Long-time correlations in company profit fluctuations: Presence of extreme events

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The accuracy of earnings predictions is hampered by the several predominantly unpredictable effects due to the complex evolution of economy. Finding out which are the dominant market features embracing uncertainty is therefore the key to get beyond present state-of-art earnings forecasts. The analysis of annual revenues and earnings data (1954–2008) from the 500 largest-revenue U.S. companies suggests a linear relation between company expected mean profit and revenue. Annual profit fluctuations are then obtained as difference between actual annual profits and expected mean values. It is found that the temporal evolution of profit fluctuations for a single company displays a slowly decaying autocorrelation, yielding Hurst exponents in the range $H = 0.75 \pm 0.17$. The study of profits cross correlations between companies suggests a way to distinguish typical earnings years from anomalous ones by looking at minimal information structures contained within the space defined by the associated covariance metric.

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I. INTRODUCTION

It is well known among market traders that company year-to-year earnings variations (often also on shorter time horizons) may lead to huge movements in public company stock (see, e.g., [1]), making earnings prediction an essential issue when dealing with stock and options pricing (see, e.g., [2]). A more predictable scenario is represented by total company revenue, being notoriously a less volatile quantity. Despite this, revenue variations can still yield conspicuous changes in the underlying stock price, although the connection between stock price (i.e., market value) and revenue remains to be understood [3].

Indeed, the several factors determining the evolution of economy make earnings forecasts to embody a high degree of uncertainty in many cases [2]. Thus, the aim is to estimate in a more realistic fashion profit fluctuations in order to improve the accuracy of earnings predictions. Several attempts have been made to incorporate a stochastic behavior of profits into the analysis in which fluctuations are assumed to be normally distributed [4–9].

Profit fluctuations can be naively evaluated by looking at their relative variations say, from year to year. As a matter of fact, profit is closely related to revenue and production costs and a different approach based on these interrelations has been recently suggested [10]. In the latter, revenue is taken as the independent driving variable and an analysis of profit fluctuations based on this assumption has been developed.

In this paper, we briefly review these basic concepts [10] and discuss empirical market data taken from U.S. companies on an year-to-year basis over a period of 55 years. The analysis of the empirical data suggests a form for the expected mean profit, being a function of company revenue, with respect to which earnings fluctuations can be determined once they are scaled by a power of revenue. The probability distribution function of scaled fluctuations displays slowly decaying tails, which turn out to be of Lévy type. Furthermore, we consider single company earnings trajectories as a function of year suggesting that the corresponding scaled fluctuations are strongly autocorrelated indicating the presence of long-time memory in profit variations. The associated Hurst exponents are obtained over 58 companies for which data over the full 55 years are available. Cross correlations among companies with respect to profit fluctuations are presented permitting to extract an emerging internal market structure. The paper is concluded with some final remarks.

II. SCALED PROFITS VERSUS SCALED REVENUES AND FLUCTUATIONS

In the following, we briefly review the mean-market cost-volume-profit (CVP) analysis presented in Ref. [10]. The starting point relies on standard CVP analysis [11,12], where profit P is defined as the difference between total revenue R and costs, the latter being the sum of variable costs V_c and additional (sometimes referred to as fixed) costs $F \geq 0$, that is,

$$P = R - (V_c + F). \tag{1}$$

Further, one writes total revenue as $R = v_s n_s$, where v_s is the sale price of sold unit and n_s the total number of sold units, and total variable costs as $V_c = v_c n_c$, where v_c is the cost of produced unit and n_c is the total number of produced units. Then, one proceeds assuming [10] linear relations between sold unit values and produced ones according to $v_s \simeq \alpha_s v_c$ and $n_s \simeq \beta_s n_c$.

Since actual values of the coefficients α_s and β_s are not available, it is convenient to study first the behavior of profits and revenues in an average sense. To do this, one can resort to data from the 500 largest-revenue companies in the U.S. during the period (1954–2008) [13,10]. From these data, the mean annual values P_0 and R_0 in billions (B) of U.S. dollars have been calculated, suggesting that both quantities grow exponentially over the years [10]. Further, mean annual profit P_0 appears to be just proportional to R_0, as displayed in

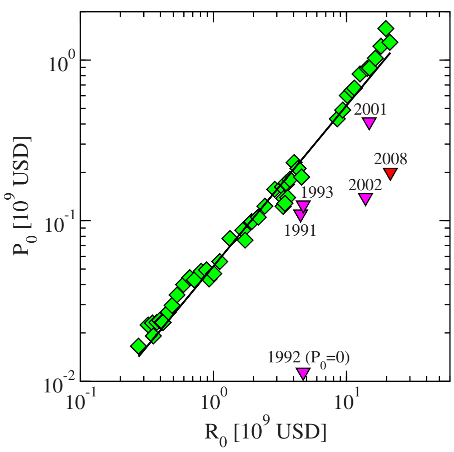

FIG. 1. (Color online) Mean yearly profit, P_0, vs mean yearly revenue, R_0 (diamonds) (in Billions of USD) (from Ref. [10]). The straight line corresponds to $P_0=0.052R_0$ (see Ref. [10] for more details). The "anomalous" years (down triangles) are indicated.

