How do system dynamic models (SD) capture path dependent and complex evolutionary behaviour in social science analysis?

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Abstract

The aim of social scientists is to capture the causal mechanisms that explain behavior of people and groups of people, such as communities, societies or firms. Such an endeavor becomes increasingly difficult as theorizing concerns patterns of behavior. A theory of behavior explains how the cause-effect structure of interaction among specific variables leads to emergent paths of behavior of these variables. Thus, building theories of behavior implies creating a narrative that connects a deep theoretical structure to a repertoire of plausible behaviors that encompass the observed critical events and behaviors. A problem challenging discursive theories of behavior is the quality and robustness of inferred connections between causal structure and emerging behaviors. Equally difficult is to understand how modifications of theoretical assumptions, crystallized into a model, lead to modifications of the phenomenon under study. To make the described endeavor even more challenging, observed patterns of behavior are often produced by path-dependent processes that amplify non-systematic and stochastic disturbances. In this essay, we suggest that the interaction between field research, computer simulation and System Dynamics allows to elicit causal models from the rich texture of everyday life.

INTRODUCTION

As Legorsol suggests in her study on privatization of land in small-scale African communities, since an observed event or phenomenon in most anthropological studies, as it was privatization in her study, is a "…natural experiment and not a controlled

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laboratory one, the causal relation of privatization to behavior should be considered indicative, not conclusive." (Legorsol, 2005).

Accurate information that emerges from an in-depth field study are very powerful indications to elicit a candidate causal structure to explain observed behaviors. Informants provide a vital vehicle to build a repertoire of candidates explanations for an observed event. Yet, collected explanations are interpretations that are necessarily more or less intentionally biased. To select among candidates explanations, the quality and robustness of inferred connection between causal structures and emerging behaviors stands as a decisive factor.

As for quality of inference we refer to the case when an inferred causal structure is sufficient to generate an observed pattern of behavior. Robustness implies that researchers are able to distinguish between phenomena that are consequences of specific simultaneous combinations of contextual factors and causal structures that might be, at least partially, transferable as a candidate explanation in other research sites[2].

Human reasoning may face limits in the articulation of the chain of causes and effects that is sufficient to give rise to a specific observed behavior. Thus, discursively presented theories of behavior may overlook variables or causal links that are necessary for a behavior to follow from a causal structure. The issue becomes increasingly crucial when phenomena under study display complex behavioral paths such as oscillations, peaks or bifurcations. Equally difficult is to understand how small modifications of a causal structure, or different calibrations of parameters, lead to modifications of the phenomenon under study. For example, an observed phenomenon may be the unique result of a very specific, hardly reproducible, calibration of a set of contextual circumstances. On the other hand, phenomena observed in different contexts and conveying different behavioral paths may nevertheless be generated by the same underpinning causal structure. This is frequent when observed patterns of behavior are produced by path-dependent processes that amplify non-systematic and stochastic disturbances.

In this paper, we suggest that computer-aided simulation experiments may support field researchers in investigating the relative roles of history, contextual circumstances and deep causal structures in generating observed paths of behavior. In particular, we focus our attention on a particular approach to modeling and simulation, System Dynamics.

This paper is articulated as follows. First, we expose the gist of our argument: how computer simulation supports theorizing. Then, we briefly describe System Dynamics and explain what peculiarities makes the approach suitable for theorizing in social science. In section three, we show how, when looking closely at behaviors captured in field studies, complexity emerges that calls for an approach informed by system thinking. Finally, we report an example of the use of computer modeling and simulation associated to a field study.

[2] Markus and Robey (1988), and Mohr (1982) suggest that when processes of change are under scrutiny, robust theorizing needs adopting an idiographic approach that emphasize how specific contextual assumptions explain unfolding behavior.

BUILDING THEORIES OF BEHAVIOR AND CHANGE

Building theories of behavior and change implies providing an explanation that infers a relationship between a structure of causes and a number of events, which are connected into an historical sequence.

We propose that computer simulation allows to move between natural and virtual experiments to understand 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 a simulation, which has been built upon accounts from field studies, and observed empirical patterns.

In this light, the use of computer simulation brings about a number of advantages.

First, in general, computer simulation may generate inputs in the form of time-series. This may result of some help when time-series can be compared directly with real-world quantitative figures, for example demographic data. In this case, the availability of real and simulated time series that are accessible in a similar quantitative format facilitates pattern-matching thereby allowing researchers to visually assess resemblance between simulated series, which follows from the quantitative simulation of a theoretical hypothesis, and an empirically observed behavior. In this respect, it is possible to generate measures of how simulated events match empirical instances of those events (Sterman 1984).

Second, computer simulation allows for a rigorous longitudinal articulation of predicted 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 find plausible sufficient conditions for complex patterns of behavior to happen such as peaks and lowest point, oscillations with different characteristics and changes in rates of growth or decline.

Third, researchers, by simulating a formal model, can articulate their predictions by contemporaneously producing behavior of different variables and the interactions of these latter. In particular, researchers can simulate the interaction of independent and dependent variables in each time step, along a given time horizon. This cross-sectional articulation of patterns of behavior increases the points of contacts between a set of behavioral hypotheses and the empirical context of a 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). Thus, a computer simulation expands the terrain where comparison between theory and empirical setting takes place by generating a rich longitudinal and cross-sectional articulation of behavior under study. In this light, the convergence of data and the concatenation of events that is necessary to obtain to use a case study to confirm a theory is increasing demanding.

In this respect, computer simulation aids researchers to design field studies to produce difficult experiments 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, at least qualitatively, into a complex web of interweaved simulated behaviors, the experiment would lead to stronger evidence to confirm propositions contained in the theory.

Following, we suggest two avenues to conduct simulation experiments and articulate a theoretical hypothesis.

Sensitivity analysis and history-convergent runs

A first possible scenario entails that the hypothesis produced in a field study, once formalized in a computer model, produce behaviors that are similar to those observed in the field. In this case, computer simulation can be used as a laboratory to produce sensitivity analysis. 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.

If, for example, we are aware that two variables affect the observed behavior, given the complex web of interactions in which these variables are embedded, it might be hard to determine their relative strengths. It might be the case that the influence of one of these two variables is insignificant, and could be omitted from the analysis to satisfy the criterion of parsimony for a good theory (Eisenhardt 1990).

