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DYNAMICS OF MACROECONOMIC INDICATORS BEFORE THE RISE OF UNEMPLOYMENT IN WESTERN EUROPE AND THE USA

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ABSTRACT

This study is aimed at a specific phenomenon in the dynamics of unemployment: episodes of a sharp increase in the rate of unemployment, called here "Fast Acceleration of Unemployment" or "*FAU.*" Our goal is to enhance the current capability to predict the time of a *FAU* by an analysis of macroeconomic indicators. We have found that simple patterns of macroeconomic indicators may allow the prediction of *FAU*s in France Germany, Italy and the United States. The methodology we use is that of *pattern recognition of infrequent events* to determine whether a *FAU* should be expected. Our first result includes an alarm for the USA for the period from February to November 2000.

1. INTRODUCTION

1.1 The problem: prediction of *FAU*s

We consider here a specific phenomenon in the dynamics of unemployment: a sharp increase in the rate of unemployment. Qualitatively this phenomenon is illustrated in Fig. 1. The thin line is the monthly number of unemployed $u(t)$, including seasonal variations. After smoothing $u(t)$ to eliminate these seasonal variations we obtain the function $U(t)$. Its slope is the rate of growth of unemployment. The target of our study is a sharp increase in this rate, such as the turning point indicated by the arrow in Fig. 1. We call this phenomenon by the acronym *FAU*, for "Fast Acceleration of Unemployment."

Our goal is to design an algorithm for predicting such *FAU*s by an analysis of macroeconomic indicators. What is the motivation for this analysis? An algorithm, if found, may be useful in two ways:

(i) As a quantitative and reproducible description of phenomena that are premonitory to *FAU*s; this would provide empirical constraints for the theoretical modeling of unemployment;

(ii) As a practical tool, complementing existing methods of predicting unemployment.

These are the usual twofold goals in any prediction research. We have found here that the economy, like many other complex systems, exhibits regular collective behavior patterns. We shall show that certain simple patterns of macroeconomic indicators, defined in a very robust way, can transcend the immense complexity of the economy and permit the prediction of critical phenomena, such as *FAU*s.

1.2 Methodology

This study belongs to the so-called "technical" analysis, consisting of a heuristic search for phenomena preceding *FAU*s. The alternative would be a "fundamental" analysis, focusing on "cause-and-effect" mechanisms leading to a *FAU*. The methodology we use for technical analysis is the *pattern recognition of infrequent events*. It was developed by the artificial intelligence school of I. M. Gelfand (*Gelfand et al., 1976*) for the study of rare phenomena of highly complex origin. This approach differs from but complements classical statistical and econometric methods such as regression analysis and ARIMA (*Engle and McFadden, eds, 1994*; see also *Stock and Watson 1989; Klein and Niemira 1994; Mostaghimi and Rezayat 1996*). For comparison of the pattern recognition with the multiple regression analysis of recessions see *Keilis-Borok, Stock, Soloviev, and Mikhalev (2000).*

This methodology has been successfully applied not only to the prediction of economic recessions (*Keilis-Borok et al., 2000*) but also to the outcome of elections in the U.S. (*Lichtman and Keilis-Borok, 1989; Keilis-Borok and Lichtman, 1993*). It had earlier been successfully applied in seismology (*Gelfand et al., 1976; Press and Briggs, 1975; Keilis-Borok and Press, 1980; Press and Allen, 1995*); in geological prospecting (*Press and Briggs 1977*); and in many other areas, as given in the references in these papers. We use here the simplest version of this methodology, called the "Hamming distance" (*Lichtman and Keilis-Borok, 1989* and references therein). Its essence will be clear from the way in which we analyze the data here.

1.3 What is the place of our approach in research on the prediction of unemployment?

The following are the specific features of our approach:

(i) We are trying to predict not the whole dynamics of unemployment but only the relatively rare and extraordinary phenomena - the *FAU*s.

(ii) Accordingly, we are looking for a quantitative and precisely defined prediction algorithm of the *"yes or no"* variety, where, at any moment of time, the algorithm would indicate whether or not a *FAU* should be expected within the subsequent *T* months.

(iii) Our analysis is intentionally robust, which makes the prediction algorithm more reliable and applicable to different *FAU*s despite the diversity of their specific causes. This is achieved at a price, however, in that details of the predictions are limited. The probabilistic nature of this prediction is reflected in the estimation of the probabilities of false alarms, failures to predict, and of the relative time occupied by alarms, as discussed below.

(iv) Our analysis is not competing with but complementary to short-term predictions of the *"cause and effect"* variety. The cause that triggered a specific *FAU* is usually known, at least in retrospect. It may be, for example, a certain governmental decision, a change in international trade, etc. Accordingly, one may predict an imminent *FAU* (possibly not so rigidly defined) in a rather straightforward way, namely when a triggering event occurs. That does not exclude predictability of *FAU*s with a longer lead-time, as in this study. On the contrary, it seems plausible that a *FAU* may be triggered only if and when the situation becomes "ripe" for a *FAU*; otherwise the government would not make that decision; unemployment would be less sensitive to international trade etc. If that conjecture is correct our approach can predict such a "ripe" situation. This may be of independent interest in the analysis of unemployment, and it may help in the short-term prediction of *FAU*s.

(v) The dynamics of the economy, including changes in unemployment, may have some basic features that are common in various complex processes and found in models of statistical physics (*Burridge and Knopoff, 1967; Newman et al., 1994; Allègre et al., 1995; Blanter et al., 1997; Gabrielov et al., 2000*). Our results may provide for such modeling the scaling and parametrization of the processes considered and a formal definition of the relevant critical phenomena.

2. THE DATA

We used databases issued by the Organization for Economic Cooperation and Development (*OECD, 1997*) and the International Monetary Fund (*IMF, 1997*). Past *FAU*s were identified by an analysis of the monthly statistics of unemployment. To explore the predictability of *FAU*s we analyzed the monthly indicators listed below. For France our data sources are sufficiently complete for the time period between January 1965 and May 1997, and it is this period that we consider here.

Composite characteristics of national economy

We use the following macroeconomic indicators:

1. *IP*: Industrial production index, composed of weighted production levels in numerous sectors of the economy, in % relative to the index for 1990.
2. *L*: Long-term interest rate on 10-year government bonds, in %.
3. *S*: Short-term interest rate on 3-month bills, in %.

These indicators are of particular interest since their analogues for the U.S. have been successfully used in research on predicting American economic recessions (*Stock and Watson, 1993; Keilis-Borok et al., 2000*). Several additional indicators were also considered there, but our databases do not include their counterparts for France.

Characteristics of more narrow areas of economy which are sensitive to its overall state

4. *NC*: The number of new passenger car registrations, in thousands of units.
5. *EI*: The expected prospects for the national industrial sector.
6. *EP*: The expected prospects for selected manufacturers.
7. *EO*: The estimated current volume of orders.

The last three indicators are subjective estimates that distinguish "good" from "bad" situations. They are available only for France, being obtained by a poll of a group of 2,500 manufacturers, with the estimates weighted by the size of their businesses.

Two indicators related to the American economy

8. *FF/$*: Value of U.S. dollar in French francs.
9. *AR*: The state of the American economy: is it close to a recession or not? These two states are distinguished by the pre-recession alarms determined for the United States economy (*Keilis-Borok et al., 2000*). They were determined by a methodology similar to that used in the present study. A brief explanation of the *AR* indicator follows.

   All five U.S. economic recessions in 1962–2000 were preceded by a certain pattern of 6 leading macroeconomic indicators for the U.S. This pattern emerged 5 to 13 months before each recession and at no other time. On that basis, a prediction algorithm was suggested. The indicator *AR* (for "American Recession") shows whether an alarm is or is not determined by this algorithm.

   Note that we refer here not to the American recessions themselves, but to certain phenomena *preceding* them. The relevance of the former to the European economy has been established for a long time and is well known, while the latter have been identified only recently.

   As a precursor to the American recessions this pattern was identified retrospectively. As a potential precursor to *FAU*s in France, however, *it was determined independently of the present study, and it includes no European indicators.*

These nine indicators are clearly *relevant* to the growth of unemployment. We explore here whether they are *sufficient* for an algorithmic prediction of *FAU*s. An analysis of other potentially relevant indicators is beyond the scope of this paper.

Data for indicators 1 - 3 and 4 - 8 were obtained from the IMF and OECD databases respectively.

3. IDENTIFICATION OF *FAU*s

We identify past episodes of *FAU* by an analysis of the monthly number of unemployed. Common notation here and below is $W^f(l/q,p)$ – the local linear least-squares regression of a function $f(m)$ within the sliding time window (q, p):

$$W^f(l/q,p) = K^f(q,p)l + B^f(q,p),\ q \le l \le p, \tag{1}$$

3.1 Definitions

We first formalize the definition of *FAU* that was qualitatively described in Section 1.1 and illustrated in Fig. 1. Let $u(m)$ be the number of unemployed in a month m (m = 1, 2, ...). *FAU*s are defined by following transformation of $u(m)$.

Smoothing out the seasonal variation of u we obtain function $U(m) = W^u(m/m\text{-}6,m+6)$ - a value in the month m of the regression (1) over the time interval $(m - 6, m + 6)$.

Next, we determine a function

$$F(m/s) = K^U(m+s,m) - K^U(m,m\text{-}s)$$

- the difference between the linear trends in regression (1) of $U(m)$ within s subsequent months s preceding months. This function $F(m) = F(m/24)$ calculated for $s = 24$ months is used as a coarse measure of the acceleration of unemployment

The *FAU*s are defined by the local maxima of $F(m)$ exceeding a certain threshold $\boldsymbol{F}$. The time m^* and the height F^* of such a maximum are, respectively, the starting point and the magnitude of a *FAU*. It ends in a month m_e of the subsequent local minimum of $F(m)$ and its duration is m_e - m^*. A long window s ensures that we identify the lasting rises in unemployment.

3.2 *FAU*s in France

The function $F(m)$ for the time period considered, from January 1965 through May 1997, is shown in Fig. 2. Seven *FAU*s are identified by the condition $F^* \geq \boldsymbol{F} = 4$ (Table 1). One may see in Fig. 2 that the threshold 4 identifies obviously outstanding peaks of $F(m)$. Three "major" *FAU*s, marked in bold, are distinctly larger than the others.

3.3 *FAU* as a target for prediction

Each *FAU* is the starting point of a lasting phenomenon, which has, in the past, extended over 16 to 24 months. Accordingly, the meaningful accuracy of prediction may hardly be better than about 2 months. This is even more so since *FAU*s are identified with a considerable smoothing of the unemployment rate.

Table 1. Episodes of fast acceleration of unemployment (*FAU*s) in France, 1965–1997

Time, *year:month*	'70:01	**'74:01**	'77:09	**'80:07**	'83:07	**'90:05**	'95:09
"Magnitude" F^*	7.6	**22.6**	5.3	**15.7**	9.2	**20.3**	9.4
Duration, *months*	22	**24**	16	**20**	19	**21**	20
"Glut" *G, person × months*	1993	**5570**	371	**2760**	1400	**3420**	2960

Besides the magnitude F^*, the scale of this phenomenon may be characterized by the *"glut"* of unemployment G (Fig. 3):

$$G = \Sigma\ \{U(l) - W^U(l/m^*\text{-}s,\ m^*)\}, \qquad m^* \leq l \leq m_e$$

Here m^* and m_e are as defined above the first and the last month of the *FAU*. The first term is the actual cumulative loss of employment, in person-months, during the *FAU*. The second term shows what this loss would have been had unemployment not accelerated but rather grew at the same rate as right before the *FAU*.

The values of G are shown in Table 1. We see that both measures, F^* and G, identify the same three *FAUs* as the largest ones. However, there is a slight discrepancy in sequencing the other *FAUs*. The choice of the measure depends, finally, on how the predictions are used.

4. PREMONITORY TRENDS OF SINGLE INDICATORS

In this section we explore the "premonitory" trends of the indicators, which tend to occur more frequently as a *FAU* approaches. Our definition of the *FAU*s is applicable only in retrospect, two years after a *FAU* occurs in order to ensure a reliable identification of past *FAU*s. Note, however, that our definition of a trend does *not* require information on the future. Therefore it may be used for prediction. This is because the trends are attributed to the *end* of the time windows where they are determined (Section 3.1).

We approximate the trends by the regression coefficients $K^I(m,m\text{-}s)$ that are defined as in (1) with U replaced by the symbol of an indicator I. An example of further analysis is given in Fig. 4. It shows the indicator $L(m)$ and its trend $K^L(m/s) = K^L(m,m\text{-}s)$. The plot of $K^L(m/s)$ suggests that its peaks (i.e. the relatively steep upward trends of L) emerge more frequently near the *FAU*s; in that sense they are "premonitory" to *FAU*s. To give a robust quantitative definition of a premonitory trend, we define the values of $K^L(m/s)$ on the lowest level of resolution, distinguishing only the values above and below a threshold $T^L(Q)$. It is defined as a percentile of a level Q, that is, by the condition that $K^L(m/s)$ exceeds $T^L(Q)$ during Q% of the months considered.

