ESG Risk Ratings Correlation with DrawDown Beta

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1 Introduction

I was assigned the task of the ESG project to learn Ding and Uryasev (2022) : Drawdown Beta and Portfolio Optimization paper and realize the calculation of the Standard Beta, $ERoD_{0+}$ Beta, $CDaR_{0.9}$ Beta, Maximum drawdown, Annual Return, like the Drawdown Beta Website from Professor Uryasev website, by writing my own code.
Drawdown Beta Website link: http://qfdb.ams.stonybrook.edu/index_SP.html
From this https: https://www.businessinsider.com/personal-finance/esg-score:
Jim Probasco claimed that Sustainalytics, a subsidiary of Morningstar, provides ESG ratings on 20,000 companies in 172 countries. ESG ratings, which are based on both quantitative ESG data and qualitative analysis, cover several different areas including governance, environmental impact, social contribution, and financial performance to provide a holistic view of the ESG profile of companies. Risk ratings cover five categories: Negligible risk (0 to 9.99), Low risk (10 to 19.99), Medium risk (20 to 29.99), High risk (30 to 39.99), and Severe risk (40 and above).
Use the calculated Standard Beta, $ERoD_{0+}$ Beta, $CDaR_{0.9}$ Beta, Maximum drawdown, Annual Return results to see their correlation with the ESG rating scores. In addition, I need to find ESG rating scores for five categories and calculate the average of Standard Beta, $ERoD_{0+}$ Beta, $CDaR_{0.9}$ Beta, Maximum drawdown, Annual Return to see their performance.

2 Problem Formulation

2.1 Drawdown

Definition :

Ding and Uryasev (2022) call a set of consecutive vectors of returns of instruments a sample-path. A sample path may be just a table of historical returns of instruments or joint returns simulated with some model. Suppose that $\{r_t\}_{1\leq t\leq T}$ is a sample path of scalar returns of some instrument. Ding and Uryasev (2022) denote:

$\{w_t\}_{1\leq t\leq T}$ = vector of uncompounded cumulative returns,

$$w_t = \sum_{\nu=1}^{t} r_\nu, \quad 1 \leq t \leq T \tag{1}$$

$\{d_t\}_{1\leq t\leq T}$ = vector of drawdowns,

$$d_t = \max_{1\leq\nu\leq t} \{w_\nu\} - w_t, \quad 1 \leq t \leq T \tag{2}$$

For every time moment t the drawdown dt is the difference between the previous peak and the current cumulative return.

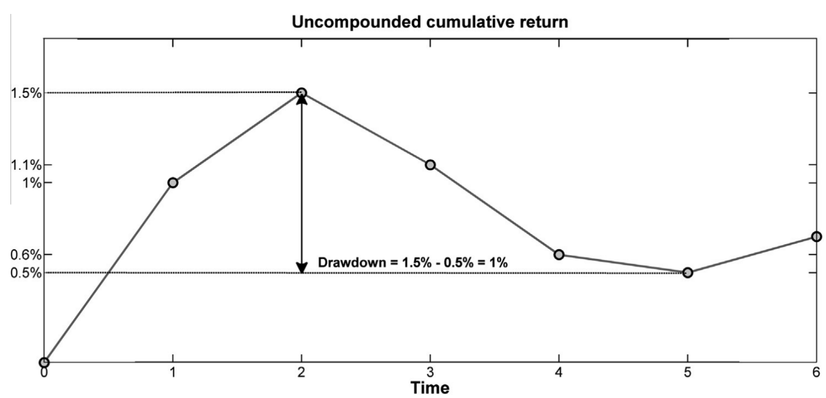

Figure 1: Drawdown Example: Solid line = uncompounded cumulative rate of return (at time t is the sum of rates of return over periods $1, ..., t$). For $t = 5$, $w_5 = 0.5\%$, whereas the maximum of w_t over time moments preceding $t = 5$ occurs at $t = 2$ with $w_2 = 1.5\%$. Consequently $d_5 = 1.5\%\ \ 0.5\%$ $= 1\%$. Maximum drawdown over time period [0, 6] occurs at $t = 5$ (Zabarankin et al., 2014).

Maximum drawdown (MaxDD), defined by

$$\text{MaxDD}(w) = \max_{1 \leqslant t \leqslant T} d_t$$

2.2 Conditional Drawdown-at-Risk (CDaR)

For a given $\alpha \in [0, 1)$ and time horizon T such that αT is an integer, the α-$CDaR$ is an average over the worst $(1-\alpha) * 100\%$ drawdowns occurred in the time horizon. Accordingly, Ding and Uryasev (2022) define the single sample-path $CDaR_\alpha$ as:

$$CDaR_\alpha(w) = \sum_{t=1}^{T} q_t^\star d_t \tag{3}$$

where $q_t^\star = \frac{1}{(1-\alpha)T}$ if d_t is one of the $(1-\alpha)T$ largest portfolio drawdowns, and $q_t^\star = 0$ otherwise.

