. A. Simon, 1997); however, if the pressing policy issues facing decision-makers are wicked problems, these

¹ In another typology of problems, Hoppe (2011, p. 16) defines problems as “a deviation between an existing state (‘is’) and a desirable one (‘ought’),” which is a fundamentally normative viewpoint. He has developed a typology of problem structures that incorporates fully structured problems, where both the knowledge required to understand the problem and the values and norms that define the problem are agreed upon by stakeholders; unstructured problems, where there is little agreement on norms and values or on available knowledge; and moderately structured problems, where there is either agreement on norms and goals defining a desired outcome but knowledge is uncertain (ends), or where knowledge is certain but there is wide divergence on norms and values (means) (Hoppe, 2011, pp. 16, 73–4).

assumptions are inaccurate, and may lead to unintended consequences if pursued to their logical conclusion.

1.3 Tools for Approaching Complex Problems

Many areas that are especially prone to complexity, such as transportation, environmental issues, and health care, fall under the purview of provincial jurisdiction in Canada; these are also areas with some federal involvement, which further contributes to complexity in the division of responsibilities and decision-making. Recent work by Howlett and Newman (2010) indicates that provincial policy analysts expressed a preference for informal analytical techniques over formal ones, a finding that is consistent with previous work which found that simple policy analysis tools were preferred by both the producers and consumers of analytical work (Nilsson et al., 2008 as cited in Howlett & Newman, 2010). In their survey of provincial public servants, Howlett and Newman (2010) found that the most commonly practiced techniques² were brainstorming, consultation exercises and checklists, which are less formal, more subjective methods of analysis. Of the more formal analytical methods, the most commonly used were cost benefit analysis, scenario analysis, risk analysis, cost-effectiveness analysis, and financial impact analysis. The development of sophisticated modeling tools, which would presumably include such methods as regression models, was only used by 11.2% of respondents.

However, as King (1993) notes, issues can arise when decision makers frame messes as tame problems and use tame methods for solving them, because the methods used to cope with tame problems are very different from those required to handle messes. Tame methods are analytical and involve breaking down issues into their component parts and assessing known failure sequences, which is highly effective with simple problems but often ineffective or dangerous when dealing with complex problems. Messes must be sorted out by taking a broader view and focusing on processes and feedback loops. As stated by King, “Messes demand a commitment to understanding how things going on here-and-now interact with other things going on there-and-later” (King, 1993, p. 106). Dealing with messes is challenging, given the limits of human cognition and prediction. As we deal with problems that are increasingly complex, and involve

² Interestingly, many of the methods listed (although some were infrequently used), including brainstorming, scenario analysis, social network analysis, Monte Carlo techniques, decision trees, problem mapping, and robustness or sensitivity analysis, could play a role in participatory model development and the modeling cycle.

the voices and input of numerous stakeholders that are both formally and informally organized, specific methods that are uniquely suited to dealing with these challenging characteristics of complexity should be applied to the policy space. One such method is agent-based modeling (ABM).

1.4 Overview of Agent-based Modeling

A model is “a purposeful representation of some real system” (Starfield et al., 1990, as cited by Railsback & Grimm, 2012, p. 4) that can be manipulated to answer specific questions. In neoclassical economic models, initial equations are generally based on assumptions that rational actors optimize their behaviour, given their current constraints, information, and available options. Because of computational constraints, modellers tend to use averages, rather than a range of representative agents, and other assumptions, such as systems seeking equilibrium, are incorporated. This type of modeling is top down, in that high-level rules are imposed on the system, and then we look for the implications and effects of those rules. In contrast, agent-based models simplify the behaviour of individuals within the system, and allow the agents to interact. This type of modeling is bottom up, because system behaviour is caused by the interactions of individual agents (Miller & Page, 2007, pp. 65–66). As neatly summarized by Miller and Page (2007, p. 66), “Thus, in top down modeling we abstract broadly over the entire behavior of the system, whereas in bottom up modeling we focus our abstractions over the lower-level individual entities that make up the system.”

ABMs are generally computer simulations that include many agents interacting with one another and their environment to reveal emergent properties (G. T. Jones, 2007). Emergence is present when the phenomena can only be described using terms that cannot be appropriately applied to the component parts of the system. Social phenomena, such as the spread of rumours or diseases, often exhibit emergent properties, given the non-linear relationships between actors within the system that affect the actors’ subsequent behaviour. Agents within the model are programmed using collections of rules so that they are able to perceive their environment, react to it, and communicate with other agents (Gilbert, 2004). As well, ABMs must be carefully specified and assumptions must be clearly evaluated in order for the model to adequately represent a social system. As such, models represent a trade-off between flexibility and precision (Miller & Page, 2007, p. 79).

Simon's (1955) seminal work on bounded rationality introduces satisficing as a feasible alternative to rational choice theory's assumptions, which require a significant amount of information and computational capacity. Simon (1955, p. 104) states that "there is a complete lack of evidence that, in actual human choice situations of any complexity, these computations can be, or are in fact, performed." Satisficing involves individuals holding an aspiration level, which defines a satisfactory outcome that can adjust as new information is processed. Rather than requiring an optimal decision, which would require fixed preferences and a complete ordering of possibilities, aspiration levels can go down if the decision-maker has difficulty in finding satisfactory alternatives, or increase if satisfactory options are easy to find. By using straightforward behavioural rules, ABMs can model decision-making in a more realistic manner.

ABMs provide an opportunity to use experimental methods on social phenomena that have very long time horizons or where experimentation would be unethical (Louie & Carley, 2008). These models are well suited for modeling complex systems, where "the behaviour of the system as a whole cannot be determined by partitioning it and understanding the behaviour of each of the parts separately, which is the classic strategy of the reductionist physical sciences" (Gilbert, 2004, p. 3). Although models may be used for predictive purposes, this is not their only function: ABMs may be employed to guide data collection, look for explanations of phenomena within a system, demonstrate trade-offs between alternatives, or generate new questions (Epstein, 2008).

A number of authors have indicated that simulation and ABMs, as a specific type of simulation, represent a "third way" of doing science: Axelrod (2003, p. 5) mentions,

like deduction, it starts with a set of explicit assumptions. But unlike deduction, it does not prove theorems. Instead, a simulation generates data that can be analyzed inductively. Unlike typical induction, however, the simulated data comes from a rigorously specified set of rules rather than direct measurement of the real world. While induction can be used to find patterns in data, and deduction can be used to find consequences of assumptions, simulation modeling can be used as an aid in intuition.

These statements are echoed by Epstein (1999, p. 44), who describes agent-based modeling as a method appropriate for 'generative social science.' Axelrod (2003, p. 5) further argues that most modeling in the social sciences is informed by rational choice theory because it allows for deduction, not because many scholars feel that its assumptions accurately represent human

behaviour. Adaptive behaviour requires simulation if it is to be a viable alternative, because the outcomes of adaptation cannot be deduced – this means that ABM fits in between deduction and induction. ABM offers an opportunity to relax the assumptions of rational choice theory to more realistically model how individuals make decisions.

1.5 Advantages and Disadvantages of ABM

Some of the advantages of ABM follow from its unusual position as a method that straddles induction and deduction. Bankes (2002, p. 7199) mentions that researchers are often enthusiastic about ABMs because they allow for departure from the restrictive assumptions of other modeling techniques, namely linearity, homogeneity, statistical normality, and stationarity. ABM's ability to deal with heterogeneous populations that can be informed by individual data, rather than aggregate data, is a unique feature with strong application to policy issues, since many policies focus on encouraging individuals to change their choices and behaviour.

Agent-based models offer a few distinct advantages. Bonabeau (2002, p. 7280) identifies three benefits of ABMs: firstly, they capture emergence; secondly, they provide a natural, bottom up description of a system; and thirdly, the method is very flexible. However, the author notes that the main benefit of capturing emergent phenomena largely powers the other two. Bankes (2002, p. 7199) also refers to the natural ability of ABMs to represent social systems due to the central place of agents within the system. Much social science is focused at the individual level, reflecting individual preferences, motivations for behaviour, and relationships; as well, policies often rest on individual choices and coordinating behaviours for system-level outcomes (Schneider & Ingram, 1990). Patt and Siebenhuener (2005) point out that the inclusion of social norms is an important factor in human decision-making, and that they are left out of traditional system dynamics models – but can more easily be incorporated in ABM because they can be modeled as a rule that agents follow, although some authors have argued that doing so can be problematic (O'Sullivan & Haklay, 2000). A further advantage of ABM, as argued by Epstein (1999, p. 47), is that modeling provides a “natural methodology” for interdisciplinary research. Although the social sciences are organized into separate academic disciplines, within society, economics, demography, epidemiology, sociology, and policy are all linked. The SugarScape model, which is a very simple model that yields surprisingly complex results, provides an example of an artificial society where everything from economic markets to cultural adaptation

to virus transmission is included (Epstein & Axtell, 1996). Although these elements do not need to be incorporated all at once, “[t]he claim is that the new techniques allow us to transcend certain artificial boundaries that may limit our insight” (Epstein, 1999, p. 47).

Although ABMs have distinct advantages for handling policy problems, they come with a unique set of challenges. Bankes (2002, p. 7199) notes that although ABM shows great promise for providing insights into social problems, uptake has been inhibited by a “lack of clarity about the uses of computational models and the requirements for credible arguments using them.”

Bonabeau (2002, p. 7287) notes a number of possible issues with ABM. In particular, ABMs must be purpose-built; general models are not feasible. Determining the appropriate level of detail to incorporate into a model so that it tells the researcher something useful about the problem but has been simplified enough to be understandable is a difficult skill to master – Bonabeau (2002) notes that this is more of an art than a science. This can make it difficult to evaluate and compare ABMs against one another if they are not properly documented. As well, the specification of models is very technical and can be complicated, and since the currently available software packages require coding skills, the implementation of ABM may be out of reach for some who wish to study a problem well suited to modeling but lack the coding skills to build a model.

Additionally, introducing the ‘potentially irrational’ choice behaviour of humans can be difficult to incorporate into models, since it can be problematic to quantify these aspects of decision-making. There may also be difficulties in accessing appropriate individual-level data³ with which to inform model parameters, particularly as this method has not been widely used in the social sciences. Finally, Bonabeau (2002) introduces a practical issue: computing power. Although huge advances in computation capacity have been made in the decade since his paper was published, this is still a practical concern.⁴

³ Some very interesting research in this area is ongoing at the University of Saskatchewan, where researchers in the Department of Computer Science have developed an Android App called iEpi, purpose-built for accessing individual-level health data to inform ABMs (Mohammad Hashemian et al., 2012).

⁴ Some of the issues related to computing power is for ‘parallel problems’ that can be spread between different computational units, such as separate cores, processors, or machines.

On a deeper level, O’Sullivan and Haklay (2000, p. 1413) critique the tendency of ABMs to lean towards methodological individualism. They note that although this may not be avoidable, it is often an unstated assumption.⁵ They are concerned this leads to a “one way notion of emergence: the social can emerge from the individual but not the other way around” (O’Sullivan & Haklay, 2000, p. 1414). The failure of some ABMs to allow for the pre-existence of culture and social norms, which shape our actions, choices, and development as individuals is considered by the authors to be an “impoverished” view of society (O’Sullivan & Haklay, 2000). Lastly, a criticism of applying ABM within the policy space is that the bottom up nature of ABM may make it difficult to apply some top down structures, such as the economic, social and political aspects of public policies, in simulations, without embedding them into the individual agents. Modellers may cope with this by incorporating these structures within agents, which hides the influence of the overall system on the individual agents and limits the modeller’s ability to look at whether the agents influence these global structures over time (Ghorbani, Dechesne, Dignum, & Jonker, 2014, p. 70); another alternative is that these structures could be incorporated into the agent environment and could include environmental dynamics. These concerns are valid and should be investigated further in order to build models that adequately reflect the constraints and opportunities for human interaction and choice within social structures.

1.6 ABM in Practice

Given the preceding background on ABM as a methodology and the advantages and disadvantages of using it, a discussion is needed on the types of problems ABM is well-suited to examining and the documentation required to effectively explain, evaluate and compare ABMs.

The process of building and testing models is both time and resource intensive, and it also requires individual data to inform the rules that agents follow. As such, it can be well-suited to solving problems that meet certain criteria, but may not be a good fit for all issues facing policy-makers. ABM is well-suited for handling complex problems, often involving heterogeneous actors and linked systems, which would result in a large, expensive program or policy with high set up costs and where initial choices would be difficult or impossible to revise at a later point in

⁵ Methodological individualism is likely compounded by the tendency of modellers to focus on individual agents, rather than the relationships between agents. Modellers can alleviate this by thinking critically about the model’s scope and key indicators.

time. For example, there have been some ABMs examining transportation infrastructure and comparing the results with other types of modelling (Doniec, Mandiau, Piechowak, & Espie, Stephane, 2008). Placing a new road, intersection or bridge in the wrong location could be an exceptionally expensive endeavour that cannot be undone, so an initial investment of time and money into building an ABM to investigate different options could be money well-spent.

As well, programs or policies that depend on the behaviour of individuals to be successful can be modeled using ABM. For example, Chen and Zhan (2008) conducted a study comparing staged and simultaneous evacuation strategies using an ABM – the method was particularly well-suited to this problem because it depends both on the behaviour of individuals, so a model based on individuals is a natural fit, and because the stakes are too high to ‘learn from experience’ in this case. Evacuations tend to be uncommon, and if one evacuation strategy is substantially better than another given the population density and road network of a given city, emergency management staff want to have this information ahead of time so it can be incorporated into plans and communicated.

These two facets are not necessarily mutually exclusive; ABMs may be most useful when both the program would be expensive to set up and difficult to change, and when its success hinges on individuals complying with a certain kind of behaviour. Food safety in retail outlets is a problem that exhibits both of these traits, which is why it was chosen as the case study for the remainder of this dissertation.

As noted above, one of the disadvantages of ABMs is that they can be difficult to compare and re-implement models if they are not properly documented. Following discussions within the field for a more systematic means of documenting ABMs (Richiardi, Leombruni, Saam, & Sonnessa, 2006), the Overview, Design Concepts, and Details (ODD) protocol was developed (Grimm et al., 2010). The ODD protocol is designed to facilitate model replication by other researchers, as well as improve reader understanding by explaining models in a concise, complete and consistent way.

The ODD begins by describing the purpose of the model; the entities, state variables, and scales used; and an overview of the processes in the model and their scheduling. The design concepts section covers basic principles, emergence, adaptation, objectives, learning, prediction, sensing,

interaction between agents, stochasticity or randomness, any collectives used, and observation⁶ – the data that comes out of the model. The details section focuses on initialization, any input data that is incorporated, and describing in detail the submodels within the model (Railsback & Grimm, 2012). The ODD forces the researcher to carefully think through all of the model’s key assumptions and document them, which both aids in the formulation of the model and in communicating it to others. As such, the ODD is a key element of transparency in model-building; this transparency is important when building models using input from stakeholders, including policy-makers.

1.7 ABM and the Policy Process

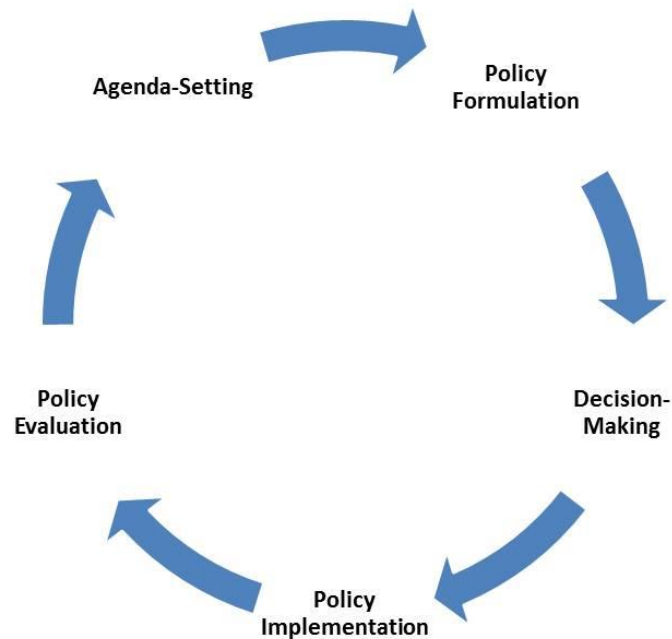
Policy-making is fundamentally a deliberative, discursive process where actors operating under resource, time, and search constraints identify policy problems, articulate goals, make choices to match solutions involving policy tools to problems, and assess whether or not these goals have been met through evaluation (Howlett, Ramesh, & Perl, 2009, p. 4). Thus, policy-making incorporates both technical and political dimensions – the technical side defines which tools are best suited to addressing problems, whereas the political side deals with how the problem is framed, often involving competing interests and causal theories from different stakeholder groups (Stone, 1989), what kinds of tools are considered socially acceptable, and what types of knowledge are considered legitimate (Howlett et al., 2009). Implementing policies is complex, especially when dealing with wicked problems, because complexity limits our ability to predict and control outcomes in social systems which increases the significance of unintended consequences of policy actions (Sanderson, 2002). A further aspect of complexity in achieving policy goals, as noted by Schneider and Ingram (1990, p. 513), “public policy almost always attempts to get people to do things that they might not have done otherwise. For policies to have the intended impacts on society, a large number of people in different situations must make decisions and take actions in concert with policy objectives.” The role of individual choices in achieving desired policy outcomes via the application of policy tools to change behaviour is emphasized here. Given the importance of individual learning, choices, perceptions and

⁶ For a detailed list of key questions related to each design concept, see Railsback & Grimm, 2012, p. 41.

preferences in achieving system-level outcomes, ABM has great potential for generating insights in the policy process.

The policy process is a conceptual model that simplifies policymaking by dividing it into discrete steps. The five step model is most commonly used (see Figure 1.1). The cycle begins with agenda-setting, where problems are brought to the attention of governments, then policy formulation, which involves devising policy alternatives, decision-making, where one of those alternatives is selected, implementation, where the chosen alternative is implemented, and evaluation, where the extent to which the policy outcomes match the policy goal is evaluated. The results of that evaluation, which may be undertaken by either the government itself or by outside actors, may contribute to adjustments or termination of the policy (Howlett et al., 2009). The advantage of breaking the policy process down into this series of steps is that it allows for better understanding and theory building of the overall process, and it is general enough that it can be used at all levels of government (Howlett et al., 2009), and by policy analysts to guide them in their work (Bridgman & Davis, 2003). The disadvantage of the policy cycle model is that it may appear that policy analysis proceeds in a linear fashion, although in reality the process is iterative and steps may be repeated. The policy process is not a causal theory; policy-making is embedded in a broader social and political context. As noted by Bridgman and Davis (2003, p. 100), “A policy cycle is just a heuristic, an ideal type from which every reality will curve away.” The following section will examine the potential application of ABM to each stage of the policy process.

Figure 1.1 The policy cycle



Adapted from Howlett, Ramesh & Perl (2009) *Studying Public Policy*.

Agenda-setting: The agenda-setting process “is concerned with the way problems emerge, or not, as candidates for government’s attention. What happens at this early stage of the policy process has a decisive impact on the entire subsequent policy cycle and its outcomes” (Howlett et al., 2009, p. 92). Recognizing problems is not a neutral process. Difficulties need to be recognized as responsive to human intervention in order to be seen as problems, otherwise they are viewed as accidents or the work of nature (Stone, 1989, p. 281). Once problems have been framed into the realm of human involvement, the way they are defined shapes how they are approached and what solutions are viewed as viable: “Problem definition is a process of image making, where the images have to do fundamentally with attributing cause, blame and responsibility” (Stone, 1989, p. 282). Causal theories factor into problem definition, and often, different stakeholders will advance competing causal stories. Successful causal theories are powerful: they can challenge the established social order or protect the status quo, assign responsibility for the problem, empower certain stakeholders and their solutions, and create new political relationships amongst those who have been harmed (Stone, 1989, p. 295).

Stone discusses complex systems, but describes complexity stories as weak from a causal point of view because such systems involve so many actors and interactions that breakdowns are inevitable, and it is impossible to assign blame to any one actor for these failures. However, ABM can be used to make failures associated with complexity stories clearer by articulating causal pathways, with the possibility for assigning responsibility for system breakdowns.⁷ As well, science can be a powerful asset to those stakeholders who are advancing or refuting a causal theory. ABM, with its roots in Computer Science and its ability to incorporate real data as well as assumptions about how the world works, could potentially be used by policy entrepreneurs to show support for a specific causal theory.

Policy formulation: Policy formulation, the second stage in the policy cycle, “refers to the process of generating options on what to do about a public problem” (Howlett et al., 2009, p. 110). Formulation can be divided into four sub-stages. Firstly, the appraisal phase considers data and evidence on the identified policy problem and possible solutions. Secondly, the dialogue phase initiates communication and consultation between governments and other stakeholders and policy actors on potential solutions. Thirdly, governments weigh the evidence and draft a proposal in the formulation phase. Fourthly, feedback on the proposal and specific recommendations on a policy option to pursue will be generated in the consolidation phase (Howlett et al., 2009, pp. 111–112). Exploring these alternative courses of action and deciding which to take depends on both technical and political constraints. A specific policy option may be a reasonable idea for addressing the defined problem, but if it is politically unpalatable, it will not be accepted by government (Blakeney & Borins, 1998).

Once an initial feasibility assessment is complete, there is clear potential for ABM to examine different policy tools and alternatives. Policy tools are the specific instruments that government uses to achieve policy goals, and policy goals will not be reached unless “target populations . . . comply with policy directives, utilize policy opportunities when these are offered, or engage in other forms of coproduction to promote socially desired results” (Schneider & Ingram, 1990, p. 527). Different policy tools are designed to induce different behaviour in targeted individuals:

⁷ See Goldstein, 2011 for a preliminary effort to simulate the causal pathways of the 2008 financial crisis.

- Authority tools rely on the legitimacy of governments to induce behaviour;
- Incentive tools, such as inducements and sanctions, assume that individuals maximize their utility and will change their behaviour in order to do so;
- Capacity tools assume that individuals rely on heuristics because they lack information, and will make better decisions if given that information;
- Symbolic tools assume intrinsic motivation, and manipulate symbols and values to induce the desired behaviour; and learning tools are more flexible and assume that targets do not know what they should do or what their options are; and
- Policy tools should promote learning (Schneider & Ingram, 1990).

Because these tools employ different assumptions about the nature of human behaviour and the best way to encourage behavioural change in order to meet policy goals at the global level, the focus of ABM on individual agents and their choices makes this method a natural fit for examining different policy tools and their emergent, system-wide effects.

An ABM could be developed to test the application of the different policy tools listed above and their effects on agent behaviour. Following an initial testing of policy tools using such a model, these results could be used in the dialogue phase to engage with stakeholders and get their input on policy options, and to further improve the model. This phase may also allow for expert consultation, which is often needed to get the subject specific information and data required to build a grounded ABM. However, building and testing ABMs, then refining them to better reflect assumptions and key agent behaviour, requires a substantial input of time which may not be feasible at the earliest stages of policy formulation.

Because ABMs require a lot of time to build and test, they are likely to be most useful at the formulation and consolidation phases of policy formulation. Following the dialogue phase, the preferred options could be simulated and the results may be useful in determining which option should be pursued and determining initial policy settings. A further advantage of ABM is that it can be used in areas where there are little empirical data, and thus may offer new insights for novel policy instruments. Sanderson (2002) critiques policy pilot projects that are actually prototypes, where prototyping emphasizes how the initiative worked, rather than whether or not it worked. Because ABMs are built with flexible parameters and many repeated simulations can be run quickly, ABMs can be subject to analyses to determine initial conditions that are most

amenable to success over many replications. This attribute has the potential to allow policymakers to focus on ‘prototyping’ *in silico* to get initial conditions closer to success, and then focus on setting up pilot projects for longer term evaluations where the focus is on whether or not the initiative was successful.

Decision-making: The decision-making stage is where an option from the previous stage is approved and advanced in either a formal or informal statement indicating the government’s intent to proceed (Howlett et al., 2009, p. 139). Decisions can either be positive, in that they alter the status quo, or negative, in that they maintain the status quo. Negative decisions halt the policy cycle at this stage. Importantly, the decision-making stage is inherently political, and inevitably involves winners and losers, even if the status quo is maintained. The main role for ABM at this stage in the policy process would be to add to the evidence base for choosing which alternative to implement, as noted above.

