RESEARCH ARTICLE

A Social Science-Inspired Complexity Policy: Beyond the Mantra of Incentivization

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This study suggests that cross-fertilization between complexity and social science could provide a new rationale for policy. We look at the weakness of conventional policy thinking and excessive faith in incentives and the underestimation of social interaction on individual choices. Recent examples of experimental and computational research on social interaction indicate the importance of understanding preexisting social norms and network structures for targeting appropriately contextualized policies. This would allow us to conceive policy not as something that takes place "off-line" outside systems but as a constitutive process interacting with self-organized system behavior. This article aims to pave the way for a complexity-friendly policy that allows us to understand and manage more than predict and control top-down. © 2014 Wiley Periodicals, Inc. Complexity 19: 5–13, 2014

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INTRODUCTION

We live in a complex and largely unpredictable world where boundaries between technology, economic, and social systems are more and more porous. This implies that changes in one system, even apparently insignificant ones, might have serious consequences on another system's behavior. This in turn could have implications on the original system in a cumulative, nonlinear way. For instance, the advent of Facebook and Twitter has modified how people interact and has increased available information on preferences and behavior of distant people. This in turn increased the extent and spatiotemporal magnitude of social influence everyone is exposed to. Thus, there have been significant changes, for instances, in the relationship between customers' behavior and companies' marketing strategies or between political election candidates and the public opinion, with mass collaboration in information sharing and peer-to-peer communication in all sectors. New applications have been developed to support innovative sharing activity between users, reinforcing in turn the importance of Facebook and Twitter users' opinion in these sectors.

Even just a few years ago, nobody could have predicted this complex coevolution of technological, social, and

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economic systems. The social adaptive behavior of agents and unpredictable complex network effects has generated intricate cross-sectoral implications, favored by large-scale, real-time peer-to-peer communication [1]. On the other hand, growing economic and social uncertainty, associated with periods of innovation and changes, has increased the demand for effective policy. Unfortunately, recent policy failures, such as the 2008 financial crisis, have cast serious doubts on the adequateness of policy and created widespread frustration. Recently, new policy analytics have been advocated that follows a complexity perspective and aims at importing exact science methods and tools, advanced computing techniques and complexity mathematics into social and economic policy (e.g., Refs. 2–4).

This study aims to promote cross-fertilization between complexity and social sciences to challenge traditional views and to promote new policy analytics. We argue that importing advanced mathematical and computational techniques or increasing the scale of data mining and analysis is not sufficient. A new policy requires better understanding of human and social foundations of complex social systems. We will focus especially on the role of social interaction, which has been neglected in mainstream policy and has not yet been satisfactorily considered even in physics-oriented complexity models.

We will consider three sources of policy inadequacy: (i) an anticomplexity way of thinking, (ii) a partial theory of human behavior, and (iii) limited data for policy. All these deficiencies are interrelated. First, a mechanistic way of thinking which equates policy and top-down, outside-in control has impeded the development of a "conducive," bottom-up approach toward guided self-organization of socioeconomic systems. This approach is more compatible with complex socioeconomic systems. Once complexity is considered, a policy shift follows from the "prediction mantra" of mechanistic approaches to focus better on understanding and governance of these complex systems [5].

Second, the theoretical deficiency of conventional policy depends on overconfidence on the explanatory power of economic theory. The influence of standard economics has led economic and social policy to make two biased assumptions: (i) individuals are rational decision makers responding to a set of given incentives, and (ii) they are isolated from any social context. This has in turn nurtured the mantra of economic incentivization eliminating any consideration of individual heterogeneity and social interaction. Stronger reference to recent experimental and computational research in social science, which contradicts these assumptions, would help us to calibrate complexity-friendly policy better.

Finally, another important problem is the limitation of "evidence-based" policy mainly based on econometric estimations of longitudinal (national and cross-sectional) data. This embraces an anticomplexity notion of social aggregates as the mere sum of behavior of individual agents (e.g., individuals, households, and organizations) and statistically overestimates historical aggregate trends. This could give a fatal statistical illusion of excessive confidence of the law of large numbers. Given that past trends are overprojected in future estimations of the system, extreme events and complex network effects cannot be considered (e.g., Ref. 6). Indeed, the data typically used for policy are individual-level data that cannot capture systemic effects. These include social network effects, which are of paramount importance when individual choices are socially influenced and social contacts can influence aggregate desirable outcomes [7]. This is true not only for cohort studies and randomized controlled trials in health policy but also in longitudinal, cross-sectional data used in economic and social policy. Overcoming certain limitation of current data for policy is essential to better understand institutional dynamics and large-scale socioeconomic changes (e.g., Refs. 8 and 9).