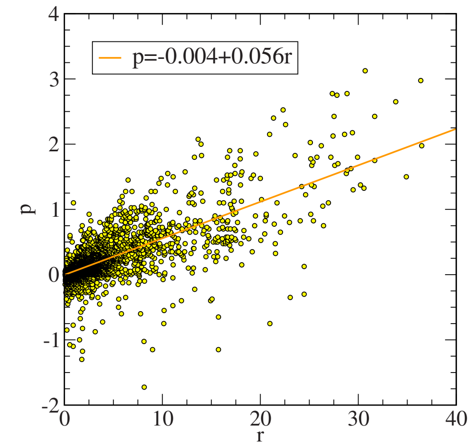

FIG. 2. (Color online) Scaled company profit $p=P/R_0$ versus scaled revenue $r=R/R_0$, for all U.S. companies considered in this study. The straight line is a linear regression over the whole data.

Fig. 1. Few "extreme" years, in the sense that they do not fall on the same linear relation as the majority does, can be detected corresponding to the groups: the three-year period (1991, 1992, 1993), the two-year one (2001 and 2002) and 2008. These extreme or "anomalous" years have been identified by looking at mean annual global quantities. As we will see below, Sec. IV, other types of anomalies can be detected by studying the way in which company-company profits are cross correlated. Despite the presence of these six extreme years, a definite linear relation between mean profits and revenues seems to occur, suggesting a new perspective from which analyzing profit data. To take the (exponential) year-to-year growth of economic activity into account, the value $\bar{R}_0=0.27\exp[(\text{year}-1954)/12]$ B is used as the scaling quantity [10], yielding scaled revenues $r=R/\bar{R}_0$ and scaled profits $p=P/\bar{R}_0$.

Next, we discuss the issue of profit fluctuations. The latter are considered to be a function of scaled revenue r, defined as the difference between actual scaled profit p and its expected mean value, here denoted as $\bar{p}$,

$$\Delta p = p - \bar{p}. \tag{2}$$

In order to determine the expected mean profit $\bar{p}$, we have plotted all available values of p and r in the database (including the anomalous years) and performed a linear regression to the data, $p \simeq a+br$, here representing the behavior of $\bar{p}$ versus scaled revenue r. The fit is shown in Fig. 2 yielding a rather small intercept value, $a \simeq -0.004$, which can be neglected for our present purposes, while $b \simeq 0.056$. Therefore, the expected mean profit $\bar{p}$ can be taken to be a function of r, obeying

$$\bar{p} = \langle \gamma_g \rangle r, \tag{3}$$

where $\langle \gamma_g \rangle$ is the constant of proportionality and the symbol $\langle \ldots \rangle$ indicates the average market behavior over each single company factor γ_g. Thus, in the present context, company mean profit is a function of solely actual company revenue r, times a global market parameter $\langle \gamma_g \rangle$, which is taken the same for all companies (see also [10] for how to relax this condition and how to deal with single company factors γ_g).

Notably, profit fluctuations defined in Eq. (2) are not stationary as a function of scaled revenue and a more suitable variable has been suggested [10],

$$\Delta \pi = \frac{\Delta p}{r^{\eta}}, \tag{4}$$

with $\eta \simeq 0.6$. A value of $\eta \neq 0$ does not guarantee the vanishing of the first moment $\langle \Delta \pi \rangle$. This can be achieved by fine tuning $\langle \gamma_g \rangle$, yielding $\langle \gamma_g \rangle \simeq 0.052$, the value used in this work [10], which is however very close to the above result 0.056.