Similar analyses of other indicators are summarized in Table 2. We see that *FAU*s are preceded by relatively steep upward trends in the composite indicators *IP, S,* and *L.* Their analogues for the U.S. behave in the same way prior to American recessions (*Keilis-Borok et al., 2000*). The other indicators (## 4 - 8 in Section 3.1) have the opposite pre - *FAU* trend - a steep downward one, as would be expected.

Summing up, we have reduced the description of the unemployment-relevant situation to a monthly time series of a binary vector with 9-components, as is usual in the pattern recognition of infrequent events. For convenience, we give the same code, 1, to the "premonitory" trend of each indicator, regardless of whether it is an upward or a downward one. The history of indicators, thus transformed, is given in the Appendix I.

Table 2. The thresholds

	Indicator	**Premonitory trend**	*s*	*Q, %*
1	*IP*: Industrial production index	Upward	12	50%
2	*L*: Interest rate, long-term bonds	Upward	12	33%
3	*S*: Interest rate, short-term bills	Upward	12	25%
4	*NC*: New passenger cars registrations	Downward	6	33%
5	*EI*: Prospects for industrial sector	Downward	6	33%
6	*EP*: Prospects for selected manufacturers	Downward	6	33%
7	*EO*: Orders	Downward	6	33%
8	*FF/$*: French francs per USD, exchange rate	Downward	6	33%
9	*AR*: Recession alarm in the U.S.	Is current		

Premonitory behavior of the indicators considered has a transparent qualitative explanation.

(*i*) A steep rise in macroeconomic indicators (## 1 – 3 in Table 2) reflects the "overheating" of economy. For industrial production (# 1) this may sound counterintuitive, since the rise of production is supposed to create more jobs. However, premonitory to *FAU*s is only a rise, which is too steep, above 50% percentile, which creates oversupply.

(*ii*). The next four indicators reflect the expectations of the general public (# 4) and the appraisal of economic trends by the business community (## 5 – 7). These indicators seem better substantiated, than, say, public opinion polls. We see that their steep decline indeed does precede the *FAU*s.

(*iii*). The last two indicators are related to the American economy (## 8 and 9). Their premonitory behavior would be more difficult to foresee – an equally plausible explanation could be probably found for the opposite behavior. Accordingly, these indicators yield particularly strong constraints on the modeling of the dynamics of unemployment.

5. COLLECTIVE BEHAVIOR OF PRECURSORS

Here, we consider how the approach of a *FAU* is reflected in the *collective* behavior of the indicators. The simplest description of this behavior is $\Delta(m)$ - the number of non-premonitory indicators at the month m, given in the Appendix I. If our identification of premonitory trends is correct then the value of $\Delta(m)$ should decrease as a *FAU* approaches. By definition $\Delta(m)$ is the number of zeros in the binary code of the situation. This is the so-called "Hamming distance" between that code and the code of the "perfect" premonitory situation, when all the components are equal to 1, that is, all the trends are premonitory. This measure was used in several applications of the pattern recognition to elections (*Lichtman and Keilis-Borok, 1989*), to recessions (*Keilis-Borok et al, 2000*), and to earthquake prediction (*Keilis-Borok and Kossobokov, 1990; Vorobieva and Levshina, 1994*).

5.1 Three composite indicators

We consider first only the composite indicators *IP*, *L*, and *S*. The value of $\Delta(m)$ may vary in this case from 0 to 3. The minimal value $\Delta(m) = 0$ appears within 1 to 12 months before a *FAU* and at no other time (see column 1 in the Appendix I). This temporal change of $\Delta(m)$ suggests the following hypothetical prediction algorithm: *An alarm is declared for 6 months after each month with $\Delta(m) = 0$ (regardless of whether this month belongs or not to an already determined alarm).* A waiting period of 6 months is introduced because in three cases (1977, 1980, and 1995) our premonitory pattern does not appear right before a *FAU*. The possible outcomes of predictions - successful ones, false alarms and failures to predict - are illustrated in Fig. 5.

Note that a *FAU* lasts for about 20 months and its date may be determined with an accuracy of about 2 months (see Section 3.3). For that reason, the case when a *FAU* emerges simultaneously with an alarm or a month before it does not constitute a failure to predict. In addition, after a *FAU* is recognized the alarm is terminated so that an uninterrupted continuation of an alarm after a *FAU* does not constitute a false alarm.

The top row in Fig. 6 shows that this algorithm predicts 6 out of 7 *FAU*s, including all three major ones. Its meaning is simple: a simultaneous steep rise of all three indicators. It is referred to as "precursor **E**". We juxtapose also the *FAU*s and pre-recession alarms for the U.S. ("precursor **AR**"). The result is shown in Fig. 7.

5.2 Stability of prediction (sensitivity analysis)

The prediction described above involves a retrospective analysis, with a certain freedom in the ad hoc choice of indicators and of adjustable numerical parameters. Here, we explore the stability of these predictions, repeating it with various indicators and parameters and comparing the ensuing alarms. For that purpose, we generalize the rule for declaring the alarms as follows: an alarm covers a continuous sequence of the months with $\Delta(m) \leq D$; this sequence is extended to r subsequent months, where the previous analysis (Fig. 6) corresponds to the case $D = 0$, $r = 6$.

Prediction with various indicators. We considered six groups of indicators listed in Table 3, and we show the results in Fig. 8. They are compared in the error diagram (Fig. 9) showing three major characteristics of any prediction method: the total duration of alarms $\boldsymbol{\tau}$ (in per cent of the total time considered), the number of failures to predict $\boldsymbol{n}$, and the rate of false alarms $\boldsymbol{f}$. The values of these characteristics are given also in the last three columns of Table 3. As a tool for evaluation of a prediction method and for the optimal choice of a response to a prediction, the error diagrams are described by *Molchan (1997)*. The error diagrams were also very helpful for understanding the results of prediction of recessions (*Keilis-Borok et al, 2000*).

Table 3. Variation of the groups of indicators used for prediction
The last three columns show the performance of a prediction algorithm.

#	Indicators	*D*	*r*		τ	*n*	*f*
1	*IP, L, S*	0	6		23%	1	0
2	*IP, L, S, FF/$*	0	6		13%	3	1
3	*NC, EO*	0	3		31%	0	5
4	*IP, L, S, NC, EO*	1	6		26%	1	1
5	*IP, L, S, NC, EO, FF/$*	1	6		19%	2	1
6	*IP, L, S, NC, EO, AR*	2	6		28%	1	0

Table 4. Variation of adjustable parameters for indicators *IP*, *L*, and *S*
The last three columns summarize the performance of a prediction algorithm

#	Indicator(s), for which variation of a parameter is made	Variation of the parameter	τ	*n*	*f*
Variation of *Q*					
1	*IP*	60%	23%	1	0
2		40%	22%	1	0
3	*L*	40%	28%	1	1
4		25%	15%	2	0
5	*S*	30%	30%	1	2
6		20%	23%	1	0
Variation of *s*					
7	*IP, L, S*	15	20%	1	0
8		9	24%	2	1

We see in this table that the group 3, the polling of manufacturers, is the only one to give no failures to predict; however that is achieved at the price of 5 false alarms, which are hard to avoid. We tried to replace the indicator *EO* in groups 3 – 6 by a subjective indicator, *EI* or *EP*, but in each case the number of failures to predict and false alarms increased simultaneously.

Variation of adjustable parameters. We varied both the percentile Q (by 5-10%) and the window for determination of the regression coefficients s (from 9 to 15). The outcomes of several experiments on the variation of the adjustable parameters are shown in Table 4. These experiments were made for the prediction based on the first group of indicators: *IP*, *L*, and *S* (line 1 in Table 3).

Variation of definition of FAU. Two adjustable parameters are used to define the moment of *FAUs* (Sect. 3): the time window *s* for evaluation of the trend of unemployment and the threshold ***F*** for identification of "fast" acceleration. Previous analysis corresponds to the case s = 24 months and ***F*** = 4. Variation of *s* from 21 to 27 does not shift the moments of *FAUs* by more than 1-2 months – quite within the meaningful accuracy of prediction. The variation of ***F*** in the range from 3.6 to 5.0 does not lead to the emergence or disappearance of the targets of our prediction – the local maxima of $F(m)$.

Summing up, we conclude that the *most stable results are obtained with group 1 — the three composite economic indicators.* This group produces no false alarms, it sustains changes of numerical parameters, and the same results are obtained using this group jointly with other indicators.

6. GERMANY AND ITALY

We have performed similar analyses for unemployment in Germany and Italy, using, as in the case of France, the three composite national economic indicators *IP*, *S*, and *L* (Section 5.1) and the pre-recession alarms for the U.S. The results are shown in Figs. 6-8 and summarized in Table 5.

Again the steep rise of three national economic indicators (*E*) is the best predictor, but there are some false alarms.

Table 5. Comparative performance of the prediction algorithm for France, Germany and Italy

Country	*FAUs*			"False alarms"
	Total	"Predicted"	"Missed"	
France, 1965–97	7			
E		6	1	none
R		4	3	1
Germany, 1962–95	6			
E		4	2	2
R		4	2	1
Italy, 1971–93	4			
E		2	2	1
R		2	2	2

7. THE UNITED STATES

We have explored above (Sect. 5.1 and 6, Fig. 6) the possibility of predicting unemployment in France, Germany, and Italy using national macroeconomic indicators *IP*, *S*, and *L* for each of these countries. These indicators were selected, among the relevant available ones, because similar indicators were useful for the prediction of American recessions. Here, we return to the same American indicators and use them to predict not the recessions themselves but rather unemployment in the U.S. We shall see below (Fig. 10, Table 6) that these problems are not identical despite the obvious correlation between recessions and unemployment.

7.1 Periods of unemployment growth

We use the data on monthly unemployment rates for the U.S. civilian labor force, as given in *BLS (1999)*. Smoothing out the seasonal variations of these rates, we obtain the curve shown in Fig. 10. Note that for the U.S. we use the data on unemployment rates, while for Europe the unemployment data are not normalized and given in thousands of people. This difference is due to the fact that in each case we used the longest data set available in the databases.

Fig. 10 shows alternating periods of growth and decline of unemployment without a general time trend. In the absence of a trend the *FAUs* become the times when unemployment started to rise, that is local minima of the unemployment rate. These times were used as a target for prediction. They are formally defined as follows. Let $R(m)$ be the smoothed monthly unemployment rate in month m. Then $R(m)$ has the local minima in a month m^* if for $j = 1, 2, 3, 4$ $R(m^*-j) \geq R(m^*)$ and $R(m^*+j) > R(m^*)$. Seven such minima are identified within the period 1960-1999 (Table 6). The corresponding months m^* are the targets of our prediction.

Table 6. Periods of unemployment growth, recessions in the U.S., and pre-recession alarms (*Keilis-Borok et al., 2000*)

Local minima m^*	End of unemployment growth	Recessions	Pre-recession alarms
1959:11	1961:05	1960:04 – 1961:02	
1962:08	1963:05		
1967:03	1967:06		
1969:02	1971:06	1969:12 – 1970:11	1969:07 - 1969:12
1973:07	1975:07	1973:11 – 1975:03	1973:06 - 1973:11
1979:05	1980:12	1980:01 – 1980:07	1979:03 - 1980:01
1981:03	1982:12	1981:07 – 1982:11	1981:02 - 1981:07
1989:05	1992:07	1990:07 – 1991:03	1989:06 - 1990:07

7.2 Transfer of the prediction algorithm

Definitions of indicators *IP*, *S*, and *L* have the following American equivalents:

IP - "industrial production, total": index of real (constant dollar) output in the entire economy (dimensionless).

S - interest rate on 90 day U.S. treasury bills, annual rate (in percent).

L- interest rate on 10 year U.S. treasury bonds, annual rate (in percent).

These series were obtained from the CITIBASE, where *IP*, *FYGM3*, and *FYGT10* are their CITIBASE mnemonics.

According to Section 5.1 and 6, the fast acceleration of unemployment in the three European countries is preceded by a steep upward trend of these three indicators. Let us check whether this prediction algorithm, which we developed for Europe, can be transferred to the U.S. For simplicity we use *exactly* the same algorithm as described in Section 5.1, including the definition of the trends $K^I(m,m\text{-}s)$; the values of level Q for discretization of trends (Table 2); and the rule for declaration of alarms.

The application of this algorithm is shown in the bottom row of Fig. 6. We see that 4 out of 7 periods of unemployment growth are preceded by alarms. Three periods, in 1962, 1969, and 1981 are missed by alarms, and 3 alarms are false, in 1968, 1983, and 1994. All alarms preceding the periods of unemployment growth are continuing within these periods, and these continuations should obviously not be regarded as false alarms. Two alarms within the periods of unemployment growth, in 1969 and 1981, are also not regarded as false ones. The error diagram for prediction with these indicators is shown in Fig. 11 for all four countries.

Note that the rigorous count of successes and errors gives a *lower* estimate for the performance of the algorithm. In the case of the U.S. this may be misleading for the potential end user.

Two examples are shown in the bottom panel in Fig.6:

1981: The alarm in 1981:04 begins one month after the start of unemployment growth.

1969: There is a one-month gap between the end of an alarm, in 1968:12, and the start of unemployment growth, in 1969:02.

