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Applied nonlinear dynamical system in social science. A nonlinear model for social control system: an application to Italian coercion system

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Abstract Does an increase in police strength discourage an increase in crime levels? It would seem very likely so, despite the many platitudes common everywhere, even in the most serious literature on the subject. This research study, using Non-Linear Analysis on the Italian crime situation from 1985 to 2003, shows an almost non controvertible result. The police force *really* does seem to have a deterrence function on crime, particularly evident from the 90s on, where, as police strength increases, the number of crimes decrease. One of the most interesting aspects deriving from the non-linear model used, is the *specific measurement* of the number of crimes that might have been committed and that were not in virtue of the deterrent action of the Police Force. Up to now, such an acquisition seems to be lacking from other so called 'traditional' research, where such 'indirect' deterrence appears easily hypothesized, but impossible to determine. For this reason too, the adoption of a non-linear analysis logic shows its heuristic superiority able to shed light on certain aspects that in other analysis models would remain in the shadows.

Keywords Deterrence · Noncompliance · Coercion · Complexity theory · Non-linear competitive model

1 Rule-breaking and social control activities: problems with the linear model

Traditional Sociology has amply dealt with the delicate mechanisms of law enforcement, attempting to codify types and systems of crime control. When not focusing on the interiorization process of social rules, social order enforcement has been based on the *coercive action (coercibility)* of the Law. In other words, it was based on the premise that punishment is an effective deterrent to deviant behavior and is able to make one conform to the establishment. Sanctions, legal coercive apparatus, such as police, law enforcement agencies, magistrates

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and so on, provide essential basic maintenance of social integration without which there would be no society at all.

The above conviction that views punishment as an actual deterrent, already animated the works of Plato, Seneca, Hobbes as well as Bentham, Austin and Feuerbach's philosophy. Furthermore, exponents of the penal pursuers of the Enlightenment such as Beccarria, Romagnor, and Carmignani, felt that coercion was basic and justifiable on a simply utilitarian level rather than on the mere level of retribution-repression. It was considered a necessary tool to defend society by virtue of its inherent force of intimidation.

The view of economic actors as rational, purposeful decision makers seemed to justify and support a linear proportional type of logic, where the greater the cost was, in breaking the law, compared to the gains of breaking the law, the lower the crime rate would be. The quicker and more certain the punishment/sanction was, the more useful and effective it would be as a deterrent.

As far as severity was concerned, Beccaria subordinated effectiveness to certainty, refusing to accept "punishment that was too severe, greater than the damage done, because it was unjust and useless, contrary to the dictates of "prevention". His famous opposition to capital punishment was the result of his stand on punishment in general.

Gibb's new orientation, known as "Modern Theory of Deterrence" systemized and translated fundamental aspects of the theory into concrete empirical terms and identified precise relationships, created by various variables—crime rates on one hand, and levels of punishment, on the other hand. Not only do we appreciate the serious, rigorous work of these modern deterrence theorists (e.g. Tittle 1969; Tittle and Rowe 1974; Logan 1972, 1975; Loftin and McDowall 1982; Bailey and Lott 1976; Liska, 1981), we admire, above all, their intellectual honesty, since their heaviest criticism came from their own ranks. It was they who eventually pointed out how some central issues (the relationship between degree of punishment and crime rate, intervening variables, the rapport between the severity and certainty of the sanction, just to mention the most relevant) revealed problems that had not even been thought of before hand. Further research still has not resolved significant major basic points. For instance, the fact that increasing the punishment not always decreases noncompliance. In fact, Logan noted that if the sentence was too severe, judges were more loath to find the party guilty and to give prescribed sentences unless there was very sure proof of guilt with (no cause of reasonable doubt). Therefore, excessive severity weakened *certainty of punishment* and its effectiveness as a deterrent. In this scheme of things, *severity* would likewise be rendered less effective. It is easy to infer the reason for this: when certainty of punishment is "too low", 'punishment is no longer a real threat, therefore its severity has no effect'(Logan 1972, p. 71). To safeguard deterrence mechanisms, severity cannot reach the critical threshold, as the function of certainty would then be depressed. This is the rub! What exactly is this critical threshold after which *severity* of the punishment works to the detriment of *certainty* of the punishment? Up to what point can we increase the severity of the sentence without risking the opposite affect—a rise instead of a fall of the crime rate. Logan does not add any information on this topic. Yet, without this detail, our theory faces a disturbing level of *non falsificability*. In view of sentence enhancement and substantially unvaried crime rates, we might come to the conclusion that the critical threshold has not yet been reached. However, there is still another curious aspect to this issue. To say that there is a threshold beyond which an increase in severity does not produce a proportional increase in certainty implies that the relationship of these two variables is not linear. Now, Logan has come to he conclusion that the relationship is likely to be non-linear while still applying … *linear* tools.

Recent literature has brought up the problem of deterrence-severity relationships again. In general, studies on whether increases in prison sentence length serve as a deterrent suggest that increases in the severity of punishment have at best only a modest deterrent effect, and that increasing the risk of apprehension and conviction is more influential in reducing crime (e.g. Kelaher and Sarafidis 2011). Or example, Stolzenberg and D'Alessio (1997) and Greenwood and Hawken (2002) examine crime trends before and after a California sentence enhancement law, and find small crime prevention effects. Kessler and Levitt (1999) estimate a 20% decline in crime within five to seven years of another California sentence enhancement law, Proposition 8. Indeed, they acknowledge that the incapacitation effect may dominate the deterrent effect. Taken as whole, the literature shows that the use of the linear model is the most widespread which has led authors like Durlauf and Nagin to affirm a "need for research on the likely non-linear relationship between deterrence and severity" (Durlauf and Nagin 2011, p. 22).

In any case, the question of severity and certainty of punishment as deterrents and the related issue of the deterrent power of police enforcement has not been resolved in previous literature. Studies provide mixed evidence, insufficient in drawing clear-cut conclusions.

On one hand, there is no clear evidence of any systematic negative rapport between levels of punishment and crime rates. Nor is there proof of any systematic confirmation of the bi-directional relationship hypothesis. According to this perspective, the two variables would influence each other reciprocally. At the same time, they would be both cause and effect. The crime would have a causal effect on the punishment, and the punishment, according to deterrence theory would have a reciprocal causal effect on the crime. This assumes, for example, the *public choice theory*, according to which high criminal activity would increase collective fear and the need for safety, to the point that the community is willing to spend more money on law enforcement and on law enforcement agencies. The allocation of added resources, increasing police patrols and the probability of finding officers at the scene of the crime, would increase certainty levels which would in turn, reduce crime. Although these preliminaries seem to be acceptable, actual research results are nevertheless contradictory. By using the minimal quadrant technique in two stages for estimating the systems of simultaneous equations (2SLS), some studies seemed to have confirmed only the deterrence hypothesis (Orsagh 1973), while others have come to the exactly opposite conclusion, ascertaining a rather negative effect for crime rates on certainty of punishment (Nagin 1978). Likewise, two stage panel studies concluded that crimes influences the sanctions and not vice a versa (Logan 1975), while no reciprocal effect was seen from multivariate panel analysis (Greenberg and Kessler 1982). The same results came from time series studies on reciprocal effects (both simultaneous and lagged) between crime and punishment, according to ARIMA procedure. Some researchers only confirmed the deterrence hypothesis, not finding any relationship between crime and punishment (Chamlin et al. 1992), while others ascertained the existence of a reciprocal relationships with different temporal structure. In other words, crime exerts an instantaneous positive effect on sanction; growing levels of crime would increase, at least in the short term, the certainty level (the rapport between the number of police arrests for crime x in respect to the sum of crimes x committed). Whereas, an increase in punishment levels, (e.g. more arrests) would exert a negative, deterrent effect on crimes at a later time, within a few months, in the time span that would allow the information of probability of arrest to spread among the noncompliers population (Chamlin et al. 1992),

Recently, Durlauf and Nagin (2010, 2011) reviewed studies on the relationship between crime rates and certainty of punishment, measured by the ratio of prison admissions to reported crimes (Ehrlich 1973; Sjoquist 1973; Forst 1976; Marvell and Moody 1994; Spelman 2000; Liedka et al. 2006). They found that both cross-sectional and simultaneous and lagged time series studies on deterrent effect of imprisonment suffer from serious issues involving endogeneity, measurement error and theory openendedness, and lack of attention to robustness with respect to the way variables are measured, the possibility of parameter heterogeneity across geographic units, difficulties of distinguishing between deterrence and incapacitation, Finally, they use Granger causality and fall into the misinterpretation of marginal time series predictive power as evidence of causality in a counterfactual sense.

Inconclusive outcomes also appear from the huge corpus of studies on the relationship between police force measurement and crime (e.g. Swimmer 1974a,b; Wellford 1974; Jones 1974; Pogue 1975; Land and Felson 1976; Wilson and Boland 1978; Loftin and McDowall 1982; O'Brien 1996; Marvell and Moody 1996; Zhao et al. 2002; Weisburd and Eck 2004; Spelman 2005; Worrall and Kovandzic 2007; Muhlhausen 2006, 2007; Braga 2008a,b; Weisburd 2008).

According to the utilitarian perspective, in principle, a greater police force presence would produce a deterrent affect on crime. It would deter *would-be* offenders by increasing their perception of the risk of apprehension and thereby certainty of punishment (expected inverse correlation between police strength and crime: the greater the increase in police force, the lower the crime level). This is the reason why increased pro-capita expenditure for security measures would be needed in case of crime rate rise (expected positive relationship between crime and police force).

