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DISCUSSION PAPER

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CONTENTS

ABSTRACT

Complex systems' approach and methodologies emphasize interactions, diversity and dynamics. Complex systems perspectives also enable public policies to be considered comprehensively and simulated in all their multiplicity of sectors and scales, of cause and effect. This paper attempts to summarize the content of the book of the project "Modeling Complex Systems for Public Policies". In doing so, it presents the main concepts and methodologies and it associates the characteristics of social, economic, urban and environmental issues of policy with complex systems approaches. The paper makes a brief list of the existing literature in Brazil related to the applications of complex systems and discusses the applications in education, transport, and the legislative process. The paper concludes that public policies may benefit methodologically if studied within this approach, mainly because of the observed heterogeneity of their agents; the connectedness of agents and policies; and the non-linear fashion of interactions among policies. Further, the formal modeling framework, the adequacy of its data treatment and the communication facilitated by modeling together may help the emergence of more sensible, insightful, and full-scope policy-making.

Keywords: complex systems; public policy; agent-based modeling; network analysis; dynamical systems; non-linearity; emergence.

1 INTRODUCTION

Complex systems can be defined in a broad manner and embrace concepts from different fields of science, from physics to biology, to computing and social sciences. Mainly, the definition includes nonlinear dynamical systems that contain large number of interactions among the parts. These systems learn, evolve, and adapt, generating emergent non-deterministic behavior.[1] Public policies are to be applied upon a vast range of issues that involve the public, the broad community of citizens and communities, firms and institutions. Public policies are also to be employed in a number of sectorial issues which are intertwined, asynchronous, and spatially superposed. This coupled understanding of complex systems and public policies suggests that most objects of public policies – be them of economic or urban nature, be them of environmental or political consequences – can be viewed as complex systems. Thus, if public policies' objects can be seen as complex systems, their understanding may benefit from the use of associated methodologies, such as network analysis, agent-based modeling, numerical simulation, game theory, pattern formation and many others within the realm of complex systems. These methodologies have been applied to different aspects of science, but less frequently to public policy analysis.[2] We hypothesize that the use of these concepts and methodologies together improves the way policies of complex objects are viewed, adjusted, and operated upon from a public point of view.

Given these definitions of complex systems and public policies, this paper summarizes the concepts, methodologies and computing implementation of complex systems; details the adherence of those concepts and methodologies to social policies, economic, urban and environment analysis; and highlights some applications on transport planning, on the study of the legislative and on education. Finally, it provides a brief panorama of some of the existing scientifically published applications in Brazil. This paper aims to introduce and summarize the contents of the book (and project) of

1. A didactically complete discussion of Complexity is available at Mitchell (2011). The initial concepts that compose the complexity sciences can be found in Furtado and Sakowski (2014).

2. Initially, one could look at Colander and Kupers (2014) who provide a review focused on economics. Edmonds and Meyer (2013) give a detailed background. An earlier report can be found at OECD (2009).

the same name, delineating what is to be found in the detailed authorial publication.[3] Thus, it is our objective to define complex systems and its more prominent attributes; to list the more common methodologies associated with complex systems; to discuss yet briefly the advantages of applying these approaches to a public policy context; and to present a varied scope of applications of complex systems modeling to public policies.

2 CONCEPTS AND PUBLIC POLICIES

Complex systems definition is usually attached to a specific context; however, it usually incorporates the following set of features.

Firstly, the idea of interaction among parts from and across scales, space and time is relevant. These interactions, in turn, lead to a system that is not reducible; a system that cannot be described by the attributes of the parts alone. Basically, to quote Anderson's classic "More is different" paper (1972, p. 395 our emphasis): "In this case we can see how the whole becomes not only *more than but very different from the sum of its parts*".

Secondly, the interaction among parts can lead to self-organization of the system without the need of central control. This implies that local interactions can generate bottom-up emergent behavior. This powerful concept can be illustrated for the novice reader with the example of a bird flocking. No actual bird controls the direction and position of all birds in a given flock flight. Each one bird only observes those near it and synchronizes with their immediate neighbors. As a result, coordinated flight emerges.

A third attribute to highlight is that complex systems can experiment feedback. In complex systems, interactions have effects in time: actions in a given moment reflect on possibilities and constraints in the following moments. That is why complex systems are said to be adaptive and evolutionary.

3. We would like to thank and acknowledge the contribution to this paper of the extended summaries (Products 1 of the Project) delivered by William Rand, Miguel Fuentes, Jaime Simão, Claudio Tessone, Herbert Dawid, Luis Bettencourt, Bernardo Mueller, Dick Ettema, Michael Jacobson and Acir Almeida. We would also like to thank and acknowledge other members of the project´s team: Rogerio Boueri Miranda, Leonardo Monteiro Monasterio, Cleandro Krause, Julio César Roma, Nilo Saccaro Jr.

All these briefly mentioned characteristics of complex systems seem to be useful to the study of public policies. As stated in section 3 – *Public policies as complex objects* – most objects of public policies contain similar characteristics and can be easily labeled complex systems. The relevance of viewing objects of public policies as complex systems is that the associated methods and methodologies available for the study of such systems could be applied to public policies, helping improve their analysis.

Essentially that means that modeling and simulation can be used to investigate public policies. This is especially relevant in areas of public policies where experiments are usually not simple, cheap or even viable.