2.3 CDaR Beta

Zabarankin et al. (2014) developed CAPM relationships based on $CDaR$. Ding and Uryasev (2022) derived necessary optimality conditions for $CDaR$ portfolio optimization. These conditions resulted in $CDaR$ Beta relating cumulative returns of a market (optimal portfolio) and individual securities. $CDaR$ Beta equals:

$$\beta^i_{CDaR} = \frac{\sum_{s=1}^{S} \sum_{t=1}^{T} p_s q^\star_{st} \left(w^i_{s,\tau(s,t)} - w^i_{st} \right)}{CDaR_\alpha\left(w^M\right)},$$

where

i = index of a security, $i = 1, ..., I$;

s = index of sample path of returns of securities, $s = 1, ..., S$;

p_s = probability of a sample path s;

t = time, $t = 1, ..., T$;

w^i_{st} = uncompounded cumulative return of asset i at time moment t on sample path s;

w^M = vector of uncompounded cumulative returns of market portfolio (optimal portfolio) including components w^M_{st}, $t = 1, ..., T, s = 1, ..., S$;

$\tau(s,t)$ = time moment of the most recent maximum of market cumulative return preceding t on scenario s;

$q^\star_{st}$ = indicator which is equal to $\frac{1}{(1-\alpha)T}$ for the largest $(1-\alpha)T$ drawdowns of market portfolio w^M and zero otherwise;

$CDaR_\alpha\left(w^M\right) = \sum_{s=1}^{S}\sum_{t=1}^{T} p_s q^\star_{st}\left(w^M_{s,\tau(s,t)} - w^M_{st}\right)$ =average of the largest $(1-\alpha)\%$ drawdowns of market portfolio w^M (e.g., if $\alpha = 0.9$ then $CDaR$ accounts for 10% largest drawdowns).

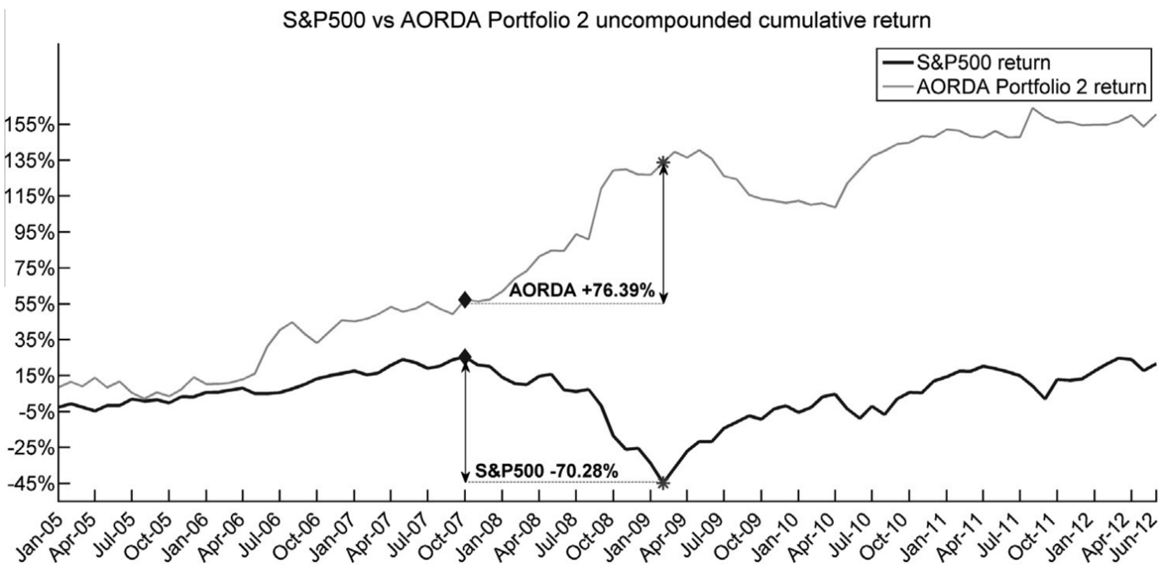

Figure 2: Example: Uncompounded monthly cumulative rates of return of the SP500 index and AORDA Portfolio 2 ($T = \tau = 90$). The S&P500 index had its largest drawdown in February 2009, marked by ($*$): it peaked in October 2007 (♦) and lost 70.28% from October 2007 to February 2009. During the same period, the AORDA Portfolio 2 earned 76.39%; therefore, $\text{CDaR}_{\alpha=1}$ Beta $=$ MaxDD Beta $= 76.39\%/(-70.28\%) = -1.09$ (Zabarankin, Pavlikov, Uryasev (2014)).

2.4 Expected Regret of Drawdown (ERoD) Beta

Ding and Uryasev (2022) introduced a new drawdown based risk measure called Expected Regret of Drawdown (ERoD). By definition, ERoD is an average of drawdowns exceeding a threshold ϵ. The Expected Regret (also termed Low Partial Moment) is defined as the average of losses exceeding a fixed threshold. Therefore, ERoD is the Expected Regret of drawdown observations over considered period. Formula for ERoD Beta can be derived similar to CDaR Beta. Moreover, CDaR Beta and ERoD Beta coincide for some confidence level α in CDaR and some threshold ϵ in ERoD.