Nevertheless, a survey of 36 studies, by Marvell and Moody (1996), presents an eloquent "measurement" of the inconclusive results obtained up to 1996 on this matter. The research clearly demonstrates how these studies, on the whole, have given little evidence that police enhancement discourages deviant acts. These studies used *linear regression analysis* to analyze the deterrent effect of police on crime. Only 10 (11 if we include Marvel and Moody's work) of 29 studies regressing crime on police found significant negative coefficients for any crime type. Then, if we consider the total number of types of crime used as dependant variables, only 14 of 78 separate studies had "significant negative coefficients on police variable, fewer than those with significant positive coefficients" (Marvell and Moody 1996, p. 613).

These *see-saw* results would encourage theorists' attack on more than one front. Some were convinced that the police did not reduce crime at all, but that this truth was so unpopular that it had to be kept hidden from the public. Bayley, for instance, declared that "one of the best kept secrets of modern life "was that "the police did not prevent crime" (Bayley 1985, p. 1; see also Benson et al. 1994; Sherman 1992; Sparrow et al. 1990). A line of attack is that the traditional theory presents a superficial view of the reasons that lead one to non-compliance and a superficial view of the available options. According to this view, offenders did not choose rationally in the manner suggested by traditional theory, limiting cost-benefit calculations to the choice between legal and illegal activity only. The cost-benefit calculation is however decisive even when the offender decides *what* crime type to commit, *how often*, *how and where* to commit it. Therefore, if in a given area control agencies are re-enforced, criminals can decide to move their activity elsewhere, in places with less formal control, rather than be discouraged from committing crimes (Lattimore and Witte 1986; Wright and Decker 1994). Likewise, when facing more risk of being caught, criminals are more likely to turn to less risky crimes and methods which will reduce the chances of being apprehended (Cook 1979). But since these crimes are also economically less lucrative, criminals have to commit more of them to maintain their usual income and standard of living. Consequentially, more police could eventually cause more criminal activity. They could reduce the more visible crimes like armed robberies, but increase simple thefts.

According to critics, the extreme divergence of results, stems then, from two prime factors. According to some, the variable which is the indicator of the coercive capacity of the State juridical-penal control apparatus, or, in other words, the budget dedicated to reinforcing the police is not adequately controlled in the composition of it components

(Marvell and Moody 1996). For example the increase in police force funding may go to other sectors like policemen's retirement pensions and not have anything to do with empowering the efficiency of the police force itself. According to other critics, the divergence might derive from the adoption of different time structural criteria (*temporal patterning*) of crime and police ratio. In their view, the economic theory does not mention anything about the time interval needed for one variable to influence another, resulting in the justification of a wide range of assumptions in the studies, sometimes soliciting simultaneous reciprocal effects between police and crime (Swimmer 1974a) and sometimes lagged time effects according to different time lags (lags of 1, 2 or even 3 years) (e.g. Greenwood and Wadycki 1973; Wellford 1974; Land and Felson 1976; Fox 1979). Different time specifications would naturally give different results:

> These specifications imply very different structural relationships between basically identical sets of variables. It is therefore understandable that they come to different conclusions (Loftin and McDowall 1982, p. 394)

Other critics complain about the use of insufficiently robust causality testing (i.e. two-stage last squared simultaneous equations) and about the inaccurate control of intervening variables such as demographics and economics (Marvell and Moody 1996).

According to a large number of theorists, beside the resources allotted to police force activity, the explosive increase in the crime of the early 90s was supposedly due to ineffective intervention strategies, with a standard model of policing low on the *diversity of approaches* and *level of focus* dimensions. In 2004, Weisburd and Eck reviewed research on police effectiveness in reducing crime focusing on types of interventions used. From this perspective, the decrease of crime rates since the mid-1990s (in particular 1994–2004) could be due to concurrent innovative strategies of intervention, in particular, geographically focused police practices, such Hot-Spots Policing, and Problem-Oriented Policing (POP). On doing statistical analysis of the effectiveness of various police techniques, including COP, they found that Community Oriented Policing (e.g. Neighborhood Watch, crime newsletters, and community education meetings) does not effect crime rates unless implemented with models of POP.

Over the last decade a substantial number of research studies showed that focused police interventions (HSP and POP) could produce significant gains in crime prevention in targeted sites (e.g. Brantingham and Brantingham 1999; Eck 2002; Skogan and Frydl 2004; Weisburd and Eck 2004; Weisburd et al. 2004, 2006; Braga and Weisburd 2006; Mazerolle et al. 2007; Braga 2007, 2008a,b; Weisburd 2008; Weisburd et al. 2010; Weisburd and Telep 2010), reporting, via quasi or natural experiments, little evidence of immediate *spatial* displacement of crime to non-targeted areas and strong evidence for diffusion of crime prevention benefits in areas near the targeted sites of intervention. Nevertheless, several studies also suggested some caution underlining the need to investigate possible *non-spatial* displacement outcomes (e.g., change in methods of committing illegal acts) in Hot Spots Policing. Weisburd et al. (2006) found that offenders will often try other modes of adaptation to police interventions. Prostitutes and drug dealers, for example, may begin to move their activities indoors to avoid heightened police activities on the street. These findings suggest the importance of continued investigation of possible nonspatial displacement and the need to carefully examine the interaction of different strategies with different Hot Spots settings. According to Durlauf e Nagin, "policies that are effective for one type of crime may have little effect on others. For example Hot Spots Policing is unlikely to be effective in reducing crimes such as domestic violence or homicide that generally occur in nonpublic places"

(Durlauf and Nagin 2011, pp. 49–50). Insofar, the authors go on to say that, "more attention should be paid to the effects of policies on particular types of crimes …. Just as in medicine where a portfolio of treatments is required to address heterogeneous diseases, a well designed crime control policy requires a portfolio of crime control treatments to address diversity in type of crimes and the people who commit them" (ibid.).

In comparison to these studies, we have other perspectives which attribute the decrease of crime from 1994 to 2004 to an increased use of incarceration (*incapacitation effect*) and to State prison buildup expansion (Worrall and Kovandzic 2007; Spelman 2005; Muhlhausen 2006, 2007).

Beside these considerations, in my judgment, there is still another valid hypothesis that I would like to present. Before reaching any more or less definitive discussion on the prevention effectiveness of the police, we must reflect on the *form* of relationship between the variables in play. Mainly, in the studies reported, the relationship between degree of violation of rules and system of control activity has been viewed in terms of linear relationships, i.e. on the assumption that the dependent variable varies proportionately to the changing of the independent variable (the greater the punishment, or the greater the human and economic resources at disposal of the legal apparatus, the lower the level of non-compliance). Hypothesizing a linear relationship between the variables involved means thinking that a 20% increase in the police strength will correspond to a 20% decrease in the crime rate, or that a 20% increase of severity or certainty can proportionately decrease crime by 20%, or again that a 20% increase in crime will necessarily lead to the same proportional increase in the police strength.

However, this type of orientation is subject to a high degree of ambiguity. As already seen, it is not reasonable to believe that, for instance, doubling the degree of severity reduces the number of violations by half (Logan 1972; Liska 1981). Similarly, how reasonable is it to believe that a tot increase in the police strength can induce a proportional reduction in the crime rate, or that a small decrease in police strength can produce a small, proportional increase in the crime rate? The linear approach, acknowledging the proportionality of ratios between variables, portrays a *predictable world, without surprises or instability*. But can we reasonably conceive crime as a phenomenon lacking instability, uncertainty and unpredictability, un-controllability? If this were the case, how do we explain crime waves in certain historical periods. How do we explain certain situations of *chaos*, of breakdown in control and predictability? In such situations, experience tells us that no police intervention is able to control the phenomenon very easily (e.g. the case of cocaine use studied by Priesmeyer 1995). Similarly, when we deal with the relationship between crime and police strength, how is it reasonable to postulate that a doubling of the crime rate, due to the most contingent causes, ensures *by itself* a doubling of human and economic resources at the legal apparatus' disposal? Clearly, this possibility, not considering the incidence of ideological currents more or less in favor of reinforcing coercive strength, would require unlimited state funding, a not very realistic situation according to Pontell (1978). On the whole, the linear model seems to introduce *an automatism* into the variables in play which, basically, even deterrence theorists do not fully agree with.

In light of these theoretical reflections, I asked myself if the tendency of crime levels in rapport to the postulated deterrent activity of the police strength could not be better structured by using a nonlinear explicative logic and if the consequential use of models from the *Theory of Complex Non-linear Systems* would not be able to clarify the terms of the problems in some manner.

2 Complexity and chaos theory: a brief discussion

Complex and Chaos Systems Theory is the state of the art, the "new frontier" of modern science. It marks the eclipse of the classic Newtonian–Laplacian conception expressing linear, deterministic, relationships among real phenomena, and it revolves around the acknowledgement of non-linearity and thus instability, uncertainty and unpredictability of natural and social systems. As Crutchfield underlined, this "new" formulation would provoke a "revolution, involving numerous branches of science" (Crutchfield et al. 1986, p. 22), with research and applications regarding a wide range of disciplines (Grebogi and Yorke 1997).

In synthesis, the sense of the current revolution lies in the elaboration of three "principles". *First*, we must take into adequate consideration the existence of a class of phenomena with non-linear trends which means that natural phenomena may be characterized by non-proportional cause and effect relationships.

