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1 September 2011

Online at <https://mpra.ub.uni-muenchen.de/49226/>  
MPRA Paper No. 49226, posted 22 Aug 2013 09:14 UTC

**Empirical Evidence on the Predictability of Stock Market Cycles: the Behaviour  
of the Dow Jones Index Industrial Average in the Stock Market Crises of 1929,  
1987 and 2007.**

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2011 (September).

## **ABSTRACT.**

Based on a deterministic hypothesis, this paper aims to verify the regularity of the stock market cycles and, if this regularity is found, the ability to predict major stock market crises. Harmonic analysis, or Fourier series, is applied in order to, decomposing into sinusoids curves, find the constant periodicities hidden under the series of observed data. Starting from the industrial stock market data in the U.S., considering three periods of similar length of 165 months: 1919:01 to 1932:09, 1977:01 to 1999:09 and 1997:03 to 2010:11, I stand in the moment of maximum growth of the Dow Jones Industrial Average and I check if the most significant hidden periodicities allowed to predict the sharp drop in the index that was coming and the subsequent development. The evidence is inconclusive. A small number of theoretical cycles reasonably explain the stock market evolution. In terms of predictive power, in two cases there is this ability, while not in another. The conclusion reached indicates that, due to the regularity in the data, the application of the a deterministic hypothesis is reasonable. However, it is necessary to perform a deeper analysis of the data to be able to describe and predict major stock market cycles, including crises or large declines in stock market prices.

**KEYWORDS:** Stock Market , Periodogram, Business Cycles Prediction.

**JEL CODES:** C10, C22, E32, E37.

## 1. INTRODUCTION.

This work is based on two successive hypotheses.

Firstly, the stock market evolves according to a factual structure that can be explained with a determinist theory as a starting point, which will therefore allow prediction. In this sense and according to Nagel, I understand that a theory is determinist if its internal structure implies that the theoretical state of a system in a given moment, by inference determines a unique state of this system in any other given moment (Nagel, 1981, p 377).

However, at the moment we do not have a complete determinist theory regarding stock market value behaviour. I am basing this paper on the hypothesis that said theory should exist, thereby assuming that a market state determines a single group of values of variables in the following instance.

This hypothesis cannot be observed: it is not possible to empirically confirm the determinist character of economic agent behaviour. However, the alternative hypothesis of randomness can also not be observed. The only criteria applicable in order to decide between the two hypotheses is their productiveness.

Secondly, the stock market behaves cyclically as a consequence of its determinist character. The factors responsible mark a cyclical movement on the effects. Thus, its observed movements can split into fixed regular theoretical cycles through harmonic analysis. The hypothetical existence of a true determinist theory implies regular and cyclical behaviour.

The determinist hypothesis would be developed in a uni or multi-equational structural model where responsible factors explained the behaviour of the independent variables. But a complete theory on stock market behaviour that enables said model to be built does not exist. This is when harmonic analysis needs to be employed.

Consequently, using stock market share price data, sudden or intense crises can be predicted, among other occurrences. Predictions are made based on harmonic splitting. It is this second hypothesis that allows empirical contrasting. This was carried out for the Dow Jones Industrial Average in relation to the stock market crises of 1929, 1987 and 2007. The contrast that I have performed has the adjustment of a slightly longer than a three-year prediction (37 months) as its decision criteria. The adjustment is acceptable in two cases, but not in the other.

The predictions that allow harmonic analysis are not comparable with those that correspond to a random-walk model or Markov chain, in general. If we look at the simplest random-walk:  $X_t - X_{t-1} = \varepsilon_t$ , we see that the current value depends directly on the preceding one, without the series' past having any significance and without us being able to predict beyond the following value. The difference between the observed and the past value is random. Forecasting based on past  $X_t$  values makes no sense as they move randomly.

In my opinion, the correct or incorrect adjustment of a random-walk supposes an irrelevant question, since this model does not allow prediction, a vital factor of any scientific theory. As Popper (1963) affirms: "Confirmations should count only if they are the result of risky predictions" p. 36. But the random-walk is incapable of either long-distance predictions or predicting sudden changes in the evolution of the series (it always predicts that past evolution will continue to occur in the future). By contrast, harmonic analysis does allow long-distance predictions, which can contain radical changes in evolution. This forecast is the object of the current paper. If we managed to detect undulatory movements that predict the observed movements, factors that produce these hidden frequencies via oscillation could be investigated.

## 2. DATA.

The series of “Dow Jones Industrial Stock Average”<sup>1</sup> share prices is used, which is the most commonly used index to understand the evolution of the US stock market. It is an aggregate index calculated as a mean, without considering the relative importance of each of the companies that form it. Since May 1896, said index has gathered monthly values of the share prices of the thirty US industrial companies considered as the most important and representative of the different sectors. The figure of thirty was established in October 1928, with the number previously being less. This composition has gradually changed in order to reflect the relative importance of companies and the sectors which they belong to. For example, Cisco Systems replaced General Motors in June 2008. Consequently, it is a series of non-standardised data that has all the characteristic problems of the aggregate series' whose compositions are changeable. It is no surprise that periodicities of differing frequency occur during harmonic analysis. We therefore have a series with the problems characteristic of aggregation and heterogeneity.

In order to compare the ability to foresee stock market crises, periods of similar duration are used (165 months):

- Jan 1919 to Sep 1932, series DJIA1.
- Mar 1997 to Nov 2010, series DJIA2.
- Jan 1977 to Sep 1990, series DJIA3.