To further investigate the importance of that variable, an experiment could be run to detect what happens if the variable is omitted from the model. This sensitivity analysis may help revising an explanation by suggesting that specific variables may not be necessary to explain a behavior whereas others are fundamental since the change in their calibrations produces simulated behavior to diverge from the one observed.

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. For example, some longitudinal *event* studies have compared *polar cases*, that is, objects of study 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 new sites are theoretical experiments that reinforce internal validity of a theory. Thus, computer simulation helps researchers in thinking how 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 this light, the issue of transferability of insight from one research site to another proceeds through a process of *déjà vu*; observing a pattern that is included within the repertoire of behaviors that are generated by a single causal structure a researcher may receive an hint on candidate explanation for that specific pattern. If we consider a case study as an experiment, computer simulation allows learning from this experiment by exploring how small changes in some conditions generate different behaviors. These behaviors are near-histories that may materialize and become visible in other empirical contexts.

Sensitivity analysis and history-divergent runs

When comparing computer-simulated and empirical patterns of behavior, a researcher may observe a mismatch. In this case, the problem is to understand why behaviors diverge. In this respect, computer models provide a theoretical laboratory that is relatively easy to manipulate in order to investigate possible explanations of the discrepancy between simulated predictions and observed behaviors.

In this respect, we 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, which is captured in the computer model, is isomorphic to the causal relationships at work in a specific empirical setting 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. 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 simulation study of organizational ecology's density model of legitimization and competition (1994), the presence of positive feedback among variables generates behaviors that unfold in a way that is history-dependent. Given an environment in which populations compete that are characterized by different organizational forms, depending on researcher's calibration of the time of entry of a new population in a simulated environment, not necessarily this new population will survive independently of its fitness to the environment.

The second avenue to explore discrepancy between predictions and observed behaviors is the analysis of a model's structure. 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.

More interestingly, the analysis of the discrepancy unveils to researchers the perils and hazards that arise when formalizing descriptions that were originally provided in a verbal form. Formalization requires dubious and arguable interpretations but the very cycle that embeds collection of data, building verbal explanations, formalization of these explanations, simulation of formalizations and analysis of discrepancies between simulated and expected patterns of behaviors produces knowledge by forcing researchers to appreciate the consequences of different conceptualizations.

In this case, knowledge building may be not directly, and immediately, on the empirical issue at hand but on the way of thinking at it. When playing with computer simulations generates cognitive dissonances between expected and observed patterns, the depth of our interpretations is potentially augmented by the opportunity to explore consequences of a rich and colorful repertoire of possible conceptualizations.

The fairly intuitive idea here is that those formalizations that are directly obtained from descriptions sufficiently clear and less questionable are not good candidates to generate insightful dissonances; on the other hand, those formalizations 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.

Along this path, computer simulation experiments may reveal that and history-divergent simulation run has been observed because interviewed informants describe processes on the basis of existing formalized procedures whereas everyday activity is grounded on institutionalized informal and tacit routines which are different from those crystallized in official manuals, codes of rules or blueprints.

THEORISING WITH COMPUTER SIMULATION: ABDUCTION AND FALSIFIABILITY

What is theorizing about dynamics behavior, then, and how computer simulation may support the endeavor?

We posit that generating theories of behavior requires to explore the plausibility of an explanation by defining sufficient conditions for a pattern to emerge. Computer simulation, by allowing researchers to play with calibration of parameters or to manipulate portions of a formal model, provides a virtual theoretical laboratory in which ‘what if’ analysis can be conducted to activate plausible but dormant alternative histories. This exercise is illuminates deep causal structures.

In this light, theorizing is selecting a candidate causal structure that plausibly underpins an observed pattern of behavior, and to build a repertoire of alternative plausible histories that are connected to the same common deep common structure of causation (this can be obtained by manipulating a model’s parameters and structure).

Thus, a formalized simulation model complements findings of field studies by facilitating a process of abduction. Abduction is an inference that goes from the observation of a fact to the hypothesis of a principle that explains the observed fact (Burks, 1964; Fann, 1970). In this vein, the model is a candidate explanation; had the world portrayed into the computer model to be true, observed patterns of behaviors would be reasonable.

Differently, from typical research in social science conducted through statistical generalizations, in which falsification is focused on behavior, here, causal structure as well is object of direct falsification. Each field site is to be considered as an experiment in which a model’s findings can be confirmed, falsified or amended and the generalization sought after is analytical rather than statistical (Yin, 1994).

In this perspective, having a detailed (often formalized) description of a causal structure and a description of a repertoire of plausible histories, a field researcher will have a variety of points in which the theoretical hypothesis, which crystallized in to the model, can be falsified (Bell and Bell,1980).

POSITIVE FEEDBACK AND STRUCTURAL ANALYSIS OF BEHAVIOR: THE SYSTEM DYNAMICS APPROACH

System dynamics (SD), which is connected to the work of Forrester (1961), grounds modeling on difference equations and impinges upon the assumption that the behavior of individuals that are embedded within a social system can be explained by the feedback nature of causal relationships that characterizes the structure of the system. Thus, SD approach aims at reducing emerging aggregate, and often puzzling, behaviors into underlying feedback causal structures.

We suggest that SD has two features that makes this approach suitable for social sciences.

First, SD illuminates the <u>Inertia of social processes.</u> The approach impinges upon a conceptual framework, and a symbolic language, that emphasizes the distinction between flow and stock variables. This distinction facilitates the representation of social processes that unfold over time. The role of stocks is one of accumulating results of past processes, these latter crystallised in flow variables. Stock variables represent the inertial features and properties of a social system that cannot be changed instantaneously (for example, the stock of accumulated knowledge or institutionalized routines). Stock variables embody the state of a social system in a particular time, independently of processes that are at work to change such a state. On the other hand, flow variables represent the processes that work to change the state of a social system (for example, the flows of knowledge distribution, which proceed from one area of a social system to another one, the processes of knowledge creation or the processes of knowledge erosion).

Second, SD takes a feedback perspective and treats a social system as a complex system consisting of one or more feedback loops. The dynamic interplay of these feedback loops explains emerging non-linear behavior carried by multi-level actors in complex social systems, which is not necessarily intuitively understood, nor can be replicable using other conventional research methodologies.