The article is structured as follows. The first section examines what is missing in conventional policy, whereas the second section focuses on social interaction and presents recent experimental findings on social interaction. These findings restrict the universal applicability of incentivization policy. The third section discusses implications of these new findings for a complexity-friendly policy making. The point here is that policy cannot conceived itself as something taking place "off-line" outside the systems involved but should be viewed as a constitutive process interacting with self-organized system behavior [10]. New policy analytics could considerably benefit from big data mining and innovative collaboration platforms across sectors and actors. These are essential to transform policy in an adaptive, experimental, and collaborative process.

WHAT IS MISSED IN CONVENTIONAL POLICY

Conventional policy is based on two simple assumptions: (i) agents are rational decision makers responding to a set of given incentives, and (ii) they are isolated from any social context. The first dictates that, in order to decide which school to choose for our kids or which family health insurance plans to enroll in we have a stable set of preferences, formulate rational expectations for any alternative, find everything we need to know in prices, and maximize our utility function. The second implies that our decisions are made individually without any influence of social networks in which we are embedded, from Facebook to peers, friends, or the family.

These two assumptions are reflected in the policy idea that individuals would similarly, predictably respond to

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incentives. As a result, this "rationality" at the microlevel would give planned rational outcomes at the system level. The pipe-dream of policy as top-down control is to regulate socioeconomic systems mechanistically toward desirable outcomes, by manipulating positive/negative incentives addressed to individual choices. This idea stems directly from the economic idea of the universal application of the rational choice model. This is the case, for example, for a wide range of social and economic policies, from the labor market to retirement plan reforms, not to mention mechanism designs to regulate economic systems. Do we want to reduce staggering healthcare costs? Then, simply increase taxes on unhealthy products and rational people will stop eating junk food or smoking.

This approach has various problems. Even if in principle the theory is true, no one knows the extent to which positive/negative incentives should be pushed to modify the equilibrium of the system. Experimental studies show that positive/negative incentives might have a magnitude effect, that is, their effectiveness may be threshold-dependent (e.g., Ref. 11). Not only could this threshold be heterogeneous at the individual level, for example, depending on agent resources and preferences, but even getting to it could be economically unfeasible and socially undesirable. For instance, an educated guess could lead us to believe that putting all smokers in prison would eradicate smoking. On the other hand, this would generate immense economic costs (e.g., monitoring and punishing violators), not to mention violent social protests by everybody, including nonsmokers. This means that policy cannot always maneuver positive/negative incentives to an optimal level and that this level is not always known in advance by policy makers.

Second, this approach does not consider that preferences and behavior are socially constructed under various social influences and pressures. Sociological investigation indicates that social structure may influence individual behavior in various ways (e.g., Ref. 12). This influence increases when individuals face operational and strategic uncertainty or when there is asymmetry of information between interacting parties [13,14]. The strong sensitivity toward other opinions and behavior, especially more relevant contacts, has also been found in "pure" market situations, such as among traders in financial markets [15]. Here, individuals have the best decision of technology available and all quantitative, structured information needed. This applies even to the relationship between policy and people's response in a variety of situations. Therefore, in a variety of policy-sensitive situations, more behavioral heterogeneity is expected than has been conventionally contemplated as a pure effect of social network structures.

As argued by Ormerod [16], if these structure and network effects are not considered, policy can dramatically fail its objectives as it follows only a very partial account of how people behave. Network effects can in fact swamp the impact of incentives or magnify their effect, depending on complex information transmission mechanisms, positive/negative externalities triggered by (virtually and physically) observed behavior, and the way people react to behavior and relevant opinion. Recent studies on disease, obesity, and substance abuse showed the explanatory relevance of social networks and the complex interconnectedness of individuals to understand people's choices. They also showed that any policy intervention in these fields may fail if it is targeted on isolated individuals (e.g., Ref. 17). For example, policies to reduce smoking, alcohol abuse, and obesity that provided peer support were more successful than traditional policies based on negative incentives as they were capable of changing the social network of individual targets involved [7].