Ding and Uryasev (2022) show that the ERoD Beta equals:

$$\hat{\beta}^i_{ERoD} = \frac{\frac{1}{T}\sum_{s=1}^{S}\sum_{t=1}^{T} p_s q^{\star}_{st}\left(w^i_{s,\tau(s,t)} - w^i_{st}\right)}{\tilde{E}_\epsilon\left(w^M\right)}$$

where

i = index of a security, $i = 1, ..., I$;

s = index of sample path of returns of securities, $s = 1, ..., S$;

p_s = probability of a sample path s;

t = time, $t = 1, ..., T$;

w^i_{st} = uncompounded cumulative return of asset i at time moment t on sample path s;

w^M = vector of uncompounded cumulative returns of market portfolio (optimal portfolio) including components w^M_{st}, $t = 1, ..., T, s = 1, ..., S$;

$\tau(s,t)$ = time moment of the most recent maximum of market cumulative return preceding t on scenario s;

$\tilde{E}_\epsilon\left(w^M\right) = \frac{1}{T}\sum_{s=1}^{S}\sum_{t=1}^{T} p_s q^{\star}_{st}\left(w^M_{s,\tau(s,t)} - w^M_{st}\right)$ = threshold adjusted ERoD with threshold ϵ for return w^M;

$d^M_{st} = w^M_{s,\tau(s,t)} - w^M_{st}$ = drawdowns of the market portfolio;

$q^{\star}_{st} = \mathbb{1}\left(d^M_{st} \geq \epsilon\right)$ = indicator function which is equal to 1 for $d^M_{st} \geq \epsilon$ and 0 otherwise.

ERoD Beta indicates good hedges against market drawdowns. Instruments with low and negative ERoD Beta are quite beneficial portfolio construction.

3 Numerical Study

Using the sustainability function of Python's yfinance package, I loop through all the stocks on Yahoo Finance with ESG rating scores.

	ticker	totalEsg
0	MMM	33.61
1	AOS	24.20
2	ABT	24.98
3	ABBV	27.84
4	ACN	9.71
...	...	...
435	XEL	23.70
436	XYL	15.95
437	YUM	20.55
438	ZBH	27.30
439	ZTS	18.47

440 rows × 2 columns

Figure 3: stocks with ESG rating score

I calculated Standard Beta, $ERoD_{0+}$ Beta, $CDaR_{0.9}$ Beta, Maximum drawdown, Annual Return for all stocks with ESG rating score from 2016/11/1 to 2022/11/1. All adjusted Close prices data were obtained from Yahoo Finance using Python's pandas datareader package.

	ticker	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
0	MMM	1.157728	1.372000	0.819897	-0.013297	0.513593	33.61
1	AOS	1.589278	1.592544	0.851002	0.051687	0.468063	24.20
2	ABT	0.910582	0.628401	0.866542	0.188647	0.316732	24.98
3	ABBV	-0.206989	0.218182	0.704196	0.226182	0.450898	27.84
4	ACN	1.525763	1.328573	1.075946	0.178986	0.389819	9.71
...	...	...	...	...	...	...	...
435	XEL	-0.046353	-0.296847	0.589422	0.112734	0.292807	23.70
436	XYL	1.268983	1.339998	1.089086	0.152210	0.466932	15.95
437	YUM	0.890151	0.674884	0.805223	0.136890	0.521706	20.55
438	ZBH	0.888738	0.967530	0.917750	0.027934	0.497319	27.30
439	ZTS	1.412501	0.785067	0.921918	0.221556	0.412293	18.47

440 rows × 7 columns

	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
Average	0.816408	0.780146	1.001557	0.116293	0.501333	21.498591

Figure 4: Standard Beta, $ERoD_{0+}$ Beta, $CDaR_{0.9}$ Beta, Maximum drawdown, Annual Return calculation result

	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
CDaR_beta	1.000000	0.879059	0.486974	-0.194931	0.274649	-0.311466
ERod_Beta	0.879059	1.000000	0.598110	-0.320490	0.450465	-0.199261
Standard_Beta	0.486974	0.598110	1.000000	0.050847	0.661465	-0.009661
Annual Return	-0.194931	-0.320490	0.050847	1.000000	-0.417941	-0.105915
Max Drawdown	0.274649	0.450465	0.661465	-0.417941	1.000000	0.196590
TotalEsg	-0.311466	-0.199261	-0.009661	-0.105915	0.196590	1.000000

Figure 5: all correlation matrix using use pearson standard correlation coefficient

	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
CDaR_beta	1.000000	0.866321	0.519213	-0.177445	0.383053	-0.248177
ERod_Beta	0.866321	1.000000	0.604927	-0.269501	0.493107	-0.144288
Standard_Beta	0.519213	0.604927	1.000000	0.069763	0.662962	-0.016361
Annual Return	-0.177445	-0.269501	0.069763	1.000000	-0.376769	-0.106528
Max Drawdown	0.383053	0.493107	0.662962	-0.376769	1.000000	0.111638
TotalEsg	-0.248177	-0.144288	-0.016361	-0.106528	0.111638	1.000000

