FORMAL MODELLING, COMPUTER SIMULATION AND GROUNDED FIELD RESEARCH TO CONDUCT ENQUIRY IN MANAGERIAL SCIENCES

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INTRODUCTION

With different fortunes and oscillating enthusiasm, computer simulation has supported theoretical investigation in managerial disciplines since the 60's. In the attempt to further corroborate the role of formal modeling and computer simulation in the repertoire of research strategies available to social scientists, the aim of the present essay is to sketch out a framework for an enquiry that combines computer simulation and field-based investigation, this latter a typical research strategy in social sciences.

To begin with, it is important to set up in the front a definition for computer simulation. Computer simulation has to do with the manipulation of symbols using a computer code; more specifically, it uses algorithms to derive propositions from the assumptions that come together in a computer model. A computer model is a formal model in which '[…] the implications of the assumptions, that is, the conclusions, are derived by allowing an electronic digital computer to simulate the processes embodied in the assumptions' (Cohen and Cyert 1961: 115).

In this respect, computer models can be regarded as special cases of mathematical models (Cohen and Cyert 1961) in which conclusions are derived from assumptions by using a computer simulation rather than a process of analytical solution. On the other hand, however, computer models not necessarily have to be stated in mathematical and numerical form (Clarkson and Simon 1960) since they allow manipulation of symbols that can be words, phrases and sentences. Therefore, computer models make up the subset of mathematical models that are solved numerically rather than analytically but not all the computer models are stated in mathematical terms since they may incorporate not-mathematical symbols. In this respect, Troitzsch suggests that computer simulation is a third system beside natural language and mathematics (1998: 27).

In principle, computer simulation is just a technologically-aided process of deduction. Yet, the crude technology can vary strongly from different approaches and, more importantly, the difference in the adopted technology often unveils profound differences in the philosophy that lies beneath modeling.

System Dynamics approach is inspired by the idea that behavior of individuals that are embedded within a social system as determined by the feedback nature of the causal relationships that characterize the system (Forrester 1958, 1961). In this line, System Dynamics models reduce aggregate and often puzzling behaviors into underlying feedback causal structures and, a consequence, typically aggregate agents into a relatively small number of states, assuming their perfect mixing and homogeneity (Rahmandad and Sterman 2004).

Taking as an example another modeling and simulation approach, Agent-based modeling, we observe that underpinning viewpoint is notably different. In Agent-Based models logic of investigation is typically inclined to show how interaction among individual decision-making and learning may generate complex aggregate behavior. Consequently, modeling needs to preserve heterogeneity and individual attributes.

However, independently of the approach adopted and the inspiring philosophy, research work employing computer simulation has frequently been regarded, in social sciences, as influenced by an autonomous logic in respect to mainstream research. Too formalized to effectively capture the complexity of social processes for someone, leading to results excessively dependent of specific parameters' calibrations for others. Simulation studies, however, have a long tradition in organizational research. Going back to seminal work in the area of the behavioral theory of the firm and organizational decision theory, some of the most important theoretical pieces are based on a simulation approach. This is true, for example, for the well known Garbage Can model (Cohen, March and Olsen, 1972) and for the work leading to the development of The Behavioral Theory of the Firm (Cyert, Feigenbaum and March 1959; Cyert and March 1963).

In recent times, computer simulations have recuperated terrain in mainstream management journals and the aim of this essay is to contribute to this process of legitimization process by laying bare an approach to associate formal modeling, computer simulation and field study to conduct an enquiry in managerial sciences. The approach that we describe is conceived of independently of different philosophies beyond formalization and simulation.

The article is organized as follows; in the next section I consider a sample of recent works that use simulation and I muse on the differences in the underlying logic of enquiry. In the following section, I focus on a specific issue: the association of formal modeling, computer simulation and grounded field research. In the last section of the chapter I draw some conclusions.

COMPUTER SIMULATION FOR THEORY DEVELOPMENT IN STRATEGY AND ORGANIZATION

In examining early contributions that adopt a research design that includes formal modeling and computer simulation, three groups of typical justifications recur to justify the adoption of this methodology.

First, computer simulation, in comparison to formal analytical approaches, allows retaining a greater richness of details. Economists that adopted computer simulation operated in a cultural milieu in which research method, and rhetoric, was erected upon the rock-hard plinth provided by mathematical modeling. The typical way of proceeding demanded consequences of modeled assumptions to be deducted by the means of analytical solution of a mathematical model. The rigor of the approach, however, does not come without costs since the need to solve analytically a model bounds the complexity that the model can incorporate. The portrayal, for example, of non linear relationships among variables introduces in a model a considerable amount of complexity so to possibly impair its analytical solution.

Under this perspective, we can interpret the candid enthusiasm that permeates writings of Cohen, for example, who explains that 'It requires a much more extensive knowledge of mathematics to obtain an analytical solution to a complex mathematical model than it does to formulate the model' and, thus, computer simulation '… allows a more flexible and easy approach and preserves richness of details…' (Cohen 1960: 535). This enthusiasm is shared by Orcutt that gives the idea of how powerful computer simulation appeared to these pioneers as a tool to deal with complex systems:

> The use of simulation techniques by the authors of this demographic study does not, of course, offer any guarantee in itself that they have produced an acceptable and useful population model. However, by producing a feasible means of solution it permitted them to introduce a variety of interactions, variables, nonlinearities and stochastic considerations into their model which they otherwise would have been forced to leave out despite strong evidence of their importance.
>
> (Orcutt 1960: 905)

This characteristic rescues the researcher from a typical dilemma. The dilemma requires a researcher to either abandoning the idea to represent the object of study closely, thereby accepting costly simplification in order to rigorously generate testable hypotheses through mathematical analysis, or to preserve complex representations of the object of study at the cost of producing appreciative theories of behavior that have to deal with the ambiguity of natural language.

