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Prediction of Crime Surges

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ON PREDICTABILITY OF HOMICIDE SURGES IN MEGACITIES

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Dynamics of crimes reflects important aspects of sustainability of our society and the risk of its destabilisation – a prelude to a disaster. Here, we consider a prominent feature of crime dynamics – surge of the homicides in a megacity. Our study integrates the professional expertise of the police officers and of the scientists working on pattern recognition of infrequent events. The latter is a type of artificial intelligence methodology that has been successful in predicting infrequently occurring phenomena that result from highly complex processes.

In this paper we analyse statistics of several types of crimes in Los Angeles over the period 1975-2002. Our analysis focuses on how these statistics change before a sharp and lasting rise ("a surge") of the homicide rate. The goal is to find an algorithm for predicting such a surge by monitoring the rates of different crimes.

Our hope for feasibility of that goal comes from two sources. First is the set of available crime statistics, showing that a surge of major crimes is preceded by the rise of less severe crimes. Second is recent research in the prediction of critical phenomena (i.e. abrupt overall changes) in various complex non-linear systems, such as those in theoretical physics, earth sciences, social sciences, etc.

Data. Out of a multitude of relevant data we analyse statistics of robberies, assaults, burglaries, and the homicides themselves.

Results. Our findings may be summarised as follows: Episodes of a rise of burglaries and assaults simultaneously occur 4 to 11 months before a homicide surge, while robberies decline. Later on, closer to the rise in homicides, robberies start to rise. These changes are given unambiguous and quantitative definitions, which are used to formulate a hypothetical algorithm for the prediction of homicide surges.

In retrospective analysis we have found that this algorithm is applicable through all the years considered despite substantial changes both in socio-economic conditions and in the counting of crimes. Moreover, it gives satisfactory results for the prediction of homicide surges in New York City as well. Sensitivity tests show that predictions are stable to variations of the adjustable elements of the algorithm.

What did we learn? 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 consideration. That implies the existence of a "universal" scenario of crime escalation, independent of a concrete reasons triggering each surge. These findings provide heuristic constraints for the modeling of crime dynamics and indicate promising lines of further research.

Perspective. Decisive validation of our findings requires experimentation in *advance prediction*, for which this study sets up a base. Particularly encouraging for this further research is the wealth of yet untapped possibilities: we have used so far only a small part of the data and mathematical models that are currently available and that are relevant to crime dynamics.

On the practical side, our results enhance our capability to identify a situation that is "ripe" for homicide surges and, accordingly, to escalate the crime prevention measures. In a broader scheme of things, a surge of crime is one of potential ripple effects of natural disasters. Accordingly the risk of a natural disaster is higher in such a situation.

1. Introduction

Understanding and prediction of crime dynamics is one of the problems important for coping with the risks threatening the humanity. These risks are to a large extent concentrated in megacities, whose role in the global village is rapidly growing along with their vulnerability to natural and socio-economic disasters. Present study is focused on the crime dynamics in Los Angeles; its experience, we believe, might be useful for studying similar problem in other megacities.

1.1. PREDICTION TARGET

We consider prediction of a specific phenomenon in crime dynamics: a large and lasting increase in the homicide rate. Qualitatively, this phenomenon is illustrated in Figure 1; we call it by the acronym *SHS*, for "Start of the Homicide Surge". Our goal is to find a method to predict an *SHS* by monitoring the relevant indicators. Among a multitude of such indicators, we consider here statistics on assaults, burglaries, robberies and the homicides themselves.

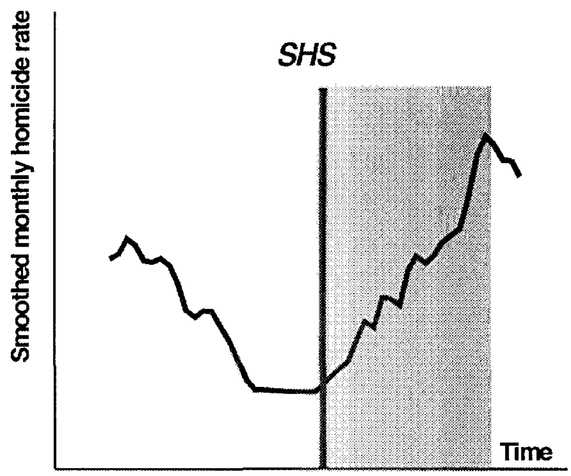

Figure 1. Target of prediction – the Start of the Homicide Surge ("*SHR*"); schematic definition. Gray bar marks the period of homicide surge

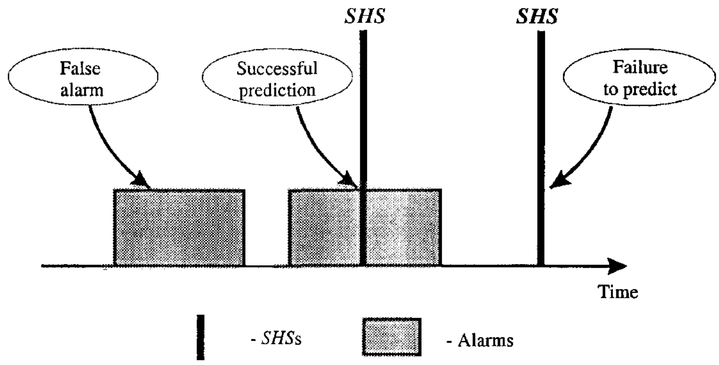

Figure 2. Possible outcomes of prediction

1.2. THE PROBLEM

Our goal is to develop a method for predicting the surge of homicides by monitoring the relevant observed indicators. We hope to recognise the "premonitory" patterns formed by such indicators when an *SHS* approaches. In terms of pattern recognition we look for an algorithm (a "recognition rule") that solves the following problem:

given the time series of certain crime rates (or of other 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 $(t, t+\tau)$; in other words, whether the lasting surge of homicides will or will not start during that period.

If the prediction is "yes", this period will be the "period of alarm." The possible outcomes of such a prediction are illustrated in Figure 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.

1.3. METHODOLOGY

We use *pattern recognition of infrequent events* – a methodology developed by the artificial intelligence school of the mathematician I.M. Gelfand [1] for the analysis of infrequent phenomena of highly complex origin. Using this methodology, we here conduct a so-called "technical" analysis that involves a heuristic search for phenomena preceding episodes of *SHS*. A distinctive feature of this methodology is the robustness of the analysis, which helps to overcome both the complexity of the process considered and the chronic imperfection of the data; in that aspect it is akin to exploratory data analysis, as developed by the statistics school of J. Tukey [2]. Robust analysis – "a clear look at the whole" – is imperative in a study of any complex system [3]. The surest way *not* to predict such a system is to consider it in too fine detail [4].

Pattern recognition of infrequent events has been successfully used in geophysics, geological prospecting, medicine, and many other areas. Close to the present study are recent studies of the prediction of economic recessions and surges of unemployment [5, 6]. We use the same pattern recognition algorithm, called "Hamming distance," that has been applied in these studies, as well as in predictions of American elections [7] and in seismology, e.g. [8, 9]. The essence of the algorithm will be clear from the way we analyse crime statistics here.