Implementation: The implementation stage is comprised of “[t]he effort, knowledge, and resources devoted to translating policy decisions into action” (Howlett et al., 2009, p. 160). The main role for ABM in implementation would be to assist bureaucrats with determining initial policy settings. Initially, using models can show a level of needed resources in order to have an effect, and sensitivity analyses can be conducted to show where the boundaries of that effect are. This could assist with implementing a more efficient policy from the beginning, and potentially resulting in less iteration between evaluation and implementation to get the policy settings ‘right.’

The tractability of the problem and the severity of the constraints facing government are also key factors affecting implementation. When practical constraints are low and the problem is relatively clearly defined and solvable, full implementation can be achieved. However, when the problem is intractable but constraints are low, policy experimentation may occur. High constraints and tractable problems experience contested implementation, where stakeholders continue to vie for resources to solve the problem. Intractable problems facing high constraints experience symbolic implementation. To overcome constraints, policymakers can increase their capacity for monitoring and forecasting in order to develop better policies (Howlett et al., 2009, pp. 175–176). ABM could play a role in this process by incorporating monitoring data into a

simulation that could then experiment with changes to policy implementation or different policy instruments.

A further application of ABM to implementation research could come through the operationalization of ‘backward mapping’ (Elmore, 1979). Forward mapping begins with a clear statement of the policy’s objective and then describes a set of steps for achieving it, and defines an outcome for measuring success or failure. The forward mapping perspective emphasizes centralized control, consistent adherence to standards, and a focus on factors such as budget allocation that are easily controlled by policymakers. Elmore (1979, p. 603) points out that the weakness of this approach is that it assumes that policy implementation is controlled in a top down way. Top down approaches are not well suited to handling complexity or the ‘messiness’ of policy-making (Schofield, 2001).

Forward mapping is contrasted with backward mapping, which begins “at the point at which administrative actions intersect private choices” (Elmore, 1979, p. 604). By beginning with a description of behaviour at the end of the implementation process that policy should affect, backward mapping questions the assumptions that policymakers control implementation from the top. Once the behaviour has been described, an objective is stated from an organizational operations standpoint, and then desired outcomes are described. Bottom up approaches pay attention to the actions and motives of actors in the policy system (Schofield, 2001). Importantly, the backward mapping approach, in contrast to forward mapping, disperses control and focuses on factors over which policymakers have little influence, such as incentive structures, bargaining relationships, and knowledge of administrators (Elmore, 1979). Backward-mapping focuses on problem-solving processes, rather than outputs, and views discretion and adaptive behaviour by lower level administrators as valuable for policy learning. Since ABM is well-suited to incorporating adaptive behaviour and heterogeneity of agents, the method is a natural fit for exploring the backward mapping approach.

Evaluation: Policy evaluation is the stage of the policy cycle that “assesses the effectiveness of a public policy in terms of its perceived intentions and results” (Gerston, 1997, p. 120, as cited by Howlett et al., 2009, p. 178). Following evaluation, the problems, solutions and policy options involved may be revised, which re-starts the policy cycle, the policy may continue unchanged, or it may be judged a complete success or failure and the policy cycle may be terminated (Howlett

et al., 2009). Although some scholars present a normative view that broader policy analysis should remain separate from the more rational, objective task of evaluation (Geva-May & Pal, 1999), others argue that evaluation maintains a political element and its results are open to judgment, interpretation and re-framing – policy successes may come to be viewed as failures over time, and vice versa (Bovens & 't Hart, 1996).

A new focus on evaluating outcomes came from reforms under the New Public Management (NPM) paradigm of public administration which included an emphasis on performance measurement, improving quality while reducing costs, and improving accountability (Borins, 2002). In the UK and New Zealand, NPM was inspired by public choice theory, which assumes that bureaucrats are self-interested, rational actors, and agency theory, which focuses on principal-agent relationships where the agent makes decisions that impact the principal. The agency dilemma occurs because the agent is motivated to act in his own interests, not those of the principal, because of information asymmetry. ABMs can be used to represent principal-agent problems,⁸ and it is straightforward to model information asymmetry; the models described in later chapters of this thesis include information asymmetry, although not in a principal-agent context. Despite the emphasis that some NPM reformers placed on evidence-based learning, reforms were not always informed by evidence (Hood & Peters, 2004).

Although governments have come to value improved efficiency and effectiveness (Hood, 1991), and place an emphasis on building the evidence base for public policy by explaining “what works for whom in what circumstances,” which “relies on the assumption that we can make policies work better if we understand how policy mechanisms bring about change in social systems to achieve desired outcomes” (Sanderson, 2002, p. 2). This process of examining what works, for whom, and why and adapting it to a new context is referred to as lesson drawing (Rose, 2005). As the social space in which policies are implemented has grown increasingly complex, the need for effective monitoring and evaluation to provide feedback and allow for policy course corrections has grown. Under these circumstances, “a major burden is placed upon policy experimentation and evaluation as key institutional practices in interactive governance to

⁸ It should be emphasized that although ABM can be used to represent theories of involving rational actors, one of the strengths of the method is that rationality is not required.

provide the basis for reflexive social learning” (Sanderson, 2002, p. 9). Although Sanderson highlights the role of pilot projects in policy experimentation and evaluation, this is also an area where ABM could be beneficial.

There are some significant barriers to successfully evaluating policy pilot projects. Policies often effect change slowly, particularly when enacted on a small scale, and measuring these small changes and attributing them to the pilot, not other factors, can be challenging. Political interests often run counter to those of evaluation, in that politicians want shorter pilot projects so that politically relevant policies can be fully implemented, whereas evaluation is better served by longer time horizons and in depth study (Sanderson, 2002, p. 11). Although randomized control trials have been attempted, it is impossible to design a true control: similar communities will have important differences and may be influenced by other factors over the course of the study period that researchers could not have anticipated. Ethical objections also arise from withholding benefits from eligible participants. Finally, researchers cannot control all aspects of policy implementation and there may be variation between contexts, particularly in initiatives that are specific to individual or group needs (Sanderson, 2002, p. 12).

ABMs provide a potential solution to these difficulties of evaluation. ABMs are well suited to situations with long time horizons (Louie & Carley, 2008). Simulations can be run numerous times with the exact same initial conditions, avoiding the problem of reflexivity that is inherent in complex problems. Because simulations can be run many times and quickly, an ABM that represents the pilot project could give insight into the amount of time needed to see an effect, which could help policymakers convince political interests that a longer time horizon is needed for effective evaluation. An ABM could be constructed to show the environment without the pilot, to give evaluators a counterfactual and highlight differences between the simulation and data generated from the pilot, and to serve as an *in silico* control. If ABMs were employed to test different policy options during the formulation stage, these models could be updated and used in evaluation to advance policy learning, and further link the policy cycle with the modeling cycle.

ABM has practical implications for different stages of the policy process, particularly in testing policy alternatives and policy evaluation, which have not been fully explored even though the method has been touted as having great potential for policy development (Ghorbani et al., 2014; Moss, 2008). The discussion here has advanced this line of thought by illustrating potential areas

for ABMs to generate insight in the policy process. However, because ABM is a relatively new tool in the policy space, it must be made relevant and accessible to policymakers.

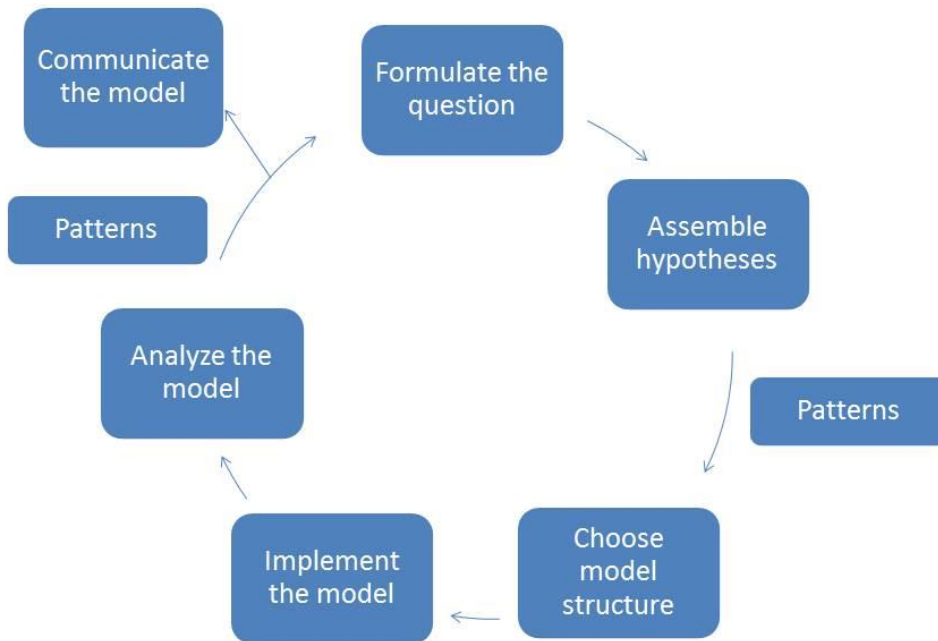
1.8 How can ABM be made relevant to policymakers?

Although ABM has been used in some policy areas, namely land use management and water demand, it has not been frequently applied as a public policy tool (Moss, 2008). Some other areas where ABM has been discussed in a policy-relevant way are infrastructure (Rinaldi, 2004) and health (Maglio & Mabry, 2011), which are also areas that generally fall under provincial jurisdiction. Provincial public servants tend to work on a fairly small subset of issues, and spend a great deal of their time ‘firefighting,’ or working on problems that require immediate attention. As well, provincial policy analysts tend to mostly be trained in the social sciences,⁹ with little training specific to policy analysis and little experience outside of government; they are ‘process related’ experts, without much expertise to devote to gathering and interpreting evidence in their specific subject areas (Howlett & Newman, 2010). Howlett and Newman (2010, p. 131) note that this preoccupation with firefighting, relative inexperience, and lack of substantive subject area and policy analysis training indicate that provincial policy analysts “may not have the capacity to practice a high level of evidence-based policy analysis and policy-making.”

ABM has a great deal of applicability to various stages of the policy cycle, particularly in adding to the evidence base of policy formulation and policy evaluation. It is a method well suited to the study of complex problems, which often fall into the realm of provincial jurisdiction. Model building has its own cycle, consisting of formulating the question, assembling hypotheses, choosing the model structure, implementing the model, analyzing the model, and looking for patterns in between stages (Railsback & Grimm, 2012, p. 7).

⁹ Howlett & Newman (2010) found that only 1.6% of the provincial public servants they surveyed had a degree in Computing Science.

Figure 1.2 The modeling cycle



Adapted from Railsback & Grimm (2012) *Agent-Based and Individual-Based Modeling*.

As with the policy cycle, the modeling cycle is not a linear process (see Figure 1.2): modellers will often move back and forth between steps and repeat the cycle several times before finally leaving the cycle to communicate the model. The model building process, which has the potential to generate as many or more insights as the actual model, can be very time consuming. Although ABM has a great deal of potential for generating insights in policy development, policy analysts likely require specialized training to interpret the results of ABM research, and will not contract out for ABM studies nor use the results if they are unfamiliar with them or view them as too difficult to interpret. Governments value efficiency and emphasize outcomes (Hood, 1991) and will not invest time and money on a time-consuming method for policy analysis, particularly one that falls outside of the comfort zone and training of its policy analysts, unless there is significant value for money. Although ABM shows great promise for generating insights on the policy process, researchers must make the results of these models accessible to policymakers in order for them to become an accepted tool for policy analysis. How can researchers make ABMs accessible to policymakers?

Stakeholder engagement: Firstly, researchers need to open the ‘black box’ of model building through collaboration. As other authors have noted, “it is frequently the case that policymakers dismiss academic research as too theoretical, unrelated to the actual problems they are wrestling with, or in other ways irrelevant to their concerns...” (Gilbert, 2002, as cited by Ramanath & Gilbert, 2004, para. 2.1). Collaboration between subject matter experts, technical modellers and policy analysts is essential. By involving stakeholders in the modeling cycle, the finished product will better address their needs for policy formulation and evaluation, and the researcher will likely need to do fewer revisions to the model.

Stakeholder involvement¹⁰ is particularly crucial in formulating a clear research question, which can be especially challenging when dealing with complex problems. A key element of ABMs is that they be simplified as much as possible, only focusing on key elements needed to understand the system (Railsback & Grimm, 2012), and subject matter experts are often helpful in narrowing down potential hypotheses. Policy analysts as model stakeholders may not be directly involved in devising parameters and state variables for the entities in the model; however, a policy maxim is ‘what gets measured gets managed’ so their understanding of the system, what they are interested in managing, and what data is available could be of use here. Technical experts should manage the technical aspects of model parameterization, implementation and testing. Lastly, following analysis of the model’s output, stakeholder groups should be involved in a discussion on how to revise the model. A further advantage of participatory model building is that it gives researchers an opportunity to inform policymakers as to the limitations of the model so that expectations for what ABM can achieve are in line with reality, and also to provide training on how to understand models and their associated documentation. Ghorbani et al. (2014, p. 70) note that “[a]lthough simulation results can be communicated to problem owners to facilitate participatory decision making, building collaborative agent-based models is not a common process.” Researchers must make an effort to change this in order for ABMs to become more widely used in the policy space.

¹⁰ See Ramanath & Gilbert, 2004 for a discussion of lessons drawn from agent-based participatory simulation studies.

Model Transparency: Model transparency is important for policy-making for two reasons. Firstly, given the iterative nature of the policy cycle, evidence used to construct policy may be revisited by different stakeholders again at a later time, and these stakeholders may have competing problem frames and evidence to contribute to defining the policy problem, formulating policy alternatives, and evaluating the effectiveness of current policies. In order to use models in this feedback process, their assumptions must be documented in a clear and transparent way. Secondly, whether or not a model is used in policymaking, researchers must also maintain detailed model documentation for models to be accessible and transparent to outside audiences. The documentation for any model must be complete and clear to allow for model replication by other researchers and a thorough understanding of all assumptions and data used. One such method for documentation is the ODD framework, a standard framework for describing models so that they can be understood and replicated.

Engaging policymakers in modeling and developing transparent models for policy problems is not simply a benevolent exercise for researchers. One of the difficulties of building ABMs is access to reliable, individually-based data to inform ABMs. Governments often collect a great deal of data for their own evaluation purposes, and researchers could potentially influence this data collection activity to better suit the needs of ABM if governments see the value of ABMs for evidence-based policy-making. Although the full potential of ABMs for policy-making has yet to be unlocked, there are certainly opportunities for them to add value if researchers and policymakers are open to collaboration.

1.9 Specific Case Study of a Complex Problem: Food Safety

The following section describes food safety, which serves as a case study of a complex problem. The Public Health Agency of Canada estimates that approximately 4 million people, or 1 in 8 Canadians, become sick each year. There is a great deal of uncertainty as to the full extent of foodborne illness because many cases are mild and those affected do not seek medical treatment, which contributes to underreporting. Of those who do seek treatment, laboratory testing is not always completed and cases may not be reported to the appropriate authorities (Buzby & Roberts, 2009; Schlundt, 2002). Further, the food product that causes the illness is not always known (Batz et al., 2005). The actual number of foodborne illness outbreaks is thought to have declined in recent years, but there has been an increase in the number of food recalls, which has

negatively impacted public trust (Kramer, Coto, & Weidner, 2005). The uncertainty associated with estimates of foodborne illness impedes the development of effective interventions and policies to prevent foodborne illnesses.

Ensuring that safe food reaches consumers, from a regulatory perspective, is a semi-structured problem (Hoppe, 2011), as the outcome, safe food, is widely agreed upon, but our methods of achieving it are sometimes ineffective and not always agreed upon. For example, the use of growth-enhancing hormones in beef has been judged to be safe when used according to sound veterinary practices in Canada and the United States, but many of these same hormones are banned in beef production in the European Union, leading to trade disputes (Kerr & Hobbs, 2005). However, some disagreement exists as to the definition of ‘safety’ and what constitutes safe food. Nestle (2010) notes that although microbial food contamination sickens and kills people each year, many consumers are more concerned about the safety of genetic engineering, which has not sickened or killed anyone to date. Thus, viewing food safety from a broader systems perspective, it can be considered a complex problem – both the problem and the means of solving it are contested.

The following section explores the interconnected changes in terms of animal, environmental, processing, and human factors that contribute to the complexity of food safety.

Animal factors: There have been numerous changes in animal production that have been linked to emerging foodborne diseases. Rocourt et al. (2003) cite changes in feeding practices, such as the move to including bone meal in cattle feed, as one of the factors behind the emergence of BSE in the 1980s. As well, increasingly intensive livestock operations have been linked to a greater prevalence of *Salmonella* and *Campylobacter* in poultry, pigs, and cattle (Rocourt et al., 2003). Meanwhile, changes in public perception and animal welfare requirements have led to more animals being raised free-range; however, this potentially exposes animals to parasites like *Trichinella*, which can only be avoided if animals are housed completely indoors (Newell et al., 2010). Trade-offs between animal welfare and safety concerns are often difficult to resolve.

Environmental factors: Climate change has the potential to affect disease distribution through vectors like different mosquito species entering new habitats, changes in water supply, and possible disruption of cold chains in shipping due to higher temperatures (Havelaar et al., 2010,

p. S85). The continued intrusion of cities and agricultural production into wildlife habitat also presents opportunities for new pathogens to come into contact with people (Wolfe, Daszak, Kilpatrick, & Burke, 2005). Moreover, the popularity of organic production has led to more manure being used to fertilize fields; more outbreaks have been linked to fresh produce recently. While the mechanism of contamination is not always clear, there is concern that contaminated irrigation water and unsafe handling of produce may be contributing factors (Islam, Doyle, Phatak, Millner, & Jiang, 2004). Meanwhile, pathogens are evolving. There are many new strains of anti-microbial resistant bacteria, some of which may be foodborne; a Dutch study found methicillin-resistant *Staphylococcus aureus* (MRSA) in 11.9% of 2217 samples of raw meat at the retail level (De Boer et al. 2009, as cited in Newell et al., 2010).

Processing factors: New production methods that incorporate technological advances in packaging, preservatives and storage have allowed for a wider variety of foods to travel longer distances to consumers (Rocourt et al., 2003). Trends in consumer preferences, such as minimal packaging and natural preservatives, may affect contamination, as packaging may minimize pathogen growth (Havelaar et al., 2010). An exponential increase in global trade has led to a greater distance between farm and fork. The resulting global trade system has increased in complexity now that fewer staples are traded, and many of the food products moving around the globe are branded, finished products (Ercsey-Ravasz, Toroczka, Lakner, & Baranyi, 2012). Ercsey-Ravasz et al. (2012) argue that such a complex trade network could allow for foodborne pathogens to spread worldwide very quickly, with consequences for traceability. Some food products appear to be sourced from new supplier countries where regulations are less stringently enforced or monitored; the adulteration of fresh milk with melamine in China caused significant angst amongst China's trading partners. Even in well-managed supply chains, it is impossible to assure absolute safety: testing for potential contaminants should be specific, sensitive, cost effective, deliver fast results, and be incorporated effectively into the supply chain (Kennedy, 2008), but these goals often conflict with one another.

Systemic risk refers to when “a system fails to perform because of the ways in which its various components interact” (Hennessy, Roosen, & Jensen, 2003, p. 78). Given the interactions within the food system, there is likely to be asymmetric information within the processing chain, where the actions of other processors are not known. Hennessy et al. (2003) report that this may result

in a failure to coordinate with respect to food safety, as some operators may not treat food with sufficient care if they feel that others have not done so. Information asymmetry trickles down to the consumer, as well, as food safety is an experience good (Hobbs, 2002), and is only fully detectable after the food is eaten (mold is one obvious exception).

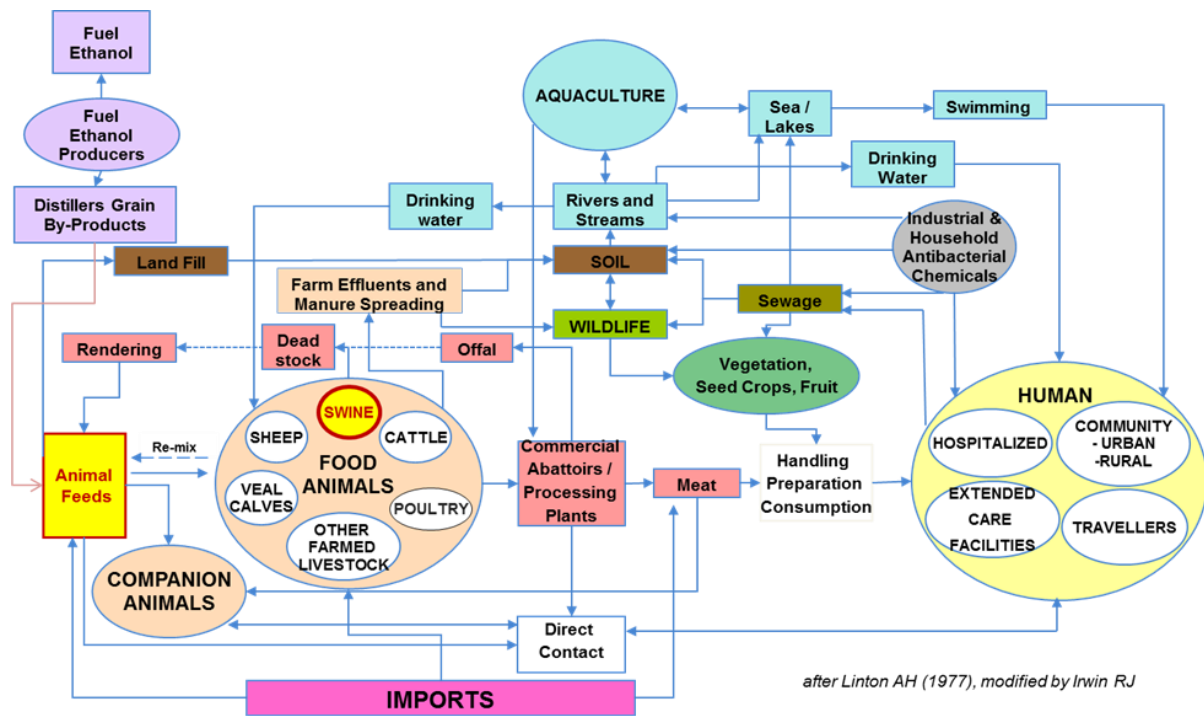
Human factors: Other factors, related to changes in consumer preference and lifestyles, also have an impact on food safety. People travel more by air than ever before, which gives pathogens new opportunities to move from one population to another incredibly quickly (Rocourt et al., 2003). Consumers also eat in restaurants much more frequently than they did fifty years ago; now, eating in restaurants is a risk factor¹¹ for contracting foodborne disease (T. F. Jones & Angulo, 2006). Consumers also demand more variety, in the form of more exotic, and in some cases, more locally-grown foods (DeWeerd, 2009; Newell et al., 2010). Ready-to-eat foods are also more widely available, which has interesting implications for foodborne disease and traceability. For instance, the horsemeat scandal in the EU largely involved prepared foods, and *Listeria*, a pathogen that thrives in cooler conditions, depends on refrigeration and cold chains in supply networks. Lastly, older people are more susceptible to foodborne disease, which will become increasingly important as the population in OECD countries ages (Rocourt et al., 2003). The *Listeria monocytogenes* outbreak in Canada in 2008 linked to Maple Leaf luncheon meats was particularly deadly because some of the contaminated meat was served in nursing homes to people vulnerable to being more severely affected by foodborne diseases (Weatherill, 2009). As medical technologies like anti-retroviral drugs and chemotherapies improve, it is likely that more immune-compromised people will be living longer; they are also more prone to foodborne diseases (Gerba, Rose, & Haas, 1996).

