Relational Methodologies and Epistemology in Economics and Management Sciences

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Conclusion: Methodological Pluralism and Epistemology between and beyond Relational Methods

METHODOLOGICAL PLURALISM AND EPISTEMOLOGY

The years of epistemological – and a fortiori, methodological – Manicheism waded: since the seventies, excepted for the supporters of positivism, as an epistemological position, and mathematical analytical approach, as a methodological position, methodological pluralism and non-positivist epistemologies widely diffused and consolidated (Mingers & Gill, 1997). On the methodological side, qualitative studies, laboratory case studies, statistical analysis, case-based reasoning, network-based methodologies and computational modeling have been accepted and practiced. What we want to underlie here is that, in search of better explanations of a given phenomenon, all these methodologies can be viewed not necessarily as competing, but rather feeding each other. As for most human behaviors, besides competition there is also collaboration as a possible approach. Contextualized on methodological pluralism, it means that, for instance, a qualitative study could provide salient data to better calibrate an agent-based model, whose findings in turn could lead to better empirical or statistical studies. The scarce practice of these methodological cross-fertilizations derive much more on the tendency of scientific communities to close into a self-referential world rather than to the undeniable methodological difficulties in combining different methodologies. On the other hand, some recent studies seem to demonstrate that mixed methods research has a major impact on scientific growth (Molina-Azorin, 2012), thus, witnessing a certain demand for richer and more articulated approaches. Likely, most researchers perceive, more or less knowingly, that socio-economic phenomena are complex and that such a complexity require finer and deeper and multiple methodological perspectives.

Although network-based methodologies share a lot in common, its multiple adoption in a single study or its cross-fertilization are far to be a common practice or orientation, and most researchers are closed into a single methodology, often forcing it to work in not well appropriate phenomenological contexts. This has been the main reason to design this book, and this concluding chapter intends to try providing some ideas on what network-based methodologies have in common and in what differ, and finally offering criteria to choose among them.

On the epistemological side, if we roughly identify positivism with the idea that there is only a single right explanation for each problem, that facts are objective, that theory building and testing/confirming is as well objective and a-historical, and hence that between rival theories will win the best one, then it is likely that, even in natural sciences, this is not more the prevalent philosophical position. Various kinds of evolutionary falsificationism (Radnitzky & Bartley, 1987), metaphysical (or internal) realism (Putnam, 1983, 1987, 1988), and pragmatism (Rorty, 1979, 1982, 1991) diffused within large communities of researchers. In social sciences the distance from positivism has been much bigger than in natural sciences, giving citizenship also to radical anti-realist positions, like constructivism (Mingers, 1995; Newton *et al.*, 2011; von Foerster, 1982; von Glasersfeld, 1995; von Krogh, 1996, 1998), and critical realism (Al-Amoudi & Willmott, 2011; Archer *et al.*, 1998; Buch-Hansen, 2013; Fleetwood, 1999; Hodgson, 2004; Lewis, 2004). The main reason is that the complexity of socio-economic phenomena is much higher than that of natural or artificial phenomena. A fact that it is still difficult to be accepted, especially by natural scientists. In other words, it is the acknowledgment of the pervasiveness and intensity of complexity that forced social and natural sciences to depart from positivist (and even realist) epistemologies. Analogously, complexity legitimates a multi-methodological perspective (Mingers & Gill, 1997), because reality offers so many different facets that they are impossible to be grasped with a single one. Roughly speaking, each facet requires an appropriate methodology to be dealt with, and often even just to be acknowledged. In other words, methodologies that are inappropriate for a certain facet do not allow even to recognize the existence of the corresponding phenomena. Moreover, for overlooking certain phenomena might imply overlooking certain essential aspects of reality, the lack of appropriate methodologies could have epistemological implications. That is, methodology and epistemology are not independent: specific choices in one can influence the other.