The probability distribution function (PDF) of scaled profit fluctuations, $G(\varepsilon)$, for $\varepsilon \equiv \Delta\pi/\langle|\Delta\pi|\rangle$, Eq. (4), with $\langle|\Delta\pi|\rangle=0.03$, has been found to be consistent with a Lévy-type distribution of the form [10]

$$G(\varepsilon) = \begin{cases} a/(1+|\varepsilon/b|+|\varepsilon/c|^{2.7}), & \text{for } \varepsilon \geq 0 \\ a/(1+|\varepsilon/d|^{2.7}), & \text{for } \varepsilon \leq 0, \end{cases} \tag{5}$$

with $a=0.55$, $b=0.6$, $c=0.9$, and $d=0.75$, implying power-law tails with a Lévy-like exponent $\alpha=1.7$. To validate further the determination of η we have studied, complimentarily to what has been done in Ref. [10], the behavior of the PDF $G(\varepsilon)$ for different values of $0.5 \leq \eta \leq 1$. The result is quite remarkable, as all the corresponding PDFs display a power-law decay with an exponent $\alpha \simeq 1.7$, suggesting a robust behavior. In addition, different types of minimizations of the variance of scaled fluctuations all yield results consistent with $\eta \simeq 0.6$. To be noted is that according to the argument presented in Ref. [10], a given fluctuation ε can be seen as a sum over $n_r \propto r$ independent, identically distributed variables ε_i, $1 \leq i \leq n_r$, which do not need to be sequentially related to each other in time. This argument then yields the relation $\eta = 1/\alpha \simeq 0.6$, suggesting that η can be determined from the PDF power-law exponent.

To be noted is that processes resulting from other human-based activity, such as price variations in financial markets [14] and speed fluctuations of an ensemble of cars in a closed

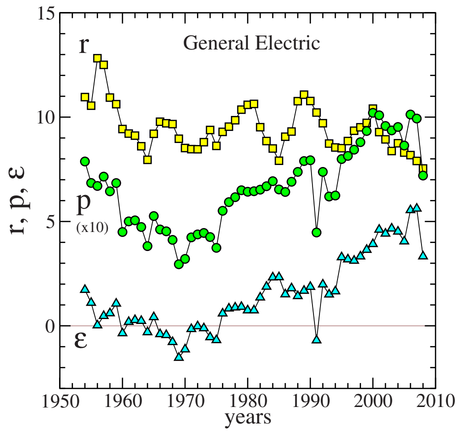

FIG. 3. (Color online) Scaled revenue r (squares), profits p (circles), and corresponding profit fluctuations ε (triangles) versus time [years] for General Electric (GE). Note that scaled profits have been multiplied by 10 for convenience.

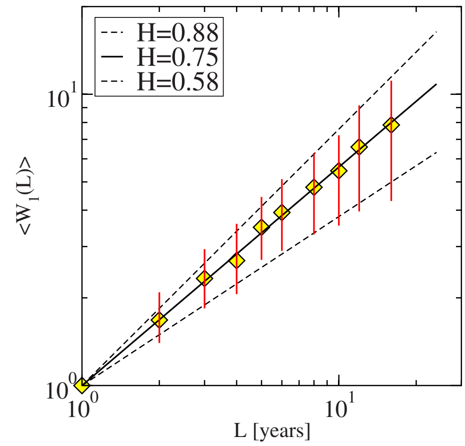

FIG. 4. (Color online) Fluctuation analysis of scaled annual company profits. Plotted is the first-order mean wavelet fluctuation $\langle W_1(L)\rangle$ versus time scale L [years]. The symbols represent averages over 58 U.S. companies having earnings data over the full period of 55 years (1954–2008). The straight line has slope $H=0.75$ and the vertical bars represent $\pm\sigma$ standard deviations of $W_1(L)$ for each time scale L. The dashed lines are drawn as a guide, suggesting that $H=0.75\pm0.17$.

circuit traffic [15], just to name a few examples, also display strongly fluctuating features typically characterized by fat-tail distributions.

III. PROFIT FLUCTUATIONS AND HURST EXPONENTS

In what follows, we study the temporal behavior of scaled profit fluctuations ε. We consider first a typical long-standing U.S. company as an example, then we study the scaling behavior of the corresponding autocorrelations.

In Fig. 3 we plot a prominent player in U.S. economy, the General Electric (GE) company. GE data span the full 55 year period, and from the plot one can see the scaled revenue and profit, together with the scaled profit fluctuations ε. It is instructive to watch at the result and note that while scaled revenue remains confined to some extent within a band around $r=10$, scaled profits have grown consistently after 1975, reaching rather large values in 2007. Recently, however, available published data indicate that GE profits have been reduced drastically during 2008 producing a significant correction to the trend observed in those previous years (see Fig. 3).

From both a practical and theoretical point of view, it is important to know whether scaled profit fluctuations are correlated with each other year over year. An affirmative answer to this question may turn essential for helping predicting profit scenarios. Moreover, should fluctuations decay slower than exponentially in time (i.e., being long-time autocorrelated), it would imply that strongly departures from uncorrelated Gaussian behavior is taking place, making the problem even more challenging than expected.

Let us study then the scaled profit fluctuations ε over the years, L, to extract information on the autocorrelation function, $C_{\text{auto}}(L)$, of the associated time series. To do this, we apply the method known in literature as the fluctuation analysis (FA) based on Haar wavelets (HW) [16,17]. A brief summary of the FAHW method has been discussed recently [18], and will not be repeated here.