Behind the SD approach is an emphasis on the analysis of the relationship between a causal structure and a connected emerging behavior. This attitude to the exploration of system structure is appropriate to detect typical situations in which different observed patterns of behaviors may be generated by the same causal structure.

For example, in presence of systems with strong stable attractors, the existence of a common causal structure explains equifinality, when different behaviors converge to the same steady state equilibrium from different initial conditions.

On the other hand, a robust explanation in term of causal structure is particularly important in presence of positive feedbacks and systems with self-reinforcing properties. In this case, path-dependence and casual disturbances in the early history of a system may give raise to very different, often diverging, behaviors. Yet, the underlying causal structure is unchanged. When systems are characterized by path-dependence, actions and decisions produce different consequences depending on the time in history in which decisions are conceived of and actions are implemented. Yet, had researchers a clear framework that connects a given causal structure to a repertoire of alternative possible behaviors, observation of diverging behaviors in similar contexts may result less puzzling.

Thus, detecting the presence and investigating the behavioral consequences of positive feedback loops facilitates theorizing in presence of historical inefficiency.

The concept of historical inefficiency has been mentioned by Carrol and Harrison (1994) to indicate a social process “…with positive feedback (or self-reinforcement) that can generate outcomes that arise from "chance" rather than a systematic force.” Carrol and Harrison use the term ‘historical inefficiency’ as the contrary of ‘historical efficiency’ defined by March and Olsen (1989: 5-6) as follows: “Institutions and behavior are thought to evolve through some form of efficient historical process. An efficient historical process, in these terms, is one that moves rapidly to a unique solution, conditional on current environmental conditions, and is independent of the historical path.”

When behavior is historical inefficient, actions and decisions become irreversible: actions or forces applied upon a social system are progressively ineffective as the pressure of existing positive feedback unfold.

Reproducing *in vitro* these phenomena enriches theorizing with hypotheses concerning the points in time that were crucial in deciding the pattern of behavior of a specific.

HOW COMPUTER SIMULATION INTERACT WITH FIELD STUDY

To illustrate the way in which modeling and computer simulation support field studies in theorizing, we describe, as an example, a study of interaction dynamics between two clusters of firms geographically co-located that has been previously conducted by the author. We borrow this example of studies in organization theory and management, but the employed logic, we hope, may as well prove useful to other social scientists.

Geographical clusters can be defined as spatially concentrated groups of small entrepreneurial firms competing in the same or related industries that are linked through vertical (buyer-supplier) or horizontal (alliance, resource sharing, etc.) relationships. What characterizes geographical clusters is that a complex network of firms is bound together in a social division of labor (Scott, 1982).

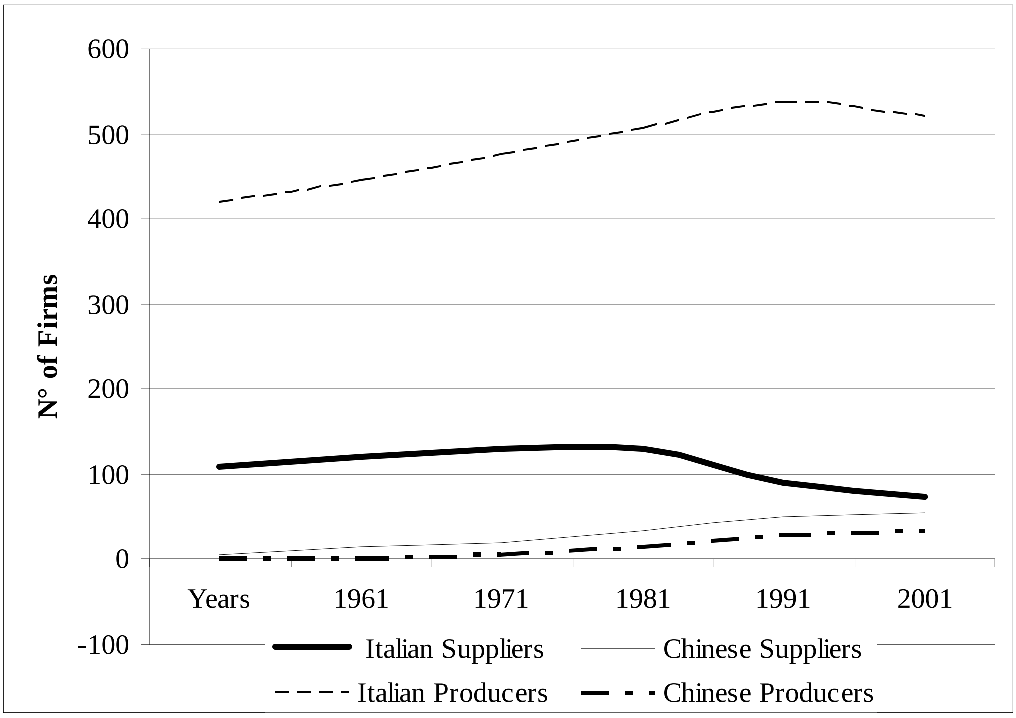
Within geographical clusters, the development of a dense web of social relationships among firms facilitates the exchange of knowledge, in particular, of the most valuable knowledge that is highly tacit, difficult to replicate and not easily purchased (Keeble & Wilkinson 1999).

Mollona and Presutti (2006) highlighted a process of passive internationalization that influence the internal equilibrium of industrial districts. Passive internationalization occurs when a high number of newly established small firms embedded in a dense web of social relationships establish in an area geographically close to a pre-existing network of firms that are themselves embedded in a web of social relationships.

In this respect, Mollona and Presutti (2006) documented how in Italy, in the textile district of Val Vibrata, in the region of Abruzzo (centre of Italy), a newly emerged cluster of firms, which are owned by entrepreneurs that moved in Italy from China, competes with firms co-located into a pre-existing cluster.

The two clusters have sharply distinct traits and, each is characterized by strong internal homogeneity that follows form shared language, similar modes of production and kinship relationships. Both the network of firms, which we call ‘Chinese’, and the preexisting network of firms, which we call ‘Italian’ are articulated in two populations: a population of suppliers and one of producers. Graph in figure 2 display the historical patterns of behavior of firms in the Val Vibrata district.

