

Exact multivariate amplitude distributions for non-stationary Gaussian or algebraic fluctuations of covariances or correlations in correlated financial markets

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Abstract Correlated financial markets are perfect examples of highly non-stationary systems. In particular, sample averaged observables of time series as variances and correlation coefficients are continuously fluctuating, directly depending on the time window in which they are evaluated. Thus, models that describe the multivariate amplitude distributions of such systems are of considerable interest. Extending previous works, we apply a methodology, where a set of measured, non-stationary correlation matrices are viewed as an ensemble for which is set up a random matrix model. This ensemble is used to average the stationary multivariate amplitude distributions measured on short time scales and thus obtain for large time scales multivariate amplitude distributions which feature heavy tails. We explicitly use four cases, combining Gaussian and algebraic distributions to compare the distributions with empirical returns distributions using daily data from companies listed in the Standard & Poor's 500 (S&P 500) stock market index in different periods of time. The comparison in the four cases with the empirical data reveals good agreement.

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1 Introduction

A bunch of different characteristics in complex systems can be tracked down to non-stationarity [1, 2]. These systems lack any kind of equilibrium [3, 4, 5, 6]. Financial markets are perfect examples of non-stationarity as they fluctuate considerably in time. In general, the business relations between companies and agents can change due to market expectations. During state of crisis, non-stationarity becomes dramatic [7, 8, 9, 10, 11, 12, 13].

The fluctuation of the correlations induces generic features in financial time series, where we showed that these fluctuations lift the tails of the multivariate amplitude distributions, making them heavy-tailed [14, 15].

Our goal is to use the analytical results for the multivariate distributions of amplitudes, measured as time series in correlated, non-stationary financial markets and provide quantitative measures for the degree of non-stationarity in the correlations using the methodology first proposed in [14] and extended in [15]. These amplitudes refer to the stock price changes for the entire market.

We carry out a detailed data analysis that exposes generic features. Then we use a random matrix model to explain them. We show that non-stationarity of the correlations leads to heavy tails in the multivariate return

distribution and finally, we use the approach in [14, 15] to map a non-invariant situation to an effectively invariant one.

A remarkable feature of the multivariate distributions we use to compare with the financial data, is that eventually, they are of closed form or involve only single integrals. Moreover, they use a low number of free parameters: one measuring how strongly the non-stationary correlations fluctuate, and one or two shape parameters for the tails. All the other parameters can be directly measured from the data [15].

Random matrix models [16, 17] fall into two classes: (I) The ensemble is fictitious. It comes into play via an ergodicity argument only. (II) The ensemble really exist and can be identified in the system. The issue of ergodicity does not arise. It is conceptually important that we here use a random matrix model in class (II) which may be seen as a new interpretation of the Wishart model and generalizations thereof for random covariance or correlation matrices [18]. In finance there are numerous random matrix applications [19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31] including non-Gaussian ensembles. To the best of our knowledge, all of them fall into class (I) and focus on other observables. The distributions we use arrive at rather universal and generic results, supporting view that non-stationarities can lead to universal features.

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The paper is organized as follows: in Sect. 2 we present our data set of stocks and define the analyzed time intervals. We define the key concepts and the general considerations in Sect. 3. In Sect. 4 we show compare the theoretical distributions with the aggregated distribution of returns. Our conclusions follow in Sect. 5.

2 Data set

In this study, we analyze stocks from different continuously traded companies in the S&P 500 stock market index in different periods of time. We use daily adjusted closing prices obtained from [Yahoo! Finance](#).

To compare the distributions, we use two different time intervals. The first interval is between the years 1992 and 2012. This interval is selected to compare with the results obtained in Ref. [14] and to extend this previous work with the new proposed distributions. In this interval we have data from $K = 277$ companies. The second interval is between the years 2012 and 2020. We want to explore the stock data for recent years and validate the universal and generic results of the distributions. In this interval we have data from $K = 461$ companies. All the companies used in the different intervals are listed in Appendix A.

3 Exact multivariate amplitude distributions

In Sect. 3.1 we introduce the fundamental quantities used in the distribution definitions. An example of the non-stationarity in financial markets is shown in Sect. 3.2. In Sect. 3.3 we set the theoretical considerations to construct the distributions. In Sect. 3.4 we define the four distribution cases and in 3.5 we show their graphical representation.