To be rigorous, we count both episodes of unemployment growth as unpredicted and the second alarm - as a false one. However the one-month difference hardly matters for practical applications, and it is within the uncertainty of our data analysis (Sect. 5.2). Accordingly, for the end user only the three errors may be counted: a failure to predict in 1962 and false alarms in 1983 and 1994. Here we counted errors in all six cases (Fig. 11).

7.3 Recessions and unemployment

Fig. 10 and Table 6 compare the periods of unemployment growth and recession in the U.S. We see that all six American recessions during the time period under consideration, 1960-1999, did occur within the six longest periods of unemployment growth. Three of the five pre-recession alarms determined by *Keilis-Borok et al. (2000)* begin before the relevant months m^* (Table 6). The level of unemployment, measured in a different way, was actually used for the determination of these alarms. This confirms that the prediction of unemployment is indeed not equivalent to the prediction of recessions.

8. DISCUSSION

1) We have identified a robust pattern of macroeconomic indicators that since 1962, precede certain persistently reoccurring structures in the dynamics of the unemployment in France, namely the episodes of fast acceleration of unemployment (*FAU*s). This pattern has emerged within 12 months prior to six out of seven *FAU*s and at no other time, suggesting a possible prediction algorithm, to be tested by advance predictions. The retrospective alarms defined by this algorithm are encouragingly stable with respect to the choice of indicators and to variation of adjustable numerical parameters.

The pattern recognition methodology used here inherits some of the features of the diffusion indexes of classical business cycle analysis (*Mitchell and Burns, 1946; Mitchell, 1951; Moore, 1961*), reformulating these features in the robust language of pattern recognition. More detailed comments on that connection are given in (*Keilis-Borok et al., 2000*).

2) It is commonly known that the economy, like many other complex systems, exhibits regular collective behavior patterns, transcending its immense complexity. This is true of the premonitory patterns identified here. Moreover, they are applicable in very different conditions:

(*i*) Through the whole time period considered (the last third of the twentieth century) despite extraordinary changes in the economy and the relevant labor market.

(*ii*) To the *FAUs* of different origin. Specifically, the *FAUs* in Europe reflect the cyclical fluctuations in the economy, with unemployment raising from a moderate or high level to a yet higher one. Similar phenomena in the U.S. reflect the onset of a recession, with unemployment rising from the very low level to a high one.

(*iii*) Finally, the prediction algorithm is applicable without readaptation to Germany, Italy, and the U.S.

That wide applicability of the uniform premonitory patterns is achieved at a price, as is usual in the prediction of highly complex processes: the magnitude and time of an incipient *FAU* are indicated with a limited accuracy, and the rate of errors is not negligible. On the other hand, such a robust prediction may be used as a first approximation in the search for more accurate prediction methods.

3) If the results of this study are correct, what do they tell us about the unemployment and the dynamics of the economy in general?

(*i*) Our results (if confirmed by advance prediction) will expand the known limits of predictability of economy, and the realm of robust behavior patterns in macroeconomics. More specifically, we have found important regularities: a minimal set of indicators influencing unemployment; the necessary level of their averaging; and the definition of *FAU* as a critical phenomenon. These regularities constitute heuristic constraints for macroeconomic models of unemployment. Besides econometric models, as reviewed in (*Engle and McFadden, eds, 1994*), this refers also to models that are based on a statistical mechanics approach (*Burridge and Knopoff, 1967; Newman et al., 1994; Allègre et al., 1995; Blanter et al., 1997; Gabrielov et al., 2000*).

(*ii*) We have defined (algorithmically) the situation when episodes of the *FAU*s become possible in an intermediate - term scale, within about a year. Accordingly, it is only in such unstable situations that *FAU*s may be triggered in the short-term scale by usually known causes, such as the announcement of new economic regulations, an oil crisis, etc.)

4) The quantitative explanation of our prediction algorithm may, however, be more complicated. Unemployment has been traditionally associated with a decline in the economy. This relation becomes more complex and can even be reversed in a tight labor market. A decrease of unemployment can be regarded as a threat of "inflation by wages", leading to declines in stock market indexes. On the contrary, when a corporation announces massive layoffs of employees the price of its stock often increases, with the stock owners (especially the pension funds) considering the wage bill a fixed "cost". For those kinds of reasons, Western economic and financial executives no longer consider a low unemployment rate good news and appear to prefer corporate "downsizing," leading to job destruction (*Brito, Intriligator, and Worth, 1998*). Several other factors in the functioning of the economy, by contrast, reduce unemployment. For example, the acceleration of technological progress leads to the fast growth of small and medium-size enterprises in the new sectors of the economy and accordingly to job creation.

Thus, *a fine balance between the forces leading to job creation and those leading to job destruction determines the level of unemployment. The FAUs reflect a change in that balance.* Will the evolution of these forces render our prediction algorithm invalid? Not necessarily, since our algorithm depicts a rather common phenomenon using a very robust definition. Nothing can be taken for granted, of course, and the above considerations merely indicate a promising direction for further research: to use for the prediction of unemployment the separate indicators for different branches of the economy and the distribution of businesses according to their size.

5) Our results suggest some other directions for further research:

(*i*) We have identified here the indicators that are *sufficient* for prediction, but not *all* indicators potentially useful for that purpose. In particular, we did not yet explore such prominent measure of expectations as the difference between interest rates of long-term bonds and short-term bills, that is, the steepness of the yield curve. A similar indicator was very useful for the prediction of American recessions (*Keilis-Borok et al., 2000*). The level of averaging of indicators considered here may be used as a start in the study of other indicators.

(*ii*) With less robust predictions, premonitory patterns may be considered in the context of the accelerator hypothesis and, more generally, the cointegration of each indicator separately and in combinations, using Dickey-Fuller tests and Granger causality concepts (*Ericson, 1997; Ericson and MacKinnon, 1999; Watson, 1994*).

(*iii*) In the search for subsequent approximations to prediction it would be interesting to explore the changes of unemployment *during* the *FAUs*. Also, it may be preferable for purely computational reasons to consider the reciprocal of unemployment as used in previous studies.

(*iv*) Finally, the prediction of a *decrease* of unemployment obviously deserves a separate study of that kind.

6) The economic integration of the European Union is increasing, along with the general globalization of the economy. This will not necessarily render our analysis irrelevant, since our algorithm is very robust. In any case, economic integration would make it easier to develop new algorithms of this kind, with an even higher level of averaging of the processes considered.

Similarly, our results may not become irrelevant due to some drastic change of the mechanisms controlling the quickly accelerating modern economy, since the premonitory patterns considered here probably reflect some type of scenario of transition to critical phenomena (one that is common for many mechanisms in the case of non-linear dynamics). An indirect confirmation the uniform performance of the prediction algorithm through the last 35 years.

7) Our optimism is guarded, however, since we had certain freedom as to the choice of data and formulation of the algorithm. Such a retrospectively designed prediction algorithm could possibly depict random coincidences, which eliminate the errors by chance and may not reoccur. We have encouraging evidence that supports the validity of the algorithm described here, including successful application to out-of-sample data; robustness; and stability of the alarms to variations of the prediction rule. This justifies a further test of the algorithm by advance prediction.

8) The final test of a prediction method is advance prediction (Appendix II). We will describe now the first results of an experiment in advance prediction by the algorithm suggested here. We have started with prediction for the USA. Analyzing the data up to December 2000 we have found that $\Delta(m) = 0$ during four months, from February to May 2000. Accordingly, the algorithm declares the alarm for the period from February to November 2000. The credibility of this alarm remains unknown, until the rate of false alarms is estimated. We can make however the following exact statement, based on the data in Table 7.

- The current pattern of macroeconomic indicators, defined unambiguously by the condition $\Delta(m) = 0$, has emerged 9 times in 1960-1999.
- Five times this pattern was followed within a year (after the first month of its emergence) by a period of the unemployment growth (lines 1, 2, 4, 5, and 8 in Table 7).
- Two times it occurred shortly (within 4 months) after the start of the unemployment growth (lines 3 and 6 of Table 7).
- And two more times it was a false alarm: the pattern emerged far (by 4+ years) from a subsequent period of the unemployment growth (lines 7 and 9 of Table 7).

In real (advance) prediction such success to failures ratio would be quite satisfactory.

The alarm is expired at the time when this is written. Was the prediction correct? To identify the minimum of the smoothed unemployment rate $R(m)$ we need to know the monthly unemployment rates up to the time $(m + 10)$. Accordingly, we may check whether the alarm is correct or false when the data on unemployment rate up to October 2001 will be available. (Note that the data on the future are *not* used for prediction itself – see Section 3).

9) We have used so far only a part of the relevant data and methods. In that sense this study is preliminary and exploratory. We believe that further applications of the pattern recognition analysis of economic phenomena are promising.

Table 7. Alarm periods declared for the U.S. in 1960-1999.

#	Alarm periods	Relevant periods of the unemployment growth		
		Initial month	Duration, months	Increase of the unemployment rate, %
1	1966:05 – 1967:05	1967:03	3	0.06
2	1968:02 – 1968:12	1969:02	28	2.53
3	1969:06 – 1970:02	- " -	- " -	- " -
4	1973:03 – 1974:05	1973:07	24	3.55
5	1978:06 – 1979:10	1979:05	19	1.63
6	1981:04 – 1982:02	1981:03	21	2.80
7	1983:10 – 1985:04	No		
8	1989:01 – 1989:08	1989:05	38	2.23
9	1994:06 – 1995:09	No		

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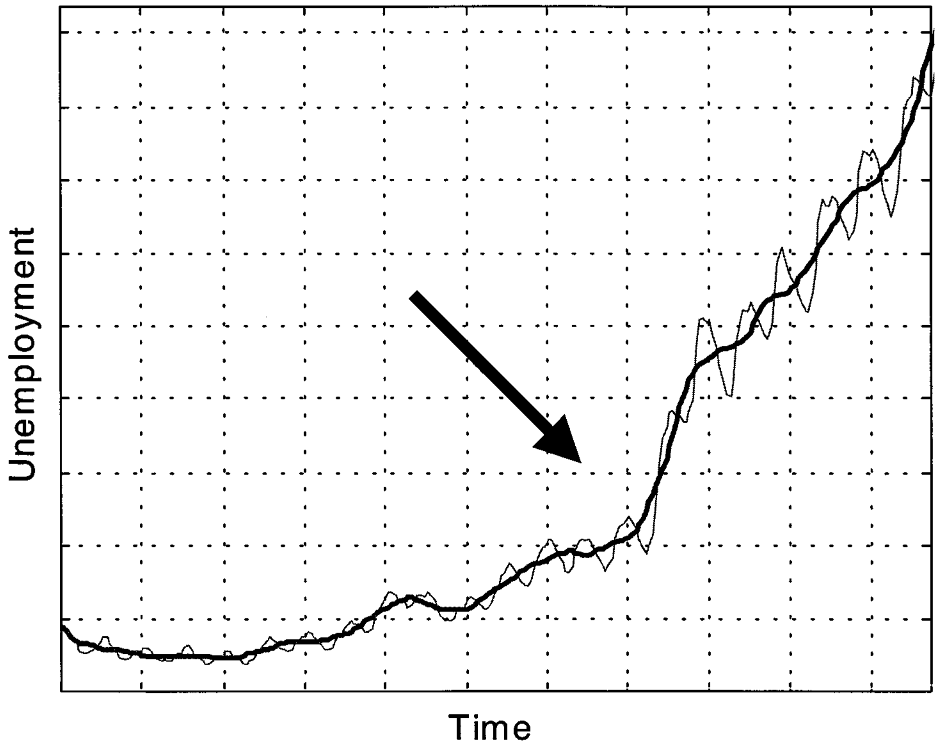

Figure 1 Fast acceleration of unemployment (*"FAU"*): schematic definition.

Thin line - monthly unemployment; quasiperiodic variations are seasonal ones. Thick line - monthly unemployment, with seasonal variations smoothed away. The sharp bend of the smoothed curve is a *FAU* - the target of prediction – as indicated by an arrow.

