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ON THE PREDICTABILITY OF CRIME WAVES IN MEGACITIES – EXTENDED SUMMARY

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We continue here the series of studies in the predictability of critical phenomena i.e. abrupt overall changes ('crises') in complex systems. That problem is particularly challenging in the absence of fundamental equations governing the systems' behavior. The prediction of critical phenomena is important both for a fundamental understanding of the systems under consideration and for crisis preparedness and control. Such is the usual twofold goal of prediction research. The critical phenomenon considered in this study is a sharp and lasting rise of the homicide rate. Qualitatively, this phenomenon is illustrated in Fig. 1; and we call it by the acronym *SHS*, for 'Start of the Homicide Surge'.

This study integrates the professional expertise of the police officers and of the scientists studying complex systems.

The problem

Our goal is to develop a method for predicting the surge of homicides by monitoring the relevant observed indicators. We hope to recognize the 'premonitory' patterns formed by such indicators when an *SHS* approach-

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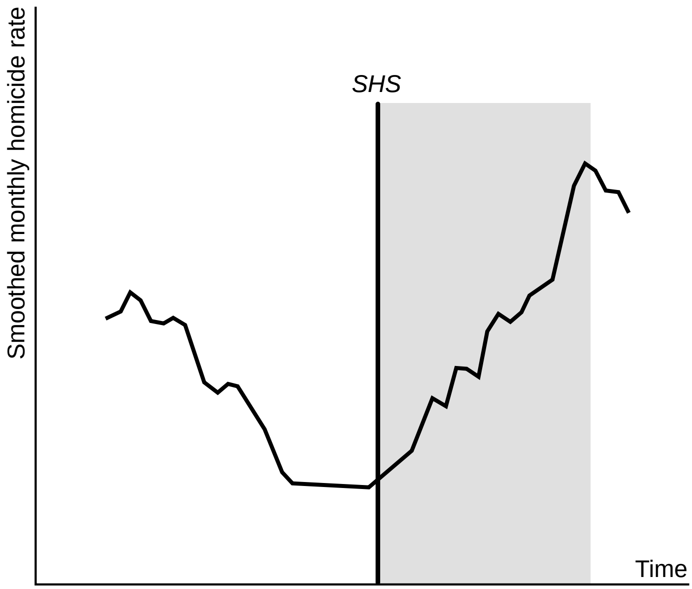

Figure 1. Target of prediction: schematic definition. The vertical line shows the target (the start of the homicides surge, or 'SHS'). Gray bar marks the whole period of the homicide surge.

es. In terms of pattern recognition we look for an algorithm that solves the following problem.

Given the time series of certain relevant indicators prior to a moment of time *t*, *to predict* whether an episode of *SHS* will or will not occur during the subsequent time period (t, $t+\tau$). If the prediction is 'yes', this period will be the 'period of alarm', The possible outcomes of such a prediction are illustrated in Fig. 2.

The probabilistic component of this prediction is represented by the estimated probabilities of errors – both false alarms on one side and failures to predict on the other. That probabilistic component is inevitable, since we consider a highly complex non-stationary process using imprecise crime statistics. Moreover, the predictability of a chaotic system is, in principle, limited.

Such 'yes or no' prediction of specific extraordinary phenomena is different from predictions in a more traditional sense – extrapolation of a process in time, which is better supported by classical theory.

