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Pattern of Macroeconomic Indicators Preceding the End of an American Economic Recession

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Abstract

This study concerns the fields of economics and the dynamics of complex systems, specifically the process of recovery of American economy from recession. We identify a robust pattern of six macroeconomic indicators that appears within 6 months before the end of each American recession since 1960 and at no other time during these recessions. Its definition is formal and reproducible; as a precursor to the incipient recovery it is corroborated by sensitivity analysis (i.e. variation of its adjustable parameters) and application to out-of-sample data; noteworthy, it emerged before the end of the 2001 recession, which was not being considered while its definition developed. That pattern identified here appears through the whole time considered despite extraordinary changes in the economy. This reflects a well-known general feature of complex systems: they exhibit regular collective behavior patterns, transcending the complexity. Like many other complexity studies, identification of such patterns requires a robust holistic analysis; accordingly we used here a methodology combining pattern recognition of infrequent events and techniques developed in non-linear dynamics. This methodology inherits some of the features of the diffusion indicators of classical business cycle analysis, reformulating these features in the robust pattern recognition language. That includes formulation of the prediction problem *per se*, given the time series up to a moment t, to recognize whether this moment belongs or not to the last Δ months of recession. In terms of time series analysis our targets of prediction are extreme point events, and prediction is a discrete sequence of alarms; this is different from more traditional (Kolmogoff-Wiener) formulation, where prediction targets and predictors are continuous functions. That methodology is complementary to and compatible with other approaches to predictive understanding of recessions. The present study is a natural continuation of our previous one, aimed at predicting the start of a recession. We find that precursory trends of financial indicators are opposite during transition to a recession and recovery from it. To the contrary, precursory trends of economic indicators happen to have the same direction (upward or downward) but are steeper during recovery.

Keywords: Economic recession, Precursory pattern, Pattern recognition of infrequent events, Macroeconomic indicators, Complex system, Critical phenomenon, Extreme events, Economic recovery, Economic activity, Hamming distance.

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1. Problem

We analyze macroeconomic indicators in order to find phenomena preceding the end of an American economic recession. We formulate a rule, which indicates a 6 months long time interval, during which recession will end. Our point of departure is our previous study in prediction of the start of a recession [1]. As in that study, we consider the problem as a pattern recognition one. Given is the dynamics of macroeconomic indicators within the recession period. An object of recognition is a moment t belonging to the recession period. The problem is to recognize whether or not it belongs to the time interval preceding the recession end, i.e. whether the recession will or will not end during the subsequent time interval $(t, t + \tau)$.

The methodology of this study combines the pattern recognition of infrequent events (e.g., [2–4]) with techniques developed in non-linear dynamics and mathematical statistics [5–12]. This methodology is oriented to the study of rare phenomena of highly complex origin. Its socio-economic applications include prediction of the outcome of American elections [13, 14], economic recessions in the U.S. [1], homicide surges in megacities [15], unemployment surges in Western Europe and the U.S. [16]. Other, also successful, applications of that methodology concern prediction of earthquakes [5] and volcanic eruptions [17], correlation between geophysical fields [18, 19], geological prospecting [20], medical diagnosis [21], etc. That methodology is complementary to and compatible with other approaches to predictive understanding of recessions (see Section 8).

The first application of the algorithm to out of sample data (not used in its development) is successful: it indicated that the last recession, that started in April 2001, would end between July and December 2001; as established by the National Bureau of Economic Research (NBER) in 2003 that the recession indeed ended in November 2001.

2. Data

We consider the time period from 1960:01 to 2002:04, when seven recessions did occur according to the NBER [22]; they are listed in Table 1. We analyze the time series, consisting of monthly values of the following leading macroeconomic indicators (mnemonics in bold are the same as in the data sources).

IP Industrial Production, total: indicator of real (constant dollars, dimensionless) output in the entire economy. This represents mainly manufacturing because of the difficulties in measuring the quantity of output in services (services include travel agents, banking, etc.). At the beginning of this study we used, as in [1], the Stock-Watson indicator of overall monthly economic activity (**XCI**) defined in Stock and Watson [23]. But at the present time this indicator is not published and we have replaced **XCI** by **IP** in this study and in the algorithm for prediction of recessions as well. Our

Table 1: American Economic Recessions, 1960-2003. Peak is the last month before a recession, and trough is the last month of a recession (a recession ends in this month).