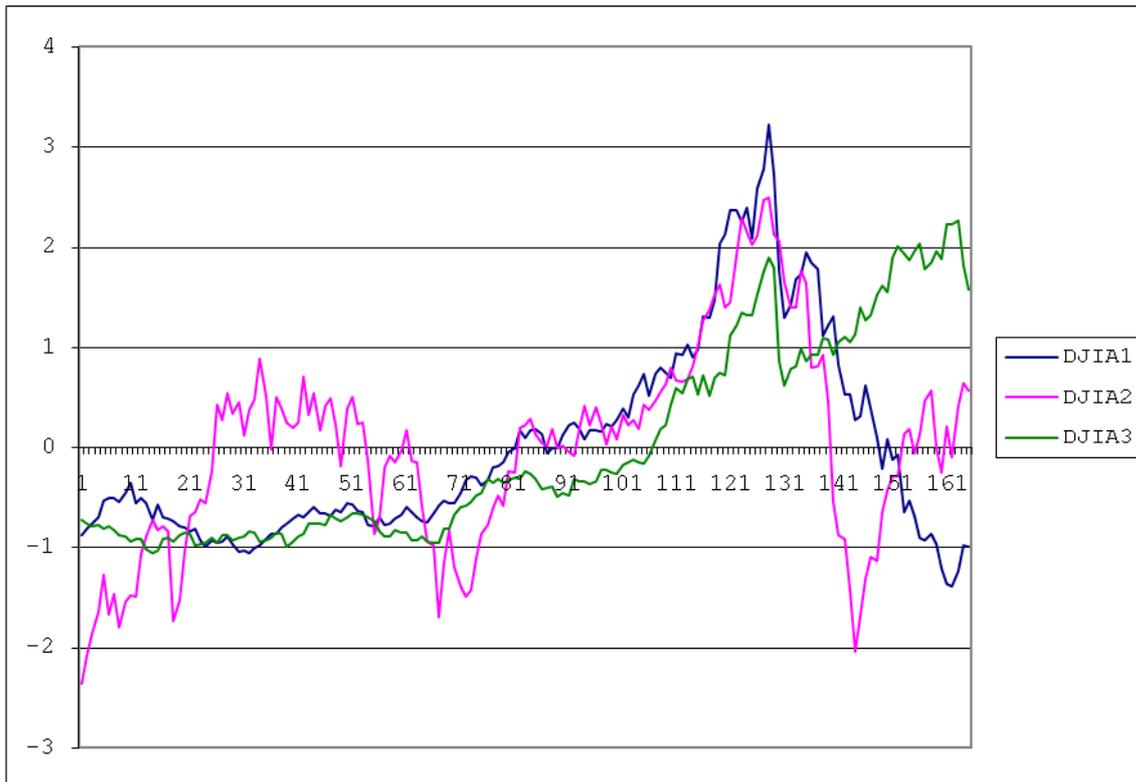
On one hand the period is affected by the First World War, which is an external factor that can alter the evolution of stock market share prices. And on the other hand, by the latest data available from 2010.

Hereinafter, I refer to Aug 1929, Aug 1987 and Oct 2007 (128 months), dates on which share prices reach their maximum. This is when I confirm whether the application of the harmonic analysis would enable the subsequent stock market crisis to be foreseen. Beforehand, the arithmetic mean is subtracted from the series of data in order to apply harmonic analysis upon a stationary series in the average. Lastly, this data is submitted to analysis.

The graphic representation of the series is the following.

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<sup>1</sup> Data source: Dow Jones, Wren Research.



A similar evolution is observed between DJIA1 and DJIA2, with the most relevant differences referring to the DJIA2 series being: a rising cycle around Dec 1999 and a recovery at the end of the period in question. DJIA3 closely follows the DJIA1 series, except at the end of the period, since this series maintains a sustained positive evolution that prevents the stock market crisis being as significant as the other two series. Series DJIA1 and DJIA2 contain a much deeper stock market crisis than DJIA3. The 1987 crisis was temporary.

### 3. METHODOLOGY.

The method applied is harmonic analysis. My assumptions, from the hypothesis already stated, are that regular movements exist (theoretical cycles or hidden periodicities) which comprise of the observed changes (empirical changes). Therefore, the price series of the main US industrial companies' quoted shares can be broken down into sinusoid functions, and a reduced number of these functions should explain and foresee their evolution with a correct approximation.

The Fourier method of breaking down into trigonometrical series is used in this paper, a method that separates into a discrete or discontinuous number of functions. The results are presented in a periodogram, where each frequential component makes a contribution to the series variance. Prior to this, harmonic analysis specifies that the trend of the original series is removed, as stated beforehand. The trend is a movement whose recurrence cannot be seen: cyclical movement is not observed, meaning it has a period equal to or greater than the temporal length of the series. However, the trend increases the contribution to the variance of the series of cycles with lesser frequency, thus masking the real cycles.

I remove the series mean in this case, since the data series does not present a clear increase and cannot be broken down into cycles in the long term. Nonetheless, the

doubt remains as to whether the perceived increases from the beginning of the series are cyclical or based on trend. This is the main hindrance when trying to predict correctly.

I do not transform the series into one of first differences, subtracting the previous  $X_{t-1}$  value from each  $X_t$  value, since this process reduces the variance and amplifies the seasonal and regular components, as stated by Bachiller (1992). The long-period, long-frequency cycles are lost with this transformation and can be, however, key to understanding the markets in the long and short term.

The series without trends receive a C at the end.