On a micro level, there is also a growing body of literature related to how people make decisions in situations of uncertainty. It is well documented that people do not behave in a fully rational way when making choices, and this also applies to safety; as noted by Green et al. (2003, p. 49), “Concern about food safety is theoretical, and abstract, informing decisions about food choice in short term and contingent ways.” Although Havelaar notes that consumers view safety as a non-

¹¹ Jones and Angulo (2006) note that foodborne diseases cases originating in restaurants may be more frequently reported.

negotiable characteristic that is often not considered unless it becomes a problem, there are a few factors that influence ebbs and flows in consumer concern over food safety. One is risk perception. Risk is defined¹² as the probability of a hazard occurring and the severity of the consequences should it occur (Smyth & Phillips, 2006; Yeung & Morris, 2001). In risk assessment, risks that are very unlikely, but cause serious problems, are considered to be low risk. However, “for many situations hazardous to public and environmental health, the identities and relative probabilities¹³ of outcomes are not fully known and therefore, by definition the context is one of ‘uncertainty’ rather than ‘risk’” (Yeung & Morris, 2001, p. 171). As noted above, individual consumers may have differing conceptions of safety; safety may be viewed as short-term, as in food that will not cause immediate illness, or in the long-term, as in foods that will not cause future health problems (Green et al., 2003).

Figure 1.3 Complex interactions in the food system



¹² Smyth and Phillips (2006) note that this is the scientific definition of risk, whereas the socially constructed definition of risk incorporates hazard and outrage.

¹³ However, Tversky and Kahneman (1974) note that even those individuals with training in statistics are prone to errors of judgment when dealing with intricate problems.

1.10 Organization and Purpose of this Study

The remainder of this dissertation follows the three paper model: chapters two, three and four were written as independent journal articles, and are followed by a conclusion. As such, some background information was required for each of the articles, and there is some repetition.

The ABMs used in the following three articles namely explore possible policy alternatives, rather than all aspects of the policy cycle, and are stylized in nature and are not intended to be used as predictive tools. The first two articles follow a similar structure; the ODD framework has been used to describe the model in detail. The last paper, in order to account for length restrictions of the journal it will be submitted to, has not followed the ODD structure as explicitly.¹⁴ As well, it should be noted that these models followed the steps of the modeling cycle during their development, and the final product does not show all of the iterative steps.

The three models, although distinct pieces each discussed in their own chapter, are related. The first model is the most simple of the three. It represents a simplified food safety system representing stores, consumers, and inspectors, with very simple procedures. The model was intended as a proof of concept and to test my own abilities with modelling. This model was implemented in NetLogo: firstly, because NetLogo is an open-sourced program, and secondly, because the visual representation and line by line coding is fairly easy to get started with. This model was extended in the second paper to incorporate restaurants, more sophisticated consumer and inspector agents, a more complex role for information, and some new procedures. Although NetLogo is an easier program to begin with, it is more rigid and requires considerable coding ability to implement more complicated agents and environments, and it also uses discrete time steps. AnyLogic, a more sophisticated and flexible program, was chosen for the third model, since this software allows for continuous time, an easier implementation of more complex agents and agent memory to allow for crowdsourcing information from agents, and it can run many iterations much more quickly. The third model is the most complex and involves even more sophisticated consumer agents, the ability to divide consumer agents into groups, an inspector with the ability to sort information given by consumers, and much lengthier experiments involving more model realizations. AnyLogic also incorporates structures that allow for

¹⁴ However, a full ODD can be accessed in the CoMSES model library, along with the model code.

messages to be passed between agents, which will facilitate extending this model for future work incorporating agent communication.

The first paper has been accepted for publication in the *Journal of Artificial Societies and Social Simulation*. The models used in this paper were also presented as part of a poster at the ZIBI Summer School Scientific Symposium in Berlin, Germany in June 2013. Early drafts of this paper benefited from substantial comments from Drs. Peter Phillips and James Nolan. The second paper was presented at the Mapping the Global Dimensions of Policy 3 at McMaster in January 2014, and has been accepted for publication in the *Journal on Policy and Complex Systems* following comments from Drs. Phillips, Nolan and Osgood. The third paper will be submitted to the *American Journal of Public Health* and its development has been substantially influenced by Dr. Osgood's other work in the Department of Computer Science. The model was built in AnyLogic¹⁵ which was greatly facilitated by his M.Sc student, Wenyi An. The work in these three articles advances the literature by contributing to the small existing base of ABMs focusing on food safety, while also discussing their application from a policy perspective.

¹⁵ For a detailed comparison of different software for designing ABMs, see Nikolai & Madey, 2009.

CHAPTER 2

GROWING FOOD SAFETY FROM THE BOTTOM UP: AN AGENT-BASED MODEL OF FOOD SAFETY INSPECTIONS

2.1 Abstract

The overall burden of foodborne illness is unknown, in part because of under-reporting and limited surveillance. Although the morbidity associated with foodborne illness is lower than ever, public risk perception and an increasingly complex food supply chain contribute to uncertainty in the food system. This paper presents an agent-based model of a simple food safety system involving consumers, inspectors and stores, and investigates the effect of three different inspection scenarios incorporating access to information. The increasing complexity of the food supply chain and agent-based modeling as an appropriate method for this line of investigation from a policy perspective are discussed.

2.2 Introduction

Food exhibits multi-dimensional features; food plays a role in many contexts, including basic survival, cultural norms, economics, trade, and social situations. We all have a vested interest in food because we all have to eat. Underpinning all of these different roles is the notion that food should be safe. There are many stakeholders, from consumers,¹⁶ to industry, food scientists, farmers, retailers, and regulatory agencies who have different criteria for determining appropriate food choices, leading to trade-offs and tensions in determining the best policy options for food safety systems.

Over the past few decades, the global food supply chain has grown more complex, and breakdowns in food safety have garnered a lot of public attention. There are many notable examples of food safety crises that have ignited public discussion, changed consumer habits, and impacted legislation and industry practices: the bovine spongiform encephalopathy (BSE) outbreak in the United Kingdom, which peaked in 1993 with approximately 1000 new cows being infected weekly (Centers for Disease Control and Prevention, 2013a); the Maple Leaf

¹⁶ For a more detailed discussion of food safety from a consumer perspective, see Smith DeWaal, 2003.

Foods *Listeria monocytogenes* outbreak in Canada in 2008, which resulted in 57 confirmed cases and 23 human deaths, partly because the deli meat in question was served to high-risk populations (Birk-Urovitz, 2011); and, most recently, the scandal in the European Union when horsemeat was found in prepared foods, such as lasagna and burgers, that were labeled as beef products (Waldie, 2013). These all led to demands for new and more stringent production methods and legislation. Food safety challenges have arisen from population growth and an aging population, a global market for food products and global supply chains, increased demand for protein, and climate change pressures on agricultural practices (Newell et al., 2010). These changes in food systems raise policy questions related to the optimal management of risk, which is also tied to food safety at an affordable cost.

In order to investigate these concerns, a basic agent-based model (ABM) has been developed to explore the impact of small changes in system-level rules. Much of the literature examines consumer, industry, or government responses to food safety incidents in isolation; the agent-based model considers the interaction between consumers, retailers, and inspectors. The model is intended to provide insight into these interactions, rather than serve as a predictive tool (Epstein, 2008). Three model versions, representing different inspection scenarios, are described using the Overview, Design Concepts and Details (ODD) framework and compared. This paper provides background on the complexity of the food safety environment, the theory surrounding ABMs, employs the ODD framework for describing ABMs, the model results, and conclusions.

2.3 Background

The global food safety system is complex: trade, culture, microbiology and spatial and economic aspects all interact to form a system with interdependent elements (Miller & Page, 2007, p. 9). As defined by Simon (1962), a complex system is one where “a large number of parts ... interact in a nonsimple way.” A distinction must be made here between complex and complicated systems; in complicated systems, the elements within the system maintain some degree of independence and can be studied independently. Complex systems are, by definition, not reducible (Miller & Page, 2007).

A contributing factor to food safety’s complexity is a lack of certainty; the overall infection and disease burden from unsafe food, even in OECD countries, is unknown (Newell et al., 2010; Rocourt et al., 2003) and small breakdowns at any stage of the system can lead to widely

distributed outbreaks, given the interconnected trade system and extensive movement of people (Havelaar et al., 2010; Newell et al., 2010; Rocourt et al., 2003). Consumers may also assess safety along competing dimensions (Green et al., 2003); the safety of a food can be defined in the immediate term, for example, food that is not contaminated by bacteria, or in the long-term, as in food that will not cause health problems, such as high cholesterol, in the future. Food safety can also be viewed through the competing lenses of values and science (Nestle, 2010): food produced in large, industrialized plants may be free from contamination and therefore considered safe, but consumers may express distrust of a complicated system involving industrialized agriculture, and its associated environmental effects, as well as the concentration of the food industry into the hands of a few very large, powerful companies. As noted by Havelaar et al., (2010) “The consumer demands fresh, tasty, healthy and wholesome food products. Nevertheless, safety is in this framework considered an absolute requirement; placing unsafe food on the market is not an option in the consumer’s mind”. However, defining exactly what safe food means to consumers can be a challenging exercise.

Food-borne disease, for the purposes of this paper, refers to all diseases caused by consuming food contaminated¹⁷ by any bacterial, viral, prion, or parasitic agent (Rocourt et al., 2003). Currently, the overall disease burden of food-borne diseases is unknown (Newell et al., 2010). The Centers for Disease Control and Prevention (CDC) estimates that there are 48 million cases, 128,000 hospitalizations, and 3000 deaths related to foodborne illness annually in the United States; this means that 1 in 6 Americans are sick each year (Centers for Disease Control and Prevention, 2013b). The Public Health Agency of Canada estimates that 4 million Canadians, or 1 in 8, are sick each year (Public Health Agency of Canada, 2013). These estimates come with many built-in assumptions, and both organizations acknowledge that there is underreporting. Although foodborne disease is caused by a variety of pathogens, including common bacteria such as *Escherichia coli*, *Salmonella*, and *Campylobacter jejuni*, viruses such as Hepatitis A and noroviruses, and parasites such as *Trichinella* and *Toxoplasma gondii*, the most common symptom is diarrhoeal disease. Most cases of foodborne disease are relatively mild, and many people do not view diarrhoea as a serious outcome of disease but rather an inconvenience, which

¹⁷ Contamination by chemical hazards or environmental pollution is beyond the scope of this study.

contributes to underreporting of pathogens that cause milder disease (Rocourt et al., 2003). However, in more serious cases, foodborne diseases may result in severe complications or death, particularly among vulnerable segments of the population: pregnant women, young children, immune-compromised individuals, and older adults (Gerba et al., 1996). Given differences with reporting structures and surveillance, it can be difficult to compare data across countries and jurisdictions, since a higher number of reported cases could simply be the result of a better surveillance system and not necessarily from more illnesses (Rocourt et al., 2003).

It should be clarified that the current regime of Hazard Analysis Critical Control Points (HACCP) and risk analysis¹⁸ (Verbeke, Frewer, Scholderer, & De Brabander, 2007), developed over the last 30 years (Phillips, 2009), has led to declines in estimated foodborne disease incidence (Centers for Disease Control and Prevention, 2013b). One definition of regulation that is applicable here is that it “is the sustained and focused attempt to alter the behaviour of others according to defined standards or purposes with the intention of producing broadly identified outcome” (Black 2002, p. 20, as cited in Havinga, 2006). Most of the time, the system works at mitigating hazards, but when it does not, there can be serious illnesses and death, and public trust in the food system more generally is damaged. Changes in production systems and trade present new opportunities for pathogens to proliferate or adapt to new hosts. Food safety policies are often national or regional, but as the system has become increasingly globalized, current management systems of risk analysis and HACCP may be overwhelmed by new pathogens and hazards.

Despite new efforts in testing and safety, no pathogens have been eradicated or contained, and new ones are emerging (Newell et al., 2010). Increasingly, viral pathogens are a food safety concern, as shown by recent hepatitis A outbreaks in the US which have been linked to frozen berries and pomegranate seeds imported from Turkey (Centers for Disease Control and Prevention, 2013c), but global microbiological quality control criteria focus on bacterial counts, which is insufficient for dealing with viral contamination (Newell et al., 2010). The food system is also changing rapidly, challenging current policies.

¹⁸ For a discussion of principles for managing food safety, see Schlundt, 1999.

Rules that inform decision-making are fundamentally different in areas of uncertainty. The perception of risk by people exposed to a hazard tends to also be fundamentally different from the technical assessment of risk. When social and psychological aspects are included, consumers tend to consistently overestimate some risks while underestimating others, and they are often keen to listen to negative information while ignoring positive information (Thaler & Sunstein, 2008; Verbeke et al., 2007; Yeung & Morris, 2001). This has led to a gap between how experts and the general public view food risks, leading to frustration on both sides. Heuristics, or mental shortcuts used to make decisions, are prevalent in consumer decision-making and lead to persistent biases. The availability heuristic, for example, leads people to view events that are recent, dramatic, or otherwise easily recalled as more likely to occur (Tversky & Kahneman, 1974). Verbeke et al. (2007) highlight fright and panic elements in the social amplification of risk. Fright is related to the individual's perception of the severity of the risk, and is increased if the risks are perceived as unavoidable or if there are differing stakeholder perspectives on managing the risk. Whether information is perceived as reassuring or frightening depends on one's opinion (Sandman, 1994). Panic relates to the perception of risk: for example, how many people are exposed to the risk, whether it is unknown or uncertain, and whether it may come with long-term consequences has differing impact. Since food is a complex area, and a lot of information available may sound uncertain, incomplete, and contradictory (especially in the media and online), there is a lot of opportunity for public fear following foodborne illness outbreaks.

The consequence is that while there is now a lower morbidity due to foodborne diseases, more recalls than ever are leading to poor public perception (Kramer et al., 2005). Outbreaks, due to the nature of our changed food system, tend to be spread out over a wide geographic area due to low-level contamination in processed foods (Rocourt et al., 2003, p. 8) and may require new approaches to dealing with their associated illnesses, in part because of anti-microbial resistance (Newell et al., 2010). As stated by Havelaar et al (2010, p. S80) "Due to the nature of microbes and our food chain, measures to ensure food safety have to be implemented on a global scale, necessitating a global approach." Part of this global approach requires interdisciplinary research and new methods to understand and promote food safety from farm to fork in an interconnected, complex system.

2.4 Rationale for using Agent-Based Modeling

ABM has been met with enthusiasm in some fields of the social sciences, but has not yet been extensively used in public policy. Although some success has been seen in modeling land use management, public health, and water policy, there have been fewer applications in business and policy analysis (Moss, 2008). This is especially true with respect to food policy.

The strength of ABMs is that they provide a way to represent complex systems more simply, by focusing on the system's individuals and their behaviours (Railsback & Grimm, 2012). Axelrod (2003, p. 5) states that most modeling in the social sciences is informed by rational choice theory, not because many scholars feel that its assumptions accurately represent human behaviour, but because it allows for deduction. Adaptive behaviour offers a viable alternative to optimization; however, it requires simulation since the consequences of adaptation cannot be deduced. ABM offers an opportunity to relax the assumptions of rational choice theory to more realistically model how individuals make decisions by using straightforward behavioural rules.

ABM's ability to deal with heterogeneous populations that can use individual data, rather than aggregate data, is a unique feature with strong application to the social sciences. In many cases, social science problems are dealing with heterogeneous populations where variation is masked by aggregate data. The individual-based perspective marks an important departure from many theoretical positions in sociology and policy studies, which view society as a "hierarchical system of institutions and norms that shape individual behavior from the top down" (Macy & Willer, 2002, p. 144). Since people react to changes in their environment, and these reactions can cause further changes, this leads to difficulties in backtracking and applying different solutions to complex problems (Rittel & Webber, 1973). Methods that can incorporate change over time and control for these changes are able to more accurately capture social processes, and this is one area where simulation holds a lot of promise.

Although many people consider prediction to be a primary goal of modelling, depending on the data available and the goals of the modeling exercise, it is not the only one. Epstein (2008) notes that there are many other reasons to build models, including explaining a phenomenon, guiding data collection, discovering new questions, illuminating uncertainties and dynamics, demonstrating trade-offs, challenging theory, and opening new opportunities for policy discussion. Importantly, since all models are simplified abstractions, Epstein (2008, para. 1.12)

also states that “all the best models are wrong. But they are fruitfully wrong.” Stylized models that are designed to offer insight to a complex system or problem so that further discussion of policy alternatives, legislative changes, or other adjustments may take place may still be very useful, even if they are incapable of prediction.

Only a few authors have explored food safety using agent-based models.¹⁹ One example used the BSE outbreak in the United Kingdom as a case study to evaluate public risk perceptions using Cultural Theory (Bleda & Shackley, 2012). The archetypes (individualist, hierarchist, fatalist and egalitarian) from Cultural Theory were used to inform assumptions about agent perceptions. Social amplification of risk by the media and trust of government of science were also incorporated into the model. Verwaart and Valeeva (2011) constructed a model looking at producer decisions for improving animal health practices. The model incorporated economic incentives with social influence and was grounded in the theory of planned behaviour. Tykhonov et al. (2008) constructed an ABM of the trust and tracing game designed to collect data on decision-making behaviour in a food supply chain where there is asymmetric information about food safety and food quality. The model incorporated trading agents, representing producers, middlemen, retailers, and consumers as well as a tracing agent. The agents were separated into thrifty, opportunistic, or quality-minded categories, which affected their behaviour. Although it is possible to run experiments with human subjects to collect data on their behaviour in a trust and tracing game, these experiments are very time-consuming. By constructing a model, the authors could figure out which iterations of the game were the most interesting and then conduct these as experiments with human subjects. By incorporating theories of human behaviour with food safety scenarios, these models indicate the potential for advancing ABM in this area.

A concern voiced in the literature involves the scientific rigor and reproducibility of ABMs. Many of the models published in the literature are not described using a standard format that allows for others to reproduce them, making independent replication of results impossible (Richiardi et al., 2006). In order to contribute a reproducible model, a model description following the Overview, Design Concepts, and Details (ODD) protocol is given below.

¹⁹ Another ABM looking at compliance and pig farmers is available in Dutch (van Asselt, Osinga, Asselman, & Sterrenburg, 2012).

2.5 Model Description

The following section follows the ODD framework (Grimm et al., 2010) to clearly outline the objectives and implementation of a basic food safety inspection model. Using NetLogo (version 5.0.1),²⁰ a simulated environment was programmed where consumers, stores, and inspectors interact. One of the goals of the model was to observe the effect of information asymmetry on consumer behaviour. The system-level rules governing these interactions were changed in different versions of the model, allowing for comparisons between the scenarios. Insights from these scenarios can then be used to inform policy discussion.

Purpose: The purpose of this model is to provide insight into the role of information and its influence on the optimal level of inspectors in a food system. To explore this, we compare three search strategies used by inspectors: a random strategy,²¹ one where stores can signal to inspectors and consumers that there is a problem,²² and lastly, an adaptation of the signalling stores scenario that includes false positive and false negative signals.²³

Entities, state variables and scales: The entities included in the model are stores, consumers and inspectors. Food products and suppliers are assumed to be embedded within the stores. The tick counter is used to keep track of discrete time steps. Each time the ‘go’ procedure is called, the tick counter increases by one tick.

Patches: Patches have a variable called ‘store’; 100 store patches are scattered throughout the model. All other patches represent empty space. Stores are either contaminated or clean – these are represented by red and green in the model. In the scenario that includes possible errors in store signals, store patches also have a variable for the chance of a false positive or false negative signal, which ranges from .01 to .1.

Consumers: Consumer agents are a breed of turtle in NetLogo. There are 2000 of them at the start of the model run.

²⁰ NetLogo is available here: <https://ccl.northwestern.edu/netlogo/>

²¹ View this model in the CoMSES Model Library: <https://www.openabm.org/model/4137/version/2/view>

²² View this model in the CoMSES Model Library: <https://www.openabm.org/model/4141/version/2/view>

²³ View this model in the CoMSES Model Library: <https://www.openabm.org/model/4139/version/2/view>

Table 2.1 Variable description

Variable name	Description
Range	Consumers use a range of patches within which to search for potential destination stores
Immune system	Consumers have a probability that ranges from 10% to 50% of becoming sick should they land on a contaminated patch
Sick	Consumers become sick if they land on a contaminated store and the random number generated is less than immune-system
Bad store patches	List of stores that have made this consumer sick in the past
Destination	Changes each time step; set to the most suitable store within the consumer's range that is not a member of bad-store-patches
Heal counter	If a consumer becomes sick, it remains sick for 3 time steps and does not move

Inspectors: Inspectors have a range within which they look for patches to inspect; this range is twice the range of consumers. The number of inspectors in the model has been varied. Firstly, experiments were run using 1-15 inspectors to get a sense of model outcomes. More detailed experiments were then run using 1 inspector, 3 inspectors, and 5 inspectors, respectively.

Minimal spatial element: Consumers and inspectors both have a range within which they can see potential destinations. There are no collectives in the model. Simulations last for 150 time steps (or ticks, in NetLogo); the length of one time step is not specified.

Process Overview and Scheduling: Once the model is set up, the following processes, described under submodels, are executed in the following order.

- One store per time step is randomly selected and becomes contaminated.
- Consumers execute their consume procedure, as follows:
 - Destination-set
 - Consumers evaluate all stores within their range, and choose a store patch that is not on their list of bad-store-patches. If no such store exists, the consumer wanders by randomly setting its heading and moving forward three patches.
 - Eat

- If the store is contaminated and the random-number generated is less than immune-system, the consumer becomes sick and adds this patch to the list bad-store-patches. The consumer also sets its heal counter to 1.
 - If the consumer is sick, it does not execute the above two procedures, but instead adds 1 to its heal-counter.
 - Inspectors test
 - The testing procedure varies depending on the complexity of the model version.
 - In this most basic model, inspectors move randomly to a store within their range. If the store happens to be contaminated, the inspector changes the contaminated variable from 1 back to 0 and changes the store's colour to orange. If the store is not contaminated, the inspector does nothing.
 - In the 'stores signal' scenario, 5 stores per time step are selected to signal; if they are contaminated, they turn pink, which lets consumers know to avoid the store and lets inspectors know to come check it first.
 - In the 'stores signal with errors' scenario, 5 stores per time step are selected to signal. If the store is contaminated and a random floating point number is greater than the store's 'signal-error' variable, then the store signals. If the floating point number is smaller, then the store will not signal even though it is contaminated (a false negative). As well, if the selected store is not contaminated, but the random floating point number is less than the store's 'signal-error variable, then the store will signal even though it is not contaminated (a false positive.)
 - Consumers that have been sick for three time steps heal.

Since there are no collectives in the model, the order in which each consumer, inspector or patch executes the above is not important.

Design Concepts:

A number of concepts and theories underlie the model's design, and they have been used to influence the variables and the submodels used in the model.

The following basic principles, adapted from the literature on food safety, have been incorporated into the model.

Embedded supply chain: In the model, suppliers and producers are embedded and only stores are explicitly shown in the model. Since consumers only interact with stores and restaurants, and they bear the brunt of responsibility for supplying ‘safe’ food products, this element greatly simplified the construction of the model. The literature also supports this point: “When major food safety issues arise, both retailers and manufacturers will be affected (if not harmed) by any recall, even if they are not to blame for the problem” (Grievink, Josten and Valk, 2002, p. 481-2, as cited by Havinga, 2006).

Inspection system: In the Canadian context, the Canadian Food Inspection Agency is responsible for enforcing policies set by Health Canada that govern the safety of food sold in Canada; the CFIA fulfills this mission by inspecting federally-governed abattoirs and food processing plants. When food safety emergencies occur, the CFIA responds along with Health Canada, provincial ministries, and industry to respond; food recalls are coordinated by CFIA staff. The CFIA is also responsible for enforcing laws on labeling and packaging, regulating products derived from biotechnology (although Health Canada is responsible for assessing the safety of new foods) and certifying exports and initial import inspections of food and agricultural products, among other responsibilities (Government of Canada, 2013). Provincial governments are responsible for provincially-licensed abattoirs, which can only sell meat in the province in which they are licensed. Restaurant and food service inspection is quite fragmented, and is generally carried out by municipalities, regional health authorities, or the provincial government, depending on the province (Government of Canada, 2014). Although products sold in grocery stores and restaurants have generally been inspected further up the supply chain, these inspections are not represented in the model. The model presented in this paper most closely mirrors the inspection of restaurants and food service outlets.

Immune system: This is one area where there is no real answer in the literature. Although there have been advancements in predictive microbiology, a method used to predictively model pathogen spread, persistence, and death in a food source (Lammerding & Paoli, 1997; Walls & Scott, 1997), this research does not provide a clear translation of how pathogen loads in a food

source affect the actual occurrence of illness.²⁴ Certain groups, such as the elderly, young children, pregnant women, and immune-compromised people are more susceptible to foodborne pathogens than others (Gerba et al., 1996), but there is uncertainty as to the actual likelihood of illness from consuming contaminated food products. As such, model runs were completed using an immune system parameter that is heterogeneous and varies throughout the population between .1 and .5.