Secondly, we must give due weight to the concept of *emergency* and *sensitivity to changes in initial conditions* theorized by Poincarè, the precursor of Complex Systems Theory, as discriminating features of non-linear systems. In linear systems any change in the cause variable produces a *proportional* change in the effect variable (namely, *the greater the increase/decrease of x, the greater the increase/decrease of y*). Therefore, they are structurally stable: they "damp" external disturbances, responding to external 'shocks' in a smooth and proportionate manner. Even large waves or pulses will be dispersed over time. Consequently, "linear systems exhibit smooth, regular, and well-behaved motion" (Elliott and Kiel 1997a, p. 5) and are resilient to any attempts of destabilization. Naturally, this is a guarantee of system predictability. In non-linear systems, instead, any "small" change in the cause variable can produce a "big", *non proportional*, change in the effect variable. Vice a versa, a "big" change in the cause variable can generate "small" changes in the effect variable. During some time periods behavior may reveal linear continuity. However, during other time periods relationship between variables may change, resulting in dramatic structural and behavioral change (*bifurcation*). The system can be so sensitive to even the slightest changes from external disturbance that it appear unstable and discontinuous. Positive feedback amplify these changes, breaking up existing structures and behavior and creating *unexpected* outcomes in the generation of new structure and behavior. So, new forms of equilibrium, novel forms of increasing complexity, may *emerge*, or even the state of *chaos*, a temporal behavior that appears random and devoted of order, in which uncertainty dominates and predictability breaks down.

Thirdly, in respect to the above two conditions, the new science loosens the ties between determinism and predictability supported by Laplace's theory The Newtonian-Laplacian *weltanschauung* portrayed the world as a machine with perfect, predictable clock-like precision. From this deterministic conception comes the future predictability of phenomena in time. We all remember Laplace's famous saying, "give me the state of the universe at any given time and I will predict the future". Now, however, determinism and predictability have to be kept separated due to the discovery that even if behavior is unexpected, unforeseeable, and random, there are nevertheless *deterministic laws* involved in its unfolding. Along with *deterministic chaos* comes a new landscape for mathematics, where we no longer ask whether God is playing dice with the world but rather what the rules of his game are (Stewart 1989, p. 8).

In light of these "principles", new science seems intrinsically interdisciplinary. Complexity theory can be applied to a wide range of fields including: Meteorology, Physics, Chemistry, Biology, Geology, Engineering, Medicine, as well as Economics, Sociology, and Political Science. *Complexity and Chaos Theory* can describe fluid turbulence, earthquakes, epidemics as well as Stock Market crashes, the electoral volatility (Brown 1991; McBarnett 1997), the arms race (Saperstein 1984, 1997a,b; Grossmann and Mayer-Kress 1989), population dynamics, the spread of crime (Priesmeyer 1995), and of innovations (West 1997), urban growth (Dendrinos 1985, 1992) or in general, the dynamics of new forms of social aggregation.

Of course, we do concede that basic discontinuity of natural and social processes is hardly a new discovery. Over two thousand years ago, Greek philosophy had theorized about it. Even classic science was aware of atmospheric "disorder", in fluid turbulence, in running faucets, in falling leaves, in stones rolling down a cliff, in oscillations of magnetic waves, in plant and animal population dynamics, in heart beats, in the diffusion of nervous impulses and so on. These irregularities, however, were considered real brain teasers or monstrosities, at worst (Gleick 1987). Nowadays, thanks to ever more refined mathematics (Topological studies, Ergodicity theories, Differential Non-linear Equation Analysis) and computational instruments (computers able to run complex Nonlinear programs), we are able to do what Poincaré was not able to do, that is, theorize while controlling the terms of a problem. In conclusion, the real *novelty* today is that we are able to formulate assertions on discontinuity and unpredictability of certain phenomena while ensuring rigorous empirical control over these assertions

3 Complexity and social control

The main objective of this work is to try out the effectiveness of modern analysis techniques in the study of social control processes, by using the *Complex Nonlinear Systems Theory*. As seen above, from a deterrence point of view, the effectiveness of Law enforcement would lead to a decrease in rule-breaking through its effects on certainty of punishment. In this case, the level of norm violations and the coercive capacity of the penal system are functions of one another.

This paper hypothesizes that the relationship between the level of norms violation (*Noncompliance*) and police strength (*Coercion*) can be structured in terms of a *Nonlinear competitive model*, namely the *prey–predator model of Lotka–Volterra*. In this scenario, the crime rate is seen as a complex system, with an intrinsic nonlinear structure, likely to show positive feedback under certain conditions and chaotic interludes—unpredictable and uncontrollable behavior by crime control system. On the other hand, this model allows the control of competing actions of coercion apparatus on crime, it predicts to what measure law enforcement activity is able to *slow down* the growth of criminality in other words, it predicts to what measure law enforcement activity is able to *slow down* criminality.

The prey/predator model has received particular attention in the field of Mathematical Ecology (May 1974; May and Leonard 1975; May and Oster 1976). However, it has been employed successfully in the theory of competitive innovation diffusion (Sonis 1984), urban-regional growth/decline dynamics (Dendrinos and Mullally 1985; Dendrinos 1992), political competition (Brown 1991) and political revolutions (Tsebelis and Sprague 1989).

This paper proposes an *empirical application* of the *prey–predator Model* to Italian Crime Control System data from 1985 to 2003. As far as we know, literature on the subject does not mention any application of this model to real data. Only Huckfeldt (1989, 1990) *simulated* a Nonlinear Dynamical Interdependence model using "proportion of population failing to comply with a given law at time *t*" (Noncompliance), and "proportion of system resources dedicated to coercion" (Coercion) (1990, p. 420). This model was a "system of Nonlinear difference equations, which specified predatory dynamics in the Lotka–Volterra tradition" (Huckfeldt 1990, p. 421). Although my analysis contains several theoretical aspects that are different from Huckfeldt's, it does not detract interest for the author's model, which represents a truly innovative turning-point in the vast literature on deterrence. This article is organized as follows. In the next Sect. 1 explain in details the Huckfeldt's model, suggest some theoretical adjustments, and analyze the model I apply to Italian Crime Control System data. In the end, I apply the model to Italian data and discuss the results.

4 Noncompliance and coercion model

Huckfeldt conceives *Coercion* and *Noncompliance* as two states of an interdependent system defined as:

$$\begin{aligned} \mathrm{N}_{t+1} - \mathrm{N}_t &= a - c\mathrm{N}_t - b\mathrm{C}_t \\ \mathrm{C}_{t+1} - \mathrm{C}_t &= d\,(\mathrm{S}_\mathrm{C} - \mathrm{C}_t) + e\mathrm{N}_t \end{aligned}$$

or

$$\begin{aligned} \mathrm{N}_{t+1} &= a\mathrm{N}_t\,(\mathrm{L}_\mathrm{N} - \mathrm{N}_t) - b\mathrm{N}_t\mathrm{C}_{t+1} \\ \mathrm{C}_{t+1} &= d\mathrm{C}_t\,(\mathrm{S}_\mathrm{C} - \mathrm{C}_t) + e\mathrm{C}_t\mathrm{N}_{t+1} \end{aligned}$$

This model is a system of non-linear difference equations. It is the logistic version (May and Oster 1976) of Lotka–Volterra's *prey–predator* Model. In principle, it is assumed that an increase in the degree of coercion produces a decrease in the level of noncompliance. Both C and N are measured at 0 and 1 intervals.

According to the author, "the model is written in discrete time and assumes an intrinsic lag in the response of two systemic behaviors. In other words, the interdependent monitoring processes are inherently delayed. Coercion at one point affects noncompliance at the next time point, and vice versa" (Huckfeldt 1990, p. 421). In Huckfeldt's conceptualization, this is only one of the basic suppositions of the model. In fact, according to our author the change in the levels of the two variables would be explainable in light of ulterior fundamental assumptions. Below we present the complete list of Huckfeldt's assumptions:

The rates of changes are defined deterministically according to the following assumptions:

(a) Increased levels of noncompliance produces increased levels of coercion by political systems.
(b) Increased levels of coercion generate decreased levels of noncompliance
(c) There is a constant intrinsic rate of change in the level of noncompliance related to the gains of benefits in breaking a particular Law, the legitimacy of the political system, and so on.
(d) At least for deviant behavior—behaviors that result in social cost—noncompliance is self-limiting. Increased levels of noncompliance produce decreased rates of increase in noncompliance. (non si potrebbe dire in modo più semplicemente) Of course, this assumption runs counter to Hobbes' world in which coercion is the only factor that controls noncompliance.
(e) Within political systems, there is a *fair share* conception for every expenditure category (Wildavsky 1974). If the fair share for coercion is 20% of thee system resources, the political system will attempt to monitor actual expenditure and keep it at the 20% level. Expenditure levels above the fair share lead to downward expenditure adjustments Expenditure levels below fair share lead to upward expenditure adjustments (Huckfeldt 1990, p. 420).

That being stated, it would be opportune to single out the constituents of the model to render the assumptions more explicit.

The first equation explains the rate of change in noncompliance:

$$N_{t+1} = aN_t (L_N - N_t) - bN_tC_{t+1},$$

where N_t denotes the proportion of citizens who disobey the law at time t, a is the growth rate of N_t, $L_N - N_t$ is the proportion of citizens who *might* break the law although they currently do not, L_N represents the maximum limit of citizens who *might* refuse to obey the given law, C_t denotes the resource level devoted by the political system to coercion. Huckfeldt refers to the proportion of the budget devoted to state's coercive effort, and b represents the competitive advantage of C over N: it is the rate at which the proportion of citizens that fails to comply to a given law reduces because of the system's coercive effort.