Considering the data definitively (128 months), the amplitudes are calculated for each period, and, consequently, the contribution of each sinusoid to the variance of the variable to be explained. Thereafter, when there are relevant theoretical cycles, the sum of the most significant theoretical cycles are checked to see if they correctly predict the subsequent movement of the curves from September 1929, August 1987 and October 2007, over 37 months (three years and one month).

Formally, if  $f(t)$  is a periodic function, the values it takes are repeated at regular intervals of the independent variable  $t$  [ $f(t) = f(t + k \cdot T)$ ]. Consequently, the function may be broken down into harmonics and it is possible to estimate it with a reduced number of them.

$$f(t) = A + a_1 \times \cos(t) + a_2 \times \cos(2t) + \dots + b_1 \times \sin(t) + b_2 \times \sin(2t) + \dots$$

The simplest periodic function is the harmonic function with amplitude  $R$ , frequency  $w$  and phase  $F$ :

$$f(t) = R \times \cos(w \times t + F)$$

Where the size of the series is  $T = 2\pi/w$ .

A compound oscillation is obtained through the addition of various harmonics, which can constitute a satisfactory approximation of the perceived economic phenomena, as stated by Alcaide et al. (1992). If  $Y_t$  is a trend free series of size  $T$ ,  $T$  coefficients and  $T/2$  harmonics may be estimated:

$$Y_t = a_0 + \sum_{p=1}^{\frac{T}{2}-1} (a_p \times \cos(p \times w_0 \times t) + b_p \times \sin(p \times w_0 \times t) + a_{T/2} \times \cos(\pi \times t))$$

Where  $p$  is the order of the harmonic and  $a_{T/2}$  is the coefficient corresponding to the highest frequency that we are able to estimate. By regression, the coefficients  $a_0$ ,  $a_p$ ,  $b_p$ , with the explanatory variables  $\cos(p \cdot w_0 \cdot t)$  and  $\sin(p \cdot w_0 \cdot t)$ , may be estimated.

The square of the amplitude for one period is:

$$R^2 = a_p^2 + b_p^2$$

A high amplitude value indicates that there is a significant cycle in the series for the estimated frequency.

#### 4. THE STATE OF THE QUESTION IN SCIENTIFIC LITERATURE.

The main discussion is centred on whether stock markets are predictable or not. Does knowledge of past evolution in changes of values allow for the future prediction of these price modifications?

Efficient market hypothesis postulates that knowing past evolution in no way aids the prediction of future share prices. If all information available is rapidly included in the formation of prices, these prices reflect the value of the agents, which, therefore, cannot predict the evolution of said prices better than anyone else. Any behavioural pattern in price increases would be spotted by the agents who would, in turn, nullify it.

Therefore, efficient market is understood as that in which all information available is taken into account by the agents which operate within it. If all information available is taken into account and all new information is offered without the ability to be predicted, and with no type of autocorrelation or order, this implies that market evolution is therefore going to be random. Random selection of a share portfolio produces the same results as selecting one after having tried to guess a pattern from past evolution.

Numerous studies have centred on the empirical confirmation of this efficient market hypothesis. As such, the hypothesis is not empirically demonstrable, therefore it is necessary to deduce another model that is. The efficient market hypothesis does not necessarily imply the random-walk model, but concerns the model that has most commonly been proposed. In effect, this model establishes that price changes do not depend on previous data.

Thereby, scientific literature considers that the efficient market hypothesis leads to the random-walk model. I have already considered the fundamental equation of this walk, which equals the difference between past and present values to white noise or the stochastic process. This model is equivalent to saying that the majority of people speculate because prices at period  $t+1$  will be the same as prices at period  $t$ .

The studies which have attempted to empirically confirm the correctness of the random-walk model are divided. Lo et al. (1988) and Chen (1996) ("From an empirical analysis, stock market movements are not pure random-walks" p.25) reject the correction of the random-walk model, since the price series of market share values is predictable: there is first-order autocorrelation in the data. Granger et al. (1963) signal that shares follow a random-walk in the short term, but have non-stochastic components in the long term.

By contrast, Malkiel (2003) supports the unpredictability of the stock markets. Fama (1970) reviews various studies that support the predictability of the stock market, based on the existence of a significantly non-zero autocorrelation, in order to conclude that these attacks on the empirical validity of the efficient market model are insufficient. "Many of the predictable patterns that have been discovered may simply be the result of data mining" p.23. Kendall (1953) already found that the growth series in share prices seems stochastic.

Besides, Fama (1970) recognises that the efficient market hypothesis, completely reflecting the prices and all the information available, is not an empirically demonstrable formulation. But the random-walk model is. In terms of past knowledge not contributing to knowing what will occur in the future, Fama finds that the evidence

in favour of the efficient market thesis is better than evidence to the contrary. The  $t+1$  value is independent of the  $t$  value. Fama (1965) affirms that the observable independence will never be perfect or complete, but that empirical confirmation is founded on a very small, observed dependence, which, in principle, does not exceed a fixed limit. The limit is based on the fact that no investor can use knowledge of the past to improve their investment, compared to an investor who speculated randomly. He concludes: "None of the tests in this section give evidence of any important dependence in the first differences of the logs of stock prices" (Fama, 1970, p. 87).

The problem lies in that the stochastic character of a series can only be defined negatively, as an absence of a systematic evolution pattern, without possible positive contrast (Houthakker, 1961, p 164). Randomness, as such, cannot be confirmed, it is only negatively demonstrable.