> To simulate means to model the action and the interaction among citizens, firms, institutions, and the environment constrained by legislation and regulation, the budget, politics and spatial boundaries (…) *working with complex systems applied to public policy means to create computational experimental environments in which the essence of the systems is present and from which one can withdraw elements of improvement of public policies in a relatively simple and cheap way, besides increasing the understanding of the effects (spatially and temporally) of the policies* (Furtado and Sakowski, 2014, our emphasis).

Thus, complex systems methods have the potential to inform public policies effects, effectiveness, direct and indirect costs.

3 METHODS

The first relevant methodology to support the ideas presented as concepts is that of nonlinearity.[4] Put simply, nonlinear systems are those in which the outputs are not proportional to the inputs. Nonlinearity is attached to the idea that interaction among elements may generate emergent behavior. In addition, the system's outcome cannot be entirely deductible *ex ante*.

4. Parts of this section are based on Miguel Fuente, as proposed in "Methods and Methodologies of Complex Systems", p. 3, Product 1 of the project Modeling Complex Systems for Public Policies.

Nonlinearity and pattern formation can be studied using reaction-diffusion equations. The first part – reaction – describes the interactions, chemical interactions for example, whereas the second part – diffusion – describes the spreading of the influence of those chemical reactions. Approaches that include nonlinearity have been used in applications of physics (laser, superconductors, fluid dynamics, and engineering), biology (biological rhythms, insect outbreaks, genetic studies), chemistry and cryptography (Strogatz, 2014).

The use of networks – being grouped under the common name of network science – uses the bases of graph theory from mathematics and matrix analysis to study interactions (edges) among parts (nodes). How strong, how lengthy and how relevant are the links among people or institutions? How connected is a given network so that a change in a specific node would affect the connections significantly? Those are some of the questions that network analysis may help answering.[5]

Strictly connected to the analysis of networks is information theory or, according to Shannon (1948), theory of communication. Information theory was proposed before network science and it is related to the definition of what information is; to the quantification and definition of the elements involved in any information exchange, and its storage and compression. It is from this theory (and probability theory) that quantities such as entropy and mutual information come into play. These quantitative measures are applied to different areas of science from telecommunications to biology to probability theory[6] to statistical physics, computer science and medicine.

A central aspect of information theory and its associated measures is the quantification of uncertainty. Given past information, how uncertain is the next bit? This is related to the notion of a measure of complexity and to the definition of entropy (Crutchfield and Feldman, 2001; Gell-Mann and Lloyd, 2004; Szilard, 1964; Turing, 1952).

Two other very commonly used methodologies within complex systems are cellular automata (CA) and agent-based models (ABM). They are similar in the sense that both use agents – of free and ample design – that follow rules. The usage of ABMs and CA is a way to simulate the interactions in the system and the ensuing emergent properties. The difference between CAs and ABMs is that the former is fixed in space

5. See Newman (2003), Newman, Barabási and Watts (2006); Williams and Martinez (2000).

6. Such as in clustering and decision tree procedures.

and the latter may be mobile. CAs are more relevant to study spatial analysis where local interactions, physically bounded, are relevant to the problem at hand. ABMs, in turn, can be modeled to be fixed or mobile and they can be in such a framework that space is completely irrelevant. They can even be thought so that the agents are connected through links, thus resembling network analysis.

Finally, it is worth mentioning efforts arising from computing science and contemporary availability of detailed, micro, spatially-precise data. This abundance of data is fertile land for the use of methodologies such as data mining, machine learning and artificial intelligence, which are collections of techniques that can be put together to help simulate complex systems and which are likely to improve insightfulness.

3.1 Methodologies' tools

Most methodologies are implemented using computational methods. Actually, it is the availability of computing power along with databases that are temporally-spatially-individually detailed that helped fuel complex systems in recent years.[7] There is a number of customized software developed to run specific proprietary and open-source models.[8]

Models can also be simulated in typical program language such as C++, Java, or statistical and modeling programs (Matlab or Mathematica). As a high-level, flexible language, Python has been used quite a lot for simulation and modeling (Downey, 2012; McKinney, 2012; North, Collier and Vos, 2006) – for example using the SimPy[9] library – or associated to spatial software, such as QGIS. Specifically for network analysis, Python's library NetworkX[10] is very useful for both creating and analyzing networks.

A software program that has been around for some time now is NetLogo.[11] Based on Java, it contains a user-friendly set of commands that quickly takes the beginner

7. Journals dedicated to complex systems include: Journal on Policy and Complex Systems, Complex Systems, The Journal of Artificial Societies and Social Simulation, Complex Adaptive Systems Modeling, Ecological Modelling, Advances in Complex Systems, Computers, environment and urban systems, Complexity, Computational Economics. A list of 41 complexity centers can be found at: <http://en.wikipedia.org/wiki/Complex_systems>.

8. Examples include, not exhaustively: MASON, Swarm, RePast, NetLogo, Flame, MASS, and at least 78 others. See <http://goo.gl/O6Ievg>.