The opposite is true for the recent global financial crisis. In this case, the preexisting network structure of financial markets, completely neglected by policy makers, inhibited policy targets despite the huge amount of public money made available. Indeed, the presence of a global network of interlinked, global financial institutions frustrated authority regulation in mitigating risk of toxic assets. This plan was pursued by presuming that financial institutions were independent, rational, and socially disembedded agents instead of components of a complex adaptive system (e.g., Refs. 18 and 19).

It is worth noting that even the idea of "nudges," suggested by more behaviorally informed policy analysts and popularized by the British Prime Minister David Cameron, follows the same bias. In this case, the idea is that by tweaking the decision context and altering the way individuals perceive available options, people are helped to frame their decision more rationally. The potential of this approach has been suggested in a variety of policy situations, for example, health, education, and environment initiatives [20] (see also Ref. 21). For instance, by requiring restaurants to list the calorie content of all menu items or adding energy consumption to customer bills, people are expected to order food with less calories and to moderate their energy consumption. This would also help to reduce policy expenses in terms of positive/negative incentives by simply targeting a definition of the decision context that could trigger desirable outcomes. Although it is an important advance when compared with the conventional economic theory, nudges are expected to fail in various circumstances as they underestimate the influence of the social embeddedness of individual choice (e.g., Ref. 22).

In summary, the mechanistic approach of conventional policy has been theoretically built-in by the influence of mainstream economic theory and this has been one of the most serious reasons for recent policy failures. Neglecting

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agent heterogeneity and the strength of (whether virtual or "real") social interaction in determining individual behavior, in an era where mass-scale information and communication technologies (ICTs) are so important, is a fatal error.

THE STRENGTH OF SOCIAL INTERACTION

The fact that people's behavior deviates from standard rationality predictions and that this has significant influence on the complexity and predictability of aggregate outcomes has been widely acknowledged in experimental and computational social science studies (e.g., Refs. 23 and 24). For the sake of simplification, we can ideally distinguish between "bounded rationality" and "social structure" effects. The former is more linked with relations between decision and information of an individual decision maker, whereas the latter points to social context constraints on individual choice.

An example of the former is the classical experimental study by Tversky and Kahneman on the "frame effect." Here, it was found that people's behavior is conditioned upon how a given problem and decision is presented as individuals gain and lose weight differently [25]. Rather than exploring the optimal level of positive/negative incentives to change people's preferences, here the challenge for policy making would be to formulate the decision context in a way that the cognitive bias of people could be managed to induce desirable outcomes, such as in the nudge idea. An example of the second case is the recent experiment on cultural markets by Salganick et al. [26], where the emergence of market bestsellers was found to be strongly dependent on customers' information on others' preferences. The nonlinearity of social influence processes determines the unpredictability and path dependency of market behavior even when individual preferences were known (see also Ref. 27).

This applies to a variety of situations other than books, movies, or art markets. For example, the same social influence effect was found in a large-scale experiment on political mobilization in Facebook performed on November 2, 2010. Here, the simple fact of seeing the faces of previous friends expressing their "like" on a link was found to influence information seeking and friends' voting, as well as friends of friends, thus extending to offline networks [28]. The lesson here is that individual choices are not socially independent as they trigger positive/negative externalities that are channeled by social network structures. If these aspects are not considered in advance, it is hard to predict reactions to any given policy "stimuli."

To complicate the situation even more, it is worth noting that the effects of bounded rationality and social influence are intimately interlinked. What is new today is the pace and spatiotemporal magnitude of these effects due to the diffusion of global-scale ICT networks in all spheres of our life. On one hand, the amount of information has dramatically increased, making selective attention, information search heuristics and all other typical cognitive sources of bounded, adaptive rationality essential to survive information overloading (e.g., Ref. 29). Bombarded by information (of various types and sources) and embedded in various, overlapping (virtual and real) social networks, individuals are induced to extensively exploit social information and this increases their exposure to social influence effects.

