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Rho Has No Role: Correlation Coefficient Instability and Non-asymptotic Simulation Volatility

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Abstract This paper calculates the per quarter pairwise correlation coefficients (Rho) of the daily returns from December 5, 2005 to December 8, 2014 of 30 stocks randomly selected from the Russell 3000 index. For the time series correlation coefficients of 435 pairs of assets, we employ the Elliot-Rothenberg-Stock Point Optimal procedure to examine the stability of correlation coefficients. Our results indicate the inappropriateness of using correlation coefficients in portfolio management and Monte Carlo simulation. More than one-third of the correlation coefficient series generate non-asymptotic simulation volatility and using *ex post* correlation coefficients in Cholesky decomposition performance forecast can lead to severe deviation from the investment policy mandate.

Keywords Correlation Coefficient, Cholesky Decomposition, Portfolio Risk, Monte Carlo

JEL codes: G11, G17, C22

1. Introduction

This paper examines the volatility of correlation and the implication of the non-constant correlation coefficients. The purpose of this paper is to remind the users of Pearson correlation about its inappropriateness in measuring and simulating portfolio performance. The finance academia and industry frequently adopt Pearson correlation coefficient to measure the dependence and linkages. One of the most famous uses of Pearson correlation coefficient is in portfolio management, in which the variance of the portfolio is computed as:

$$\sigma_p^2 = \sum_i \omega_i^2 \sigma_i^2 + \sum_i \sum_j w_i\, w_j \sigma_i \sigma_j \rho_{ij} \quad (1)$$

However, to use this variance of portfolio with historical data to simulate future performance of assets in the Monte Carlo procedure, which is the common practice in academia and industry, the implicit assumption is the stability of the correlation coefficient. In other words, the previously realized correlation coefficient matrix

$$\begin{pmatrix} 1 & \cdots & \rho_{1j} \\ \vdots & \ddots & \vdots \\ \rho_{i1} & \cdots & 1 \end{pmatrix} \quad (2)$$

is able to describe the future correlations of assets. This assumption has not been thoroughly discussed, and the broader issue is what the impact of instable correlation coefficient is. The meanings of such question is not limited to portfolio management but to all the fields in finance theory that use previous correlation coefficients as measure the correlation nature of assets. The implication is particularly important in terms of Cholesky decomposition, which is the standardized modeling procedure in Monte Carlo simulation.

Specifically, the Cholesky decomposition of a positive-definite matrix $\mathbb{A}$ is a decomposition of the form

$$\mathbb{A} = \mathbb{L}\mathbb{L}^* \quad (3)$$

where $\mathbb{L}$ is a lower triangular matrix with real and positive diagonal entries, and $\mathbb{L}^*$ is the conjugate transpose of $\mathbb{L}$. Every positive-definite matrix has a unique Cholesky decomposition.

Using Cholesky decomposition, independent variables can be re-calculated to be correlated at designated level so that simulations can be performed with dependence amongst variables. The first step is to decompose the correlation matrix and obtain the lower-triangular $\mathbb{L}$. Applying this to a vector of uncorrelated samples, $\vec{r}$, produces a sample vector $\mathbb{L}\vec{r}$ with the covariance properties of the historical values being modeled. Particularly, to generate two correlated normally distributed variables with correlation coefficient equals ρ, one can first generate two uncorrelated normal variables ω_1 and ω_2, and then re-calculate ω_2 by changing it to $\rho\omega_1 + \sqrt{1-\rho^2}\omega_2$. Now ω_1 and $\rho\omega_1 + \sqrt{1-\rho^2}\omega_2$ are correlated at the level of ρ.

The Cholesky decomposition, very frequently used in Monte Carlo simulation of portfolio returns, again assumes a constant correlation coefficient between assets. The simulated asset returns carry the same correlation coefficient as the realized returns. However, if the correlation coefficients amongst assets are not constant over time, then the volatility of the simulated asset performance might be underestimated. Furthermore, if the historical correlation coefficient is negative and such assumption is delivered by correlation coefficient into future simulations, the outcome can be misleading and land investors the illusion of risk being hedged while in fact the risk of the portfolio might be amplified by the volatility of correlation coefficients.