1.4. CONTENT

Following is a schematic outline of our analysis:

Data comprise the monthly rates of homicides, robberies, assaults, and burglaries for Los Angeles, 1975 – 2002 (Section 2).

Five targets of prediction (*SHS*) are defined during the time period under consideration (Sections 3, 7). Those are the moments when a years-long trend of the homicide rate turns from decline to a long steep rise.

We have found *premonitory changes of crime statistics* as illustrated in Figure 3. First comes the escalation of burglaries and assaults, but not of robberies (Section 4). Later on, closer to a homicide surge, robberies also escalate (Section 8).

On the basis of these changes we suggest a *hypothetical prediction algorithm.* In retrospect, it provides a robust satisfactory prediction. However it has to be further validated by application to independent data. As always in prediction research, *the final validation of our algorithm requires prediction in advance*, for which this study sets up a base.

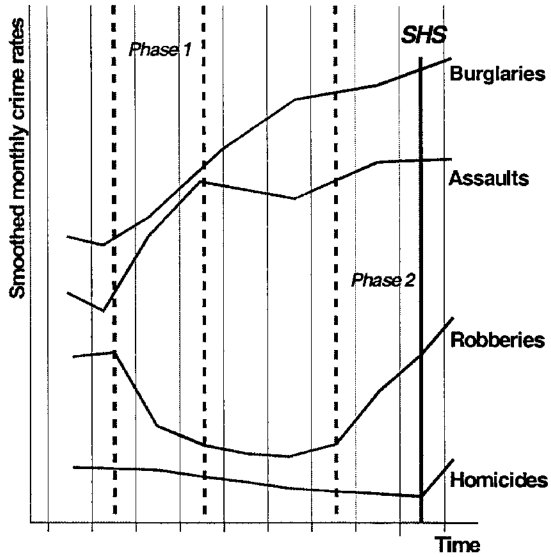

Figure 3. Scheme of premonitory changes in crime statistics

1.5. COMMON NOTATION

Our analysis focuses on trends in the crime rates. We estimate these trends by linear regression, using the following notations:

$$C(m),\ m = 1,2\ldots,$$

Is the time series of a monthly indicator, where m is the sequence number of a month.

$$W^C(m/q, p) = K^C(q, p)m + B^C(q, p),\ q \le m \le p, \qquad (1)$$

is the local linear least-squares regression of the function $C(m)$ within the sliding time window over the time period (q, p).

2. The Data

We use the following data sources:

(i) The National Archive of Criminal Justice Data (NACJD), placed on the web site (http://www.icpsr.umich.edu/NACJD/index.html). Carlson [10] gives its description. This site contains data for the years 1975-1993.

(ii) Data bank of the Los Angeles Police Department (LAPD Information Technology Division); it contains similar data for the years 1990 – May 2001.

TABLE 1. Types of crimes considered
(after [10]; abbreviations are indicated in brackets)

Homicide	Robberies	Assaults	Burglaries
• All (**H**)	• All (**Rob**) • With firearms (**FRob**) • With knife or cutting instrument (**KCIR**) • With other dangerous weapon (**ODWR**) • Strong-arm robberies (**SAR**)*	• All (**A**)* • With firearms (**FA**) • With knife or cutting instrument (**KCIA**) • With other dangerous weapon (**ODWA**)* • Aggravated injury assaults (**AIA**)*	• Unlawful not forcible entry (**UNFE**) • Attempted forcible entry (**AFE**)*

* Analysed in sensitivity tests only (Section 6)

Out of numerous crime statistics given in these sources, we analyse the monthly rates of the four types of crimes listed in Table 1, homicides, robberies, assaults, and burglaries.

3. Prediction Targets

Here and in the next two sections we analyse the data for 1975 – 1993 as taken from the National Archive of Criminal Justice Data [10].

Definition. Let $H(m)$, $m = 1,2\ldots$, be the time series of the monthly number of all homicides. Figure 4 shows the plot of $H(m)$ in Los Angeles, per 3,000,000 inhabitants of the city. To identify the episodes of *SHS* (Fig. 1) we smooth out the seasonal variations, which are clearly seen in Figure 4, by replacing $H(m)$ by its linear least square regression (1): $H^*(m) = W^H(m/m\text{-}6, m+6)$. Since $H^*(m)$ is defined on the time interval $(m - 6, m + 6)$, it depends on the future. Thus, it is admissible to define prediction targets (but not precursors).

The function $H^*(m)$ is shown in Figure 4 by the thick curve. Three time periods of a lasting homicide rise are clearly seen: 1977 – 1980, 1988 - 1992 and a relatively shorter period 1985 - 1986. We choose as prediction targets the starting months of these periods: 04:1977, 03:1985, and 08:1988. They are marked in Figure 4 by vertical lines.

4. Premonitory Trends of Single Types of Crimes

Here we analyse the monthly data on seven types of crimes out of the 13 types listed in Table 1. We look for "premonitory" trends of each crime that tend to appear more frequently as an *SHS* approaches. Prediction itself is based on the collective behaviour of these trends, as analysed in the next Section. Orientation on a *set* of precursors has been found to be rather successful in prediction research: an ensemble of "imprecise" precursors usually gives better predictions than a single "precise" precursor [11, 12].

4.1. OBSERVATION

According to police experience, the crimes considered here often rise before an *SHS*.

To smooth out seasonal variations, we replace the plot $C(m)$ of each type of crime by its regression (1): $C^*(m) = W^C(m/m\text{-}12, m)$. Regression is done over the prior 12 months and does not depend on the future, so that it can be used for prediction. These plots exhibit two consecutive patterns:

(*i*) First, we see a simultaneous escalation of burglaries and assaults within several (4 to 11) months before an *SHS*; at the same time robberies are declining.

(*ii*) Later on, closer to an *SHS*, we see, albeit not so clearly, a simultaneous escalation of different kinds of robberies.

The first pattern is formally defined and explored in this study. The second pattern, briefly discussed in Section 8, will be explored elsewhere.