Consumer avoidance: Previous research conducted by the Food Standards Association in the UK indicates that, if they had concerns about hygiene, up to 70% of respondents would not purchase again from a food service outlet (as cited by Choi, Nelson, & Almanza, 2011). As well, focus group research from the UK has indicated that personal experience with food poisoning is an important source of knowledge for changing food safety behaviour, and some quoted participants indicated that getting sick after eating specific products from a supermarket meant that they would never return (Green et al., 2003, p. 44). Since the literature did not provide adequate explanation of what factors would influence a consumer to return to a food service outlet where they believed they had contracted an illness, this concept was simplified for use in the model: consumer agents will not return to stores where they have become sick in the past.

Store signals: It is possible for a store to close temporarily and trigger an investigation from inspectors if it realizes that there is a problem with its food. For example, during the 2012 XL Foods *E. coli* outbreak, a Regina restaurant called Flip decided to close its doors when five people reported cases of *E. coli*, and the only common feature with all five cases was that they had recently eaten at Flip (CBC News, 2012a). Although the restaurant had recently been inspected and had passed, the owner voluntarily closed the restaurant to keep any other customers from becoming sick while the source of the contamination was determined. This element has been incorporated as a signalling mechanism, where stores change their colour to

²⁴ One such example that was decided by the courts took place in the United States, where FSIS tried to shut down a processing plant that had exceeded Salmonella counts. The plant refused on the basis that the product had come contaminated from the slaughterhouse, and the plant never failed any sanitation tests. A federal judge ruled that FSIS could not withdraw inspection based on Salmonella counts alone: “The appeals court ruling supports arguments of those who say that pathogen testing results should not be a basis for enforcement actions until scientists can determine what constitutes a unsafe level of Salmonella in ground meat” (Rawson & Becker, 2004).

communicate with inspectors that they should be inspected first and so consumers can avoid that location until the contamination has been rectified.

Store signals with errors: On occasion, stores with a suspected problem may choose to ignore it and not close; there is also the possibility that a store will close unnecessarily. The restaurant Flip, as mentioned above, closed temporarily to undergo thorough testing, which found no E. coli present on surfaces or food samples (CBC News, 2012b). This has been represented in the model by stores signalling with a small chance of either a false positive or false negative signal. This allows for less than perfect information in signalling, which reduces the efficiency of inspections.

Asymmetric information: This principle is informed by Akerlof's (1970) work on asymmetric information in markets. Consumers and inspectors are unable to tell if a store is contaminated prior to landing on it. An interesting application of this theory in future models would be to incorporate signals of quality, such as branding, inspection certificates, or other quality assurance methods.

No consumption while sick: Given the typical symptoms of diarrhea and vomiting that accompany foodborne illness, the assumption that one would stay home and avoid going out to stores or restaurants seems reasonable. This was also implemented for practical modeling reasons, as it prevents a consumer from landing on a contaminated store and becoming sick while already infected from a previous visit.

Emergence: The important results from the model are the overall numbers of sick agents, contaminated stores, inspected stores, and "naïve" agents at the end of the model. Since the changes between model versions are imposed by changes in the rules that agents follow, the results are built in and not the result of emergent behaviour.

Adaptation/learning: Consumers adapt their behaviour by updating the list bad-store-patches. If they have gotten sick from eating at a contaminated store, they add this store to the list and avoid this patch in the future (even if the store has since been inspected and it is no longer contaminated). Consumers also avoid signalling stores.

Objectives: Consumers want to avoid getting sick, and this fits into their adaptive behaviour of avoiding stores that have made them sick in the past. Store patches want to avoid contamination, and if that is not possible, avoid making consumers sick by signalling – although this is imposed. An implicit assumption is that inspectors should inspect efficiently; again, the different inspection strategies are imposed, rather than allowing the agents to choose which they prefer.

Sensing: Inspectors and consumers have the same sensing capabilities: both types of agent can sense when a patch is signalling, and they can tell whether a store is contaminated once they land on it. However, landing on a contaminated store may make consumers sick, but inspectors can reverse the contaminated variable so that the store is safe again. Consumers cannot sense whether a patch has recently been inspected or whether consumers near them are sick.

Interaction: At this stage, neither consumers nor inspectors interact with one another directly. Consumers interact with stores by visiting them (although other consumers may be present there at the same time) and consuming, and inspectors interact with stores.

Stochasticity is used in generating a random number to determine whether or not the consumer will get sick. Also, if consumers complete the ‘wander’ procedure, they determine a heading randomly and move three patches in that direction. Prediction is not used. There are no collectives, or “aggregations of agents that affect the state or behavior of member agents and are affected by their members” (Railsback & Grimm, 2012, p. 41), in the model.

Observation: The following attributes are tracked using BehaviorSpace at each time step. This output was then analyzed in R (version 2.15.1)

- The number of agents that are sick (indicated by brown agents in the model)
- The number of signalling (pink) stores at any one time
- The number of contaminated (orange) stores that inspectors inspect
- The number of stores that stay contaminated (red)
- The number of “naïve” consumers (those that have never gotten sick over the course of the model run, indicated by yellow agents)

Initialization: Model runs were executed with 2000 consumers, 100 stores, and 1, 3 or 5 inspectors. The world was set to 33x33, for 1089 total patches, with a centre origin point. The world wraps both horizontally and vertically. Each simulation was run for 150 time steps.

To determine the appropriate number of consumers and stores, simulations were run at various levels of stores and consumers. The actual density of food service outlets is about 1 for every 350 Canadians (Statistics Canada, 2006). However, approximating this density in NetLogo would have a prohibitive time cost; running very large simulations in BehaviorSpace is extremely slow. To balance the effects of scaling up with the time cost of running multiple scenarios, 2000 consumers and 100 stores were included in the model.

Consumers: All consumers have immune-system set to between .1 and .5, sick set to 0, heal-counter set to 0, and range set to 5. The lists destination and bad-store-patches are empty. Consumers are scattered randomly throughout the world.

Patches: Of the 1089 patches in the environment, 100 are selected, and store is set to 1. All store-patches have the contaminated variable set to 0 at initialization.

Inspectors: All inspectors have a range of 10. They are scattered randomly throughout the world.

Most of these initial values were estimated, as there is little empirical data available. No data was incorporated from other models or external data files.

Submodels:

Consumers: “Healthy” consumers are asked to complete the consume procedure; consumers that are sick must remain on their last destination for 3 time steps. The consume procedure contains two sub-procedures: destination-set and eat. To destination-set, consumers identify which patches within their range are stores that are not on the list bad-store-patches (and are not signalling that they are contaminated, depending on the model version). They then choose one of these destinations from the patch-set and move there. If no patches within their range meet the criteria, the consumer wanders by setting their heading randomly and moving forward three patches. In the eat procedure, the consumer identifies whether or not the patch they have landed on is contaminated. If it is contaminated and the random number generated is less than the consumer’s ‘immune-system,’ the consumer’s sick variable changes to 1 from 0 and the

consumer changes its colour to brown, then adds this patch to the its list bad-store-patches. All consumers execute this code in a random order. More than one consumer can land on a store at the same time.

Inspectors: Inspectors are asked to complete the test procedure. Depending on the model version, the inspector is instructed to test any signaling (pink) stores within its range first, since these ones are signaling that they may be contaminated. Otherwise, the inspector chooses a store within its range at random and checks it. When the inspector lands on a store that is contaminated, it changes the store’s contaminated variable back to zero and changes the patch colour from red (or pink, if it was signaling) to orange. If the patch is not contaminated, the inspector does nothing.

Patches: Only patches that are stores and belong to the agent-set ‘store-patches’ will be discussed here. All other patches simply represent empty space. Store patches all start out green to indicate that they are not contaminated, and one store per turn is instructed to change its contaminated variable to 1 from 0 and its colour to red. Agents cannot sense this information prior to landing on the store, unless the store is pink to signal contamination. In versions that incorporate signaling, five patches per time step are instructed to check themselves for contamination. If a selected patch is contaminated, it signals this to consumers and inspectors by changing its colour to pink. In the scenario that allows for signals with errors, the signal procedure incorporates a random floating point number. If the store is contaminated and the random number is less than its ‘signal-error’ variable, the store will not signal even though it should, and if the patch is not contaminated but the random number is less than its ‘signal-error’ variable, the store will signal, even though it is clean.

Table 2.2 Scenario summary

	Baseline	Signal	Signal with errors
Consumers	Avoid “bad stores”	Avoid “bad stores” & signalling stores	Avoid “bad stores”& signalling stores
Inspectors	Test randomly	Test signalling stores first; if none in range, test randomly	Test signalling stores first; if none in range, test randomly
Patches	Random contamination	Random contamination, up to 5 stores signal per time step	Random contamination, up to 5 stores signal per time step (but signals are uncertain)

2.6 Analysis of Model Results

Initially, all model scenarios were run with the number of inspectors ranging from 1-15. The marginal returns of adding additional inspectors are minimal once there are five inspectors in the model; therefore, more detailed runs were conducted using 100 repetitions each of one, three, and five inspectors. Each model run lasted for 150 time steps and all data was collected at the end of the model run. Analysis of variance (ANOVA) was conducted to check the statistical significance of having one, three, and five inspectors for each scenario, and was followed by post-hoc analysis using pair-wise t-tests, using the Bonferroni correction to account for multiple comparisons. Unless otherwise stated, the pairwise analysis results are statistically significant ($p < .001$).

The first scenario is the most simple (see Table 2.3); inspectors move randomly from store to store and consumers receive no information besides whether or not they become ill. The number of sick consumers declines substantially as the number of inspectors goes up, but with decreasing marginal returns. As well, the number of contaminated stores decreases as inspectors are added, and the number of inspected stores increases, again with decreasing marginal returns. The decrease in contaminated stores is likely fueling the declines in the number of sick consumers. Lastly, the number of naïve consumers increases as there are more inspectors in the model, but even with five inspectors, only a very small percentage (1.2%, on average) of the total population never experiences an illness over the course of the model run.

Table 2.3 Random inspection scenario

	1 inspector		3 inspectors		5 inspectors		ANOVA	
	Mean	SD	Mean	SD	Mean	SD	$F(1,298)$	p -value
Sick Consumers	499.22	38.41	310.21	38.02	227.48	35.36	1807	$p < .001$
Contaminated Stores	49.02	3.86	26.24	3.06	17.03	2.69	2463	$p < .001$
Inspected Stores	29.47	3.36	51.97	3.84	60.62	4.09	1947	$p < .001$
Naïve Consumers	0.91	1.627	8.35	3.83	25.66	10.58	633.2	$p < .001$

The next step in advancing the model was to allow five randomly selected stores per tick to signal. This signaling mechanism would be similar to a store realizing that there was a problem and voluntarily closing its doors and inviting in inspectors to help rectify the issue. In this

scenario, signaling information is perfect; that is, a signal indicates that the store is definitely contaminated. The results of this scenario are shown in Table 2.4.

Since inspectors move first to signaling stores within their range and consumers avoid these stores, even though very few stores were self-testing at any given time, the number of sick consumers was considerably reduced compared to the random inspection model. The effect of signaling information is profound: outcomes are better with only one inspector when there is signaling (209.8 sick consumers, on average), compared to having five inspectors conducting random inspections (227.48 sick consumers, on average). Inspectors are also able to control the number of contaminated stores more effectively, particularly when there are few inspectors. Increasing the number of inspectors from 3 to 5 shows that the effectiveness of the signal mechanism is subject to considerable decreasing marginal returns, likely because the inspectors' ranges begin to overlap and a signaling store could end up with more than one inspector there at the same time. In the case of signaling stores, there was no significant effect in post-hoc testing ($p > .05$) of increasing the number of inspectors from three to five, even though the overall ANOVA results were still significant. The number of naïve consumers also increases compared to the random inspection scenario, but even with five inspectors in the model only about 6% of the total population, on average, avoids becoming ill over the course of the model run.

Table 2.4 Stores signal with certainty

	1 inspector		3 inspectors		5 inspectors		ANOVA	
	Mean	SD	Mean	SD	Mean	SD	$F(1,298)$	p -value
Sick Consumers	209.8	39.24	161.32	30.67	136.63	30.04	231.6	$p < .001$
Contaminated Stores	20.57	2.55	11.92	2.22	9.21	2.15	883.4	$p < .001$
Inspected Stores	57.61	3.62	66.16	3.75	68.6	3.97	368.8	$p < .001$
Naïve Consumers	34.69	11.22	74.39	18.12	120.52	25.61	992.5	$p < .001$
Signaling Stores	5.09	2.12	0.44	0.61	0.17	0.4	439.5	$p < .001$

Finally, a scenario was constructed to investigate the impact of imperfect information in store signals. This variation on the stores signal scenario included errors: when stores are selected to signal whether or not they were contaminated, there is a chance between 1% and 10% that a 'clean' store may signal, or that a contaminated store may not. In this variation, there were slightly more sick consumers, on average, compared to the version with perfect signaling

information, as well as slightly higher levels of contaminated stores and lower levels of inspected stores. However, the difference between the two scenarios shrinks as more inspectors are added. Once again, in the case of signaling stores, there was no significant effect of going from three to five inspectors in post-hoc testing ($p > 0.05$), even though the overall ANOVA results were still significant. Table 2.5 shows the results for the scenario with stores signaling with errors.

Table 2.5 Stores signal with errors

	1 inspector		3 inspectors		5 inspectors		ANOVA	
	Mean	SD	Mean	SD	Mean	SD	$F(1,298)$	p -value
Sick Consumers	223.55	37.37	168.63	26.64	139.81	31.72	327	$p < .001$
Contaminated Stores	23.58	2.45	13.06	2.11	9.72	2.12	1224	$p < .001$
Inspected Stores	48.26	4.11	55.55	4.33	58.7	4.31	287.4	$p < .001$
Naïve Consumers	26.22	8.39	63.04	17.52	103.72	25.21	890.3	$p < .001$
Signaling Stores	9.1	3.04	0.87	0.97	0.29	0.57	574.1	$p < .001$

To check for a significant effect of scenario type while controlling for the number of inspectors present, analysis of variance was conducted. Post-hoc analysis using pair-wise t-tests was also completed. Unless otherwise stated, the pairwise analysis results are statistically significant ($p < .001$). The ANOVA results are reported in Table 2.6.

Table 2.6 All three scenarios

	1 inspector		3 inspectors		5 inspectors	
	ANOVA		ANOVA		ANOVA	
	$F(2,297)$	p -value	$F(2,297)$	p -value	$F(2,297)$	p -value
Sick Consumers	1812	$p < .001$	666	$p < .001$	252.5	$p < .001$
Contaminated Stores	2678	$p < .001$	1013	$p < .001$	350.1	$p < .001$
Inspected Stores	1494	$p < .001$	343.6	$p < .001$	161.8	$p < .001$
Naïve Consumers	465.5	$p < .001$	575.5	$p < .001$	547.8	$p < .001$

The post-hoc analysis showed that as inspectors are added, the difference between the scenarios shrinks; this is especially true for the stores signal with certainty and stores signal with errors scenarios. When there is one inspector, the difference in the number of sick consumers between stores signaling with certainty and stores signaling with errors is significant ($p < .05$), but with three inspectors, the results are not statistically significant ($p > .05$) and with five inspectors, they

are identical ($p = 1$). As well, with three inspectors, the difference in the number of contaminated stores is significant between the stores signal with certainty and stores signal with errors scenarios ($p < .01$), but once there are five inspectors, the results are no longer significant ($p > .05$).

Figure 2.1 shows the differences in the number of sick consumers for all three scenarios. The considerable difference in the number of sick consumers in the signaling scenarios compared to the random inspection scenario is clearly shown, as is the diminishing marginal returns of adding additional inspectors.

Figure 2.1 Sick consumers, all scenarios

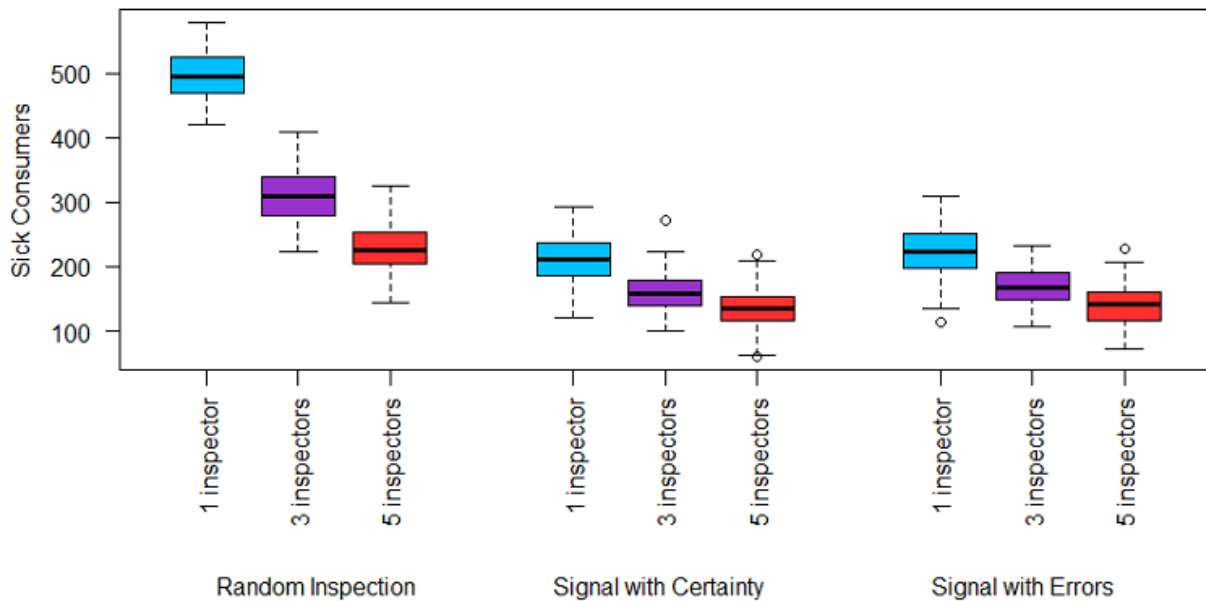


Figure 2.2 shows the number of contaminated stores for all three scenarios. Giving inspectors more information through signaling, even if that information is flawed, considerably reduces the number of contaminated stores.

Figure 2.2 Contaminated stores, all scenarios

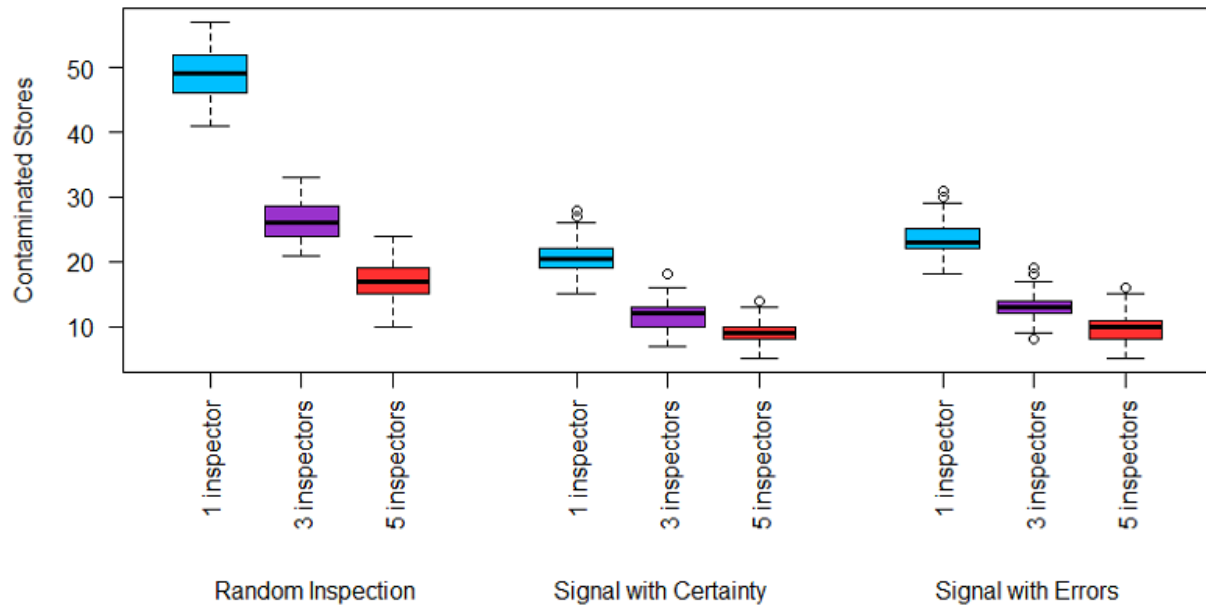
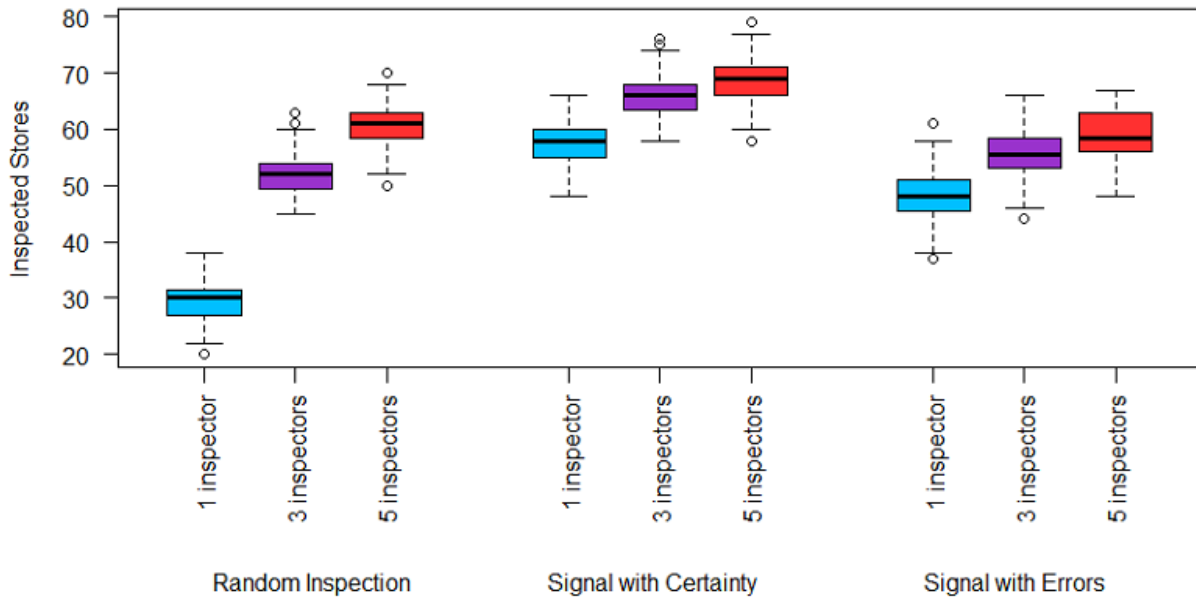


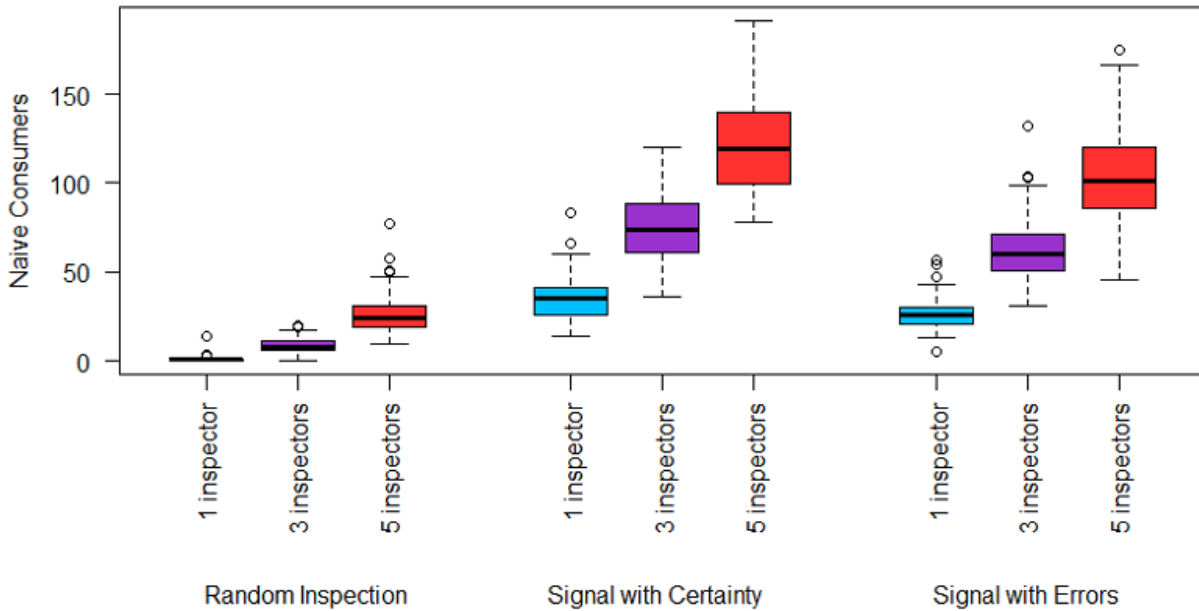
Figure 2.3 shows the number of inspected stores for all three scenarios. Since in the signal with errors scenario, some stores are signaling without actually being contaminated, fewer stores are successfully inspected.