Moreover, if we look at epistemology with the Bateson's (1980) broad view of "a way to look at the world" or with its ontological-cognitive aspect of "what are the constituents of reality", then the interconnection between methodology and epistemology appears much clearer, and evidenced by the development of relational methodologies. If we overlook connections among elements and focus only on its attributes, we embrace an epistemology of reality without structures, let say, an attribute-based epistemology, which does not need any relational methodology. Conversely, if we adopt a network-based epistemology, that is if we acknowledge that, regardless of its attributes, elements are interconnected and the resulting structure is a fundamental property of reality, then we need relational methodologies. A research area whose main theoretical frameworks acknowledge the relevance of structure, that is the role played by connections, will develop sooner or later relational methodologies. A research program – or research tradition, the weaker concept proposed by Laudan (1977) – creates a demand for new appropriate methodologies, if the existing ones cannot accomplish the research questions around which the research program is developing. Structuralism required a relational methodology to check the existence of structures, and to grasp and penetrate its implications. To some extent, systems science and cybernetics could satisfy those requirements, and in fact they started up during the thirties and forties. However, these two powerful approaches could not completely match the methodological needs, because they limit to aggregate properties, and the inner system's structure is touched only marginally. Network analysis was the right methodology, and in fact it started during the thirties too, and developed rapidly after the second world war in US and UK (Freeman, 2004).

The disciplinary areas where structuralism were stronger and more demanding of getting appropriate methodologies were psychology, sociology, and anthropology, and in fact applied social network analysis – besides its pure mathematical development as graph theory – was nurtured in those areas. Conversely, a research area whose main theoretical frameworks neglected the relevance of structures, like standard (neoclassical) economics, employed attribute-based methodologies, and resisted the adoption of network-based methodologies, because they would be incompatible with its theoretical frameworks. They would contradict the epistemological ground of its theoretical frameworks. As Lucio Biggiero argued in Chapter 1, this is what is happening to economics, where the late but fast-growing adoption of relational methodologies is undermining the theoretical mainstream. This is an interesting case in which a paradigm change does not occur *only* because of a theoretical debate more or less supported by empirical findings, but also through a methodological change that brings forth new facts, which could not be seen by means of the traditional (attribute-based) methodologies.

Interestingly, we see a case in which the hyper-rational view according to which tools (methods) follow goals (theories) is contradicted. Methods are not docile and neutral tools in the hands of theorists, but rather they might be the lever with which rival theories crowd out the current paradigm (Greenwald, 2012). Once economics has been "infected" by relational methodologies, its mainstream is challenged by new rival theories or even by old rival theories reformulated with new empirical supports obtained through relational methodologies.

Of course, network-based methodologies do not replace attribute-based methodologies, as some extreme form of structuralism in sociology argued in the past. They are two complementary aspects of reality, which should be taken together and combined in order to have a better and more integrated understanding. Indeed, they are irreducible one another, just as distances cannot be reduced to weights. Of course, one can say that being isolated or connected is, in abstract, an attribute, but a structure cannot be expressed and measured in terms of attributes and cannot say anything about the attributes of its elements, excepted for those topological properties that, in a second-order analysis, might be treated as attributes. As well, a mix of attributes – else than topological attributes - cannot be expressed and measured by structures and cannot say anything about structures.

Not incidentally, another one of three main relational methodologies – ANN (Artificial Neural Networks) - started up right after network analysis and the second world war, while the remaining two - NK simulation modeling and ABSM (Agent-based simulation modeling) - only during the seventies, and then developed during the nineties. In fact, in the meanwhile, complexity theory put new methodological demands on the scientific research program developing the old structuralism and transforming it into a new (much richer) paradigm. Static network analysis was definitely not enough, if not for simple and temporary analyses. The strong methodological need for dynamic and richer analyses exerted a pressure also on standard network analysis, which elaborated promptly two methods - SAOM (Stochastic Actor-Oriented Models) and ERGM (Exponential Randon Graph Models) – to accomplish it (see Chapter 1).

HOW TO CHOOSE BETWEEN RELATIONAL METHODOLOGIES

What Do They Have in Common

As we have seen, all the four methodologies are network-based and put the relation and not the attribute at the focus of analysis. This does not prevent that they, alongside its specific technical and conceptual development, became progressively able to take into account also nodes (components, agents) attributes, and to combine relational with attributive analysis. We have seen concrete examples of this methodological evolution in some chapter of Part II, provided that agent-based models, being the richest and more powerful methodology, offer the combination of the two dimensions, as well as that of the static and dynamic dimensions.