This paper is not the first one that realizes the non-constant issue of correlation coefficients. [1] suggests that there is significant increase in the correlation coefficients of returns across countries during periods of high turbulence. [1] concludes that correlation coefficients can be biased downward under heteroskedasticity when returns are following stochastic unit root processes, and correlation coefficients are very useful in measuring relations between asset returns. [2] also documents the structural issues of correlation coefficient that lead to the invalidity of using correlation coefficients to measure the interdependence of asset returns.

There are massive literatures discussing the measures of dependence and contagion of asset returns. For example, the most widely cited papers are [3], [4], [5], and [6]. However, the methods that the previous studies suggest to correct the shortfall of correlation coefficient are used to measure, rather than simulate, dependence and contagion of asset returns. These methods, including causality, cointegration, GARCH, cannot be used to simulate future returns of assets. When it comes to simulation methods, the most frequently seen procedure is still Cholesky decomposition. While employing copulas can avoid the instability shortfall of correlation coefficient, copulas are not widely adopted in both industry and academia.

Another school of correlation coefficient measures is the rank-based correlation. However, Kendall's tau, Spearman's rank correlation coefficient, and Goodman and Kruskal's gamma ignore the magnitude of asset returns and fail to give guidance in terms of return simulation.

We employ 30 randomly selected stocks from Russell 3000 index and investigate the pairwise correlation coefficients at each quarter. The data of the assets are the daily returns for 9 years and thus we computed 16095 correlation coefficients for the representative stocks. The market capitalization of the 30 selected assets is from U.S. \$268.74 million to U.S. \$799.72 billion; the forward P/E is from 7.09 to 62; and the EV/EBITDA is from -21.13 to 43.88.

Rather than using the Dickey-Fuller procedure, we then perform ERS unit root tests to test the stability of the correlation coefficients. If the correlation coefficients are stable, the time series of the 36 quarterly computed correlation coefficients should not present any unit root and should therefore be mean-reverting. While the Augmented Dickey-Fuller unit root test is the most frequently used procedure to test for the autoregressive series with one degree of integration, we do not adopt the Dickey-Fuller procedure, as there is no evidence to nest correlation coefficient data as being linear. Without presumably nesting the relationship amongst the historical correlation coefficients, the optimal method should be the Elliot, Rothenberg, and Stock point optimal unit root test.

The results of this paper are significant: of the 435 pairs of assets in our investigation, 171 series of correlation coefficients, or 39.31% in the sample, follow random process as Table 3 presents. On the other hand, 264 series of correlation coefficients, or 60.69%, follow stationary process, as Table 4 indicates. The fact that more than one-third of assets have random correlation coefficients suggests that it is inappropriate to use correlation coefficients and Cholesky decomposition in the Monte Carlo process.

The rest of the paper is organized as follows: Section 2 discusses the processing and sampling of asset prices; Section 3 explains the methods incorporated in our paper; Section 4 presents the results of the unit root tests; and Section 5 concludes.

2. Data

This paper employ the daily returns of 30 stocks randomly selected from the Russell 3000 index. The membership of the Russell 3000 index is according to the index list published on June 27, 2014. The random selection process is to assign a random value between 0 and 1 for all 3000 assets, and then select assets with random values between 0.498 and 0.502 that carry full nine-year historical data. The random value assigned follows an uniform distribution, which warrants the process free of data mining concerns.

For each of the 30 stocks we obtain 2269 daily adjusted close price information from CRSP and then covert the prices into continuously compounded returns using the following Equation (4).

$$r_t^\gamma = \log_e p_t^\gamma - \log_e p_{t-1}^\gamma \tag{4}$$

For each stock γ incorporated in this paper we obtain 2268 daily return observations. These are nine years of returns, with 252 observations per year and 63 observations per quarter. This long and complete dataset justifies the robustness of the conclusion and spans different periods of market. Specifically, Table 1 summarizes the periods of data. Apparently the S&P 500 in the entire periods of observations is chaotic and does not present any trend. This justifies the robustness of the conclusion in our paper, as the conclusion is summarized from various market environments.