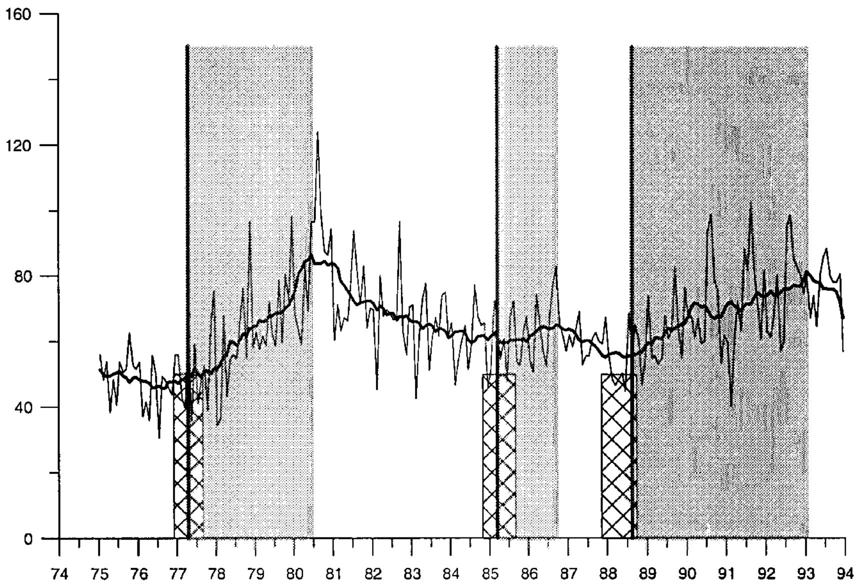

Figure 4. Total monthly number of homicides in Los Angeles city, 1975-1993. Data are taken from the National Archive of Criminal Justice Data [10]. Thin curve – original time series, *H(m)*, per 3,000,000 inhabitants. Thick curve - smoothed series *H*(m)*, with seasonal variations eliminated as described in Section 1. Vertical lines show the targets of prediction – episodes of *SHS* (Section 3). Gray bars are the periods of homicide surge. Checkered bars are the alarms declared by the hypothetical prediction algorithm (Section 5)

4.2. DISCRETIZATION OF CRIME TRENDS

To quantify the above observation we approximate the trends of the crimes by the regression coefficients $K^C(m\text{-}s, m)$ where C identifies the type of crime. The value of K^C is attributed to the month m so that it does not depend on information on future months; therefore it can be used for prediction.

Next, following the pattern recognition approach, we discretize the trends (the values of K^C) on the lowest level of resolution: a binary one distinguishes only the trends above and below a threshold $T^C(Q^C)$. It is defined as a percentile of a level Q^C, that is, by the condition that $K^C(m\text{-}s,m)$ exceeds $T^C(Q^C)$ during Q^C percent of the months considered.

According to the above observations, we expect that "premonitory" trends lay above the respective thresholds for assaults and burglaries, while they lay below these thresholds for robberies. One can see this in Figure 5, showing the functions $K^C(m\text{-}12, m)$ for 7 crime types. For convenience, we will give the same code, "1", to the "premonitory" trend of each crime, regardless of whether it is above or below the threshold of discretization. The seven monthly crime statistics considered here are thus reduced to a binary vector with 7 components.

We discretize the crime statistics using the values of Q^C indicated in Table 2. The crime history, thus transformed, is given in the Appendix, Table A1.

TABLE 2. Premonitory trends for selected crime types

#	Crime type	Premonitory trend $K^C(m\text{-}s, m)$	s	Q^C, %	$T^C(Q^C)$
1	Rob	Below threshold	12	66.7	-3.69
2	FRob	"	12	66.7	-1.29
3	KCIR	"	12	50.0	1.73
4	ODWR	"	12	87.5	-3.87
5	FA	Above threshold	12	50.0	1.89
6	KCIA	"	12	50.0	1.94
7	UNFE	"	12	50.0	-1.32

See notations in the text.

5. Collective Behaviour of Premonitory Trends: Hypothetical Prediction Algorithm

Here, we consider how the approach of a homicide surge is reflected in the *collective* behaviour of the trends. The simplest description of this behaviour is $\Delta(m)$ - the number of *non*-premonitory trends at a given month m. If our identification of premonitory trends is correct then $\Delta(m)$ should be low in the proximity of an *SHS*. By definition $\Delta(m)$ is the number of zeros in the binary code of the monthly situation. This is the so-called "Hamming distance" between that code and the code of the "pure" premonitory situation, {1,1,1,1,1,1,1} when all seven trends listed in Table 2 are premonitory [5, 13, 14].

The values of $\Delta(m)$ are given in Appendix, Table 1. Figure 6 shows the change of $\Delta(m)$ with time. The value of $\Delta(m)$ may vary from 0 to 7 but the minimal observed value is 1; the corresponding lines in Table A1 are marked by "+". That value appears within 4 to 11 months before an *SHS* and at no other time. An examination of the temporal change of $\Delta(m)$ in Table A1 suggests the following hypothetical prediction algorithm:

An alarm is declared for 9 months each time when $\Delta(m) \leq D$ for two consecutive months (regardless of whether these two months belong or not to an already declared alarm).

Possible outcomes of such a prediction are illustrated in Figure 2. The condition $\Delta(m) \leq D$ means, by definition, that D or less trends are not premonitory at the month m. A count of $\Delta(m)$ in Table A1 suggests that we take D = 1. A waiting period of 9 months is introduced because the premonitory trends do not appear right before an *SHS*. The requirement that this condition holds two months in a row makes prediction more reliable and reduces the total duration of alarms.

The alarms obtained by this algorithm are shown in Figure 4 by the grey bars. The total duration of these alarms is 30 months, representing 14 percent of all months considered. In real prediction that score would be quite satisfactory.