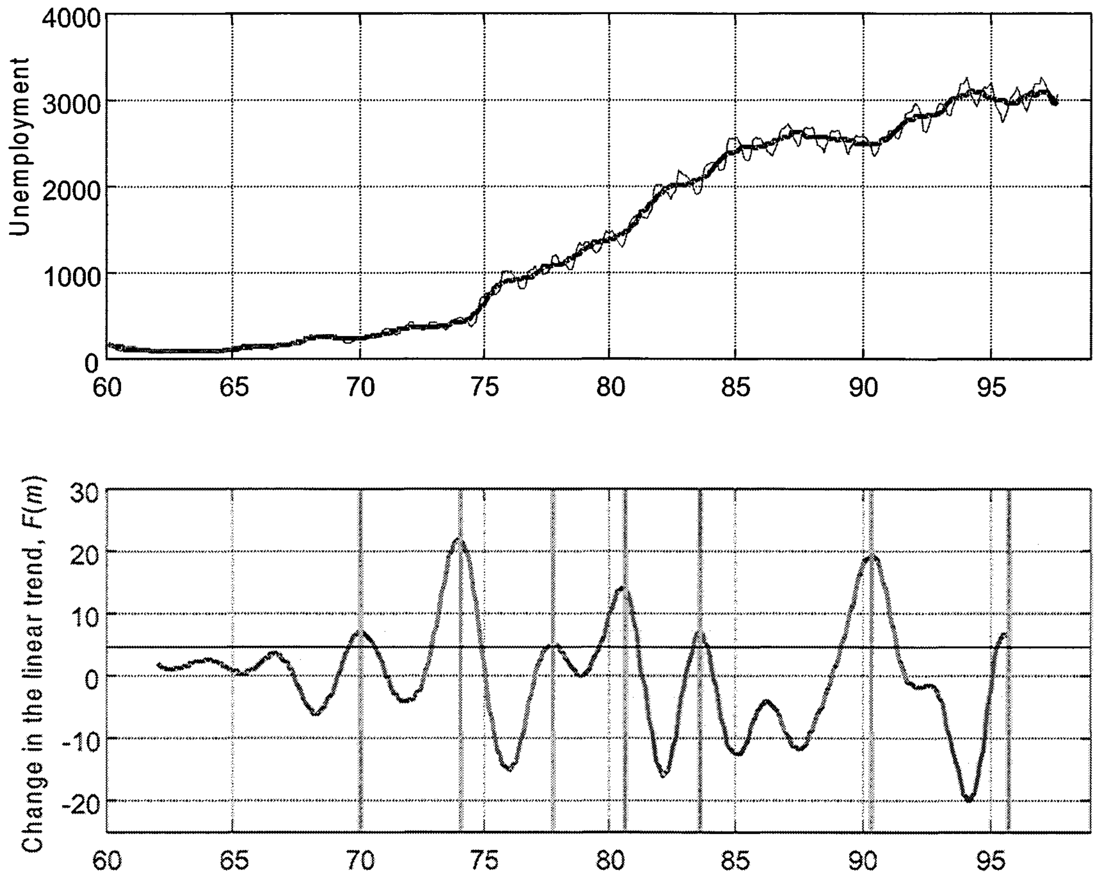

Figure 2 Unemployment in France.

Top: Monthly unemployment, thousands of people. Thin line: $u(m)$, data from the OECD database; note the seasonal variations. Thick line: $U(m)$, data smoothed over one year.

Bottom: Determination of *FAU*s. $F(m)$ shows the change in the linear trend of unemployment $U(m)$. *FAU*s are attributed to the local maxima of $F(m)$ exceeding threshold $\boldsymbol{F} = 4.0$ shown by solid horizontal line. The thick vertical lines show moments of the *FAU*s.

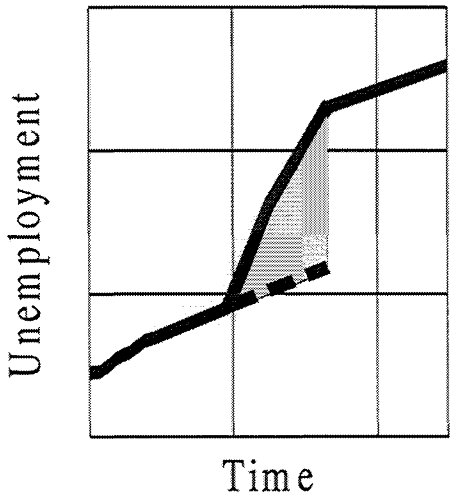

Figure 3 Glut of unemployment: schematic definition.

Its measure is the shaded area, showing the amount of person-months of jobs lost. The dashed line is the extrapolation of the pre-*FAU* trend.

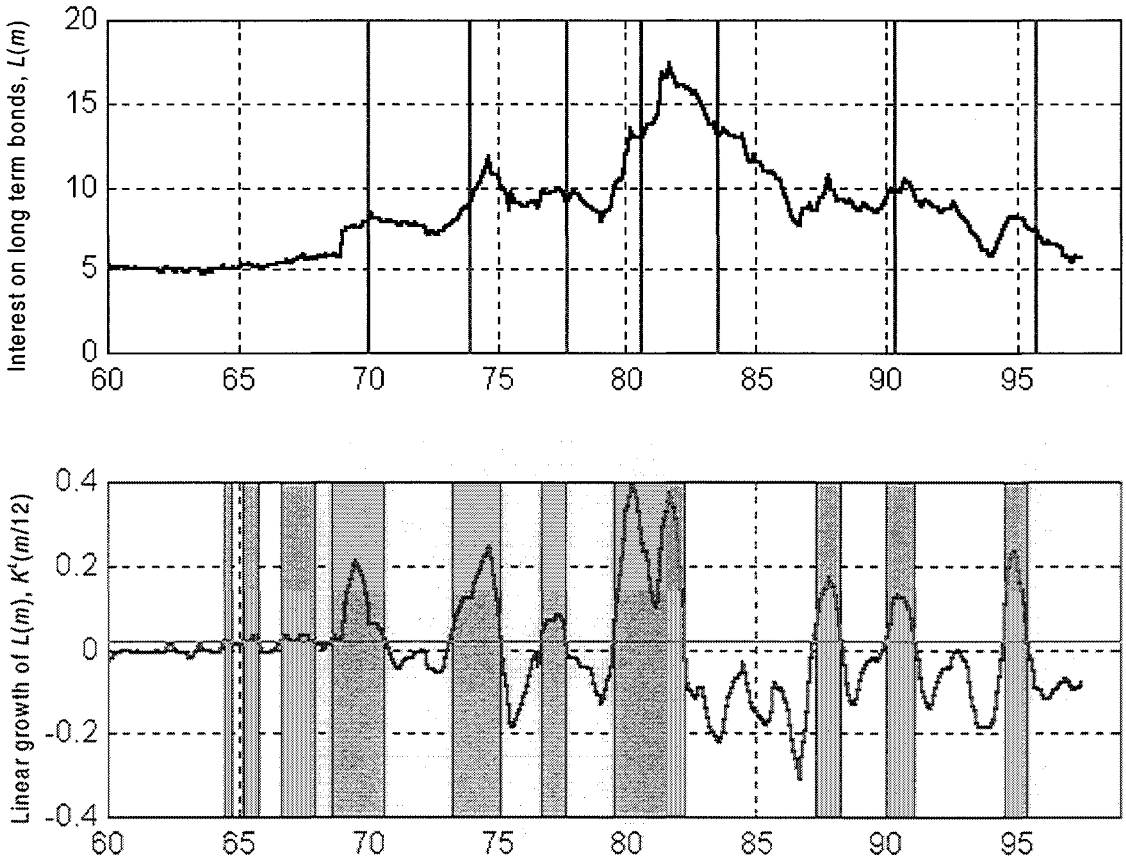

Figure 4 Robust discretization of an economic indicator, starting in 1960.

Top: $L(m)$, interest rate on long-term (10 year) governmental bonds, %. Source: OECD.

Bottom: $K^L(m/12)$, linear growth of $L(m)$ in the sliding time window $(m - 12, m)$. The thin horizontal line is the upper 33% percentile for K^L so that K^L exceeds this threshold 33% of time. The gray bars mark time intervals when the value of $K^L(m/12)$ exceeds the threshold.

The thick vertical lines show moments of *FAU*s. Note that after a quiet period before 1967 "large" values of $K^L(m/12)$ tend to appear more frequently when a *FAU* is approaching. However, with this threshold they would "predict" the *FAUs* only in combination with other indexes. Finer tuning of the threshold is possible but it would be premature until tested by forward prediction.

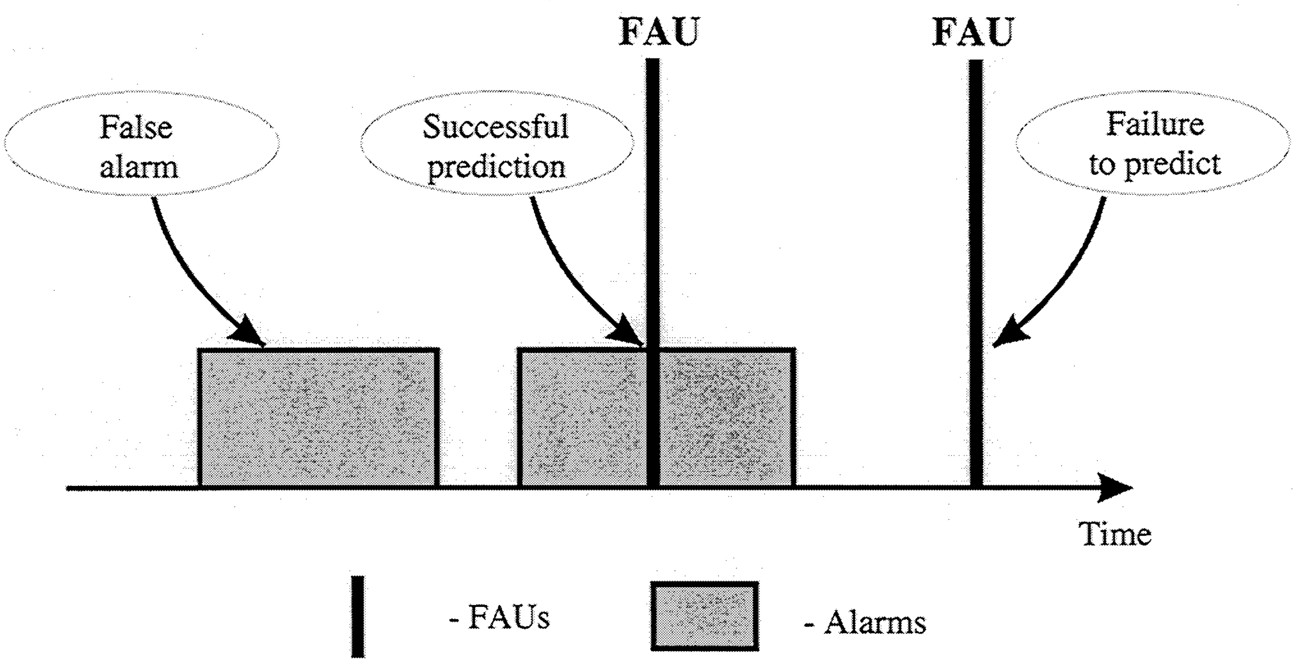

Figure 5 Possible outcomes of prediction.

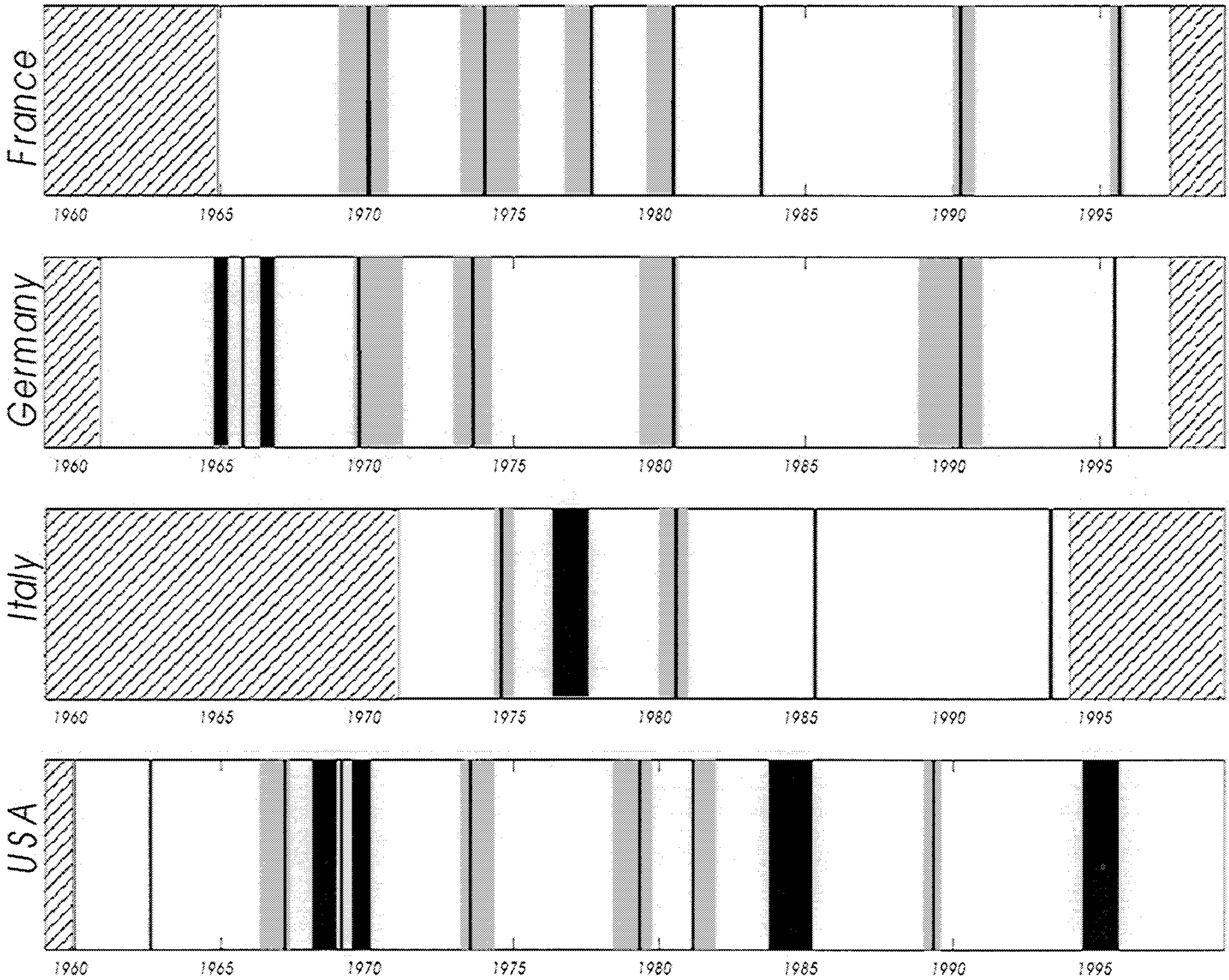

Figure 6 *FAUs* and the hypothetical "precursor **E**" – simultaneous steep rise of 3 macroeconomic indicators.