Network analysis is a relational methodology by definition, and through network-formation and longitudinal modeling is able to acquire also a generative and a dynamic dimension (see Chapter 1). Further, it is able also to integrate attributes and to take into account the mutual influence between relations and attributes. In addition, it is able also to take into account multi-level analysis, and likely the bottom-up processes and global constraints. More difficult, but likely in principle not impossible, it will be the consideration of the mutual influence between multiple types of relationships.

NK-BN – the Boolean network simulation modeling - is a clear relational methodology, in that it puts network dynamics at the core of the analysis, makes it depending on network topology and activation rules (see Chapter 2). By modifying the original model with the insertion of activation threshold and its dependence on nodes attributes, this methodology is also able to take into account elements attributes, even though the reverse, the influence of relations or activation rules on nodes attributes has not yet been developed. NK-FL – the fitness landscape simulation modeling - is a full relational methodology either when the model concerns only a single network (agent, system) relations in its own evolutionary path, or (and even more) when it considers also inter-agents connections – the *C* variable of the NKC modeling (see Chapter 2) – corresponding to the meta-network constituted by two or more agents and their relations. In the latter case, inter-connections between agents co-exist with the intra-connections structuring each single agent.

ANN is as well a network-based methodology in that it employees a multilayer network with input nodes corresponding to the explanatory variables connected to a hidden layer of nodes, which are in turn connected to a layer of output nodes. As underlined and discussed in Chapter 3, while ANN most traditional usage was devoted to provide optimization tools more effective and efficient than the ones developed by traditional optimization theory and operations research, there is an interesting and promising usage as a simulation modeling too. Kauffman (1993) highlights that this way of approaching ANN has very much in common to NK-BN modeling, because an ANN behaves analogously to a Boolean network, with the obvious difference that connections have weights and that the action of Boolean functions (activation rules) is submitted to activation thresholds. In this methodology "attractors may be thought either as memories held by the neural network or as concepts", and hence ANN can be viewed as classifier systems. However, in order to be effective, they should be in the ordered regime or at most at the edge of chaos, because otherwise a chaotic ANN would not stabilize in a given attractor, neither be trained to learn how to reach any attractor. Conversely, changing connection weights – links values, in the language of social network analysis – and/or activation thresholds it is possible to convert an ANN from a chaotic to an ordered regime. The similarity of NK-BN and ANN as simulation modeling methodologies occurs – not by chance – also in terms of the computational load[1] that they imply, as underlined by Lucio Biggiero and Eliano Pessa in their respective Chapter 2 on NK models and Chapter 3 on ANN.

ABSM are relational methods because they take into account not only agents attributes but also (and mostly) their interaction mechanisms, that is their relationships. Therefore, agent-based modeling is a relational methodology, with which either attributes or relationships are taken into account, and left free to interact reciprocally and recursively according to the rules designed by the modeler.

In What They Differ

So far, we have remarked the common relational trait of these four methodologies. However, they differ under many respects, that we have synthesized in nine main criteria. Besides briefly addressing each one, we will try to combine them into a single schema, helpful to choose which of the four methodologies is more appropriate according to research goals and resources. We are aware that this comparison would deserve an entire new contribution – or likely more than one, for a systematic analysis – and that therefore it could be seen as misplaced in a concluding chapter. However, in a less orthodox view this choice appears as a stimulus for future studies in this direction.

The first criterion is that of the capability to take into account dynamics: needless to say, socio-economic phenomena are dynamic, and hence, the capability to take into account this aspect is of primary importance to choose a useful methodology, and this criterion must hold also between relational methodologies. Nevertheless, most traditional theoretical models in economics and management are static. General economic equilibrium models are static, and the few ones that attempts to develop a dynamic analysis are even less realistic than the (already completely unrealistic) static models. Evolutionary economics is radically changing standard economics also on this fundamental respect. Although not constrained by the neoclassical chains, management and organization sciences developed mostly static models until last few years[2].