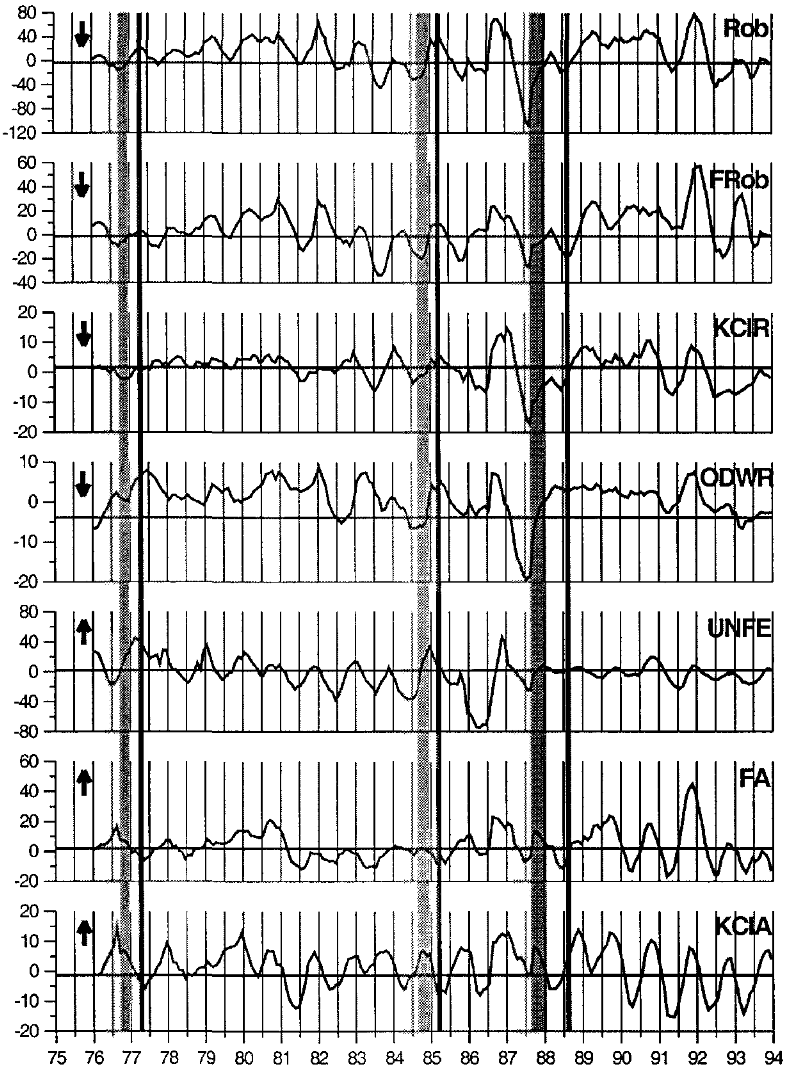

Figure 5. The regression coefficients $K^C(m\text{-}12, m)$ for seven crime types. See the definition in Section 4 and notations in Table. 1. Original data are taken from the National Archive of Criminal Justice Data [10]. Horizontal lines and arrows show respectively discretization thresholds and premonitory trends in accordance with Table 2. Vertical lines show episodes of *SHS*. Gray bars indicate months when $\Delta(m) \leq 1$

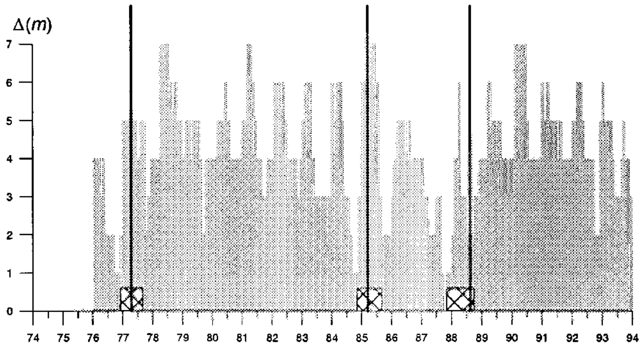

Figure 6. Homicide surges and alarms determined by the prediction algorithm. Start of a homicide surge is shown by the vertical line. Function $\Delta(m)$ is the number of crime statistics *not* showing premonitory trends at a month m. Alarms (shown by checkered bars) are declared for 9 months, when $\Delta(m) \leq 1$ during two consecutive month. Adjustable parameters correspond to version 10 of the algorithm

6. Stability of Prediction (Sensitivity Analysis)

Inevitably in lieu of a set of fundamental equations for crime dynamics we have a certain freedom in the retrospective ad hoc choice of adjustable elements: the types of crimes considered, numerical parameters, such as percentiles Q^C, etc. An algorithm thus developed makes sense only if it is not too sensitive to variation of these choices; as Enrico Fermi put it, "*with four exponents I can fit an elephant*".

To explore that sensitivity we repeat the prediction with different sets of the kinds of crimes considered and with different values for the numerical parameters. These sets are described in Table 3. The outcomes of prediction are compared on the error diagrams (Fig. 7). Molchan [15] has introduced such diagrams as a tool for evaluating prediction methods and optimising disaster preparedness. Their application to research in prediction of recessions and unemployment are described in [5, 6].

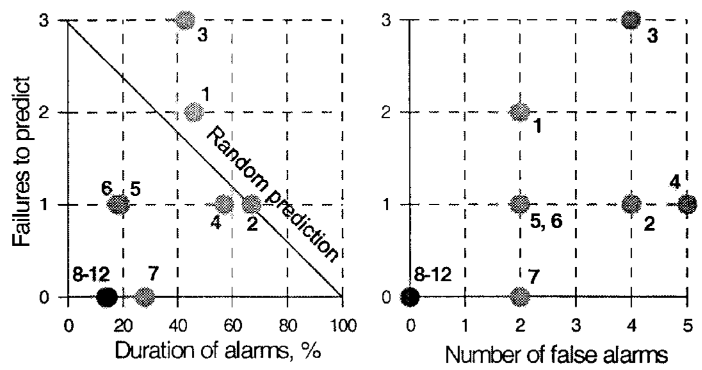

Figure 7. Error diagram.
Numbers near the dots identify the variant of the algorithm in Table 3. Black dots show the variants suggested for advance prediction. See further explanations in Section 6

The "basic" variant (Section 4) is # 10 in Table 3. We now discuss the variations considered. *Variation of the percentiles* Q^C, defining discretization thresholds (#8, 9, 11, 12). Lowering them, we obviously increase the total duration of alarms, but the results of prediction do not change much and remain acceptable. *Using only two kinds of crimes* (#12) we obtain comparable results. However it would be risky to make advance prediction with only two indicators. *The limits of acceptable variations* are reached in the other variants (#1–7). We tried to find a premonitory *rise* of robberies, simultaneous with rise of other crimes and consider other kinds of crimes; in all variants its performance remains unacceptable.

TABLE 3. Variation of the adjustable elements

		Variants											
		1	2	3	4	5	6	7	8	9	10	11	12
	Value of D*	3	5		8	4		3	1				0
Crime type		Trend and percentile											
Rob	Premonitory trend	upward			downward								
	Q^C, %	33	25	20	80	67						50	
FRob	Premonitory trend				downward								
	Q^C, %				80	67						50	
KCIR	Premonitory trend				downward								
	Q^C, %				80	67					50		67
ODWR	Premonitory trend	upward			downward								
	Q^C, %	33	25	20	80	67	87.5						
SAR	Premonitory trend	upward			downward								
	Q^C, %	33	25	20	80	67							
A	Premonitory trend	upward											
	Q^C, %	33	25	20	20	33							
FA	Premonitory trend	upward											
	Q^C, %	33	25	20	20	33				50			
KCIA	Premonitory trend	upward											
	Q^C, %	33	25	20	20	33				50			
ODWA	Premonitory trend	upward											
	Q^C, %	33	25	20	20	33							
AIA	Premonitory trend	upward											
	Q^C, %	33	25	20	20	33							
UNFE	Premonitory trend				upward				Upward				
	Q^C, %				20	33			33	50			33
AFE	Premonitory trend				upward								
	Q^C, %				20	33							

*The values that give relatively best performance for that variant.

For advance prediction variants 8–11 might be used in parallel. Such parallel predictions might better suit the needs of a decision-maker, determining possible disaster preparedness measures [12, 16].

7. Applications to Independent Data

Here we test our algorithm by application to "out of sample" data not used in its development. Such tests are always necessary to validate and/or improve a prediction algorithm. Such a test is possible since our algorithm is self-adaptive: the thresholds $T^C(Q^C)$ are not fixed but are adapted to crime statistics, as the percentile of a level Q^C.

7.1. LOS ANGELES, 1994-2002

So far we used the data source [10] covering the years 1975 – 1993. To extend the analysis past 1993, we have the data of the LAPD Information Technology Division, covering the time period from January 1990 to May 2002. Comparing the data for the overlapping three years we find that they are reasonably close, particularly after smoothing.