#	Peaks	Troughs
1	1960:04	1961:02
2	1969:12	1970:11
3	1973:11	1975:03
4	1980:01	1980:07
5	1981:07	1982:11
6	1990:07	1991:03
7	2001:03	2001:11

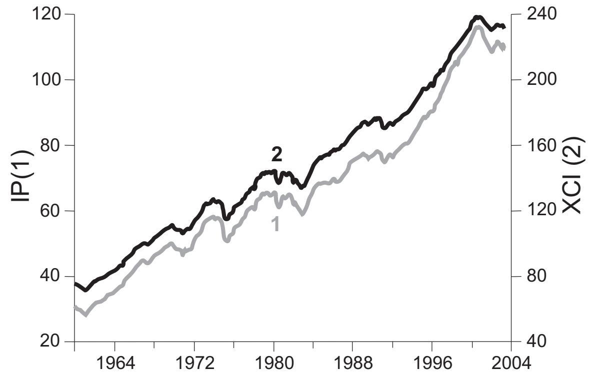

Fig. 1: Indicators **IP** (1) and **XCI** (2).

analysis shows that in both cases the results are not sensible in this replacement. It is explained by the fact that the indicator **XCI** is calculated mainly on the basis of **IP** that is illustrated by their plots given in Fig. 1.

LHELL. Indicator of help wanted advertising. This is put together by a private publishing company that measures the amount of job advertising (column-inches) in a number of major newspapers.

LUINC. Average weekly number of people claiming unemployment insurance.

INVMTQ. Total inventories in manufacturing and trade, in real dollars that includes intermediate inventories (for example held by manufacturers, ready to be sent to retailers) and final goods inventories (goods on shelves in stores).

FYGM3. Interest rate on 90-day U.S. treasury bills at an annual rate (in percent).

G10FF. Difference between interest rate on 10-year U.S. Treasury bonds, and federal funds interest rate, on an annual basis, a measure of the steepness of the yield curve.

The first four indicators concern the economy, the two others concern the financial market.

3. Precursory Changes of Individual Indicators

As in [1] we will use for prediction the values of the indicator **G10FF**; trends of the indicators **LHELL** and**LUINC**; and deviations from the long-term trend of the indicators **IP**, **INVMTQ**, and **FYGM3**.

Time periods. At the time of our study the trough for the last recession had not been yet established by the **NBER** and we used the data concerning only the first 6 recessions. Thus the following 6 periods were considered (for each recession a month before it (the peak) and its last month (the trough) are included).

$W_1 : 1960 : 04 - 1961 : 02$ (11 months);
$W_2 : 1969 : 12 - 1970 : 11$ (12 months);
$W_3 : 1973 : 11 - 1975 : 03$ (17 months);
$W_4 : 1980 : 01 - 1980 : 07$ (7 months);
$W_5 : 1981 : 07 - 1982 : 11$ (17 months);
$W_6 : 1990 : 07 - 1991 : 03$ (9 months)

The total duration of these periods $W = W_1 \cup W_2 \cup W_3 \cup W_4 \cup W_5 \cup W_6$ is 73 months. The last recession is considered separately, in Section 6.

The trends of the indicators and deviations from the long-term trend of the indicators are defined as follows.

Notations. We denote $W^f(l/q, p)$ the local linear least-squares regression of indicator $f(m)$ within the time window (q, p):

Table 2: Trends and thresholds.

Function $F(m)$	Precursory values	Q, %	Threshold $T^F(Q)$	"Predictive potential" [a]
IPR	low	75.0	-3.71	67
INVR	low	50.0	6.50	20
G10FF	high	33.3	0.82	67
LHK5	low	75.0	-29.71	45
LUK10	high	50.0	112.15	70
FYG3R	low	50.0	-0.64	20

a Difference $P_e - P_b$ where P_e is percent of months with "precursory" value of a function in a set consisting of the last four months of each recessions; P_b is percent of such months in a whole set W with the last six months of each recession eliminated.

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

Here the time is counted in months.

We approximate the trend of indicator $f(m)$ by a function $K^f(m/s) = K^f(m-s,m)$ i.e. by regression coefficients $K^f(m-s,m)$ that are defined as in (1) in a time window of s months long, $(m-s,m)$. The value of $K^f(m/s)$ may be used for determination of a precursory pattern since it is attributed to the *end* of the time window where it is determined; accordingly it does *not* depend on information on the future (after month m).