A second criterion is twofold: on one side it refers to the capacity to deal with large size networks, while on the other it concerns the type of network topology. As regarding the former aspect, it should be noted that because some of the four methodologies imply a huge computational load, but many socio-economic networks are made by thousands if not million nodes, it's necessary to wonder whether a methodology can afford large size networks. It should be underlined that also each of the criteria 3 to 8 exerts a tremendous pressure in terms of computational load, which becomes particularly strong when considering learning mechanisms in combination with actors' number and heterogeneity. However, because of its technical and logical characteristics, computational load can remarkably differ between the four methodologies. As concerning the question of network topology, it should be remarked that the denser and cyclic the network, the more complex are propagation processes, and the impact of recursive processes. In other words, network complexity – meant in this partial sense – is related much more to network density and cyclicity rather than to network size[3].

The third criterion refers to the capacity to take into account the potential mutual influence between different *types* of relations. For instance, in an inter-organizational network the topology and intensity of knowledge exchange relationships can substantially influence the topology and intensity of trade relationships, which in turn can influence the other. This phenomenon of inter-relations influence is, especially in a dynamic perspective, much more (complex) then the characteristic of simple multiplexity, which is just the acknowledgment of the existence of different types of relationships connecting the same set of nodes, and its separate (static) analyses. It is not just a question of overlapping or confronting two (or more, depending on the number of different relationships) network topologies made by the same nodes, but rather of studying how the two (o more) types of relationships holding between each dyad can influence each other.

An analogous phenomenon of inter-relations influence might hold between relationships and actors, and this constitute the fourth criterion. In fact, according to the type or number or weights of his incumbent relationships, an actor could change his behavior, and thus, he could propagate a chain (or even an avalanche) of effects on the rest of the network. Therefore, a topological change could produce a change in actors' behavior, which in turn could change topology.

Weak learning – the fifth criterion - refers to a situation in which agents hold: i) the same interaction patterns, that is, the number and types of other agents with whom they interact; ii) the same type of interaction mechanisms, that is, the variables that define such mechanisms; iii) and the same behavioral profile, that is, their attitude towards opportunism, loyalty, etc. Then, what do they learn? Looking at the past behavior, they may vary the quantity of answer parameters, because they improve their capacity to calculate and predict better future states. In so doing, they become more efficient, and possibly also more effective. This is a way to look at single loop learning or Bateson's learning process of logical type 1 (Argyris & Schoen, 1996; Bateson, 1972; Biggiero, 2012).

With strong learning these limitations are removed, and agents can change their interaction patterns, and change or create new mechanisms and behavioral models: for instance, they can become loyal or trustworthy from being opportunist. We remind that these two types of learning processes address to two corresponding families, because each one could be implemented in a huge variety of ways and related degree of complexity. Moreover, both them – and especially strong learning – are forms in which recursiveness play a crucial role, because an agent adapts (changes his structural position into the network or his interaction mechanism or behavioral model) to others changes, and in turn, by changing one or more of these three aspects, gives others the necessity or just the opportunity to change as well. Notice that when an iteration involves a combination of two variables (or even a variable with itself) nonlinearity is already into recursiveness, because it reminds to a view of each structural (topological) cycle among nodes as a recursive function. In other words, nonlinearity at network (or sub-network) level does not need that all single dyads are connected through a nonlinear relation, but just that there is a cycle with a positive feedback mechanism.

Actors' entry or exit refers to the possibility that new actors may be created or cancelled, that is, the network changes size and possibly also its degree of actors' heterogeneity. New actors can add to the incumbent, and they might be different from the existing ones, increasing the degree of heterogeneity. Incumbent actors might exit as well, so depicting a true network evolution that touches also network size and topology. Even more importantly, under this criterion can be listed also another phenomenon the characterizes and distinguishes social phenomena from biological phenomena: the merge between one or more actors.

The micro-macro-micro (MMM) relationship addresses to the ability of the methodology to take into account not only the (bottom-up) formation of emergent phenomena, but also the (top-down) effects that such phenomena can cause in terms of enlargement or restriction of actors' possible behaviors. An emerging event might become also the creation of a new type of agent: for instance, the group of automotive producers can create an association to enhance their interests and facilitate inter-organizational collaboration.

The final criterion is that of resource consumption, either in terms of time for designing and applying and interpreting results or in terms of costs for people working on the implementation of the methodology. Clearly, every researcher has to balance the most appropriate methodology in absolute sense with its resource consumption, and then he has to confront it with his budget constraint. If the budget or the available time (or perhaps the right competencies) were not available to employ the most appropriate methodology for the given research goals, it could be the case to slightly modify them and choose a second best.