A second motive that is frequently mentioned is that in a computer model the relationship between assumptions and deducted consequences can be easily manipulated to account for a variety of changes and amendments in the model structure. The fact that a computer simulation does not require an analytical solution to derive consequences from assumptions entails that researchers can explore how modifications in a model's structure have an impact on the unfolding behavior of the model without remaining entrapped into the quandaries of often laborious mathematical analysis. As Cohen explains:

> A further advantage of computer models is the ease of modifying the assumptions of the theory. When suitable programming languages become available, relations can be inserted, deleted, or changed in the model, and only local changes, which can be quickly made, will be required in the computer program.
>
> Modifications of this kind will have a much smaller effect on the procedures for simulating a forma1 model than they would on the means used for obtaining analytical solutions to the model
>
> (Cohen 1960: 536)

Considering the work done by Hoggatt (1957), for example, Shubik noted that ‘The number of cases and conditions worked out by Hoggatt would have been unfeasible without a simulation’ (Shubik 1960: 917). As Cohen and Cyert suggest (1961), the work of Hoggatt is a good example of how computer simulation may help to revive an old model (in this case the neoclassical decision model for determining output of firms given a market price) addressing complex questions that were not practicable with other techniques of analysis. The easiness in the manipulation of computer models is also connected to the fact that computer models may be structured in a modular format. Thus, ‘It is extremely convenient to be able to formulate a complex model in terms of several component submodels, to dea1 with each component separately at first, and then to integrate them into a complete model.' (Cohen 1961: 45). In similar veins, Gilbert and Troitzsch (2005) suggest that simulation is more appropriate for formalizing social science theories than mathematics because programming languages are more expressive and less abstract than most mathematical techniques and because computer models are often modular, so that major changes can be made in one part without the need to change other parts of the program.

Finally, computer simulation allows researchers to generate complex hypotheses of a system's behavior that are testable against empirical world. This is because deductions obtained with computer simulation, besides being as rigorous and reliable as those obtained through mathematical analysis, may be cast in the form of time series to be directly compared with observed behaviors. Imagine a theory that predicts, in specified circumstances, the emergence of a particular behavior over time of a specified variable. In this case, a verbal description of the behavior has to be compared with empirical paths of behavior. This verbal description may be ambiguous in comparison to the string of reported quantities collected over time as appearing into an empirical time series. On the other hand, computer simulation, to produce hypothesis of behavior, adopts the same language that is used to collect empirical time series: a string of quantities reported in specific intervals of time. In this way, computer simulation improves the capability to generate testable hypotheses of behavior (Meinhart 1966). As Orcutt explains: computer simulation makes it '... possible comparison of generated results with observed time series and cross sectional data and thus permitted testing of a sort that would not otherwise have been possible.' (Orcutt 1960: 905).

THE LOGIC OF ENQUIRY USING COMPUTER SIMULATION

As Cohen and Cyert suggest (1961), computer models are of two types: synthetic and analytic. In synthetic models, the modeler knows with a high degree of accuracy the behavior of the component units of the phenomenon under scrutiny. On the other hand, in analytic models, the behavior of the phenomenon is known and the problem is to capture the mechanisms that produce the behavior. In this classification, synthetic and analytic models reveal different underpinning logics of enquiry. While synthetic computer models are informed by a pure deductive logic, analytic models are characterized by an inductive logic (Cohen 1961).

To start with, however, a word has to be said to better define what we mean by inductive or deductive process. More specifically, the associations synthetic/deductive and analytic/induction may sound not necessarily intuitive.

Deductive process has been acknowledged as a key component of scientific reasoning since Aristotle. A deductive inference moves from general assumptions to specific consequences; in this respect, consequences drawn from assumptions have an inferior degree of universality than their premises. Deductive inferences have two properties; first, the information embodied in the deducted consequences is more or less explicitly, included in the assumptions; second, deducted consequences originate necessarily from assumptions. In other words, if assumptions are correct, deducted consequences must be correct as well.

On the other hand, inductive processes move from particular instances to general conclusions. In this respect, in inductive inferences, derived conclusions are not entirely included in the premises. In other words, the information content in inducted conclusions is greater that the one crystallized into the premises. Thus, inductive inferences say something new, or different, in respect to premises; thus, they add information. This property conceals an hazard because correctness of premises does not necessarily imply that conclusions are correct as well.

As for the distinction between *analytic* and *synthetic*, starting from Kant's Critique of Pure Reason (firstly published in 1781), an analytic statement is purely explanatory of an existing concept and it does not add more information than that already contained into the concept itself. A classic example reported by Kant regards the statement that affirms that an entity of matter is extended in the space. The fact that an entity of matter is extended in the space is already implicit in the definition of entity of matter. It does not add information regarding the concept *entity of matter*; rather it provides an extension, or further explanation, of the concept. On the contrary, a synthetic statement is *extensive* because it adds more information than that contained originally in a concept. For example, the fact that an entity of matter has a weight, explains Kant, is not included necessarily in the concept of entity of matter (it suffices to think of a state of absence of gravity) and rather it stems from a synthesis between an original concept and a quality external to the concept.

Given this distinction between synthetic and analytic statements, Peirce, for example, put forward a dichotomy between deductive/analytic and inductive/synthetic inferences (Harshorne and Weiss 1931/1935).

Thus, we have to be very careful in interpreting the distinction proposed by Cohen and Cyert between analytic/inductive and synthetic/deductive, since in their framework the concept of synthesis pertains to the use of simulation to aggregate local, or partial, components of a phenomenon, into a global emerging behavior. On the other, analysis concerns the dissection of behavior of interest into its components, or determinants.

To be clear about the wording we are going to use and to avoid misunderstanding, we focus on the distinction between computer simulations that adopt a deductive or an inductive logic of inference and we ignore the dichotomy between analytic and synthetic computer models. Within this framework, deductive computer models focus on the specification of a set of mechanisms or processes and explore unfolding consequences of such specifications whereas inductive computer models move from the definition of an aggregate behavior and use simulation to test whether candidate mechanisms or processes are able to determine *in vitro*, and thus explain, the aggregate behavior.

We suspect, however, that simulation studies show a much broader variety of approaches that blend elements of deduction and induction. In addition, in computer simulations induction and deduction are intertwined in a cyclical process of theoretical investigation. Induction works when we introduce in a model a casual mechanism that we deem possibly responsible for an observed behavior. In this case, we run history backward to reproduce the conditions for the behavior under study to emerge. On the other hand, once we have found a candidate causal mechanism that we think may explain observed behavior, we might be interested in understanding how robust is the relationship between causal structure and the emerging behavior. Additionally, we may want to understand if the causal mechanism is connected to other possible behaviors. In other words, we may be interested in the relationship between the causal mechanism, or a class of similar causal mechanisms, and a class of behavioral phenomena. In both cases, we can generate a sensitivity analysis by simulating the model with different calibration of model's parameters or we can simulate the model with a variety of modifications in the structure of key causal mechanisms. In this way, we can explore near-histories or hypothetical histories (March, Sproull and Tamuz 1991) in order to articulate our understanding of a phenomenon. When we run a computer model and we observe simulated consequences of changes in parameters' calibration or amendments in the model's structure, we are embarking into a deductive inference. Thus, deduction and induction are inseparable in a research design based on computer simulation. We thus expect differences among simulation studies to be detected in the degree of accuracy of the description of the elements that compose an aggregate phenomenon or of the features that characterize the aggregate phenomenon itself. Simulation studies in which a deductive logic of inference prevails will move from accurate modeling of components while simulation studies informed by an inductive logic will set forth from the description of an aggregate behavior.