The deviation of indicator $f(m)$ from its long-term extrapolation is depicted by the function

$$R^f(m) = f(m) - W^f(m/j, m-1). \tag{2}$$

Here regression $W^f(m/j, m-1)$ is determined within a time window $(j, m-1)$, j being the first month after the end of the previous recession (the trough). An exception is the first recession for which j is the first month of the time period considered, 1960:01 (since the previous recession ends before this period).

The following six functions are used to determine the precursory pattern (lower row indicates abbreviations):

$R^{\mathbf{IP}}(m)$	$R^{\mathbf{INVMTQ}}(m)$	**G10FF**(m)	$K^{\mathbf{LHELL}}(m/5)$	$K^{\mathbf{LUINC}}(m/10)$	$R^{\mathbf{FYGM3}}(m)$
IPR	**INVR**	**G10FF**	**LHK5**	**LUK10**	**FYG3R**

Discretization. Analyzing the histograms of the above six functions during the recession periods we have an impression that large values of G10FF and LUK10 and small values of other functions occur more frequently, as termination of a recession approaches. To check whether this impression is correct, we give a robust quantitative definition of these changes. Following the procedure of the pattern recognition algorithm, called Hamming distance [5, 13, 24], we identify the values of each function $F(m)$ on the lowest level of resolution, 1 or 0, distinguishing only the values above and below a threshold $T^F(Q)$; here F is one of the functions considered. This threshold is defined as a percentile of a level Q, that is, by the condition that $F(m)$ exceeds $T^F(Q)$ during $Q\%$ of the months considered. Analyzing behavior of each function, we determined the values of Q and $T^F(Q)$ indicated in Table 2.

The last column of Table 2 presents for each function its precursory potential - difference $P_e - P_b$ where P_e is percent of months with precursory value of a function in a set consisting of the last four months of each recessions; P_b is percent of such months in a whole set W with the last six

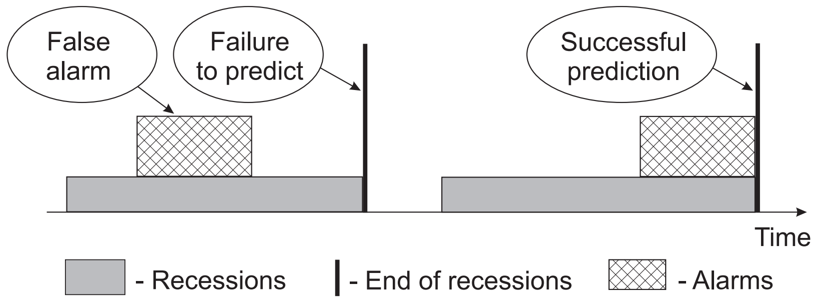

Fig. 2: Outcomes of predictions.

months of each recession eliminated. Looking at these data one can conclude that some indicators (e.g., **LUK10**) may be used individually for determination of the precursory pattern. However our experience shows that using several indicators makes the result more reliable.

With the thresholds given in Table 2 the situation during the recession is robustly described relevant to its proximity to a recession's end. This description is reduced to a monthly time series of a binary vector with 6 components. For convenience, we give the same code, "1" to the "precursory" trend of each function, regardless of whether it is above or below the threshold. Accordingly, code "1" is given to the values $F(m) > T^F(Q)$ for the functions **G10FF** and **LUK10**, and to the values $F(m) \leq T^F(Q)$ for the four other functions. Other values receive code "0".

The time series of functions, thus transformed, are given in Table 3. It shows the monthly vectors through the whole time period considered (W set).

4. Collective Behavior of Indicators: the Precursory Pattern

Here we explore how the collective behavior of indicators considered is changing as the end of a recession approaches (it is defined, as the first month after the trough indicated in Table 1).

The goal. We look for the precursory pattern indicating that a recession will end within a time interval a few months long after this pattern appears. Continuous intervals of this kind are called "larms". Possible outcomes of prediction based on this pattern are illustrated in Fig. 2. The probabilistic nature of prediction is reflected in probabilities of the errors of each kind and in the percent of the time occupied by the alarms. This formulation of the prediction problem is discussed in [25]; it was applied in [1] for predicting of the start of a recession.