Figure 2

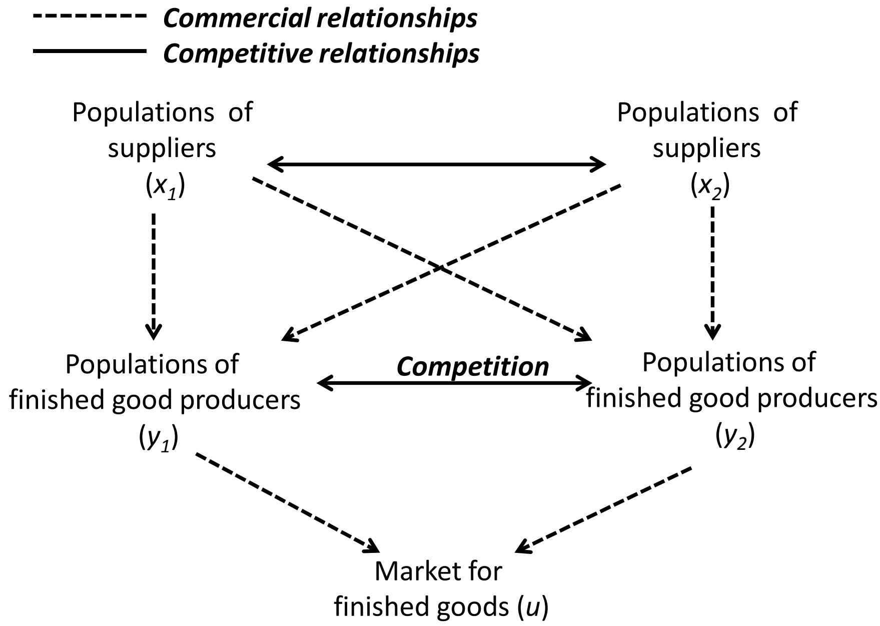


Capturing the causes of observed unfolding dynamics of interactions among the four populations of firms located in different geographical clusters is a fairly complex matter since intra-cluster relationships are intertwined with inter-cluster competitive and commercial relationships.

Once presented with this data, we thought that our aim was to elicit a structure of causation that could explain the behavior observed. This objective oriented the design of a field study, this latter illuminated the role played by two classes of processes. First class of processes is the horizontal competitive dynamics between populations of firms positioned at the same stage of a value chain while the second class of processes includes the vertical commercial relationships that connect suppliers and finished goods producers. The diagram in figure 3 sketches the relationships among four populations that were elicited in the field study.

More importantly, we felt we that needed a tool to rigorously think through the phenomenon observed (and reported in figure 2), exploring the soundness or flaws of interpretations. While most of the informants found the diagram in graph 3 a reliable description of dynamics at work in Val Vibrata (actually the same model was considered an appropriate interpretation by informants placed in other geographically distant clusters that were experiencing similar phenomenon), role of specific variables in generating behavioral consequences was much more ambiguous for everyone.

Figure 3



To conduct our theoretical exploration, we proceeded in the following steps.

First, on the basis of secondary data and interviews conducted in Val Vibrata, we modeled the interaction among the four populations as a system of four differential equations[3]. Second, we run a set of simulation experiments to understand if, and at what conditions, the selected causal structure could generate the observed behavior. Third, a set of simulation experiments provided a number of hints that guided a second round of interviews that were used to further parametrize the model. Finally, we run another set of simulation experiments to produce a sensitivity analysis of the behavior to change in

[3]The system of differential equations in the following, where: g_1, g_2, $\tilde{g}_1$ $\tilde{g}_2$ are positive constants representing the growth rate of each population x_1, x_2, y_1 and y_2; c_{12}, c_{21}, $\tilde{c}_{12}$, $\tilde{c}_{21}$ are positive constants which represent the competition rate, that is the extent to which each population is able to reap resources (in our case clients) to the competing population.

$$\begin{cases} \dfrac{dx_1}{dt} = \dfrac{g_1 x_1 (y_1 + y_2 - c_{21} x_2 - x_1)}{y_1 + y_2} \\ \dfrac{dx_2}{dt} = \dfrac{g_2 x_2 (y_1 + y_2 - c_{12} x_1 - x_2)}{y_1 + y_2} \\ \dfrac{dy_1}{dt} = \dfrac{\tilde{g}_1 y_1 (u - \tilde{c}_{21} y_2 - y_1)}{u} \\ \dfrac{dy_2}{dt} = \dfrac{\tilde{g}_2 y_2 (u - \tilde{c}_{12} y_1 - y_2)}{u} \end{cases}$$

In our modeling, we were inspired by the competing species model, a theoretical framework that addresses competition among species (Boyce and Diprima, 1997) model’s parameters. The sensitivity analysis produced a repertoire of plausible alternative histories connected to the same deep causal structure.

Creating insight with history-divergent simulation runs

After having worked with our formal model, we started to simulate the model and we investigated whether the behavior reported in figure 2 is in some respect similar to one of those produced by our formal model.

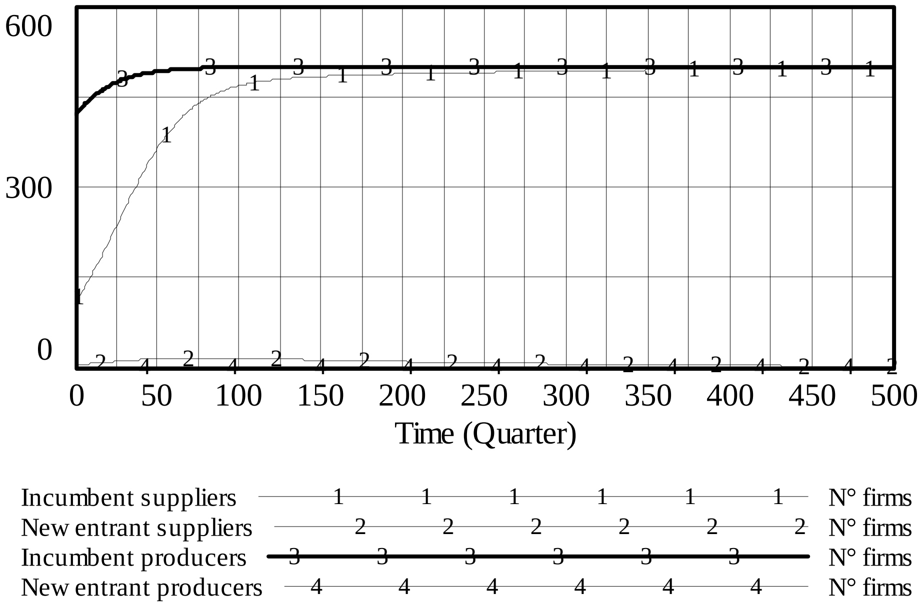
To start with, the collected time series suggest that, at the beginning of the time span over which the phenomenon unfolds, Chinese producers and suppliers were very few. We thus performed a first simulation experiment to see whether, once calibrated with the values empirically collected in 1961, the formal model was able to generate a behavior that shares any characteristics with the real time series.