Figure 2.3 Inspected stores, all scenarios



Finally, Figure 2.4 shows the number of naïve consumers for all scenarios. Since consumers avoid stores that are signaling under the assumption that they are contaminated, fewer consumers become sick over the course of the model run in the stores signal with certainty scenario. However, when stores signal with errors, some stores that are contaminated should signal but do not, which results in slightly more consumers becoming ill at some point during the model run.

Figure 2.4 Naive consumers, all scenarios



2.7 Discussion and Conclusions

The above research shows that food safety is a complex problem, and that ABMs are an insightful way of studying complex problems. A simple model of a food safety system was presented using the ODD framework. The model results have a few applications to policy. Firstly, as stated by Bonabeau (2002) and Moss (2008), ABMs were noted as having great potential for policy but had been applied in only a few situations. This approach advances the literature by providing a model that incorporates inspectors, consumers, and stores into a food safety simulation. Only a handful of other models have been found in this area (Bleda & Shackley, 2012; Tykhonov et al., 2008; Verwaart & Valeeva, 2011). The model results also show the effect of giving inspectors and consumers more information: even if the information provided by stores signaling is uncertain, the outcome of having one inspector with access to imperfect signaling information (223.55 sick consumers, on average) is similar to five inspectors using random inspections (227.48 sick consumers, on average). In the current climate of government austerity, employing new means of improving consumer and inspector access to food safety information could improve outcomes without taxing already thin resources.

There are a number of avenues for future work using this model. Namely, the model should be adapted to better take advantage of the strengths of ABM by incorporating more heterogeneity

and complexity into individual agents. As well, inspection rules that are closer to the real world system, such as a tiered system of oversight which is used by the Regional Health Authorities in Saskatchewan and has been proposed by the CFIA (Canadian Food Inspection Agency, 2012), will be incorporated in future work, as will the influence of retailer compliance on outcomes. Some jurisdictions have also made inspection results public, giving consumers more information with which to make decisions on where to eat (Filion & Powell, 2009; P. A. Simon et al., 2005); the effect of this information on decision making will be used to inform future models. Green et al.'s (2003) work on the social meanings of food choice, the influence of social norms on decision making, and the role of information in social networks could be incorporated by including communication between neighbouring agents to share information on experiences with the safety of certain food outlets. Different types of information could be incorporated, which could provide additional insights on the effect of information on choice and adaptive agent behaviour.

In his work discussing New Public Management, Hood (1991) discusses three sets of core values in public management: sigma (efficiency), theta (fairness), and lamda (robustness). He characterizes sigma values as most closely related to New Public Management, where frugality is the standard of success and waste is the standard of failure. For theta values, the achievement of fairness is the standard of success and unfairness or bias is the standard of failure. Lastly, for lamda values, resilience is the standard of success and catastrophe, risk or breakdown is the standard of failure. These value sets apply to food production systems as well as to public management. In many supply chains, the tendency of business interests is to lean towards sigma values, where efficiency is king. However, as supply chains increase in complexity and change ever more rapidly as more actors are involved in the production and distribution of food, a movement towards greater resilience may be warranted,²⁵ even as this results in redundancies. As noted by Miller and Page (2007), a certain level of redundancy in complex systems may make them more readily adaptable. The balance of valuing efficiency or resilience is another trade off within the food policy space, as Hensen and Caswell (1999, p. 591) note:

²⁵ This sentiment is echoed by Hennessey (2003), who comments that narrow technology development platforms that may not be able to adapt to changes may introduce systemic risk into food production.

Rather, it is evident that policy is the outcome of a complex trade-off between alternative demands that reflect the interests of the different groups that might be affected. In the case of food policy this will include consumer, food manufacturers, food retailers and farmers, both at home and abroad, as well as government itself and taxpayers. One of the key challenges facing policymakers is to balance these alternative demands because, in many cases, these different groups apply alternative criteria, both when judging the need for food safety regulation, ex ante, and the success/failure of food safety regulation, ex post. Furthermore, these criteria are generally not explicitly stated, with the result that the policy debate lacks coherence and, in some cases, transparency.

Complex problems, if they are to be effectively handled by regulatory structures, require transparency and information shared between all stakeholders. Agent-based models that incorporate transparency, accountability and information exchange may be a useful source of insight for accomplishing these objectives.

CHAPTER 3

WHAT'S ON THE MENU: ASSESSING MANUFACTURED RISK IN RESTAURANT INSPECTION SYSTEMS USING AGENT-BASED MODELS

3.1 Abstract

To explore elements of foodborne disease as ‘manufactured risk’, an agent-based model (ABM) has been developed using NetLogo. The model shows a stylised version of the current policy environment for inspecting restaurants, and illustrates opportunities for improving the transparency of current inspection systems by disclosing inspection scores. The model also examines the effect of increasing restaurant compliance. The results show that giving consumers access to restaurant inspection scores results in a slightly higher mean number of sick consumers, but much less variation overall in the number of sick consumers. In both scenarios, more compliant restaurants results in fewer sick consumers.

3.2 Introduction

In his seminal work on the risk society, Beck (1992, p. 19) posited that “the social production of wealth is systematically accompanied by the social production of risks.” The way these risks are produced, distributed and defined by technical and scientific systems is a key source of conflict in modern society. A particularly interesting group of ‘manufactured risks’ is associated with foodborne disease. Given the modern, globally connected supply chain, and embedded threats to food safety combined with an aging population that is more likely to suffer from foodborne illnesses, it is clear that foodborne disease will become an increasingly important issue for Canadians. Eating outside the home has also been highlighted as a risk factor for foodborne disease (T. F. Jones & Angulo, 2006), and that Canadians continue to spend more on restaurant meals (GE Capital Franchise Finance, 2013; Statistics Canada, 2006), potentially increasing their chances of coming into contact with foodborne illness.

To explore elements of foodborne disease as manufactured risk, we developed an agent-based simulation model (ABM). The model is designed to represent a stylized version of the current policy environment for inspecting restaurants, illustrating opportunities for improving the transparency of current food inspection systems by disclosing inspection results. Although this policy issue has been explored using other methods including surveys (Henson et al., 2006) and

statistical modeling (P. A. Simon et al., 2005), the application of ABM is a new method for investigating this space. Results from the simulation analysis show that giving consumers more information about restaurant inspection scores results in a slightly higher average number of sick consumers, but much less variability. Overall, as the number of restaurants that comply with regulations increases, the number of sick consumers decreases.

3.2 The Risk Society

Risks in the modern world are different. Whereas most hazards in the pre-industrial era were based on natural causes, we now deal with new risks that stem from our attempts to control the natural world – they are caused by the industrial advancement of society. These manufactured risks,²⁶ as defined by Beck (1992, p. 21), are “a systematic way of dealing with hazards and insecurities induced and introduced by modernization itself.”²⁷ Manufactured risks, such as the risks associated with nuclear power or widespread pollution from agricultural fertilizers, transcend the boundaries of individual households, regulatory jurisdictions, and nation-states. They are generally imperceptible and thus require expert assessment using the tools of modern science, and they are prone to social constructions and definitions, while also having an equalizing effect because they often affect people across classes and countries (Beck, 1992, p. 23). The consequences of manufactured risks are political in nature. A key element of the risk society is that societal intervention involving decision-making and governance processes are what “transforms incalculable hazards into calculable risks” (Elliott, 2002, p. 295). This societal intervention changes the nature of society itself, and thus further changes the nature of risk through process known as reflexive modernization (Beck, 1992, p. 153).

Although concerns related to food safety are ancient (Keusch, 2013), the role of science, technology and scale in food production has arguably led to more uncertainty now in food systems than previously. Many of the key features of manufactured risks are applicable to foodborne disease. In fact, the concept of food risks as manufactured risks has been explored elsewhere (Green et al., 2003), but will be expanded here. The first aspect of manufactured risks

²⁶ Manufactured risks should be distinguished from manufactured uncertainty, which is when there is scientific consensus on the issue, but outside stakeholders (who may have questionable motives) “try to inject uncertainty into the equation” (Lofstedt, 2006, p. 882).

²⁷ As well, it should be noted that Beck, a philosopher, uses a very specific definition of risk. Risk definitions (such as hazard x exposure), as used in the bureaucratic Risk Analysis Framework, are more quantitative.

is their invisibility. Risks are hidden in everyday life, and are only brought to our attention through the application of the tools of science, such as risk assessments and microbiological analysis (Beck, 1992, p. 21). What is more confusing for consumers is that food that has been contaminated by bacteria generally looks, tastes and smells completely normal (Alberta Health, 2014). The invisibility of modern food risk means that consumers need assurance about the safety of food by experts or inspection agencies. Since these modern risks are invisible, they are socially constructed and defined, and these definitions shift over time as the media and other factors influence public attention and risk perception. Indeed, because risks are invisible and require ‘scientization’ in order to be perceptible to individuals, it is often unclear whether exposure to the risk has increased, or whether public perception of it has become heightened (Beck, 1992, p. 55).

A second aspect of manufactured risks is that they emerge from the production of wealth in modern, post-industrial societies (Beck, 1992). Like wealth, risks are distributed throughout society, but risk distributions are not directly tied to wealth distributions. Some risks affect the poor disproportionately, as some argue wealthy people may be able to “*purchase safety and freedom from risk*” (Beck, 1992, p. 35) in the form of higher quality of food that they perceive to be safer, for example, produce grown without the use of pesticides. Certainly, it could be argued that risk, globally, is dropping, thanks to many of the advantages of modernization such as vaccines and improved sanitation, but that it is not dropping equally for everyone. In terms of risks related to food, in many cases the ultimate consequence of foodborne disease is borne by the individual consumer who becomes ill. In these cases, knowledge about sources of food risk serves to shift risk distributions, as well as risk perceptions.

Some foodborne illnesses result from inappropriate handling or other problems at the final preparation stage. Recent work by Batz, Hoffman and Morris (2011, p. 13) indicates that 70 to 80% of outbreaks²⁸ from multi-ingredient dishes resulted from foods prepared outside the home. This means that such risks can be equalizing in a distributional sense – even those with money or power may not be able to avoid them. Foodborne disease risk is present everywhere. In 2013,

²⁸ The CDC (2014b) defines a foodborne disease outbreak as “an incident in which two or more persons experience a similar illness after ingestion of a common food, and epidemiologic analysis implicates the food as the source of the illness.”

Noma, a Copenhagen restaurant that is considered to be among the world's finest, was the source of a norovirus outbreak that sickened 63 diners (Abend, 2013). Food risks also have a "boomerang effect" (Beck, 1992, p. 37) where even those who are producing the risks are afflicted by them. This is especially the case with food since we all need to eat.

Lastly, modern risks are often politically explosive. There are extensive social, economic and political side effects of health risks, a situation made apparent in the fallout following the discovery of the link between bovine spongiform encephalopathy (BSE) and Creutzfeldt-Jakob Disease (vCJD) in the United Kingdom (Palmer, 1996). Following such an outbreak, people tend to employ risk avoiding behaviours (Yeung & Morris, 2001) and reduce their consumption of implicated foods, but then slowly return to previous consumption levels (Bocker & Hanf, 2000; Knight, Worosz, & Todd, 2009). This element of consumer behaviour is consistent with the risk society: "Where everything turns into a hazard, somehow nothing is dangerous anymore ... The risk society shifts from hysteria to indifference and vice versa" (Beck, 1992, pp. 36–37).

3.3 Emerging Issues Related to Foodborne Disease

Food supply chains now are more interconnected and complex than ever. Global food trade has increased from approximately 50 billion USD in 1960, to 438 billion USD in 1998, to 1060 billion in 2008 (Ercsey-Ravasz et al., 2012). Such a rapid increase has obvious implications for foodborne disease outbreaks, especially since trade has moved away from staples and into finished, ready to eat products, which pose challenges for traceability. Ultimately, the modern dense, complex global supply chain could allow for foodborne pathogens to spread very quickly and thus make it extremely difficult to isolate the source of an outbreak (Ercsey-Ravasz et al., 2012; Keusch, 2013; McEntire, 2013). Risks that are global in nature and extend beyond national boundaries are key elements of the risk society (Beck, 1992). Since many foods are now imported, "food safety in Canada is not simply an outcome of a nationally bound system, but depends also on how well Canada's food safety system interacts with global institutions and systems" (Munro, Le Vallee, & Stuckey, 2012, p. 3).

However, there is uncertainty about the number of foodborne disease cases per year in North America. The overall disease burden of food-borne diseases is unknown (Newell et al., 2010). The Public Health Agency of Canada (PHAC) estimates that 4 million Canadians, or 1 in 8, are sick each year from foodborne illnesses (Public Health Agency of Canada, 2013). The Centers

for Disease Control and Prevention (CDC) estimates that there are 48 million cases, 128,000 hospitalizations, and 3000 deaths related to foodborne illness annually in the United States. This means that 1 in 6 Americans are sick each year (Centers for Disease Control and Prevention, 2013b). These estimates are built upon numerous assumptions; and both the CDC and PHAC acknowledge that there is underreporting, in part because many cases are relatively mild and thus not officially diagnosed.

Given differences between national reporting structures and surveillance, it can be difficult to compare data across countries and jurisdictions. A higher number of reported cases could simply be the result of better surveillance and improved reporting, and not necessarily because of more illnesses (Rocourt et al., 2003). Additional data from the Conference Board of Canada suggests that there are 6.8 million cases of foodborne disease in Canada each year (Munro et al., 2012 Appendix A) while survey data²⁹ indicates that approximately 8.5% of Canadians missed work in the last year because of foodborne illness (Munro et al., 2012, p. 9). However, the uncertainty associated with these estimates makes evaluating the effectiveness of current monitoring systems difficult. Although the goals of risk governance in the food system are to reduce the number illnesses caused by foodborne diseases, determining whether this has occurred is tricky when there are gaps in our understanding of the true burden of foodborne diseases.

Further uncertainties in demographic shifts illustrate the interconnectedness of foodborne diseases and demographics. In Canada, as in other OECD countries, population is aging at a rapid rate. Between 2006-2011, the number of seniors over 65 in Canada increased by 14.1% and now comprise around 5 million people, while the 60-64 age group grew by 29.1% over the same time period (Statistics Canada, 2013). The Canadian Food Inspection Agency identifies adults over 60 as an at-risk population for foodborne disease (Canadian Food Inspection Agency, 2013). Additionally, pregnant women, young children, and immunocompromised people are more prone to foodborne illness (Gerba et al., 1996). As the Canadian population ages, the incidence of diseases that accompany age such as cancer and diabetes are likely to increase. Individuals who suffer from these illnesses are necessarily more prone to foodborne illness. Additionally, advancements in medical technology such as chemotherapy and anti-retroviral

²⁹ The Conference Board of Canada obtained this data based on respondents self-reporting foodborne illness.

drugs will lead to a greater number of immunocompromised individuals living longer, with associated implications for foodborne illness incidence and severity. These interconnected elements of the food system further contribute to the uncertainty of managing risks related to foodborne diseases.

Consumer Perceptions of Foodborne Illness Risk

Particularly in the absence of a recent food illness catastrophe, focus group research shows that safety is just one of many attributes influencing food purchasing decisions. People report generally feeling quite competent at making food decisions (Green et al., 2003). But is this feeling correct? Although pronounced uncertainty remains as to the overall incidence and sources of foodborne illness (Jacob & Powell, 2009), estimates indicate that up to 70% of foodborne illnesses can be linked to foodservice establishments (as cited by Filion & Powell, 2009, p. 287). In turn, Canadians are spending an increasing amount of money on restaurant meals (GE Capital Franchise Finance, 2013; Statistics Canada, 2006). Due to these issues, the remainder of this paper will focus specifically on foodborne illness risks associated with eating food prepared by others in a restaurant environment.

Although restaurant inspection systems seek to lower the incidence of foodborne disease, evidence is mixed on how well inspection scores predict future illness outbreaks (P. A. Simon et al., 2005). In fact, the uncertainty in data on restaurant-related outbreaks makes it difficult to structure an effective study in this area (Filion & Powell, 2009, pp. 293–294). There are also inconsistencies between jurisdictions as to what constitutes a critical violation as well as the frequency of inspections (Filion & Powell, 2009). The complexity of the food chain implies that a systems-level perspective on restaurant food safety from ‘farm-to-fork’ is required to fully understand what is happening. But often the final responsibility for such decisions is simply shifted to the consumer, leaving it up to her to make sound choices with the (often incomplete) food safety information available. In this regard, some scholars have advocated for a greater level of transparency to encourage trust in food systems affected by contemporary risks, such as genetically modified food products (Clark, 2013; Goncalves, 2004). This raises the question – will improving transparency in the restaurant inspection system help consumers stay safe?

Some jurisdictions employ methods for giving consumers better access to inspection scores. For example, other jurisdictions, including the province of Saskatchewan, make recent restaurant inspection results available online.³⁰ In other areas, consumers must formally request a copy of inspection results (Filion & Powell, 2009), a situation presenting a strong ‘default’ barrier for accessing appropriate information (Thaler & Sunstein, 2008). Although the former is an improvement with respect to information transparency, the process still requires a consumer to choose a restaurant ahead of time and look it up in advance. Other areas have chosen to make information available to the consumer at the actual decision point. For example, Toronto requires all restaurants to post their most recent inspection notice at or near the main entrance (City of Toronto, 2012),³¹ while the city of Los Angeles requires that inspection scores, in the form of letter grades, be posted near the entry of a restaurant, as well as in an online database (P. A. Simon et al., 2005).

Previous related research in this area has focused on the economic concept of asymmetric information (Akerlof, 1970): by disclosing inspection results, consumers can incorporate this information in their decision-making, and restaurants have an economic incentive to comply with food safety statutes, lest they lose customers (Chatterji & Toffel, 2010; Jin & Leslie, 2003; P. A. Simon et al., 2005; Weil, Fung, Graham, & Fagotto, 2006). By giving consumers access to inspection information, transparency in the system would be improved, which could improve consumer trust; however, the interaction between increased trust and its effect on swings in consumer behaviour between hysteria and indifference requires further attention.

3.4 Methodology

This paper explores the questions of transparency in food inspection systems using an agent-based simulation model. This type of modeling provides a way to represent a complex system more simply by focusing on the system’s individuals and their behaviours (Railsback & Grimm, 2012). Agent-based modeling represents a significant departure from other methods that focus on reducing a system to its component parts, or on aggregating data and looking at averages. New methods are required to assist with unpacking system-level behaviours that may help us

³⁰ Saskatchewan Online Restaurant Inspection Information: <http://orii.health.gov.sk.ca/rhaReport.aspx?RHA=6>

³¹ See Filion & Powell, 2009 for a more in-depth discussion of other jurisdictions and their disclosure systems.

cope with the interconnected nature of the risk society. As described by Bonabeau (2002, p. 7280), “ABM is a mindset more than a technology. The ABM mindset consists of describing a system from the perspective of its constituent units.” This type of “microscopic modeling” involves modeling a system as a collective of semi-autonomous individuals making decisions (Bonabeau, 2002). Agents within the system are given simple rules for decision-making at the individual level; depending on these rules, agents can interact with others and react to changes in the environment (Gilbert, 2004). Emergence, a key concept in agent-based modeling, is present when these local interactions can give rise to interesting, and unexpected, macro-phenomena due to agents’ adaptive behaviour.

A further advantage of agent-based models is that they avoid the issue of reflexivity, where the problem shifts as solutions are applied, in a fashion similar to wicked problems (Rittel & Webber, 1973), because the simulations provide a controlled environment that allows for policy experiments. ABMs are also useful studying situations where real experiments would endanger subjects and therefore be unethical, for example, modeling the spread of disease (Louie & Carley, 2008). Furthermore, the incremental nature of building social computational models allows for continued refinement, repurposing, and data collection as new insights are gained. Although these simulation models may be used for predictive purposes, that is not their only use. Such models, even if stylized, can be used to provide insight into hypothetical policy scenarios (Epstein, 2008). What follows is a basic description of our stylized restaurant inspection simulation model. It has been used to compare and evaluate two relevant food safety policy scenarios.

3.5 Model Overview, Design Concepts, and Details

The Overview, Design Concepts and Details (ODD) framework has been suggested as a foundation for describing agent-based models in a consistent, detailed manner so as to facilitate re-implementation (Railsback & Grimm, 2012). The ODD protocol will be used in this section to describe the simulation model and environment.

The restaurant inspection model was implemented in the NetLogo³² (version 5.0.1) software. As a purposely designed agent-based software package, NetLogo supports three kinds of agents. These are referred to as turtles, patches, and links. Turtles are mobile agents and are used here to represent consumers and inspectors. Patches are locations (on a grid) as defined in the NetLogo computational environment. These have been used here to represent restaurants. Finally, link agents were not necessary to model this particular problem.

Purpose: The purpose of the model is to create a stylized food safety inspection system and compare two relevant policy scenarios. The first scenario incorporates elements of the current inspection system in the Canadian province of Saskatchewan.³³ In this case, restaurants are inspected by local health authorities and are assigned a re-inspection priority on a scale of low, moderate or high depending on risk factors identified during the inspection procedure. The second scenario to be examined builds on the first by giving consumers access to the re-inspection priority scores, and also incorporates elements of risk aversion in consumer choices.³⁴ Each scenario is evaluated based on the number of inspected restaurants, number of contaminated restaurants, and number of sick consumers over the course of the model run.

Entities, state variables and scales: The model contains three kinds of agents: consumers, inspectors, and restaurants. Consumers are endowed with state variables. These describe; i) whether they are sick, ii) whether they belong to an at-risk group, iii) the range over which they can travel, iv) their choice of next destination, v) a list of restaurants that have made them sick in the past, and vi) a count of how long they stay sick. In the second scenario, a risk aversion parameter is added for the consumer. In turn, the inspector only has a state variable describing their geographic range of operations. Finally, restaurants are defined by a global variable that describes whether or not a given patch is a restaurant, and also possess state variables describing where they are located, whether they are contaminated, their re-inspection priority, and whether they are compliant. Patches in the computational environment that are not defined as restaurants represent empty space. As in most NetLogo models, the computational environment is a torus that measures 33x33 grid squares with a central origin point, comprised of 1089 patches.

³² NetLogo is available here: <https://ccl.northwestern.edu/netlogo/>

³³ View this model in the CoMSES Model Library: <https://www.openabm.org/model/4304/version/1/view>

³⁴ View this model in the CoMSES Model Library: <https://www.openabm.org/model/4300/version/2/view>

Realizations of the model last for 75 time steps. The temporal scale of a time step and spatial scale of a patch are not specified.

Process overview and scheduling: The following processes take place once per time step in the following order.