Contrasting the Four Relational Methodologies

In tab. 1 the four relational methodologies are briefly addressed in the light of the nine criteria. Three possible evaluations are employed, depending whether the given methodology fully matches the criterion, or not at all, or the criterion could be (in principle) accomplished, but only with heavy modifications of the "standard" or original version of the methodology – this is the "hard-to-do" cell label. In general, such modifications have not yet been experimented, or they have but with a substantial effort of reformulation and often with a sort of radical "mutation" of the original version. Indeed, often there are no precise and insurmountable boundaries between the four methodologies, and especially between some of them: for instance, between NK and ANN or between NK and ABSM. Implementing the opportune

Table 1.

Tab. 1	**Criteria for choosing**								
Criteria Methodologies	Dynamics	Network size and topology	Relation ↕ relation	Actor ↕ Relation	Weak learning	Strong learning	Actors' entry or exit	Macro ↕ micro	Resource consumption
NA	Yes (SAOM)	Yes	Yes (ERGM)	Yes (ERGM, SAOM)	Yes (SAOM)	No	Yes	No	Small
NK-BN	Yes	Hard-to-do	No	No	No	No	No	No	Medium
NK-FL	Yes	Hard-to-do	Hard-to-do	Hard-to-do	Hard-to-do	Hard-to-do	Hard-to-do	Hard-to-do	Medium
ANN	Yes	Hard-to-do	No	No	Yes	Hard-to-do	No	Hard-to-do	Medium
ABSM	Yes	Hard-to-do	Yes	Yes	Yes	Yes	Yes	Yes	Variable
	Complexity →								

modifications and enrichments (or impoverishments) it is possible to hybridize one methodology with another, in the sense of "implanting" some new functions and possibilities into a given framework. However, these transformations, to the extent they leave untouched the basic framework, make the new transformed version often rather inefficient – computationally heavy and resource consuming - and ineffective – scarcely manageable.

What happens sometimes is another way to face with complexity and methodological enrichments: focusing and delimiting the enrichment on some side, that is "compensated" by an impoverishment on some other side. Network formation modeling into the field of network economics is an interesting case like this (see Chapter 1): for instance, actors' turnover is considered at the price of a radical simplification of the interaction rules between actors and at the price of providing actors' simple goals, usually represented by optimizing some utility function, and some other restrictive assumption in order to reach an equilibrium state. A similar complexity reduction is adopted also by SAOM in order to achieve a longitudinal analysis: here actors obey some form of utility maximization rules as well. In so doing, these models approach, to some extent, network economics and neoclassical economics.

The first eight criteria have been ordered into an ascending order of complexity: from the capacity to take into account some form of dynamics until MMM processes. In some case, as for learning rules or MMM processes, the attribution of highest complex situation is quite intuitive and (not so often and clearly) addressed by current literature (as a good exception, see Squazzoni, 2012). We are aware that in other cases this ordering is less evident and questionable, but the purpose here is to open a scientific debate advancing a reasonable proposal to be deepened and discussed in future studies, rather than to claim a definitive view in such a complex matter.

With its recent modeling developments, network analysis can take into account also the dynamic dimension, and the mutual influence between types of relationships and between actor attributes and relationships. It can consider also weak forms of learning and actors' turnover, as it is done since many years especially in network economics (see Chapter 1). However, network analysis could hardly model strong forms of learning, and neither MMM processes. Traditionally, network analysis can deal also with large network size and does not require heavy resource consumptions. However, the more accentuated is the dynamic dimension and the complexity of behaviors – that is, the more moving towards columns on the right of tab. 1 – the more consuming will be resources, especially in terms of computational load. Indeed, this effect characterize more or less all the four methodologies, and likely any bottom-up methodology.