For our purposes, we just remind the reader that long-range memory, or slowly decaying autocorrelations, can be detected by studying, for instance, the dependence of the (first-order wavelet) $W_1(L)$ on L, which is expected to behave as

$$W_1(L) \sim L^H, \quad 0 < H < 1, \tag{6}$$

which defines the Hurst exponent H. The value $H=1/2$ indicates uncorrelated fluctuations, or standard random-walk behavior. Cases in which $H\neq 1/2$ correspond to signals in which autocorrelations are present. Common situations are those where an exponent $H\neq 1/2$ can be defined on a finite range of time scales L. Then, one says that the signal features "long-time correlations." Cases in which $H>1/2$ denote persistence, where $C_{\text{auto}}(L)\sim L^{-\gamma}$ with $0<\gamma<1$, and those with $H<1/2$ antipersistence, where $C_{\text{auto}}(L)\sim -L^{-\gamma}$ with $1<\gamma<2$. In both cases, the general result $\gamma=2(1-H)$ applies.

Results for $\langle W_1(L)\rangle$, averaged over the 58 companies spanning profit data over the whole period of 55 years, are shown in Fig. 4. The error bars have been obtained from the calculation of the standard deviations over the 58 values of W_1 for each time scale L. The dashed lines indicate the lower and upper bounds for the Hurst exponent, giving an idea of the variability of H within the present database.

It should be emphasized that the exponent H describes the autocorrelations of a time series, where the fluctuations ε are necessarily taken according to their actual temporal occurrence. This is different than the case of fluctuations in "revenue space," in which the issue is the stationarity of profit fluctuations and the associated PDF. In other words, the exponent η characterizes the stationarity of profit fluctuations, while H the temporal behavior of their autocorrelations, thus both exponents are in principle independent of each other. In support of this assertion, we have calculated the mean fluctuation function $\langle W_1(L)\rangle$ from the above 58 companies whose times series ε_i have been generated using different

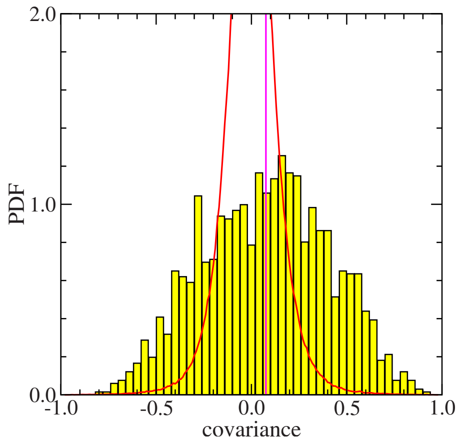

FIG. 5. (Color online) PDF of profit cross correlations versus covariance value. The vertical line indicates the mean covariance within the subset of 58 companies considered, $\langle C\rangle=0.08$. The continuous line represents the case of uncorrelated Lévy-type time series of length 55 years each. The latter is well fitted by a Gaussian shape around the center with the form: $F=a\exp(-0.5x^2)$, with $a=3.85$ and $x=C/0.09$.

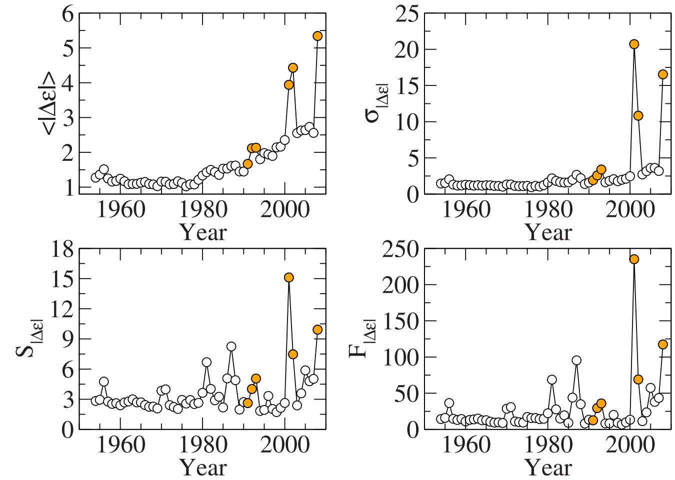

FIG. 6. (Color online) Moments of the absolute difference of scaled profits fluctuations as a function of year, defined as $|\Delta\varepsilon_{i,j}|=|\varepsilon_i-\varepsilon_j|$, for the mean, standard deviation, skewness S, and flatness F, for the Fortune 500 U.S. companies. The filled circles correspond to the anomalous years found in Fig. 1.

values of η. In all cases, the results for H are indistinguishable from those shown in Fig. 4.