The assets selected in this paper are summarized in Table 2. As of December 9, 2014, the market capitalization of the 30 selected assets is from U.S. \$268.74 million to U.S. \$799.72 billion; the enterprise value (EV) is from U.S. \$223.35 million to U.S. \$46.27 billion; the trailing twelve month P/E is from 8.72 to 222; the forward P/E is from 7.09 to 62; the PEG is from -2.26 to 23.66; the P/S is from 0.1 to 20.89; the P/B is from 0.65 to 5.7; the EV/Revenue is from 0.11 to 16.59; and the EV/EBITDA is from -21.13 to 43.88. The key statistics of the sample well represents the Russell 3000 index.

Table 1. Periods of Data and Performance of S&P 500 as Benchmark

Y/Q	Start	End	S&P 500	Y/Q	Start	End	S&P 500
9Q4	9/10/2014	12/8/2014	0.03238	5Q2	3/10/2010	6/8/2010	-0.07298
9Q3	6/11/2014	9/9/2014	0.022918	5Q1	12/7/2009	3/9/2010	0.033719
9Q2	3/12/2014	6/10/2014	0.044208	4Q4	9/8/2009	12/4/2009	0.078594
9Q1	12/9/2013	3/11/2014	0.03277	4Q3	6/9/2009	9/4/2009	0.078489
8Q4	9/10/2013	12/6/2013	0.071913	4Q2	3/10/2009	6/8/2009	0.305086
8Q3	6/11/2013	9/9/2013	0.02803	4Q1	12/5/2008	3/9/2009	-0.22777
8Q2	3/12/2013	6/10/2013	0.058184	3Q4	9/8/2008	12/4/2008	-0.33331
8Q1	12/7/2012	3/11/2013	0.097421	3Q3	6/9/2008	9/5/2008	-0.08772
7Q4	9/6/2012	12/6/2012	-0.01269	3Q2	3/10/2008	6/6/2008	0.068566
7Q3	6/7/2012	9/5/2012	0.067263	3Q1	12/6/2007	3/7/2008	-0.14195
7Q2	3/8/2012	6/6/2012	-0.03718	2Q4	9/7/2007	12/5/2007	0.021644
7Q1	12/6/2011	3/7/2012	0.074821	2Q3	6/8/2007	9/6/2007	-0.01931
6Q4	9/7/2011	12/5/2011	0.048773	2Q2	3/9/2007	6/7/2007	0.062644
6Q3	6/8/2011	9/6/2011	-0.08934	2Q1	12/5/2006	3/8/2007	-0.0091
6Q2	3/9/2011	6/7/2011	-0.02658	1Q4	9/6/2006	12/4/2006	0.083722
6Q1	12/7/2010	3/8/2011	0.080139	1Q3	6/7/2006	9/5/2006	0.045456
5Q4	9/8/2010	12/6/2010	0.113071	1Q2	3/8/2006	6/6/2006	-0.01144
5Q3	6/9/2010	9/7/2010	0.034243	1Q1	12/5/2005	3/7/2006	0.010926

Table 2. The 30 Assets Incorporated in Correlation Coefficient Instability Investigation

Company	Ticker	Company	Ticker
ASPEN INSURANCE HOLDING	AHL	INGRAM MICRO INC	IM
BE AEROSPACE INC	BEAV	MARKEL CORP	MKL
Belmond	BEL	MONARCH CASINO & RESORT	MCRI
COCA COLA BOTTLING	COKE	MOSAIC COMPANY	MOS
DIEBOLD INC	DBD	NU SKIN ENTERPRISES	NUS
MULTI-COLOR	LABL	PEPCO	POM
DOT HILL SYS CORP	HILL	POWELL INDUSTRIES INC	POWL
EZCORP INC	EZPW	PRAXAIR	PX
FIRST FINL BANKSHARES	FFIN	RAMCO-GERSHENSON	RPT
FIRST LONG ISLAND CORP	FLIC	ROCKWOOD HOLDINGS INC	ROC
GENERAL COMMUNICATION	GNCMA	SCHOLASTIC	SCHL
HEARTLAND FINANCIAL USA	HTLF	SANGAMO	SGMO
HOVNANIAN	HOV	SKYWORKS SOLUTIONS INC	SWKS
J & J	JJSF	MOLSON	TAP
INTER PARFUMS	IPAR	UNIFI	UFI