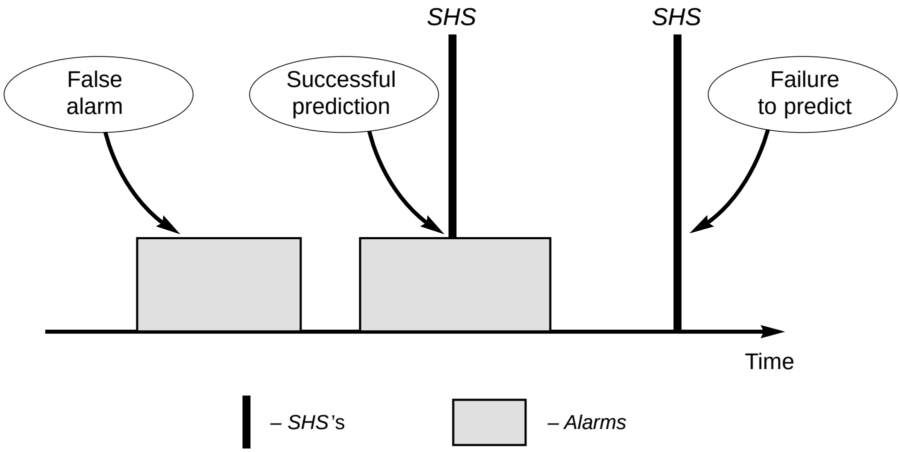

Figure 2. Possible outcomes of prediction.

Methodology

Our methodology is *pattern recognition of infrequent events* – a methodology developed by the artificial intelligence school of I.M. Gelfand [6, 18] for the analysis of infrequent phenomena of highly complex origin. It has been successfully applied in many problems of natural [6, 14, 18] and socio-economic [10-12] sciences, helping to overcome the complexity of phenomena under consideration and the chronic imperfection of observations. A distinctive feature of this methodology is a robust analysis that provides 'a clear look at the whole', which is imperative in a study of complex system [7-9]. This methodology is, in a way, akin to exploratory data analysis, as developed by the school of J. Tukey [22].

We also take advantage of mathematical modeling of critical phenomena in complex systems [1, 5, 13, 14, 19-21, 23, 24].

The data

Among a multitude of relevant indicators we consider, in this initial analysis, monthly rates of homicides and lesser crimes, including assaults, burglaries, and robberies (see Table 1). These data are taken from [3, 4].

TABLE 1. CRIME RATES CONSIDERED

Homicides	Robberies	Assaults	Burglaries
• All	• All • With firearms • With knife or cutting instruments • With other dangerous weapons • Strong-arm robberies*	• All* • With firearms • With knife or cutting instrument • With other dangerous weapon* • Aggravated injury Assaults*	• Unlawful Not Forcible Entry • Attempted Forcible Entry *

* Analyzed in sensitivity tests only.

Our findings can be summed up as follows:

1. We have found that the upward turn of the homicide rate is preceded within 11 months by a specific pattern of the crime statistics: *both burglaries and assaults simultaneously escalate, while robberies and homicides decline*. Both changes, the escalation and the decline, are not monotonic, but rather occur sporadically, each lasting some 2-6 months.

2. Based on this pattern we have formulated a *prediction algorithm*, giving it a robust and unambiguous definition. Its performance is illustrated in Fig. 3. Data for 1975-1993 have been used for developing the algorithm. It was then applied as is to the data for 1993-2002.

It is noteworthy that the performance of the algorithm did not change through all the years, when Los Angeles has witnessed many changes relevant to crime. This stability is due to the robustness of the algorithm and it is achieved at a price, in that the time of a homicide surge can be predicted with only limited accuracy.

Fig. 4 shows in more detail the case history of prediction of the last homicide surge one that continued for more than two years. We see that the algorithm gave a warning about this rise as early as December 1999.

3. *Sensitivity tests* [11, 17] demonstrated that these predictions are stable to variations in the adjustable elements of the algorithm. The algorithm is self-adapting to average crime statistics, so that we could test it by *application to independent ('out of sample') data* not used in its