Figure 6: all correlation matrix using Spearman rank correlation method

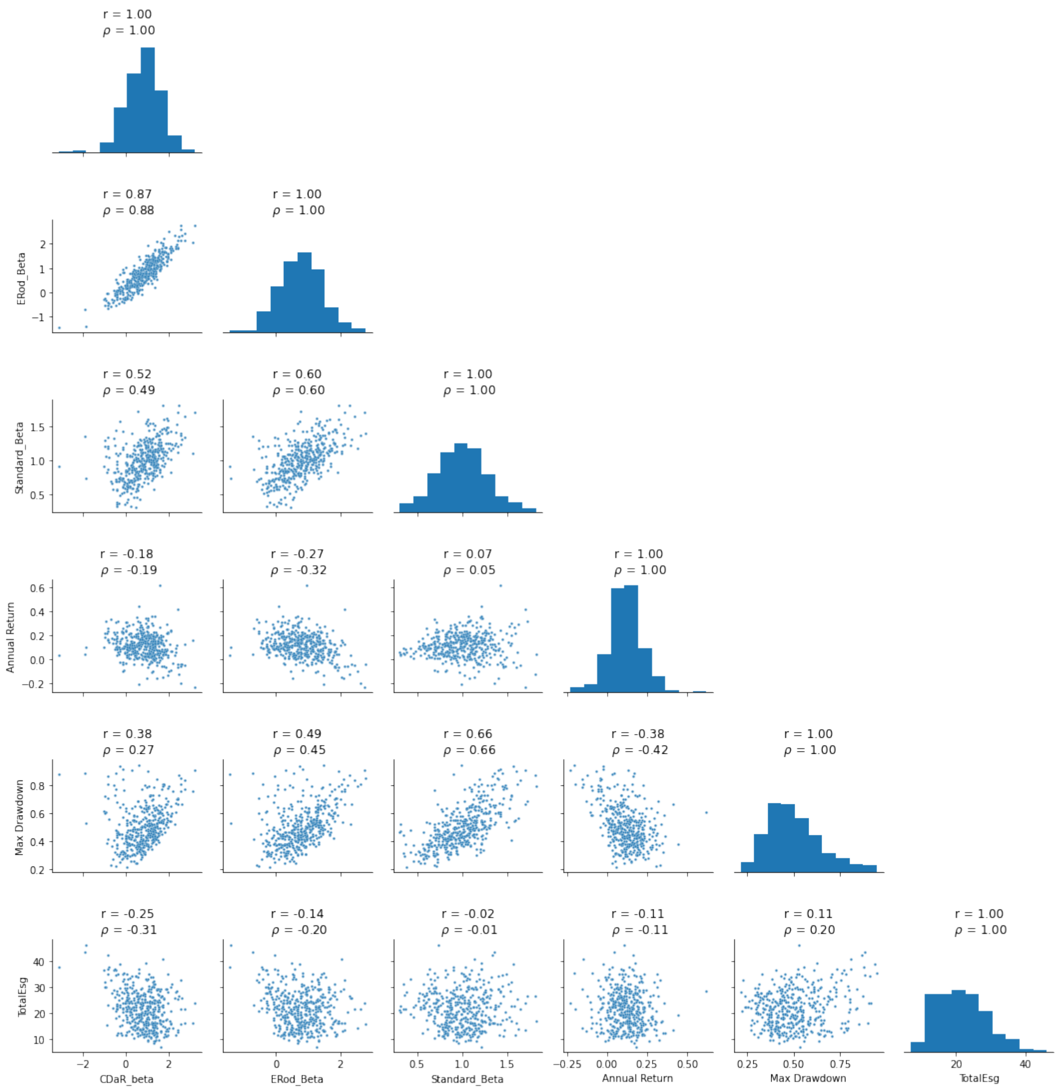

Figure 7: Correlation graph r(use Spearman rank correlation method) and ρ(use pearson correlation coefficient method)

I found the five ESG ratings categories following the Sustainalytics Company definition, and calculated the mean of their Standard Beta, $ERoD_{0+}$ Beta, $CDaR_{0.9}$ Beta, Maximum drawdown, Annual Return to see their performance.

	ticker	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
4	ACN	1.525763	1.328573	1.075946	0.178986	0.389819	9.71
81	CBRE	1.640290	1.257751	1.217167	0.183480	0.535720	6.99
82	CDW	1.010611	0.698679	1.156875	0.265560	0.448341	9.14
199	HAS	1.323473	1.335865	0.936902	-0.009806	0.638429	9.36
201	PEAK	1.398076	0.663757	0.900404	0.005859	0.465577	9.73
240	KEYS	1.019078	0.390347	1.089903	0.322489	0.371856	9.42
334	PLD	1.299031	0.672323	0.959737	0.169666	0.420587	8.51
352	RHI	1.358794	0.946228	1.036018	0.150827	0.555554	9.26

	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
Average	1.32189	0.91169	1.046619	0.158383	0.478235	9.015