- a) *Contamination spread:* The likelihood of restaurants becoming contaminated depends on whether or not they comply with regulations. Restaurants that are compliant have a 0.5% chance of becoming contaminated each time step, but restaurants that are not compliant have a 3% chance of becoming contaminated each time step. Restaurants that become contaminated change their contaminated variable from 0 to 1. This is shown visually in the model by changing the colour of the restaurant to red.
- b) *Consume:* Consumers who are not sick select a restaurant within their operating range that does not belong to their current list of ‘bad restaurants’ (places where they previously became ill) and move there to eat. If the consumer lands on a contaminated restaurant they have a chance of becoming sick, which also varies depending on whether they belong to an at-risk group. If the consumer becomes sick, they update their list of ‘bad restaurants’ and remain sick for a specified number of time steps, depending on whether the agent is part of an at-risk group. In the second scenario, the consumer also behaves in a risk averse manner for fifteen time steps after healing, meaning that they will only go to low re-inspection priority restaurants. If there are no suitable restaurants, i.e. restaurants that are not on the consumer’s ‘bad restaurants’ list, or, if the consumer has healed within fifteen time steps, are also at the lowest priority for re-inspection, within the consumer’s range, the consumer simply wanders to look for restaurants in future time steps.
- c) *Test:* Inspector agents prioritize restaurants based on three levels of re-inspection priority. Each time step they select a restaurant to inspect. They first choose high priority restaurants within their range, then moderate, then low. If the chosen restaurant is contaminated, the inspector fixes this by changing the restaurant’s contaminated variable from 1 to 0, and subsequently raises the re-inspection priority of that restaurant. If there is no contamination upon inspection, the inspector lowers the restaurant’s re-inspection priority (if possible).

- d) *Heal*: Consumers that have been sick for three time steps heal and then re-circulate. If they belong to an at-risk group, it takes five time steps to heal.

Design Concepts: Since this model represents a stylized restaurant inspection system, much of its design has been informed by the food safety literature. The following basic principles are incorporated into the design of the current model.

Embedded supply chain: Producers, distributors and suppliers that make up the global supply chain are not explicitly observed in the model. Since consumers only directly interact with the supply chain at the retail level and the model focuses on restaurant inspections, only restaurants are included. Grover and Dausch (2000, as cited by Knight et al., 2009) estimate that a foodborne illness outbreak could cost food service outlets \$100,000 and up to a 30% loss in sales due to decreased consumer trust. During a 1993 *E. coli* outbreak associated with 73 Jack in the Box restaurants in the US, 700 people became sick, and four children died. Although the contamination likely occurred during processing, the restaurant was held responsible for improper preparation³⁵ and lost US \$160 million in decreased sales, recall and legal costs in the 18 months following the outbreak (Knight, Worosz, & Todd, 2007, pp. 476–478). Even though a restaurant may not actually be at fault for contaminating a food product, in this model if they serve the product to customers they bear responsibility.

At-risk population: As noted, people who are elderly, very young, pregnant, or immunocompromised are more prone to foodborne illnesses and often suffer more severe consequences should they become sick (Gerba et al., 1996). For example, *Listeria monocytogenes* has a high mortality rate in high-risk individuals (up to 30%) and pregnant women who become infected with listeriosis may miscarry (Ramaswamy et al., 2007). In this model, 30% of consumer agents were designated as being at risk. This level was based on 2011 Canadian census data on the number of Canadians five and under, and over age 60 (Statistics Canada, 2013). The number of pregnant women in the model was extrapolated from the census using the number of children under the age of one. The number of individuals suffering from diseases that contribute to immune-compromised status were available prior to 2011 but not in a

³⁵ *E. coli* is killed by high temperatures, so proper preparation at the end of the supply chain would have limited the outbreak.

useful format. To avoid double-counting, this data was excluded, but the final level used in the model was rounded up to 30% from the prior estimates based on age and pregnancy (see Table 3.1). We recognize that this estimate is incomplete and that the total number of at-risk individuals in Canada is likely to be even higher.

Table 3.1 At-risk population³⁶

Total Canadian Population	33,476,690
Adults over 60	6,997,725
Children 5 and under	2,241,840
Pregnant women	367,930
Total at risk	9,607,495
Percentage of population	28.70%

In addition, exactly what level of contamination in a food product is unsafe and will thus translate into illness is unclear (Rawson & Becker, 2004). Therefore, any parameter for the probability of contracting an illness if a consumer goes to a contaminated restaurant is necessarily difficult to justify. The main point we seek to emphasize is that all else equal, the at-risk population is more likely to become ill from exposure to a contaminated restaurant. In this context, the probability of an at-risk consumer becoming sick from exposure is set at 0.3 whereas we assume the rest of the population has a probability of 0.15 of becoming ill given exposure. Additionally, at risk consumers remain sick for five time steps as opposed to three, to reflect the more severe consequences of foodborne illness for high risk individuals.

Consumer avoidance: Restaurant food is an experience good in that its quality cannot be ascertained prior to consumption (Henson et al., 2006). One survey that investigated consumers' perception of restaurant food safety found that 56.4% of consumers stopped frequenting a restaurant based on food safety concerns (Henson et al., 2006, p. 285). In addition, research conducted by the Food Standards Association in the UK indicates that, if individuals had concerns about hygiene, up to 70% of respondents would not purchase again from a food service outlet (as cited by Choi et al., 2011). In this model, this concept of avoidance has been

³⁶ Author's calculations based on The Canadian Population: Age and Sex from Census 2011 (Statistics Canada, 2013).

incorporated in a simplified way. Consumers that have become sick simply do not return to that restaurant. While a bit extreme, it does capture the notion of consumer memory and is not completely out of touch with actual reactions to this issue. This assumption is made recognizing that in reality, consumers may not be able to directly pinpoint the cause of foodborne disease, or may not realize that they have been affected by a foodborne illness if it is a mild case. Further research to determine the exact factors that would cause consumers to return to a restaurant where they had hygiene concerns will be needed to refine this assumption in the model.

Risk aversion: Consumers in the second or alternative scenario will only go to restaurants with a low re-inspection priority rating for fifteen time steps after healing. This is consistent with hysteria and indifference swings (Beck, 1992) and the observed tendency of consumers to gradually resume prior consumption patterns following an outbreak (Bocker & Hanf, 2000).

Asymmetric information: One assumption used in the model is that consumers and inspectors are unable to tell if a store is contaminated prior to arrival. This assumption is driven by the notion of asymmetric information (Akerlof, 1970). Elements of a restaurant that are relevant to safety, such as the cleanliness of food preparation and storage areas, are generally hidden from consumers, providing a further element of asymmetric information (Filion & Powell, 2009). However, the simulation allows for this fundamental asymmetry to be gradually eliminated, depending on agent type and scenario. In the first or base scenario, do recall that inspectors are privy to additional information in the form of the re-inspection priority levels. In the second or alternative scenario, consumers are able to see these levels as well, choosing only those restaurants with a low re-inspection priority following healing.

The model's key results and outputs include the number of sick consumers, the number of sick and at-risk consumers, the number of consumers that never get sick, the number of inspected and contaminated restaurants, and the number of restaurants for each re-inspection priority level. Most of the results seem to arise because of the rules and assumptions of the model. However, the reduction in variability seen in the second scenario is likely an emergent result that requires further discussion.

Consumers adapt their behaviour by updating the list of bad restaurants and avoiding these locations in the future, even if an inspector has inspected the restaurant. This captures the

consumer objective of avoiding sickness. In the alternative scenario, consumers further pursue this objective by only visiting low-risk restaurants following illness, a behaviour motivated by risk aversion and imposed by the model's rules. In the current model, there is no adaptive or learning behaviour exhibited by restaurants or inspectors. Given that some literature has shown that the introduction of grade score cards in Los Angeles County restaurants led to increases in inspection scores (Jin & Leslie, 2003), some form of adaptive restaurant behaviour should be introduced in future versions of this model.

Inspectors have different sensing abilities than consumers in the baseline scenario. Inspectors are able to observe the re-inspection priority level of a restaurant and search for a restaurant to inspect based on this criterion. Consumers are only able to use this information in the alternative scenario. Importantly, neither consumers nor inspectors can tell if a restaurant is contaminated prior to arriving at it. In addition, consumers cannot sense whether a restaurant has recently been inspected or whether consumers near them are sick (from the restaurant).

Consumers and inspectors do not interact in the model. Consumers interact with restaurants by visiting them, but they do not interact with other consumers who may also be present at that location at that time step. Inspectors interact with restaurants by inspecting them and changing their re-inspection priority and reversing contamination scores.

Stochasticity has been incorporated into the simulation in a number of places. Consumers are randomly assigned a travel range between three and eight units. This is based on the assumption that consumers have differing access to restaurants depending on where they live and their transportation options. Consumers with a larger range can move around the environment faster and have more choices available to them each time step. As well, consumers that cannot find any suitable restaurants in their range adjust their heading randomly and wander. Consumers are also randomly assigned to either the at-risk or normal population groups. Probabilities also determine whether a consumer will get sick at a contaminated restaurant, while a Bernoulli distribution is used to select which restaurants will be contaminated each time step.

BehaviorSpace, a built-in NetLogo extension for running simulation experiments, is used to track model output at the end of each model run. The data was then analyzed in R (version 2.15.1).

This data includes:

- The number of sick consumers
- The number of sick, at-risk consumers
- The number of contaminated restaurants that inspectors inspect
- The number of restaurants that are contaminated
- The number of what we call “naïve” consumers (those that have never gotten sick over the course of the model run)
- The number of restaurants at each level of re-inspection priority

Initialization: Model realizations are executed with 2000 consumers (30% of which belong to the at-risk group) and 100 restaurants.³⁷ There is one inspector in the model. Each realization lasts 75 time steps. The percentage of compliant restaurants is initially set at 60%, and is scaled up to 70%, 80% and 90%. For each change in the simulation model (i.e., for each increase in the percentage of compliant restaurants) the simulation is run 100 times, so each “experiment” lasts for 400 realizations.

Consumers: Consumers have their travel range set between 3 and 8 units, while their sickness variable, heal counter and risk aversion variables are all initially set to 0. Thirty percent of the consumers are randomly assigned to the at-risk group. Initially, individual lists for destination and bad restaurants are empty. Consumers are then scattered with equal probability throughout the operating environment.

Inspectors: All inspectors have a range of 10 units. They are initially scattered with equal probability throughout the environment.

Patches: Of the 1089 patches in the environment, 100 are randomly selected to serve as restaurants, with their restaurant variable set to unity to indicate this. These patches are then added to a patch-set. Finally, restaurant patches are randomly assigned with a re-inspection level of 0, 1, or 2, 0 being low priority and 2 being highest priority.

³⁷ The actual density of restaurants to consumers in Canada is approximately 1 to 350 (Statistics Canada, 2006). However, given the computational limits of NetLogo, this version of the model could not be scaled up to that level. Further work is ongoing with implementing a variation of this model in a software package called AnyLogic where the number of agents can be scaled up to more realistic levels.

3.6 Model Results

Initially, both model scenarios (that is, where consumers do not have access to re-inspection priority scores, and where they do and display risk averse behaviour for 15 time steps following healing) were run for 150 time steps and runs were measured at every step. Given that there was a ‘burn-in’ period of about 35-40 time steps, we decided to end the model run at 75 time steps and collect data at the end of the model runs. Both scenarios were repeated 100 times at each setting of 60%, 70%, 80% and 90% compliant restaurants. The Kruskal-Wallis test was conducted to check the statistical significance of each increase in the percentage of compliant restaurants within each scenario, and this was followed by post-hoc analysis using pair-wise Mann-Whitney-Wilcoxon tests, using the Holm correction to account for multiple comparisons. Unless otherwise stated, the pairwise analysis results are statistically significant ($p < .05$). For comparisons between scenarios, Mann-Whitney-Wilcoxon tests were used to check for statistical significance of consumer risk aversion at each setting of 60%, 70%, 80% and 90% compliant restaurants (see Table 3.4).

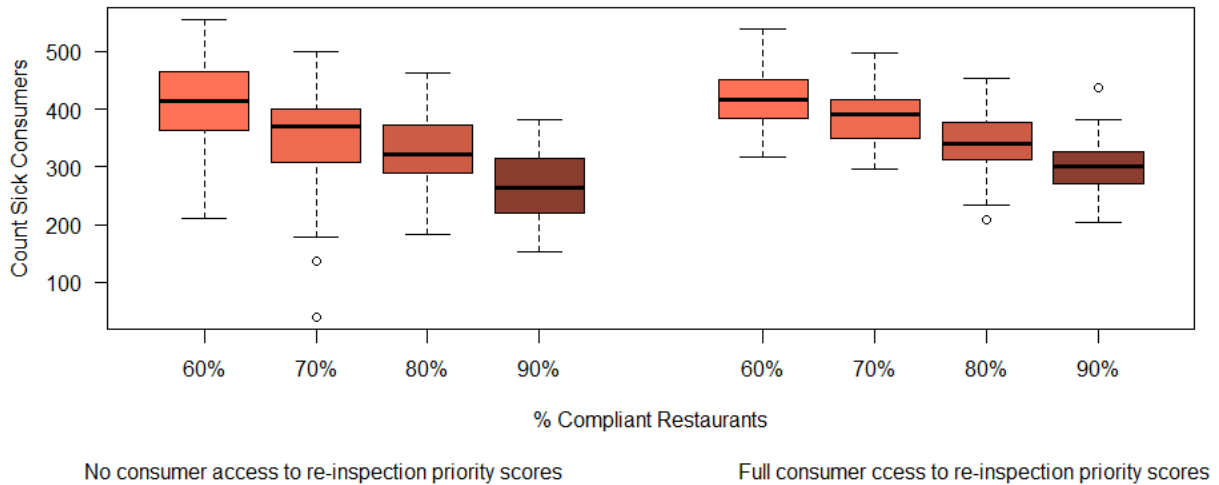
Table 3.2 Kruskal-Wallis results from both scenarios

	No consumer access to inspection scores									
	0.6 Compliant Restaurants		0.7 Compliant Restaurants		0.8 Compliant Restaurants		0.9 Compliant Restaurants		Kruskal-Wallis (3 df)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Chi-Sq	p-value
Sick Consumers	412.1	64.5	353.1	75.3	328.2	56.8	267.3	59	164.8	$p < .001$
Sick, At Risk Consumers	205.2	30.7	179.1	37.7	167.3	26.7	139.2	29.8	151	$p < .001$
Naïve Consumers	63.6	55.4	123.2	152.9	146	100.6	267.2	141.8	169.4	$p < .001$
Inspected Stores	9.6	2.1	9.6	2	9.3	2.3	8.7	2	9.8	$p = 0.02$
Contaminated Stores	45.5	4.8	38.6	4.1	34.4	3.9	28.4	4.1	285	$p < .001$
Low Risk Stores	47.9	7.2	50.3	9.3	52.8	8.4	55.3	7.2	438	$p < .001$
Moderate Risk Stores	51.6	7.2	49.3	9.3	46.9	8.4	44.3	7.2	41.4	$p < .001$
High Risk Stores	0.5	0.6	0.3	0.5	0.3	0.4	0.3	0.5	13.1	$p = 0.004$
	Full consumer access to inspection scores									
	0.6 Compliant Restaurants		0.7 Compliant Restaurants		0.8 Compliant Restaurants		0.9 Compliant Restaurants		Kruskal-Wallis (3 df)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Chi-Sq	p-value
Sick Consumers	418.9	45.9	385.8	45.8	342.1	47.4	297.9	41.2	209.5	$p < .001$
Sick, At Risk consumers	206.4	24.1	192.6	24.2	175.2	26.1	154.7	21.4	166.7	$p < .001$
Naïve Consumers	51.4	20.7	84.4	28.8	138.4	47.5	212.6	78.2	287.5	$p < .001$
Inspected Stores	10.1	2.1	9.5	2.2	9	2.5	8.6	2.2	24.6	$p < .001$
Contaminated Stores	44.7	4.2	38.8	3.9	33.8	4.2	28.7	4.1	278.3	$p < .001$
Low Risk Stores	47.7	8	50.9	8.3	54.5	8.4	56	8.5	51.6	$p < .001$
Moderate Risk Stores	51.9	7.9	48.8	8.3	45.3	8.5	43.8	8.6	49.4	$p < .001$
High Risk Stores	0.4	0.5	0.4	0.5	0.2	0.5	0.2	0.4	10.6	$p = 0.014$

In the first scenario, consumers do not behave in a risk averse manner following an illness. Interestingly, the mean number of sick consumers is slightly lower compared to the second scenario, where consumers are risk averse by only going to restaurants with a low re-inspection priority for 15 time steps following an illness (see Figure 3.1). However, note that this difference

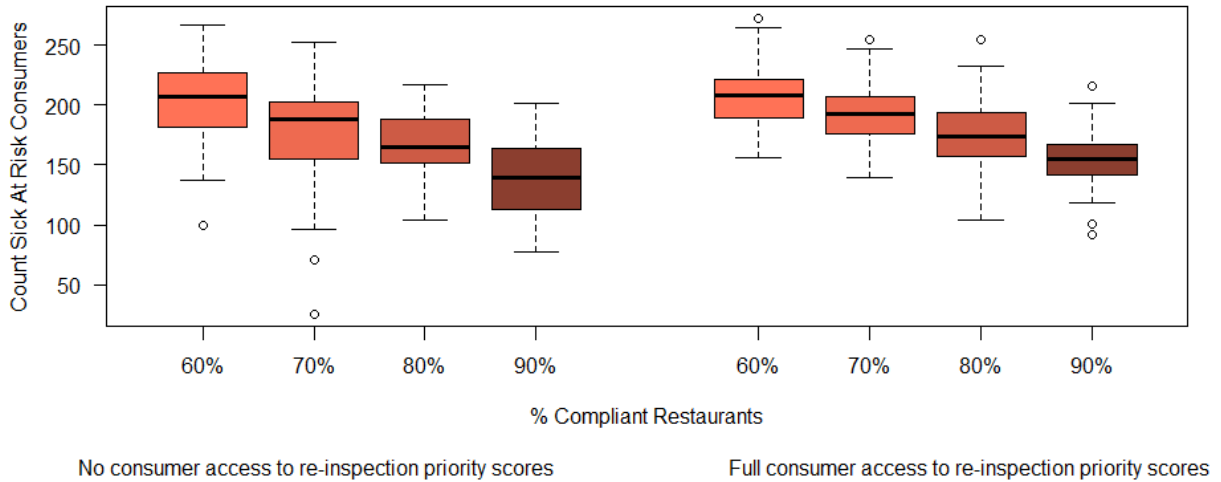
between scenarios is only significant ($p < .05$) when there are 70% and 90% compliant restaurants in the model (see Table 3.4). Also, even though the mean number of sick consumers is slightly higher in the second scenario, the overall variation in the number of sick consumers is reduced substantially.

Figure 3.1 Sick consumers, both scenarios



The results for the number of consumers in the at-risk group who experience sickness are very similar: in the first scenario, the mean number of sick, at-risk consumers is slightly lower, but there is less variation in the second scenario (see Figure 3.2). However, this difference between scenarios is only statistically significant when there are 90% compliant restaurants ($p < .001$).

Figure 3.2 Sick, at-risk consumers, both scenarios



Generally, the results from the first scenario are more skewed and often leptokurtic, whereas the results from the second scenario were less skewed and closer to a mesokurtic, or normal, distribution. A leptokurtic distribution is more peaked than normal and has fat tails, meaning that there are higher densities of values at the extremes. This phenomenon was most apparent in the numbers of naïve consumers (see Figure 3.3), that is, the number of consumers that never became ill throughout the course of the model run.

Table 3.3 Skewness and kurtosis test results for count naïve consumers

No consumer access to inspection scores			
	Skewness	Kurtosis	Standard Error
0.6 Compliant Restaurants	2.41	8.39	5.54
0.7 Compliant Restaurants	5.89	43.38	15.29
0.8 Compliant Restaurants	2.61	12.08	10.06
0.9 Compliant Restaurants	0.72	-0.33	14.18
Full consumer access to inspection scores			
	Skewness	Kurtosis	Standard Error
0.6 Compliant Restaurants	0.81	1.13	2.07
0.7 Compliant Restaurants	0.8	0.39	2.89
0.8 Compliant Restaurants	1.05	1.81	4.75
0.9 Compliant Restaurants	0.91	0.74	7.82

Figure 3.3 Naive consumers, both scenarios

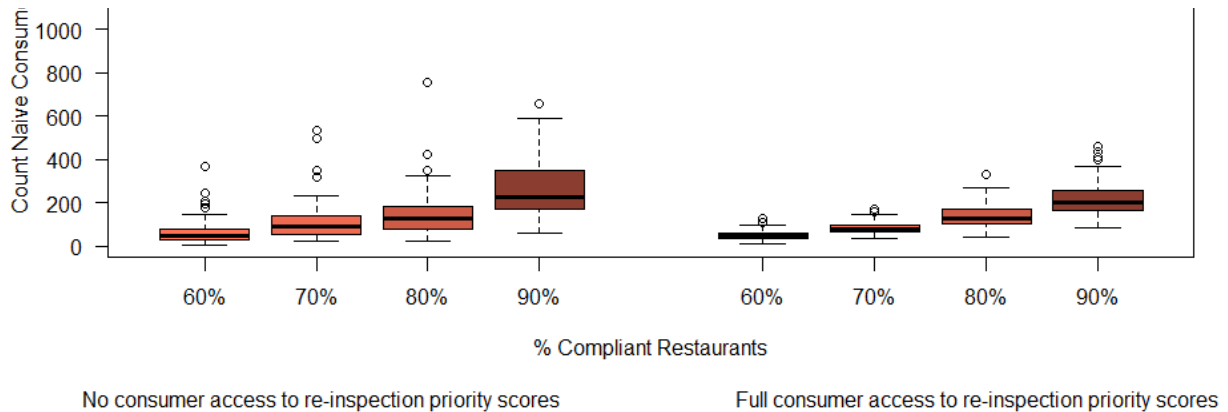
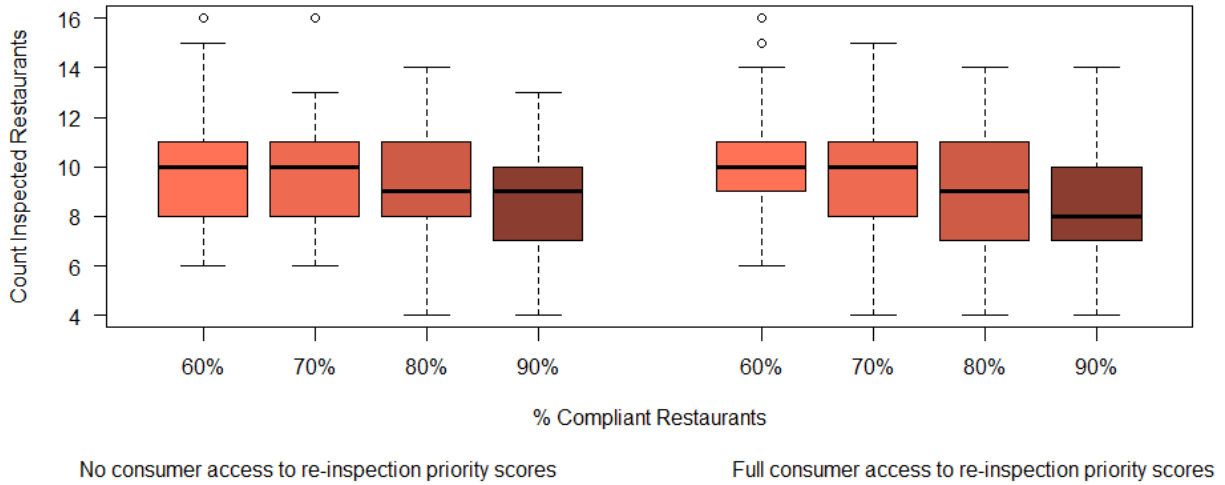


Figure 3.4 shows the numbers of inspected restaurants in each scenario. The post-hoc analysis showed that, for the first scenario, showed that the differences between 60% and 70% compliant restaurants, between 60% and 80% compliant restaurants, between 70% and 80% compliant restaurants, and between 80% and 90% compliant restaurants were not statistically significant ($p > .05$). For the second scenario, the post-hoc analysis showed that the differences between 60% and 70% compliant restaurants, between 70% and 80% compliant restaurants, and between 80% and 90% compliant restaurants, were not statistically significant ($p > .05$). When the two scenarios were compared (see Table 3.3), none of the differences were statistically significant ($p > .05$). As well, for this indicator, the variation was not greatly reduced in the second scenario. The number of inspected restaurants appears to decline as compliance increases; this is in part due to the model's construction, since compliant restaurants are less likely to become contaminated in the first place.