NK simulation models put different methodological problems depending on the BN or FL versions, the former being much more rigid and less applicable than the latter. Both them are dynamic by its own nature, but NK-BN imply a heavy computational load, and therefore they can hardly face with large networks, if not reducing average connectivity to very low values and limiting the exploration to only small portions of the state space. What NK-BN cannot do is taking into account relation-relation and actor-relation mutual influence, and neither weak or strong forms of learning, nor actors' turnover or bottom-up effects on the micro-level. In other words, NK-BN modeling requires topological, behavioral and interactional invariance, which prevents to deal with the true and deep forms of socio-economic complexity (Biggiero, 2001; Casti, 1994; Jörg, 2011; Mainzer, 1994; Vega-Redondo, 2007; Waldrop, 1992). NK-FL is a much more flexible methodology, which can accomplish all the first eight criteria, but at the price of remarkable simplification and likely not matching all at once, because in this methodology each of them would dramatically raise the computational load.

ANN are dynamic methods because they are based on the "progressive self-tuning" of a network to give a predefined output: it learns how to reach the goal. In its applications for simulations and not as optimization algorithms, this aspect of training the network to reach a goal dissolves, but weak learning capabilities remain. However, the downside is that the computational load increases sharply, especially for large network size (see Chapter 3). Strong forms of learning could be hardly implemented, as well as MMM processes, and relation-relation, actor-relation, and actors' turnover seem impossible to be designed.

ABSM can easily accomplish all the eight criteria but that of large size networks, especially if the characteristics related to the criteria from 3 to 8 are intensively employed (Edmonds & Meyer, 2013; Jörg, 2011; Lane *et al.*, 2009; Levy, 2009; Liu, 2001). Indeed, each of them could be lightly or massively designed, and the computational load will vary accordingly, and exponentially pushed by network size. For instance, an actor can remember few or many things, react to few or many agents with few or many types of behaviors, etc. Hence, the question – which indeed concerns (more or less) even the other three relational methodologies – is not only if (and which) one of the 2-8 criteria is accomplished, but also the number of variables accompanying each of them, that is, the variety and intensity with which they condition actors' behaviors and network topology.

RELATIONAL METHODOLOGIES AND COMPLEXITY IN ECONOMICS AND MANAGEMENT SCIENCES

As we have seen, in the proposed perspective ABSM is the most powerful methodology, because it accomplishes all the nine criteria and has no limits in the complexity of the phenomena to be modelled, excepted for the computational load and the difficulties of design, validation, experimentation, and results interpretation. If the model is very complex, then all these aspects of computational simulations become very hard, and possibly unmanageable. We cannot go too deeply into the determinants of the complexity of an ABSM, but it is important to underline that, as already hint above, the most relevant are the degree of heterogeneity and interconnectedness among agents, the multiplicity of their interaction mechanisms, and its recursiveness and nonlinearity. Model size – for simplicity reduced to the number of agents, but indeed involving also other parameters – comes secondarily, but of course strongly amplifies the effects of the other determinants. To these difficulties, one more should be added, one that in the pioneering stage of ABSM was substantially overlooked: the more complex a model, the more complex the understanding of its inner structure, with its explicit or tacit hypotheses and assumptions, its specific algorithms to express each behavior, its calibration, and validation processes. In other words, the more complex a model, the less comprehensible, and especially less contestable (and contendible) becomes the model.

This has been a warning raised by Valente (Chapter 4 of this book) and Merlone *et al.* (2008), this latter also underlining the problem that different program languages can give, ceteris paribus, qualitatively identical results, but different quantitative replications and sensitivity to parametric changes. These methodological concerns have been also accompanied and sustained by a misleading epistemological persuasion that science should always find the more general laws and thus, should be the more abstract possible. All these factors determined the triumph, during the early years of ABSM development, of the so-called KISS principle (Axelrod, 1997): Keep It Simple, Stupid. That is, researchers dedicated almost exclusively to build stylized, essential models, which oversimplify real phenomena. However, this produced a sharp proliferation of social science computational models, but a substantial lack of empirical validation and results comparison (Ashworth & Carley, 2007; Carley, 2009; Read, 2010).