9. Full documentation is available at: <https://simpy.readthedocs.org/en/latest/>.

10. Full documentation is available at: <https://networkx.github.io/>.

11. See <https://ccl.northwestern.edu/netlogo/>.

programmer to an operational modeler. It allows for cellular automata spatially-bounded modeling as well as for full agent-based models. More recently it has incorporated network-like link capabilities and it is easily coupled with other languages and analysis programs such as Python, R or QGIS.

4 PUBLIC POLICIES AS COMPLEX OBJECTS

This section discusses the complex nature of objects of public policies, such as social, economic, urban and environmental systems.

4.1 Social[12]

Social systems can be described as a collection of heterogeneous agents (individuals, banks, countries etc.), whose state (opinion, liquidity, wealth, etc.) influences and is influenced by the state of others, and whose interactions give rise to global properties of the system that are more than the sum of individual behavior. These features characterize social systems as complex.

Acknowledging the heterogeneity of agents as opposed to assuming a representative element is of major importance in the analysis of social systems, as heterogeneity can crucially alter the properties of a system and generate unexpected phenomena. Heterogeneity can be intrinsic (or previously acquired) or arise as the result of the evolution of the system (generated, emergent heterogeneity).

The evolution of the system results from the interactions of agents. In some cases, one agent interacts with all the others. For instance, the demand of one individual in an open market affects the price for all other agents. In other cases, one agent interacts only with a subset of the others. For example, an individual infected with a disease will affect those with whom he has contact. These relations can be represented by a network, in which the nodes represent the agents and the links, their interaction.

12. This section is based on the contributions of Claudio Tessone "Society as complex objects", Product 1 of the project Modeling Complex Systems for Public Policies.

As a result of these interactions, evolving patterns emerge from the system, such as waves of product adoption, disease propagation, cascade of bankruptcy, opinion formation etc. Persistent inhomogeneities can also arise in social systems, as is the case of unequal wealth distribution or social segregation.

Understanding how these systems respond to external influences is of particular interest for the analysis of public policy. For example, how does a social system respond to an external signal such as a change in policy? Simulating the effects of policy change is particularly useful to steering policy measures.

To this extent, modeling can help tackle the complexity of social systems. As Claudio Tessone describes, "a model is an abstract, and to some extent idealized, description of reality that still captures a particular phenomenon". Although they are limited by construction, they are useful to shed light on the mechanisms of social systems.

Building realistic models to help effective policy involves four steps: *i*) qualitative understanding of the process; *ii*) simple modeling to capture mechanisms at work; *iii*) feedback with real-world data; and *iv*) refinement of the modeling approach to gain a quantitative insight.

4.2 Economy

An economic system is composed of heterogeneous actors, with different characteristics, expectations and behavioral rules that interact with each other and with the environment.[13] Besides, the actors are in constant adaptive learning, generating evolutionary systems. The traditional or classic view, based on the assumptions of market clearing, perfect foresight, and equilibrium behavior, does not focus on the aforementioned elements, producing a more abstract analysis, which makes it difficult to comprehend the system as a whole.

Standard economic policy models usually encompass dynamic (stochastic) equilibrium (DSGE) models which take as main assumptions: *i*) rational expectations; *ii*) infinite horizon optimization; *iii*) perfect information; and *iv*) market clearing.

13. This section was based on Herbert Dawid's "Economics as Complex Objects", Product 1 of the project Modeling Complex Systems for Public Policies.

With these assumptions dynamic equilibrium models argue to identify and predict economic policy outcomes.

However, important aspects of economic policy analysis are not fully incorporated by these models. Dynamic equilibrium models look primarily to behavior at long-run steady-states, usually with lesser contributions to short and medium run policy effects.

DSGE models also do not emphasize transient dynamics, institutional setup, and their aggregate analysis fails to capture heterogeneities and feedbacks between micro behavior and macro outcomes, as well as the interactions between the economic agents. Another important limitation of these models is that they cannot handle nonlinearity and endogenous uncertainty resulted from the interactions of bounded rational markets agents. In fact, "non-linear stochastic dynamic models were linearized, often log-linearized, at a deterministic (non-stochastic) steady state" (Buiter, 2009).

In this context, alternative models that incorporate such elements are recommended in order to increase the availability of alternate understanding of economic processes. The heterogeneity of agents and the features of institutional setups that drive economic interactions should not be ignored. Many methodologies, already presented in section 2, have been used in order to capture such elements. One of the most used methodologies in economic modeling has been the agent-based simulation approach. This method is the basis of the Eurace@unibi model,[14] a closed agent-based macroeconomic model that has been used as a unified framework for policy analysis in different economic policy areas, such as fiscal policy, labor market, and issues related to income inequality. Besides, not only Agent-based Computational Economics models (Farmer and Foley, 2009; LeBaron and Tesfatsion, 2008), but also network analysis (Jackson, 2010; Newman, 2010), and analytical approaches for the analysis of agent models (Alfarano, Lux and Wagner, 2008; Dawid, 1996; Delli Gatti *et al.*, 2012), are useful for a clearer picture of the dynamics of economic systems.