We assigned to the four populations and to the final market the values that they had in 1961 and we run the model of 500 time step each representing one quarter. Thus, we were simulating a time period that is much longer than the actual time span observed in order to play out the entire behavior of the model until it eventually sets in an equilibrium point.

Results are reported in the graph in figure 4. Incumbent Italian populations grow to saturate the entire final market that represents a sort of carrying capacity of the industry while the new population of Chinese suppliers surges but does not take off and in the long term is defeated and driven out from the market.

On the contrary, we observe in figure 2 that the real history is quite a different one. The new population of Chinese firms grows and challenges the population of Italian incumbent suppliers. This dynamic is very clear among the suppliers, in which Italian firms are decreasing dramatically, and much weaker among producers of finished goods, in which Chinese firms are imperceptibly growing and Italian firms are losing small portions of the market.

Figure 4



One conclusion that we could draw was that our formal model wasn't able to capture the deep causal structure that underpins observed behavior. Another solution was that the calibration of the model wasn't able to capture the specific empirical circumstances under which the behavior of figure 2 was originally observed. This history-divergent run, however, was an opportunity rather than a complication.

The behavior reported in figure 4 suggests that Chinese populations are not strong enough to emerge. If our model was correct, the mismatch between observed and simulated behaviors had to be connected to a problem in the calibration of the simulation model. In calibrating the model, we probably had overlooked some key empirical information that explains the strength demonstrated by Chinese firms.

Since one of the recurring explanation of the phenomenon of such 'invasions', not only in Val Vibrata but in a variety of industrial clusters in Italy, refers to the argument that newly established firms often operates illegally and that this status produces an advantage in terms both of low cost of labor (because illegal immigrants are employed without any form protection) and flexibility (because the lack of control in new firm creation makes easier and faster the constitution of new enterprises), we explored these cases.

May be that our neglecting these factors was the cause of an history-divergent run?

Figure 5 reports results of an experiment in which we re-calibrated the model to simulate a situation in which Chinese firms grow at a rate that is fivefold the rate of grow of Italian firms. As shown, the picture does not change much. This was an interesting hint to address the role of perceptions in inducing explanations from interpretation of informants embedded in the context which his object of study. The speed at which Chinese firms have grown is a consequence rather than a cause; yet, is the most clearly visible, emotional and alarming fact in the community.

We then explored the argument that deals with the differences competitive advantages between Chinese and Italian firms[4]. We collected information in the research field concerning the average prices of the products. We learnt that the price of an intermediate goods sold by a Chinese supplier is on average three times cheaper that the product sold by Italian suppliers. In addition, very low brand recognition and product differentiation protects Italian intermediate products. As far the finished goods producers, here the situation is slightly different; price difference is similar but the Italian finished good is more recognizable and, thus, maintains a competitive advantage to the Chinese product.

Grounding on this information, we recalibrated our simulation model amending the values of parameters that represent competitive advantages of Chinese and Italian populations of firms.

We assumed that Chinese suppliers are three times more competitive than Italian suppliers, and that Chinese producers of finished goods are twice as competitive as their Italian competitors[5]. In the case of finished goods producers, we balanced out the price disadvantage of Italian producers with the brand recognition that Italian finished goods. We simulated the model again and obtained results reported in graph 6.

The simulation suggests that the observed empirical behavior may be an instance of a class of behavior that is produced by our causal structure. This structure, among the others, may produce a behavioral path in which the population of incumbent producers of finished goods survives and shifts its procurement from the incumbent population of supplier to the population of Chinese suppliers that offer cheaper supplies. The incumbent population of Italian suppliers is forced out of the market and the new population of Chinese producers is not able to take off.

In figure 7, we report results of a further experiment in which we stopped the simulation after 160 quarters that correspond to 40 years, which is the time span of the phenomenon empirically observed and reported in figure 2. In this graph, the similitude between the simulated and the empirically observed behaviors suggested to us that the causal mechanisms described in our formal model may give us some hints to articulate theoretical hypotheses to explain the observed phenomena.

[4] A mathematical analysis conducted on the model (Fioresi and Mollona, 2010) confirms that an important determinant of the type of behavior produced by our formal model is the value assigned to the parameters c_{12}, c_{21}, $\tilde{c}_{12}$, $\tilde{c}_{21}$, which represent the reciprocal competition rates among populations; that is, the impact that a population has on the survival of the competing population, what we defined a 'competitive advantage'.

[5] We amended the values of parameters c_{12}, c_{21}, $\tilde{c}_{12}$ $\tilde{c}_{21}$. More specifically, we set $c_{12} = 1$, $c_{21} = 3$, $\tilde{c}_{12} = 1$ and $\tilde{c}_{21} = 2$.