There are two reasons for this structuralization of the equation.

First, According to Huckfeldt, the rate of change or growth rate (a) in noncompliance summarizes the incidence of factors that would induce a subject to disobey the law (profitability and aggregate noncompliance or the assumption that "people are more likely to disobey the law to the extent that others also disobey the law") (Huckfeldt 1989, p. 534). But, there is a limit upon noncompliance under normal circumstances, a point beyond which the noncompliance cannot go. This maximum limit is defined as L_N (or *carrying capacity*): the proportion of citizens who *might* refuse to comply with a given law. In other words, the level of noncompliance cannot have an unlimited increase: it is the function of *carrying capacity* that in turn is regulated by *legitimacy*, $(1 - L_N)$, or "the proportion of citizens who would never break the law under normal circumstance" (ibidem.). In brief,

> Some people obey laws because they are laws, regardless of any penalties that might be levied against law breakers and regardless of any benefits that might be obtained from noncompliance (ibidem.).

This is the reason why the wider the sphere of *legitimacy* $(1 - L_N)$ is, the narrower the space for potential rule-breakers, and the lower the limits of growth and expansion of crime. On the contrary, the more the sphere of legitimacy is restricted, larger the number of potential rule-breakers are, who if not yet deviant are however oriented to be so if profitable $(L_N - N_t)$. As level N of actual noncompliers increases the proportion of citizens eligible to become noncompliers will become small more and more, till *noncompliance* growth is restrained.

Second, The supposition is that the level of noncompliance is influenced by competition with the coercive apparatus set up against crime fighting. From this point of view, an increase in resources geared to strengthening the political system's coercive action, reduces the level of noncompliance. The second term of the equation $(-bN_tC_{t+1})$ expresses the competitive success of C on N in slowing down noncompliance: b is, as already mentioned, the rate at which the proportion of citizens who *might* break the law reduces because of system's coercive, deterrent, effort, "the rate at which noncompliers become compliers" (Huckfeldt 1989, p. 535). b's larger weight signifies a more effective effort.

In conclusion, the a and b parameters capture, according to Huckfeldt, the *net* result of a complex process. Thus, the level of nonconformity to legal prescriptions encounter two limits which would limit its growth: a limit identified with the proportion of citizens likely to assume deviant behavior and a limit obviously represented by the coercive action of the penal system. N_t therefore increases according to logistic rules combined to a reduction factor (*discount factor*) which comes from competition with C.

The second equation

$$C_{t+1} = dC_t (S_C - C_t) + eC_tN_{t+1}$$

describes the rate of coercion change:

d is the rate of the C growth, S_C is the maximum amount of resources or the limit of State's resources available for running the coercive apparatus. The so called *fair share* or the just amount of resources from public expenditure allotted to coercion. Huckfeldt sees Sc as the level of resources for coercion *in absence of noncompliance* as an "investment of the system in *preventive coercion"* (Huckfeldt 1989, p. 537).

e expresses the effect of *noncompliance* on coercive response of Law enforcement agencies: it represents the rate a political system is likely to increase coercive resources as noncompliance rises.

The logics of the equation is significant.

First of all, the level of *coercion* at time t_{+1} depends on its value at time t according to a growth parameter of d. Even in this case, d is not conceived as a constant but rather as a function of the *carrying capacity* of the system expressed by Sc. In other terms, the State's coercive response finds its limit in the resources available. Pontell's arguments on this issue are relevant. It is plausible to say that these resources do not increase proportionately to the increase in crime rates, thus being unable to adequately cope with crime increase (Pontell 1978). At this point, Huckfeldt states:

> No political system has unlimited resources, and the coercive function of the political system must compete with other functions for the resources that are available. Borrowing from the vocabulary of the budgeting literature, political system develops conceptions of 'fair share' in the distribution of resources. All else being equal, an agency or function that receives more than its "fair share" will have its allocation lowered, and one that receives less will have its allocation raised (Huckfeldt 1989, p. 537)

Meager available resources, or limitation in the system's carrying capacity, intervenes to slow down the rate of the coercion level. In this case, d is not constant, but it is a function of a factor of resource adjustment, the *resource strain factor*, Sc-C_t: the more C_t nears the maximum limit Sc, the less resources are available to convert into ulterior increases in resources devoted to coercion. The more C_t is under the maximum limit Sc, the greater are the resources that can be allotted to crime fighting. Since the actual value of Sc is unknown, it is made equal to 1.

The second term of the equation describes *how* the State's coercive apparatus responds to the immediate direct incidence of *noncompliance*. The 'normal' response, which Huckfeldt sees as "typical short- term response" (1989, p. 535) consists in an increase of the resources level dedicated to coercion: higher levels of *noncompliance* would require an added investment for coercion. Thus, in principle, if crime rose tumultuously, the system would have to take it into consideration and would have to increase its coercive capacity in time t_{+1}. The e parameter, thus, represents the rate which the political system is likely to increase resources allotted to coercion for noncompliance increase. Thus, it measures the degree of "sensitivity of the system to noncompliance" (1989, p. 536), or, in other words, its degree of flexibility, and adaptability in reinforcing the coercive apparatus against changes in crime rates. The product eC_tN_{t+1} measures the added increase of coercive resources.

This description of coercion logic can be thus summarized in one conclusion: the change in resources dedicated to coercion is an "*additive function*" of logistics growth factor (or *resource strain*) and a *short term response* to noncompliance (1989, p. 537).

According to Huckfeldt, the first and second equation, combined together, constitutes the mechanism of dynamic interdependence between *coercion* and *noncompliance*.

Now we come to the most interesting implication of the prey–predator model. It has been shown to identify different trends in the phenomenology under examination. The analysis shows that simple deterministic structures are *wholly* capable of generating seemingly infinite complexity. In particular, the value of the parameter a describes the *whole* of characteristics which cause the system to be either stable, oscillating (period 2-type), oscillating in a complex manner (period 4-type) or chaotic. When the parameters were repeatedly reset, and the combination of the initial values of the two C and N variables were modified, it has been shown *at which values* noncompliance demonstrates to settle down to a single equilibrium point ($a \leq 3$), or demonstrates a stable two-period cycles or cycles of any higher period ($3 < a \leq 3.78$) or, at higher levels of intrinsic increase ($a = 3.8$–4), a bounded but aperiodic or chaotic behavior (Marion 1999).

Simply said, the model is able to identify the conditions that would result in a equilibrium situation: the coercive resources are maintained at their fair share level and do not need ulterior adjustments to face a crime situation that is stable. Or in *chaos*, in a unpredictable and an uncontrollable situation. Here we find ourselves facing a rather alarming perspective. In a chaos scenario, the behavior of the noncompliance level shows that it "drags" the coercive response. In other terms, the chaos of noncompliance *spills over*: it produces a *cascade effects* inducing chaos even in interdependent behaviors of coercion levels. This result can be considered "disquieting", being that it is produced even if parameters of the equation governing coercion are not in the chaotic range. "Chaos is infectious", concludes Huckfeldt (Huckfeldt 1990, p. 426).

5 Some reflections

Huckfeldt's analysis, without doubt, provides interesting and promising suggestions for social control policies. Nevertheless, it has definitely raised some issues. One point concerns the question, central in any study on deviant behavior, *why* an individual turns to deviation. Huckfeldt's answer is quite clear: a person deviates for "profitability", for personal gain. In an ulterior clarification on the subject, the author agrees with Gary Becker's economic theory and quotes him: "a useful theory of criminal behavior can dispense with special theories of anomie, psychological inadequacies, or inheritance of special traits and simply extend the economist's usual analysis of choice" (Becker in Huckfeldt 1989, p. 534).

What the notion "profitable" means in the field of economics is relatively simple. However, it is rather complicated to identify criteria of "profitability" in the field of deviance and show how it is structured. It would not be too wrong to say that this criteria is structured on the basis of elements just like those of *classic* theories: anomy, differential associations, heredity of certain traits, and so on. It is on the basis of certain values, or certain differential associations, or of a particular, unique experience, or of other factors, that the individual can get an idea of what for him is more "profitable". A cascade of theoretical and concrete problems flow from this concept which can only be briefly mentioned in this paper.

Let us give a concrete example of "these complications".

Imagine that Sutherland's differential associations regulate the growth of the noncompliance. Let us also imagine that enforcement agencies effectively act to deter crime, contributing to lowering the crime rate. At this point what happens to differential associations?

We should reach the problematic conclusion that deviance is caused by certain types of associations which however lose their effectiveness in the face of deterrence work. In which case "both types of theories" would be wrong: the economic because it does not take into consideration differential associations and Sutherland's because it does not consider the economic factor.

Another problem is the *fair share (Sc)* in the coercion function. It depends on the available resources of the political system. But it is likely to postulate the incidence of a series of particular circumstances in all this (social alarm, to begin with) able to determine the level of "fair share" dedicated toward the coercion function. With all probability, the author conceives the *fair share* level as the final result of a balance, where, given a certain amount of available resources, the incidence of the possible circumstances were taken into account. In any case, further precise information would have been needed.

The real problem, however seems to be another. The factors of the *second equation* end up expressing the process indicated by the model too "mechanically". For example, the political system responds *immediately* to the more or less critical contingencies with instantaneous "adjustments", showing no hesitation in identifying "fair share" criteria and so on. A perspective which in generalizing terms perhaps seems a little problematic to support. So, this article intends to show in an empirical manner the plausibility or reasonableness of my doubts concerning the second equation of the *Noncompliance–Coercion* Model.