The thick vertical lines show the moments of *FAU*s in a country. The gray "area of alarm" starts when a precursor emerges, while black bars show the false alarms. Shaded areas on both sides indicate the times for which data on economic indicators were unavailable.

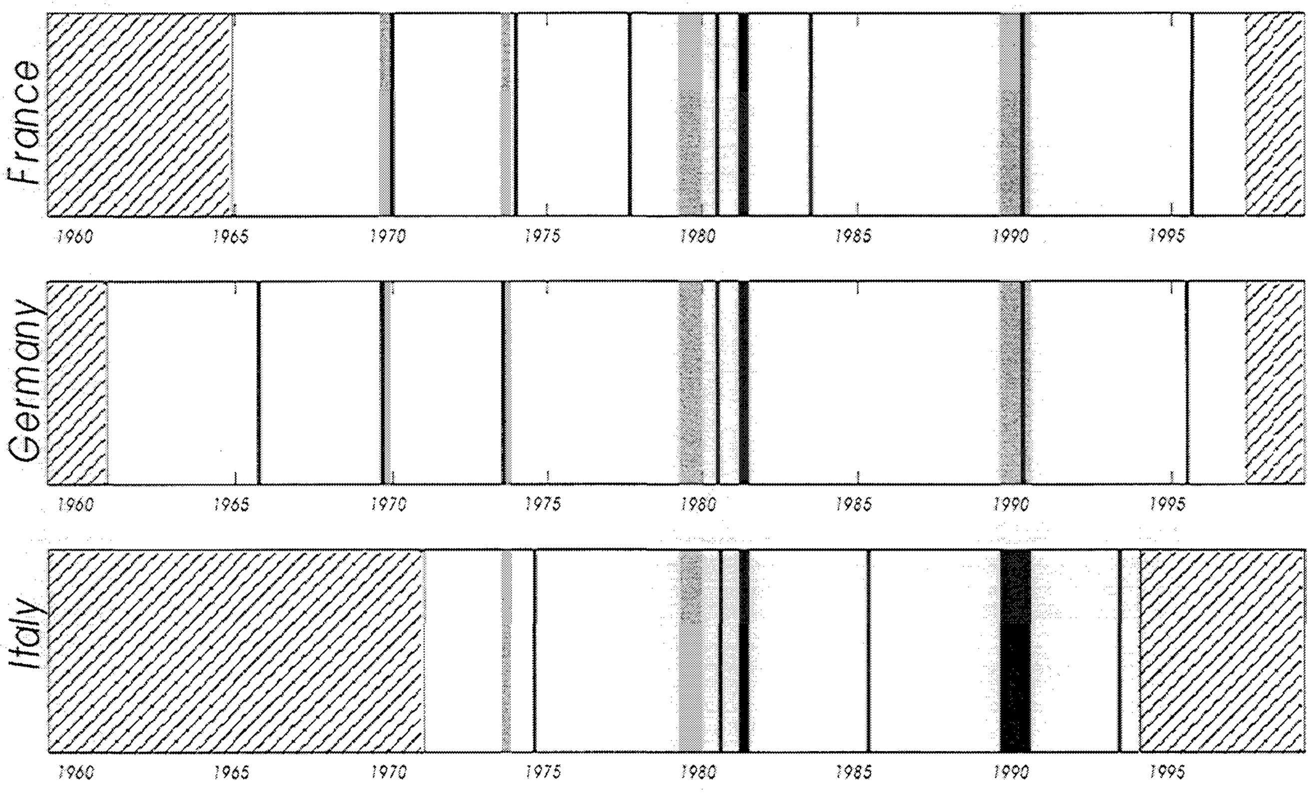

Figure 7 *FAUs* and the pre-recession alarms in the USA.
The alarms are taken from *Keilis-Borok et al, 2000*. Notations are the same as in Fig. 6.

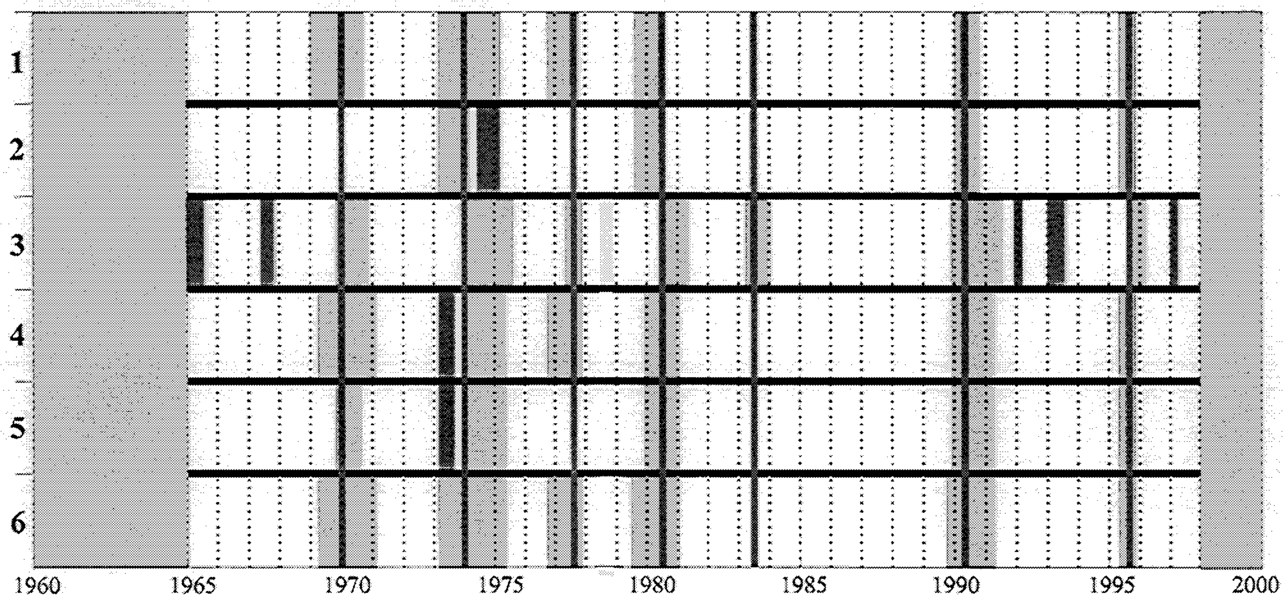

Figure 8 *FAUs* and alarms obtained with different groups of indicators.

The number of a group according to Table 3 is shown on the left. The thick vertical lines show the moments of *FAUs*, the gray "area of alarm" starts when precursors emerge, and black bars show false alarms. Gray areas on both sides indicate the time for which the data on economic indicators were unavailable in the OECD database.

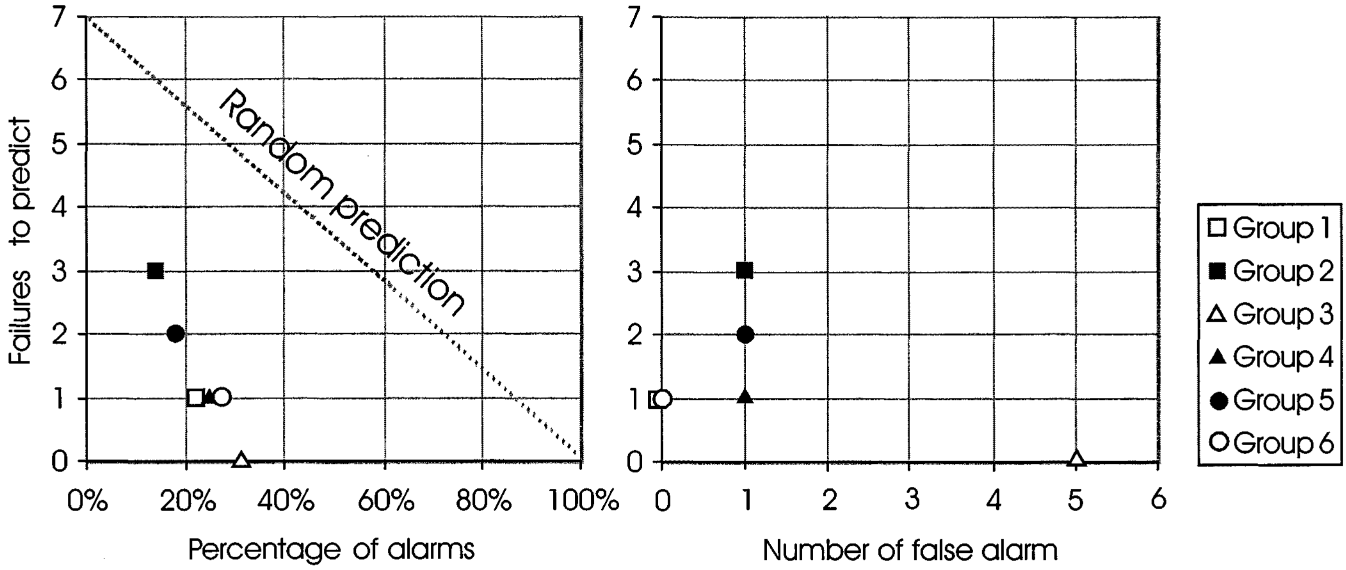

Figure 9 Error diagrams for predictions with various groups of indicators.

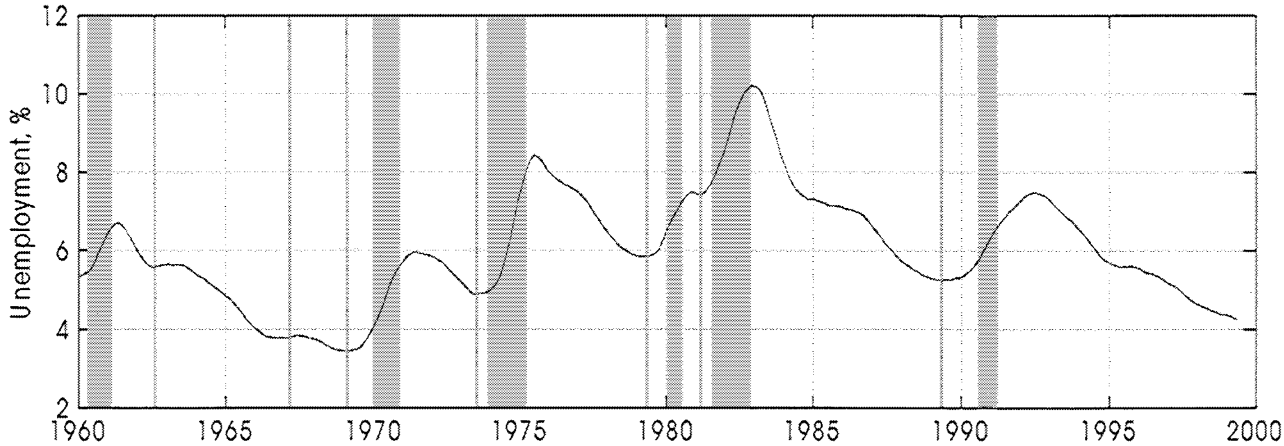

Figure 10 Unemployment rates in the U.S. after smoothing out the seasonal variations.
The thick vertical lines show the moments when unemployment started to rise (local minima of unemployment rate). Gray bars mark periods of recessions in the U.S.

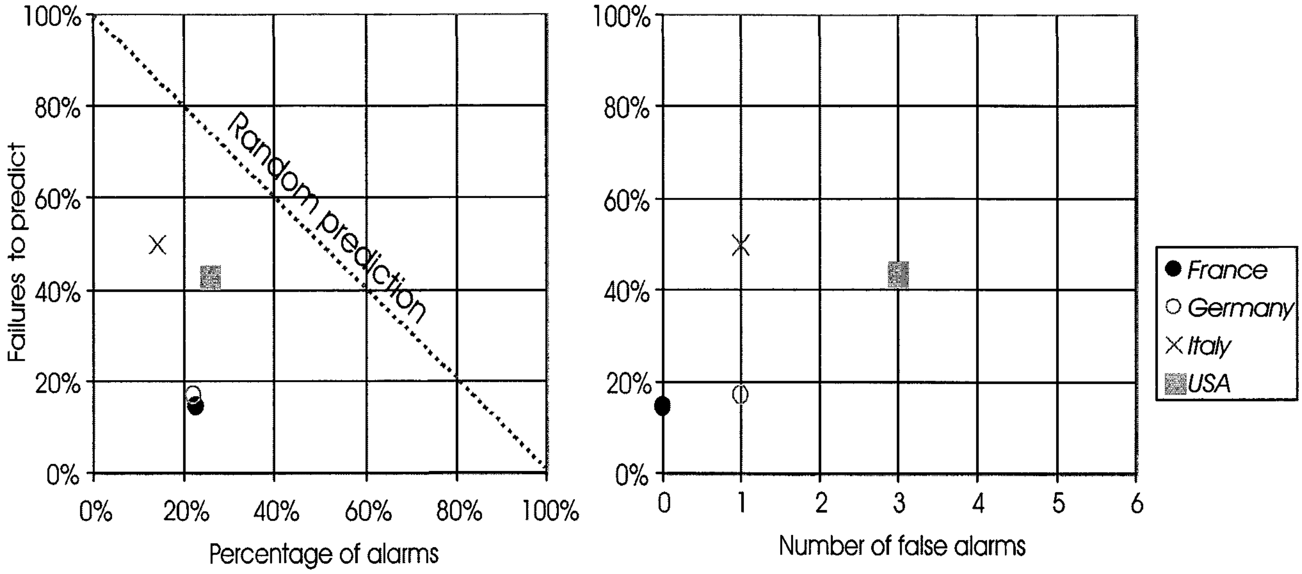

Figure 11 Error diagram for predictions based on three economic indicators for all four countries.