Nonetheless, maintaining two idealtypes of computer models, deductive and inductive, seems a good strategy, or at least a safe point of departure, to get the picture of what logic of enquiry simulation studies have adopted in the field of strategy and organization. Differently from other typical, qualitative and quantitative, research strategies that are more legitimized and disciplined, simulation-based research has been structured in a variety of different guises. Only recently, Davis, Eisenhardt and Bingham (2007) have convincingly positioned simulation studies among other methods of enquiry within strategy and organization research developing a roadmap for rigorous simulation-based research. To carry on this avenue, we apply the two idealtypes to capture the often subtle differences in the logic underlying simulation studies.

To address typical features of deductive inference in simulation studies, we begin from the classic Cohen, March and Olsen's *Garbage Can* simulation model (1972). The authors do not specify in details a reference mode of behavior to be explained, beyond the broad idea that they want to address the way in which *organized anarchies*[1] embark in decision-making activity. Rather, the emphasis is on the modeling of the structural features of decision-making processes in specific types of organizations. The aim is to develop 'a behavioral theory of organized anarchy' (1977: 2). To do so, the authors develop a model that describes decision making within organized anarchies and examine '…the impact of some aspects of organizational structure on the process of choice…' (1972: 2). The structure of the research design encompasses the modeling of organizational decision-making processes and the analysis of the behavioral consequences of such modeling.

More specifically, the authors adopt a view of an organization as a *garbage can* in which are collected '…choices looking for problems, issues and feelings looking for decision situations in which they might be aired, solutions looking for issues to which they might be the answer, and decision makers looking for work.' (1972: 2). Along these lines, they modeled problems that require a specific amount of energy devoted by members of the organization to be solved and depicted two matrix structures that describe organizational features. The first matrix defines the *access structure* that associates choices to problems by determining what choice is accessible to what problem. The second matrix represents the *decision structure* and associates decision-makers to choices by establishing what decision maker is eligible to make what choice.

In their experimental design, they portrayed different kind of organizations with different energy distribution, different problem loads and different organizational structures. Through simulation experiments, the authors derived emerging decision-making behaviors with typical features. For example, they observed that, depending of the different assumptions crystallized into the initial calibration of the model, organizations may show different styles in decision-making and problem-solving.

We define this type of work deductive since the curiosity that triggers the effort of researchers regards the deduction of typical emerging patterns of organizational behavior given the description of organizational structures and decision-making processes.

On the other hand, researchers adopt an inductive inference when they proceed from a phenomenon, more specifically, from the description of a behavior that unfolds longitudinally over time, and use computer simulation to select plausible determinants of the phenomenon among alternative causal mechanisms.

For example, Adner (2002) studied the emergence of disruptive technologies and he set up his research design by stating at the front the description of the characteristics of the phenomenon he wanted to investigate. After clarifying that his contribution is to explain the emergence of disruptive technologies, Adner modeled consumers' individual preferences and firm technological strategy to obtain mechanisms that are sufficient to produce the phenomenon.

A similar logic inspires the work of Sastry (1997). Sastry analyzed Tushman and Romanelli's verbal theory of punctuated change to demonstrate that the verbal theory does not contain the necessary causal mechanisms to explain the described behavior. Sastry conducted a textual analysis of the verbal theory and used qualitative descriptions of behavior to produce a dynamic behavior to test the theory. Then, she identified constructs and causal relationships that provided the basis of the formal model. Once a computer model that formalized key traits of the theory was built, Sastry simulated the model and compared simulated behavior with those crystallized into the theory. The discrepancy between theoretical and simulated behaviors guided Sastry to introduce two new mechanisms that were not originally included into the verbal theory but that proved necessary to produce the behavior purported in the theory. The two mechanisms are a routine for monitoring organization-environment consistency and a heuristic that suspends change for a trial period following each reorientation. The work of Sastry provides the opportunity to speculate further on the features of inductive simulation research. As we said in the foregoing, typically, inductive inferences bring about additional information that is not necessarily crystallized into the premises. The inductive nature of the study of Sastry emerges when we appreciate that in the original premises of the study, which are captured in Tushman and Romanelli's verbal theory, there was not mention or any sort of indication that pointed at, or give a clue about, the causal mechanisms that Sastry included into the theory ex-post.

To clarify the position taken in this essay, however, when I suggest that inductive simulations bring in a study information content that is not included in the stated premises, we are not speaking about empirical information. Computer simulation may interact with empirical information and help to investigate real instances but do not *per se* say anything about the empirical world. What I am suggesting is that given a set of initial premises, a simulation study has an inductive nature when it facilitates the enlargement or the modification of this set of premises.

Nevertheless, often computer simulation studies maintain a more or less close relationship with empirical data. Malerba, Nelson, Orsenigo and Winter (1999), for example, propose a class of computer models that they define *history friendly* because of the adherence of these latter to the empirical realm that is the object of exploration.

To elucidate their approach, they focused on an appreciative theory that describes the pattern of evolution of the computer industry and developed a formal representation of that theory. Through simulation, they checked the consistency between the appreciative and the formal version of the theory by examining whether the formal version is able to reproduce the same stylized facts as described in the appreciative theory. The empirical information is the pedestal to build the computer model but the contribution of the simulation study is not one of extending such information. The contribution of the study rests in its corroborating the relationship between causal mechanisms and emerging behaviors as observed in the real world.