This has been found even in "supposed," high-intelligence contexts, such as financial markets. Here, highly trained professional investors and traders are equipped with the best available knowledge technology to make investment decisions, but continue to rely heavily on the opinion of anonymous users in online forum and peer-to-peer communication platforms (e.g., Ref. 30). On the other hand, when the exposure to social influence networks increases, individuals are more sensitive to observation, judgment, and they tend to imitate others' behavior. As shown by recent sociological studies, in interaction contexts characterized by operational, strategic, or reflexive uncertainty, this can create conditions for information cascades and herd behavior. This in turn can make system behavior difficult to predict, even if policy makers ideally have complete knowledge of individual preferences (e.g., Ref. 31).

It is worth noting that these aspects were found even in cold, artificial interaction settings, such as the typical laboratory, where individuals are called to make decisions based on perfect knowledge of the rules of a game and without direct communication. Here, we will focus on two aspects, which have been completely neglected by conventional policy: (i) the role of social norms, and (ii) the fact that social structure may influence and coevolve with individual behavior toward self-organized paths.

The first is the idea that policy interacts with systems characterized by preexisting social norms, which could also induce individuals to under-react or overreact to incentivization. The second is the idea that individuals are embedded in complex social networks, which may determine social influence pressures that inhibit rational responses to incentivization. Both can be considered as social interaction effects, which, once understood, help to contemplate a "less is more," conducive, self-organization-friendly policy alternative to top-down, outside-in incentivization.

Mainstream economists argue that incentives can reduce market failure, by managing negative externalities, superseding contract incompleteness, conveying information of other people's interests, influencing the long-term development of individual preferences, and making strategic interaction more intelligible and predictable for everyone involved. Their argument is that without the

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enforcement of incentives, any social and economic interaction would be subject to failure, unpredictability, and underdetermination (e.g., Ref. 32).

Experimental and behavioral research contradicts this argument, by suggesting that in many real situations, social and economic systems self-organize around social norms and patterns that might resist against or inhibit incentivization, whereas they could be ideally exploited for social and economic benefits. A good example is the problem of public goods and commons provision, such as the maintenance of natural resources (e.g., forests, pasture, fisheries, and irrigation systems), and the development and access to knowledge and software. Rational choice predicts that individuals would not have any incentive to limit their own self-interest, for example, consuming common resources independently of others' needs or not sharing their knowledge to protect their own business. However, empirical reality is full of cases where individuals were capable of overcoming this "rational" trap. Studies of commons indicate that in all cases where people were capable of overcoming this trap, the reason was the endogenous existence of social norms, such as moral values, reciprocity, trust, and social approval. On the other hand, in cases where market incentives were introduced, this tended to induce overexploitation and suboptimal outcomes (e.g., Refs. 33 and 34).

A first crucial insight of these studies is that incentives and norms are not clearly separable (e.g., Refs. 35 and 36). While adding or manipulating economic incentives, imposing fines, or changing the rules of the game, policy can crowd out preexisting positive social behavior and contradict self-organization processes. This may even generate unintended consequences and favor counterproductive behavior, for example, local maximum traps or lack of cooperation needed.

The most famous example of how incentives could backfire is blood donations by Titmuss [37]. He argued that the British system of voluntary blood donation led to healthier and more timely blood donations than the American system, which was based on incentivization. The idea was that incentives could compromise the moral foundation of the donor's decision. This was also found in a field study on a group of daycare centers in Israel. In this case, the objective was to reduce delays in the collection of children by parents, and the solution was adding monetary fines to latecomers. Once fines were imposed, parents reacted by doubling the delay and continued to do so even 12 weeks after the fine was revoked [38]. The explanation is that adding fines undermined parents' sense of obligation to avoid inconveniences to teachers and transformed delay in a market good everyone could purchase [36]. These cases indicate that material incentives might trigger calculative rationality and transform a broad range of economic and social situations, where preexisting normative scaffolds exist that help to regulate social interaction, in self-interest traps that lower existing normative equilibria.

The sensitivity of individuals to moral values, such as fairness, inequality aversion, and reciprocity, which is not fully explained by self-interest or rational behavior (e.g., Ref. 39), is also associated with our tendency to overestimate other people's opinion and judgment. Recent laboratory experiments showed that in conditions of uncertainty and asymmetry of information, individuals tend to follow social information, even if undoubtedly biased. They also consider the impact of reputation even if it has no impact on their immediate or future pay-offs. Again, uncertainty about behavior of other people and overestimation of the impact of others' opinion triggers this tendency (e.g., Ref. 40).