6 The *Noncompliance–Coercion* model: some theoretical 'adjustments'

This analysis, considering former observations on the Noncompliance–Coercion model, suggest only the use of the *first equation* of the prey–predator model.There are several differences in respect to Huckfeldt's original formulation in some significant aspects. Basically, there is one substantial difference: Huckfeldt meant to *simulate* with his model; I mean to *apply* it. Therefore, the way in which the variables of noncompliance and coercion are rendered operative have changed. Following the general trend in literature, we have operationalized N with crimes committed in time *t* and *C* with the amount of law enforcement agents employed by the Penal System in fighting crime. The number of law enforcement agents is considered by various research studies (see Marvell and Moody 1996). It is the best way to operationalize coercive activity of crime control in respect to variables like quota of budget geared to crime control, a sum that includes also allotments not pertaining to actual enforcement but to other ends such as pensions, disability benefits and so on.

Even some arguments to justify the components of the equation differ from those of Huckfeldt. Below we again present the first equation of the model with a detailed explanation of the single factors. From time to time we shall indicate the points that differ from Huckfeldt's model.

From my analytical point of view, the equation

$$\mathrm{N}_{\mathrm{t}+1} = k_1 \mathrm{N}_{\mathrm{t}} \left(\mathrm{L}_{\mathrm{N}} - \mathrm{N}_{\mathrm{t}}\right) - b\mathrm{N}_{\mathrm{t}}\mathrm{C}_{\mathrm{t}+1}$$

describes crime trends, so that:
N_{t} is the proportion of crimes committed in time t.

> Here is the first difference compared to Huckfeldt's theory, where N_{t} represents the proportion of citizens who disobey the law in time t. However, the number of deviants constitutes an empirically unreliable variable, as conceptualized by Huckfeldt who obeyed purely simple model simulation needs. Instead, in search of greater empirical specificity, N, for my, represents the proportion of crime committed in time t and its calculation is based on a simple division of the number of crimes and total population.

This choice appears to be in accord with the need to set the variables at a 0–1 range, according to the dictates of logistic map.

C stands for the level of level of police officers used by the political system to control and discourage the crime. It is calculated by dividing the number of law enforcement agents in time t by the total population
k is the rate of crime growth N.

We differ from Huckfeldt on this point also.

As already noted above, according to Huckfeldt, what pushes a subject to rule-breaking is the so called "profitability" factor, in other words, the benefits connected to the crime. Therefore, the noncompliance rate of growth depends on that element. Nevertheless, as noted above, the concept of profitability can be structured on the basis of factors that are those conceptualized by classic theories of deviance such as anomie, personal features and so on. Thus, the entire theoretical formulation eventually reveals a fundamental theoretical contradiction. On one hand these factors explain the deviance, but, on the other hand, they lose any influence they might have in the face of deterrent action by crime control agencies. In other words, this theoretical approach leads to an a-syntony between cause and effect.

To overcome this a-syntony, I will reconsider the general formulation in light of a unitary theoretical matrix, that is, according to deterrence theory. From our perspective, the rate of crime growth is regulated by the fear of being caught, arrested and punished. This fear influences the calculation of subjective utility of cost/gains connected to committing a crime: when the cost is lower than the benefits/profitability, the crime rate increases and vice-versa This fear factor acts both as a motor and as a harness. The element of deterrence is not only important *per se* but can come to the aid of "classic" deviance theories. It is my belief that Tittle an Rowe was right when they criticized the fact that these theories were not able to explain negative cases. It is quite clear that people who are "differentially associate", who have no feelings of moral obligation towards norms or towards significant others "do not necessarily become deviants"(1974, p. 460). Likewise, people who "experience inconsistency between goals and means do not always "innovate", and all who are labeled do not always follow careers of crime. Perhaps, the missing link is fear of sanctions" (ibid.). So, I too am convinced that a social behavior theory would be more congruent if we postulated that "the major factor in human behavior is fear of sanctions" (ibid.) and if the identified factors of classic theories were only conditions that could influence perception and fear of punishment. This would be the general rule. "So, many theories of deviance could be integrated within the deterrence framework" (1974, p. 461). On one hand, elements identified by classic theories like differential association, disjuncture between goals and means, or being labeled could be thought as conditions that "erode rational contemplation of the costs of non-conformity" (ibid.). In this theoretical framework, even attempts to interpret mental disease in terms of its effects on punishment perception would be justified. But on the other hand, in certain conditions, fear of sanctions would limit behavior even when motivation to non- compliance exists. In conclusion, "such an approach would make it possible develop a general theory of behavior that subsumes most of the separate theories that now abound" (ibid.).

Then, this growth is not constant and unlimited. It would reach a limit thus providing a *brake* in the maximum number of crimes perpetrated which can be sustained by the system (*carrying capacity*), considering the deviance opportunity which the context offers the potential deviant in terms of formal control deficiency, that is, in terms of factors like the shortage of law enforcement agents, the shaky certainty of sanctions, the ineffectiveness of punishment, the presence of weak enforcement, more or less disposed to "turn a blind eye" on deviant behavior considered 'normal' according to the 'civic' community, like fixed contract bids, illegal building, pollution, wrongful appropriation of public soil etc…etc. These possible deviances can exist within a maximum limit of social sustainability (L_N). Thus, violations can spread but only up to a certain point, until they reach that limit which society can no longer support.

Before this limit, that is, up to that maximum diffusion of deviant acts (L_N), the higher the level N of crimes, the lower the possibility of ulterior violations ($L_N - N_t$), slowing down /discouraging their increase. In this sense, we can say that ($L_N - N_t$) represents the proportion of crimes which could be potentially perpetrated due to opportunity deriving from lack of control. L_N constitutes the maximum limit, and for mathematical reasons, not to mention the theoretical ones already cited, it is fixed at 1

b expresses the success of the State's coercion action in discouraging the expansion of infractions against the legal order. It measures by *how much* crimes N are reduced by *every single* law enforcement agent.
So that, in my analysis,

bN_tC_{t+1} indicates the total number of offences which *could have been committed* but *were not committed* due to the preventive, deterrent action ensured by police.

This component of the equation has an importance which should not be underestimated. As we know, numerous research studies were not able to clarify *whether* and *how much* State crime fighting agencies are able to exercise a deterrent function. The fact remains that in all these research studies, deterrence was and remains conceived in so called 'realistic' terms, controlling, that is, whether the number of crimes decrease with the increase of police force. But, beside this 'direct' deterrence, we can conceive another 'indirect' deterrence, conceptualized as the number of offences that are discouraged from being perpetrated. Up to now, the current linear models apparently have not been able to say anything about this 'indirect' deterrence, simply giving it a 'dark figure' role. Huckfeldt does not say anything about it. From my perspective, in my analysis the model makes it a numerically determinable factor.

That being said, here is an example,

- 2,200,000 crimes (only an example) were recorded on national territory, over a one year span in 1980
- the following year, 200,000 police officers were employed
- During that same year there were 2,000,0000 crimes with a decrease of 200,000 offences.
- *b*, the rate of change in crimes for every single agent, is calculated by dividing the decrease of crimes and the product obtained by the number of crimes and by the number of police officers ($200{,}000/(2{,}200{,}000 \times 200{,}000)$, from which $b = 0.00000045$). Translating the rate in absolute values (by the product 0.00000045), the entity of the crime reduction is quantified for every single police officer, i.e. 1 crime per officer
- At this point the factor $b \times N_t \times C_{t+1}$ ($0.0000005 \times 2{,}200{,}000 \times 200{,}000 = 200{,}000$) denotes the number of crimes *not* committed due to the deterrence effectiveness of the police strength, named 'indirect' deterrence.

Table 1 Estimation of model parameters and good-fit

Parameters	Estimated values	SE	t
k	1.792	0.359	4.98
b	150.148	73.789	2.03
R^2 (adjusted)	0.67		

R^2 (adjusted) $= 1 - (\sum \text{residual square})/(\sum \text{adjusted squares})$

7 Application of the model to the Italian context

In the present research paper I attempted to empirically apply the *nonlinear competitive model* to the Italian situation. My fundamental hypothesis advances the prospect of a nonlinear relationship between the number of crimes and police strength on the Italian territory, from 1985 to 2003 (Table 4 in Appendix; *Source*: ISTAT). The analysis takes into consideration the total number of crimes reported from 1985 to 2003 (statistics for later years are still no definitive), and the control "machine" (C) made up of all law enforcement agencies which together, with coordinated orchestration of every officer, exerts an action of contrast on the crime level (C = consistency of law enforcement in relation to the entire population).The adaptation of the model for observed empirical data was estimated by using non-linear regression techniques expressed in the model's equation. The procedure takes into consideration the annual delay (lag 1) between N and C. The results are presented in Table 1.

Table 2 shows the results of the application for all the years involved:

The modal accounts for 67% of the variance in the crime level. Naturally, this does *not* mean that 67% of the crime level is determined by deterrent effectiveness of police strength. This 67% expresses the quality of fit of the model as a whole, considered in its structural totality. From this perspective, the model can be said to exhibit a "good fit" to the data, legitimizing the idea of postulating the relationship between N and C in terms of a nonlinear competition (this idea seems to be corroborated by other researchers in *non-decomposable* models like nonlinear ones which consider "satisfactory enough"). In so called *non-decomposable* models such as nonlinear ones, several research studies consider "satisfactory enough", a good fit index not above 59% and sometimes 46% (Brown 1991, p. 62). In this general framework, the estimate of b, expressing the deterrent effectiveness of the control system, suggests that crimes decrease by $150.148\mathrm{N_t}$[1] every single police officer.