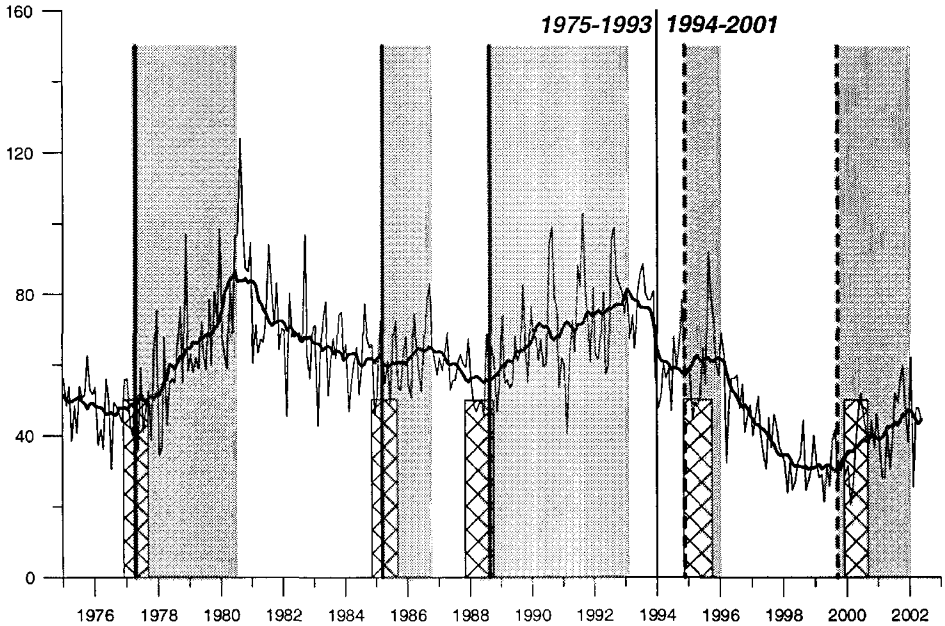

Figure 8. Performance of prediction algorithm through 1975-2002.
Data from the National Archive of Criminal Justice Data [10] for 1975 – 1993 have been used to develop the algorithm. It was than applied to the data from the Data Bank of the Los Angeles Police Department (LAPD Information Technology Division) for subsequent 9 years. Notations are the same as in Figure 4. Dashed vertical lines indicate *SHS* episodes that occurred after 1993

Figure 8 shows the homicide rates through the whole period from 1975 to May 2002. Two *SHS* episodes are identified in the later period 1994-2001. They are indicated in Figure 8 by dashed vertical lines. The first episode is captured by an alarm, which starts in the month of *SHS* without a lead time. The second episode is missed in that an alarm has started two months after it. That error has to be put on the record; nevertheless the prediction remains informative: during these two months homicide rose by only a few percent, giving no indication that a lasting homicide surge has started.

7.2. NEW YORK CITY

Figure 9 shows the monthly total homicide rates in New York City per 7 million inhabitants of the city. We identified two *SHS* episodes (02:1978 and 02:1985). Our prediction algorithm gives two alarms, as shown in Figure 9 by chequered bars. One of them predicts the second *SHS*, while the first one is missed. We consider another alarm as a false one; this has to be confirmed by processing the data for the period after 1993. Though the failure to predict and a false alarm are disappointing, the results as a whole appear to be useful: one of the two *SHS* is captured by alarms lasting together 21 months, amounting to 10 percent of the time interval considered.

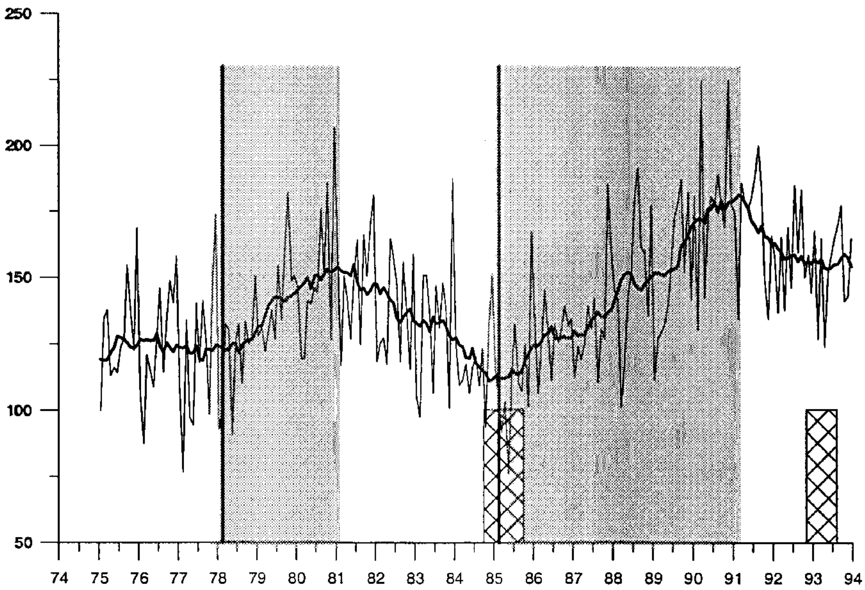

Figure 9. Application of the prediction algorithm to New York City.
Notations are the same as in Figure 4. Data are taken from the National Archive of Criminal Justice Data [10].
Homicide statistics is shown per 7,000,000 of inhabitants

8. On a More Precise Prediction

Here, we outline a conjecture, one that we believe is worth exploring in the future. We have observed two consecutive patterns of the crimes considered. The first one precedes an *SHS* with a lead time of 4 to 11 months; it is formally defined and explored in Sections 4, 5. We will discuss now in more detail the second pattern. It emerges with a shorter lead time, promising a more accurate prediction of the time of an incipient *SHS*.

A distinctive trait of the second pattern is a steep simultaneous rise of the different types of robberies. Let us replace this pattern by a less specific one that is more broadly defined: the absence of a steep decline. By definition, that pattern will be captured by the zeros in the first four columns of Table A1. Counting them, we find that three or more emerge within 6 months before each *SHS*. This result suggests the following second approximation to the prediction algorithm described above. Consider the period of alarm declared by the algorithm; let us call it "the first phase alarm". Within that period *a "second phase alarm" is declared for 6 months after the first month when* $\Delta_1(m) \leq 1$. Here $\Delta_1(m)$ is the number of ones in the codes of the robberies (the first four columns in Table A1). In the absence of the first-phase alarm the second one is not declared.

Alarms obtained by this rule are shown in Figure 10. The alarms became much shorter; their total duration drops to 18 months, that is, from 14 percent to 8 percent of all the months considered. We will possibly get even better results directly capturing *a rise* of robberies, but that probably requires weekly if not daily crime rates (since the lead time of the rise in robberies is relatively short).