The present results indicate that accurate predictions of profit fluctuations, on a year-to-year basis, are indeed much more complex than previously thought. This indicates, in other words, that sophisticated models possessing long-range memory features are required to describe actual profit fluctuations. Simpler, uncorrelated models can therefore be seen as a poor approximation to real market effects.

IV. COMPANY PROFITS, CROSS-CORRELATIONS, AND TOPOLOGY

Another aspect related to profit predictions is the question of whether a company business scenario can affect the profit behavior of another company. Such additional information on cross-profits correlations may turn also useful for better assessing future earnings expectations of a given company.

In what follows, we deal with the issue of cross correlations between companies by using scaled profit fluctuations time series as a mean to establish an internal metric for the 58 U.S. companies considered here. From the $\varepsilon_i(t)$ and $\varepsilon_j(t)$ time series for companies i and j $(1\leq i,j\leq 58)$ we calculate the cross correlation (or covariance) $C_{i,j}$ as

$$C_{i,j}=\frac{1}{\sigma_i\sigma_j}(\langle\varepsilon_i(t)\varepsilon_j(t)\rangle_T-\langle\varepsilon_i\rangle_T\langle\varepsilon_j\rangle_T), \quad (7)$$

where σ_i and σ_j are the corresponding standard deviations of ε_i and ε_j over the $T=55$ years considered. The distribution of cross correlations, as shown in Fig. 5, is rather broad, much broader than for logarithmic returns among stocks (see, e.g., [19]), having a slightly positive skewness. To be noted is that for uncorrelated Lévy-type time series of length 55 years, Eq. (5), the PDF (continuous line in Fig. 5) is fully symmetric and much narrower than for the empirical results.

This result is an indication that profit cross correlations can be quite strong. Hence, for making accurate profit predictions on a single company, additional information on what other companies are doing seems also to be required. Further, the internal structure of such a "profit network" appears to be seemingly complex as we will see in the following.

In order to further characterize cross-profit correlations between companies and being able to attempt a quantitative description of the associated internal market structure, we begin our study by considering the absolute values $|\Delta\varepsilon_{i,j}|=|\varepsilon_i-\varepsilon_j|$, for all companies $i\neq j$ for each year. The first two moments, $\langle|\Delta\varepsilon_{i,j}|\rangle$ and standard deviation, are plotted in Fig. 6, together with the skewness, S, and flatness, F. The anomalous years discussed in Fig. 1 develop "peaks" emerging from the more smooth background behavior, notably in the first two moments as one can clearly see in the plot. Flatness and skewness also show anomalous peaks at other years prominently during the 1980s and the recent years. These features may hint to additional sources of anomalies not apparent from the mean behavior of profits (Fig. 1).

Another way of identifying profit anomalies is to consider the number of companies which remain within the Fortune 500 list over a period of n consecutive years. As an example, we consider $n=5$, and plot the number of survived companies in Fig. 7. We see a rather flat and smooth behavior from 1954 until 1992, when a dramatic drop in the survival number took place, shrinking it to about half its value. This anomaly lasted four years. During the last ten years, however, the number kept oscillating quite wildly too, indicating a rather uncertain economy's scenario.

Based on the results of Fig. 7, we turn back to the issue of cross correlations within the Fortune 500 companies. To this end, we define a metric, i.e., a distance between companies, as the quantity [20]

$$\rho_{i,j}=\sqrt{2(1-C_{i,j})}, \quad (8)$$

where $C_{i,j}$ is defined in Eq. (7) for the case $T=5$ years. Values of the distribution function of cross correlations, $P(C)$,

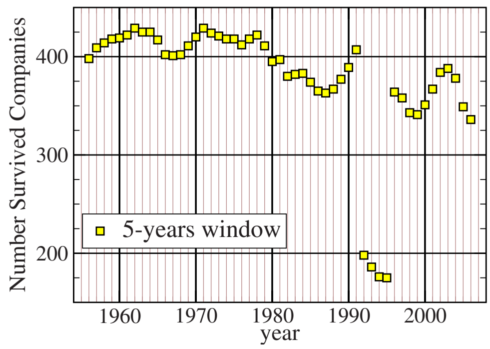

FIG. 7. (Color online) Survival of companies within the Fortune 500 list over a period of five consecutive years as a function of year. The five years period is taken as the two previous and the two following years from the considered one (open squares).

are shown in Fig. 8, for selected five-year periods, i.e., (1960–1964) centered around 1962, (1970–1974) centered around 1972, (1980–1984) centered around 1982, (1992–1996) centered around 1994, and (2000–2004) centered around 2002. For comparison, four distributions are also shown: the random uniform case $P(C)=1/2$, the case of random uniformly distributed distances ρ, yielding $P(C)=1/\sqrt{8(1-C)}$, uncorrelated Lévy-type variables [fulfilling Eq. (5)], and the mean PDF obtained from all the five-year periods in the empirical data.