Figure 3.4 Inspected restaurants, both scenarios



In both scenarios, the number of contaminated restaurants declines as the percentage of compliant restaurants increases; this is in part because of the model’s structure, since compliant restaurants are less likely to become contaminated (see Figure 3.5). The differences between scenarios were not statistically significant ($p > .05$).

Figure 3.5 Contaminated restaurants, both scenarios

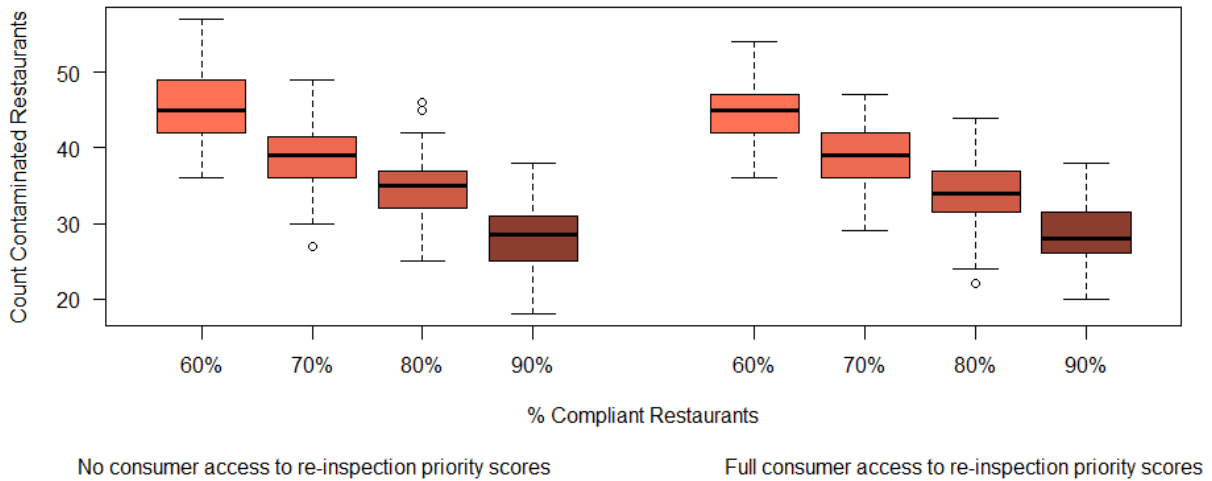


Table 3.4 sums up the comparisons between scenarios, divided by percentage of compliant restaurants.

Table 3.4 Mann-Whitney-Wilcoxon results

	0.6 Compliant Restaurants		0.7 Compliant Restaurants		0.8 Compliant Restaurants		0.9 Compliant Restaurants	
	Mann-Whitney-Wilcoxon		Mann-Whitney-Wilcoxon		Mann-Whitney-Wilcoxon		Mann-Whitney-Wilcoxon	
	W	<i>p</i> -value	W	<i>p</i> -value	W	<i>p</i> -value	W	<i>p</i> -value
Sick Consumers	4805	<i>p</i> = 0.63	3764	<i>p</i> = 0.003	4225	<i>p</i> = 0.058	3456	<i>p</i> < 0.001
Sick, At Risk consumers	4989	<i>p</i> = 0.98	4019.5	<i>p</i> = 0.016	4279	<i>p</i> = 0.078	3527.5	<i>p</i> < 0.001
Naïve Consumers	4915.5	<i>p</i> = 0.84	5530.5	<i>p</i> = 0.19	4757	<i>p</i> = 0.55	6005.5	<i>p</i> = 0.014
Inspected Stores	4308.5	<i>p</i> = 0.09	5192.5	<i>p</i> = 0.63	5299.5	<i>p</i> = 0.46	5293.5	<i>p</i> = 0.47
Contaminated Stores	5397	<i>p</i> = 0.33	4864	<i>p</i> = 0.74	5360	<i>p</i> = 0.38	4826	<i>p</i> = 0.67
Low Risk Stores	5142.5	<i>p</i> = 0.73	4916	<i>p</i> = 0.84	4375.5	<i>p</i> = 0.13	4719	<i>p</i> = 0.49
Moderate Risk Stores	4821	<i>p</i> = 0.66	5103.5	<i>p</i> = 0.80	5620.5	<i>p</i> = 0.13	5246.5	<i>p</i> = 0.55
High Risk Stores	5703	<i>p</i> = 0.045	4882.5	<i>p</i> = 0.73	5087	<i>p</i> = 0.78	5550	<i>p</i> = 0.07

3.7 Policy Implications and Conclusions

This study represents the application of a method for policy analysis that can be useful for shedding light on risks that typify the risk society, including foodborne illness, although further work is needed to improve the system perspective of the ABM featured here. The results from the model indicate that, overall, having access to restaurant inspection scores results in a slightly higher mean number of sick consumers, but much less variation in the overall number of sick consumers, over 100 realizations. This also holds true for the number of sick, at-risk consumers. For both scenarios, more compliant restaurants results in fewer sick consumers. As well, although there tended to be more naïve consumers when the consumers did not have access to inspection scores and therefore did not act in a risk averse way following an illness, these distributions tended to be leptokurtic, which indicates a higher probability of outcomes from the extremes; the results from the second scenario, when consumers did have access to inspection scores and behaved in a risk averse manner for 15 time steps following an illness, were generally

much closer to a normal distribution, with more predictable outcomes. Again, in both scenarios, a higher percentage of compliant restaurants results in more naïve consumers.

Our basic findings have implications for policy systems. First of all, the model reflects a basic tension between how much policymakers can and should do through regulation and how much should come from informing citizens and allowing them to make choices. Although the mean number of sick consumers was slightly lower when consumers did not have access to re-inspection scores, the high degree of variability in outcomes could present a challenge for inspectors; it may be preferable to have a slightly higher average number of illnesses, but more predictable and steadier outcomes, rather than large swings which could contribute to public panic and negative risk perceptions.³⁸ As well, given that many statistical procedures rely on assumptions of normality, outcomes that more closely conform to a normal distribution could contribute to better understanding of what is going on within the system and better predictive capacity from a policy perspective, which would be an advantage despite the slightly higher average number of illness.

Having a higher number of restaurants comply with regulations results in fewer sick consumers; empirical evidence shows that disclosing inspection results leads to increases in inspection scores (Jin & Leslie, 2003). Although a mechanism for restaurants choosing to comply with regulations was not explicitly considered in the model, there is evidence to suggest that disclosing scores would increase compliance, while improving transparency in the inspection system which would provide consumers with more information to make choices. However, Restaurants Canada, an industry lobby group, has indicated that they do not support the use of grades or scores to inform consumers about the hygiene of restaurants, indicating that “complex inspection findings based on subjective interpretations by individual inspectors cannot accurately or fairly be reduced to a single grade” (Griffith-Greene, 2014). The response from industry indicates that government intervention would be necessary to encourage transparency within the system. A further complicating factor is that restaurant inspections are the responsibility of regional health

³⁸ Although large, widespread outbreaks of foodborne illness are relatively uncommon, it seems likely that they are subject to the availability heuristic (Tversky & Kahneman, 1973), whereby people assume they occur more frequently because they are easily recalled. The availability heuristic could influence panic and public risk perception related to foodborne illness.

authorities or provincial authorities, depending on the province (Government of Canada, 2014); thus, there is inconsistent information available across the country depending on what each jurisdiction has opted to make public and how.

The incremental nature of model building will allow for additional exploration of inspection methods or information delivery methods in the future, one of the advantages of ABM modeling. Some possible extensions for this model include: communication between consumer agents, for example, a rumor mill indicating restaurants to avoid; a mechanism that allows restaurants to choose whether or not to comply with regulations, which may depend on whether they are receiving fewer visits from consumers; mechanisms that allow for the restaurant's level of compliance to vary over time; for example, this could mimic the effect of more experienced staff working, or hygiene measures sliding somewhat when the restaurant is extremely busy; or incorporating agents who 'learn-by-doing.' The ability to incorporate heterogeneity in agents' adaptive behaviour is a further advantage of ABM.

As well, this model needs further analysis and verification. At this point many assumptions are embedded in this stylized model, including those about the probability of illness in at-risk and typical consumer populations, the connection between re-inspection scores, compliance and contamination probability, and consumer behavior. The assumption that risk averse behaviour is homogeneous throughout the population, in particular, requires further investigation. To truly provide transparency and gain insight into this aspect of consumer behaviour, experiments could be conducted with consumers to determine which method of inspection information delivery is preferred and works most effectively. This avenue for research in the area has been mentioned before in the literature (Filion & Powell, 2009). Results from such experiments could then be used to inform future versions of an agent-based model through parameter setting and proper scaling of the analysis.

CHAPTER 4

AGENT-BASED MODELS AND HEALTH-ORIENTED MOBILE TECHNOLOGIES

4.1 Abstract

Objectives: Using system science techniques, we investigate the potential for health-oriented mobile technologies to improve the surveillance system for foodborne illness, using an agent-based model as a proof of concept.

Methods: An agent-based model features consumers, restaurants, and an inspector. Three scenarios were developed to include a sentinel population equipped with a mobile technology: firstly, the mobile technology allows sentinels to report instances of mild to moderate symptoms of foodborne illness (namely, diarrhea and vomiting); secondly, the device's location sensors report which restaurants sentinels have frequented more accurately than retrospective data collection; and thirdly, both aspects are combined.

Results: The model results indicate that a substantial reduction in the number of clinical and mild to moderate cases can be achieved with a sentinel population of just 1%, when the sentinels self-report symptoms of foodborne illness. These reductions were somewhat larger in the scenario involving sensor-based location records. However, the scenario where sentinels only had sensor-based location records for restaurants they had visited, but did not self-report symptoms, was not successful.

Conclusions: The model supports the application of health-oriented mobile technology in foodborne illness surveillance, and lends insight into the number of sentinels needed to effectively implement a pilot study using this technology.

4.2 Introduction

Each year in the United States, there are an estimated 47.8 million foodborne illnesses, resulting in 127,839 hospitalizations, and 3,037 deaths. The vast majority (80%) are caused by unspecified agents (Centers for Disease Control and Prevention, 2014a). The Public Health Agency of Canada estimates that approximately 4 million people, or 1 in 8 Canadians, become sick each year (Public Health Agency of Canada, 2013). Based on these estimates, an enhanced cost-of-

illness model that incorporates pain, suffering, and disability, as well as medical cost and illness-related mortality, found that the economic burden of foodborne illness in the United States was \$77.7 billion (Scharff, 2012). Data on the full extent of foodborne illness is incomplete because many cases are mild, so those affected do not seek medical treatment; of those who do, cases are not always confirmed through laboratory testing and reported to the appropriate health department (Buzby & Roberts, 2009; Schlundt, 2002). A further area of uncertainty is attributing diseases to specific foods (Batz et al., 2005); however, eating in restaurants has been identified as a risk factor for foodborne illness (T. F. Jones & Angulo, 2006). The uncertainty associated with estimates of foodborne illness and its associated costs impedes the development of effective interventions and policies to prevent foodborne illnesses.

Recently, there has been increasing interest in the application of crowdsourcing and mobile technology to complement existing public health surveillance. In the field of foodborne illness, researchers have linked Tweets about foodborne illness to GPS tags from mobile phones indicating restaurants, and then correlated the data with health department inspections (Sadilek, Brennan, Kautz, & Silenzio, 2013). Another project used reviews on the website Yelp to find unreported cases where customers experienced foodborne illness in New York City. In partnership with the Department of Health and Mental Hygiene (DOHMH), reviews were triangulated with 311 reports on restaurants, and in some cases DOHMH investigation was required. Three outbreaks were identified that had not previously been reported (Harrison et al., 2014). These studies have reported some successes, but the authors also noted that they are extremely labour intensive and could overwhelm local health departments. Most recently, IBM has built a system designed to help food retailers and public health officials detect the most likely sources of food contamination to assist with foodborne illness investigations: the system uses the location of supermarket food items sold each week to identify a set of possible sources that are likely causing the outbreak, using as few as 10 case reports. By integrating existing retail and public health data, public health investigators can see maps, distributions of potential foods, and case reports and lab reports from clinical cases. Additional reports feed into the algorithm used in order to update the probability that suspected food products are causing the illnesses (IBM, 2014).

Although mobile health technology is a growing field with many applications for gathering health data that has generated much research interest recently, designing such studies is time consuming, expensive and difficult. To avoid such pitfalls, we were interested in using an agent-based model (ABM), a simulation methodology that allows for many interacting agents to reveal emergent properties of systems (G. T. Jones, 2007), to investigate the potential for crowdsourcing study design and to develop a proof of concept. ABM has grown in popularity in the social and health sciences for its ability to simulate possible outcomes and test alternative scenarios. We have employed an ABM to evaluate the possibilities for an intervention: using a mobile technology that would crowdsource data on foodborne illness.

4.3 Methods

The purpose of the ABM³⁹ is to investigate the effect on health and investigation length of a small proportion of the population, referred to as sentinels, equipped with a mobile technology that allows sentinels to collect data on visited restaurants and/or report mild to moderate signs of foodborne illness, and then transmits this information to public health inspectors in the event of an outbreak.

The model contains three different entities: consumers, restaurants, and an inspector. The consumers have two important state variables: whether or not they are sick, and if they are, whether they are experiencing either mild to moderate or severe symptoms; and whether or not they are a sentinel. Consumers also have parameters that govern how frequently they eat in restaurants and whether or not they practice good food handling habits when cooking at home. Restaurants may either be in a contaminated or uncontaminated state; one restaurant is contaminated at the model's initialization. The inspector begins in the routine inspection state, and if an outbreak occurs, it changes its inspection strategy to focus on restaurants most frequently reported as having been visited by ill consumers.

The model was implemented in AnyLogic (version 6.9.0). Model time is continuous and measured in days, and there is no fixed stop time – the model stops when the inspector finds the contaminated restaurant. The model does not depend on spatial relationships, but the

³⁹ View this model in the CoMSES Model Library: <https://www.openabm.org/model/4325/version/1/view>

implementation in AnyLogic used some spatial elements to improve understanding and allow for easier communication and debugging.

The following processes occur continuously, not sequentially. The inspector conducts routine inspections by first forming a collection of all restaurants, ordered randomly. The inspector goes through the list in a round-robin fashion, inspecting restaurants at a rate of one per day. The inspector has a 50% chance of correctly identifying a contaminated restaurant; this estimate is meant to reflect the fact that inspectors may inspect a restaurant when it is less busy, and sloppy errors in food handling may be less likely to occur, or when staff members who are more safety conscious may be working. A contaminated restaurant will comply with routine inspection 50% of the time. If the inspector correctly identifies the affected restaurant during a routine inspection, and if the restaurant complies with the inspector, the model realization ends.

Consumers eat once per day either at home or at a restaurant. The likelihood of a consumer becoming ill depends on where they are eating; if they are eating at home, their likelihood of becoming ill depends on whether they practice good food handling, and if they are eating at a restaurant, it depends on whether they have been to the contaminated restaurant in the model. The risks associated with food handling practices were derived from empirical data; for further details, please see the calculations summarized in Appendix A.

Once a consumer has been exposed to a pathogen, either in the home or in a restaurant, the consumer will transition from the healthy state to the illness exposure state, where they remain for one day in model time. Next, the consumer either experiences mild to moderate or severe symptoms. Symptoms severe enough to warrant a visit to the doctor and subsequent reporting to public health were assumed to occur in about 0.5% of cases and last for five days. Mild to moderate cases, that were not reported to a physician and hence were unrecognized by public health authorities, were assumed to last for two days.

Two severe cases will trigger an outbreak investigation. If an outbreak is declared, the severely ill consumers update a list of visited restaurants. Recollection is treated as imperfect, as consumers have a certain chance per day of forgetting restaurant locations that they have visited, and they are more likely to forget restaurant visits which occurred more distantly in the past. The consumers then pass their list of visited restaurants to the inspector, who maintains a count of

reports originating in each restaurant. Once an outbreak has been triggered, and on an ongoing basis until the contaminated restaurant is identified, the inspector will seek to visit the restaurant with the highest cumulative count of reports that has not yet been visited as part of the outbreak investigation. This process continues until the inspector correctly identifies the contaminated restaurant, which ends the model realization. During an outbreak investigation, the model treats the inspector as capable of recognizing the contaminated restaurant with perfect sensitivity and specificity; the elements of uncertainty in identification and compliance that are present in routine inspections are not used in outbreak investigations, because inspectors have more information to guide their investigation and could shut down the affected restaurant.

Sentinel consumers behave in accordance with all of the above consumer processes, with minor changes depending on the scenario. The first scenario involves sentinels whose mobile devices track which restaurants have been visited, allowing sentinels to report with greater accuracy than consumers who must remember where they have been, and sentinels report mild to moderate symptoms of foodborne disease. In the second scenario, sentinels report mild to moderate symptoms, and report which restaurants they have visited with the same imperfect memory as non-sentinel consumers once an outbreak has been triggered. In both of these scenarios, four sentinels reporting any symptoms, or two severe cases, will trigger an outbreak. In the third scenario, sentinels do not report symptoms; however, if they experience mild to moderate illness, they provide visited restaurant data to the inspector once two severe cases have been reported. These scenarios will hereafter be referred to as scenarios one, two and three, respectively.

An output file is created that keeps track of the time of the first severe case, the time between the first severe case and the inspector beginning an outbreak investigation, the length of the investigation, the count of severe illnesses, the count of mild to moderate illnesses, the number of sentinel consumers who experienced mild to moderate illness, the number of consumers who become sick eating at home, the number of consumers who become sick from eating at restaurants, the total time length of the simulation, and the number of routine inspections. However, only a subset of these indicators is discussed here.

The model is initialized with 5000 consumers and 100 restaurants, one of which is contaminated. There is one inspector in the model. Upon model initialization, consumers are placed in categories based on frequency of eating in restaurants: 6.7% of consumers eat out daily, 30.9%

three times a week, 23% once a week (Canadian Restaurant and Foodservices Association, 2010), and the remaining 39.4% of consumers visit a restaurant once every two weeks. Each consumer selects a subset of 10 restaurants with uniform probability to form their list of possible restaurants to visit. Consumers are also randomly assigned to either practice good or poor hygiene while cooking at home: 20% of consumers practice good food handling habits, and 80% do not. Studies observing food safety practices while preparing meals in the home (Anderson, Shuster, Hansen, Levy, & Volk, 2004; Redmond, Griffith, Slader, & Humphrey, 2004) were used to inform this aspect of the model; the data reported by these studies is quite nuanced, so the 80/20 figure is an abstraction. The per day chance of illness from eating a home meal prepared with good food safety practices, as backed out from empirical data, is 0.0001511385888.⁴⁰ We conducted 1000 realizations with 0% (baseline), and then 1%, 2%, and 4% sentinels for each of the three scenarios.

4.4 Results

The results from the model were analyzed in R (version 2.15.1). The Kruskal-Wallis rank sum test was used to compare the results within each scenario with 1% of the population acting as sentinels, 2%, and 4%, to the baseline (see Table 11), as well as the results between scenarios with the same percentages of the population as sentinels (see Table 12). Next, post-hoc analysis using pairwise Mann-Whitney-Wilcoxon tests was completed, using the Holm correction to account for multiple comparisons. Unless otherwise stated, the pairwise analysis results are statistically significant ($p < .001$).

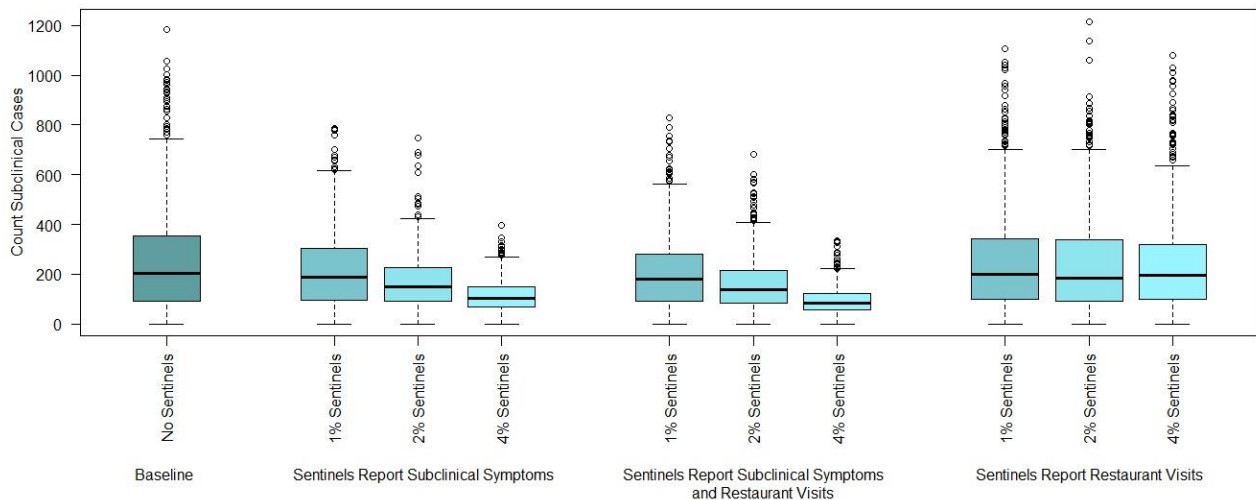
⁴⁰ See Appendix A for details.

Table 4.1 Kruskal-Wallis test results for all scenarios, by sentinel percentage

Scenario 1: Sentinels Report Mild to moderate Symptoms and Restaurant Visits										
	Baseline		1% Sentinels		2% Sentinels		4% Sentinels		Kruskal-Wallis	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Chi-sq (3 DF)	p-value
Length of Investigation	18.6	51.9	10.2	34.4	10.8	28.3	6.4	15.8	65.4	p<.001
Count Clinical Illnesses	1.3	1	1	0.9	0.8	0.9	0.5	0.7	347	p<.001
Count Mild Illnesses	249.2	205.4	199	138.8	155.4	100.4	92.7	53.2	556.7	p<.001
Count Sentinel Illnesses	0	0	2	1.6	2.9	1.7	3.6	1.5	2137.1	p<.001
Overall Model Time	230.5	187.5	184.3	127	144.1	93.1	86.4	49.5	567.1	p<.001
# of Routine Inspections	211.9	177	174.1	119.2	133.3	84.3	80	45.2	562.9	p<.001
Scenario 2: Sentinels Report Mild to moderate Symptoms										
	Baseline		1% Sentinels		2% Sentinels		4% Sentinels		Kruskal-Wallis	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Chi-sq (3 DF)	p-value
Length of Investigation	18.6	51.9	27.8	57.6	26.8	45.7	25.2	36.9	215.5	p<.001
Count Clinical Illnesses	1.3	1	10	1	0.8	0.	0.6	0.8	270.7	p<.001
Count Mild Illnesses	249.2	205.4	214.4	153.1	164.8	102.7	112.5	63.9	369.1	p<.001
Count Sentinel Illnesses	0	0	2.2	1.82	3.3	2.1	4.4	2.3	2099.1	p<.001
Overall Model Time	230.5	187.5	198.3	140.5	153.31	94.4	105.3	59.3	368.1	p<.001
# of Routine Inspections	211.9	177	170.5	119.6	126.5	77.9	80.1	45.1	544.1	p<.001
Scenario 3: Sentinels Report Restaurant Visits										
	Baseline		1% Sentinels		2% Sentinels		4% Sentinels		Kruskal-Wallis	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Chi-sq (3 DF)	p-value
Length of Investigation	18.6	51.9	9.1	30.1	5.7	24	2	7	54	p<.001
Count Clinical Illnesses	1.3	1	1.2	1	1.2	0.9	1.1	0.9	5.1	p=.16
Count Mild Illnesses	249.2	205.4	245.6	196.8	236.4	188.7	234.6	185.8	1.6	p=.66
Count Sentinel Illnesses	0	0	2.5	2.5	4.8	4.6	9.3	8	2191.5	p<.001
Overall Model Time	230.5	187.5	198.3	140.5	153.3	94.4	105.3	59.3	368.1	p<.001
# of Routine Inspections	211.9	177	217.7	178.6	212.6	171.9	214.4	169.7	1.2	p=.74

In scenario one, where sentinels report both mild to moderate symptoms and visited restaurants, the number of sick consumers declines as the percentage of sentinels increases. The length of time required to identify the affected restaurant in an outbreak investigation also decreases as sentinels are added, and the variability is substantially reduced. However, the Mann-Whitney-Wilcoxon test showed no statistically significant effect of increasing the amount of sentinels from 2% to 4% ($p > .05$). A related measure, the overall length of time that passes until the model run ends, also declines; because clinical cases are rare, relying on a second clinical case in order to trigger an outbreak results in longer model run times, which also means that there is more time for a greater number of consumers to become ill. When sentinels can report mild to moderate symptoms to trigger an outbreak, the outbreak investigation occurs earlier and is completed more quickly because inspectors have access to additional information on visited restaurants.