It would be pertinent to oppose the thinking based on efficient market analysis that promotes the random-walk model with a hypothesis that sets out the existence of determinist and cyclical movements in the economy, and, therefore, through company profits or other factors in the stock markets. This evolution is predictable. Alvarez et al. (2005) signal that an alternative exists based on the periodicity or existence of determinist regularities. Selvam (2006) affirms the existence of persistent cycles in the evolution of stock markets, from a spectral analysis, with a relevant period of approximately three to four years. Bachiller (1992), Granger (1963), Brooks (2006) are some examples of authors who find persistent and relevant long-term cyclical movements.

Granger (1966) considered that the use of spectral analysis cannot provide relevant economic results. In this respect, the difference between harmonic and spectral analysis is secondary: the first uses a series of discrete and non-continuous numbers, while the second uses a continuous series of numbers to estimate the contribution to the overall variance of each frequency or segment of frequencies. Granger's view was based on the fact that once the trend is removed from the vast majority of economic series, the same spectrum is obtained: the amplitude of the components decreases as the period reduces. In other words, the components of the smallest frequencies and longest temporal periods have greater importance in the contribution to the series' variance, and the longer the period the greater this relevance is. Component and period amplitude are reduced simultaneously. Add to this criticism the hypothesis of the trend not being able to be removed because it is entangled with the cycle: they are generated by the same factors.

These observations are debatable: that the greater part of the economic series are analysed in these types of frequencies remains to be proven, as well as the fact that this makes harmonic analysis futile. Would the fact that long-term movements were uniformly more important necessarily imply that analysis would be false and these movements merely an illusion? By contrast, it can be affirmed that cyclical movements differ from those affected by trend, responding to different responsible factors. The trend is a disturbance against the cycle that is a transitory movement.

## 5. RESULTS.

The periodograms of the series in question are displayed below: up to the values of the cosine and sine variables for those that reach an accumulated contribution to the variance of 99%.

SERIES DJIA1C	amplitudes			
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COSINES	COEFFICIENTS	SINES	COEFFICIENTS	Rp	Contribution to the variance	%	% accumulated
x11	45.4272	x21	-54.5234	70.9678212	0.534559	53.4559	53.455903
x12	20.7288	x22	-28.9599	35.6140275	0.134622	13.46216	66.918068
x13	18.3246	x23	-21.355	28.1394206	0.084043	8.404329	75.322396
x14	1.25901	x24	-18.5941	18.6366752	0.036865	3.686461	79.008857
x15	4.44389	x25	-17.3722	17.931578	0.034128	3.412791	82.421648
x16	4.29163	x26	-15.9296	16.497583	0.028888	2.888773	85.310421
x17	0.486097	x27	-14.0216	14.0300234	0.020892	2.089246	87.399667
x18	-0.0666589	x28	-11.8409	11.8410876	0.014882	1.488182	88.887848
x19	0.154805	x29	-10.1692	10.1703782	0.010979	1.09786	89.985708
x110	0.573039	x210	-7.24714	7.2697601	0.005609	0.560935	90.546644
x111	2.46488	x211	-4.96649	5.54451588	0.003263	0.326287	90.872931
x112	2.03854	x212	-7.98956	8.24552693	0.007216	0.721622	91.594552
x113	2.69679	x213	-3.84857	4.69937946	0.002344	0.234398	91.82895
x114	4.24145	x214	-4.38827	6.10301661	0.003953	0.395332	92.224282
x115	4.65825	x215	-4.53417	6.50061464	0.004485	0.44852	92.672802
x116	2.99057	x216	-4.01491	5.00629716	0.00266	0.266015	92.938817
x117	4.78459	x217	-5.20498	7.06994471	0.005305	0.530524	93.469341
x118	4.27683	x218	-5.54628	7.00374876	0.005206	0.520636	93.989976
x119	2.98634	x219	-5.16621	5.96723993	0.003779	0.377937	94.367913
x120	2.5812	x220	-3.77317	4.57158674	0.002218	0.221823	94.589736
x121	3.94301	x221	-4.61087	6.06691437	0.003907	0.390669	94.980405
x122	2.26015	x222	-5.33831	5.79705371	0.003567	0.356687	95.337092
x123	3.89719	x223	-3.54959	5.271402	0.002949	0.294934	95.632026
x124	2.74601	x224	-3.70677	4.61310251	0.002259	0.22587	95.857896
x125	3.6631	x225	-3.32511	4.94718689	0.002598	0.25977	96.117667
x126	2.43694	x226	-3.35577	4.14727246	0.001826	0.182557	96.300223
x127	2.89536	x227	-2.4969	3.82329951	0.001551	0.155149	96.455372
x128	2.70561	x228	-3.25237	4.2306307	0.0019	0.189969	96.645342
x129	2.00422	x229	-2.40523	3.13081925	0.00104	0.104037	96.749379
x130	2.70449	x230	-1.36223	3.02819034	0.000973	0.097328	96.846707
x131	2.81152	x231	-2.10813	3.51409402	0.001311	0.131069	96.977776
x132	3.6766	x232	-2.08747	4.227874	0.001897	0.189722	97.167497
x133	2.919	x233	-3.13431	4.28304333	0.001947	0.194705	97.362203
x134	1.96951	x234	-3.47268	3.9923021	0.001692	0.169169	97.531371
x135	1.7264	x235	-2.44077	2.98961789	0.000949	0.094865	97.626236
x136	1.95191	x236	-2.11473	2.87785261	0.000879	0.087904	97.71414
x137	1.74854	x237	-1.72496	2.456192	0.00064	0.064032	97.778172
x138	2.31202	x238	-1.89609	2.99008257	0.000949	0.094894	97.873066
x139	2.4793	x239	-2.16103	3.28891763	0.001148	0.11481	97.987876
x140	2.24311	x240	-2.2799	3.19835684	0.001086	0.108574	98.09645
x141	2.69035	x241	-1.03226	2.88158703	0.000881	0.088133	98.184583
x142	2.93913	x242	-0.315611	2.95602697	0.000927	0.092745	98.277327
x143	3.03342	x243	-1.38307	3.33384456	0.00118	0.117968	98.395295
x144	2.52246	x244	-1.09998	2.7518649	0.000804	0.080376	98.475671
x145	2.131	x245	-1.87915	2.8411909	0.000857	0.085679	98.56135
x146	1.83212	x246	-1.61991	2.44556172	0.000635	0.063479	98.624829
x147	1.38897	x247	-1.11731	1.78258781	0.000337	0.033727	98.658556
x148	1.56357	x248	-1.61274	2.24625944	0.000536	0.053554	98.71211
x149	1.02572	x249	-0.816994	1.31132784	0.000183	0.018251	98.730361