The interplay of induction and deduction in simulation studies

A consideration is fundamental in order not to misinterpret the distinction between deductive and inductive simulation studies. In most of the simulation studies in social sciences, inductive and deductive inferences are intertwined. However, we cannot avoid noting that the logic by which they are inspired often differs not marginally. For example, in the mentioned study of Sastry, the logic of enquiry is clearly stated and hinges upon two elements. First, the author has a clear imagine of the dynamic features of the behavior she wants to explain. Second, she uses the comparison between theoretical and simulated behavior as a trigger to import in her modeling candidate causal mechanisms.

On the other hand, at the other extreme, consider, for example, Cohen, March and Olsen’s *Garbage Can* simulation model. The authors described how problems, choices and people met within an organization but they start their enquiry without a precise idea about the aggregate decision-making behavior that follows from the premises they designed. The curiosity was exactly to understand what the consequences are of representing an organization as an organized anarchy and the contribution of the study is indeed to suggest that organized anarchies maintain a peculiar style in their decision making behavior. Most of the simulation studies, however, blend the two components.

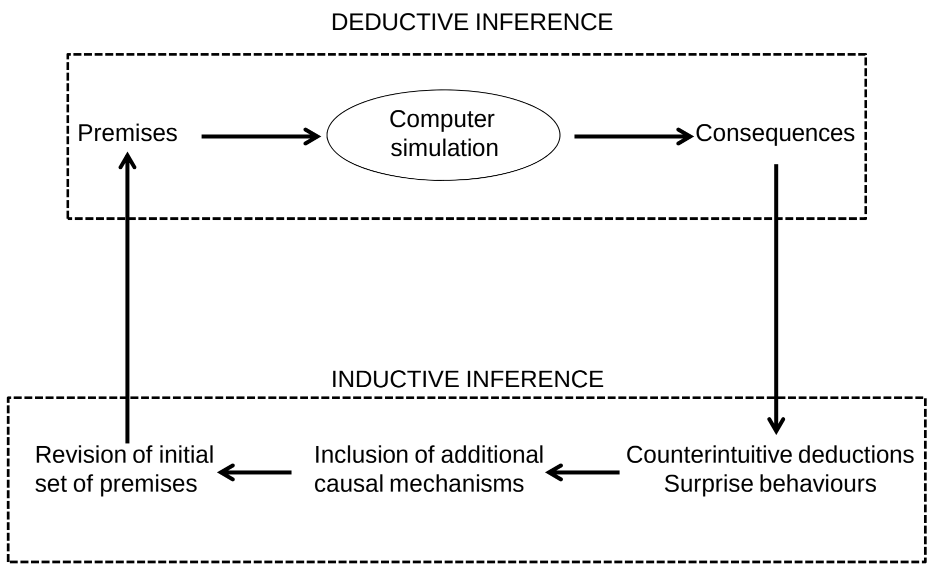
Beside cases in which the inductive or deductive approaches clearly come into view, most of studies incorporate both approaches. A simulation study may incorporate a loosely defined idea of the features of the behavior it is aimed to explain and this idea guides the modeling of the premises. The deduction of consequences from premises through computer simulation aids the refinement of the description of the behavior of interest. On the other hand, the materialization of surprising or counterintuitive behaviors induces the search for alternative causal mechanisms to modify the original set of premises.

The diagram in figure 1.1 suggests that induction and deduction are often embedded in a cyclical process of discovery. Deduction generates repertoires of patterns of behavior that represent near-histories that proceed from a common deep causal structure. This exercise contributes to theory building by making available ex-ante falsifiable hypotheses that connect casual mechanisms to behaviors. Deduction may also create counterintuitive and surprising behaviors that bring about marginal amendments in the modeling of the premises or may trigger inductive processes of revisions of modeled premises. In this case, the discrepancy between expected and simulated behavior is the incentive to refine, or deeply modify, the modeled set of premises by introducing in the model new causal mechanisms.

For example, in their study on population ecology and competition among structurally different populations of organizations, Carroll and Harrison (1994) built a mathematical model, designed a structurally superior population and simulated competition between two populations (one inferior and one superior). Through the simulation study, they demonstrated, *in vitro*, that the dominance of structurally superior populations may not emerge depending on their timing of entry in the industry. The contribution of this theoretical falsification is to delineate the hypothesis of *historical inefficiency*, according to which the explanation of an observed behavior is history-dependent and the time in which events happens modify their expected consequences.

Thus, the diagram in figure 1.1 conveys one of the key ideas that inspire this essay. Technically speaking, a computer simulation cannot be anything different than a computer-aided process of deduction. This deduction process both unveils not necessarily intuitive cause-effect relationships that are implicitly hidden in the premises and assists rigorous articulation of appreciative theories. This facilitates researchers in producing testable hypotheses. On the other hand, when deducted behaviors do not match with expectations, this mismatch activates an inductive inference that amends the original set of premises. In this respect, I suggest that by embedding a computer-based process of deduction into a richer research perspective provides a powerful environment to use of computer simulation for theory development.

Figure 1.1: Logic of enquiry underpinning computer simulation



A FRAMEWORK TO INTEGRATE COMPUTER MODELING AND GROUNDED FIELD RESEARCH

In this section, I outline some ideas to inspire the use of computer modeling and simulation as a support for theory building associated to grounded field research. This area of methodological development is under investigated and hopefully the few directions offered in this essay may indicate a possible avenue to explore.

Among the possible, and slightly different, logics that animate field studies, I take the viewpoint of grounded theorizing. Glaser and Strauss (1967) described a *grounded* approach to systematically discover theory from empirical data in field research. According to this approach, by comparative analysis, researchers first generate conceptual categories and the conceptual properties of these latter, then, they create hypotheses on the relationships among the categories. In their view, researchers need to start their research into an empirical setting without any previously structured conceptual category[2]. This approach is, for example, different from the approach based on *explanatory case study* which has a recognized tradition in management and has been thoroughly described by Yin (1994). According to this latter approach, field research is aimed at answering to *how* or *why* questions by eliciting causal links among variables over time. Interestingly, Yin draws a distinction between the case study approach, which he describes, and the grounded theorizing as described by Glaser and Strauss. Yin affirms that the key difference is that in a case study researchers use a previously developed theory as a template and the design of a case study is tantamount the conceiving of a theoretical experiment aimed at further articulating the theory.

To assess the contribution of formal modeling and computer simulation to the enhancement of the quality of grounded field research, I focus on two typical problems: the internal validity problem and the problem of theoretical saturation of a grounded study.