APPENDIX I. Chronology of the Indicators for France

Columns 2 - 9 correspond to the single indicators. Headings show their symbols, as explained in Section 2. Code "1" indicates the "premonitory" value, which appears more frequently in the proximity of a *FAU* (Section 5).

The last six columns correspond to the group of indicators as defined in Table 3. The number of a group in that table is given in the heading. Each column shows the number Δ of non-premonitory values, where "+" marks the months when Δ ≤ *D*, that is, the *FAU* alarm is diagnosed. Thresholds *D* are indicated in Table 3.

Shaded lines show the moments of *FAU*s.

Dates	*IP*	*L*	*S*	*NC*	*EI*	*EP*	*EO*	*FF/$*	*AR*	1		2		3		4		5		6	
'65:01	.	.	.	1	1	1	1		.	3	.	4	.	0	+	3	.	4	.	4	.
'65:02	.	.	.	1	1	1	1	.	.	3	.	4	.	0	+	3	.	4	.	4	.
'65:03	.	.	.	1	1	1	1	.	.	3	.	4	.	0	+	3	.	4	.	4	.
'65:04	.	.	.	1	1	.	1	.	.	3	.	4	.	0	+	3	.	4	.	4	.
'65:05	.	.	.	1	.	.	1	.	.	3	.	4	.	0	+	3	.	4	.	4	.
'65:06	.	.	.	.	.	.	.	.	.	3	.	4	.	2	+	5	.	6	.	6	.
'65:07	.	1	.	.	.	.	.	.	.	2	.	3	.	2	+	4	.	5	.	5	.
'65:08	.	.	.	.	.	.	.	.	.	3	.	4	.	2	+	5	.	6	.	6	.
'65:09	.	.	.	.	.	.	.	.	.	3	.	4	.	2	.	5	.	6	.	6	.
'65:10	.	.	.	.	.	.	.	.	.	3	.	4	.	2	.	5	.	6	.	6	.
'65:11	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'65:12	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'66:01	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'66:02	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'66:03	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'66:04	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'66:05	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'66:06	1	.	.	.	1	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'66:07	1	.	.	.	1	1	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'66:08	1	.	.	.	.	1	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'66:09	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'66:10	1	.	.	.	.	.	1	.	.	2	.	3	.	1	.	3	.	4	.	4	.
'66:11	1	1	.	.	.	.	1	.	.	1	.	2	.	1	.	2	.	3	.	3	.
'66:12	1	.	.	.	1	1	1	.	.	2	.	3	.	1	.	3	.	4	.	4	.
'67:01	1	.	1	.	1	1	1	.	.	1	.	2	.	1	.	2	.	3	.	3	.
'67:02	.	.	.	.	1	1	1	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'67:03	.	.	.	.	1	1	1	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'67:04	.	.	.	.	1	.	1	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'67:05	.	.	.	.	1	.	1	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'67:06	.	1	.	1	1	1	1	1	.	2	.	2	.	0	+	2	.	2	.	3	.
'67:07	.	1	.	1	1	1	1	1	.	2	.	2	.	0	+	2	.	2	.	3	.
'67:08	.	.	.	1	1	1	1	.	.	3	.	4	.	0	+	3	.	4	.	4	.
'67:09	.	.	.	.	.	.	1	.	.	3	.	4	.	1	+	4	.	5	.	5	.
'67:10	.	.	.	.	.	.	.	.	.	3	.	4	.	2	+	5	.	6	.	6	.
'67:11	.	.	.	.	.	.	.	.	.	3	.	4	.	2	+	5	.	6	.	6	.
'67:12	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'68:01	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'68:02	1	.	.	1	.	.	.	.	.	2	.	3	.	1	.	3	.	4	.	4	.
'68:03	1	.	.	1	.	.	.	.	.	2	.	3	.	1	.	3	.	4	.	4	.
'68:04	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'68:05	.	.	.	1	.	.	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'68:06	.	.	.	1	.	.	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'68:07	.	.	.	1	.	.	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'68:08	.	.	1	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'68:09	.	.	1	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.

Dates	IP	L	S	NC	EI	EP	EO	FF/$	AR	1		2		3		4		5		6	
'68:10	1	.	1	.	.	.	.	.	.	1	.	2	.	2	.	3	.	4	.	4	.
'68:11	1	.	1	.	.	.	.	.	.	1	.	2	.	2	.	3	.	4	.	4	.
'68:12	1	.	1	.	.	.	.	.	.	1	.	2	.	2	.	3	.	4	.	4	.
'69:01	1	1	1	.	.	1	.	.	.	0	+	1	.	2	.	2	.	3	.	3	.
'69:02	1	1	1	.	1	1	.	.	.	0	+	1	.	2	.	2	.	3	.	3	.
'69:03	1	1	1	.	1	.	.	.	.	0	+	1	.	2	.	2	.	3	.	3	.
'69:04	1	1	1	1	.	.	.	.	.	0	+	1	.	1	.	1	+	2	.	2	+
'69:05	1	1	1	.	.	.	.	.	.	0	+	1	.	2	.	2	+	3	.	3	+
'69:06	1	1	1	.	.	.	.	.	.	0	+	1	.	2	.	2	+	3	.	3	+
'69:07	1	1	1	.	.	.	.	.	.	0	+	1	.	2	.	2	+	3	.	3	+
'69:08	1	1	1	.	1	.	.	.	1	0	+	1	.	2	.	2	+	3	.	2	+
'69:09	1	1	1	.	1	.	.	.	1	0	+	1	.	2	.	2	+	3	.	2	+
'69:10	1	1	1	1	1	.	.	.	1	0	+	1	.	1	.	1	+	2	.	1	+
'69:11	1	1	1	1	1	.	1	.	1	0	+	1	.	0	+	0	+	1	+	0	+
'69:12	1	1	1	1	1	1	1	.	1	0	+	1	.	0	+	0	+	1	+	0	+
'70:01	1	1	1	1	.	1	1	.	.	0	+	1	.	0	+	0	+	1	+	1	+
'70:02	1	1	1	1	.	1	1	.	.	0	+	1	.	0	+	0	+	1	+	1	+
'70:03	1	1	1	.	.	.	1	.	.	0	+	1	.	1	+	1	+	2	+	2	+
'70:04	1	1	.	.	.	.	1	.	.	1	+	2	.	1	+	2	+	3	+	3	+
'70:05	1	1	.	.	.	1	1	.	.	1	+	2	.	1	+	2	+	3	+	3	+
'70:06	1	1	.	1	.	1	1	.	.	1	+	2	.	0	+	1	+	2	+	2	+
'70:07	1	1	.	1	1	1	1	.	.	1	+	2	.	0	+	1	+	2	+	2	+
'70:08	1	1	.	1	1	1	1	.	.	1	+	2	.	0	+	1	+	2	+	2	+
'70:09	1	.	.	.	.	1	1	.	.	2	+	3	.	1	+	3	+	4	.	4	+
'70:10	1	.	.	.	.	.	1	.	.	2	.	3	.	1	+	3	+	4	.	4	+
'70:11	1	.	.	.	.	.	1	.	.	2	.	3	.	1	+	3	+	4	.	4	+
'70:12	1	.	.	.	.	.	1	.	.	2	.	3	.	1	.	3	+	4	.	4	+
'71:01	1	.	.	.	.	.	1	.	.	2	.	3	.	1	.	3	+	4	.	4	+
'71:02	1	.	.	.	.	.	1	.	.	2	.	3	.	1	.	3	+	4	.	4	+
'71:03	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'71:04	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'71:05	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'71:06	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'71:07	1	.	.	1	.	1	.	.	.	2	.	3	.	1	.	3	.	4	.	4	.
'71:08	1	.	.	.	.	1	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'71:09	1	.	.	.	1	1	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'71:10	1	.	.	.	1	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'71:11	1	.	.	.	1	1	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'71:12	1	.	.	.	1	1	1	1	.	2	.	2	.	1	.	3	.	3	.	4	.
'72:01	1	.	.	.	1	1	1	1	.	2	.	2	.	1	.	3	.	3	.	4	.
'72:02	1	.	.	.	.	1	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'72:03	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'72:04	1	.	.	1	.	.	.	1	.	2	.	2	.	1	.	3	.	3	.	4	.
'72:05	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'72:06	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'72:07	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'72:08	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'72:09	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'72:10	1	.	.	1	.	.	.	.	.	2	.	3	.	1	.	3	.	4	.	4	.
'72:11	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'72:12	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'73:01	1	.	1	.	.	.	.	.	.	1	.	2	.	2	.	3	.	4	.	4	.
'73:02	1	.	1	.	.	1	.	1	.	1	.	1	.	2	.	3	.	3	.	4	.
'73:03	1	1	1	1	.	.	.	1	.	0	+	0	+	1	.	1	+	1	+	2	+
'73:04	1	1	1	.	.	.	.	1	.	0	+	0	+	2	.	2	+	2	+	3	+
'73:05	1	1	1	.	.	.	.	1	.	0	+	0	+	2	.	2	+	2	+	3	+
'73:06	1	1	1	.	.	.	.	1	.	0	+	0	+	2	.	2	+	2	+	3	+
'73:07	1	1	1	.	.	1	.	1	1	0	+	0	+	2	.	2	+	2	+	2	+