Algorithm. Precursory pattern was defined by the "Hamming distance" algorithm described in [5, 13, 24] and refs. therein. In the previous section the monthly description of situation during a recession is reduced to a binary vector with 6 components. Each component has been defined in such a way, that (if our hypothesis is correct) the values "1" would became more frequent when the end of a recession is approaching. Accordingly, the "ideal" situation prior to the end of a recession, when all indicators are precursory, is the vector $(1, 1, 1, 1, 1, 1)$, which is called the "kernel". Let Δ be the number of zeros in a code of a month its Hamming distance from the kernel. We shall see next, whether the approach of the end of a recession may be recognized by the small values of Δ. *A priori* this is not clear, despite the way the zeros are defined; for example, precursory changes of the functions may appear not simultaneously, even if the above hypothesis is correct.

Table 3 shows that the end of each recession is preceded by a continuous group of months with $\Delta \leq 3$; they are marked by "+" in Table 3. This suggests the following algorithm: *the precursory pattern appears if for three consecutive months* $\Delta \leq 3$ *and the recession end is expected during an interval of three months long after displaying this pattern*. The alarms (continuous intervals of this kind) obtained by this algorithm for the recessions considered are shown in Fig. 3. The end of

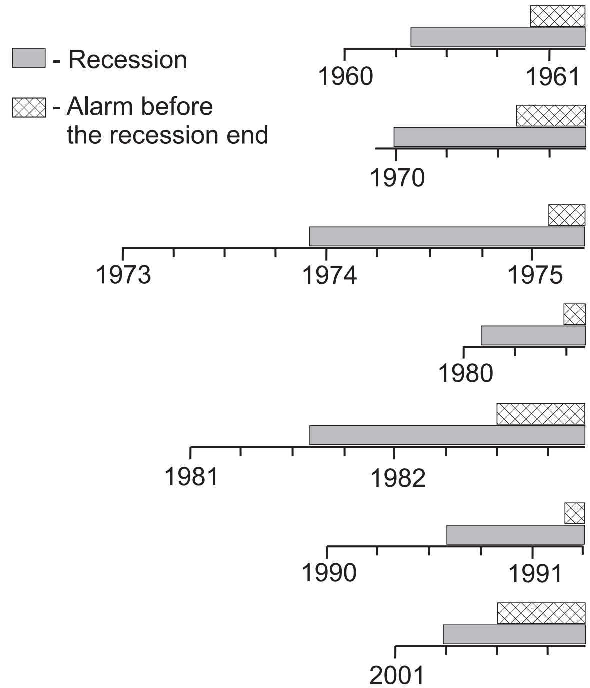

Fig. 3: Results of application of the algorithm.

each of the 6 recessions is preceded by an alarm and there are no false alarms. The duration of an alarm inside each recession is given in Table 4. The total duration of alarms in all 6 recessions is 16 months, which is 22% of total duration of the set W (73 months).

The duration of an alarm does not exceed 5 months; this means that the precursory pattern appears during the last 6 months of each recession. Let us estimate the probability P to obtain such result by chance, when the pattern appears independently on when recession ends, at a random moment uniformly distributed over the recession period. Taking into account that, accordingly to its definition, the precursory pattern may not appear during the first two months of a recession we obtain

$$P = \frac{6}{9} \times \frac{6}{10} \times \frac{6}{15} \times 1 \times \frac{6}{15} \times \frac{6}{7} = 0.055 \tag{3}$$

Here denominators are durations of a recession (Table 1) reduced by 2. The factor corresponding to the fourth recession is 1 because it is so short that the alarm for its end may not be longer than 5 moths. The probability is encouragingly low, although additional out-of-sample tests are necessary to establish statistical significance [26].

5. Sensitivity Analysis

The prediction described above (Table 4) involves a retrospective analysis, with a certain freedom in the ad hoc choice of indicators and of adjustable numerical parameters. We have explored the stability of these predictions, repeating them with various indicators and parameters and comparing the ensuing alarms.

Excluding of indicators in turn. In this experiment we study how the prediction changes if one of the indicators is removed from consideration. For that purpose we remove in turn each of 6 indicators used in the prediction algorithm. Taking into account that in this case the length of binary codes of months reduces to 5 we change the condition $\Delta \leq 3$ in the algorithm formulated above by the condition $\Delta \leq 2$. The results of this experiment are given in Table 5. Note that one can obtain these results from Table 3. The experiment shows stability of the prediction results to excluding of indicators. Only for the first recession (1960-1961) its end is failure-to-predict when the indicator **INVMTQ**, or **G10FF**, or **LUINC** is removed. In other cases there are only some variations in durations of alarms. The greatest number of differences is in the case where the indicator **LUINC** is removed that is in accordance with the largest "precursory potential" of this indicator (see Table 2).