The uncorrelated Lévy-type variables PDF can be compared with the one shown in Fig. 5 for 55 years, indicating

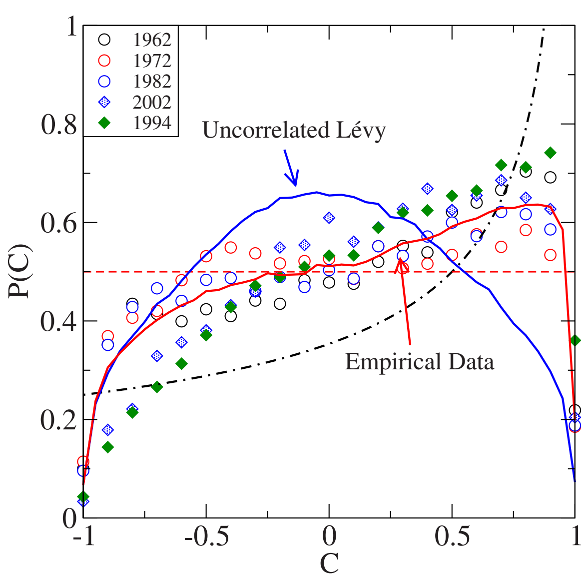

FIG. 8. (Color online) Distribution $P(C)$ of cross correlations C between companies calculated over five consecutive years for selected periods (indicated in the inset). Four additional lines are shown: (1) the case of random uniformly distributed values $-1 < C < 1$, $P(C)=1/2$ (red dashed line), (2) the case of random uniformly distributed company-company distances $0 < \rho < 1$, yielding $P(C)=1/\sqrt{8(1-C)}$, obtained from $P(C)=P(\rho)|d\rho/dC|$, with $P(\rho)=1/2$ and $\rho=\sqrt{2(1-C)}$ (black dashed-dotted line), (3) the case of uncorrelated Lévy-type variables [Eq. (5), blue full line], and (4) the mean PDF for the full empirical data (red full line).

that for five years periods as in this case, the distribution of cross correlations becomes broader due to the fact that for short-time series cancellation of terms is not effective and spurious correlations may develop. For very long time series, the distribution of uncorrelated Lévy-type variables tends to a peaked distribution centered around $C=0$.

As one can see from Fig. 8, the mean empirical PDF shares features of the three distributions for different ranges of C. That is, it is quite flat close to $C=0$ (uniform C), develops a peak for $C\to 1$ (uniform ρ), and coincides with the uncorrelated Lévy distribution for $C\to -1$. The results suggest, for the five groups considered, the occurrence of two types of distributions, a first one corresponding to the group of periods centered at 1962, 1972, and 1982, and a second distribution for the groups centered at 1994 and 2002. Although periods around 1994 and 2002 display quite similar distributions, the question arises whether such similarities are real, or whether the relevant information is hidden behind the "too-much information" contained in $P(C)$. In other words, is there any internal structure in the space defined by the metric ρ, Eq. (8), which can discern between both periods, or, otherwise, are their metrics just equivalent?

As an attempt to answer this question, we find it instructive to consider the cross correlations from a pictorial point of view. We thus construct the minimal spanning tree (MST) (see, e.g., [19] for details) from a set of N companies, where here $N=176$ corresponding to the number of survived companies around 1994. The MST can be seen as the "minimal" topological representation of cross correlations capturing the essential features regarding the interrelations between companies and economic sectors [21].

The trees are shown in Fig. 9, where one can recognize two qualitatively different types of topologies. "Normal" periods are characterized by a linearlike structure, displaying low ramification, while an anomalous period such as the 1992–1996 one (shown in the middle-right part of the plot) displays a higher ramification or fragmentation.

In the following, we argue that the difference between the two types of structures is possibly due to a randomization which takes place during strong economic crisis, such as the period around 1994. Intuitively, during such periods profits become more uncorrelated with each other, as companies may get affected at very different rates. If this picture is plausible, anomalous year trees should become similar to random ones. To check this hypothesis, we have generated random distances $\rho_{i,j}$ and obtained the corresponding MST shown in the lower-right part of Fig. 9. They look more similar to anomalous year trees than to normal ones, in qualitative support of our suggestion. From the MST analysis we may conclude that periods around 1994 and 2002, although having similar cross-correlation distributions $P(C)$, are characterized by differently ramified MSTs. This suggests that the MST analysis is able to display an existing degree of "order" if it is present in the metric, as for the 2002 period, as opposed to the 1994 anomalous period displaying a more random metric. This difference may manifest the different economic environments taking place during both periods, the 1994 one characterized by a crisis affecting a broad range of sectors, as opposed to the 2002 period when corrections concentrated over a less number of them.