For instance, in indirect reciprocity laboratory games, Sommerfeld et al. [41] found that individuals followed gossip even when they were able to use more reliable sources of information, such as direct observation. Uncertainty about partners' trustworthiness triggered the subjects' idea that other people had better information than their own direct experience. In a dictator game, Piazza and Bering [42] found that individuals overreact to the possibility of being the subject of gossip by increasing their contributions, as if gossip were an informal social control mechanism. In a repeated trust game, Boero et al. [43] found that individuals considered their reputation and cooperated more even when reputation was available to counterparts after their investment decisions, that is, when reputation-building strategies were ruled out. Haley and Fessler [44] found that even the simple presence of stylized eyespots on the computer was sufficient to significantly increase the generosity of subjects in a dictator game (see also Ref. 45). This was also found in a real-world setting by Bateson et al. [46], with people putting nearly three times as much money in a "honesty box" used to collect money for drinks in a university coffee room, when the cost of the drinks was displayed on a board along with a picture of eyes staring at the consumer than when the notice included a flower control picture.

This sensitivity has been explained as the result of adaptation to the life of hunter-gatherer groups, where individuals learnt to observe and influence each other [47]. The progressive enlargement of social circles during the evolution of modern societies implied the need to master a growing amount of information, and this required norms and institutions that regulated and amplified social information (e.g., Ref. 48). In any case, it is interesting to note that if artificial laboratory interactions are sufficient to trigger these complex forms of social behavior, we might expect that this is even more so in real life, where people might be strongly influenced by behavior of others, can communicate, and have vivid interaction

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experiences. It is worth noting that this is the typical situation where policy intervention takes place.

These findings indicate that by neglecting these aspects and concentrating only on top-down incentives, policy conflicts with preexisting self-organized normative forces, which have been internally developed in these systems (eventually inspired by moral values). It is therefore essential to understand the behavior of these complex systems to contemplate context-dependent situations and target conducive policies that harness internal forces for social and economic benefit [49].

For the second point, experimental and computational findings showed not only that social structure matters when predicting collective outcomes but also that, ideally, individual behavior can generate different outcomes depending on the social structure of the social context. This means that even if individuals ideally have fixed, predictable behavior, collective outcomes significantly depend on social structure components.

This has recently been showed in certain experimental and simulation studies on social network dynamics (e.g., Refs. 50 and 51). For instance, Buskens et al. [52] found that in coordination games where individuals had to decide which opinion to endorse and their payoffs depended on other people's choices, the density of the initial individuals' network may significantly influence system behavior. More specifically, they found that the higher the density, the stronger was the influence of the initial behavioral distribution on collective outcome. In this case, higher chances for path-dependent processes were found that perpetuated inefficient solutions. Similarly, Cortens and Buskens [53] performed laboratory coordination games played in networks by a population of N subjects ($N = 192$) who could create, maintain, or break their ties. They found that the efficiency of collective behavior was strongly influenced by the network density and the initial network topology. More interestingly, interaction structures were more efficient when not exogenously determined but coevolved with individual choices. Coevolution of individual behavior and network structure triggered positive effects that led individual behavior toward systemic efficiency without any top-down control imposition.

This was further confirmed by Bravo et al. [54] who performed a repeated investment game in the laboratory with a population of N agents ($N = 108$) randomly matched each round. Here, individuals could benefit from cooperation by taking the risk of investing on other unknown partners. However, the structure of the game included strong temptations for cheating. Subject behavior was experimentally traced and used to calibrate an agent-based model, where network topology was manipulated. The consequences of various types of networks for cooperation were tested; however, the most interesting result was that even when keeping individual behavior fixed and similar to the experiment, cooperation was higher than when agents could create and break ties following their preferences and networks coevolved with individual choices.

These studies have interesting policy implications. First, neglecting structural effects and the process interplay of individual choices and emergent social structures could induce policy to generate unplanned, counterintuitive outcomes. Second, by following an outside-in, top-down incentive strategy, the possibility of targeting more effective, context-informed policies is missed.