3. Methodology

We first calculate the pairwise correlation coefficients of the selected asset returns at per quarter level and overall level. The pairwise correlation coefficient is defined as:

$$\rho_{\gamma,\gamma'} = \frac{cov(r_\gamma, r_{\gamma'})}{\sigma_\gamma \sigma_{\gamma'}} \tag{5}$$

For the 30 assets, there are 435 pairs of asset returns, and for each pair we calculate the correlation coefficient per quarter. With 9 years of return data we obtain 36 such correlation coefficients. We also compute the correlation coefficients for each pair using the overall 9 years data. Hence we computed and present 16095 correlation coefficients, which is the product of 435 pairs and 37 correlation coefficients for each pair.

Second, we perform unit root tests to test the stability of the correlation coefficients. If the correlation coefficients are stable, the time series of the 36 quarterly computed correlation coefficients should not present any unit root and should therefore be mean-reverting. The benefit of computing the overall correlation coefficient for each pair is significant as it can act as the benchmark of the mean-reverting correlation coefficient series, if unit root is absent. While the Augmented Dickey-Fuller unit root test is the most frequently used procedure to test for the autoregressive series with one degree of integration, we do not adopt the Dickey-Fuller procedure, as there is no evidence to nest correlation coefficient data as being linear. Without presumably nesting the relationship amongst the historical correlation coefficients, the optimal method should be the Elliot, Rothenberg, and Stock point optimal unit root test.

The Elliot, Rothenberg, and Stock [7] Point Optimal procedure first defines a quasi-difference of y_t that depends on the value a representing the alternative against the original null hypothesis:

$$d(y_t|a) = \begin{cases} y_t & for\ t = 1 \\ y_t - a y_{t-1} & for\ t > 1 \end{cases} \tag{6}$$

Then in the OLS regression of the quasi-differenced data $d(y_t|a)$ on the quasi-differenced $d(x_t|a)$:

$$d(y_t|a) = d(x_t|a)'\delta(a) + \eta_t \tag{7}$$

Define the residual as:

$$\hat{\eta}_t(a) = d(y_t|a) - d(x_t|a)'\hat{\delta}(a) \tag{8}$$

And continue define:

$$SSR(a) = \sum \hat{\eta}_t^{\,2}(a) \quad (9)$$

as the sum-of-squared residuals function. The ERS point optimal test statistic of the null that $\alpha = 1$ against the alternative $\alpha = \bar{a}$ is defined as:

$$P_T = (SSR(\bar{a}) - \bar{a}SSR(1))/f_0 \quad (10)$$

where f_0 is an estimator of the residual spectrum at frequency zero.

Third, we categorize the asset pairs by various features of the assets and explore the possible pattern of correlation coefficient in a subset of the asset pairs. We attempt to explore the asset classes by size and type. Size is defined by the market capitalization which is the product of the number of common shares outstanding and the asset price per share as of December 9, 2014. Type is defined as the two-polar feature of assets, growth versus value. Growth stocks have higher Price-to-Book ratio while value stocks carry lower Price-to-Book ratio. To summarize, this paper attempts to explore the different patterns of correlation coefficients when the sizes of assets vary and the assets vary from being undervalued to being overvalued.

4. Results and Discussions

We first calculate the correlation coefficients per quarter for all the 435 pairs of asset returns for the 30 stocks. The results are available by request. We then perform the ERS unit root tests for the correlation coefficients. For the ERS Point-Optimal Unit Root Test, the critical values calculated for 50 observations are 1.87 at 1% level, 2.97 at 5% level, and 3.91 for 10% level. Using spectral OLS AR based on SIC, the Elliott-Rothenberg-Stock test statistics are presented in Table 3 and Table 4..