[1] For example, let us take into account 1986. The model is specified as follows:

$$\mathrm{N_{1986}} = 1.792\,\mathrm{N_{1985}}\,(1 - \mathrm{N_{1985}}) - 150.148 \times \mathrm{N_{1985}} \times \mathrm{C_{1986}} + \mathrm{e}, \quad \text{or}$$
$$\mathrm{N_{1986}} = 1.792 \times 0.0238455 \times (l - 0.0238455) - 150.148 \times 0.0238455 \times 0.003714 + \mathrm{e},$$

where $\mathrm{N_{1986}} = 0.04171219 - 3.580354134 \times 0.003714 + \mathrm{e}$,
and thus

$$\mathrm{N_{1986}} = 0.04171219 - 0.013297435 + \mathrm{e}$$
$$\mathrm{N_{1986}} = 0.02841385 + \mathrm{e}$$

In more explicit terms, the model shows that, for every police officer employed, crimes decreases by about 3.6 crimes per 100,000 inhabitants ($150.148 \times 0.0238455 = 3.5806$); overall, in absolute terms, the deterrent effectiveness of police strength is estimated at 1,329.94 crimes less per 100,000 inhabitants ($3.580354134 \times 0.003714 = 0.013297435$). It follows that for 1986 the model estimates a theoretical rate of 2841.38 crimes per 100,000 inhabitants. What we have to do now is see the residuals of the theoretical value and the corresponding empirical data. As noted, the residual (expressed in e) is equal to -0.003914; that is, the observed value deviates from the previous value by 391 crimes per 100,000 inhabitants. Even more explicitly, the model estimates about one million seven hundred thousand crimes in 1986, while the observed value was about one million and four hundred thousand crimes. Table 2 shows the results of the application for all subsequent years. Again,

Table 2 Observed data for level of crimes (crimes/total population) and level of police strength (police officers/total population), and fitted data for crimes—1985–2003

Year	Crimes: (crimes/pop. tot.)	Police strength: (police officers/pop. tot.)	Model
1985	0.0238455		
1986	0.0244932	0.0037140	$1.792\text{N}_{1985}(1-\text{N}_{1985}) - 150.148 \times \text{N}_{1985} \times \text{C}_{1986} + e$,
1987	0.0325273	0.0041730	$1.792\text{N}_{1986}(1-\text{N}_{1986}) - 150.148 \times \text{N}_{1986} \times \text{C}_{1987} + e$
1988	0.0329420	0.0043020	$1.792\text{N}_{1987}(1-\text{N}_{1987}) - 150.148 \times \text{N}_{1987} \times \text{C}_{1988} + e$
1989	0.0356700	0.0044310	$1.792\text{N}_{1988}(1-\text{N}_{1988}) - 150.148 \times \text{N}_{1988} \times \text{C}_{1989} + e$
1990	0.0433210	0.0044400	$1.792\text{N}_{1989}(1-\text{N}_{1989}) - 150.148 \times \text{N}_{1989} \times \text{C}_{1990} + e$
1991	0.0466500	0.0045860	$1.792\text{N}_{1990}(1-\text{N}_{1990}) - 150.148 \times \text{N}_{1990} \times \text{C}_{1991} + e$
1992	0.0419690	0.0047720	$1.792\text{N}_{1991}(1-\text{N}_{1991}) - 150.148 \times \text{N}_{1991} \times \text{C}_{1992} + e$
1993	0.0395510	0.0048850	$1.792\text{N}_{1992}(1-\text{N}_{1992}) - 150.148 \times \text{N}_{1992} \times \text{C}_{1993} + e$
1994	0.0379520	0.0049890	$1.792\text{N}_{1993}(1-\text{N}_{1993}) - 150.148 \times \text{N}_{1993} \times \text{C}_{1994} + e$
1995	0.0395490	0.0048990	$1.792\text{N}_{1994}(1-\text{N}_{1994}) - 150.148 \times \text{N}_{1994} \times \text{C}_{1996} + e$
1996	0.0421680	0.0049070	$1.792\text{N}_{1995}(1-\text{N}_{1995}) - 150.148 \times \text{N}_{1995} \times \text{C}_{1996} + e$
1997	0.0424010	0.0045350	$1.792\text{N}_{1996}(1-\text{N}_{1996}) - 150.148 \times \text{N}_{1996} \times \text{C}_{1997} + e$
1998	0.0421040	0.0046010	$1.792\text{N}_{1997}(1-\text{N}_{1997}) - 150.148 \times \text{N}_{1997} \times \text{C}_{1998} + e$
1999	0.0411580	0.0047400	$1.792\text{N}_{1998}(1-\text{N}_{1998}) - 150.148 \times \text{N}_{1998} \times \text{C}_{1999} + e$
2000	0.0381330	0.0047230	$1.792\text{N}_{1999}(1-\text{N}_{1999}) - 150.148 \times \text{N}_{1999} \times \text{C}_{2000} + e$
2001	0.0379660	0.0047490	$1.792\text{N}_{2000}(1-\text{N}_{2000}) - 150.148 \times \text{N}_{2000} \times \text{C}_{2001} + e$
2002	0.0389310	0.0047500	$1.792\text{N}_{2001}(1-\text{N}_{2001}) - 150.148 \times \text{N}_{2001} \times \text{C}_{2002} + e$
2003	0.0424410	0.0047300	$1.792\text{N}_{2002}(1-\text{N}_{2002}) - 150.148 \times \text{N}_{2002} \times \text{C}_{2003} + e$

Results	bNC	Fitted data N	Residuals
$0.0417122 - 3.58 \times 0.003714 + e =$	$0.0417122 - 0.0139743 + e =$	0.0284075	0.003914
$0.0428168 - 3.68 \times 0.004173 + e =$	$0.0428168 - 0.0153466 + e =$	0.0274627	0.0050646
$0.0563929 - 4.88 \times 0.004302 + e =$	$0.0563929 - 0.0210106 + e =$	0.0353726	−0.002431
$0.0570873 - 4.95 \times 0.004431 + e =$	$0.0570873 - 0.0219165 + e =$	0.0351610	0.0005090
$0.0616406 - 5.36 \times 0.004440 + e =$	$0.0616406 - 0.0237797 + e =$	0.0378503	0.0054707
$0.0742682 - 6.50 \times 0.004586 + e =$	$0.0742682 - 0.0298299 + e =$	0.0444254	0.0022246
$0.0796970 - 7.00 \times 0.004772 + e =$	$0.0796970 - 0.0334250 + e =$	0.0462582	−0.004289
$0.0720520 - 6.30 \times 0.004885 + e =$	$0.0720520 - 0.0307831 + e =$	0.0412564	−0.001705
$0.0680722 - 5.94 \times 0.004989 + e =$	$0.0680722 - 0.0296272 + e =$	0.0384332	−0.000481
$0.0654289 - 5.70 \times 0.004899 + e =$	$0.0654289 - 0.0279165 + e =$	0.0375010	0.0020480
$0.0680689 - 5.94 \times 0.004907 + e =$	$0.0680689 - 0.0291388 + e =$	0.0389183	0.0032497
$0.0723786 - 6.33 \times 0.004535 + e =$	$0.0723786 - 0.0287131 + e =$	0.0436530	−0.001252
$0.0727609 - 6.37 \times 0.004601 + e =$	$0.0727609 - 0.0292919 + e =$	0.0434563	−0.001352
$0.0722736 - 6.32 \times 0.004740 + e =$	$0.0722736 - 0.0299655 + e =$	0.0422956	−0.001138
$0.0707195 - 6.18 \times 0.004723 + e =$	$0.0707195 - 0.0291872 + e =$	0.0415201	−0.003387
$0.0657285 - 5.73 \times 0.004749 + e =$	$0.0657285 - 0.0271908 + e =$	0.0385263	−0.000560
$0.0654521 - 5.70 \times 0.004750 + e =$	$0.0654521 - 0.0270775 + e =$	0.0383632	0.0005678
$0.0670484 - 5.85 \times 0.004730 + e =$	$0.0670484 - 0.0276488 + e =$	0.0393879	0.0030531