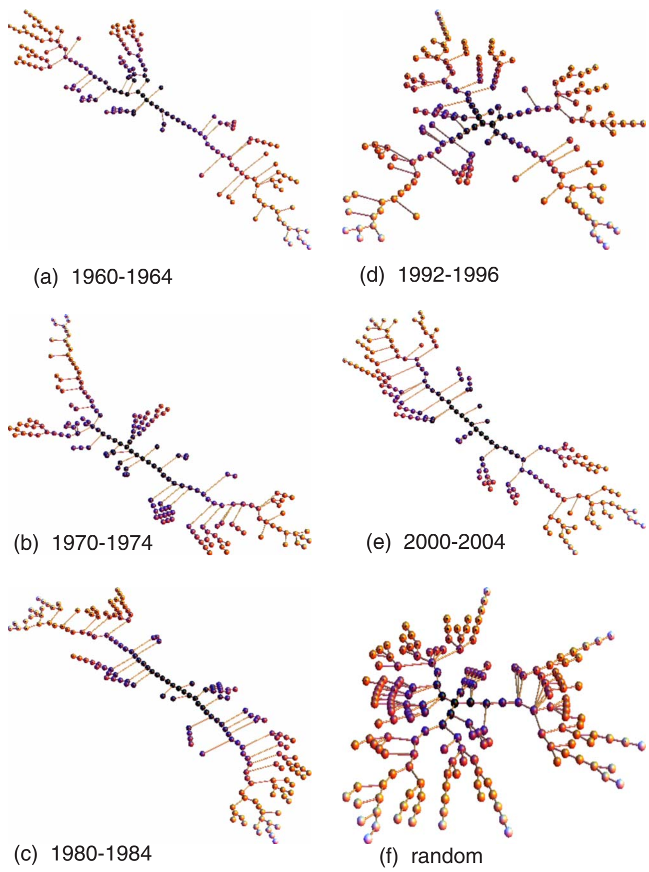

FIG. 9. (Color online) Topological cross-correlation trees, based on the minimal spanning trees. The cross correlations are evaluated within a five years period (same as in Fig. 8) indicated below each tree, and the nodes represent companies. Nodes closest to the center of the tree are the darkest, and farthest ones are the lightest. For obtaining these structures, we have considered $N=176$ companies for each tree.

In order to put these findings under a more quantitative basis we apply next a fractal analysis to the MST. To do this, we evaluate the fractal dimension d_ℓ of the tree in chemical space [22], or topological distance between nodes, $\ell_{i,j}$. We calculate the number of nodes within a distance ℓ, averaged over all pairs of nodes at that distance. According to the results of Fig. 10, we find a power-law behavior $M(\ell) \simeq \ell^{d_\ell}$, with $d_\ell \simeq 1.35$ for normal periods, and $d_\ell \simeq 1.55$ for anomalous ones.

Results for random trees are shown in the lower part of Fig. 10, suggesting that such random structures display fractal dimensions d_ℓ varying within a broad range, but on average having a well-defined value of about $d_\ell \simeq 1.65 \pm 0.1$, close to that of anomalous year trees. This result suggests that during strong financial crisis, randomization of profit fluctuations takes place yielding topological structures similar to that of random MSTs. We have verified that the fractal dimension of random trees is quite robust, in the sense that the same results are obtained independently of the distribution function used to generate the MST, being either uniformly distributed random covariances or distances, or very long time series of uncorrelated Lévy-type variables.

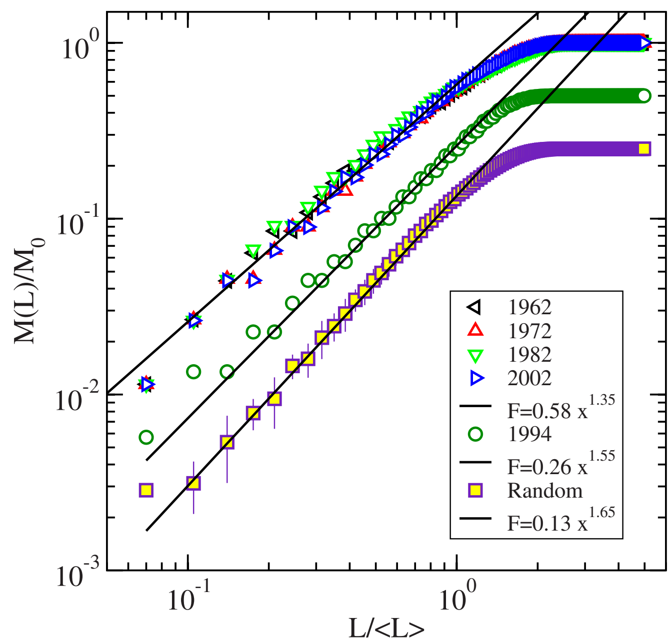

FIG. 10. (Color online) Topological fractal dimension of MST for profit periods of five years duration (taken from Fig. 9) for: Normal years (triangles), anomalous year (circles), and random trees (squares). The lines are power laws with exponents indicated in the inset. The points have been shifted vertically for clarity.