Table 3. Asset Pairs with Random Correlation Coefficients Process

Asset Pair	Test Stat.	Asset Pair	Test Stat.	Asset Pair	Test Stat.	Asset Pair	Test Stat.
AHL BEAV	3.5381	DBD NUS	5.9419	FFIN TAP	3.7028	IM MOS	3.8157
AHL EZPW	3.7577	DBD POWL	4.5092	FFIN UFI	4.1743	IM NUS	6.4953
AHL FFIN	4.2942	LABL EZPW	11.7624	FLIC GNCMA	3.4853	IM POM	4.7774
AHL GNCMA	3.4217	LABL FFIN	12.2407	FLIC HTLF	7.2868	IM PX	4.8725
AHL HTLF	4.3264	LABL FLIC	7.5126	FLIC HOV	3.1396	IM ROC	5.9918
AHL IM	6.4929	LABL GNCMA	4.4796	FLIC JJSF	4.8280	IM SCHL	3.0331
AHL MOS	3.1043	LABL HTLF	3.7095	FLIC IM	3.7469	IM SWKS	3.3305
AHL MOS	3.0412	LABL HOV	3.3708	FLIC MKL	4.9865	IM TAP	5.3153
AHL ROC	4.3865	LABL JJSF	7.9059	FLIC MOS	3.7436	MKL PX	3.1924
AHL SCHL	3.2990	LABL MOS	8.0877	FLIC PX	5.7641	MKL ROC	4.8054
AHL SGMO	4.2214	LABL NUS	5.2463	FLIC RPT	3.1724	MKL SGMO	3.5771
BEAV BEL	3.2682	LABL POM	3.3245	FLIC ROC	6.4852	MOS POWL	3.1384
BEAV DBD	7.0685	LABL PX	3.2465	FLIC SWKS	3.0756	MOS SGMO	4.4958
BEAV LABL	4.9562	LABL RPT	4.4005	FLIC UFI	25.0334	MOS UFI	3.4603
BEAV EZPW	3.2100	LABL SCHL	5.0459	GNCMA IPAR	3.5040	MOS POM	4.5604
BEAV FLIC	3.6458	LABL SGMO	3.0506	GNCMA NUS	3.1676	MOS PX	6.1824
BEAV IM	3.2838	LABL SWKS	6.9574	GNCMA SGMO	4.2627	MOS RPT	2.9860
BEAV MKL	3.2878	LABL TAP	24.4823	GNCMA UFI	3.3407	MOS ROC	3.3889
BEAV RPT	3.4654	LABL UFI	8.5587	HTLF JJSF	3.4731	MOS SGMO	3.0753
BEAV SCHL	3.3600	HILL EZPW	3.0950	HTLF MKL	4.3142	MOS SWKS	5.3654
BEAV SGMO	4.5535	HILL MKL	3.5826	HTLF ROC	3.7236	MOS UFI	3.0784
BEAV TAP	4.2874	HILL SCHL	3.2014	HTLF SGMO	3.4768	NUS ROC	3.0262
BEAV UFI	3.0205	HILL UFI	2.9871	HTLF SWKS	4.3055	NUS SCHL	3.8200
BEL LABL	6.6999	EZPW FFIN	6.4195	HTLF TAP	4.0322	NUS SGMO	2.9997
BEL HILL	3.0570	EZPW HTLF	3.9510	HTLF UFI	6.7231	POWL RPT	5.5830
BEL IM	5.1774	EZPW HOV	3.1122	HOV IM	5.0435	POWL ROC	3.2026
BEL POWL	3.1957	EZPW IM	3.4877	HOV POWL	3.2916	POWL TAP	3.0239
BEL PX	3.1115	EZPW NUS	3.6442	HOV ROC	5.2011	POWL UFI	3.7488
BEL ROC	3.2397	EZPW POM	3.4078	HOV SGMO	4.0974	POM SCHL	3.4995
BEL SCHL	3.4909	EZPW PX	3.7039	JJSF IPAR	6.9583	POM SGMO	7.9127
COKE DBD	3.5748	EZPW ROC	5.1434	JJSF IM	3.8009	PX SGMO	3.7038
COKE LABL	3.7693	EZPW SGMO	2.9992	JJSF SCHL	3.7950	PX TAP	4.0472
COKE HTLF	3.9900	EZPW SWKS	4.5412	JJSF SGMO	4.2458	RPT SCHL	5.1081
COKE MKL	3.5786	EZPW TAP	4.6984	IPAR MKL	3.7151	RPT SGMO	4.8065
COKE ROC	3.4991	FFIN FLIC	7.7663	IPAR MOS	3.8833	RPT UFI	8.9135
COKE SGMO	5.6582	FFIN IPAR	4.2385	IPAR POM	3.4911	ROC SCHL	3.4162
DBD LABL	5.1203	FFIN IM	5.5235	IPAR PX	4.3585	ROC SGMO	3.9982
DBD FFIN	5.8009	FFIN MKL	3.5776	IPAR RPT	3.5925	ROC SWKS	5.1977
DBD HTLF	4.6374	FFIN NUS	12.5381	IPAR ROC	3.8851	ROC TAP	3.1664
DBD HOV	4.1639	FFIN ROC	3.4023	IPAR SWKS	3.0717	ROC UFI	11.9831
DBD IPAR	4.5928	FFIN SCHL	3.5288	IPAR UFI	3.4570	SCHL TAP	3.0055
DBD IM	5.4782	FFIN SGMO	5.4875	IM MKL	8.1103	SGMO TAP	3.2782
DBD MOS	5.3722	FFIN SWKS	4.9278	IM MOS	4.3711		