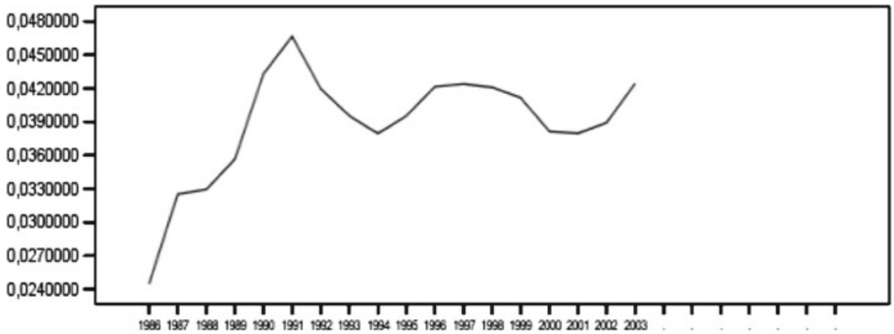

Fig. 1 Time series of number of crimes/total population—1986–2003

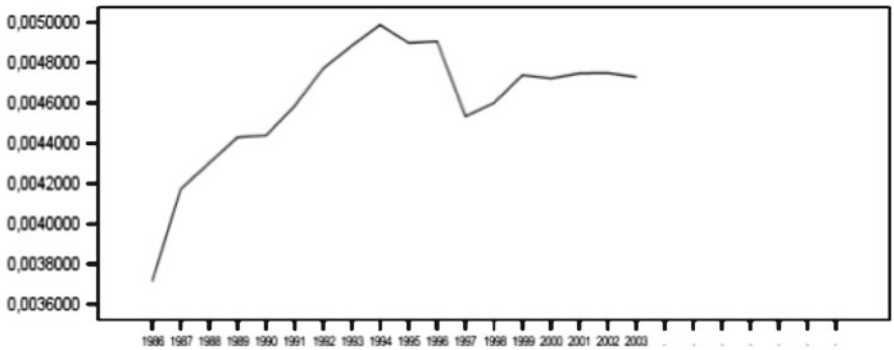

Fig. 2 Time series of number of police officers/total population—1986–2003

The analysis suggests that, in the observed time span, an increase in police strength has a deterrent action on crime. In 1990–1995 we see a very vivid empirical picture of what was happening. Figures 1 and 2 show a peak in 1990–1991. This peak is followed by progressive increases in the level of police strength, an increase that progresses from 1991 to 1996. In fact, these are the years which show a corresponding decline in the crime rate. 1994 is particularly striking, being the year which marks the greatest decline of crime, after a period of almost constant increase, and correspondently, the greatest increase in police strength. For the same reasons, crime rates rise when police strength declines, as we see during the 3 years following 1995: at lower levels of police force correspond higher levels of crime. Their subsequent rise seems able to explain crime rate decline during the last 5 years.

Still more in detail, the model estimated a rate of growth k of 1,792 for N, rather far from the chaos range. This means that the crime trend stays at a range of *stability* for the period in consideration, namely in a situation of possible controllability and predictability. Therefore, within this framework, an increase in the consistency of the police force, or yet, an increase in their operative effectiveness, would have a good probability of producing reduction in crime in the short and medium term.

Finally, the model provides a specific measurement—represented by the bNC factor—of what we have named, for expressive convenience, “indirect deterrence”, in other words, for

Footnote 1 continued
we note the residuals (positive and negative) are in a range from a minimum of 48 crimes to a maximum of 547 per 100,000 inhabitants.

the number of crimes which might have happened but did not, because of the deterrent force of the police.

This is no mere "mathematical game", in so far as the model indeed offers good adaption to empirical data, giving value to every single variable. To sum up, in the period under examination, there were *no* crimes committed in number from a minimum about 1,300 (1986) to a maximum of about 3,300 (1991) per 100,000 inhabitants (Table 2). Briefly, this means that 'indirect' deterrence seems to be able to reduce, in general, by about 40% rise of actual crimes.

8 The reasons for the refusal

In the predominately theoretical part of this discussion we decided *not* to use the second equation of Huckfeldt's model, supporting our decision by a series of considerations. Nevertheless, this refusal was not only on the 'theoretical' plane In fact, we decided to apply the model to our data even using the second equation (Table 3), to corroborate what was postulated in a purely theoretical manner.

The second equation has the following structure:

$$\mathrm{C}_{\mathrm{t}+1} = k_2\mathrm{C}_{\mathrm{t}}\,(\mathrm{S}_{\mathrm{C}} - \mathrm{C}_{\mathrm{t}}) + e\mathrm{C}_{\mathrm{t}}\mathrm{N}_{\mathrm{t}+1}.$$

Needless to say that the most important part of the equation is factor $e\,\mathrm{C}_{\mathrm{t}}\,\mathrm{N}_{\mathrm{t}+1}$. It indexes the sensitivity of the political system in "adjusting" the funds dedicated to deterrence with "short term responses" at every noncompliance increase.

It is precisely at this point that we reach an upsetting result. In fact, when applying the equation to our data, we estimate a *negative e*:-4-258. Naturally, this finding upsets the logic of the model. *If* the system were ready to face an increase in crime and *if*, consequently, it were to provide counter measures contemplated by the model, the parameter should be a *positive: an increase in crime should lead to an increase in police strength.*

This aspect seems decisive in justifying our doubts. Still, there is yet another problem. The *negative* parameter *e* determines the failure of the second equation of Huckfeldt's model, but it should be explained. What does a negative *e* parameter mean, in reference to our data? The problem is that no satisfying 'explanation' seems to exist. The only plausible perspective might be to conceive the negative *e* parameter as a 'cost'. Therefore, in performing their deterrent function, the police strength faces a 'cost', conceived as loss of human lives, officers leaving the work place, etc. However, in light of our estimates, this assumption seems highly unrealistic. In fact, this 'cost' is estimated at a minimum of 29,526 (1987) to a maximum of 50,995 (1997) 'losses' per year (this result was obtained by multiplying the *b*CN factor by total population). We find a hypothesis that predicts a yearly 14% average loss of police officers absolutely unsustainable.

9 Conclusions

The main goal of this study was to suggest the use of non-linear models in criminology. Here linear models predominate, but, from my point of view, the crime can not be framed in a linear perspective because it, acknowledging the proportionality of ratios between variables, implies a controllability and predicibility of the phenomenon that does not occur at all in real life. Therefore, the non-linear approach, allowing to model both *stable* situation and *chaotic* situation, must be a turning point rather than the linear approach. That being stated, we can distill three conclusions from the above analysis.

First of all, we stand on the side of deterrence supporters and agree that the state's coercive capacity is a central ingredient in securing compliance. Although, there is still an ongoing

Table 3 Observed data for level of police strength (police officers/total population) and level of crimes (crimes/total population), and fitted data for police strength—1985–2003

Year	Police strength: (police officers/ pop.tot.)	Crimes: (crimes/ pop.tot.)	Model
1985			
1986	0.0037140		
1987	0.0041730	0.0325273	$1.187C_{1986}(1-C_{1986}) - 4.258 \times C_{1986} \times N_{1987} + e$
1988	0.0043020	0.0329420	$1.187C_{1987}(1-C_{1987}) - 4.258 \times C_{1987} \times N_{1988} + e$
1989	0.0044310	0.0356700	$1.187C_{1988}(1-C_{1988}) - 4.258 \times C_{1988} \times N_{1989} + e$
1990	0.0044400	0.0433210	$1.187C_{1989}(1-C_{1989}) - 4.258 \times C_{1989} \times N_{1990} + e$
1991	0.0045860	0.0466500	$1.187C_{1990}(1-C_{1990}) - 4.258 \times C_{1990} \times N_{1991} + e$
1992	0.0047720	0.0419690	$1.187C_{1991}(1-C_{1991}) - 4.258 \times C_{1991} \times N_{1992} + e$
1993	0.0048850	0.0395510	$1.187C_{1992}(1-C_{1992}) - 4.258 \times C_{1992} \times N_{1993} + e$
1994	0.0049890	0.0379520	$1.187C_{1993}(1-C_{1993}) - 4.258 \times C_{1993} \times N_{1994} + e =$
1995	0.0048990	0.0395490	$1.187C_{1994}(1-C_{1994}) - 4.258 \times C_{1994} \times N_{1995} + e$
1996	0.0049070	0.0421680	$1.187C_{1995}(1-C_{1995}) - 4.258 \times C_{1995} \times N_{1996} + e$
1997	0.0045350	0.0424010	$1.187C_{1996}(1-C_{1996}) - 4.258 \times C_{1996} \times N_{1997} + e$
1998	0.0046010	0.0421040	$1.187C_{1997}(1-C_{1997}) - 4.258 \times C_{1997} \times N_{1998} + e$
1999	0.0047400	0.0411580	$1.187C_{1998}(1-C_{1998}) - 4.258 \times C_{1998} \times N_{1999} + e$
2000	0.0047230	0.0381330	$1.187C_{1999}(1-C_{1999}) - 4.258 \times C_{1999} \times N_{2000} + e$
2001	0.0047490	0.0379660	$1.187C_{2000}(1-C_{2000}) - 4.258 \times C_{2000} \times N_{2001} + e$
2002	0.0047500	0.0389310	$1.187C_{2001}(1-C_{2001}) - 4.258 \times C_{2001} \times N_{2002} + e$
2003	0.0047300	0.0424410	$1.187C_{2002}(1-C_{2002}) - 4.258 \times C_{2002} \times N_{2003} + e$