Using the trend of homicides themselves might provide a similar possibility. Values of the function $K^H(m\text{-}12, m)$, which estimates that trend (see Section 4) are given in the Appendix (column K^H). Within each alarm we see the months when $K^H(m\text{-}12, m) > 0$. Starting alarms at these months, we might further reduce the duration of alarms without having an additional failure to predict.

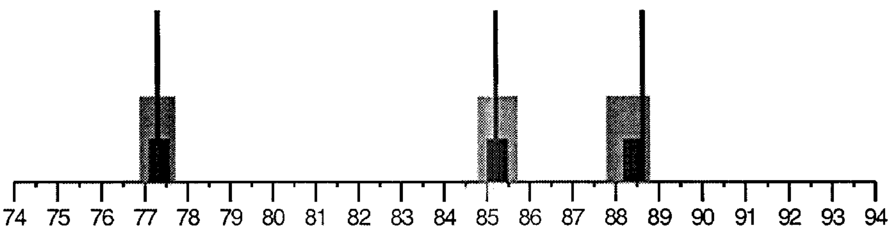

Figure 10. Possible reduction of duration of alarms.
Vertical lines –starting points of a homicide surge (*SHS*). Grey bars - alarms obtained by the suggested algorithm. Black bars – alarms obtained in a hypothetical second approximation.

9. Discussion

1. Our conclusions might be summed up as follows. We analysed crime statistics in the city of Los Angeles for the period 1975 – 2001, exploring the possibility of anticipating a turn of the homicide rate from decline to a surge. We have found that such a turn is

preceded within 4 to 11 months by a specific pattern of the crime statistics: both burglaries and assaults escalate, while robberies decline, along with the homicides themselves. Both changes, escalation and decline, are not monotonic, but occur sporadically, each lasting 2-6 months.

Based on this pattern we formulated a prediction algorithm, giving it a robust and unambiguous definition. It is self-adapting to average crime statistics, so that we could apply it to New York City as well. The major limitation of this study is that, as is inevitable for an initial study, only a small number of homicide surges was available for analysis. The algorithm remains hypothetical until it is validated by advance prediction. It is encouraging, however, that those predictions are stable as to variations in the adjustable elements of the algorithm.

Closer to the surge of homicides, the robberies also turn from decline to rise. This indicates the possibility of a second approximation to the prediction, with twice the accuracy (that is with a twofold reduction in the duration of alarms).

2. Our analysis captures the consecutive escalation of different crimes: first – of burglaries and assaults only, then of robberies, then of homicides. That sequence, albeit hypothetical so far, seems natural, being in good accord with previous experience in the following areas.

(*i*) The sequence reflects a more general phenomenon, commonly known in law enforcement practice: a consecutive escalation of more and more severe crimes, signalling that a surge of major crimes is approaching. We give a quantitative definition of a specific manifestation of this phenomenon. Similar escalation has been found in French suburban areas [17].

(*ii*) The sequence is also in accord with a well-known "universal" feature of many hierarchical complex systems: the rise of permanent background activity ("static") of the system culminated by a fast major change – a "critical transition". That feature happens to be common for different physical and socio-economic systems. It is reproduced by the "universal" models of hierarchical complex systems, such as those developed in theoretical physics, e.g., [3, 12, 18-26].

That feature was also observed in many very different real world systems. For example, in earthquakes prone regions the "static" includes background seismicity. Premonitory escalation of seismic activity is a well-known precursor to major earthquakes, which is used in many earthquake prediction algorithms [21, 27-29]. In an economy the "static" includes various macroeconomic indicators. Their premonitory escalation has been successfully used in the prediction of recessions and surges of unemployment [5, 6].

Our results are also in accord with a distinctive common trait of precursors established in many of these studies: premonitory evolution of background activity is not monotonic, but realised sporadically, in a sequence of relatively short intermittent changes.

The universality of premonitory phenomena is limited and cannot be taken for granted in studying any specific system. Nevertheless, it is worth exploring in crime dynamics other known types of premonitory patterns, e.g. the clustering of background activity and the rise of the correlation range [19, 28, 30].

3. What is the place of our study in the broad field of prediction of crime dynamics? Specific features of our approach might be summed up as follows.

(i) We are trying to predict not the whole dynamics of homicides, but only the relatively rare phenomena - episodes of *SHS*.

(ii) Accordingly, we are looking for a quantitative and precisely defined prediction algorithm of the *"yes or no"* variety: at any moment of time such an algorithm would indicate whether or not such an episode should be expected within a fixed time interval.

(iii) Our analysis is intentionally robust, which makes the prediction algorithm more reliable and applicable in different circumstances. In our case the performance of the algorithm did not change through the period considered even though Los Angeles has witnessed many changes relevant to crime over this period. This stability is achieved at a price, however, in that the time of a homicide surge is predicted with limited accuracy and the duration of a surge even more so.

4. Our approach – a heuristic "technical" analysis - is not competing with but complementary to the 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, a natural disaster etc. However, that does not render predictions considered in this study redundant. On the contrary, our approach might predict an unstable situation when a homicide surge might be triggered, thus enhancing the reliability of cause-and-effect predictions.

5. It is encouraging for further studies in this direction that we used here only a small part of the relevant and available data that can be incorporated in our analysis. Among these are other types of crimes [31], economic and demographic indicators [32] and the territorial distribution of crimes. It seems worthwhile to try the same approach with other targets of prediction – e.g. surges of all violent crimes; and to other areas, e.g. separate Bureaus of the city of Los Angeles, or to other major cities. In a broader scheme of things, our analysis discriminates stable situations from unstable, where the risk of different disasters is higher.

6. At the same time it would be important to set up an experiment in advance prediction of homicide surges in Los Angeles using the algorithm hypothesised here. Successes and errors will both provide for evaluation of this algorithm and for developing a better one.

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Appendix

TABLE A1. Binary codes of the trends for 7 types of crimes and values of $K^H(m, m\text{-}12)$
See notations in Table 1. Discretization is defined in Table 2