x150	2.62772	x250	-0.373035	2.65406622	0.000748	0.074765	98.805126
x151	2.98582	x251	0.292836	3.00014566	0.000955	0.095534	98.90066
x152	2.79809	x252	0.0159086	2.79813522	0.000831	0.083102	98.983762
x153	2.90653	x253	0.321122	2.92421545	0.000908	0.090759	99.074521
SERIES DJIA2C				amplitudes			
COSINE	COEFFICIENT	SINES	COEFFICIENT	Contribution to			
S			NT	the variance	%	% accumulated	
x11	388,586	x21	-361,503	530.738635	0.06434	6.433966	6.4339661
x12	-384,728	x22	-1192,45	1252.97751	0.358595	35.85947	42.29344
x13	453,261	x23	-627,792	774.317977	0.136948	13.69481	55.988251
x14	144,732	x24	-748,141	762.012013	0.13263	13.26298	69.251228
x15	39.1893	x25	-191,311	195.28364	0.008711	0.871062	70.12229
x16	65.5724	x26	-428,189	433.180747	0.04286	4.286034	74.408324
x17	-155,805	x27	-318,564	354.624055	0.028725	2.872458	77.280782
x18	185,164	x28	-397,838	438.81748	0.043983	4.398304	81.679086
x19	59.2859	x29	-232,234	239.681974	0.013122	1.312164	82.99125
x110	89.2932	x210	-214,021	231.90141	0.012284	1.228356	84.219606
x111	50,122	x211	-11.6241	51.4522554	0.000605	0.060468	84.280074
x112	33.9289	x212	-204,109	206.909773	0.009779	0.977866	85.25794
x113	-21.6006	x213	-106,516	108.684149	0.002698	0.269805	85.527745
x114	-58.7508	x214	-258.64	265.228781	0.016068	1.606788	87.134533
x115	113.56	x215	-155,895	192.870746	0.008497	0.84967	87.984203
x116	-66.1773	x216	-214,136	224.128672	0.011474	1.147393	89.131596
x117	69.3228	x217	-177,447	190.50745	0.00829	0.828975	89.96057
x118	43.6038	x218	-132,149	139.156924	0.004423	0.44231	90.402881
x119	80.8454	x219	-28.9903	85.8860652	0.001685	0.168486	90.571366
x120	100,849	x220	-60.5958	117.653609	0.003162	0.316175	90.887541
x121	-72.0658	x221	-87.2163	113.137803	0.002924	0.29237	91.179911
x122	125,606	x222	-134,504	184.033131	0.007736	0.773587	91.953499
x123	81.5302	x223	-99.9398	128.977274	0.0038	0.379965	92.333464
x124	153,234	x224	-123,828	197.012772	0.008866	0.886556	93.22002
x125	66,726	x225	-23.2411	70.6576804	0.00114	0.114034	93.334054
x126	75.6397	x226	-87.6282	115.758653	0.003061	0.306072	93.640127
x127	91.3577	x227	-82,967	123.408883	0.003479	0.347865	93.987991
x128	49.15	x228	-44.3599	66.208181	0.001001	0.100125	94.088116
x129	76.0567	x229	-166,245	182.816907	0.007634	0.763396	94.851512
x130	119,273	x230	-98.0332	154.390922	0.005445	0.544454	95.395966
x131	100,854	x231	-55.4021	115.069205	0.003024	0.302437	95.698403
x132	3.55543	x232	-28.6593	28.8789986	0.00019	0.019049	95.717453
x133	72.9116	x233	-106,783	129.300853	0.003819	0.381874	96.099327
x134	36.2998	x234	-18.6276	40.8002814	0.00038	0.038023	96.13735
x135	26.6411	x235	-87.1561	91.1368969	0.001897	0.189717	96.327066
x136	21.0277	x236	-40.7248	45.8331049	0.00048	0.047982	96.375048
x137	36,746	x237	-97.9223	104.589891	0.002499	0.24986	96.624908
x138	95.3177	x238	-50.0643	107.665677	0.002648	0.264772	96.88968
x139	41.7674	x239	-5.08895	42.0762773	0.000404	0.040438	96.930118
x140	52.7948	x240	-51.3536	73.6510906	0.001239	0.123901	97.05402
x141	93.0291	x241	14.1514	94.0992857	0.002023	0.202251	97.25627
x142	-10.7698	x242	-52.2142	53.3133311	0.000649	0.064922	97.321192
x143	67.8343	x243	-35.1171	76.3852274	0.001333	0.133271	97.454463
x144	51.5331	x244	-57,264	77.0378225	0.001356	0.135558	97.590021
x145	105,889	x245	-39.4222	112.989337	0.002916	0.291603	97.881624