4.3 Cities

Cities in particular or urban spaces in general are *par excellence* places where people and institutions entangle themselves, usually, in productive and innovative ways (Glaeser,

14. See Dawid *et al*. (2012; 2014) for details of the Eurace@unibi model.

2012; Jacobs, 1970). However, to reach the most out of their potentials people and institutions need to cover some basic functions within their shared space: dwell, commute, work and play.[15] On top of it all, cities are politically managed, which reinforces the fact that even those four basic actions cannot be accomplished individually. All activities share a common space. Moreover, cities are thought out to thrive, to harvest the best (and sometimes the worst) of societies, as long as they work properly. Thus, using sectorial policies, such as housing policies, sanitation policies or transport policies with no theoretical and methodological background to go firmly through the interactions – as mentioned above – makes applying policies to cities very hard work.

Even the approach to cities as an object of science may differ significantly. Are cities to be viewed as machines to be "fixed", as markets to be regulated (or freed), as organisms in a jungle ecosystem, or as a social exercise in which political or religious values prevail above all?

Cities are likely to benefit from complex systems because they have five typical properties:[16] *i*) heterogeneity (of people, places, institutions, and offer of services); *ii*) interconnectivity; *iii*) scale;[17] *iv*) circular causality, feedback;[18] and *v*) they evolve. Having these properties suggests that complex systems should be at least considered when planning (and managing) cities.

First of all, if heterogeneity and interconnectivity are present in cities, policy-makers have to understand their influence when suggesting policies. Will changing housing most likely affect transport and commuting? What about relative prices within the cities? If prices are affected, how does access to the city change?

Mainly, the message of relevance is that attempts to change the city – and occasionally even inaction and omission on policies on the city – have to be made with clear view of its consequences across all aspects and layers of the city. In short, city planning calls for integrated, connected, nonlinear and dynamic approaches. As those

15. Those are the four principles of the functional city proposed by architect Le Corbusier in *Charte d'Athènes* in 1943.

16. As suggested by Bettencourt, Luis in "Cities as Complex Objects", p. 3., Product 1 of the project Modeling Complex Systems for Public Policies.

17. See Bettencourt (2013) and Bettencourt and West (2010) for details.

18. See Furtado *et al*. (2012).

attributes are typical of complex systems, it may be of interest to apply them to the study and policy applications of cities.

4.4. Environment

Sustainable development is one of the major challenges for society today. How to manage natural resources in a world that is more and more complex, and where everything is interconnected? How to deal with sustainability problems, such as climate change or biodiversity conservation that are too complex to be tackled by a single discipline?

Complex systems views and methodologies can provide tools to help analyze these social-ecological systems and to inform environmental and sustainability policy making. Actually, many of the insights and concepts from complexity theory come from the field of biology.

Emergent behavior and information processing is often exemplified by the way ants forage for food, or how neurons interconnect to produce global cognitive behavior. The immune system is another example of self-organization, through which the interaction of simple cells leads to complex behavior without the presence of a central controller. Food webs and trophic dynamics are used to understand biodiversity and to analyze the implications of different types of disruptions to the ecosystem.

Modeling can be a valuable approach to understanding the dynamics of environmental systems. Through modeling, one aims to identify the key factors and rules governing a system, allowing the simulation of different scenarios and the performance of sensitivity analysis. This approach has been used to study climate change, the spread of diseases and the change in land use over time.

Modeling can also help identifying dangerous tipping points[19] in the social ecosystem. This can be useful, for instance, for the management of water resources, which might have a turning point, after which water pollution becomes costly and difficult to reverse.

19. Mitchell (2011, p. 253) defines tipping point as "points at which some process (...) starts increasing dramatically in a positive-feedback cycle." See also Gladwell (2006).

Similarly, conservation policy can benefit from the analysis of food webs and the resilience of ecosystems to external shocks, such as an increase in deforestation or in carbon emissions.

These and other methodologies from complex systems can help figure out how to manage natural resources, how to build sustainable cities, and how to promote more effective environmental and sustainable policies.

4.5 Education

Education systems encompass a large number of *heterogeneous agents*, whose interactions give rise to learning, teaching, cognition and education. They are comprised of interconnected *layers*, each of which provides support and restraints to the others. Through mechanisms of *feedback and adaptation*, these systems and their agents co-evolve. All these features make education systems complex.

The *heterogeneous agents* in an education system are, for example, students, teachers, and parents. Every student learns in a different way, every teacher has his/her methods of teaching, and every parent raises his/her child in his/her distinct manner. Learning emerges not only from information passed from teachers, but as the result of interactions between students and other people, both in formal and informal environments.[20]

Education systems are comprised of various interconnected *layers*. In a macro perspective, they involve government institutions, such as the Ministry of Education and the network of schools and universities. However, the Ministry of Finance, Health and Transport among others can also be considered part of this system, as they influence the allocation of financial resources, the health conditions to the population, and the accessibility to schools.

In a lower level, schools cannot be separated from the context in which they exist. Out-of-school factors, such as the safety of the neighborhood or the social-economic standing of the community, impact the attendance of students and their academic performance. Similarly, higher education influences and is influenced by basic education.

20. According to Michael Jacobson, "Complexity methods in education", Product 1 of Project Modeling Complex Systems for Public Policies.

At the interpersonal level, students interact with their peers, teachers, parents, school managers and the community as a whole, while at the intrapersonal level, learning results from mental processes influenced by personal interests, personal history, hormone levels, working memory and other specific features in response to stimuli from the environment.