3.1 Key concepts

Consider time series $S_k(t)$, $k = 1, 2, \dots, K$ of stock prices for K companies. The values $S_k(t)$ are taken in fixed time steps Δt . In general, the data contain an exponential increase due to the drift. Thus, to measure the correlations independently of this trend, it is better to use logarithmic differences instead of returns

$$G_k(t) = \ln S_k(t + \Delta t) - \ln S_k(t) = \ln \frac{S_k(t + \Delta t)}{S_k(t)}. \quad (1)$$

Anyway, logarithmic differences and returns almost coincide if the time steps Δt are sufficiently short [32, 33]

$$G_k(t) \approx r_k(t) = \frac{S_k(t + \Delta t) - S_k(t)}{S_k(t)}. \quad (2)$$

The returns are well known to have distributions with heavy tails, the smaller Δt , the heavier [14]. Furthermore, the sample standard deviations σ_k , referred to as volatilities, strongly fluctuate for different time windows of the same length T [14, 34].

The mean of the logarithmic differences reads [15]

$$\langle G_k(t) \rangle_T = \frac{1}{T} \sum_{t=1}^T G_k(t). \quad (3)$$

To compare the different K companies, it is necessary to normalize the time series. The normalized time series are defined by [14, 15]

$$M_k(t) = \frac{G_k(t) - \langle G_k(t) \rangle}{\sqrt{\langle G_k^2(t) \rangle_T - \langle G_k(t) \rangle_T^2}}, \quad (4)$$

where

$$\sigma_k = \sqrt{\langle G_k^2(t) \rangle_T - \langle G_k(t) \rangle_T^2} \quad (5)$$

is the volatility of the k company in the time window of length T . These values can be viewed as the elements of a $K \times T$ rectangular matrix M . With these normalizations and rescalings, it can be measured correlations in such a way that all companies and all stocks are treated on equal footing.

The correlation coefficient for the stocks k and l is defined as [14]

$$C_{kl} = \langle M_k(t) M_l(t) \rangle_T = \frac{1}{T} \sum_{t=1}^T M_k(t) M_l(t), \quad (6)$$

which can be written as

$$C_{kl} = \frac{\langle G_k(t) G_l(t) \rangle_T - \langle G_k(t) \rangle_T \langle G_l(t) \rangle_T}{\sigma_k \sigma_l}. \quad (7)$$

The coefficients C_{kl} are the elements of a $K \times K$ square matrix C , the correlation matrix. The limiting values of these correlation coefficients

$$C_{kl}^{\text{lim}} = \begin{cases} +1 & \text{completely correlated} \\ 0 & \text{completely uncorrelated} \\ -1 & \text{completely anticorrelated} \end{cases}. \quad (8)$$

The time average of C_{kl} can be viewed as the matrix product of the rectangular matrix M ($K \times T$) with its transpose matrix M^\dagger ($T \times K$), divided by T . Thus, the correlation matrix can be written in the form

$$C = \frac{1}{T} M M^\dagger. \quad (9)$$

The correlation matrix C is real and symmetric. Using the correlation matrix C is possible to define the covariance matrix [15, 35, 36, 37, 38]

$$\Sigma = \sigma C \sigma, \quad (10)$$

where the diagonal matrix σ contains respectively, the volatilities σ_k , $k = 1, \dots, K$.

From the results obtained in [14, 36], it does not make a difference the calculation with a covariance or a correlation matrix. Thus, to ease the comparison between works, we will use covariance matrices as in [14].

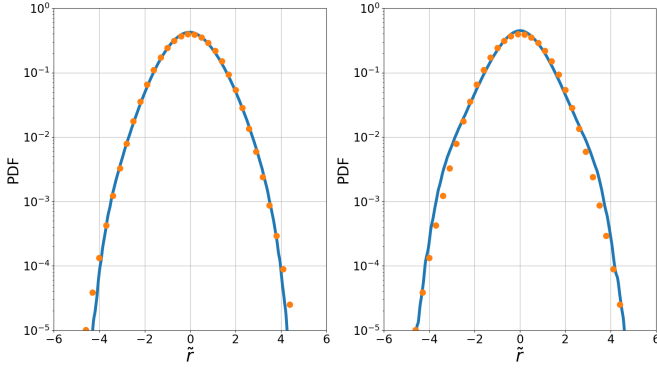


Figure 1.