There are three reasons to move in the opposite direction and violate KISS principle. The first reason is that it is obsolete, meaning that it was fundamental at the infancy of the agent-based revolution, because nobody knew exactly the relative advantages of this simulation technique. And in fact, as the history of science and technology shows, only practice can really and effectively tell the actual performance of a given methodology or discovery or technology. So, building very simple models, and trying to capitalize on them was a good guideline to be followed at the time. However, over time some features are becoming clear: i) knowledge growth and exchange from different ABSM is much harder and slow than expected; ii) besides single model's architectures and designs, even programming language properties can affect model outcomes; iii) reality is so rich that an enormous number of models almost all incomparable could be built on a same phenomenon. The second reason is that the KISS principle hides a "reductionist view", because its – tacitly invoked – knowledge growth by adding or combining simple models implies that partitioning a complex phenomenon into its smaller parts allows understanding them enough well to "recombine them on demand". Unfortunately, a true acknowledgment of complexity theory and epistemology (Anderson, 1972; Biggiero, 2001, 2013; Casti, 1994; Ekeland, 1991; Gell-Mann, 1994), especially connected to the nonlinearity and interconnectedness of socio-economic phenomena, sharply contradicts the hidden form of reductionism implied by the KISS principle. The third ground for a KISS-based critique is that, even for a rich and complex model, despite its design, implementation, and debugging would be certainly very complex, its use should not necessarily be complex too. At least, not necessarily in the sense that the model outcomes could be not really understood. In fact, variables and parameters (and eventually also agent's types) that do not matter for the purposes of *a given experiment* could be "frozen". This way they will be not involved (not computed) in the program, and thus, they would not disturb the handling of that virtual experiment. In other words, by freezing what is "superfluous" for a given purpose, model complexity is automatically downgraded. Hence, the KISS principle should not be more a must, which of course do not mean that we should stop building simple models, but that it's time to build also (rich) complex models.

This need has been perceived and stressed by Edmonds and Moss (2004), who suggested the KIDS Principle: Keep it Descriptive, Stupid. However, as many issues put in a de-contextualized and too general way, the juxtaposition KISS-KIDS is neither conclusive nor useful nor appropriate. A first reason is that, especially for complex phenomena, full descriptiveness is impossible, because there would be too many potentially pertinent things to be noted. A second reason is that an extremely precise description would have the same usefulness of a 1-to-1 scale map: none. Theorizing means of course abstracting: the challenge is to define and decide the "right" (appropriate) level of abstraction for a given research issue, and also to identify the variables and aspects that, besides its possible abstraction, are irrelevant or not pertinent.

At first sight KISS and KIDS seem symmetrically wrong, the one's advantages being the other's failures, but at a closer sight things are different, and a distinction could be useful. If we proceed through only KISS models there is a serious risk of never reaching the point at which we will know what is relevant and how a given phenomenon actually works. This risk is due mostly to two factors. The first one is that, jointly with other characteristics of complex phenomena, nonlinearity prevents results additivity and even integration and comparison. As Ekeland (1991) clearly argues: complex (nonlinear) systems are not-decomposable. The second one is that the huge variety of ways in which complex phenomena can be modeled severely hinders results comparability. This factor undermines of course rich models too, and maybe strongly, but there are two remedies. The first one is *limiting the construction of complex models to few exemplars, while developing and nurturing some corresponding researcher's community sharing a single model*. The second remedy is working hardly on empirical validation, which gives an advantage to KIDS respect to KISS, because reality of complex phenomena is integrated and complex by definition, and thus, real data are epistemologically and methodologically "homogeneous" to the results of complex models rather than simple models. Therefore, the KISS and KIDS principle had to be reformulated as KIERS: Keep It Enough Realistic, Stupid. That is, make it sufficiently rich (complex) to grasp what is relevant. Indeed, this is an end point instead of a starting point, because what is relevant can be understood only after a long theoretical and empirical research process. It is a recursive process between theory and results.

Moreover, while, seemingly, it could be argued that simple and few goals could allow working with simple models, at a closer sight, this rationale depends to a certain extent on previous considerations, because the evaluation of what is lost with simplification can be properly done only once we will know deeply the phenomenon, and not independently. Hence, less ambitious goals could be properly chosen only after having obtained a satisfying representation and analysis, and not before. Finally, it should be underlined that there is a fundamental asymmetry: with rich models one can – but is not forced to - design also complex experiments, while it is not true vice versa: with a simple model it is not possible to do complex experiments. In this perspective, a rich model is a rich lab where a researchers community can do simple and complex experiments with the guarantee of their comparability.