x146	37.9463	x246	-46.2675	59.838142	0.000818	0.081785	97.963409
x147	14.2246	x247	8.88863	16.7734012	6.43E-05	0.006426	97.969835
x148	70.3415	x248	-66.9933	97.1392241	0.002155	0.215529	98.185365
x149	56.3789	x249	-15.1957	58.3908354	0.000779	0.077877	98.263241
x150	36.8087	x250	-53.2891	64.7657979	0.000958	0.09581	98.359051
x151	64.7159	x251	-35.1831	73.6613755	0.001239	0.123936	98.482987
x152	92.5264	x252	-49.4362	104.905065	0.002514	0.251368	98.734355
x153	71.9678	x253	3.94676	72.0759402	0.001187	0.118658	98.853013
x154	59.5543	x254	-59.2077	83.9777732	0.001611	0.161082	99.014095
SERIES DJIA3C				amplitudes			
COSINE	COEFFICIENT	SINES	COEFFICIENT		Contribution to		
S			NT	Rp	the variance	%	% accumulated
x11	271,817	x21	-319,222	419.269802	0.473584	47.35842	47.358416
x12	128,217	x22	-209,22	245.382574	0.162217	16.22174	63.580157
x13	118.71	x23	-186,883	221.398554	0.132056	13.20564	76.7858
x14	-5.97177	x24	-130,727	130.863328	0.046137	4.613664	81.399464
x15	74.2026	x25	-83.5422	111.737751	0.033636	3.363643	84.763106
x16	17.5945	x26	-72.4328	74.5390968	0.014968	1.49685	86.259956
x17	40.7563	x27	-56,728	69.8508552	0.013145	1.314478	87.574435
x18	46.9619	x28	-61.1868	77.1313461	0.016028	1.602772	89.177207
x19	27,508	x29	-65,542	71.0805447	0.013612	1.361167	90.538374
x110	6.05618	x210	-69.8766	70.1385525	0.013253	1.325329	91.863703
x111	4.11974	x211	-53.1466	53.3060348	0.007655	0.765531	92.629234
x112	10.1758	x212	-51.3367	52.3354915	0.007379	0.737909	93.367143
x113	6.36241	x213	-29.0319	29.720893	0.00238	0.237976	93.605119
x114	20.7799	x214	-29.1128	35.7681334	0.003447	0.344669	93.949788
x115	23.9759	x215	-19.7589	31.0686001	0.0026	0.260048	94.209836
x116	10.0129	x216	-28.9971	30.6771898	0.002535	0.253537	94.463373
x117	19.6609	x217	-21.5624	29.1802687	0.002294	0.229397	94.69277
x118	17.6038	x218	-27.2174	32.4142043	0.002831	0.283061	94.975832
x119	17.1428	x219	-25.5408	30.7604951	0.002549	0.254916	95.230748
x120	25.6133	x220	-22.1585	33.8679828	0.00309	0.309021	95.539769
x121	21.9267	x221	-23.6859	32.2769582	0.002807	0.280669	95.820439
x122	19.55	x222	-18.3447	26.8091499	0.001936	0.193632	96.01407
x123	16.4764	x223	-29.9627	34.1940806	0.00315	0.315001	96.329071
x124	24.9926	x224	-14.98	29.1381272	0.002287	0.228735	96.557806
x125	22.4621	x225	-15.1857	27.1136759	0.001981	0.198055	96.755862
x126	16.3904	x226	-24.1767	29.2088691	0.002298	0.229847	96.985709
x127	10.1616	x227	-24.5263	26.5480226	0.001899	0.189878	97.175587
x128	13.0533	x228	-12.5845	18.1316927	0.000886	0.08857	97.264157
x129	12.2651	x229	-18.5195	22.2127116	0.001329	0.132927	97.397084
x130	15.9074	x230	-26.1295	30.5907853	0.002521	0.252111	97.649195
x131	12.3019	x231	-18.0703	21.8602947	0.001287	0.128743	97.777937
x132	18,896	x232	-15.2391	24.2752752	0.001588	0.158759	97.936696
x133	10.6194	x233	-10,128	14.6747416	0.00058	0.058016	97.994713
x134	9.05038	x234	-9.61785	13.2065293	0.00047	0.046988	98.041701
x135	13.4655	x235	-10.1547	16.8652786	0.000766	0.07663	98.118331
x136	12.1948	x236	-8.80515	15.0414033	0.00061	0.060952	98.179282
x137	14.2644	x237	-12.8295	19.1851291	0.000992	0.099161	98.278443
x138	19.5566	x238	-11.2402	22.5566553	0.001371	0.137075	98.415518
x139	10.1681	x239	-11.0866	15.0433692	0.00061	0.060968	98.476486
x140	12.8429	x240	-9.40564	15.9187356	0.000683	0.06827	98.544756

x141	14.0465	x241	-7.4966	15.921783	0.000683	0.068296	98.613051
x142	15.926	x242	-4.42527	16.5293826	0.000736	0.073608	98.686659
x143	16.5107	x243	-9.59946	19.0985038	0.000983	0.098267	98.784926
x144	17.2881	x244	-8.13294	19.1055781	0.000983	0.09834	98.883266
x145	11.8847	x245	-12.3923	17.1701833	0.000794	0.079425	98.962692
x146	10.0777	x246	-10.3607	14.4535166	0.000563	0.05628	99.018972