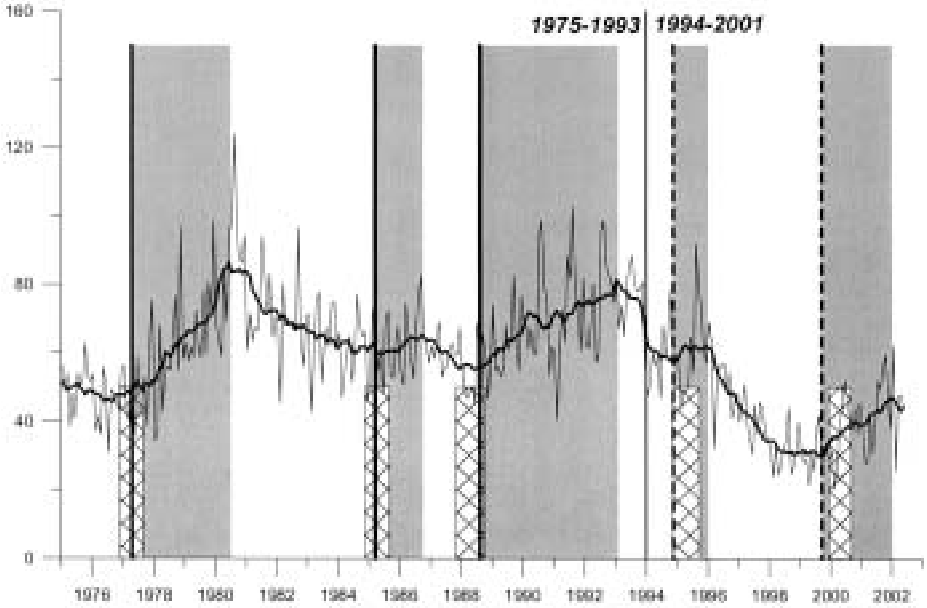

Figure 3. Performance of prediction algorithm through 1975-2002.
The thin curve shows total monthly rates of homicides in Los Angeles city, per 3,000,000 inhabitants. The thick curve shows the same rates with seasonal variations smoothed away. The vertical lines show the targets of prediction – upward turns of the smoothed homicide rate; while the solid and dashed lines show the turns that occurred before and after 1993. Gray bars are the periods when the rate of homicides remained high. Checkered bars are the alarms declared by the hypothetical prediction algorithm

development; The results of that test are also encouraging; however, as always, the algorithm remains hypothetical until it is validated by advance prediction.

4. Closer to the surge of homicides, the robberies also turn from decline to rise. This indicates the *possibility of a second approximation to prediction*, with more precise (about twofold shorter) alarms.

What did we learn about crime dynamics?

The existing qualitative portrayals of crime escalation are complemented here by a quantitatively defined set of precursors to homicide surges. The same set emerges before each surge through the time period under

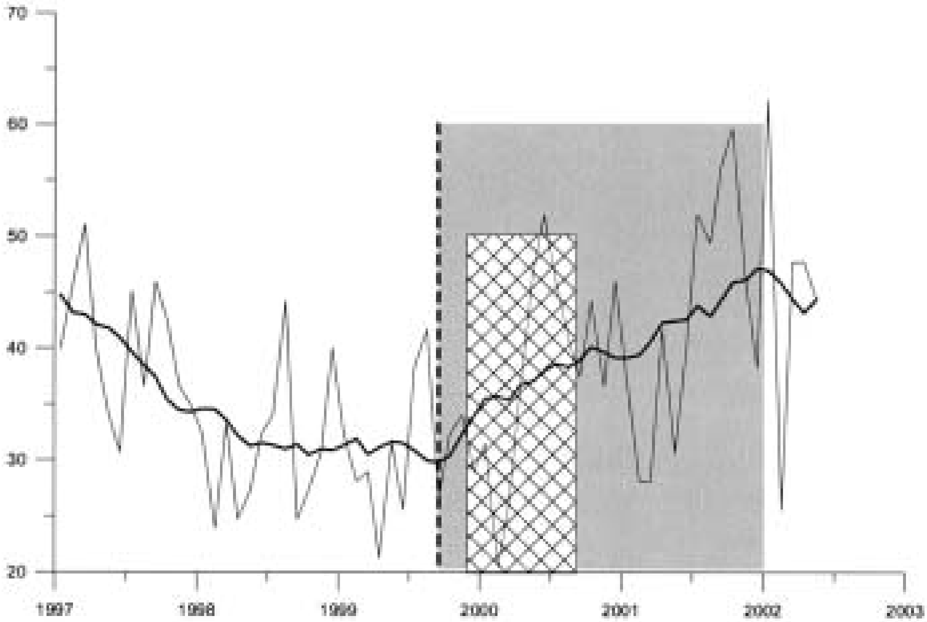

Fig. 4. Prediction of the last rise of the homicide rate: a case history. Notations are the same, as in Fig. 3.

consideration. We give a quantitative definition of this phenomenon that has been extended to a prediction algorithm.