Prediction on the basis of individual using of indicators. Table 3 gives possibility to know what results would be obtained if indicators are used individually in the prediction algorithm. In this case the length of binary codes of months is 1 and the condition $\Delta \leq 3$ in the algorithm is replaced by $\Delta = 0$. The results of the individual using of indicators are given in Table 6. One can see that the indicators used individually do not ensure good quality of prediction. Only the use of **LUINC** does not results in false alarms or failure-to-predict but the alarm before the end of the fifth recession (1981-1982) is too long.

Variation of the set of months used in determination of thresholds $T^F(Q)$. The thresholds of discretization $T^F(Q)$ given in Table 2 have been determined by using a set $W = W_1 \cup W_2 \cup W_3 \cup W_4 \cup W_5 \cup W_6$ (a training set) containing the months belonging to 6 recessions under consideration. To check the sensitivity of the result to composition of a training set we compute the thresholds $T^F(Q)$ excluding in turn subsets $W_i (i = 1, 2, , 6)$ from the training set W. The results of prediction with different values of $T^F(Q)$ are given in Table 7. These results show that the prediction is stable with respect to varying the set of months used in determination of the discretization thresholds. There is only one failure-to-predict case (the end of the second recession when the months of the third recession are excluded from the training set) and there are no false alarms.

Variation of parameter s ***in functions*** $K^{\mathbf{LHELL}}(m/s)$ ***and*** $K^{\mathbf{LUINC}}(m/s)$. The values of parameter s in functions $K^{\mathbf{LHELL}}(m/s)$ and $K^{\mathbf{LUINC}}(m/s)$ have been selected to be the same as those used in the algorithm for prediction of the start of a recession [1] ($s = 5$ and $s = 10$ respectively). These values are changed to see how the prediction results depend on them. When function $K^{\mathbf{LHELL}}(m/s)$ is calculated with $s = 4$ and $s = 6$ the alarms obtained by the algorithm are exactly the same as those given in Table 4. When the function $K^{\mathbf{LUINC}}(m/s)$ is calculated with $s = 8$ there is only one difference in respect of Table 4: the first month of the alarm for the end of the first recession is 1960:11. If $s = 8$ for this function then there are two differences: the first month of the alarm for the end of the first recession is 1961:03 and the first month of the alarm for the end of the third recession is 1975:01. Therefore, the prediction is stable with respect to varying the value of s.

6. The End of the Last Recession

The last recession (#7 in Table 1; Fig. 3) starts in April 2001. According to the score Δ in Table 3 the alarm for the end of that recession starts in July 2001. In 2003 the NBER made a conclusion that the recession did end in November 2001, so that alarm lasted 5 months, - the duration already observed before (Table 4).

7. Transition to a Recession and Recovery from It

Study [1] captures the approach of recession by the same indicators that are used here to capture recovery from it. Behavior of the indicators during these opposite processes is compared in Table 8 and Fig. 4. We see reverse trends of "financial" indicators; and, contrary to what might be expected, the trends of economic indicators have the same direction, but are steeper during recovery.

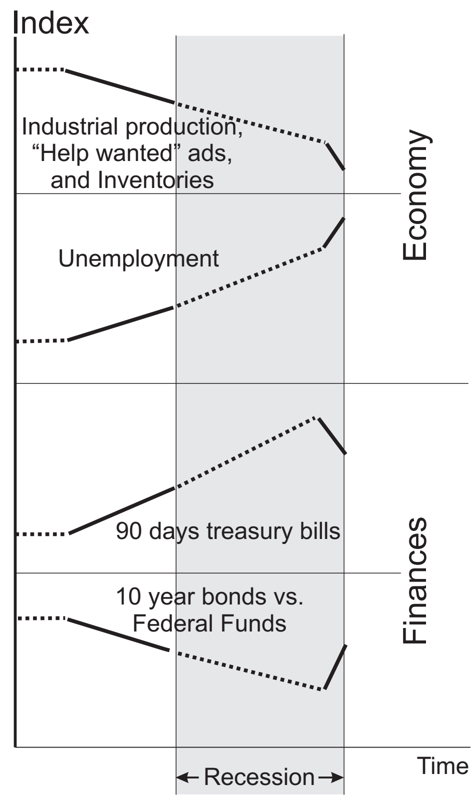

Fig. 4: Premonitory changes of indicators before the start of a recession and before its end.