In sum, we believe that the right way will be not to stop with KISS models, but to build also some few complex models, shared by a researchers community, that could become common large laboratories able to enhance theoretical and empirical advancements by exchanging data and enabling inter-theoretical comparability and empirical validation. This is exactly what happens in natural sciences, whose recent development shows just that a remarkable knowledge growth requires sometimes large projects, like the Encode project that involves 440 scientists from many countries since 2003 through 1500 experiments. All in all, once socio-economic sciences have discovered - with ABSM in its most powerful expression, and to a lesser extent other relational (and computational) methodologies like those discussed into this book – the magic of experiments (albeit virtual), it is time to learn from other sciences that benefited of laboratory experiments much earlier.

Of course, nothing prevent to reverse the complexity arrow of tab. 1 and build ABSM so KISS-like to be pure neoclassical models, even in the more restrictive category of equilibrium models. Indeed, even if at first sight it seems strange, once we remove the characteristics corresponding to the first eight criteria shown in tab. 1, a general equilibrium model could be seen as a pure KISS model. In this case, ABSM (and even the other relational methodologies) would be stripped of its properties and potentialities to be reduced to just computational models, useful to reach solutions through numerical attempts instead of analytical derivations. Agents (multiple and complex) relationships are cut or reduced to price reactions (but not inter-(re)actions) in static and oversimplified conditions: the model becomes essentially an auction model. Put in this light, the acknowledgment of interactions – even if limited only to price relationships – and behavioral changes is the first step to model complex socio-economic phenomena, and already a point of departure from neoclassical economics. If interactions are constrained by the various forms of proximity and technological combinations, then the problem assumes a network nature, and it should be dealt with relational methodologies.

While adding the complexity "ingredients" of tab. 1 in ascending order, we leave more radically from neoclassical economics[4]. Of course, the more we proceed in this direction the more we depart from the "Newtonian paradise" of general explanations and optimal solutions, falling down in the swamp of partial, local, and satisfying (at most) explanation and solutions. But there is no other way: we should choose between false or illusory general and optimal solutions on one side, and likelihood, uncertain and partial solutions on the other side. Until the development of relational methodologies, and the most powerful among them (ABSM), neoclassical economics had two crucial methodological advantages against its criticists: i) through analytical methods no solutions could be found, no matter how large was the problem; and ii) missing relational methodologies, structuralism was just a theoretical option, which could not be employed in concrete formal ways, neither applied to empirical research. The advent of relational methodologies and its combinations with complexity theory and methods has radically changed the situation, providing effective and formal tools for either theoretical or empirical research.

Being free from the neoclassical background and constraints, management sciences have been more prompt to adopt and progressively diffuse the four relational methodologies discussed in this book, with a major use of network analysis, likely for its relative simplicity respect to the others. However, despite its complexity, also ABSM are diffusing, perhaps hindered by the ones who look with suspect to formal modeling. Besides this resistance, the true problem is that these applications still reflect the huge theoretical proliferation characterizing social sciences. Hopefully, especially if the researchers community will be able to converge and collaborate to some few rich models, the shared results will give the opportunity to grow common knowledge and reduce theoretical proliferation and fictitious disciplinary barriers, like those between sociological, economic and management approaches to the same problems, like individual or organizational cooperation, innovation networks, etc.

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ENDNOTES

[1] Here we use this concept to address the broader issue of algorithmic complexity and computation time/resources. This is a specialized field with subtle questions of information theory and computational complexity (Du & Ko, 2000). More pragmatically and experimentally, whoever dealt with network-based dynamic models knows that the more "abilities" and interacting mechanisms are given to agents, the more disproportionately complex becomes the model, and the much longer, ceteris paribus, becomes computing time.

[2] References and more insights into these issues can be found in the Introduction and Chapter 1.

[3] A similar attempt has been made by Kemper (2006), who compared the most appropriate usage of network theory and cellular automata in management studies. He adopts two criteria addressed here too: network size and interconnectedness, meant as complexity of interaction. He argues that when prevails the former aspect, then it is more appropriate using cellular automata, while in presence of more complexity of interactions network analysis works better.

[4] Some clues of this view can be found, with exclusive reference to ABSM, in Gallegati & Richiardi (2009) and Moss (2009).