The problem of internal validity

Given an explanation that infers a casual relationship between two events, internal validity is a judgment on the robustness of that causal relationship. Thus, a potential threat to internal validity is the existence of spurious effects. When a researcher makes an inference, and connects an event to an earlier occurrence, a spurious effect intervenes if the appearance of the event object of observation is connected instead to another unobserved occurrence. Yin describes three techniques to improve internal validity of a case-study: *pattern-matching*, *explanation-building* and *time-series analysis* (1994: 35, 106-118).

Pattern matching implies the comparison between the predicted and the actual behavior of a variable. When empirically observed results match those predicted by a theory, the case study represents an experiment that corroborates propositions embedded in the theory. On the other hand, if patterns do not match, theory has to be questioned. The more articulated is the predicted pattern of dependent variables, the more demanding is the test of pattern matching and the stronger is the test of theoretical propositions.

For example, if a prediction involves not one pattern but a variety of patterns for a variety of dependent variables, matching of those patterns allows for strong causal inferences. Pattern matching also includes independent variables. Researchers may articulate rival explanations that imply different causal mechanisms, different independent variables and different, mutually exclusive, unfolding patterns for independent and dependent variables. The matching between one specific predicted pattern and the observed empirical behavior supports selection among rival explanations. When a complete explanation for the phenomenon under analysis does not exist at the beginning of the study, Yin suggests that the pattern-matching procedure gives the way to a more sophisticated protocol that is named *explanation-building*.

Explanation building consists of an iterative process though which researchers gradually build an explanation by making initial theoretical statements and predictions, comparing predictions with available empirical patterns and revising statements.

Finally, pattern matching can be applied on time series of variables rather than to a chain of events chronologically linked. This kind of analysis is named *time series analysis*.

At the core of the three techniques, is the problem of understanding how a causal structure is able to explain observed patterns of behavior. The key theme here is the ability of a researcher to enact and maintain a dialogue between theoretical behaviors, as predicted by an explanation, and observed empirical patterns.

The problem of theoretical saturation

In grounded research, Glaser and Strauss consider research as a process in which a researcher often starts her analysis with a 'partial framework of local concepts (1967: 45). She has a general idea of the concepts and the processes that will be parts of her theoretical investigation but she ignores the relevancy of these concepts and processes neither she knows whether additional concepts will emerge in the course of her study or if some of the concepts initially selected will result irrelevant.

In this research process, initial collection of data needs to be followed by further collections. This practice of analyzing collected data and deciding what data to collect next is defined *theoretical sampling* (Glaser and Strauss, 1967: 45) and is an emergent process that cannot be planned in advance since it guided by gaps emerging in a analysis. The objective of theoretical sampling is to fully develop a repertoire of concepts to be used in the theory being developed and to articulate the properties of each concept.

When theoretical sampling is sufficient and can be stopped?

Glaser and Strauss suggest that theoretical sampling continue until *theoretical saturation* is reached (1967: 61). The attainment of theoretical saturation implies that a researcher cannot find additional data to develop further properties of conceptual categories. The aim of theoretical saturation is to maximize the variety of empirical data connected to each conceptual category in order to achieve adequate richness of properties.

The problem of theoretical saturation entails deciding when the search for further data collection can be stopped and how to select a research site for the collection.

A framework to integrate computer modeling and grounded field research

In the following, I delineate a research design in which computer modeling and simulation, and field research are associated to support theorizing. The research design proceeds in a sequence of steps in which a researcher begins by theorizing from an exploratory field study, translates this preliminary theorizing into a formal model and through computer simulation both strengthens the causal structure of the theory and envisions new research sites to locate further field studies that serve as experiments to consolidate the theory.

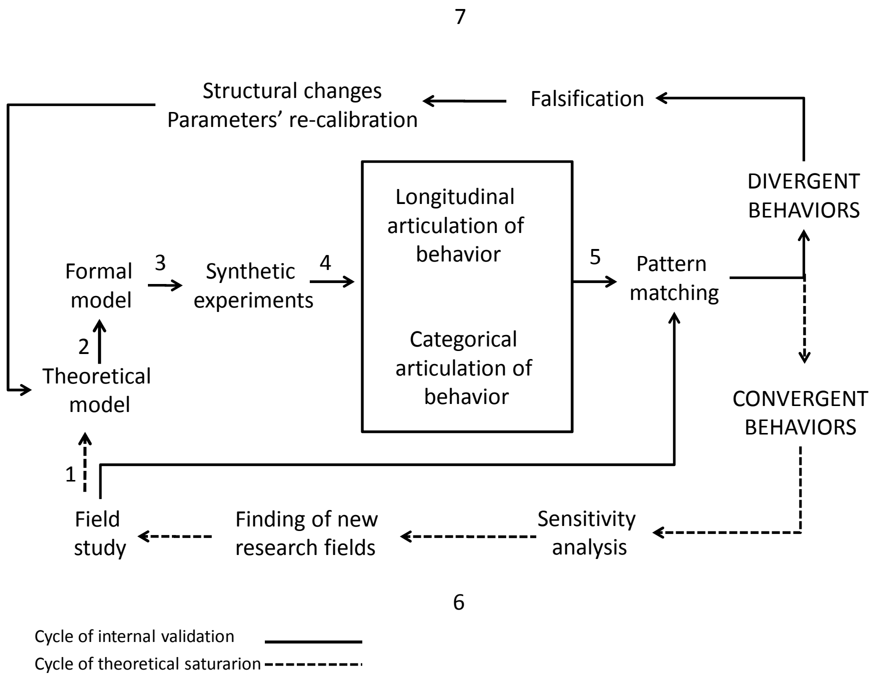
Building of a preliminary theoretical framework

In the sketched approach, the point of departure is an exploratory field study (step 1 in figure 1.2). The field-study entails the grounding of theorizing in a specific research site. As described by Glaser and Strauss (1967), the field-study leads to the building of a theoretical framework by defining conceptual categories, conceptual properties of the categories and hypotheses regarding the causal relationships among categories. The sketch of the theoretical framework needs to proceed without any '…preconceived theory that dictates, prior to the research, "relevancies" in concepts and hypotheses.' (Glaser and Strauss 1967: 33).