Dates	IP	L	S	NC	EI	EP	EO	FF/$	AR	1		2		3		4		5		6	
'73:08	1	1	1	.	.	1	.	1	1	0	+	0	+	2	.	2	+	2	+	2	+
'73:09	1	1	1	.	1	1	.	1	1	0	+	0	+	2	.	2	+	2	+	2	+
'73:10	1	1	1	.	1	1	.	.	1	0	+	1	+	2	.	2	.	3	.	2	+
'73:11	1	1	1	.	1	.	.	.	1	0	+	1	+	2	.	2	.	3	.	2	+
'73:12	1	1	1	1	1	1	1	.	.	0	+	1	+	0	+	0	+	1	+	1	+
'74:01	1	1	1	.	1	1	1	.	.	0	+	1	+	1	+	1	+	2	+	2	+
'74:02	1	1	1	1	1	1	1	.	.	0	+	1	+	0	+	0	+	1	+	1	+
'74:03	1	1	1	1	1	1	1	.	.	0	+	1	+	0	+	0	+	1	+	1	+
'74:04	1	1	1	1	.	.	1	.	.	0	+	1	.	0	+	0	+	1	+	1	+
'74:05	1	1	1	1	.	.	.	.	.	0	+	1	.	1	+	1	+	2	+	2	+
'74:06	1	1	1	1	.	.	.	1	.	0	+	0	+	1	+	1	+	1	+	2	+
'74:07	1	1	1	1	.	1	.	1	.	0	+	0	+	1	+	1	+	1	+	2	+
'74:08	1	1	1	1	1	1	1	1	.	0	+	0	+	0	+	0	+	0	+	1	+
'74:09	1	1	1	1	1	1	1	1	.	0	+	0	+	0	+	0	+	0	+	1	+
'74:10	.	1	1	1	1	1	1	1	.	1	+	1	+	0	+	1	+	1	+	2	+
'74:11	.	1	1	1	1	1	1	1	.	1	+	1	+	0	+	1	+	1	+	2	+
'74:12	.	1	.	1	1	1	1	1	.	2	+	2	+	0	+	2	+	2	+	3	+
'75:01	.	1	.	1	1	1	1	1	.	2	+	2	+	0	+	2	+	2	+	3	+
'75:02	.	1	.	1	.	1	1	1	.	2	+	2	+	0	+	2	+	2	+	3	+
'75:03	.	.	.	.	.	.	1	1	.	3	+	3	+	1	+	4	+	4	+	5	+
'75:04	.	.	.	.	.	.	1	1	.	3	.	3	.	1	+	4	+	4	+	5	+
'75:05	.	.	.	1	.	.	1	1	.	3	.	3	.	0	+	3	+	3	+	4	+
'75:06	.	.	.	.	.	.	1	1	.	3	.	3	.	1	+	4	.	4	.	5	.
'75:07	.	.	.	.	.	.	1	.	.	3	.	4	.	1	+	4	.	5	.	5	.
'75:08	.	.	.	.	.	.	.	.	.	3	.	4	.	2	+	5	.	6	.	6	.
'75:09	.	.	.	.	.	.	.	.	.	3	.	4	.	2	.	5	.	6	.	6	.
'75:10	.	.	.	.	.	.	.	.	.	3	.	4	.	2	.	5	.	6	.	6	.
'75:11	.	.	.	.	.	.	.	.	.	3	.	4	.	2	.	5	.	6	.	6	.
'75:12	.	.	.	.	.	.	.	.	.	3	.	4	.	2	.	5	.	6	.	6	.
'76:01	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'76:02	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'76:03	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'76:04	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'76:05	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'76:06	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'76:07	1	.	.	.	1	1	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'76:08	1	.	1	.	1	1	.	.	.	1	.	2	.	2	.	3	.	4	.	4	.
'76:09	1	.	1	.	1	1	.	.	.	1	.	2	.	2	.	3	.	4	.	4	.
'76:10	1	1	1	.	1	1	1	.	.	0	+	1	.	1	.	1	+	2	.	2	+
'76:11	1	1	1	.	1	1	1	.	.	0	+	1	.	1	.	1	+	2	.	2	+
'76:12	1	1	1	.	1	1	1	.	.	0	+	1	.	1	.	1	+	2	.	2	+
'77:01	1	1	1	.	1	1	1	.	.	0	+	1	.	1	.	1	+	2	.	2	+
'77:02	1	1	1	.	1	1	1	.	.	0	+	1	.	1	.	1	+	2	.	2	+
'77:03	1	1	1	.	.	.	.	.	.	0	+	1	.	2	.	2	+	3	.	3	+
'77:04	1	1	1	.	.	.	.	.	.	0	+	1	.	2	.	2	+	3	.	3	+
'77:05	.	1	1	1	.	.	1	.	.	1	+	2	.	0	+	1	+	2	.	2	+
'77:06	.	1	.	1	.	.	1	1	.	2	+	2	.	0	+	2	+	2	.	3	+
'77:07	.	1	.	1	1	1	1	1	.	2	+	2	.	0	+	2	+	2	.	3	+
'77:08	.	.	.	1	1	1	1	1	.	3	+	3	.	0	+	3	+	3	.	4	+
'77:09	.	.	.	.	.	1	1	1	.	3	+	3	.	1	+	4	+	4	.	5	+
'77:10	.	.	.	.	.	.	.	1	.	3	+	3	.	2	+	5	+	5	.	6	+
'77:11	.	.	.	.	.	.	1	1	.	3	.	3	.	1	+	4	+	4	.	5	+
'77:12	.	.	.	.	.	.	1	1	.	3	.	3	.	1	.	4	.	4	.	5	.
'78:01	.	.	.	1	.	.	.	1	.	3	.	3	.	1	.	4	.	4	.	5	.
'78:02	.	.	.	1	.	.	.	1	.	3	.	3	.	1	.	4	.	4	.	5	.
'78:03	.	.	.	1	.	.	.	1	.	3	.	3	.	1	.	4	.	4	.	5	.
'78:04	1	.	.	1	.	.	.	1	.	2	.	2	.	1	.	3	.	3	.	4	.
'78:05	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.

Dates	*IP*	*L*	*S*	*NC*	*EI*	*EP*	*EO*	*FF/$*	*AR*	**1**		**2**		**3**		**4**		**5**		**6**	
'78:06	.	.	.	.	.	.	.	1	.	3	.	3	.	2	.	5	.	5	.	6	.
'78:07	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'78:08	1	.	.	.	1	1	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'78:09	1	.	.	.	1	1	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'78:10	1	.	.	1	1	.	.	1	.	2	.	2	.	1	.	3	.	3	.	4	.
'78:11	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'78:12	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'79:01	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'79:02	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'79:03	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'79:04	1	.	.	.	.	.	.	.	1	2	.	3	.	2	.	4	.	5	.	4	.
'79:05	1	.	.	.	.	.	.	.	1	2	.	3	.	2	.	4	.	5	.	4	.
'79:06	1	.	.	1	.	.	.	.	1	2	.	3	.	1	.	3	.	4	.	3	.
'79:07	1	1	.	1	1	.	.	.	1	1	.	2	.	1	.	2	.	3	.	2	+
'79:08	1	1	1	.	1	1	.	1	1	0	+	0	+	2	.	2	.	2	.	2	+
'79:09	1	1	1	.	1	1	.	1	1	0	+	0	+	2	.	2	.	2	.	2	+
'79:10	1	1	1	.	1	.	.	1	1	0	+	0	+	2	.	2	.	2	.	2	+
'79:11	1	1	1	.	.	.	.	1	1	0	+	0	+	2	.	2	.	2	.	2	+
'79:12	1	1	1	1	.	.	.	1	1	0	+	0	+	1	.	1	+	1	+	1	+
'80:01	1	1	1	1	.	.	.	1	1	0	+	0	+	1	.	1	+	1	+	1	+
'80:02	.	1	1	.	.	.	.	.	.	1	+	2	+	2	.	3	+	4	+	4	+
'80:03	.	1	1	1	.	.	.	.	.	1	+	2	+	1	.	2	+	3	+	3	+
'80:04	.	1	1	.	.	.	.	.	.	1	+	2	+	2	.	3	+	4	+	4	+
'80:05	.	1	1	1	1	1	.	.	.	1	+	2	+	1	.	2	+	3	+	3	+
'80:06	.	1	1	1	1	1	1	.	.	1	+	2	+	0	+	1	+	2	+	2	+
'80:07	.	1	1	1	1	1	1	1	.	1	+	1	+	0	+	1	+	1	+	2	+
'80:08	.	1	.	1	1	1	1	1	.	2	.	2	.	0	+	2	+	2	+	3	+
'80:09	.	1	.	.	1	1	1	.	.	2	.	3	.	1	+	3	+	4	+	4	+
'80:10	.	1	.	.	1	1	1	.	.	2	.	3	.	1	+	3	+	4	+	4	+
'80:11	.	1	.	.	1	1	1	.	.	2	.	3	.	1	+	3	+	4	+	4	+
'80:12	.	1	.	1	.	.	1	.	.	2	.	3	.	0	+	2	+	3	+	3	+
'81:01	.	1	.	1	1	.	1	.	.	2	.	3	.	0	+	2	+	3	+	3	+
'81:02	.	1	.	1	.	.	1	.	.	2	.	3	.	0	+	2	.	3	.	3	.
'81:03	.	1	.	1	.	.	.	.	1	2	.	3	.	1	+	3	.	4	.	3	.
'81:04	.	1	.	1	.	.	.	.	1	2	.	3	.	1	+	3	.	4	.	3	.
'81:05	.	1	.	.	.	.	.	.	1	2	.	3	.	2	+	4	.	5	.	4	.
'81:06	.	1	1	.	.	1	.	.	1	1	.	2	.	2	.	3	.	4	.	3	.
'81:07	.	1	1	.	.	.	.	.	1	1	.	2	.	2	.	3	.	4	.	3	.
'81:08	.	1	1	.	.	.	.	.	.	1	.	2	.	2	.	3	.	4	.	4	.
'81:09	.	1	1	.	.	.	.	.	.	1	.	2	.	2	.	3	.	4	.	4	.
'81:10	.	1	1	1	.	.	.	.	.	1	.	2	.	1	.	2	.	3	.	3	.
'81:11	.	1	1	.	.	.	.	1	.	1	.	1	.	2	.	3	.	3	.	4	.
'81:12	.	1	1	.	.	.	.	1	.	1	.	1	.	2	.	3	.	3	.	4	.
'82:01	.	1	1	.	.	.	.	.	.	1	.	2	.	2	.	3	.	4	.	4	.
'82:02	.	1	1	.	.	.	.	.	.	1	.	2	.	2	.	3	.	4	.	4	.
'82:03	.	1	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'82:04	.	.	.	.	.	.	.	.	.	3	.	4	.	2	.	5	.	6	.	6	.
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'82:06	.	.	.	1	1	.	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'82:07	.	.	.	1	1	1	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'82:08	.	.	.	.	1	1	1	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'82:09	.	.	.	.	1	1	1	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'82:10	.	.	.	.	1	1	1	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'82:11	.	.	.	.	.	1	.	.	.	3	.	4	.	2	.	5	.	6	.	6	.
'82:12	.	.	.	.	.	.	.	1	.	3	.	3	.	2	.	5	.	5	.	6	.
'83:01	.	.	.	.	.	.	.	1	.	3	.	3	.	2	.	5	.	5	.	6	.
'83:02	.	.	.	.	.	.	.	1	.	3	.	3	.	2	.	5	.	5	.	6	.
'83:03	.	.	.	1	.	.	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.

Dates	IP	L	S	NC	EI	EP	EO	FF/$	AR	1	2		3		4		5		6	
'83:04	.	.	.	1	.	.	1	.	.	3	.4	.	0	+	3	.	4	.	4	.
'83:05	.	.	.	1	1	.	1	.	.	3	.4	.	0	+	3	.	4	.	4	.
'83:06	.	.	.	.	1	1	1	.	.	3	.4	.	1	+	4	.	5	.	5	.
'83:07	.	.	.	.	1	1	1	.	.	3	.4	.	1	+	4	.	5	.	5	.
'83:08	.	.	.	.	1	1	1	.	.	3	.4	.	1	+	4	.	5	.	5	.
'83:09	.	.	.	1	.	1	1	.	.	3	.4	.	0	+	3	.	4	.	4	.
'83:10	.	.	.	1	.	.	1	.	.	3	.4	.	0	+	3	.	4	.	4	.
'83:11	.	.	.	1	.	.	.	.	.	3	.4	.	1	+	4	.	5	.	5	.
'83:12	.	.	.	1	.	.	.	.	.	3	.4	.	1	+	4	.	5	.	5	.
'84:01	.	.	.	1	.	.	.	.	.	3	.4	.	1	+	4	.	5	.	5	.
'84:02	1	.	.	1	.	.	.	.	.	2	.3	.	1	.	3	.	4	.	4	.
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'84:05	1	.	.	1	.	.	.	1	.	2	.2	.	1	.	3	.	3	.	4	.
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'85:10	.	.	.	.	.	.	.	1	.	3	.3	.	2	.	5	.	5	.	6	.
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'86:05	.	.	.	.	.	.	.	1	.	3	.3	.	2	.	5	.	5	.	6	.
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'87:04	.	1	.	.	.	.	.	1	.	2	.2	.	2	.	4	.	4	.	5	.
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'87:06	.	1	.	.	.	.	.	.	.	2	.3	.	2	.	4	.	5	.	5	.
'87:07	.	1	.	1	.	.	.	.	.	2	.3	.	1	.	3	.	4	.	4	.
'87:08	.	1	.	.	.	1	.	.	.	2	.3	.	2	.	4	.	5	.	5	.
'87:09	.	1	.	.	.	1	.	.	.	2	.3	.	2	.	4	.	5	.	5	.
'87:10	1	1	.	.	.	.	.	1	.	1	.1	.	2	.	3	.	3	.	4	.
'87:11	1	1	.	.	.	.	.	1	.	1	.1	.	2	.	3	.	3	.	4	.
'87:12	1	1	.	.	.	.	.	1	.	1	.1	.	2	.	3	.	3	.	4	.
'88:01	1	1	.	.	1	.	.	1	.	1	.1	.	2	.	3	.	3	.	4	.