Figure 8: Negligible ESG ratings calculation

	ticker	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
5	ATVI	-0.319458	0.210689	0.697042	0.100311	0.519007	18.94
7	ADBE	1.628851	0.980486	1.262884	0.200050	0.600215	12.46
8	ADP	0.515638	0.444435	1.033099	0.211466	0.394512	13.97
9	AAP	1.095840	0.777955	0.890394	0.061998	0.591891	12.97
11	AFL	0.311942	0.287694	0.978714	0.140645	0.548902	17.30
...	...	...	...	...	...	...	...
430	WHR	1.622830	1.464654	1.183530	0.016955	0.645970	15.80
432	WTW	0.595669	0.373894	0.839865	0.114529	0.329456	18.24
433	GWW	0.244202	0.485517	0.932431	0.213813	0.415955	14.60
436	XYL	1.268983	1.339998	1.089086	0.152210	0.466932	15.95
439	ZTS	1.412501	0.785067	0.921918	0.221556	0.412293	18.47

186 rows × 7 columns

	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
Average	1.000454	0.874746	1.027019	0.12787	0.490397	15.225753

Figure 9: Low ESG ratings calculation

	ticker	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
1	AOS	1.589278	1.592544	0.851002	0.051687	0.468063	24.20
2	ABT	0.910582	0.628401	0.866542	0.188647	0.316732	24.98
3	ABBV	-0.206989	0.218182	0.704196	0.226182	0.450898	27.84
15	ALB	0.010679	1.017077	1.259873	0.241453	0.632742	28.80
17	ALLE	1.147152	1.148763	0.996771	0.099272	0.432501	23.59
...	...	...	...	...	...	...	...
431	WMB	-0.437469	-0.079135	0.945408	0.083018	0.680840	23.50
434	WYNN	1.675213	1.824548	1.462010	-0.056416	0.774003	26.50
435	XEL	-0.046353	-0.296847	0.589422	0.112734	0.292807	23.70
437	YUM	0.890151	0.674884	0.805223	0.136890	0.521706	20.55
438	ZBH	0.888738	0.967530	0.917750	0.027934	0.497319	27.30

191 rows × 7 columns

	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
Average	0.78044	0.77378	0.960808	0.107879	0.483534	24.528586

Figure 10: Medium ESG ratings calculation

	ticker	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
0	MMM	1.157728	1.372000	0.819897	-0.013297	0.513593	33.61
6	ADM	-0.578652	-0.310764	0.820271	0.162799	0.405223	36.40
10	AES	0.488674	0.192291	1.023427	0.183873	0.545411	34.15
22	AMZN	1.256257	0.786994	1.076385	0.173650	0.451628	30.28
37	APA	-0.276730	0.727498	1.575506	-0.025074	0.934866	38.81
...	...	...	...	...	...	...	...
401	USB	1.208373	1.203019	1.064911	0.024061	0.519860	30.05
405	UAL	1.057832	1.109978	1.446026	-0.042857	0.794002	30.10
409	UHS	0.958278	0.601052	1.081933	-0.002211	0.563027	32.90
410	VLO	-0.989328	-0.238229	1.206657	0.184946	0.718813	30.05
426	WFC	1.008366	1.281765	1.195361	0.029512	0.644571	32.84

49 rows × 7 columns

	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
Average	0.276422	0.475212	1.038447	0.104147	0.595097	33.638367

Figure 11: High ESG ratings calculation

	ticker	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
116	CTRA	-1.886263	-1.402544	0.734571	0.104436	0.525571	46.16
189	GE	1.736379	2.019482	1.133680	-0.148830	0.809436	40.71
260	MRO	-0.832264	-0.029804	1.337207	0.163646	0.867047	42.05
309	OXY	-1.909379	-0.717511	1.363360	0.043982	0.883888	43.23

	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
Average	-0.722882	-0.032594	1.142204	0.040809	0.771486	43.0375

Figure 12: Severe ESG ratings calculation

We found that the stocks in the extreme groups of Negligible ESG ratings and Severe ESG ratings obtained by Sustainalytics were too few, and the correlation coefficients from these extreme groups were not meaningful and reliable. So I divided the ESG rating scores into different categories. The first group was the 20% Highest ESG rating scores and the second group was the 20% Lowest ESG rating scores. I averaged the Standard Beta, $ERoD_{0+}$ Beta, $CDaR_{0.9}$ Beta, Maximum drawdown, Annual Return of the two groups respectively and showed their correlation to see their performance.

	ticker	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
0	MMM	1.157728	1.372000	0.819897	-0.013297	0.513593	33.61
3	ABBV	-0.206989	0.218182	0.704196	0.226182	0.450898	27.84
6	ADM	-0.578652	-0.310764	0.820271	0.162799	0.405223	36.40
10	AES	0.488674	0.192291	1.023427	0.183873	0.545411	34.15
15	ALB	0.010679	1.017077	1.259873	0.241453	0.632742	28.80
...	...	...	...	...	...	...	...
405	UAL	1.057832	1.109978	1.446026	-0.042857	0.794002	30.10
409	UHS	0.958278	0.601052	1.081933	-0.002211	0.563027	32.90
410	VLO	-0.989328	-0.238229	1.206657	0.184946	0.718813	30.05
419	VMC	1.156020	1.125245	0.936338	0.069614	0.492281	29.02
426	WFC	1.008366	1.281765	1.195361	0.029512	0.644571	32.84