CONCLUSIONS: THE "LESS IS MORE" LESSON

This study has been inspired by previous studies on complexity-friendly implications for policy (e.g., Refs. 55–58). These studies showed that certain typical features of complex adaptive systems, such as bottom-up emergence, path dependency, and self-organization, make it hard to predict system behavior ideally even if precise knowledge of past system behavior or detail on behavior of single components are available. By looking at the experimental literature on socioeconomic systems, this study argues that social interaction, that is, agent heterogeneity due to social structure and networks, is the main driver of this complexity.

In these cases, policy, including its role and function, must be reconsidered. First, it must be recognized that the principal cause of policy failure is not the size of the state or the magnitude of the action or resources involved, as often suggested by politicians and analysts. The real cause lies in the intellectual framework in which a policy is conceived [59]. This also includes the theory and methodology used for policy design and implementation. Complexity rationale helps to appreciate better empirically grounded knowledge of socioeconomic systems to realize that there is no "silver bullet" policy approach. This implies the need for better reflection of the relations between policy and targeted systems. When the relation between policy and targeted systems is complex, "less is more" is preferable as there is no linear, isomorphic effect between magnitude of policy stimuli and magnitude of results.

In these situations, learning to exploit social foundations of behavior and interaction is fundamental. It may also help policy makers to target smaller-scale initiatives based on conducive mechanisms, which can elicit social norms and positive behavior without embarking on outside-in, large-scale, or general-purpose incentive plans. These can, in the worst of cases, even nurture self-interested behavior and compromise long-term sustainability of these systems. This is especially true when policy aims to achieve collective outcomes that require cooperation and there are potential (both positive and negative)

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externalities. The complexity message is that by reducing policy to incentivize or nudge expected people's behavior, we lose the chance to understand and nourish fundamental internal diversity, heterogeneity, and exploration which help to harness complex system behavior.

It is worth noting that better knowledge of behavioral and structural components involved in socioeconomic systems is also essential to discriminate between situations where incentives do give good results and those where this is not expected. There are respective strengths and deficiencies of positive/negative incentives versus social norms policy scenarios which need to be better understood in order to establish contextual-based policy interventions.

Social science literature and successful implementation initiatives exist that are compatible with this idea. For instance, in the debate on the Third World economic development policy in the 1950s and 1960s, Albert O. Hirschman suggested that economic development does not mechanistically depend on the optimal combination of given resources or production factors known in advance by policy makers. It can however aid the mobilization of internal, underutilized assets of socioeconomic systems. To do this, looking for bottom-up complementarities and harnessing self-reinforcing processes on the ground is pivotal for good policy [60].

Unfortunately, this lesson was forgotten and only recently reconsidered by the so-called asset-based community development initiatives in the United States. This carried out mainly bottom-up initiatives since the 1990s in low-income neighborhoods [61]. In this case, the idea was that rather than addressing important social and economic problems in local communities by targeting incentives and investing resources from outside, important socioeconomic and long-term sustainable development initiatives could be promoted by releasing asset-based self-organization processes on the field. This favored unplanned, internal self-reinforcing processes following Hirschman's ideas. Other interesting complexity-friendly cases of policy initiatives have been reported in some urban and regeneration initiatives in the United Kingdom and the Republic of Ireland (e.g., Refs. 62 and 63).

In addition, to also consider methodological problems, it is worth outlining that the challenge for new policy analytics is neither to passively import exact methods and advanced computational techniques to master big data analysis nor to simply follow "evidence-based" policy making. Indeed, in policy literature, "evidence" often points to over-estimated aggregate socioeconomic factors in an anticomplexity way. As suggested, econometric estimations on longitudinal, cross-sectional aggregate data, which are typically used for policy decisions and evaluations, are a poor guide to illuminate and manage the complexity of socioeconomic systems [64].

We need to better understand peculiar mechanisms of social complexity and look at or generate data that point to these mechanisms. This should also consider that effects might be disproportionate to causes and that both can be separate in time and space [65]. The exploration of new ICTs for large-scale data and innovative stakeholder collaboration platforms is relatively underdeveloped, but better initiatives in this direction could help to reframe policy as a process of systemic change and complex system management rather than an exercise of top-down control.

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