8. Discussion

1. We have identified a robust pattern of macroeconomic indicators that, since 1960, precedes the ends of recessions with the lead-time one to five months. Seven recessions occurred during this period. This pattern has emerged prior to the end of each recession, and at no other time during these recessions. This suggests an algorithm for predicting the end of a recession. Such an algorithm, if further validated, would enhance predictive understanding of recessions, providing heuristic constraints for their theoretical modeling and, on the applied side, enhances our capability to predict economic recovery.

If our conclusions are correct, that pattern is equally applicable through the whole time period considered (the last third of the twentieth century) despite extraordinary changes in the economy. This reflects a well known feature of complex systems: regular collective behavior patterns, transcending the systems complexity (immense as it may be). Identification of such patterns, like the study of complexity in general, requres a robust holistic analysis a "coarse general overwiew" [6].

2. The methodology used here integrates *pattern recognition of infrequent events* [2–4] with techniques developed in *non-linear dynamics* and *mathematical statistics* [5–12]; it inherits some of the features of the diffusion indicators of classical business cycle analysis [27–29], reformulating these features in the robust language of pattern recognition. More detailed comments on that connection are given in [1]. Pattern recognition of infrequent events is an efficient tool for fairly rigorous test of not yet validated hypotheses [18–20]; it is noteworthy in that context that it was first developed for modeling animal behavior [4, 30].

3. *Scheme of the data analysis "from indicators to alarms" looks deceptively simple* while its actual implementation is not. Consecutive steps of data analysis include: (i) Definition of prediction targets (ii). Selection of indicators (Section 2). (iii) Representation of indicators by their integral characteristics (Section 3). (iv) Identification of precursory changes of each of the characteristics (Section 4). (v) Identification of precursory patterns and formulation of prediction algorithm. (vi) Testing and validation of algorithm. (vii) Using prediction for decision-making concerning disaster management. (We did consider here neither the first step, since recession ends had been known *a priori*; nor the last step, which is beyond the scope of our study). Steps (i) (vi) requires in different proportions an expertise in all the fields mentioned above. The last step might not require pattern recognition, however it does entail also the theory of optimal control and game theory. Specific techniques involved are described in publications referred to above.

4. The behavior of the indicators before the start and the end of a recession (Section 7, Fig. 4) suggests the following sequence. (i) Indicators considered signal that recession is approaching. (ii) As the recovery approaches the economic and financial indicators behave differently compared with a pre-recession period. Trends of the economic indicators do not reverse but became steeper, as if the state of economy worsens; a recession ends when the lowest point (trough) is reached. Financial indicators, on the contrary, reverse their trends, as the expectations become more "optimistic".

5. According to **NBER** the last recession ended in November 2001; this was established only much later, in 2003. That illustrates an interesting aspect of our advance prediction. If our conclusions are correct, our algorithm indicates a time interval when a recession will end. However testing the algorithm one might not know when a recession actually ended as that is decided later by the **NBER** after the comprehensive analysis. Not knowing whether the recession is still continuing we would keep using the score Δ (applicable only within recessions) and thus might extend the alarm far into the inter-recession period. We suggest a heuristic way to overcome this difficulty: since previous alarms lasted not more than 5 months (2.7 months on average) we can tentatively assume that an alarm will not last for more than, say, 6 months and put a 6 months limit for the duration of an alarm. An interesting question is whether the findings of that study (e.g. shown in Fig. 4) might help to recognize that a recession has ended.

6. Stability of the algorithm is corroborated by the fact that it gives identical results with indicators **XCI** or **IP**, which are based on different albeit correlated aspects of the level of economic activity.

7. Our results set up a base for experiment in advance prediction of the end of recessions. The advance prediction will be implemented when the next economic recession will occur. At the moment of completing this paper there is no recession declared by the NBER and the algorithm [1] does not predict a recession. At the same time another algorithm [32] based on the change of the trend of the industrial production index indicates an alarm for a recession in the U.S. The alarm starts in 2008:06 for one year. Note that this paper was written before the current financial and economic developments and therefore they are not considered here.

8. On the theoretical side our findings provide heuristic constraints for macroeconomic models. Besides econometric models, as reviewed in [31], this refers also to models of non-linear systems such as developed in statistical mechanics [7–12].