A comparison of the random and stationary correlation coefficient suggests that among the 171 pairs of assets that carry random correlation coefficients, 89 pairs consist of a company with large market cap and a company with small market cap; 98 pairs consist of a high enterprise value and a low enterprise value; 86 pairs have either a low Forward P/E ratio and a low Forward P/S ratio, or one high Forward P/E ratio and one high Forward P/S ratio; 87 pairs consist of a low Forward PEG ratio and a high PEG ratio. The results indicate that the type or category of firms do not affect the stochastic feature of correlation coefficients. The detailed comparison is available by request.

Of the 435 pairs of assets in our investigation, 171 series of correlation coefficients, or 39.31% in the sample, follow random process as Table 3 presents. On the other hand, 264 series of correlation coefficients, or 60.69%, follow stationary process, as Table 4 indicates. The fact that more than one-third of assets have random correlation coefficients suggests that it is inappropriate to use correlation coefficients and Cholesky decomposition in the Monte Carlo process.

One caveat is in terms of the interpretation of the asset pairs whose correlation coefficients are stationary. Stationary process does not warrant the validity of incorporating correlation coefficients in portfolio analysis and performance simulation. In other words, stationary process does not imply unchanged process. The variance, skewness, and kurtosis of the correlation coefficients still deviates significantly from normal distribution.

In addition, we perform the same method described in this research on the Dow Jones Industrial Average Index component equities to examine the robustness of the conclusions. The results are highly consistent and not presented here due to the concern of being concise. However, the outputs of robustness test are available by request.