88 rows × 7 columns

	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
Average	0.478437	0.590661	1.036799	0.108461	0.570848	32.138295

Figure 13: 20% Highest ESG ratings

	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
CDaR_beta	1.000000	0.900426	0.275653	-0.213386	-0.050465	-0.478221
ERod_Beta	0.900426	1.000000	0.419432	-0.346873	0.193020	-0.359101
Standard_Beta	0.275653	0.419432	1.000000	0.089928	0.703334	0.075562
Annual Return	-0.213386	-0.346873	0.089928	1.000000	-0.274462	-0.174128
Max Drawdown	-0.050465	0.193020	0.703334	-0.274462	1.000000	0.414938
TotalEsg	-0.478221	-0.359101	0.075562	-0.174128	0.414938	1.000000

Figure 14: 20% Highest ESG ratings correlation matrix

	ticker	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
4	ACN	1.525763	1.328573	1.075946	0.178986	0.389819	9.71
7	ADBE	1.628851	0.980486	1.262884	0.200050	0.600215	12.46
8	ADP	0.515638	0.444435	1.033099	0.211466	0.394512	13.97
9	AAP	1.095840	0.777955	0.890394	0.061998	0.591891	12.97
13	APD	0.836416	0.791870	0.943549	0.139472	0.309675	10.81
...	...	...	...	...	...	...	...
411	VTR	0.767902	0.286304	1.027037	-0.036414	0.769242	12.75
416	VFC	2.421051	1.814728	1.122154	-0.068139	0.702569	12.84
418	VNO	1.979087	1.487784	1.031751	-0.130200	0.687373	12.98
427	WELL	0.863126	0.410001	0.949624	0.028073	0.633284	12.01
428	WDC	1.865623	1.854016	1.455389	-0.063533	0.704929	11.07

88 rows × 7 columns

	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
Average	1.072633	0.861437	1.013172	0.121586	0.496263	12.292045

Figure 15: 20% Lowest ESG ratings

	CDaR_beta	ERod_Beta	Standard_Beta	Annual Return	Max Drawdown	TotalEsg
CDaR_beta	1.000000	0.819293	0.591566	-0.240796	0.509950	-0.071896
ERod_Beta	0.819293	1.000000	0.710707	-0.239185	0.584883	0.007399
Standard_Beta	0.591566	0.710707	1.000000	0.136102	0.528505	-0.012082
Annual Return	-0.240796	-0.239185	0.136102	1.000000	-0.594695	-0.086631
Max Drawdown	0.509950	0.584883	0.528505	-0.594695	1.000000	0.049718
TotalEsg	-0.071896	0.007399	-0.012082	-0.086631	0.049718	1.000000