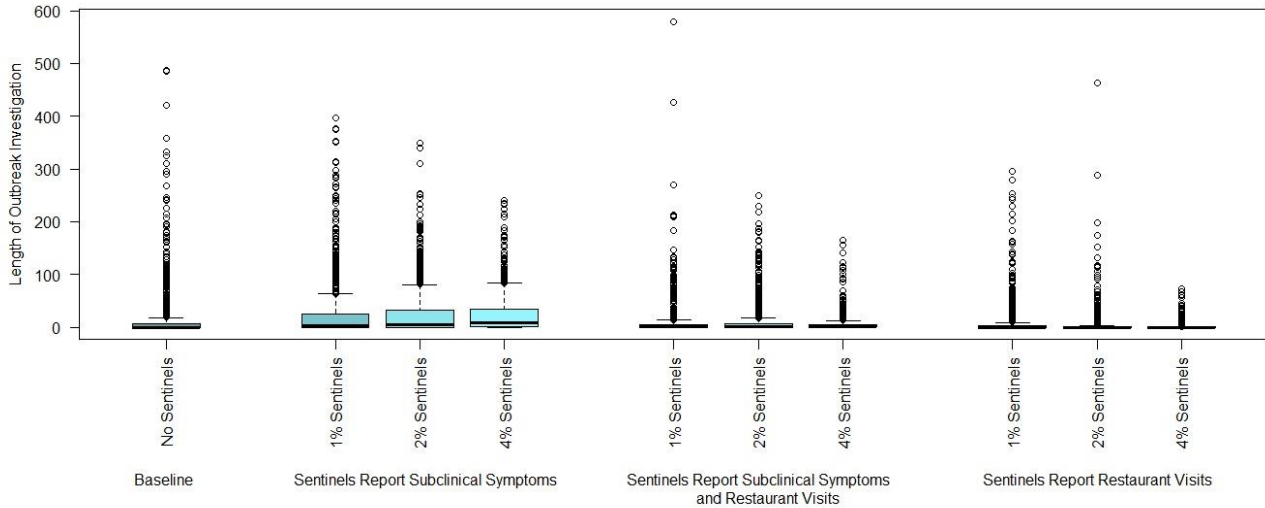
Figure 4.1 Mild to moderate cases, all scenarios



In scenario two, where sentinels report mild to moderate symptoms, the number of sick consumers decreases as sentinels are added, although the decrease is not quite as substantial as in scenario one. The difference between the baseline and having 1% sentinels for the number of consumers who became ill from home cooking, ill from eating at restaurants, and the overall length of time of the model was significant ($p < .05$). The most interesting result from this

scenario was that the length of outbreak investigation for all sentinel percentages was greater than for the baseline.

Figure 4.2 Length of investigation, all scenarios



Scenario three was not successful – there were few statistically significant differences between the baseline and sentinels. The difference between the baseline and 1% sentinels for the length of investigation was significant ($p < .01$), but the difference between 2% and 4% sentinels was not statistically significant ($p > .05$). Overall, the outbreak investigations in this scenario were the shortest, as seen in Figure 4.2. The difference between the baseline and 1% sentinels was statistically significant ($p < .05$) for the length of time from the beginning of the model when a pathogen first appears until the outbreak investigation completes.

The results from scenario one show the greatest reductions in the number of sick consumers in both severe and mild cases (see Figure 4.1). However, this scenario only performs marginally better than scenario two; the results between these two scenarios for the number of mild to moderate illnesses were not statistically significant with 1% sentinels ($p > .05$), but was significant with 2% sentinels ($p < .05$) and 4% sentinels ($p < .001$). Overall, these two scenarios performed comparably.

Table 4.2 Kruskal-Wallis test results for all scenarios

	1% Sentinels		2% Sentinels		4% Sentinels	
	Kruskal-Wallis		Kruskal-Wallis		Kruskal-Wallis	
	Chi-sq (2 DF)	<i>p</i> -value	Chi-sq (2 DF)	<i>p</i> -value	Chi-sq (2 DF)	<i>p</i> -value
Length of Investigation	78.3	<i>p</i> <.001	305.1	<i>p</i> <.001	715.3	<i>p</i> <.001
Count Clinical Illnesses	26.1	<i>p</i> <.001	111.1	<i>p</i> <.001	345.3	<i>p</i> <.001
Count Mild Illnesses	15.4	<i>p</i> <.001	85.1	<i>p</i> <.001	427.5	<i>p</i> <.001
Count Sentinel Illnesses	6.1	<i>p</i> <.05	60.4	<i>p</i> <.001	413	<i>p</i> <.001
Count Sick from Home Cooking	15.4	<i>p</i> <.001	87.8	<i>p</i> <.001	490.9	<i>p</i> <.001
Count Sick from Restaurants	15.9	<i>p</i> <.001	82	<i>p</i> <.001	472.6	<i>p</i> <.001
Overall Model Time	14.5	<i>p</i> <.001	86	<i>p</i> <.001	487.4	<i>p</i> <.001
Number of Routine Inspections	23.6	<i>p</i> <.001	132.6	<i>p</i> <.001	601.4	<i>p</i> <.001

4.5 Discussion

This model provides a proof of concept for using mobile technology to enhance foodborne illness surveillance. We have shown that even a very small proportion of the population serving as sentinels can substantially reduce the number of illnesses present in the population, which points to the feasibility of the technology. The model has generated three important insights. First, having sentinels report visited restaurants, without reporting mild to moderate symptoms to trigger recognition of an outbreak, does not substantially reduce the number of illnesses. Thus, we can infer that it is not helpful for the inspector to only receive restaurant reports from sentinels; early reports of milder symptoms of foodborne illness that can trigger an outbreak are needed for the intervention to have an effect. Second, the model illuminates Peter Drucker’s quote, “what gets measured, gets managed” as applied to policy situations. Because we have perfect reporting of mild to moderate cases in the model, we can see that although the length of investigation is longer when sentinels only report mild to moderate symptoms, fewer people are ill overall. However, if a health department were to deploy this technology and were unaware or unconvinced of the reduction in illnesses, in part because many of these mild to moderate cases are unknown to begin with, they may think that the technology is actually making things worse because of the apparent adverse effect on the duration of outbreak investigations. Third, the model shows that adding sentinels can result in more stable and predictable levels of sickness

within the population, which is likely to be more easily managed by the public health system. Wide swings in outcomes that are unpredictable can be taxing on resources and contribute to negative public perception of public health and food safety.

Crowdsourcing offers interesting possibilities for public involvement in public health, as shown here and in other recent work (Harrison et al., 2014; M Hashemian, Stanley, Knowles, Calver, & Osgood, 2012; Paul & Dredze, 2011; Sadilek et al., 2013). However, there are also limitations involving the compliance and honesty of those participating, as well as the potential for crowdsourcing initiatives to overburden public officials (Harrison et al., 2014).

There are also some limitations to this work, including two key assumptions for future research. In the model, we have assumed that sentinel consumers carry the device and use it consistently all of the time, and that there is always one contaminated restaurant in the model. Given that past studies with similar technology have shown less than perfect compliance (M Hashemian et al., 2012), the true number of sentinels required to show an effect in a pilot study might need to be slightly higher, to account for less than perfect compliance and a fuzzier definition of a contaminated restaurant.⁴¹ Such a pilot study would need to be conducted in collaboration with a local health department to ensure their needs were met and that the incoming data would not overburden staff members.

The main advantage of the model presented here is that it provides a starting point for study design. To fully synthesize simulation with novel mobile technology, we would use the data resulting from a pilot study deploying mobile technology to collect reports of foodborne illness symptoms to further refine and restructure the model's assumptions. This is especially relevant for foodborne illness, because data is uncertain, in part due to under-reporting, and many argue that interventions can prevent some cases of foodborne disease (Batz et al., 2005; Buzby & Roberts, 2009; Schlundt, 2002). By linking these two tools in a fundamental way, we can provide better evidence for decision-making in public health.

⁴¹ The percentage of sentinels used in the model could be taken as indicating the fraction of reliably compliant individuals; however, the model does not provide assistance with determining how many sentinels would need to be recruited in order to achieve this percentage.

CHAPTER 5

CONCLUSION

5.1 Summary

Many problems faced by policymakers are complex, meaning that they are not reducible and problems arise when they are approached by simple analytical tools. However, empirical evidence suggests that policymakers tend to prefer simpler methods, particularly those that are less formal and more subjective. The research presented here is fundamentally about adapting, adopting, and reducing new policy tools to practice: ABM is just one example. ABM is a method that has been touted as having great potential for analyzing policy problems, but has not been widely used. The opportunities for using ABM at each stage of the policy cycle were outlined; it appears that the method would be most useful at the policy formulation and policy evaluation stages, although there may be application at other points depending on the policy problem at hand and the rationale for choosing ABM.

Ensuring safe food is an example of a complex problem: the system is global, exhibits interrelated feedback loops, a large number of actors, asymmetric information, and uncertainty. Using food safety as an illustrative example, three models representing simplified interactions between consumers, retailers and inspectors were developed and analyzed. The first model explores three inspection scenarios incorporating access to information: a random inspection scenario, a scenario where stores signal with certainty, and a scenario where stores signal with errors. The main finding to come from this modeling exercise was that the number of sick consumers is greatly reduced by giving consumers and inspectors more information about whether a store is contaminated, even if that information may be uncertain.

The second model incorporated theories on risk and the role of transparency in encouraging consumer trust by exploring two scenarios: the first is the status quo, where consumers do not have ready access to restaurant inspection scores, whereas the second gives consumers access to inspection scores, and they behave in a risk averse manner by only frequenting low re-inspection priority restaurants for a limited time period following an illness. The percentage of restaurants that comply with regulations is increased from 60-90% over multiple simulation runs. Overall, the findings were more nuanced: having access to restaurant inspection scores results in a

slightly higher mean number of sick consumers, but much less variation overall in the number of sick consumers over 100 realizations. In both scenarios, more compliant restaurants results in fewer sick consumers.

Rather than investigating the overlying superstructure of the inspection system, the third model investigates the potential for mobile technology to crowdsource information about suspected foodborne illness. This model provides a proof of concept for the potential for health-oriented mobile technologies to improve the surveillance system for foodborne illness. The model again features consumers, retailers and an inspector. Three different scenarios compare the impact of a ‘sentinel’ population that uses a mobile technology to report mild to moderate symptoms of foodborne disease to the inspector, or sensor-based location data of the restaurants they have visited, or both. A baseline was determined by running 1000 realizations with no sentinels, which was compared to 1000 realizations involving 1%, 2% and 4% sentinels for each scenario. The scenario where sentinels report mild to moderate symptoms and visited restaurants showed the greatest decline in the number of consumers experiencing mild to moderate illness when compared to the baseline, although the scenario where sentinels only reported mild to moderate symptoms performed nearly as well. In both cases, increasing the number of sentinels led to fewer mild to moderate illnesses. However, the scenario where sentinels only report visited restaurants did not effectively reduce the number of mild to moderate cases.

The three models presented here, although stylized representations of food safety inspection systems, provide a number of insights for policy.

5.2 Policy Implications

The research presented here discusses a number of policy implications.

1) ABM has practical use in the policy cycle, particularly in demonstrating possible alternatives for policy formulation, which is what the three models in this dissertation have done. Models can be used to show a particular problem framing; the three scenarios presented in chapter two present food safety as a problem of information asymmetry, and show that greater access to even imperfect information can improve outcomes. Models can also be designed to provide a counterfactual for policy evaluation; the two scenarios presented in chapter three come close to this, as they present the status quo and then an alternative policy option for comparison. By

disclosing restaurant inspection scores to give consumers new information for decision-making, this model presents a policy tool that falls under the category of capacity tools (Schneider & Ingram, 1990). ABMs could also be used to determine the proper settings for initial policy deployment; the scenarios presented in chapter four may be used to inform the design of a pilot project, with the results of the pilot providing feedback into model design. A similar method could be used in policy development.

However, applying ABM in policy analysis requires modellers to engage with government, consumer, and industry stakeholders. Very few modeling techniques are currently used in policy analysis, and unless ABM is made accessible and shown to be useful to policy analysts, it will not live up to its potential for use in policy development. In order to achieve broader use by governments⁴² and others outside of the small field of researchers currently using ABM, the following elements are needed:

- Software that allows for drag and drop model building, rather than coding. The current software offerings for building ABMs can be intimidating for those without extensive experience with coding. To encourage use, software needs to be as simple to use as possible.
- Improved visual analytics. Models that are easy to understand visually, and offer intuitive visual results, are easier to communicate to stakeholders and allow models to be used effectively as tools for supporting decision-making.

New software that incorporates the above two elements has the potential to be used more extensively for participatory modeling, which could be a useful tool for democratic engagement. By involving stakeholders in the modeling process, the results of the modeling process are likely to be much richer. As well, there are opportunities for models to be communicated not just from researchers down to stakeholders, but for stakeholders to provide direct input on potential policy options throughout the modeling process.

⁴² For example, the Alberta government is interested in threats to the woodland caribou population and assessing the risks to herds. A project at the University of Alberta used an ABM to simulate caribou movement behaviour and study the effects of human activity on herds (Hassanali, 2014).

2) Fundamentally, all three papers have explored aspects of the role of information in a complex system and its impacts on public health policy. In chapter two, the main policy implication is that giving consumers and inspectors more information, even if that information is uncertain, results in more favourable outcomes. The outcome of having one inspector with access to imperfect signalling information is similar to five inspectors using random inspections.

In chapter three, the results reflect the tension between regulation and information. When consumers do not have additional information, and do not exhibit risk averse behaviours following an illness by only eating at low re-inspection priority restaurants, the mean number of illnesses is somewhat lower. However, when consumers are given access to restaurant re-inspection priority scores, the mean number of illnesses is somewhat higher, but there is much less variation in the overall number of illnesses. This emergent result reflects several important points: firstly, it re-emphasizes the complexity of food safety – simply changing one variable is not going to fix the problem; secondly, more stable, predictable levels of sickness within the population are likely to be more easily managed by the public health system, as wide swings in outcomes are unpredictable and may further compound the public's negative risk perception and 'swings from hysteria to indifference'; thirdly, more predictable outcomes that are close to a normal distribution are more amenable to typical statistical analyses and could contribute to understanding of the problem and future prediction.

As well, higher levels of restaurant compliance also contribute to fewer sick consumers, and empirical evidence indicates that disclosing inspection scores improves compliance. However, since the industry has indicated unwillingness to disclose this information voluntarily, government action will be required to mandate the posting of scores and encourage a coordinated approach across jurisdictions.

In chapter four, the model results showed that even having a small number of sentinels, or individuals within a population that report mild to moderate symptoms to trigger an outbreak, can substantially reduce the number of illnesses within a population.

3) The model results also emphasize 'what gets measured gets managed.' This is most apparent in chapter four. Although the length of investigation is longer when sentinels only report mild to moderate symptoms, fewer people become ill overall, which was an emergent result from the

model. However, this is only obvious since the model shows, very clearly, the total number of illnesses; in reality, many illnesses are unreported. Thus, if a health department were to use this technology, the reduction in the number of illnesses may not be clear, but the department may view the technology as causing inefficiencies in investigations since they now take longer.

There are also two broader policy implications that come out of using ABM as a policy tool:

1) The precise documentation required by the ODD framework forces the modeller to be transparent and honest about choices made during model specification. All of the modeller's assumptions and data sources must be made clear up front; this is in contrast to econometric modeling, where model fitting can be an opaque process that obscures the researcher's assumptions (Leamer, 1983).

2) Models also hold great value as communicative tools; the software available for implementing ABMs, which can allow for visual representation of processes and outputs, greatly facilitates communicating models to experts and stakeholders, and, as noted earlier, presents opportunities for the broader use of participatory modeling.

A lot of the potential for modeling comes from models acting as 'thinking tools' – the process of developing a model to address a problem forces one to think through a number of issues that may not be obvious if presented in a less systematic way. The benefit of modeling may not necessarily be tied up in the final results of a finished model, but in using the model as a tool for thinking through problems and communicating the problem, and potential solutions, to others. This allows for easier interdisciplinary collaboration and discussion on complex policy problems.

The models presented here could be expanded in a number of ways to further explore these policy implications or other research questions – a few extensions will be discussed below.

5.3 Limitations of the Research

Although the models presented in this thesis have generated some useful insights, their limitations cannot be ignored. First, as aptly noted by Epstein (2008), “[A]ll the best models are wrong. But they are fruitfully wrong.” The models presented here incorporate numerous simplifications and assumptions, as noted in the ODD model descriptions, about human behaviour, supply chains, and the level of pathogen exposure required to cause illness, among

other things. Further, the models assume that the agents, their actions, and the context in which they operate are not all changing interactively at the same time; something that cannot, in all fairness, be ruled out. They are stylized models that can generate insight, but should not be used for predictive purposes. In order for these models to serve as predictive tools, further data collection to inform initial conditions and more sophisticated representations of human behaviour, communication, and supply chain dynamics would need to be incorporated.

Further, the very nature of ABM presents some limitations. The first is that there is often a lack of individual-level data to inform models and their assumptions. Although some work is underway in this area (M Hashemian et al., 2012), this poses a problem for building grounded models. Further, the bottom up nature of ABM makes it difficult to imply top down structures; policies are generally top down, so this aspect could limit certain applications of ABM within the policy space. However, for policies that intend to affect behaviour of individual actors, ABM still holds a lot of promise.

5.4 Directions for Future Research

By their very nature, ABMs are extremely flexible. Although this can at times be a disadvantage, as a lot of time can be spent adjusting model structure, it is an advantage when it comes to extending the models for future research. First, the models presented here could be adapted to explore new questions involving:

- Changes in population structure, such as increased consumer heterogeneity with respect to likelihood of illness, more or less dense populations, and agents with more specific preferences for the type of restaurant they frequent;
- Strategies where inspectors cooperate with one another;
- Different pathogens, for example, different lengths of time between exposure and illness or pathogens that can be spread from person to person, not just acquired from a contaminated food product;
- Information sharing between consumers about restaurants to avoid;
- Restaurants that make explicit optimizing decisions about complying with food safety regulations.

These are just a few examples of possible extensions to the models demonstrated here, and they vary in their complexity to implement from very simple to substantial, complicated changes to model structure. The models could also be adapted in terms of scale to focus more on federal

inspection of meatpacking plants or border control for imported food products. In this case, the model would likely involve a more complex supply chain, including processors and distributors. Further model development in this vein could be a promising space for hybrid modeling, since system dynamics and discrete-event models are well suited to representing supply chains and could be integrated with an agent-based model of consumers and inspectors.

Second, there could be opportunities to work directly with public health officials to adapt models specifically to their needs in order to have a real policy impact. The modeling cycle may be a useful tool for building insights and opening dialogue into processes and system outcomes. Given that the current climate in health in Saskatchewan is being dominated by LEAN, process improvement, and a focus on efficiency to deal with budget pressures, models that could be adapted to investigate how changes in processes or staff reductions could affect the overall system would be especially useful.

Third, we have discussed conducting a pilot project with support from the Public Health Agency of Canada to investigate the potential for applying mobile technology and crowdsourcing, as in the model presented in chapter four.

One of the difficulties with calibrating ABMs is access to individual data to inform agent behaviour in a rich and meaningful way. A fourth extension of the research presented here would be to link the models with behavioural experiments to generate results that could better inform agent behaviour and decision-making. The advantage of using behavioural experimentation, as opposed to surveys and focus groups, is that this method allows for individuals to demonstrate what they would do in a given situation, rather than telling the researcher what they would do. Data for these experiments thus allows for a more authentic representation of decision-making on an individual level. All of these extensions have the potential to further improve the applicability of ABM to evidence-based policy-making.

APPENDIX A: SUPPLEMENTAL MATERIAL

The following formula introduces forgetfulness over time. By using a uniform distribution, there is between a 5% and 20% chance of the consumer forgetting:

$$e^{-(\text{uniform}(0.05,0.2))(time-currentMealTime)}$$

To determine the probability of a consumer becoming sick per meal, the following stylized facts were used:

- Approximately 1 in 8 Canadians become ill each year from foodborne illness (Public Health Agency of Canada, 2013).
- Consumers have been divided into categories based on how frequently they eat in restaurants: 6.7% of consumers eat out daily, 30.9% three times a week, and 23% eat out once a week (Canadian Restaurant and Foodservices Association, 2010); the remaining 39.4% visit a restaurant once every two weeks.
- Restaurants are responsible for twice as many outbreaks as private homes (Smith DeWaal & Glassman, 2014).
- Most consumers use poor food handling practices while cooking at home (Anderson et al., 2004; Redmond et al., 2004); in the model, 80% of the consumers use poor food handling practices and 20% use safe food handling practices when cooking at home. We assume that consumers who use poor food handling practices are twice as likely to contract an illness as those who use safe food handling practices.
- We also know that, in the model, one out of 100 restaurants is contaminated.
- Finally, a key assumption is that agents eat one meal per day: this means the per meal and per day chance of becoming ill are equivalent.

p refers to the probability of becoming ill from eating a meal prepared safely at home.

First, we derive the chance of becoming ill from an average home meal, based on the above.

$$(2 * 0.8 + 1 * 0.2)p = \text{the chance of becoming ill from an average home meal}$$

Next, we derive the average chance of becoming ill from a restaurant meal, which is twice the likelihood of becoming ill from the average home meal.

$$2(2 * 0.8 + 1 * 0.2)p = \text{the average chance of becoming ill from a restaurant meal}$$

Next, we determine the weighted average of becoming ill from any restaurant, which we want to equal twice the likelihood of becoming sick from a home meal. We assume that there is no risk of becoming ill from a non-contaminated restaurant.

$$\begin{aligned}
& p(\text{GettingSickInRestaurant}) \\
&= F_{\text{contaminated}} * p\left(\frac{\text{sick}}{\text{contaminated}}\right) \\
&+ (1 - F_{\text{contaminated}})p\left(\frac{\text{sick}}{\text{non - contaminated}}\right)
\end{aligned}$$

Which becomes:

$$\begin{aligned}
2(2 * 0.8 + 1 * 0.2)p &= \frac{1}{100} * p\left(\frac{\text{sick}}{\text{contaminated}}\right) + 0 \\
360p &= p\left(\frac{\text{sick}}{\text{contaminated}}\right)
\end{aligned}$$

Now, we know that certain segments of the population eat at restaurants more or less frequently, and can use that to determine the overall fraction of meals at restaurants:

$$\begin{aligned}
F_{\text{restaurantmeals}} &= (0.067 * \frac{7}{7} + 0.309 * \frac{3}{7} + 0.23 * \frac{1}{7} + 0.394 * \frac{1}{14}) \\
F_{\text{restaurantmeals}} &= 0.2604
\end{aligned}$$

This means that our overall chance per day of contracting foodborne illness, or α , is as follows:

$$\alpha = (F_{\text{homemeals}} * \text{chance of becoming ill from home meals} + F_{\text{restaurantmeals}} * \text{chance of becoming ill from restaurant meals})$$

We also know that approximately 1 in 8 Canadians become sick each year, so we must use this in determining our per day chance of illness:

$e^{-\alpha t}$, where t refers to 365.25 days.

The fraction getting sick over a year would be $1 - e^{-\alpha * 365.25}$

$$\ln\left(1 - \frac{1}{8}\right) = -\alpha * 365.25$$

$$\begin{aligned}
\alpha &= -\frac{\ln\left(1 - \frac{1}{8}\right)}{365.25} \\
\alpha &= 2.2688p
\end{aligned}$$

We then use α to solve for p , the chance of becoming sick per day from a safely prepared home meal: $p = 0.000161138588$

APPENDIX B: MODEL CODE

The model code for each of the models used in this dissertation, along with accompanying documentation, has been uploaded to the CoMSES Computational Model Library which is available at www.openabm.org/models. The interested reader may find the exact links footnoted in each of the chapters.

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