A researcher should select, at this stage, a research site because she is interested in a specific empirical phenomenon not because the site is appropriate to conduct a theoretical experiment on an existing theory. Of course, it is naïve to propose that a researcher approaches a research site without any previously crystallized theoretical lens. It is plausible to suspect that the theoretical background of the researcher, along with the state of the art of the literature to which she aims at contributing, plays a role in the sedimentation of a more or less uncovered cognitive filter that steers the attention towards one or another research site. The intellectual curiosity that illuminates a specific research site is motivated by the interest for an observed phenomenon and it is likely that this interest is, at least implicitly, driven by the fact that the phenomenon is an empirical instance that confirms or disconfirms a prior theory. Hardly can theorizing totally be disconnected from relevant literature because what captures the attention of a researcher is the observation that a conceptual category is empirically associated with a property different from the one expected, that two conceptual categories are empirically linked by a counterintuitive causal relationship or that an empirical phenomenon escapes previous conceptualizations.

It is not the purpose of this chapter to dwell into the delicate dispute regarding the selection of a research site; neither this chapter gives attention to how a researcher extracts a preliminary theoretical framework from a field study. We simply assume that a preliminary empirically grounded theoretical framework exists, this latter including a number of conceptual categories, conceptual properties that characterize the categories and a number of tentative hypotheses on causal relationships among categories.

Figure 1.2: Computer simulation and grounded field research



Building the computer model

Once the exploratory field study has generated a preliminary theoretical framework, the second step implies to transform an appreciative theorizing into a set of formal propositions (step 2). At the end of this second step, a computer model embodies the preliminary theoretical framework. This is a subtle endeavor that requires the transformation of conceptual categories into measurable constructs that reflect their theoretical properties and the formalization of causal link among constructs. Causal mechanisms included in a computer model may originate from two sources. They may be formalizations built upon a researcher's interpretation of verbal descriptions collected during the field study or they may be formalizations that replicate either existing formal theories or descriptions of processes that already exist in a quantitative format.

Let’s take for example a researcher that conducts a field study to explain the process of strategy formation in large firms. If a firm makes available to the researcher memos, blueprints and manuals with already formalized decision-making routines, then the formalization is likely to adhere more realistically to the empirical setting under scrutiny. More often, however, the researcher needs to translate verbal description of operating organizational routines into formal modeling. Furthermore, let’s suppose that the researcher wants to include in its theorizing the behavior of financial markets that respond to focal organization’s financial performances by allowing credit. In this case, modeler may take advantage of existing theory of financial markets and include in her model the formalizations that are provided in the literature to capture expected behavior of financial markets. In this case, the use of an existing theory does not really violate the mandate, stated at the beginning, to initiate an exploratory field research without previous preconceived theory since the theory employed regards the behavior of financial markets not the object of study of the research, which is the process of strategy formation. In other words, in this case, the researcher borrows elements from the theory of financial markets’ behavior to complete the description of the environmental context in which the object of study – the firm – operates.

In addition, the field study may be helpful to provide researcher with information to be used for a provisional calibration of model’s parameter. The calibration will be useful in the next step of the described research protocol that requires the simulation of the formal model. As Kaplan (1964) suggests, ‘...in all simulation experiments the fundamental problem is that of “scaling” - that is, the translating of results from a simulation model to the real world’. The grounding and calibration of a simulation model on a case study facilitates the process of translating the abstract insights of a formal model into real-world problems.

Synthetic experiments with computer simulation

The fourth step entails the use of the formal model to produce simulation runs that describe behavioral implications of the causal relationships that originated from preliminary theorizing. If the theoretical framework that a researcher has built to explain the observed behaviors is correct, simulation runs tend to replicate observed behaviors. In this light, computer simulation supports researchers in using data from field studies to detect fallacies in underpinning logic and to test a theoretical framework. The use of computer simulation as a tool to derive behavioral consequences from stated assumptions brings about a number of advantages.

First, in general, computer simulation generates time-series. This may result of some help when time-series can be compared directly with real-world quantitative figures, for example financial figures extracted from balance sheets and economic reports. In this case, the availability of real and simulated time series that are accessible in a similar quantitative format facilitates pattern matching by assigning to a researcher the possibility to generate a measure of how predicted events match empirical instances of those events (Sterman 1984).

Second, computer simulation allows for a rigorous *longitudinal articulation* of theoretical behaviors. In other words, the computer-aided process of deduction goes far beyond the human capability to appreciate the long-term features of the behavior of selected variables. Thus, computer simulation can support researcher to articulate hypotheses on behavioral properties of conceptual categories included in a theoretical framework. For example, complex patterns of behavior such as peaks and lowest point, oscillations with different characteristics and changes in rate of growth or decline may become parts of a more developed description of a behavioral property.

Third, researchers, by simulating a formal model, can generate what I define a *categorical articulation* of theoretical behaviors, that is, they can further extend their theory by contemporaneously producing behavior of different conceptual categories. For example, researchers can simulate the interaction of independent and dependent variables in each time step, along a given time horizon. Using this exercise, researchers can produce additional hypotheses on the interaction among behavioral properties of a numbers of conceptual properties contemporaneously.

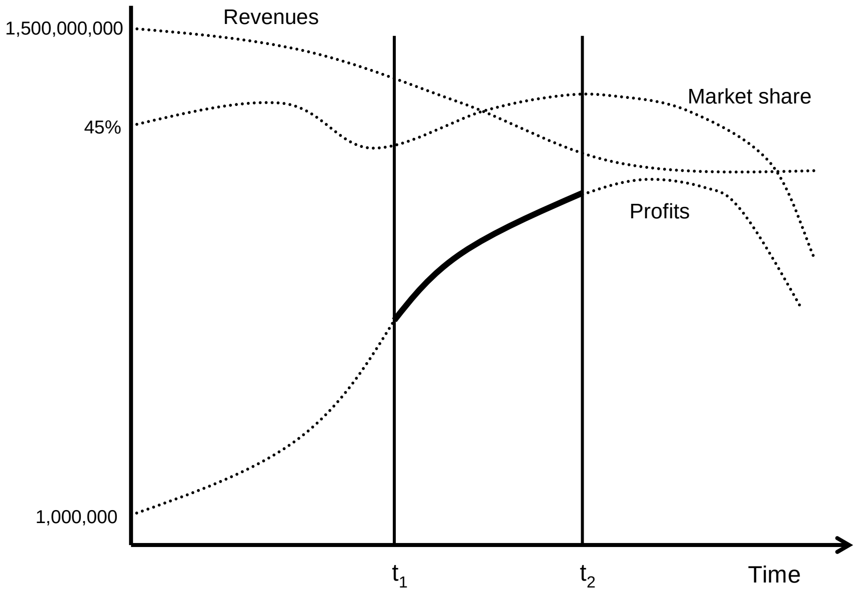
This longitudinal and categorical articulation of theoretical behavior increases the points of contacts between the theoretical propositions and the empirical world of the case study. As Kaplan suggests ‘What counts in the validation of a theory, so far as fitting the facts are concerned, is the convergence of the data brought to bear upon it […]’ (1964: 314).