Table 4. Asset Pairs with Stationary Correlation Coefficients Process

Asset Pair	Test Stat.	Asset Pair	Test Stat.	Asset Pair	Test Stat.	Asset Pair	Test Stat.
AHL BEL	2.5743	COKE POWL	2.2374	FFIN MOS	1.9103	IPAR NUS	2.3691
AHL COKE	2.7320	COKE POM	1.5299	FFIN POWL	1.4836	IPAR POWL	2.3325
AHL DBD	2.7186	COKE PX	2.7359	FFIN POM	1.6196	IPAR SCHL	2.9597
AHL LABL	2.8410	COKE RPT	1.4919	FFIN PX	1.8407	IPAR SGMO	1.5162
AHL HILL	1.4616	COKE SCHL	1.2571	FFIN RPT	1.9671	IPAR TAP	1.9987
AHL FLIC	1.9878	COKE SWKS	1.3579	FLIC IPAR	2.4421	IM POWL	2.6055
AHL HOV	2.9163	COKE TAP	2.8434	FLIC MOS	2.2870	IM RPT	2.6467
AHL JJSF	1.8192	COKE UFI	2.6085	FLIC NUS	2.8534	IM SGMO	1.5366
AHL IPAR	1.9453	DBD HILL	2.2844	FLIC POWL	2.5137	IM UFI	2.8772
AHL MKL	2.8055	DBD EZPW	2.6312	FLIC POM	1.9594	MKL MOS	1.9618
AHL NUS	2.5300	DBD FLIC	1.9624	FLIC SCHL	2.7887	MKL MOS	2.4231
AHL POWL	2.6278	DBD GNCMA	1.5049	FLIC SGMO	2.8917	MKL NUS	2.5797
AHL POM	2.8417	DBD JJSF	2.3352	FLIC TAP	1.8708	MKL POWL	2.2381
AHL PX	1.6160	DBD MKL	2.5351	GNCMA HTLF	2.5900	MKL POM	2.9538
AHL RPT	2.1963	DBD MOS	1.4197	GNCMA HOV	1.3689	MKL RPT	2.3026
AHL SWKS	1.8683	DBD POM	1.6240	GNCMA JJSF	1.8162	MKL SCHL	2.9447
AHL TAP	2.4951	DBD PX	1.9402	GNCMA IM	2.8467	MKL SWKS	1.5227
AHL UFI	2.7792	DBD RPT	0.8858	GNCMA MKL	2.7102	MKL TAP	1.1875
BEAV COKE	1.8777	DBD ROC	2.2063	GNCMA MOS	1.5811	MKL UFI	2.0504
BEAV HILL	1.6241	DBD SCHL	1.6973	GNCMA MOS	2.2583	MOS MOS	2.0753
BEAV FFIN	1.6570	DBD SGMO	1.5691	GNCMA POWL	2.0451	MOS NUS	0.7763
BEAV GNCMA	2.4035	DBD SWKS	1.6270	GNCMA POM	2.3607	MOS POM	0.7262
BEAV HTLF	2.1850	DBD TAP	1.5759	GNCMA PX	1.7570	MOS PX	1.8509
BEAV HOV	1.4424	DBD UFI	1.9777	GNCMA RPT	1.9261	MOS RPT	1.4586
BEAV JJSF	2.0726	LABL HILL	1.9100	GNCMA ROC	2.2346	MOS ROC	1.7466
BEAV IPAR	2.2080	LABL IPAR	1.6951	GNCMA SCHL	1.6878	MOS SCHL	1.2459
BEAV MOS	2.4176	LABL IM	2.6206	GNCMA SWKS	2.0239	MOS SWKS	1.5025
BEAV MOS	1.4059	LABL MKL	2.9081	GNCMA TAP	1.9589	MOS TAP	2.4435
BEAV NUS	0.7908	LABL MOS	2.4572	HTLF HOV	2.2604	MOS NUS	1.6142
BEAV POWL	1.6089	LABL POWL	2.4354	HTLF IPAR	2.5237	MOS POWL	1.6100
BEAV POM	0.8350	LABL ROC	1.4354	HTLF IM	0.0090	MOS SCHL	2.6819
BEAV PX	1.5775	HILL FFIN	1.7365	HTLF MOS	1.5075	MOS TAP	2.3467
BEAV ROC	2.6698	HILL FLIC	2.4955	HTLF MOS	1.4912	NUS POWL	0.8627
BEAV SWKS	2.4248	HILL GNCMA	1.8216	HTLF NUS	2.0215	NUS POM	1.3468
BEL COKE	1.4246	HILL HTLF	1.7245	HTLF POWL	2.1261	NUS PX	1.8416
BEL DBD	1.7289	HILL HOV	1.7939	HTLF POM	1.4931	NUS RPT	1.7148
BEL EZPW	2.3241	HILL JJSF	2.7544	HTLF PX	1.6216	NUS SWKS	1.7699
BEL FFIN	1.5675	HILL IPAR	1.5670	HTLF RPT	2.9412	NUS TAP	1.8387
BEL FLIC	2.3420	HILL IM	2.2914	HTLF SCHL	1.3689	NUS UFI	2.6011