Figure 5

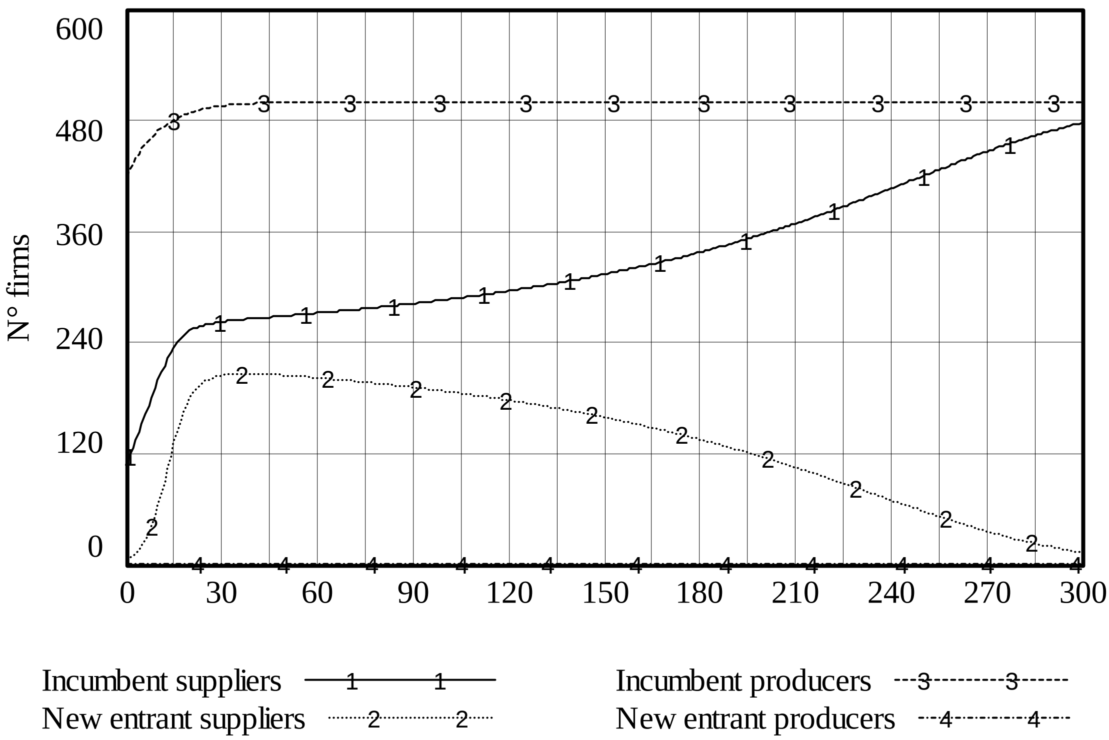


Figure 6

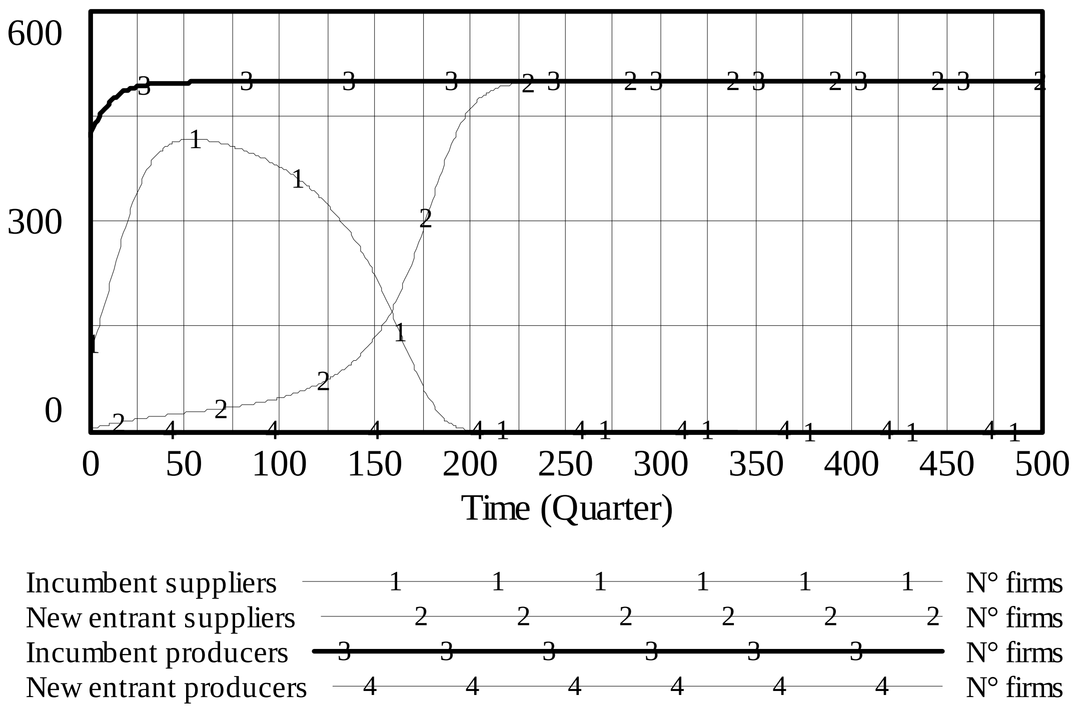
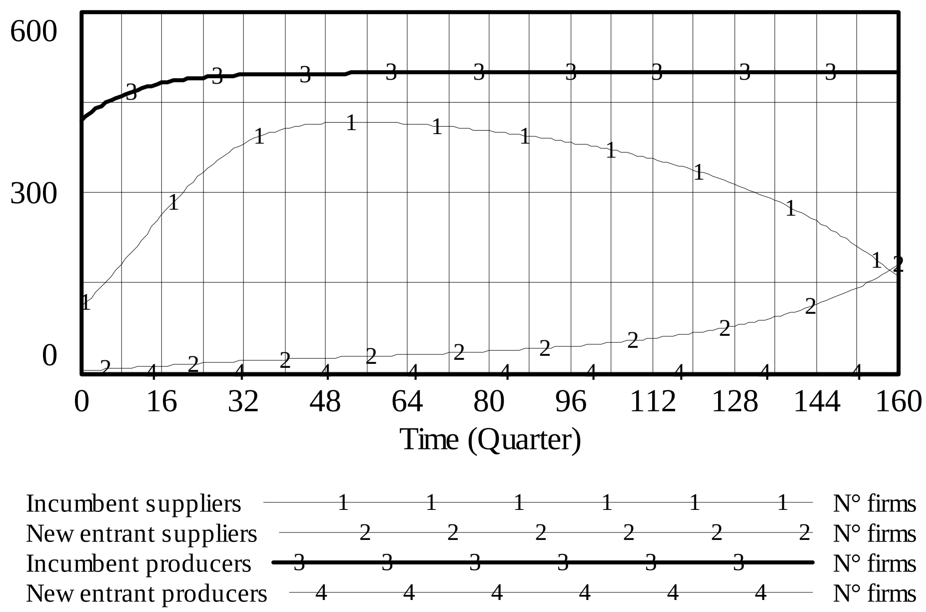


Figure 7



Playing with history-convergent simulation runs

If we now look at graphs in figures 8, 9 and 10, we observe behaviors that are more or less cognate to those depicted in figure 6. In the reported simulation runs, we manipulated parameters to explore model's sensitivity. More precisely, we hypothesize that incumbent suppliers react by decreasing prices. Behavior in figure 8 tells us a story that is not very far away from the one reported in figure 6. New entrants suppliers attempt to entry the cluster, at time 160 incumbent suppliers react by decreasing their prices and this avoids a complete elimination of the population of incumbent suppliers.