I argue that computer simulation expands the terrain where comparison between theory and empirical setting takes place by generating a rich theoretical framework that crystallizes a dense collection of interweaved theoretical behaviors. Thus, convergence of data and concatenation of events that are necessary to confirm the adherence of theory to empirical evidence are increasing demanding.

In this respect, computer simulation aids researchers to consider field research as a difficult experiment where the falsifiability of a theory is easier because fitting the facts becomes increasingly hard. Of course, on the other hand, had empirically collected facts to fit into a complex web of interweaved simulated behaviors, the experiment would lead to stronger evidence to confirm propositions contained in the theory.

In figure 1.3, we imagine to start a field study with the objective to explore the increase in profits empirically observed in the time period comprised between t_1 and t_2. A researcher can build a variety of hypotheses to explain the behavior. These hypotheses can be formalized into a computer model. Yet, there might be a large collection of computer models that are able, for different reasons, to produce a behavior similar to the one observed. However, once we use computer simulation to articulate the behavioral implications of the model beyond the observed time span t_1-t_2 (longitudinal articulation) and for both the profits and other variables such as revenues and market share (categorical articulation), then the theory of behavior captured in the model becomes more complex and easier to falsify by further data collections of empirical instances regarding market share and revenues.

Figure 1.3: Integration of empirical and simulated patterns of behavior



In this respect, in the example of figure 1.3, longitudinal articulation of behavior of the variables of interest, that is the generation of an hypothesis of behavior that extends beyond the originally considered time span t_1 -t_2, and categorical articulation, that is the generation of hypothetical behavior for a variety of relevant variables, orient further data collection and increase falsifiability of a theoretical framework. This process of data collection to falsify formalized theoretical hypotheses narrows down the set of candidate explanatory models.

Pattern matching

Now we turn to the process that involves the analysis of the matching between simulated and empirically observed patterns of behavior (step 5 in figure 1.2). In particular, we investigate this process by looking at two cases. The first case is when the field study confirms the predictions made through computer simulation. The second case applies when a researcher reports a mismatch between computer-generated predictions and empirically collected evidences and time-series.

Sensitivity analysis and history-convergent runs

When simulated and historical patterns of behavior match, computer simulation can be used as a laboratory to conduct sensitivity analysis in order to explore in what circumstances simulated and empirically observed behaviors diverge (step 6). Sensitivity analysis entails the analysis of the sensitivity of a simulated behavior to the change in the calibration of a model's parameters. Also, changes in parameters' values may often imply that parts of a model are deactivated thereby testing the sensitivity of a model's behavior to the inclusion or exclusion of specific conceptual categories.

Field cases are retrospective studies. Retrospective studies explain, *ex-post* how a set of variables interacted to drive an observed behavior of interest. However, it could become troublesome to ascertain the extent to which a theoretical explanatory model and the observed behavior are linked. This difficulty is explained by the fact that retrospective studies are not particularly efficient in connecting causes and effects (Leonard-Barton 1990).

If, for example, we are aware that two conceptual categories affect the observed behavior, given the complex web of interactions in which the concepts are embedded, it might be hard to determine their relative strengths. It might be the case that the influence of one of these two concepts is insignificant, and could be omitted from the analysis to satisfy the criterion of parsimony for a good theory (Eisenhardt 1989).

To investigate further the importance of that concept, an experiment could be run to detect what happens if it is omitted from the model.

Thus, sensitivity analysis helps revising a theoretical explanation by suggesting that specific conceptual categories are not necessary to explain a behavior whereas others are fundamental since the change in their calibrations produces simulated behavior that is divergent from the one observed (step 7 in figure 1.2).

In addition, the intentional generation of history-divergent simulation runs orients further empirical enquiry by indicating new potential research sites. Indeed, in a new site that resembles the simulation settings that have been adopted in the sensitivity analysis, a researcher can test whether, given the characteristics of the new site, a behavior closer to the history-divergent run is observed (step 8 in figure 1.2). For example, some longitudinal *event* studies have compared *polar cases*, that is, cases of organizations that have shown opposite behaviors in responding to an identical exogenous stimulus, and have explained the different unfolding of their histories as the result of different initial conditions (Noda 1994; Noda and Bower 1996).

What we suggest is that using sensitivity analysis to generate history-divergent runs may be helpful to illuminate the potential of a research site to become a polar case in which, given a change in some key features of the research context, a behavior divergent from the one observed in the original field study ensues.

In general, simulation, by connecting a theoretical structure to a variety of possible emerging, often unexpected, behaviors, activates dormant consequences of a theory, which were not observed in the original empirical study. This generation of a distribution of near-histories, or unrealized events, both strengthens the understanding of causal structures and envisions areas for further empirical investigations. Field researches conducted in these sites represent further theoretical experiments to reinforce internal validity of a theory. Thus, computer simulation helps validating a theory by supporting a researcher in demonstrating that a common theoretical engine may explain a repertoire of different behaviors in different empirical contexts. In this vein, the coupling of field-study and computer simulation speaks to the problem of learning from samples of one or fewer as presented by March, Sproull and Tamuz (1991).

In addition, when a theoretical argument includes the mention of specific parameters' calibration as necessary conditions for a predicted behavior to emerge, change in the parameters' calibration can represent a further test of the theory encapsulated in the computer model. For example, Malerba *et al.* modified parameters' calibration in order to test that model calibrations 'that are counter to those argued as strongly causal in the appreciative theory should obtain history-divergent results' (1999: 35).

Sensitivity analysis and history-divergent runs

Finally, we address the case in which a researcher observes a mismatch between computer-generated and empirically observed events and time-series. In this case, the problem is to understand why the behaviors diverge. The idea here is that computer modeling and simulation provide a theoretical laboratory that is relatively easy to manipulate in order to investigate the origins of the discrepancy between simulated predictions and observed behaviors.