3.2 Non-stationarity

In general, in non-stationary complex systems crucial parameters or distributions of observables change in an erratic, unpredictable way over time. In financial markets, the $K \times K$ correlation matrix C as a whole changes in time is an example of non-stationary. Fig. 2 shows two large correlation matrices of logarithmic differences of stock prices for companies in the Standard & Poor's 500 (S&P 500) stock market index ordered according to the Global Industry Classification Standard (GICS). The time series were measured in successive quarters. The stripes in these correlation matrices indicate the structuring of the market in industrial sectors [13, 14]

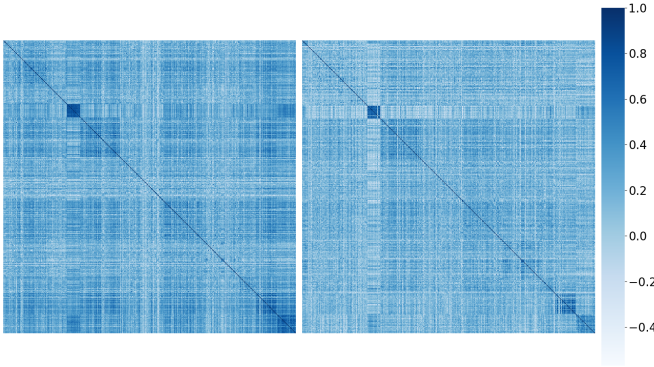


Figure 2. Correlation matrices of $K = 421$ companies for the fourth quarter of 2005 (left) and the first quarter of 2006 (right), the darker, the stronger the correlation. The companies are sorted according to industrial sectors.

In Fig. 2 it can be seen that the matrices look different for the successive quarters, because the business relations between the companies and the market expectations of the traders change in time. Despite the difference, the coarse structure remains similar, indicating some stability of the industrial sectors.

3.3 General considerations

To compare the K variate distributions with data, the crucial idea is to construct K univariate distributions out of the K variate one which are then overlaid [15]. To decouple the amplitudes, we rotate the vector r into the eigenbasis of the correlation matrix C or the eigenbasis of the covariance matrix Σ [14, 15]. More precisely, we use the diagonalization

$$C = U\Lambda U^\dagger \text{ such that } C^{-1/2} = U\Lambda^{-1/2}U^\dagger \quad (11)$$

or

$$\Sigma = U\Lambda U^\dagger \text{ such that } \Sigma^{-1/2} = U\Lambda^{-1/2}U^\dagger, \quad (12)$$

where U is an orthogonal $K \times K$ matrix and Λ is the diagonal matrix of the eigenvalues Λ_k . As they are positive definite, the square roots $\Lambda_k^{1/2}$ are real, we choose them positive. We use the rotated amplitudes

$$\tilde{r} = U^\dagger r \quad (13)$$

as new arguments of the ensemble averaged amplitude distribution.

When analyzing data, K is given, we obtain the matrices C and Σ by using the originally measured amplitudes for sampling over the long time interval. In all cases, the parameter N is a fit parameter, measuring the strenght of the fluctuations. Experience tells, that N sensitevly determines the shape and is best obtained by fitting the whole distribution to the data.