#	Month	Discretized trends									
		Rob	FRob	KCIR	ODWR	FA	KCIA	UNFE	Δ		K^H
1	1976:01	1	0	0	1	0	1	0	4		0.44
2	1976:02	1	0	0	0	1	1	0	4		0.21
3	1976:03	1	0	0	0	1	1	0	4		-0.07
4	1976:04	0	0	0	1	1	1	1	3		-0.28
5	1976:05	0	0	0	1	1	0	1	4		-0.35
6	1976:06	0	1	1	1	1	0	1	2		-0.33
7	1976:07	0	1	1	1	1	0	1	2		-1.18
8	1976:08	0	1	1	1	1	0	1	2		-0.96
9	1976:09	0	1	1	1	1	0	1	2		-0.87
10	1976:10	0	1	1	1	1	1	1	**1**	+	-0.79
11	1976:11	0	1	1	1	1	1	1	**1**	+	-0.37
12	1976:12	0	0	1	1	1	1	1	2		0.16
13	1977:01	0	0	0	1	0	1	0	5		0.68
14	1977:02	0	0	0	1	0	1	0	5		0.84
15	1977:03	0	0	0	1	0	1	0	5		0.38
16	**1977:04**	0	0	0	0	0	1	0	6		0.85
17	1977:05	0	0	0	1	0	1	0	5		0.07
18	1977:06	0	0	0	1	0	1	0	5		0.71
19	1977:07	0	1	0	1	0	1	0	4		0.58
20	1977:08	0	1	0	0	0	1	0	5		0.03
21	1977:09	0	1	0	0	0	1	0	5		0.18
22	1977:10	0	1	1	0	1	1	1	2		-0.17
23	1977:11	0	1	0	0	1	1	1	3		0.24
24	1977:12	0	0	0	0	1	1	1	4		0.81
25	1978:01	0	0	0	0	1	1	1	4		0.38
26	1978:02	0	0	0	0	1	1	1	4		0.16
27	1978:03	0	0	0	0	1	1	1	4		0.53
28	1978:04	0	0	0	0	0	0	0	7		-0.09
29	1978:05	0	0	0	0	0	0	0	7		0.55
30	1978:06	0	0	0	0	0	0	0	7		0.20
31	1978:07	0	0	0	0	0	0	0	7		0.57
32	1978:08	0	0	0	1	0	0	0	6		0.66
33	1978:09	0	0	0	1	0	1	0	5		1.19
34	1978:10	0	0	0	0	0	1	0	6		1.07
35	1978:11	0	0	0	0	1	1	0	5		1.72
36	1978:12	0	0	0	0	1	1	0	5		1.81
37	1979:01	0	0	0	0	1	1	1	4		2.52
38	1979:02	0	0	0	0	1	1	0	5		1.66
39	1979:03	0	0	0	0	1	1	0	5		0.88
40	1979:04	0	0	0	0	1	1	1	4		0.98
41	1979:05	0	0	0	0	1	0	1	5		0.66
42	1979:06	0	0	0	0	1	0	1	5		0.27
43	1979:07	0	0	0	0	1	0	1	5		-0.21
44	1979:08	0	1	0	0	1	0	1	4		-0.14
45	1979:09	0	1	0	1	1	1	1	2		-0.36
46	1979:10	0	0	0	0	1	1	1	4		0.45
47	1979:11	0	0	0	0	1	1	1	4		0.19
48	1979:12	0	0	0	0	1	1	1	4		2.15
49	1980:01	0	0	0	0	1	1	1	4		1.82
50	1980:02	0	0	0	0	1	1	1	4		1.49
51	1980:03	0	0	0	0	1	1	0	5		0.82
52	1980:04	0	0	0	0	1	1	0	5		1.08
53	1980:05	0	0	0	0	1	1	0	5		0.63
54	1980:06	0	0	0	0	1	0	0	6		1.51
55	1980:07	0	0	0	0	1	0	1	5		1.86
56	1980:08	0	0	0	0	1	1	1	4		2.79
57	1980:09	0	0	0	0	1	1	1	4		3.26
58	1980:10	0	0	0	0	1	1	1	4		2.56
59	1980:11	0	0	0	0	1	1	1	4		2.43
60	1980:12	0	0	0	0	1	1	1	4		2.22
61	1981:01	0	0	0	0	1	1	0	5		1.78
62	1981:02	0	0	0	0	1	1	0	5		0.85
63	1981:03	0	0	0	0	0	0	0	7		-0.57
64	1981:04	0	0	0	0	0	0	0	7		-2.02
65	1981:05	0	0	0	1	0	0	0	6		-2.64
66	1981:06	0	1	0	1	0	0	0	5		-3.35
67	1981:07	0	1	1	1	0	0	0	4		-2.51
68	1981:08	0	1	1	1	0	0	0	4		-2.10
69	1981:09	0	1	0	1	0	1	1	3		-0.92
70	1981:10	0	1	0	1	0	1	1	3		-0.02
71	1981:11	0	0	0	1	0	1	1	4		-0.10