It was unexpected that the premonitory pattern of indicators includes a *decline* of robberies, simultaneous with the rise of other crimes considered. That possibly might be explained by the rising influence of the gangs, temporarily suppressing ‘unorganised’ crimes.

The prediction described here is complementary to cause-and-effect fundamental analysis. The cause that triggered a specific homicide surge is usually known, at least in retrospect. This might be, for example, a rise in drug use, a rise in unemployment, etc. Our ‘yes or no’ algorithm captures the symptoms of *an unstable situation* when such a cause would trigger a homicide surge.

Relevance to the science of chaos

Our findings are in accord with the following 'universal' features of many chaotic or complex systems.

1) The permanent background activity ('static') of the system tends to rise before a fast major change, one that represents a 'critical transition'.

2) That rise, and the other premonitory changes of the static, are not monotonic, but are realized sporadically, in a sequence of relatively short intermittent changes.

The 'universal' models of hierarchical complex systems, such as those developed in theoretical physics and non-linear dynamics, exhibit both of these features. They are also observed in a variety of real-world systems, including the seismically active Earth's crust, the economics of recession, the labor market, elections, etc.

In terms of complexity the episodes of *SHS* might be regarded as critical transitions, and the changes taking place in the 'lesser crimes' – as static. The universality of the features of complexity is limited and cannot be taken for granted in studying any specific system. Nevertheless, it is worth exploring in crime dynamics using other known types of premonitory patterns [14, 23, 24].

Perspective

Altogether, the above findings provide heuristic constraints for the theoretical modeling of crime dynamics. They also enhance our capability to anticipate the possible future homicide surges. It is encouraging for further research that we used here only a small part of the relevant and available data. Among these are other types of 'lesser' crime [2] and economic and demographic indicators [16]. Decisive validation of our findings requires experimentation in *advance prediction*, for which this study sets up a base.

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REFERENCES

1. Allègre, C.J., P. Shebalin, J.-L. Le Mouel, and C. Narteau (1998). 'Energetic balance in scaling organization of fracture tectonics'. *Phys. Earth and Planet. Inter.*, 106: 139-153.
2. Bursik, R.J., Jr., H.G. Grasmick, and M.B. Chamlin (1990). 'The effect of longitudional arrest patterns on the development of robbery trends at the neighborhood level'. *Criminology*, 28(3): 431-450.
3. Carlson, S.M. (1998). Uniform Crime Reports: Monthly Weapon-specific Crime and Arrest Time Series, 1975-1993 (National, State, and 12-City Data). ICPSR 6792, Inter-university Consortium for Political and Social Research, P.O. Box 1248, Ann Arbor, Michigan 48106.
4. Data sources: National Archive of Criminal Justice Data (NACJD), 1975-1993 (http://www.icpsr.umich.edu/NACJD/index.html). Data bank of the Los Angeles Police Department (LAPD Information Technology Division), 1990-2002.
5. Gabrielov, A., I. Zaliapin, W.I. Newman, and V.I. Keilis-Borok (2000). 'Colliding cascades model for earthquake prediction'. *Geophys. J. Int.*, 143, 2: 427-437.
6. Gelfand, I., V. Keilis-Borok, L. Knopoff, F. Press, E. Rantsman, I. Rotwain, and A. Sadovsky (1976). 'Pattern recognition applied to earthquake epicenters in California'. *Phys. Earth Planet. Inter.*, 11: 227–283.
7. Gell-Mann, M. (1994). *The Quark and the Jaguar: Adventures in the Simple and the Complex*. W.H. Freeman and Company, New York.
8. Gunderson, L.H., and C.S. Holling (eds.) (2002). *Panarchy: Understanding Transformations in Human and Natural Systems*. Island Press, Washington, DC, 507 pp.
9. Holland, J.H. (1995). *Hidden Order: How Adaptation Builds Complexity*. Addison-Wesley, Reading, Mass.
10. Keilis-Borok, V.I., and A.J. Lichtman (1993). 'The Self-Organization of American Society in Presidential and Senatorial Elections'. In Yu. A. Kravtsov (Ed.), *Limits of Predictability*, Springer-Verlag: 223–238.
11. Keilis-Borok,V., J.H. Stock, A. Soloviev, and P. Mikhalev (2000). 'Pre-recession pattern of six economic indicators in the USA'. *Journal of Forecasting*, 19, 1: 65-80.