3.4 Four cases distributions

In the Gaussian-Gaussian case with the Markovian situation $D = \mathbb{1}_N$ the distribution reads

$$\langle p \rangle_{GG}^{(k)}(\tilde{r}_k | \Lambda_k, \mathbb{1}_N) = \frac{1}{2^{(N-1)/2} \Gamma(N/2) \sqrt{\pi \Lambda_k / N}} \sqrt{\frac{N \tilde{r}_k^2}{\Lambda_k}}^{(N-1)/2} K_{(1-N)/2} \left(\sqrt{\frac{N \tilde{r}_k^2}{\Lambda_k}} \right), \quad (14)$$

In the Gaussian-algebraic case with the Markovian situation $D = \mathbb{1}_N$ the distribution reads

$$\langle p \rangle_{GA}^{(k)}(\tilde{r}_k | \Lambda_k, \mathbb{1}_N) = \frac{\Gamma(L - (K + N)/2 + 1) \Gamma(L - (K - 1)/2)}{\Gamma(L - (K + N - 1)/2) \Gamma(N/2) \sqrt{2\pi \Lambda_k M/N}} U \left(L - \frac{K + N}{2} + 1, \frac{1 - N}{2} + 1, \frac{N}{2M} \frac{\tilde{r}_k^2}{\Lambda_k} \right) \quad (15)$$

In the algebraic-Gaussian case with the Markovian situation $D = \mathbb{1}_N$ the distribution reads

$$\begin{aligned} \langle p \rangle_{AG}^{(k)}(\tilde{r}_k | \Lambda_k, \mathbb{1}_N) = & \frac{\Gamma(l - (K - 1)/2) \Gamma(l - (K - N)/2)}{\Gamma(l - K/2) \Gamma(N/2) \sqrt{2\pi \Lambda_k m/N}} \\ & \mathcal{U}\left(l - \frac{K - 1}{2}, \frac{1 - N}{2} + 1, \frac{N}{2m} \frac{\tilde{r}_k^2}{\Lambda_k}\right) \end{aligned} \quad (16)$$

Finally, in the algebraic-algebraic case with the Markovian situation $D = \mathbb{1}_N$ the distribution reads

$$\begin{aligned} \langle p \rangle_{AA}^{(k)}(\tilde{r}_k | \Lambda_k, \mathbb{1}_N) = & \frac{\Gamma(l - (K - 1)/2) \Gamma(l - (K - N)/2)}{\Gamma(l - K/2) \Gamma(L + l - (K - 1)) \sqrt{\pi \Lambda_k M m/N}} \\ & \frac{\Gamma(L - (K + N)/2 + 1) \Gamma(L - (K - 1)/2)}{\Gamma(L - (K + N - 1)/2) \Gamma(N/2)} \\ & {}_2F_1\left(l - \frac{K - 1}{2}, L - \frac{K + N}{2} + 1, L + l - (K - 1), 1 - \right. \end{aligned} \quad (17)$$

For a visual comparison of the distributions, we plot the GG, GA, AG and AA distributions in the Markovian case in the same figure. In Fig. 3 we consider $K = 100$ positions with shape parameters $L = 55$, $l = 55$, as well as $N = 5$ which is a typical value from an empirical viewpoint. In the top are the probability densities in linear scale and in the bottom are the probability densities in logarithmic scales. From figure, it can be seen the more algebraic, the stronger peaked is the distribution and heavier are the tails.

3.5 Graphical representations

To plot a comparison of the distributions involving algebraic distributions with those in the Gaussian-Gaussian case, we choose values of L and l which ensure the existence of the first matrix moment (?). We notice that the conditions on the existence of the algebraic distributions, i.e., of their normalizations, are slightly weaker. The variances $\langle \tilde{r}_k \rangle_{YY'}(k)$ are simply given by Λ_k . The functional form of all distributions $\langle p \rangle_{YY'}(k)(\tilde{r}_k | D)$ then allows us to normalize the rotated amplitude \tilde{r}_k by the standard deviation

$$\tilde{r} = \frac{\tilde{r}_k}{\sqrt{\Lambda_k}} \quad (18)$$

such that all K distributions in this variable coincide and the corresponding variances are all given by one.