Figure 9 and 10 tell a slightly different story. In these graphs we hypothesized that time of incumbent suppliers' reaction takes place, respectively, at time 155 and 140. In both cases, an earlier response, in an environment characterized by path-dependence, pushes new entrants into an equilibrium in which they occupy only a share of the initial market.

The very simple reported simulation experiments helps to reflect on the potential gains of associating computer simulation and field study.

First, computer simulation promotes dialogue and circulation of insight among researchers dealing with similar research questions. The seemingly different behaviors of graphs 6, 7, 8, and 10 are generated by the same deep causal structure, by manipulating only the time of reaction by incumbent suppliers.

In this light, the repertoire of behavior that a specific model produces places an empirically observed behavior within a class of behaviors and, on the other hand, suggests to other researchers, by a process of *déjà vu*, that an observed behavior may be a different instance of a common phenomenon. Researchers that conduct similar research in different fields, in which apparently different histories have been observed, may use the same causal framework as a candidate explanatory hypothesis. The idea here is that a computer model, rather than necessarily encapsulating a causal structure isomorphic to the one at work in the context studied, is a laboratory that facilitates different researchers to think through an empirical issue by exploring logical consequences of different interpretations and representations of phenomena.

Second, the idea that a possible causal framework produces different behaviors of key variables depending on the points in time in which specific events take place is useful to direct further research in the original field and in new fields. In the reported case, simulation experiments suggested that further data on the timing of specific events had to be collected both in the original field and in other fields.