Educational features in a society emerge thus from the interaction of all these different scales, which cannot be isolated from each other. Due to the complex nature of educational systems, traditional linear methodologies are not sufficient to capture their dynamics. The presence of multiple causalities and non-linearity might even put in doubt the external validity of results obtained in rigorous randomized controlled trials, as controlling for all key variables might be unattainable in educational research (Cohen, Manion e Morrison, 2003).

So how can complex systems methodologies help analyze education? First, simply understanding the complex nature of educational systems might help researchers refrain from having a mechanistic view of education, governed by simple causalities and levers that lead to predictable results.

Second, modeling education can provide a better comprehension of the dynamics of the system. By trying to identify the key elements and rules within a system, one can little by little understand how the different agents interrelate as well as simulate possible outcomes of a given intervention, for instance. In this respect, the role of models as theory communicators should be emphasized (Heemskerk, Wilson and Pavao-Zuckerman, 2003). By means of collaborative research, models can be improved, at the same time enriching the understanding of the phenomena.

Third, the availability of loads of data on education makes viable association studies. Machine learning techniques and network analysis can provide valuable insights into general trends or specific aspects to be furthered studied.

Fourth, tackling the complexity of educational systems might be the way of finding simple solutions (Berlow *et al.*, 2012). For example, by understanding the network of relationships involved in the system, one could identify the central nodes or leverage points through which changes could be brought upon.

Finally, complex systems methodologies are not a substitute for traditional educational research methods, but a complement to them.[21] Knowledge about educational systems might emerge from the combination of evidence-based research, traditional quantitative and qualitative methods, associative studies and modeling.

A considerable amount of research has been done exploring the complex nature of educational systems, learning and teaching. A report from OECD (Snyder, 2013) investigates how to operationalize a complexity approach to educational reforms, and provides examples of educational reforms that have used complexity principles in different countries. Other studies (Lemke *et al*. 1999; Morrison, 2003; Batista and Salvi 2006; Santos, 2008) focus on the complex nature of learning, with a focus on curriculum development, calling attention to transdisciplinarity. One academic journal[22] is dedicated exclusively to the study of education and complexity (Davis, Phelps and Wells, 2004).

A study in Brazil uses dynamic systems methodology to investigate the dynamics of the undergraduate higher education system. The learning model allows the construction of different scenarios, and the analysis of complex interaction among key variables (Strauss and Borenstein, 2010).

Another prominent application on educational policy was developed by Maroulis *et al.* (2010). The authors simulate an agent-based model in order to investigate the impact of choice-based reforms in Chicago public schools. Similarly, Millington, Butler and Hamnett (2014) use an agent-based model to analyze the impact of distance-based school-place allocation policies in the United Kingdom. Agent based modeling has also been used for teaching complexity concepts and science.[23] A research at Stanford University[24] promotes the use of computational models to link physical and virtual experiments in science classes (Blikstein, 2012), for instance. Simulation models have also been used as a teaching device for pilots, nurses etc.

21. Public forum on teaching and learning as complex systems available at <http://edf.stanford.edu/events/public-forum-teaching-and-learning-complex-systems>.

22. Complicity: an international journal of complexity and education.

23. According to Michael Jacobson, "Complexity methods in education", Product 1 of Project Modeling Complex Systems for Public Policies.

24. See: <https://tltl.stanford.edu/project/bifocal-modeling>.

Big data in education seems to be the area that has advanced the most. Learning Analytics and Educational Data Mining have been used to study online courses, to support the development of more effective e-learning systems, and to explore how children "game the system"[25] (Baker and Yacef, 2009; Kotsiantis, 2012; Siemens and Baker, 2012). Eye tracking data and movement sensors, for example, can give insights into the very learning process taking place when a child is doing an assignment (Blikstein, 2011). Machine learning can help predict when a student will drop-out or fail school (Bayer *et al.*, 2012; Márquez-Vera *et al.*, 2013). Artificial intelligence methodologies help build adaptive learning platforms (Bittencourt *et al.*, 2009; Brusilovsky and Peylo, 2003), which use data from the student to provide a customized learning experience.

Complex systems methods are though relatively new in educational research. Researchers with a thorough knowledge of the theme are scarce and there is less tradition of quantitative or computationally intensive approaches in education research. Actually, most of the applications tend to come from computer science rather than education departments. Disseminating complex systems methodologies might thus be an important step towards improving educational research, which can bring important insights to educational policy.

4.6 Transport

Transport is a typical example of a system composed by a large number of interacting, independent agents, who follow some rules, and who react to their local environment; a system from which emergent, collective behavior can be observed. If a number of commuters have to travel a specific route across the city and they have some window interval to do that, they might probabilistically just decide to go at the same time. That (unlikely) decision is definitely suboptimal as it decreases the total capacity of flow of the system. In addition, if a central traffic controller established a specific, precise time of departure for all travelers, one small disturbance might once again settle total congestion. On average, neither will occur. Anyway, the example shows that transport systems are complex, within the concepts described above.

25. "Attempting to succeed in an interactive learning environment by exploiting properties of the system rather than by learning the material" (Baker and Yacef, 2009, p. 9).

Planners and transport engineers have used simulation models in order to derive scenarios or possibilities that are not able to pinpoint exact flows of traffic, but that can predict the size of the demand on the system, specifying at times, how the system has to be dimensioned.