Figure 16: 20% Lowest ESG ratings correlation matrix

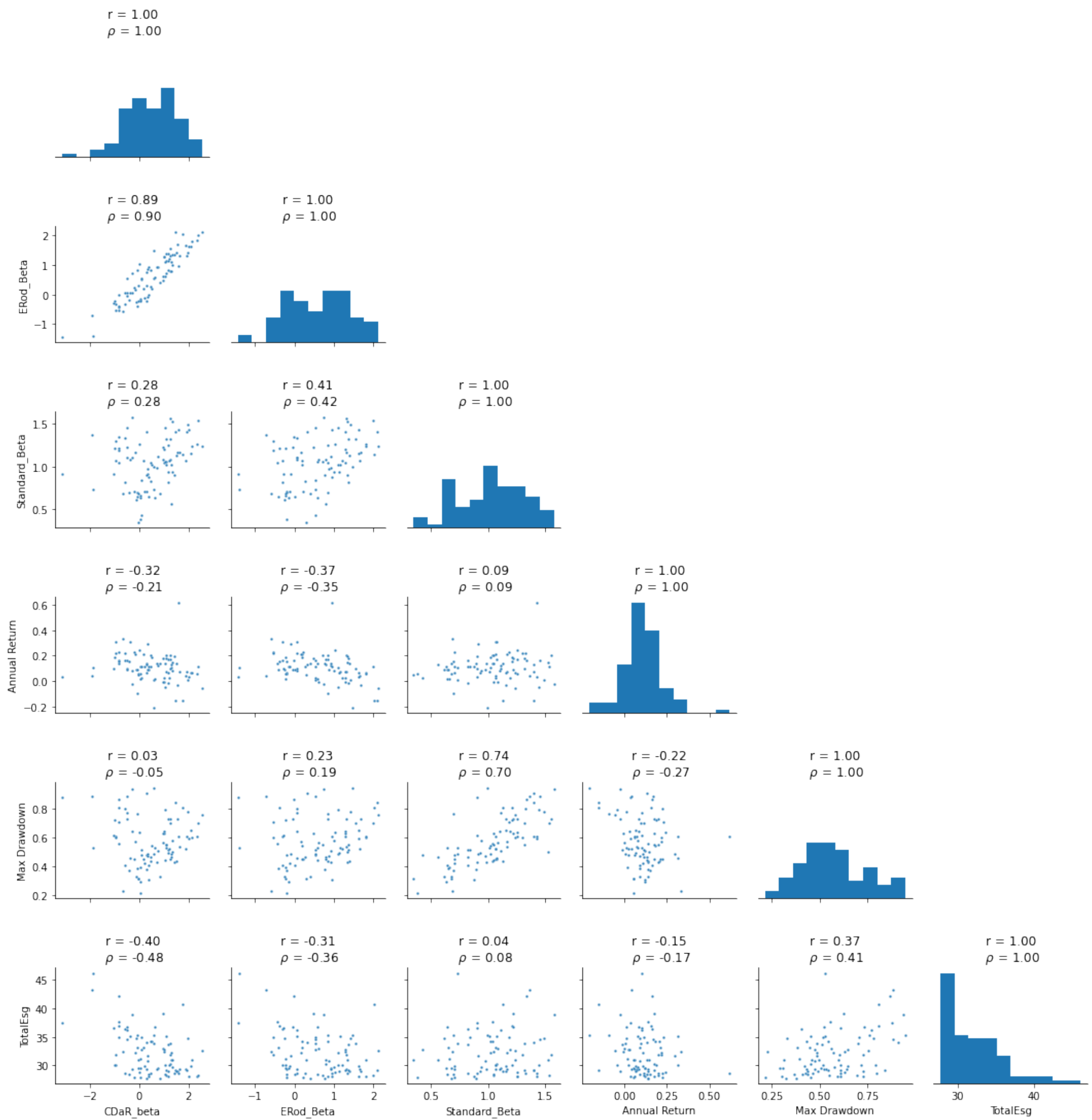

Figure 17: 20% Highest ESG ratings Correlation graph r(use Spearman rank correlation method) and ρ(use pearson correlation coefficient method)

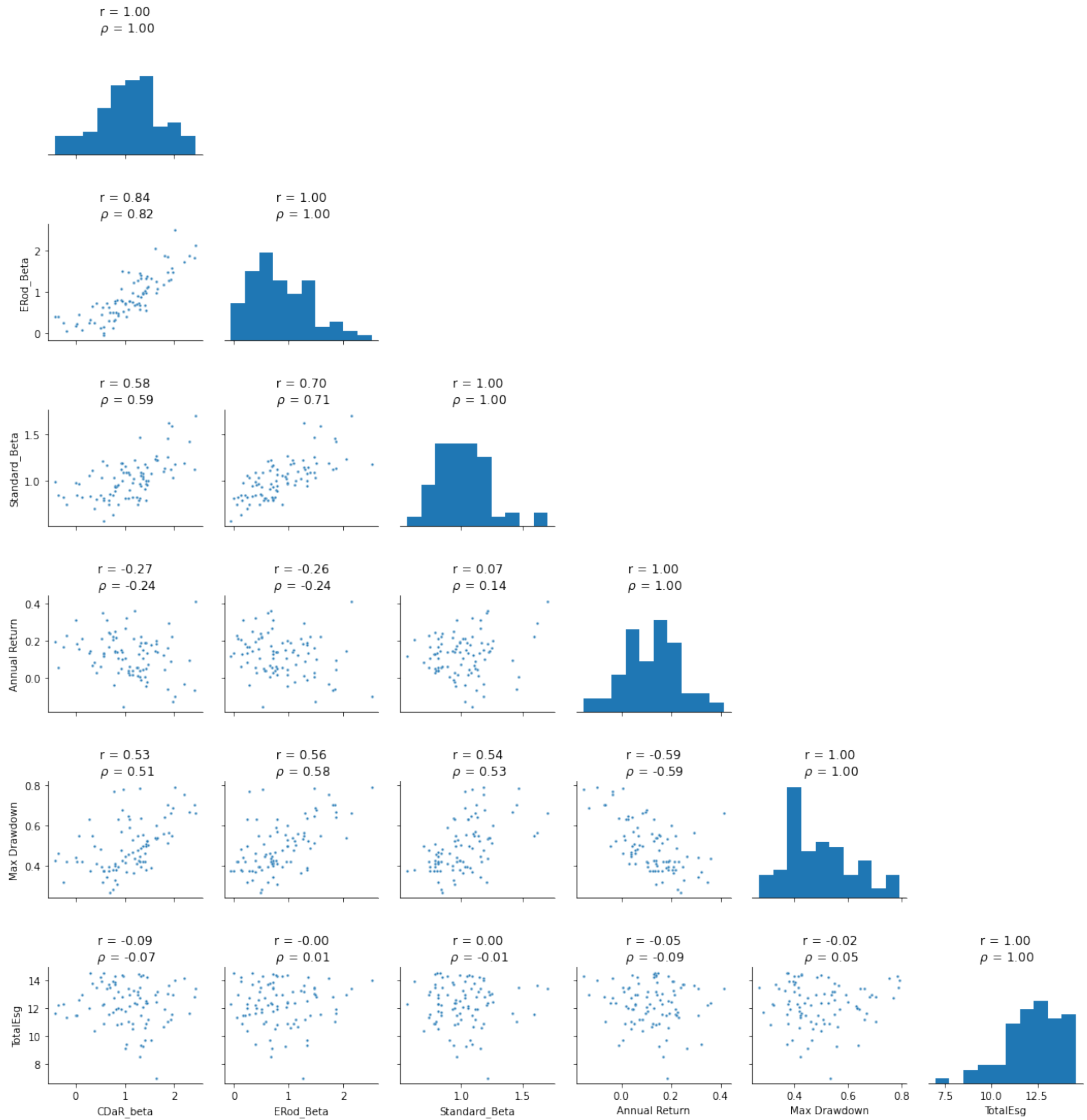

Figure 18: 20% Lowest ESG ratings Correlation graph r(use Spearman rank correlation method) and ρ(use pearson correlation coefficient method)