9. The methodology used here is complementary to and compatible with other approaches to predictive understanding of recessions. It was previously used to analyze the same indicators for predicting the *start* of recession [1] and the present study confirms the conclusion of the previous one: *"The problem (prediction of recessions) requires fitting non-linear, high-dimensional models to a handful of observations generated by a possibly non-stationary economic environment. It is striking that these models, in which the information in the data is reduced to binary indicators, has predictive content comparable to or, in many cases, better than that of more conventional models."*

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Table 3: Binary vectors and values of Δ. Each subset corresponds to a recession (Table 1).

		Binary vector							
#	Month	IPR	INVR	G10FF	LHK5	LUK10	FYG3R	Δ	
Subset W_1									
1	1960:04	0	1	0	0	0	1	4	
2	1960:05	0	1	0	0	0	1	4	
3	1960:06	0	1	1	0	0	1	3	+
4	1960:07	0	1	0	0	0	1	4	
5	1960:08	0	1	0	0	0	1	4	
6	1960:09	0	1	1	0	0	1	3	+
7	1960:10	0	1	1	0	1	1	2	+
8	1960:11	0	1	1	0	1	0	3	+
9	1960:12	0	1	1	0	1	0	3	+
10	1961:01	0	1	1	0	1	0	3	+
11	1961:02	0	1	1	0	1	0	3	+
Subset W_2									
12	1969:12	0	0	0	0	0	0	6	
13	1970:01	0	1	0	0	0	0	5	
14	1970:02	0	1	0	0	0	0	5	
15	1970:03	0	0	0	0	0	0	6	
16	1970:04	0	0	0	0	1	0	5	
17	1970:05	0	1	0	1	1	0	3	+
18	1970:06	1	1	0	0	1	0	3	+
19	1970:07	1	1	0	1	1	0	2	+
20	1970:08	1	1	1	0	1	0	2	+
21	1970:09	1	1	1	0	1	0	2	+
22	1970:10	1	1	1	0	0	1	2	+
23	1970:11	1	1	1	0	0	1	2	+
Subset W_3									
24	1973:11	0	0	0	0	0	0	6	
25	1973:12	0	0	0	0	0	0	6	
26	1974:01	0	0	0	0	0	0	6	
27	1974:02	0	0	0	0	0	0	6	
28	1974:03	0	0	0	0	0	0	6	
29	1974:04	0	0	0	0	0	0	6	
30	1974:05	0	0	0	0	0	0	6	
31	1974:06	0	0	0	0	0	0	6	
32	1974:07	0	0	0	0	0	0	5	
33	1974:08	0	0	0	0	0	0	6	
34	1974:09	0	0	0	0	0	0	6	
35	1974:10	0	0	0	1	0	1	4	
36	1974:11	1	0	0	1	1	1	2	+
37	1974:12	1	0	0	1	1	1	2	+
38	1975:01	1	0	0	1	1	1	2	+
39	1975:02	1	0	1	1	1	1	1	+
40	1975:03	1	0	1	1	1	1	1	+
Subset W_3									
41	1980:01	0	0	0	0	0	0	6	
42	1980:02	0	0	0	0	0	0	6	
43	1980:03	0	0	0	1	0	0	5	
44	1980:04	1	0	0	1	1	0	3	+
45	1980:05	1	0	0	1	1	1	2	+
46	1980:06	1	0	0	1	1	1	2	+
47	1980:07	1	0	1	1	1	1	1	+
Subset W_5									
48	1981:07	0	1	0	0	0	1	4	
49	1981:08	0	1	0	0	0	1	4	
50	1981:09	0	1	0	0	0	1	4	
51	1981:10	0	1	0	0	0	1	4	
52	1981:11	0	1	0	0	0	1	4	
53	1981:12	0	1	1	1	1	1	1	+
54	1982:01	0	0	1	0	1	1	3	+
55	1982:02	0	0	0	0	1	1	4	
56	1982:03	0	0	0	0	1	1	4	
57	1982:04	0	1	0	0	1	1	3	+
58	1982:05	0	1	0	0	1	1	3	+
59	1982:06	0	1	0	0	1	1	3	+
60	1982:07	0	1	1	0	1	1	2	+
61	1982:08	0	1	1	0	1	1	2	+
62	1982:09	0	1	1	0	1	1	2	+
63	1982:10	0	1	1	0	1	1	2	+
64	1982:11	0	1	1	0	1	1	2	+
Subset W_6									
65	1990:07	0	0	0	0	0	0	6	
66	1990:08	0	0	0	0	0	0	6	
67	1990:09	0	0	0	0	0	0	6	
68	1990:10	0	0	0	0	0	0	6	
69	1990:11	0	0	0	1	0	0	5	
70	1990:12	1	1	0	1	1	0	2	+
71	1991:01	1	0	1	1	1	0	2	+
72	1991:02	1	1	1	1	1	1	0	+
73	1991:03	1	1	1	1	1	1	0	+
The last recession									
74	2001:03	1	0	0	0	0	1	4	
75	2001:04	1	1	0	1	1	1	1	+
76	2001:05	1	1	1	1	1	1	0	+
77	2001:06	1	1	1	1	1	1	0	+
78	2001:07	1	1	1	1	1	1	0	+
79	2001:08	1	1	1	1	1	1	0	+
80	2001:09	1	1	1	0	0	1	2	+
81	2001:10	1	1	1	1	1	1	0	+
82	2001:11	1	1	1	1	1	1	0	+