A more recent usage of modeling in transport attempts to simulate both the dynamics of the city – considered as density and land-use type – coupled with the dynamics of commuters. UrbanSim (Waddell *et al.*, 2007) is a pioneer example. More sophisticated modeling also tries to compute location and change of the job market and the behavior of housing markets. Together, the models try to anticipate the "movement" the city is taking – along with its possibilities or "vocation" – and attach the planning of the transport system accordingly.

When implementing transport models, Ettema[26] highlights two central representational processes: the agents and the rules. Models need to be populated with predetermined agents (vehicles, drivers, pedestrians, regulators) in a coherent and empirically relevant way. Those agents follow rules that resemble actual behavior, that are enough to generate emerging properties and that are not overfitted – in the sense that they would apply to one specific case alone. Furthermore, the modeling has to account for the interactions among agents and with the rules (and the physical environment, infrastructure). In addition, the modeling should encompass dynamic feedback in the sense that some actions of agents in a given time may reflect on agents (and the environment) in the future and that reflection, in turn, may change original behavior of agents (or the environment).

All in all, as most other modeling experience, modeling in transport may help policy-makers envision scenarios in which key adjusting parameters are visible and their consequences measured.

4.7 The legislative process

The process of law-making entails heterogeneous individuals (legislators), usually under no centralized control, who strategically interact with each other in order to produce

26. See Dick Ettema, Product 1, p. 3-4, "Complexity methods applied to transport planning".

collective decisions.[27] When this interaction occurs under a majority rule institution, collective choice problems may arise.

One main problem faced by the legislators is instability. According to the social choice theory (Arrow, 2012), majority-rule decisions tend to be unstable and chaotic. Another important problem is related to information. From the game theory perspective (Riker, 1959), legislators have incomplete and asymmetric information, which reduces their capacity to reach a collective decision. One way to overcome these collective action problems is through legislatures' organizational features. These features may induce stability and enhance information. However, the reasons for the adoption of one organizational model over the other are not clear, as well as the effect of the historical process over this choice.

Two contrasting theories try to explain the emergence and change of legislative institutions. On one side, rational choice theory (Downs, 1957) states that rational individuals design the institutions according to their interests, and when unforeseen consequences happen, these individuals may make changes that contribute to the institutional development. On the other side, the evolutionary perspective (Smith and Price, 1973), embodied in complexity theory, emphasizes the adaptation property of the system itself. According to this view, institutional development is the outcome of the interactions between institutions and the environment.

In this sense, complexity theory might help explain why outcomes vary within the context in which they are embodied, and how legislative institutions emerge and change. Following this perspective, it is of main interest in the Brazilian context to analyze the organizational evolution of the Brazilian Congress, especially, the institutional changes that have occurred since 1987, as a way to highlight the potential contribution of the application of complex systems to legislative studies.

5 APPLICATIONS IN BRAZIL

Considering the particular characteristics and problems of Brazil, it is of great interest to investigate the applications of complex systems to public policies in the country.

27. This section is based on the contributions of Acir Almeida to the Project "Modeling Complex Systems for Public Policies".

The goal is to find out in which fields of public policy the methodologies of complex systems have mostly been used, how they have been applied, and if they could help increase effectiveness of public policy.

Which methodologies are these? Which methodologies best fit each particular policy? Are there similarities among applied cases in Brazil and those observed in other countries? By studying the Brazilian possibilities, one can examine not only the advantages but also the challenges of applying such methodologies into specific public policies. The following table provides a picture of the most common areas of public policy that have applied complex systems' methodologies. The list is preliminary and was mainly compiled by Bernardo Mueller. He found studies concerning urban and transportation, economics, public health and social issues.[28]

Most of urban and transportation studies apply cellular automata and agent-based modeling, but one can also find network analysis and machine learning methodologies being used. Regarding economics, there is research on economic growth using agent-based modeling and network analysis, but most applications are concentrated on the analysis of financial market, with a wide use of superstatistics. Concerning public health, there are many researches on epidemics and some environmental studies applying agent-based modeling and network analysis. Finally, in social studies, there is research on migration and crime using agent-based modeling, on social movements applying social analysis, and on education employing machine learning, dynamic systems and network analysis methods. As already pointed out, this is a simple examination of the methodologies that have been used in Brazil. Much more investigation is needed to draw a better and more complete picture of the reality in Brazil, to compare with applications in other countries and to gain insight about the application of each methodology in distinct public policies.

28. It is important to point out that this table is the result of a quick examination of the applications of complex systems´ methodologies in Brazil. Clearly, many more studies were unfortunately not covered by this investigation.