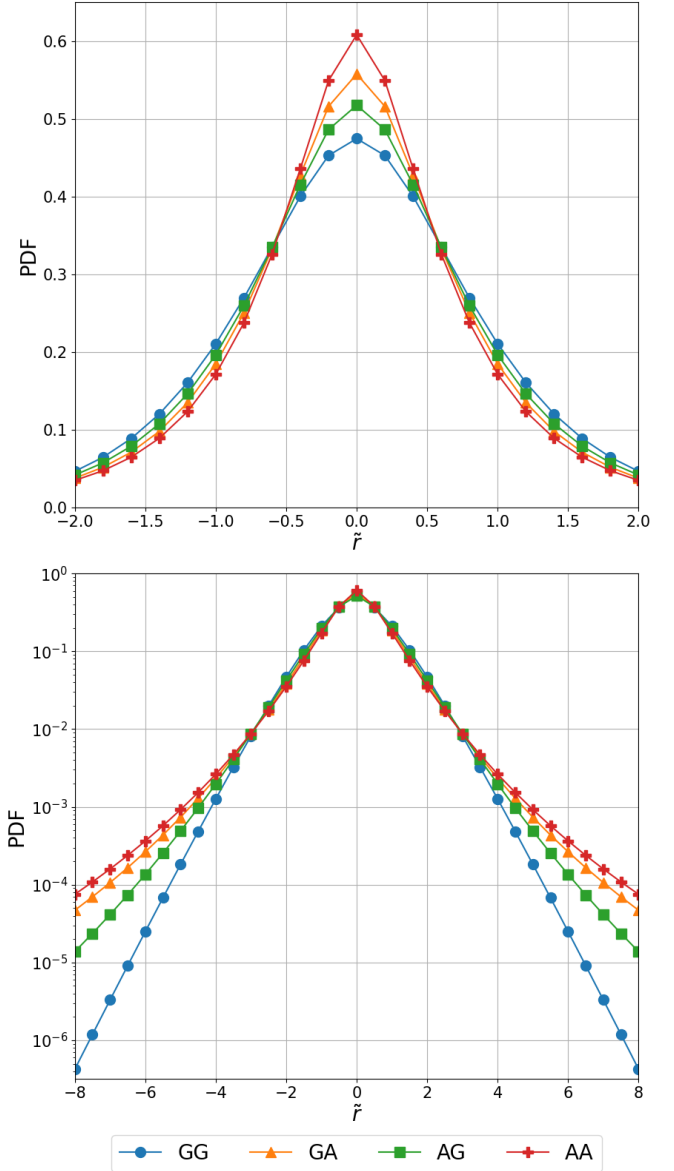


Figure 3. Probability densities $\langle p \rangle_{YY'}^{(k)}$, in the Markovian case versus the rotated amplitudes \tilde{r} , normalized to unit standard deviation. The four cases Gaussian-Gaussian, Gaussian-Algebraic, Algebraic-Gaussian and Algebraic-Algebraic are labeled $YY' = GG, GA, AG$ and AA , respectively. Number of positions $K = 100$, shape parameters $L = 55$ and $l = 55$, strength parameter for fluctuations of correlations $N = 5$. (Top) Linear scale, abscissa between -2 and $+2$ and (bottom) logarithmic scale, abscissa between -8 and $+8$.