Figure 8

Incumbent suppliers react at t=160

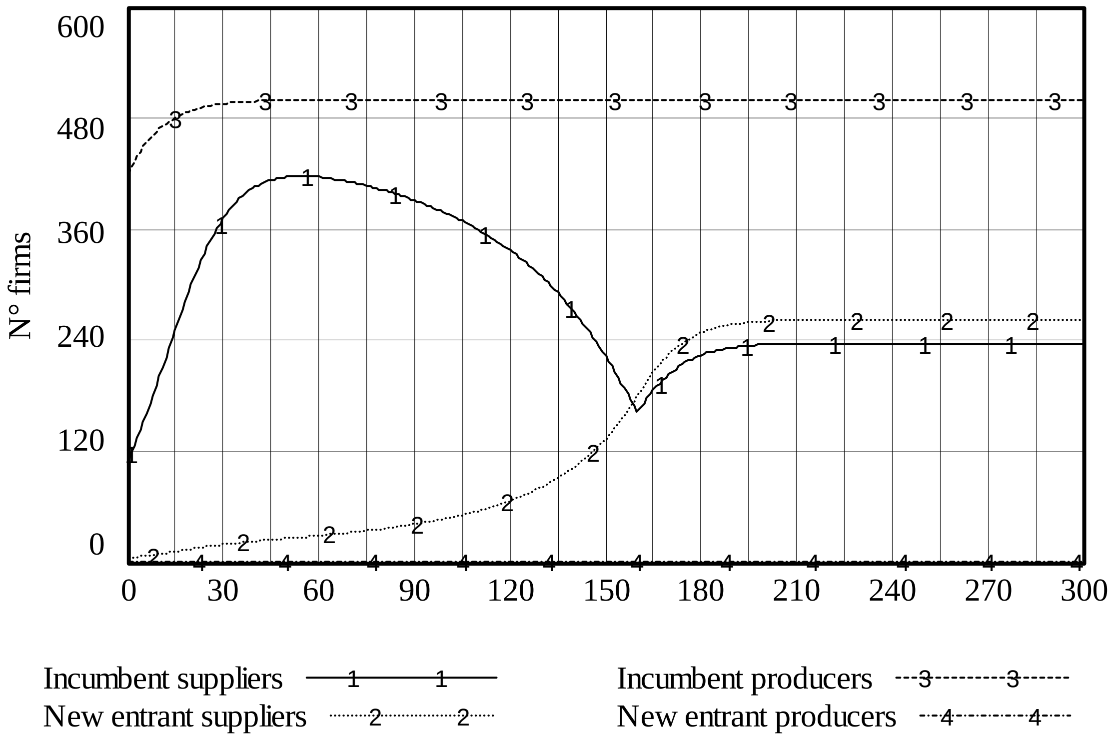


Figure 9

Incumbent suppliers react at t=155

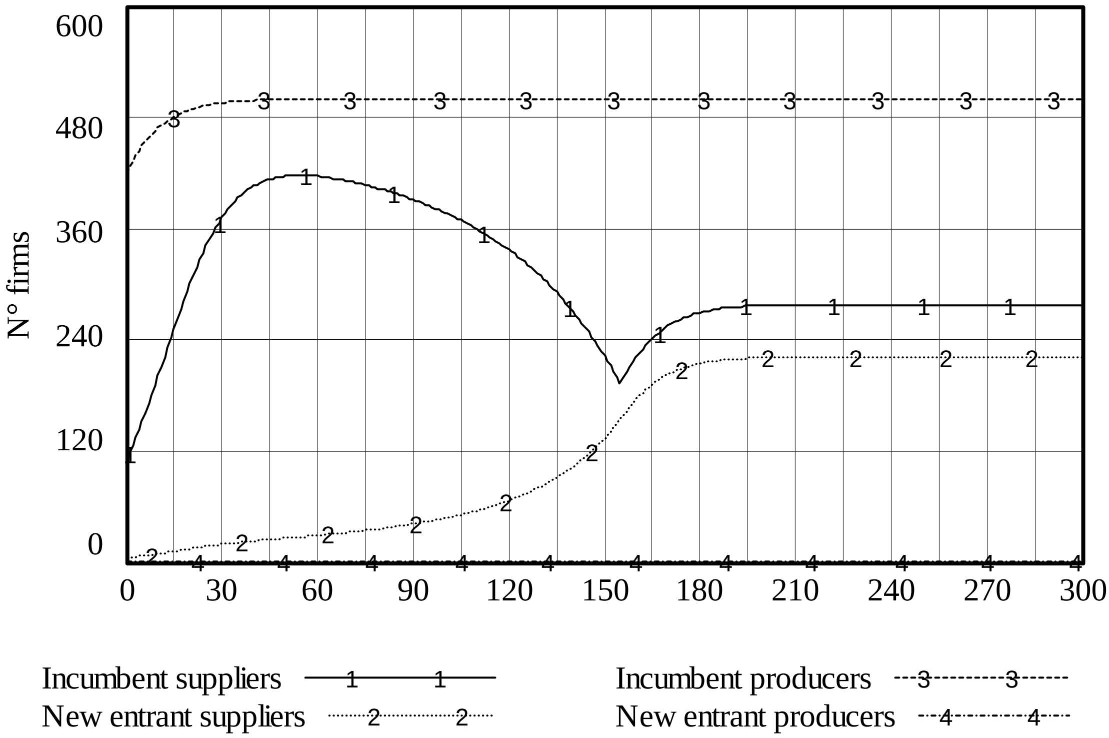
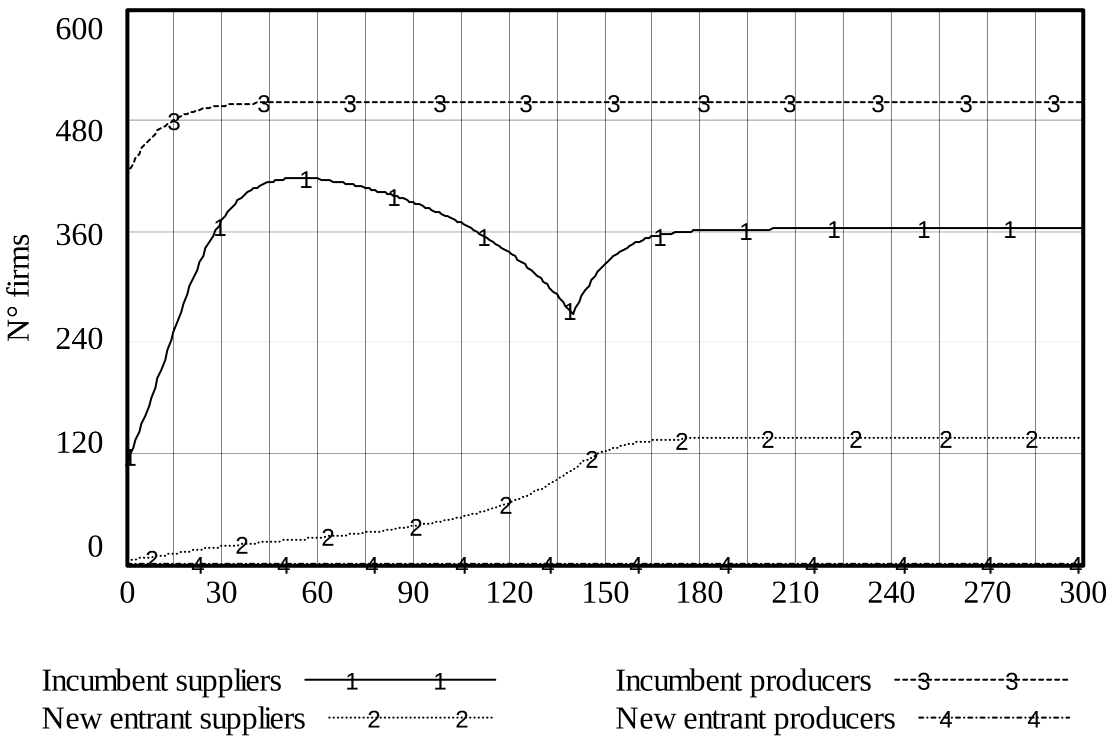


Figure 10

Incumbent suppliers react at t=140



CONCLUSION

The objective of our work was twofold.

First, we suggested that formalization, and computer simulation of formalized hypotheses, may support field research in generating theories of behavior. We articulated the argument both theoretically and suggesting an example. We also depicted the structure of a large research project in which formal modeling, computer simulation and field research are integrated.

Second, we proposed that System Dynamics, a specific modeling and simulation approach, is particularly well suited to be employed to study behavior of complex social systems when inertia and self-reinforcing properties are likely to influence unfolding behaviors.

The body of literature dealing with SD models validation has interestingly emphasized intellectual liaisons between SD scientific approach and a particular tradition of philosophy of science. The development of new epistemological challenges stimulates further analysis. In physical and social science has emerged a thread of epistemological studies which has been referred to as epistemology of complexity[6]. This approach challenges the ambition of scientific tradition stemming from logical empiricism paradigm to reduce the complexity of real-world (Morin, 1984). I. Prigogine claims (1984) for a scientific approach which emphasizes diversity in unity (opposed to unity in diversity) and the constructive role of dis-equilibrium. According to this stream of thought, laws are not sufficient, it is necessary to explain singular and unexpected events. The traditional idea of science as *control* and *prediction* is challenged, the new dimension of *game* is proposed (Bocchi, 1984) and the possibility of a causal description of systems complexity by determination of relation among variables is explored (Pribram, 1984).

The concept of science as *game* is intriguing and calls for a modeling approach able to offer a playground in which different states of the world interact with different futures, all the possible futures, not only the future of statistical convergence. This point is worth stressing because every discipline decides how to locate itself along the continuum which connects rich and exhaustive descriptions to rigorous - but sometimes less savoury - predictions.

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[6] This area of research stemmed from pioneer studies, among the others, at Biological Computer Laboratory directed by Heinz Von Foerster and at Centre International d'Epistemologie Genetique directed by Jean Piaget.

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