TABLE 1

	Urban economics and transportation				Economics				Public health						Social					
	Urban economics land use/transport				Economic growth		Financial market		Epidemics and health				Environment		Migration	Crime	Social movements	Cooperation	Education	
Literature/methodologies	CA	Network analysis	ABM	Machine learning	ABM	Network analysis	Super-statistics	Network analysis	Network analysis	ABM	Analytical	CA	MAS	CA	ABM	ABM	Network analysis	Machine learning	Dynamic systems	Network analysis
Abdoos Mozayani and Bazzan (2011)				■																
Almeida-Filho (2006)[1]																				
Alston *et al.* (2014)[1]																				
Alvarenga (2008)[1]										■										
Amarante and Bazzan (2012)			■																	
Andrade and Frazzon (2012)[1]					■															
Avancini and Silveira (2013)[1]			■																	
Barbosa Filho, Neto and Fusco (2013)[1]															■					
Bastos (2011)														■						
Bazzan, Oliveira e Silva (2010)				■																
Bazzan *et al.* (2011)	■																			
Berger and Borenstein (2013)[1]																■				
Cajueiro and Tabak (2005)[1]							■													
Cajueiro and Tabak (2008)[1]								■												
Carvalho (2012)[1]									■											
Costa *et al.* (2012)													■							
Delaneze *et al.* (2011)[1]	■																			
Feitosa *et al.* (2012)[1]			■																	
Furlan (2012)	■																			
Furtado (2009)[1]	■																			
Furtado and Delden (2011)[1]	■																			

(Continues)

(Continued)

	Urban economics and transportation				Economics				Public health						Social					
	Urban economics land use/transport				Economic growth		Financial market		Epidemics and health				Environment		Migration	Crime	Social movements	Cooperation	Education	
Literature/methodologies	CA	Network analysis	ABM	Machine learning	ABM	Network analysis	Super-statistics	Network analysis	Network analysis	ABM	Analytical	CA	MAS	CA	ABM	ABM	Network analysis	Machine learning	Dynamic systems	Network analysis
Gagliardi and Alves (2005)												■								
Gleria, Matsushita and Silva (2002)[1]							■													
Guimarães *et al*. (2009)																				■
Hausmann and Hidalgo (2014)[1]						■														
Jacintho *et al*. (2010)[1]										■										
Lim *et al*. (2002)[1]			■																	
Marteleto (2001)																	■			
Matsushita *et al*. (2006)[1]							■													
Mello (1999)[1]																				
Mello *et al*. (2010)[1]		■																		
Melotti (2009)												■								
Mesquita *et al*. (2008)																				■
Mueller (2014)[1]																				
Nepomuceno (2005)[1]										■										
Peteleiro, Burguillo and Bazzan (2012)																		■		
Pinheiro Filho and Sarti (2012)[1]											■									
Pires *et al*. (2010)																■				
Possas (2001)[1]											■									
Possas and Dweck (2006)[1]																				
Saraiva (2012)[1]	■																			
Silva *et al*. (2007)[1]							■													

(Continues)

(Continued)

	Urban economics and transportation				Economics				Public health						Social					
	Urban economics land use/transport				Economic growth		Financial market		Epidemics and health				Environment		Migration	Crime	Social movements	Cooperation	Education	
Literature/methodologies	CA	Network analysis	ABM	Machine learning	ABM	Network analysis	Super-statistics	Network analysis	Network analysis	ABM	Analytical	CA	MAS	CA	ABM	ABM	Network analysis	Machine learning	Dynamic systems	Network analysis
Soares-Filho *et al*. (2002)[1]																				
Strauss and Borenstein (2010)																				
Tabak, Cajueiro and Serra (2009)[1]																				
Tabak *et al*. (2009)[1]																				
Takahashi *et al*. (2008)[1]																				
Vasconcellos (2013)[1]																				

Authors' elaboration.
Note: 1 Preliminarily compiled by Bernardo Mueller: "Applications in Brazil", Product 1 of the project Modeling Complex Systems for Public Policies.

6 DISCUSSION

This section summarizes the main insights regarding the use of complexity concepts, methods and methodologies to public policy.

First, complexity concepts can prevent an oversimplified view of the objects of public policy. Complexity points out that, when thinking of public policy, one has to consider that:

- Agents are heterogeneous

  Assuming a representative agent, such as an average consumer or firm, can be highly inaccurate and produce misleading insights for public policy. This is specially the case in countries like Brazil, where inequalities of different types are prevalent.

  As Claudio Tessone summarizes it, "heterogeneity can crucially affect the observed properties of the system, and also be the source of *a priori* unexpected phenomena in socio-economic systems".

- Everything is interconnected

  This is another way of saying that "the whole is more than the sum of the parts"; that non-trivial complex behavior emerges from the interaction among agents; or that systems are nonlinear. In public policy, this brings awareness to the fact that many traditional linear type analysis might be inadequate or insufficient. This feature also points out that the connections among agents, sectors, and scales should not be neglected, suggesting an interdisciplinary and systemic view of policy objects.

  The analysis when viewed by a multiplicity of sectors warrant that externalities, interests and perspectives are properly weighted among each other. The multiplicity of scales links the microanalysis – at the level of individuals, firms or the household – to the macro analysis of communities and parties, large sectors of the economy, neighborhoods, and cities and metropolis.

The multiplicity of scales seems central given that the emergence of patterns or, similarly, the effectiveness of public policies across scales is specific to the scale and not automatically valid over other scales. There are continuous interaction and idiosyncrasies in interaction across scales. This is especially true when considering public policies objects, especially across federative levels. Macroeconomic policy, such as interest rate setting, generates results that vary by regions, sectors, and firm size. It may affect suppliers and buyers differently. Further, actions of multiple agents with multiple interests, means and views may generate results that can also differ in scope, speed of occurrence, qualitative characteristics and permanence of effects.