12. Keilis-Borok, V.I., A.A. Soloviev, C.B. Allègre, A.N. Sobolevskii, and M.D. Intriligator (2003). 'Patterns of macroeconomic indicators preceding the unemployment rise in Western Europe and the USA'. Submitted to *Advances in Complex Systems*.
13. Keilis-Borok, V.I. (2002). 'Earthquake prediction: State-of-the-art and emerging possibilities'. *Ann. Rev. Earth Planet Sci.*, 30: 1-33.
14. Keilis-Borok, V.I., and A.A. Soloviev (eds.) (2003). *Nonlinear Dynamics of the Lithosphere and Earthquake Prediction*. Springer Ser. Synerg., Springer-Verlag, Berlin-Heidelberg, 337 pp.
15. Lichtman, A., and V.I. Keilis-Borok (1989). 'Aggregate-level analysis and prediction of midterm senatorial elections in the United States', 1974-1986. *Proc. Natl. Acad. Sci. USA*, 86: 10176-10180, December 1989, Political Sciences.
16. Messner, S.F. (1983). 'Regional differences in the economic correlates of the urban homicide rate'. *Criminology*, 21(4): 477-488.
17. Molchan, G.M. (1997). 'Earthquake prediction as a decision-making problem'. *Pure Appl. Geophys.*, 149: 233-237.
18. Press, F., and C. Allen (1995). 'Patterns of seismic release in Southern California region'. *J. Geophys. Res.*, 100: 6421 –6430.
19. Rundle, B.J., D.L. Turcotte, and W. Klein, eds. (2000). *Geocomplexity and the Physics of Earthquakes*. Am. Geophys. Union, Washington, DC.
20. Shnirman, M.G., and E.M. Blanter (1998). 'Self-organized criticality in a mixed hierarchical system'. *Phys. Rev. Letters*, 81: 5445-5448.
21. Sornette, D. (2000). *Critical Phenomena in Natural Sciences. Chaos, Fractals, Self-organization and Disorder: Concepts & Tools*. Springer Ser. Synerg., Springer-Verlag, Berlin-Heidelberg, 432 pp.
22. Tukey, J.W. (1977). *Exploratory data analysis. Addison-Wesley Series in Behavioral Science: Quantitative Methods*. Addison-Wesley, Reading, Mass.
23. Yamashita, T., and L. Knopoff (1992). 'Model for intermediate-term precursory clustering of earthquakes'. *J. Geophys. Res.*, 97: 19873-19879.
24. Zaliapin, I., V. Keilis-Borok, and M. Ghil (2003). 'A Boolean delay model of colliding cascades'. 'II: Prediction of critical transitions'. To appear in *J. Stat. Phys.*, 110.

DISCUSSION ON THE PAPER BY KEILIS-BOROK

ZICHICHI: Is the full line your mathematical predictions?