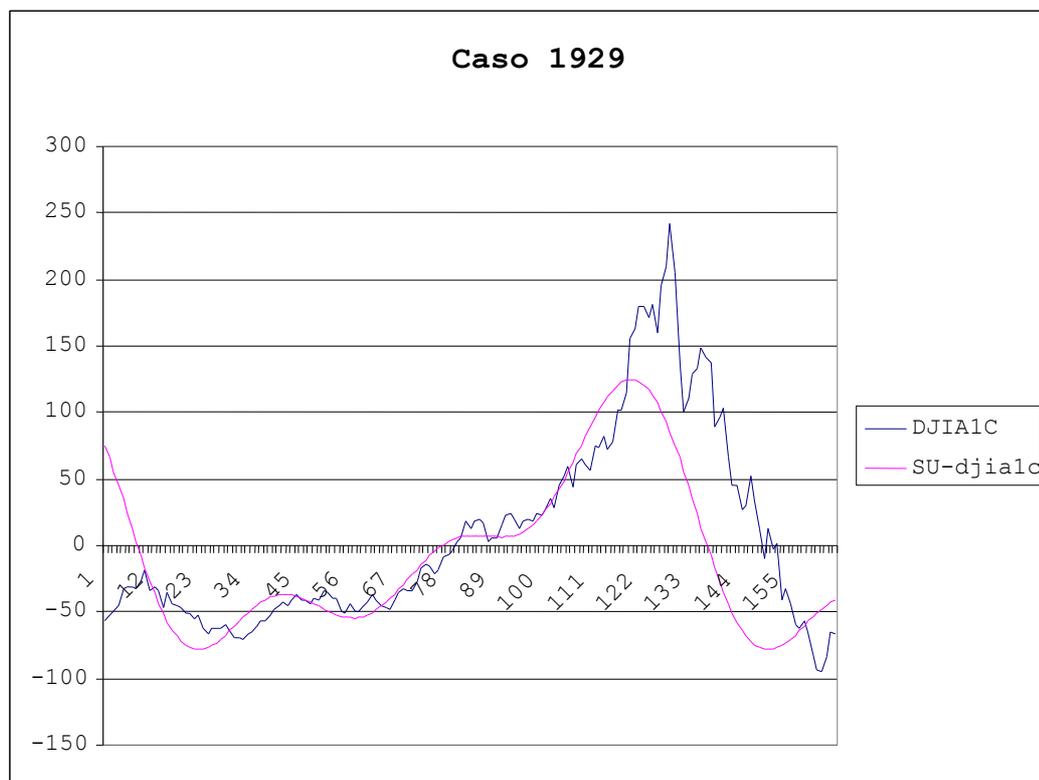
The periodograms show that the majority of the series variance is explained with very few theoretical cycles. Thus, both the hidden, fixed periodicity and determinist hypotheses are plausible.