Dates	IP	L	S	NC	EI	EP	EO	FF/$	AR	1		2		3		4		5		6	
'88:02	1	1	.	.	1	.	.	1	.	1	.	1	.	2	.	3	.	3	.	4	.
'88:03	1	1	.	1	.	.	.	1	.	1	.	1	.	1	.	2	.	2	.	3	.
'88:04	1	1	.	1	.	.	.	.	.	1	.	2	.	1	.	2	.	3	.	3	.
'88:05	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'88:06	1	.	.	1	.	.	.	.	.	2	.	3	.	1	.	3	.	4	.	4	.
'88:07	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'88:08	1	.	.	.	.	1	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'88:09	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'88:10	1	.	.	1	.	.	.	.	.	2	.	3	.	1	.	3	.	4	.	4	.
'88:11	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'88:12	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'89:01	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'89:02	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'89:03	1	.	.	.	.	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'89:04	1	.	.	1	.	.	.	.	.	2	.	3	.	1	.	3	.	4	.	4	.
'89:05	1	.	1	1	.	.	.	.	.	1	.	2	.	1	.	2	.	3	.	3	.
'89:06	1	.	1	1	.	.	.	.	.	1	.	2	.	1	.	2	.	3	.	3	.
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'89:08	1	.	1	.	1	.	.	.	1	1	.	2	.	2	.	3	.	4	.	3	.
'89:09	1	.	1	.	.	.	.	1	1	1	.	1	.	2	.	3	.	3	.	3	.
'89:10	1	.	1	.	.	.	1	1	1	1	.	1	.	1	.	2	.	2	.	2	+
'89:11	1	.	1	.	.	.	1	1	1	1	.	1	.	1	.	2	.	2	.	2	+
'89:12	1	.	1	1	.	1	1	1	1	1	.	1	.	0	+	1	+	1	+	1	+
'90:01	1	1	1	1	.	1	1	1	1	0	+	0	+	0	+	0	+	0	+	0	+
'90:02	1	1	1	1	.	1	1	1	1	0	+	0	+	0	+	0	+	0	+	0	+
'90:03	1	1	1	.	.	.	1	1	1	0	+	0	+	1	+	1	+	1	+	1	+
'90:04	1	1	1	.	.	.	1	1	1	0	+	0	+	1	+	1	+	1	+	1	+
'90:05	1	1	.	.	.	.	1	1	1	1	+	1	+	1	+	2	+	2	+	2	+
'90:06	1	1	.	1	1	.	1	1	1	1	+	1	+	0	+	1	+	1	+	1	+
'90:07	1	1	.	1	1	.	1	1	1	1	+	1	+	0	+	1	+	1	+	1	+
'90:08	1	1	.	.	1	1	1	1	.	1	+	1	+	1	+	2	+	2	+	3	+
'90:09	1	1	.	.	1	1	1	1	.	1	+	1	+	1	+	2	+	2	+	3	+
'90:10	1	1	.	1	1	1	1	1	.	1	+	1	+	0	+	1	+	1	+	2	+
'90:11	.	1	.	1	1	1	1	1	.	2	.	2	.	0	+	2	+	2	+	3	+
'90:12	.	1	.	1	1	1	1	1	.	2	.	2	.	0	+	2	+	2	+	3	+
'91:01	.	1	.	1	1	1	1	1	.	2	.	2	.	0	+	2	+	2	+	3	+
'91:02	.	.	.	1	1	1	1	1	.	3	.	3	.	0	+	3	+	3	+	4	+
'91:03	.	.	.	1	.	.	1	.	.	3	.	4	.	0	+	3	+	4	+	4	+
'91:04	.	.	.	1	.	.	1	.	.	3	.	4	.	0	+	3	+	4	+	4	+
'91:05	.	.	.	1	.	.	.	.	.	3	.	4	.	1	+	4	.	5	.	5	.
'91:06	.	.	.	.	.	.	.	.	.	3	.	4	.	2	+	5	.	6	.	6	.
'91:07	.	.	.	.	.	.	.	.	.	3	.	4	.	2	+	5	.	6	.	6	.
'91:08	.	.	.	.	1	.	.	.	.	3	.	4	.	2	.	5	.	6	.	6	.
'91:09	.	.	.	.	.	.	1	1	.	3	.	3	.	1	.	4	.	4	.	5	.
'91:10	.	.	.	.	.	1	.	1	.	3	.	3	.	2	.	5	.	5	.	6	.
'91:11	.	.	.	1	1	1	.	1	.	3	.	3	.	1	.	4	.	4	.	5	.
'91:12	.	.	.	1	1	1	1	1	.	3	.	3	.	0	+	3	.	3	.	4	.
'92:01	.	.	.	.	1	1	1	1	.	3	.	3	.	1	+	4	.	4	.	5	.
'92:02	.	.	.	.	.	.	.	1	.	3	.	3	.	2	+	5	.	5	.	6	.
'92:03	.	.	.	.	.	.	.	1	.	3	.	3	.	2	+	5	.	5	.	6	.
'92:04	.	.	.	.	.	.	.	.	.	3	.	4	.	2	.	5	.	6	.	6	.
'92:05	.	.	.	1	.	.	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'92:06	.	.	.	.	.	.	.	1	.	3	.	3	.	2	.	5	.	5	.	6	.
'92:07	.	.	.	.	.	1	.	1	.	3	.	3	.	2	.	5	.	5	.	6	.
'92:08	.	.	.	.	1	1	.	1	.	3	.	3	.	2	.	5	.	5	.	6	.
'92:09	.	.	1	.	1	1	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'92:10	.	.	1	.	1	1	1	1	.	2	.	2	.	1	.	3	.	3	.	4	.
'92:11	.	.	.	.	1	1	1	.	.	3	.	4	.	1	.	4	.	5	.	5	.

Dates	*IP*	*L*	*S*	*NC*	*EI*	*EP*	*EO*	*FF/$*	*AR*	**1**		**2**		**3**		**4**		**5**		**6**	
'92:12	.	.	.	.	1	1	1	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'93:01	.	.	1	1	1	1	1	.	.	2	.	3	.	0	+	2	.	3	.	3	.
'93:02	.	.	1	1	1	1	1	.	.	2	.	3	.	0	+	2	.	3	.	3	.
'93:03	.	.	1	1	.	.	1	.	.	2	.	3	.	0	+	2	.	3	.	3	.
'93:04	.	.	.	1	.	.	1	1	.	3	.	3	.	0	+	3	.	3	.	4	.
'93:05	.	.	.	1	.	.	1	1	.	3	.	3	.	0	+	3	.	3	.	4	.
'93:06	.	.	.	.	.	.	.	.	.	3	.	4	.	2	+	5	.	6	.	6	.
'93:07	.	.	.	1	.	.	.	.	.	3	.	4	.	1	+	4	.	5	.	5	.
'93:08	.	.	.	1	.	1	.	.	.	3	.	4	.	1	+	4	.	5	.	5	.
'93:09	.	.	.	1	.	1	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'93:10	.	.	.	1	.	1	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'93:11	.	.	.	1	.	.	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'93:12	.	.	.	1	.	.	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'94:01	.	.	.	1	.	.	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'94:02	.	.	.	.	.	.	.	.	.	3	.	4	.	2	.	5	.	6	.	6	.
'94:03	.	.	.	.	.	.	.	1	.	3	.	3	.	2	.	5	.	5	.	6	.
'94:04	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'94:05	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'94:06	1	.	.	.	.	.	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'94:07	1	1	.	.	.	.	.	1	.	1	.	1	.	2	.	3	.	3	.	4	.
'94:08	1	1	.	.	.	1	.	1	.	1	.	1	.	2	.	3	.	3	.	4	.
'94:09	1	1	.	.	.	1	.	1	.	1	.	1	.	2	.	3	.	3	.	4	.
'94:10	1	1	.	.	.	.	.	1	.	1	.	1	.	2	.	3	.	3	.	4	.
'94:11	1	1	.	.	.	.	.	1	.	1	.	1	.	2	.	3	.	3	.	4	.
'94:12	1	1	.	.	.	.	.	1	.	1	.	1	.	2	.	3	.	3	.	4	.
'95:01	1	1	.	.	.	1	.	1	.	1	.	1	.	2	.	3	.	3	.	4	.
'95:02	1	1	.	.	.	1	.	.	.	1	.	2	.	2	.	3	.	4	.	4	.
'95:03	1	1	.	.	.	.	.	1	.	1	.	1	.	2	.	3	.	3	.	4	.
'95:04	1	1	.	1	.	.	.	1	.	1	.	1	.	1	.	2	.	2	.	3	.
'95:05	1	1	1	1	.	.	.	1	.	0	+	0	+	1	.	1	+	1	+	2	+
'95:06	1	.	1	.	1	1	.	1	.	1	+	1	+	2	.	3	+	3	+	4	+
'95:07	.	.	1	.	1	1	1	1	.	2	+	2	+	1	.	3	+	3	+	4	+
'95:08	.	.	1	.	1	1	1	.	.	2	+	3	+	1	.	3	+	4	+	4	+
'95:09	.	.	1	1	1	1	1	.	.	2	+	3	+	0	+	2	+	3	+	3	+
'95:10	.	.	.	1	1	1	1	.	.	3	+	4	+	0	+	3	+	4	+	4	+
'95:11	.	.	.	1	1	1	1	.	.	3	+	4	+	0	+	3	+	4	+	4	+
'95:12	.	.	.	1	1	1	1	.	.	3	.	4	.	0	+	3	.	4	.	4	.
'96:01	.	.	.	.	1	1	1	.	.	3	.	4	.	1	+	4	.	5	.	5	.
'96:02	.	.	.	.	1	.	1	.	.	3	.	4	.	1	+	4	.	5	.	5	.
'96:03	.	.	.	.	.	.	1	.	.	3	.	4	.	1	+	4	.	5	.	5	.
'96:04	.	.	.	.	.	.	.	.	.	3	.	4	.	2	.	5	.	6	.	6	.
'96:05	.	.	.	.	.	.	.	.	.	3	.	4	.	2	.	5	.	6	.	6	.
'96:06	.	.	.	1	.	.	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'96:07	.	.	.	1	.	.	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'96:08	.	.	.	.	1	1	.	1	.	3	.	3	.	2	.	5	.	5	.	6	.
'96:09	1	.	.	.	1	1	.	1	.	2	.	2	.	2	.	4	.	4	.	5	.
'96:10	1	.	.	.	1	1	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'96:11	1	.	.	.	1	.	.	.	.	2	.	3	.	2	.	4	.	5	.	5	.
'96:12	.	.	.	1	.	1	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.
'97:01	.	.	.	1	.	1	1	.	.	3	.	4	.	0	+	3	.	4	.	4	.
'97:02	.	.	.	1	.	.	.	.	.	3	.	4	.	1	+	4	.	5	.	5	.
'97:03	.	.	.	1	.	.	.	.	.	3	.	4	.	1	+	4	.	5	.	5	.
'97:04	.	.	.	1	.	.	.	.	.	3	.	4	.	1	+	4	.	5	.	5	.
'97:05	.	.	.	1	.	.	.	.	.	3	.	4	.	1	.	4	.	5	.	5	.

APPENDIX II. Confirmed Prediction of the Last Rise of Unemployment in the USA

Here we report the first result of the experiment in verification of the prediction algorithm suggested in this paper. Prediction of a *FAU* for the USA in the year 2000 is described above in the Section 8 of the Discussion. Fig. A1 compares this prediction with actual monthly unemployment rates for the U.S. civilian labor force given in BLS (2001). We see that the rise of unemployment did start in July 2000, as shown by a local minimum of the smoothed unemployment rate. This moment is within the period of alarm, February-November 2000.

Numerous other warnings of a coming rise of unemployment in the USA did appear during the first months of 2000, including in newspapers. The particular feature of prediction discussed here is that our formal and unambiguous algorithm obtained it. Also, it indicates a specific time interval when the unemployment will start to rise and the minimal rate of this rise. Obviously, while this confirmation is encouraging, many more and much longer experiments are necessary to validate our algorithm.

References

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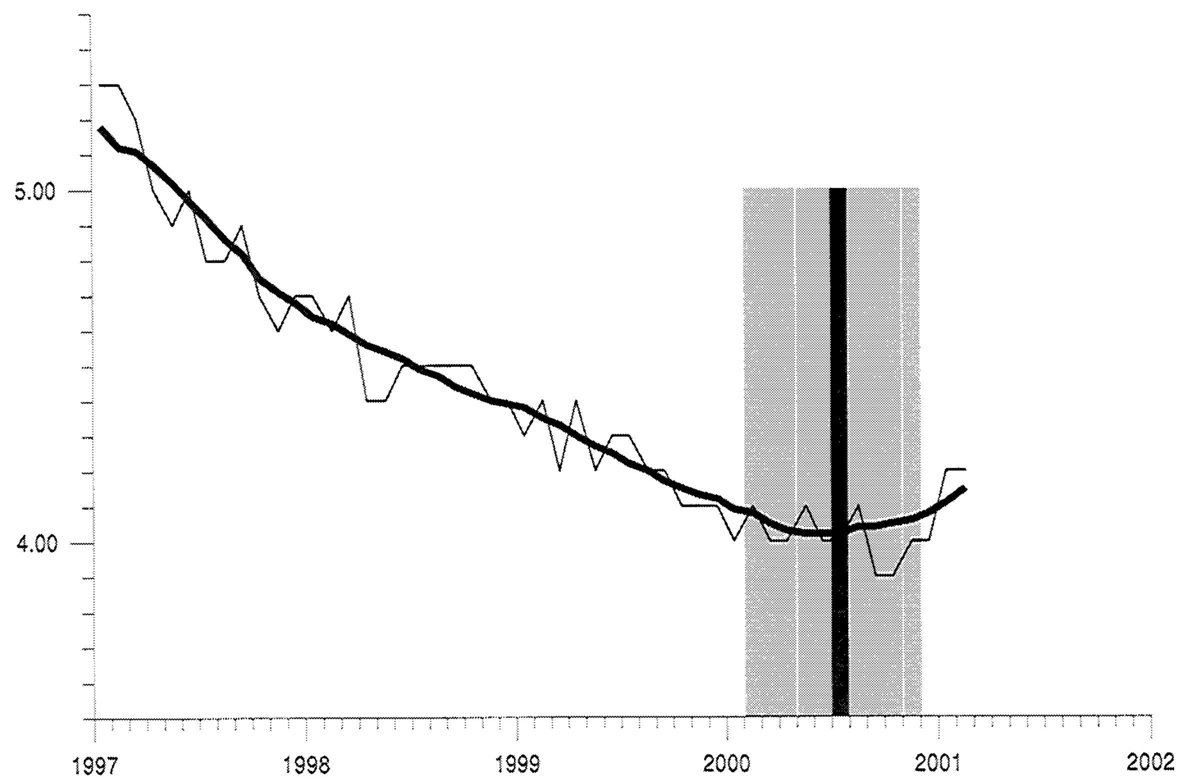

Figure A1 Unemployment rate in the U.S., 1997-2001: original monthly data (thin curve) and the rate with seasonal variations smoothed out (thick curve). The gray bar shows the alarm period, the black bar – start of the unemployment rise.