V. CONCLUSIONS

We have studied annual profit fluctuations for the set of Fortune 500 companies between years 1954 and 2008. The temporal evolution of profit fluctuations for single companies are obtained, suggesting that the associated autocorrelations display slow power-law decay, having Hurst exponents in the range $H=0.75 \pm 0.17$. Thus, profit fluctuations are endowed with a rather strong memory, in contrast to price returns which lack of any memory related to past changes. This indicates that realistic profit fluctuation predictions are more complex than commonly thought suggesting that sophisticated models, possessing long-range memory features, are required to describe them. Simpler, uncorrelated models can thus be judged to be a poor approximation to real market effects. Future studies should go beyond the year-to-year basis, and consider for instance profits data on a quarterly time horizon.

Extreme profit years are identified by studying the behavior of the moments of absolute scaled profit fluctuations differences between companies, within a single year. In addition, cross correlations between company profits are calculated suggesting that "normal" profit periods are characterized by a linearlike structure of the corresponding minimal spanning tree, while anomalous periods display a rather fragmented tree topology, similar to that of purely random trees. The corresponding topological fractal dimensions are obtained, yielding a quantitative measure of fragmented profit periods as compared to the standard profit ones.

Profits cross correlations of companies should be studied on shorter time scales and for longer time series in order to yield further support to the present picture. Work in this direction is under investigation and will be considered elsewhere. The results should complement the present study helping for a better assessment of profits on shorter time scales.

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[1] R. Jennings and L. Starks, J. Financ. **41**, 107 (1986).
[2] M. Keil, G. Smith, and M. H. Smith, Appl. Financ. Econ. **14**, 937 (2004).
[3] V. J. Cook, Jr., *The Value/Revenue Ratio: A Semi-Long-Wave Marketing/Accounting Metric* (Tulane University, New Orleans, LA, 2007), URL http://ssrn.com/abstract=961167
[4] R. K. Jaedicke and A. A. Robichek, Account. Rev. **39**, 917 (1964).
[5] C. Kim, Decision Sci. **4**, 329 (1973).
[6] Z. Adar, A. Barnea, and B. Lev, Account. Rev. **52**, 137 (1977).
[7] J. F. Kottas and H.-S. Lau, Account. Rev. **53**, 247 (1978).
[8] J. A. Yunker and P. J. Yunker, J. Account. Educ. **21**, 339 (2003).
[9] J. A. Yunker and D. Schofield, Manage. Dec. Econ. **26**, 191 (2005).
[10] H. E. Roman, R. A. Siliprandi, C. Dose, C. Riccardi, and M. Porto, EPL **84**, 68003 (2008).
[11] D. Colander, *Economics* (MacGraw-Hill, New York, 2004).
[12] J. Soper, *Mathematics for Economics and Business* (Blackwell Publishing, Oxford, 2004).
[13] Fortune 500 (http://money.cnn.com/magazines/fortune).
[14] R. N. Mantegna and H. E. Stanley, Nature (London) **376**, 46 (1995).
[15] H. E. Roman, F. Croccolo, and C. Riccardi, Physica A **387**, 5575 (2008).
[16] E. Koscielny-Bunde, A. Bunde, S. Havlin, H. E. Roman, Y. Goldreich, and H.-J. Schellnhuber, Phys. Rev. Lett. **81**, 729 (1998).
[17] J. W. Kantelhardt, H. E. Roman, and M. Greiner, Physica A **220**, 219 (1995).
[18] H. E. Roman and M. Porto, Phys. Rev. E **78**, 031127 (2008).
[19] H. E. Roman, M. Albergante, M. Colombo, F. Croccolo, F. Marini, and C. Riccardi, Phys. Rev. E **73**, 036129 (2006).
[20] R. N. Mantegna, Eur. Phys. J. B **11**, 193 (1999).
[21] G. Bonanno, G. Caldarelli, F. Lillo, and R. N. Mantegna, Phys. Rev. E **68**, 046130 (2003).
[22] D. Ben-Avraham and S. Havlin, *Diffusion and Reactions in Fractals and Disordered Systems* (Cambridge University Press, Cambridge, 2000).