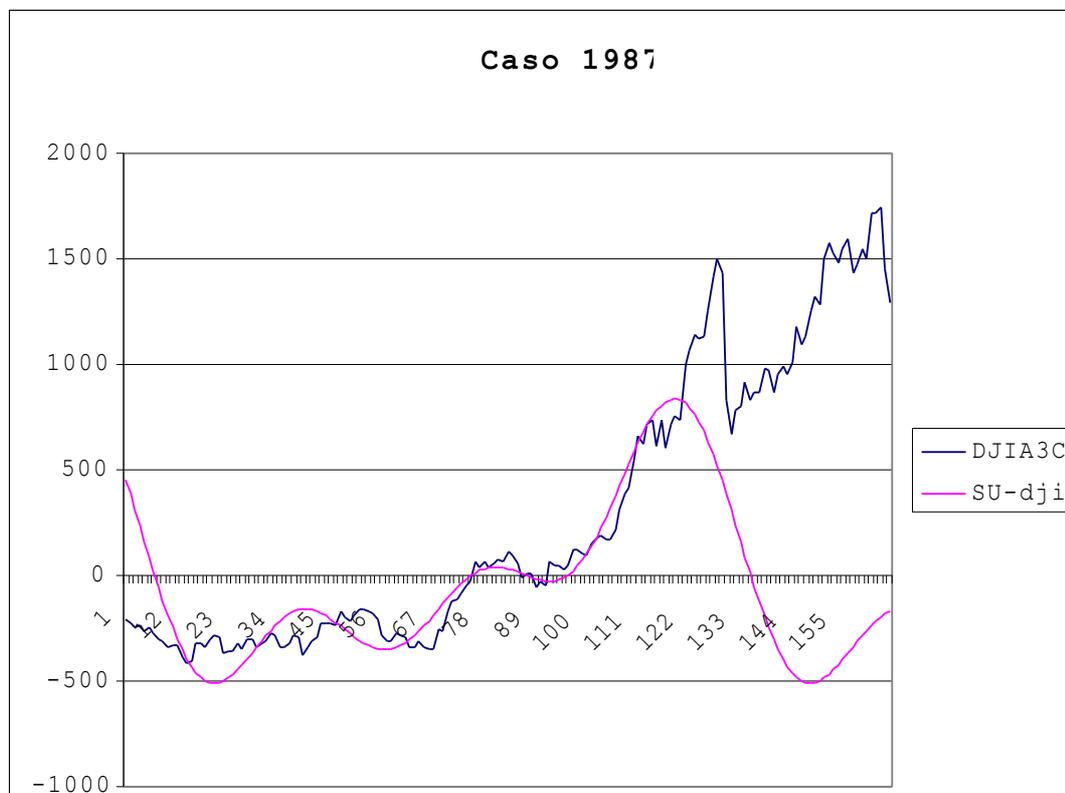
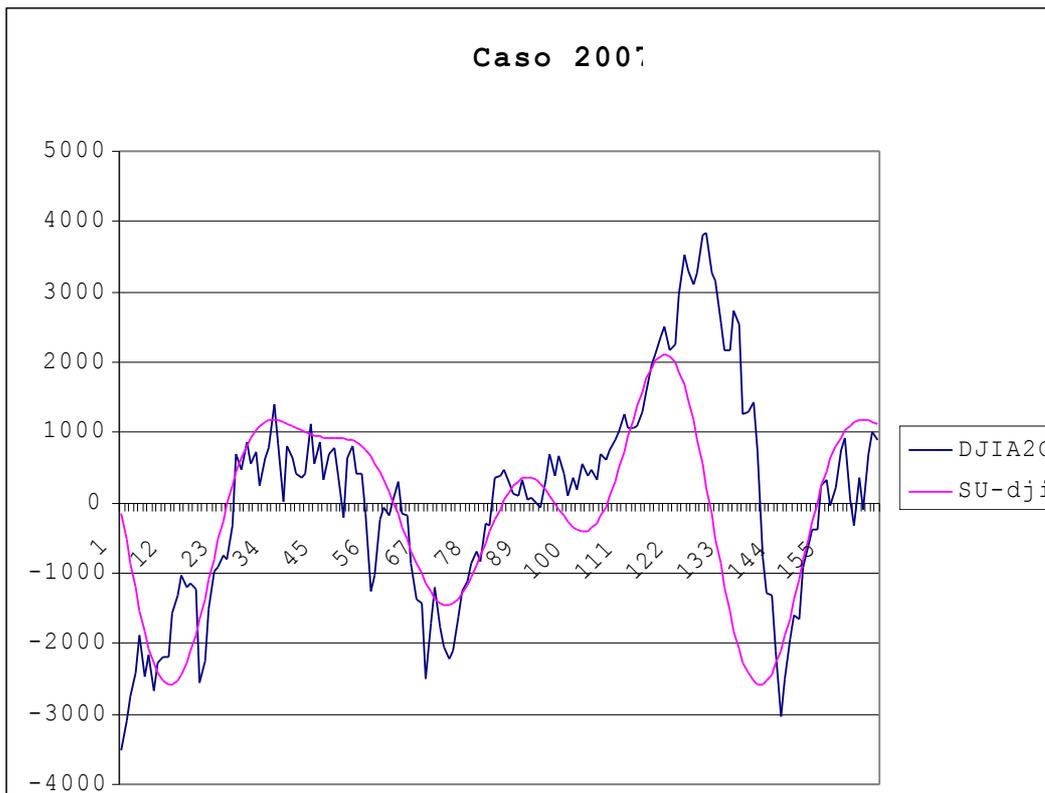
The three main theoretical cycles are:

- Series DJIA1C: cycles of 128, 64 and 43 months, that explain 75% of the variance. The sum of the cycles is the SUDJIA1C variable.
- Series DJIA2C: cycles of 64, 43 and 32 months, explain 63%. The sum is SUDJIA2C.
- Series DJIA3C: cycles of 128, 64 and 43 months, explain 77%. SUDJIA3C.

However, as I stated previously, I consider that the fundamental criteria to decide on the accuracy of any structural scientific model or otherwise, is its proven ability to make predictions. Thus, I refer to a point in time when share prices are at their highest, just before they start falling, and I confirm the correctness of the adjustment between the prediction of the three main calculated theoretical actions and the true evolution of the share price index. Therefore, 128 observations have been used to calculate the theoretical cycles and the values of 37 months are predicted. As stated previously, the peaks are: Aug 1929, Aug 1987 and Oct 2010.

The following is observed graphically.





It is possible to respond to this question by comparing the original series with the extrapolation of the relevant theoretical fluctuations.

The predictions of the cases in 1929 and 2007 can be considered as acceptable. This was not true in the third case, that of 1987. Then, the theoretical curves predicted a continuous fall in contrast to the reality of the index recovery, distancing the predicted values from the real ones. In all cases, the stock market crisis is anticipated nine months beforehand.

Consequently, empirical evidence is not negative for the fixed periodicity hypothesis. Similarly, it is contradictory and inconclusive for the predictability hypothesis. It is not possible to correctly predict the evolution in the three cases. However, the data does not respond to a random-walk model.

## 7. CONCLUSIONS.

The application of harmonic analysis to stock market index evolution offers partial results. By setting out three disparate cases in relation to the same stock market index, I have found that significant continuous index falls allow capacity for prediction if we use series of 128 months. However, the prediction is incorrect in the other case.

I understand that the problem is found in three elements. Firstly, the use of relatively short temporal series. Secondly, the use of aggregated temporal series, calculated as a mean of changing elements. Thirdly, the identification of the trend in temporal series. It is the inability to understand if a movement of a series of aggregated and heterogeneous data is a trend or a cycle; something that prevents the correct prediction of future behaviour. It is necessary to continue investigating.

In any case, the determinist and cyclical hypotheses are not rejected in this study, although they neither receive unwavering support. By contrast, the random-walk model does not respond to the data and, in this sense, is incorrect.

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