- Policy does not work with clear, linear or immediate cause and effects

  The hope for action-reaction policies might be somehow naive, as complex systems do not work in a mechanical way, but change, evolve, and adapt. They are dynamic. Policy should thus take into consideration multiple causalities and indirect effects that arise because of the interaction among different agents.

Romanian philosopher Basarab Nicolescu (1999) lists three fundamental principles of the hard sciences that are not easily applicable to human sciences. They are: *i*) the existence of general, fundamental laws; *ii*) the use of experiments to decode such laws; and *iii*) the possibility that given the same conditions (*ceteris paribus*), independently, it would be possible to replicate the experiments and thus the laws that they attest.

The difficulties to apply the fundamental laws, their experimentation and replicability is clear in social phenomena and public policies by realizing the: *i*) discontinuities, jumps and ruptures; *ii*) unique, discrete events, that do not follow a clear universal pattern which could be decoded into mathematics in any immediate way; and *iii*) uncertainties which together with subjectivity of actors and lack of coherent and strict rationality leads to a non-deterministic social environment.

Therefore, policy might be more effective if geared towards: *i*) improving the resilience of the system and decreasing its vulnerabilities; *ii*) avoiding (promoting) dangerous (positive) tipping points; and *iii*) identifying the key actors in a network that can promote changes in the system.

In other words, an OECD document states: "it is not uncommon for small changes to have big effect; big changes to have surprisingly small effects; and for effects to come from unanticipated causes" (OECD, 2009, p. 2). This means that policy-making should try to understand the underlying mechanisms of the system under analysis in order to identify how to steer it towards the desired path.

Second, complexity methods and methodologies can help take into account the complex features of the systems under analysis.

- Modeling is a good strategy to obtain better understanding of how a system works, and one that allows incorporating the complex features of the system. Modeling can help identify the important players in the system under analysis (agents), their different characteristics (heterogeneity), their interrelations (interconnectedness), and how these components together give rise to complex and sometimes unexpected behavior. Examples of such modeling techniques are cellular automata and agent-based modeling. Heemskerk and colleagues collect a clarifying sequence of modeling definitions:

> A model is an abstraction or simplification of reality. Scientists often use models to explore systems and processes they cannot directly manipulate (Jackson *et al*. 2000). Models can be more or less quantitative, deterministic, abstract, and empirical. They help define questions and concepts more precisely, generate hypotheses, assist in testing these hypotheses, and generate predictions (Turner *et al*. 2001). Model building consists of determining system parts, choosing the relationships of interest between these parts, specifying the mechanisms by which the parts interact, identifying missing information, and exploring the behavior of the model. The model building process can be as enlightening as the model itself, because it reveals what we know and what we don't know about the connections and causalities in the systems under study (Levins 1966, Jackson *et al*. 2000, Taylor 2000). Thus modeling can both suggest what might be fruitful paths of study and help pursue those paths (Heemskerk, Wilson and Pavao-Zuckerman, 2003).

- Modeling permits simulating scenarios as a decision-support tool to inform policy making. Models work as platforms for so-called *in silico* experiments, by means of which different policy options can be computationally simulated and "cheaply" tested.
- Modeling stimulates a forward-looking, prospective view of policy, by allowing scenario building and testing. Models can enable prognosis that are less based solely on probabilities but that include essential interactions at various scales and with various agents' interests considered. Policy-makers can thus work with spaces

of scenarios and realms of probabilities that occur given known rupture points.

- Models can be continuously improved, as more knowledge is gained about the system. Models can also be simple and provide general or specific insights to help tackle a particular problem.

Third, data are a valuable resource for policy making and complexity methods give insights into how to use them to the best extent.

- Data can help visualize, describe and identify features of the system to be better explored. Social network analysis, for instance, relies on the visual representation of networks to convey complex information
- Data mining, machine learning, network analysis and other association studies can provide insights into the functioning of the system
- Data can help validate and improve models.

Fourth, public policy can benefit from collective knowledge

- Communication through models

  Models are means of communicating one's ideas and theories and can work as a "meeting point" for collaborative work among interdisciplinary teams. "Models not only help formulate questions, clarify system boundaries, and identify gaps in existing data, but also reveal the thoughts and assumptions of fellow scientists." (Heemskerk, Wilson and Pavao-Zuckerman, 2003).

- Multiple models

  The notion of multiple models contributes to the understanding of social phenomena in particular and of public policies in general because it is based on the richness of diversity, difference and dissimilarities (Page, 2007). As Page argues, no single model can independently cover comprehensively the intricacies of some phenomena, especially those of subjective nature, complex ones. He also states that models section the analysis with specific parameters, be it from the theoretical, methodological or procedural point of view. Thus, the diversity of models imply a larger coverage of possible scenarios that are more keen to envelope unexpected sequences, unlikely important events, unique tipping points.

Knowledge can be viewed as a feedback process, "an endless cycle of proud proposing and disdainful doubting" (Mitchell, 2011, p. 295). Modeling provides a way to structure this process and to improve the understanding of the system one wants to impact. The cycle of data analysis, modeling, validation, simulation, implementation, data analysis, remodeling and so on might be the "strange loop" that can provide decision support for tackling complex problems through public policy. If not a certain, determined path to be tread on, complex systems may illuminate the key pathways to policy-makers, clarifying what is likely to happen given choices of sets of paths, after so much has been traveled on.

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