BEL GNCMA	1.9676	HILL MOS	1.7122	HOV JJSF	1.7267	POWL POM	1.8996
BEL HTLF	2.6208	HILL MOS	1.3950	HOV IPAR	2.7364	POWL PX	1.5551
BEL HOV	1.4457	HILL NUS	1.9241	HOV MKL	1.7029	POWL SCHL	2.6369
BEL JJSF	0.9638	HILL POWL	1.6104	HOV MOS	1.7461	POWL SGMO	2.8539
BEL IPAR	2.9446	HILL POM	1.4439	HOV MOS	1.5119	POWL SWKS	2.1701
BEL MKL	2.7035	HILL PX	1.9364	HOV NUS	2.3898	POM PX	1.5431
BEL MOS	1.6020	HILL RPT	1.8533	HOV POM	2.2232	POM RPT	1.8278
BEL MOS	1.4923	HILL ROC	1.5102	HOV PX	1.5650	POM ROC	2.5238
BEL NUS	0.5552	HILL SGMO	1.1568	HOV RPT	1.8822	POM SWKS	1.6691
BEL POM	1.6777	HILL SWKS	2.4324	HOV SCHL	2.0579	POM TAP	2.3803
BEL RPT	2.0504	HILL TAP	0.3853	HOV SWKS	1.8726	POM UFI	2.3921
BEL SGMO	2.4924	EZPW FLIC	2.7260	HOV TAP	1.7578	PX RPT	2.1211
BEL SWKS	2.7864	EZPW GNCMA	2.0372	HOV UFI	2.7719	PX ROC	2.3117
BEL TAP	0.8714	EZPW JJSF	2.8093	JJSF MKL	2.1005	PX SCHL	1.3170
BEL UFI	2.0315	EZPW IPAR	1.4809	JJSF MOS	1.6902	PX SWKS	1.6255
COKE HILL	1.5388	EZPW MKL	2.7558	JJSF MOS	1.5783	PX UFI	2.8653
COKE EZPW	2.3960	EZPW MOS	2.6111	JJSF NUS	2.8284	RPT ROC	2.7316
COKE FFIN	1.4782	EZPW MOS	1.7504	JJSF POWL	2.9095	RPT SWKS	2.5355
COKE FLIC	2.1071	EZPW POWL	2.2850	JJSF POM	1.6696	RPT TAP	2.1148
COKE GNCMA	1.4800	EZPW RPT	1.5404	JJSF PX	1.4674	SCHL SGMO	1.5379
COKE HOV	1.4041	EZPW SCHL	1.7895	JJSF RPT	2.0362	SCHL SWKS	0.0002
COKE JJSF	1.6642	EZPW UFI	1.5642	JJSF ROC	2.7644	SCHL UFI	1.6822
COKE IPAR	1.6417	FFIN GNCMA	2.3884	JJSF SWKS	1.3636	SGMO SWKS	1.7607
COKE IM	2.5096	FFIN HTLF	1.8966	JJSF TAP	2.9552	SGMO UFI	1.8805
COKE MOS	2.4511	FFIN HOV	2.0260	JJSF UFI	2.1491	SWKS TAP	1.7934
COKE MOS	1.7535	FFIN JJSF	1.6846	IPAR IM	1.4504	SWKS UFI	1.7227
COKE NUS	1.9243	FFIN MOS	1.5322	IPAR MOS	2.3080	TAP UFI	2.4324

5. Conclusions

This paper calculates the per quarter pairwise correlation coefficients (Rho) of the daily returns from December 5, 2005 to December 8, 2014 of 30 stocks randomly selected from the Russell 3000 index. The 30 stocks are computer-selected from Russell 3000 index and the data of the assets are the daily returns for 9 years. We computed 16095 correlation coefficients for the representative stocks. The market capitalization of the 30 selected assets is from U.S. $268.74 million to U.S. $799.72 billion; the forward P/E is from 7.09 to 62; and the EV/EBITDA is from -21.13 to 43.88.

For the time series correlation coefficients of 435 pairs of assets, we employ the Elliot-Rothenberg-Stock Point Optimal procedure to examine the stability of correlation coefficients. Our results indicate the inappropriateness of using correlation coefficients in portfolio management and Monte Carlo simulation. Of the 435 pairs of assets in our investigation, 171 series of correlation coefficients, or 39.31% in the sample, follow random process. On the other hand, 264 series of correlation coefficients, or 60.69%, follow stationary process. The fact that more than one-third of assets have random correlation coefficients suggests that it is inappropriate to use correlation coefficients and Cholesky decomposition in the Monte Carlo process. In addition, such conclusion is stable and robust across various types of assets.

The next step of the research is to attempt to answer the further question: what can be used to model the correlation of asset returns, as this study proofs the answer is not correlation coefficient. Any model that uses deterministic coefficients, rather than time varying variables suffers from similar problems presented in this study. A plausible answer is to use the independent distributions of asset returns and the copula that fits the joint distribution of the returns to describe and simulate the dependence of asset performance.

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