In this respect, I agree with Malerba *et al.* (1999) in suggesting that computer simulation provide an appropriate terrain to nurture a friendly dialogue between empirical evidence and theory. When history-divergent simulations appear, researcher tries to explain where discrepancies come from. Investigators can intervene on the structure of a computer model or on the calibration of model's parameters and rigorously deduct whether these interventions narrow down the gap between predicted and actual behaviors.

Pressures for historical and simulated behaviors to diverge arise in two cases. The first pressure intervenes when the causal structure of the theory that is captured in the computer model is isomorphic to the causal relationships at work in a specific empirical context and the discrepancy is the consequence of flaws in the specifications of parameters' calibrations. The second pressure for historical and simulated behaviors to diverge arises when the causal structure of the theory and the causal relationships at work in the real world are not isomorphic in some respects.

This may be the result either of the fact that a researcher has not properly formalized a theoretical argument arising from a field study or the fact that the researcher was not able to select the key causal mechanisms at work in the case studied.

The first direction to explore is the analysis of sensitivity of model's behaviors to change in parameters to check whether simulating the model with a new calibration improves the match between simulated and observed behaviors (step 9). The fact that the fit between simulation and empirical data is improved by manipulating a model's parameters points at two areas of analysis. First, it may suggest that the model is characterized by non-linear causal relationships among variables so that slightly different model's calibrations yield very different emerging behaviors.

Second, the causal structure at work may include positive feedback among variables and initial calibration of variables has a mounting weight in molding unfolding patterns of behavior. For example, as reported in Carrol and Harrison (1994), the presence of positive feedback among variables generates behaviors that unfold in a way that is history-dependent, that is, depends on the research's calibration of a parameter: time of entry in the simulated scenario of a population.

Finally, in general, the fact that a computer model produces history-replicating simulation runs only after implausible values are assigned to parameters casts an alarming light over the robustness of causal structure of the theory.

The second avenue to explore discrepancy between predictions and observed behaviors is the analysis of the structure of the model, that is, the causal relationships among variables that are deemed necessary to produce behaviors of interest. Different formalizations may exist for specific relationships and including in the model one or the other may have different behavioral implications. To revise formalization, researchers need to go back and compare the formal structure of the computer model and the real processes at work in the case study. This further investigation plays as a catalyst to define possible amendments to the theory (step 7).

To begin the analysis of the discrepancy between the structure of the computer model and the structure of the phenomenon under study, those formalizations that are directly obtained from descriptions sufficiently clear and less questionable are not good candidates to look for the origins of the discrepancies. Researcher ought to start to generate alternative formulations for those descriptions that were originally provided in a verbal form and, thus, to be formalized, required a more dubious and arguable interpretation. The fairly intuitive idea here is that formalization that required a researcher's translation of verbal descriptions into quantitative formulations are more debatable, more prone to conceal misinterpretation and hence good candidates for the analysis of history-divergent simulations.

However, such an instinctive expedient ought not to veil another potential source of history-divergent simulation runs that materializes when firms describe processes on the basis of existing formal procedure whereas everyday activity is grounded on informal and tacit routines which are different from those crystallized in official manuals and blueprints.

Theoretical saturation and internal validity

In the iterated process of pattern matching, structural adjustment and theory refinement that I delineated in the foregoing, field study informs computer model and this latter puts on the right track empirical research.

Once the dialogue between computer model and field research kicks off the critical issue is whether a researcher is able to mediate the dialogue by pursing two critical processes. First, the researcher has to feed the model with the information extracted from a case study. Second, the researcher needs to understand what information the observed gap between simulated and historical behavior provides that can be utilized to both indicate further research sites and to refine underlying theoretical argument.

Associated with a simulation study, the field study is not more a retrospective photograph of what has happened, but rather becomes a living picture illustrating what could have happened in different circumstances. Capturing in a simulation model the rich but static appreciative theorizing grounded on a field study, the researcher can build a laboratory where simulation experiments are used to pursue two endeavors.

First, analysis of history-divergent runs triggers a *cycle of internal validation* thereby missing variables and hidden assumptions are elicited, emerging theory is tested for internal consistency (Langley 1999).

Second, sensitivity analysis on history-convergent prompts a *cycle of theoretical saturation* thereby new research sites are selected to refine the set of theoretically relevant conceptual categories, to capture the properties of these categories and to describe the nature of causal relationships among conceptual categories.

CONCLUSION

As Montgomery, Wernerfelt and Balakrishnan suggested almost 20 years ago (1989), a serious problem that may compromise the quality of theory development in strategy and organization is the looseness and the lack of logical consistency in developing implications from a set of assumptions where "Small changes in assumptions or parameters can alter dramatically the implications of a model." (Montgomery, Wernerfelt and Balakrishnan 1989: 192)

In this article I proposed that computer modeling and simulation support theory generation in managerial studies and, in general, in social sciences by contributing to amend for the critical shortcomings that emerge in theory development when implications are not rigorously derived from assumptions. In particular, computer modeling forces a researcher to tease out unambiguously her theoretical argument. A simulation experiment entails the formalization of a theory. Formalization enhances simplicity and parsimony and helps to clarify the morphology and to sharpen the discussion of the theory thereby supporting both its audit trial (Saloner 1994: 170) and its communication. In this respect, I suggest that formalization and computer simulation of a theory represent devices that support communication among scholars of different disciplines.

Furthermore, the discourse articulated in this chapter suggests that computer modeling and simulation offer a helpful tool to enhance quality of field-based theory building. Field research and simulation studies, although both having strong roots in management and organization theory research, have not often been used in combination. This essay contains the sketch for a research protocol that integrates simulation-based research and field study.

The idea that motivates this attempt is that computer simulation, by producing artificial time series that are directly comparable with real time series, sets basis for a fruitful dialogue between the observation of empirical patterns of behavior and the modeling of theoretical hypotheses. As Cohen and Cyert suggest (1961), this dialogue both strengthens the theoretical argument and directs field research:

> The requirements of a computer model can provide a theoretical framework for an empirical investigation, and, in return, the empirical information is utilized in developing a flow diagram for the model. Through this process of working back and forth, it is possible to know when enough empirical information has been gathered and whether it is of the proper quality.
>
> (Cohen and Cyert 1961: 127)

This dialogue between available empirical data, in the forms of detailed description of observed behavior, and a theory, or a set of hypotheses, formalized in a computer model establishes the premises to develop sound theories of behavior.

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