Table 4: Alarms before the ends of the recessions

Recession	Trough	The first month of an alarm and its duration (in months) before the recession end [a]
1	1961:02	1960:12, 3
2	1970:11	1970:08, 4
3	1975:03	1975:02, 2
4	1980:07	1980:07, 1
5	1982:11	1982:07, 5
6	1991:03	1991:03, 1

a Recessions are numbered as in Table 1.

Table 5: Changing of the alarms given in Table 4 when the indicators are removed.

Recession	Indicators removed and the first month of alarms obtained and its duration (in months) before the recession end.[a]					
	IP	**INVMTQ**	**G10FF**	**LHELL**	**LUINC**	**FYGM3**
1	-	No alarm	No alarm	-	No alarm	1961:01, 2
2	1970:10, 2	1970:10, 2	-	1970:09, 3	1970:10, 2	-
3	-	-	-	-	-	-
4	1980:08, 0	-	-	1980:08, 0	1980:08, 0	-
5	-	1982:10, 2	-	-	1982:10, 2	1982:10, 2
6	-	-	-	-	-	-

a "-" indicates cases where there is no difference with the result given in Table 4. Recessions are numbered as in Table 1.

Table 6: Changing of the alarms given in Table 1 when the indicators are used individually

Recession	Indicators used individually and the first month of alarms obtained and its duration (in months) before the recession end. [a]					
	IP	**INVMTQ**	**G10FF**	**LHELL**	**LUINC**	**FYGM3**
1	No alarm	1960:07, 8	-	No alarm	1961:01, 2	1960:07, 7 (False alarm)
2	1970:09, 3	-	1970:11, 1	No alarm	1970:07, 5	No alarm
3	-	No alarm	No alarm	1975:01, 3	-	1975:01, 3
4	-	No alarm	No alarm	1980:06, 2	-	1980:08, 0
5	No alarm	1981:10, 6 (False alarm) 1982:07, 5	1982:10, 2	No alarm	1982:03, 9	1981:10, 14
6	-	No alarm	1991:04, 0	1991:02, 2	-	No alarm

a "-" indicates cases where there is no difference with the result given in Table 4. Recessions are numbered as in Table 1.

Table 7: Changing of the alarms given in Table 4 when different training sets are used in determination of the thresholds $T^F(Q)$

Recession	Training sets and the first month of alarms obtained and its duration (in months) before the recession end. [a]					
	W/W_1	W/W_2	W/W_3	W/W_4	W/W_5	W/W_6
1	1960:09, 6	1961:01, 2	1961:01, 2	-	1960:11, 2	1961:01, 2
2	1970:11, 1	1970:07, 5	No alarm	-	1970:10, 2	-
3	-	-	-	-	-	-
4	-	-	-	-	-	-
5	1982:06, 6	1982:06, 6	-	-	1982:06, 6	-
6	-	-	-	-	-	-

a "-" indicates cases where there is no difference with the result given in Table 4. Recessions are numbered as in Table 1.

Table 8: Precursory behavior of indicators

	Before the recession start after [1]		Before the recession end (Table 2)	
Function $F(l)$	Precursory values	Threshold $T^F(Q)$	Precursory values	Threshold $T^F(Q)$
IPR	low	-0.86	low	-3.71
INVR	low	8.85	low	6.50
G10FF	low	-1.38	high	0.82
LHK5	low	2.00	low	-29.71
LUK10	high	25.07	high	112.15
FYG3R	high	1.01	low	-0.64