72	1981:12	0	0	0	1	0	1	1	4		0.09
73	1982:01	0	0	0	1	0	1	1	4		0.70
74	1982:02	0	0	0	1	0	0	0	6		-0.63
75	1982:03	0	0	0	1	0	0	0	6		-0.27
76	1982:04	0	0	0	1	0	0	0	6		-0.71
77	1982:05	0	0	0	1	0	0	0	6		-0.97
78	1982:06	0	0	1	1	0	0	0	5		-1.31
79	1982:07	1	1	1	1	0	0	0	3		-1.32
80	1982:08	1	1	1	0	0	0	0	4		-0.63
81	1982:09	1	1	1	0	0	0	0	4		0.73
82	1982:10	0	1	0	0	0	1	1	4		0.45
83	1982:11	0	1	1	0	0	1	1	3		0.43
84	1982:12	0	1	0	0	0	1	1	4		0.33
85	1983:01	0	0	0	0	0	1	1	5		0.48
86	1983:02	0	0	0	0	0	1	0	6		-0.35
87	1983:03	0	0	0	1	0	0	0	6		-1.32
88	1983:04	0	0	0	1	0	0	0	6		-0.62
89	1983:05	0	1	0	1	0	0	1	4		-0.22
90	1983:06	0	1	1	1	0	0	1	3		-0.73
91	1983:07	0	1	1	1	0	0	1	3		-0.85
92	1983:08	0	1	1	1	0	0	1	3		-0.78
93	1983:09	0	1	1	1	0	0	1	3		-0.92
94	1983:10	0	1	1	1	0	0	1	3		0.59
95	1983:11	0	1	1	0	0	1	1	3		0.90
96	1983:12	0	1	1	0	1	0	1	3		0.41
97	1984:01	0	0	0	0	1	0	0	6		0.58
98	1984:02	0	1	0	0	1	0	0	5		0.20
99	1984:03	0	0	0	0	1	0	0	6		-0.93
100	1984:04	0	0	1	0	0	0	0	6		-1.16
101	1984:05	0	0	1	1	0	0	0	5		-0.76
102	1984:06	1	1	1	1	0	0	0	3		-0.57
103	1984:07	1	1	1	1	0	0	0	3		-1.04
104	1984:08	1	1	1	1	0	0	1	2		-0.55
105	1984:09	1	1	1	1	1	0	1	**1**	+	-0.21
106	1984:10	1	1	1	1	0	1	1	**1**	+	-0.20
107	1984:11	1	1	1	1	0	1	1	**1**	+	0.33
108	1984:12	0	1	0	1	0	1	1	3		0.25
109	1985:01	0	0	0	0	0	1	0	6		0.01
110	1985:02	0	0	0	0	0	1	0	6		0.73
111	**1985:03**	0	0	0	0	0	1	0	6		0.45
112	1985:04	0	0	0	0	0	1	0	6		-0.08
113	1985:05	0	0	0	0	0	0	0	7		-0.15
114	1985:06	0	0	0	0	0	0	0	7		-0.51
115	1985:07	0	1	0	0	0	0	0	6		-0.61
116	1985:08	0	1	0	1	1	0	1	3		-0.34
117	1985:09	0	1	1	1	1	0	1	2		-0.08
118	1985:10	0	1	1	1	1	0	1	2		-0.11
119	1985:11	0	1	1	1	1	0	1	2		0.19
120	1985:12	0	1	1	1	1	0	1	2		0.70
121	1986:01	0	1	0	1	1	0	1	3		-0.04
122	1986:02	0	0	1	1	1	0	0	4		-0.74
123	1986:03	0	0	1	1	0	0	0	5		0.29
124	1986:04	0	0	1	1	0	0	0	5		0.77
125	1986:05	0	0	1	1	0	0	0	5		0.42
126	1986:06	0	0	1	1	0	0	0	5		0.15
127	1986:07	0	0	1	1	1	0	0	4		-0.08
128	1986:08	0	0	0	0	1	0	1	5		0.76
29	1986:09	0	0	0	0	1	1	1	4		1.90
130	1986:10	0	0	0	0	1	1	1	4		1.56
131	1986:11	0	0	0	0	1	1	1	4		0.98
132	1986:12	0	0	0	0	1	1	1	4		0.59
133	1987:01	0	0	0	0	1	1	1	4		0.66
134	1987:02	1	0	0	0	1	1	1	3		0.11
135	1987:03	1	0	0	0	1	1	1	3		-0.43
136	1987:04	1	0	1	1	1	0	1	2		0.14
137	1987:05	1	1	1	1	0	0	1	2		-0.20
138	1987:06	1	1	1	1	0	0	1	2		-0.76
139	1987:07	1	1	1	1	0	0	0	3		-1.52
140	1987:08	1	1	1	1	0	0	0	3		-1.48
141	1987:09	1	1	1	1	1	0	1	**1**	+	-0.90
142	1987:10	1	1	1	1	1	1	1	**0**	+	-0.13
143	1987:11	0	1	1	1	1	1	1	**1**	+	-0.01
144	1987:12	0	1	1	1	1	1	1	**1**	+	0.29
145	1988:01	0	1	1	1	1	1	0	2		-0.01
146	1988:02	0	0	0	1	1	1	0	4		-0.35
147	1988:03	0	0	0	1	1	1	0	4		-0.84
148	1988:04	0	0	0	1	0	0	0	6		-0.96
149	1988:05	0	1	1	1	0	1	0	3		-0.69
150	1988:06	0	1	1	1	0	1	0	3		-1.21
151	1988:07	0	1	1	1	0	1	1	2		-0.68
152	**1988:08**	0	1	1	1	0	1	1	2		-0.66
153	1988:09	0	1	1	0	1	1	1	2		-0.13
154	1988:10	0	1	0	0	1	1	1	3		0.27
155	1988:11	0	1	0	0	1	1	1	3		0.04
156	1988:12	0	0	0	0	1	1	1	4		0.15
157	1989:01	0	0	0	0	1	1	1	4		1.38
158	1989:02	0	0	0	0	1	1	1	4		1.41
159	1989:03	0	0	0	0	1	0	0	6		1.13
160	1989:04	0	0	0	0	1	0	0	6		0.62
161	1989:05	0	0	0	0	1	0	1	5		0.21
162	1989:06	0	0	0	0	1	0	1	5		0.34
163	1989:07	0	0	0	0	1	0	1	5		-0.15
164	1989:08	0	0	0	0	1	0	1	5		0.39
165	1989:09	0	0	0	0	1	1	1	4		1.19
166	1989:10	0	0	0	0	1	1	1	4		1.47
167	1989:11	0	0	0	0	1	1	1	4		1.20
168	1989:12	0	0	0	0	1	1	1	4		1.18
169	1990:01	0	0	0	0	1	1	1	4		0.97
170	1990:02	0	0	0	0	0	0	0	7		1.60
171	1990:03	0	0	0	0	0	0	0	7		1.15
172	1990:04	0	0	0	0	0	0	0	7		0.92
173	1990:05	0	0	0	0	0	0	0	7		0.21
174	1990:06	0	0	0	0	0	0	0	7		-0.44
175	1990:07	0	0	0	0	1	1	0	5		0.74
176	1990:08	0	0	0	0	1	1	1	4		1.63
177	1990:09	0	0	0	0	1	1	1	4		1.64
178	1990:10	0	0	0	0	1	1	1	4		2.25
179	1990:11	0	0	0	0	1	1	1	4		1.24
180	1990:12	0	0	0	0	1	1	1	4		0.20
181	1991:01	0	0	0	0	0	1	0	6		0.04
182	1991:02	0	0	0	1	0	1	0	5		-1.16
183	1991:03	0	0	0	1	0	0	0	6		-1.38
184	1991:04	0	0	1	1	0	0	0	5		-1.40
185	1991:05	0	0	1	1	0	0	0	5		-1.60
186	1991:06	0	0	1	1	0	0	0	5		-1.14
187	1991:07	0	0	1	1	1	0	0	4		-1.10

188	1991:08	0	0	0	1	1	0	0	5	1.12
189	1991:09	0	0	0	1	1	0	1	4	2.63
190	1991:10	0	0	0	0	1	1	1	4	3.04
191	1991:11	0	0	0	0	1	1	1	4	2.86
192	1991:12	0	0	0	0	1	1	1	4	2.60
193	1992:01	0	0	0	0	1	1	0	5	1.84
194	1992:02	0	0	0	0	1	1	0	5	0.95
195	1992:03	0	0	0	0	1	0	0	6	-0.58
196	1992:04	0	0	0	1	0	0	0	6	-0.88
197	1992:05	0	0	1	1	0	0	0	5	-1.70
198	1992:06	0	1	1	1	0	0	0	4	-2.75
199	1992:07	0	1	1	1	0	0	0	4	-1.21
200	1992:08	0	1	1	1	0	0	0	4	0.10
201	1992:09	0	1	1	1	0	0	0	4	1.72
202	1992:10	0	1	1	1	1	0	1	2	2.35
203	1992:11	0	1	1	1	1	0	1	2	2.47
204	1992:12	0	0	1	1	0	0	0	5	1.76
205	1993:01	0	0	0	1	0	0	0	6	2.04
206	1993:02	1	0	0	1	0	0	0	5	1.04
207	1993:03	1	0	0	1	0	0	0	5	0.21
208	1993:04	1	0	0	1	0	0	0	5	-0.74
209	1993:05	1	0	1	1	0	0	0	4	-0.46
210	1993:06	1	1	1	1	0	0	0	3	-1.05
211	1993:07	1	1	1	1	0	0	0	3	-1.60
212	1993:08	0	1	1	1	0	0	0	4	-1.00
213	1993:09	0	0	0	1	0	0	1	5	-0.20
214	1993:10	0	0	0	1	0	1	1	4	0.14
215	1993:11	0	0	0	1	0	1	1	4	0.52
216	1993:12	0	0	1	1	0	1	1	3	-0.12