PIETRONERO: I have worked a bit with Volodya on earthquakes, using similar methods. The issue is very fascinating and rather complex. I would put it in the following framework: all the scaling and universality are for asymptotic time and space, so you have a distribution which eventually refers to infinite space and infinite time. Now, this is not good for prediction, but it's usually the target of theoreticians like myself. This means that with a renormalization group you predict nothing, I mean, in terms of what is useful, such as earthquakes. You predict other things for physics. Now, the issue that Volodya raises, and of course by which I have been fascinated, is: can you do something like the opposite? Can you forget about asymptotia and go into finite time and finite space predictions? This is essentially the opposite of what physicists have been doing. So we've been disoriented, because that's not the usual approach, and recently we've tried to invent methods which may also be good for small time-scales. That's what they have been doing for many years. So, I would say this is a new frontier of complexity in which one does not look at the asymptotic but at the opposite, at short time, at short space, and I think this is where the frontier is.

ZICHICHI: But the data represented by the grey pieces are supposed to be in agreement with the predicted derivative. This does not seem to be the case.

PIETRONERO: I think Volodya should answer.

KEILIS-BOROK: Prediction is aimed at increase of time derivatives. And you see that the smoothed (thick) curves change their trend upwards at some moment within each gray area. Generally speaking, increased derivative may still be negative, but actually the trend only flattened once, and went up in other cases.

ZICHICHI: You are predicting with your mathematics the behaviour of the function. In one case it goes up, in the other case it goes down. This is not a prediction, it's a contradiction.

KEILIS-BOROK: We predict the sharp upward bend of the smoothed function (the thick curve). The function first goes down, then it turns upward. If the turn is strong enough it goes up, otherwise it becomes nearly horizontal. It could be horizontal first then climb upwards. To predict specific realization of that bend would be the next approximation, I can describe it in 15 minutes.

ZICHICHI: No, no, I just want to know if what you show is your prediction. You should only say yes or no.

KEILIS-BOROK: We do not predict derivative of the function (the drop or the rise). We predict when the derivative will quickly rise. Next questions are how long will last the new trend, and how steep it will be, we are doing this piece by piece.

ZICHICHI: Take the grey line, then the function goes down. If this is your prediction, the same function cannot go up.

KEILIS-BOROK: It can go up after it was going down. We predict the time of the change.

ZICHICHI: You cannot have a mathematical model which goes up and down at the same time. The disagreement is between the model and the data.

KEILIS-BOROK: There is no disagreement – the function goes up and down not at the same time. It goes first down then it goes up or horizontally, that change is what the model predicts. But it does not predict how the rise of derivative will be realized; these are major unsolved problems.

HASSAN: Can I just ask you: I know that you've developed a model for predicting earthquakes in the same region. Some time ago I remember you explained it to us in Trieste. Can you tell us whether that graph that you developed for earthquake prediction is rather similar to what you have presented here? What is the correlation between them?

KEILIS-BOROK: Yes, prediction is based on evolution of background activity of a complex system prior to a critical transition. Scenarios of that evolution are partly universal for different systems; but partly they are system-specific. In case of homicides static consist of the rates of lesser crimes. Before a homicide surge some rates rise and some drop; police experts with whom we worked explain that by impact of intruding organized crime. In case of earthquakes the static we studied consists of small earthquakes, and their rate grows before a strong one. So, you are right – a certain similarity exists.

SZCZEKLIK: Professor Keilis-Borok. Predicting or prognosing was always considered part of an important medical skill, and about ten years ago, an attempt was made to introduce so-called expert systems into medicine using computers which were supposed to give right prognoses. They didn't work very well, didn't become much of use. Has there been some progress in this field very recently?

KEILIS-BOROK: The key to developing expert system is collaboration of mathematicians with the experts in the field, medicine in your case. A mathematician cannot take the data from a physician and put them through pattern recognition algorithm; neither a physician can do the opposite. There is a culture of interaction with experts for such purposes, not widely known, but not really new. About 30 years ago Gelfand's school developed a very successful expert system for predicting the outcome of operations on the brain. You might recollect T.S. Eliot: 'Where is our wisdom, lost in knowledge? Where is our knowledge, lost in information?'.