Results	bCN	Residuals C	Fitted data
$0.0043921 - 0.0158142 \times 0.0325273 + e =$	$0.0043921 \times 0.0005144 + e =$	0.0038771	0002959
$0.0049327 - 0.0177686 \times 0.0329420 + e =$	$0.0049327 \times 0.0005853 + e =$	0.0043466	−0.000045
$0.0050845 - 0.0183179 \times 0.0356700 + e =$	$0.0050845 \times 0.0006534 + e =$	0.0044303	0.0000007
$0.0052363 - 0.0188672 \times 0.0433210 + e =$	$0.0052363 \times 0.0008173 + e =$	0.0044181	0.0000219
$0.0052469 - 0.0189055 \times 0.0466500 + e =$	$0.0052469 \times 0.0008819 + e =$	0.0043641	0.0002219
$0.0054186 - 0.0195272 \times 0.0419690 + e =$	$0.0054186 \times 0.0008195 + e =$	0.0045982	0.0001738
$0.0056373 - 0.0203192 \times 0.0395510 + e =$	$0.0056373 \times 0.0008036 + e =$	0.0048328	0.0000522
$0.0057702 - 0.0208003 \times 0.0379520 + e =$	$0.0057702 \times 0.0007894 + e =$	0.0049798	0.0000092
$0.0058924 - 0.0212432 \times 0.0395490 + e =$	$0.0058924 \times 0.0008401 + e =$	0.0050513	−0.000152
$0.0057866 - 0.0208599 \times 0.0421680 + e =$	$0.0057866 \times 0.0008796 + e =$	0.0049061	0.0000009
$0.0057960 - 0.0208940 \times 0.0424010 + e =$	$0.0057960 \times 0.0008859 + e =$	0.0049092	−0.000374
$0.0053586 - 0.0193100 \times 0.0421040 + e =$	$0.0053586 \times 0.0008130 + e =$	0.0045448	0.0000562
$0.0054363 - 0.0195911 \times 0.0411580 + e =$	$0.0054363 \times 0.0008063 + e =$	0.0046291	0.0001109
$0.0055997 - 0.0201829 \times 0.0381330 + e =$	$0.0055997 \times 0.0007696 + e =$	0.0048292	−0.000106
$0.0055797 - 0.0201105 \times 0.0379660 + e =$	$0.0055797 \times 0.0007635 + e =$	0.0048153	−0.000066
$0.0056103 - 0.0202212 \times 0.0389310 + e =$	$0.0056103 \times 0.0007872 + e =$	0.0048222	−0.000072
$0.0056115 - 0.0202255 \times 0.0424410 + e =$	$0.0056115 \times 0.0008584 + e =$	0.0047522	−0.000022

controversy over "cop" effectiveness in literature, our specific case confirms the deterrence role of our police enforcement agencies. Our results show, particularly since the 90s, that as police strength increases, crime rates fall in Italy. The model does not explain all the variability of crime, but it does explain a good 67%. One might object that other theorists find that police strength deters crime rates using linear models. But, just to stay in the field of criminology, the same end can be achieved by lawful means and by illegal means: it is the mean that makes the difference.

Secondly, far from minimizing the crime problem in Italy (we could not justifiably do so either scientifically or politically) its growth rate (k) which remains stable at a value of 1.792 is rather comforting; it is far from values expressing a *chaos* situation (k = 3.8–4). As already mentioned, in a nonlinear model like ours, as long as the growth parameter k of a phenomena stays in the *stable* range, i.e. where variability remains in a situation of possible controllability and predictability, any action aimed at influencing the system's current trend can produce expected outcomes. This is not so if the k parameter expresses a chaotic situation. In this latter case, if the crime level flows into chaos, it would drag the police strength into chaos too, which means adjusting, i.e. adapting the police strength and its work to increase Note, we are not saying that we would not know what to do in such a situation—or what line of action to take. We are saying something much different, namely that *crime flowing into chaos produces absolutely unpredictable outcomes for any intervention adopted*. For example, a law enforcement agency may increase the number of police officers but we have no idea what the outcome will be. Thus, measures taken to reduce crime*might* have a completely opposite outcome; they may produce even a rise in crime rates or an actual fall in these rates. The problem is that we are unable to predict what outcome will emerge.

Priesmayer provides us with an exemplifying case, regarding cocaine use in the USA from 1985 to 1990. In his investigation, the logistic equation fits cocaine use with a value k of 3.6, dangerously close to the critical threshold of 3.8, a value inducing the author to the following disarming conclusion:

> Put simply, actions which decrease current use may contribute to higher future use or they may not; actions which contribute to higher current use may contribute to lowering use in the future or they may not. [...] Does it suggest that [...]attempts to lower cocaine use by aggressive intervention are far less certain? If cocaine use is not controllable in this way, what then is to be used to control cocaine use? (Priesmayer 1990, p. 333).

In brief, no one is able to define the terms of a scenario. Or rather, any type of scenario is *equally* possible. Possible scenarios might mirror films such as *Escape from New York* or, on the contrary, film series where enforcement agencies become powerful managers of criminal enterprises. In an extreme case (not so extreme if we judge by current situations), crime agencies and police could form alliances creating strange symbiotic phenomena. This idea is suggested by the situation in Russia where, from my point of view, the actual situation appears dangerously on the *edge of chaos* or pre-chaotic. Within a few years, Russia's crime rate increased by 40%, causing a paradoxical situation. The rise in the crime rate led to a rise in police enforcement yet the reduction of crime was not forthcoming but there was more and better orchestrated collusion and corruption. In this scenario, it is not rhetorical to ask where crime control efforts will end up and what line of action to take against noncompliance.

Fortunately the Italian situation is very different from the Russian one. The k parameter is far from critical values and this means that crime is under control: a certain deterrence action will be able to achieve expected outcome, perhaps limited outcomes, but nevertheless there will be a positive outcome. This is precisely what the model application shows: as crime increases, so does police strength and its deterrent action.

The heuristic importance of a *nonlinear analytical approach* now seems evident. One might ask whether it is a waste of time insisting on the *Complexity and Chaos Theory*; whether it is worth studying its analytical tools only to conclude that the system is ....unpredictable? However, the *Complexity and Chaos Theory* introduces a different way of thinking about predictability. In my modest opinion, an acquisition attesting whether a phenomenon is or is not in a chaotic situation, by specifying the value of critical threshold where control and predictability capacity disappears, provides valuable information. In other words, the use of these models allow us to find out a very important element that is whether or not the system is near to the threshold beyond which it flows into chaos, so that we can intervene to prevent this outcome. As Elliott and Kiel ascertained, only "by better understanding the confluence of chance and determinism in social systems evolution we may better learn when and how to direct policy responses" (Elliott and Kiel 1997b, p. 68).

The last acquisition to be added to the above statement which the nonlinear model offers is "indirect" deterrence. As already mentioned, in traditional research, it is impossible to determine "indirect" deterrence. We derive two different theoretical implications from this. The first, according to my, is the need to add this dimension to studies dedicated to deviance studies—dimensions systematically reduced to two, namely, real crimes, i.e. those reported to the police, and those called "dark figure" crimes. The second implication involves the problem of *social alarm*. The common citizen is right to be afraid of the increasing crime rise. However, it is the job of social researchers to get more precise, well balanced ideas on this problematic issue by using the right tools. Having a possible valid measurement tool at our disposal can only provide added benefit.

In conclusion, to sum up, the *non linear approach* seems to exhibit a heuristic superiority able to shed light upon issues which in other approaches were hidden in the shad. Two widely shared convictions are the result. The first conviction concerns the suitability of lowering our expectations in control and prevention for such an unexpectedly widespread sphere. Today many social researchers are persuaded that *non-linearity*, *complexity*, structure social systems and that linear determinism has dominated our thinking process to an extent that it has hindered a more realistic representation of the human condition. From this perspective, according to Brown (1996), we need to understand the nonlinearity, complexity, and interdependencies of our individual and collective life so that

> we are no longer passive riders on an evolutionary voyage that touches every level of our existence. [...] To be in control of our own fate, we need to see clearly who we are and how we came to be (Brown 1996, p. 146).

In fact,

> where is self-determination among the blind? (1996, p. 144)

The second conviction is that—given the pervasiveness of non-linear structures—*Complexity and Chaos Theory is the* "protagonist" of a *cultural unification process* involving all branches of science. What has been traditionally considered separate objects of study- on one hand, *free human acts*, bearing uncertainty and unpredictability, and on the other hand, *nature*, with its inner order—has created a gap between the social and the natural sciences. The *Complexity and Chaos Theory* shows this *gap* to be largely artificial, redeeming the social sciences from being a *minority* science, in Kant's terminology, or in Kiel and Elliott's modern terminology, a "*scientific stepchild*" compared to the so-called *"hard'* sciences (Elliott and Kiel 1997a, p. 3).

Appendix

See Table 4.

Table 4 Crimes and police officers—1985–2003

Years	Population	Crimes	Police officers	Crime rate (ratios per 100.000 population)	Rate of police officers (ratios per 1,000 pop.)
1985	57,202,000	1,364,010		2384.55	
1986	57,290,000	1,493,214	212,804	2449.32	3.714
1987	57,399,000	1,867,035	239,524	3252.73	4.173
1988	57,505,000	1,894,327	247,361	3294.20	4.302
1989	57,576,000	2,053,522	2,55,133	3567.00	4.431
1990	57,746,000	2,501,640	256,378	4332.10	4.440
1991	56,757,000	2,647,736	260,316	4665.00	4.586
1992	56,960,000	2,390,539	271,797	4196.90	4.772
1993	57,139,000	2,259,903	279,113	3955.10	4.885
1994	57,268,578	2,173,448	285,757	3795.20	4.989
1995	57,332,996	2,267,488	280,908	3954.90	4.899
1996	57,460,977	2,422,991	281,987	4216.80	4.907
1997	57,563,354	2,440,754	261,082	4240.10	4.535
1998	57,612,615	2,425,748	265,093	4210.40	4.601
1999	57,679,895	2,373,966	273,422	4115.80	4.740
2000	57,844,017	2,205,778	273,211	3813.30	4.723
2001	56,993,742	2,163,826	270696	3796.60	4.749
2002	57,321,070	2,231,550	272,282	3893.10	4.750
2003	57,888,245	2,456,887	273,829	4244.10	4.730

Source: ISTAT (Annuario Statistico Italiano)

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