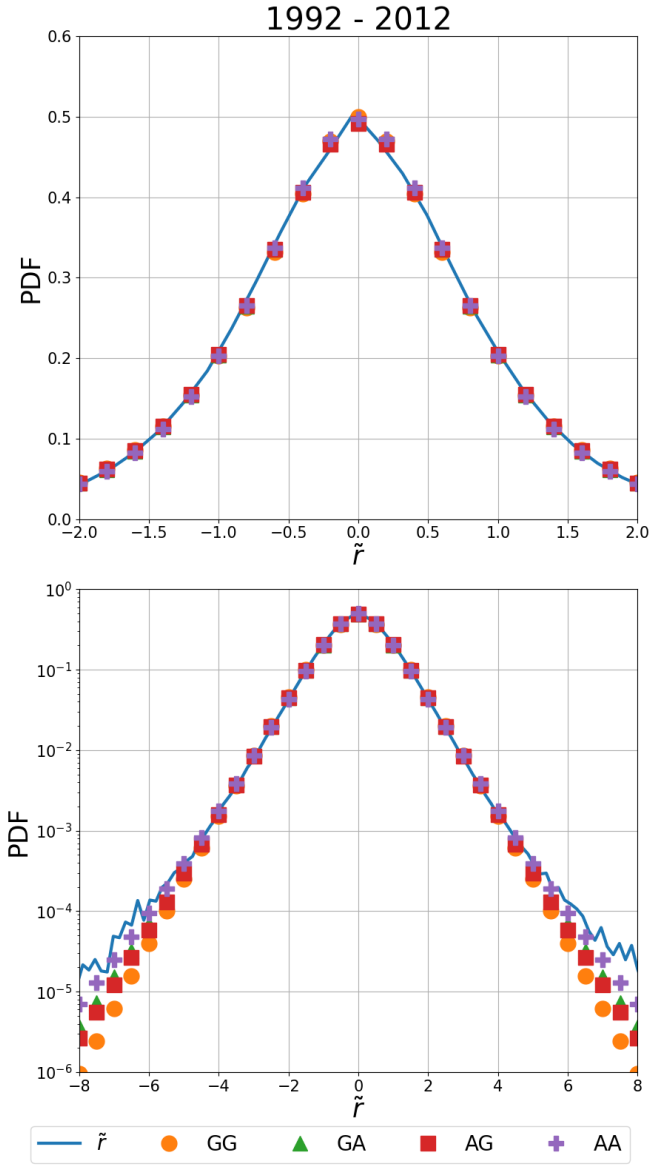


Figure 4.

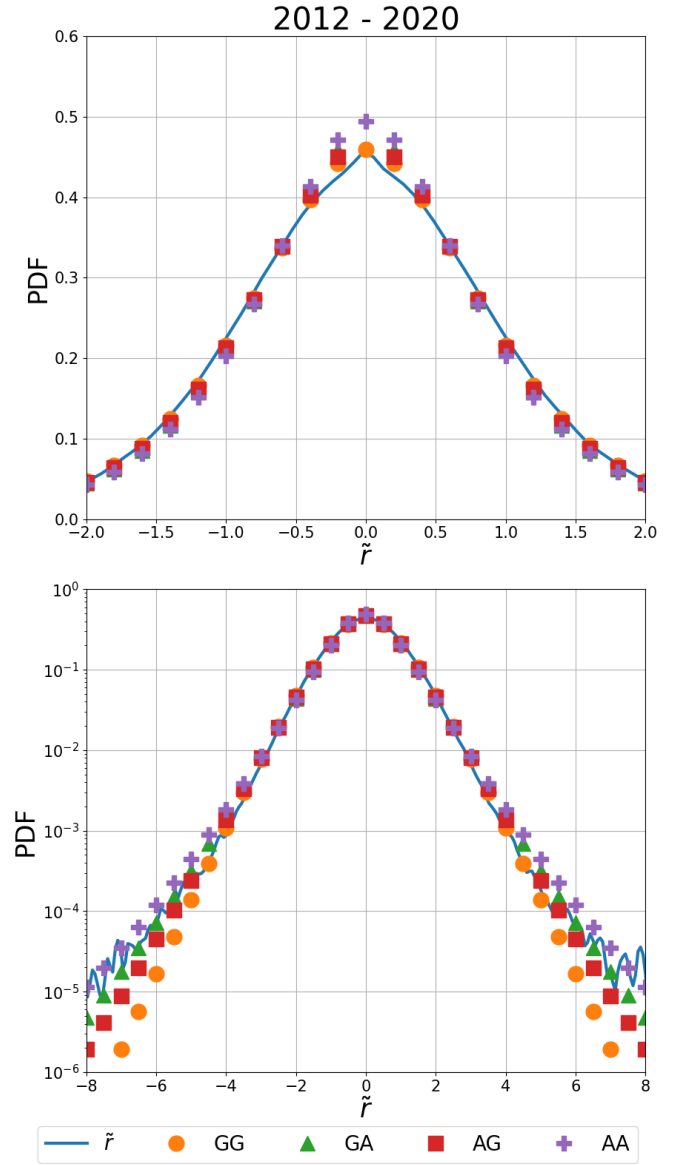


Figure 5.

4 Comparison with empirical portfolio returns

4.1 Response functions on trade time scale

4.2 Response functions on physical time scale

5 Conclusion

6 Author contribution statement

TG proposed the research. JCHL carried out the analysis. All the authors contributed equally to analyzing the results and writing the paper.

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Appendix A S&P 500 stocks used to compare the distributions

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