The results and graphs show that the 20% lowest ESG ratings do not correlate with $ERoD_{0+}$ Beta, $CDaR_{0.9}$ Beta, while the 20% highest ESG ratings correlate slightly negatively with $ERoD_{0+}$ Beta, $CDaR_{0.9}$ Beta.

References

Ding, R. and Uryasev, S. (2022). Drawdown beta and portfolio optimization. *Quantitative Finance*, pages 1–12.

Zabarankin, M., Pavlikov, K., and Uryasev, S. (2014). Capital asset pricing model (capm) with drawdown measure. *European Journal of Operational Research*, 234(2):508–517.

4 Appendices: code

```
library(quantmod)
library(PerformanceAnalytics)

# calculate the ERoD Beta function
data <-
  function(R,Rm){
    R = checkData(R)
    R <- as.matrix(R[,6])
    R1 <- (R[2:nrow(R),]-R[1:nrow(R)-1,])/R[1:nrow(R)-1,]
    R2 <-cumsum(R1)
    R2 <- as.matrix(R2)
    Rm = checkData(Rm)
    Rm <- as.matrix(Rm[,6])
    Rm1 <- (Rm[2:nrow(Rm),]-Rm[1:nrow(Rm)-1,])/Rm[1:nrow(Rm)-1,]
    Rm2 <- cumsum(Rm1)
    Rm2 <- as.matrix(Rm2)

    T <- 1/nrow(R2)
    w_tao <- matrix(NA,nrow = nrow(R2),ncol = ncol(R2))
    for (i in 1:nrow(R2)) {
      w_tao[i,] <- R2[which.max(Rm2[1:i,]),] }

    drawdown_market <- matrix(NA, nrow = nrow(Rm2),ncol = ncol(Rm2))
    for (i in 1:nrow(Rm2)) {
```

```
      drawdown_market[i,] <- Rm2[which.max(Rm2[1:i,]),] }


    wm_tao <- matrix(NA,nrow = nrow(Rm2),ncol = ncol(Rm2))
    for (i in 1:nrow(Rm2)) {
      wm_tao[i,] <- Rm2[which.max(Rm2[1:i,]),] }

    w_tao <- as.vector(w_tao)
    R3 <- as.vector(R2)
    Rm3 <- as.vector(Rm2)

    qst <- matrix(NA, nrow = nrow(Rm2),ncol = ncol(Rm2))
    dst <- wm_tao-Rm3
    for (i in 1:nrow(Rm2)) {
      if(dst[i,] >0){ qst[i,] <- 1
      }else{
        qst[i,] <- 0
      } }
    qst <- as.vector(qst)
    dst <- as.vector(dst)
    Ei <- qst%*%(w_tao-R3)*T
    Em <- qst%*%dst*T
    ERoD_beta <- Ei/Em

    ERoD_beta
  }

# all esg rating stock ticker name
dat <- read.csv(file ="/Users/dazhiyi/Downloads/sustainability_scores.csv",header = T)
# get Sp500 price data
SP <- getSymbols(Symbols = "^GSPC",from="2016-11-01",to= "2022-11-01", auto.assign = FALSE)
SPr <- as.matrix(SP[,6])
```

```
SPret <- (SPr[2:nrow(SPr),]-SPr[1:nrow(SPr)-1,])/SPr[1:nrow(SPr)-1,]


newd <- dat[,2][1:440]

#test
# DA <- list()
# DAT <- list()
# for (i in newd){
#
#
#   DA[[i]] <- getSymbols(Symbols = i,from="2016-11-01",to=
    "2022-11-01", auto.assign = FALSE)
#   DAT[[i]] <- data(DA[[i]],SP)
#   # DAT <- as.data.frame(DAT)
#   # print(DAT)
# }
#
# newd <- dat[,2][1:5]


# calculate ERoD beta, standard Beta, annual return, and max drawdown
    for all esg rating score(440) stock
DA <- list()
DAAA <- list()
DAret <- list()
ERodBeta <- list()
maxdd <- list()
aunnalret <- list()
standBeta <- list()
for (i in newd){
  DA[[i]] <- getSymbols(Symbols = i,from="2016-11-01",to= "2022-11-01"
    , auto.assign = FALSE)
  DAAA[[i]] <- as.matrix(DA[[i]][,6])
```

```r
  DAAA[[i]] <-  (DAAA[[i]][2:nrow(DAAA[[i]]),]-DAAA[[i]][1:nrow(DAAA[[i]])-1,])/DAAA[[i]][1:nrow(DAAA[[i]])-1,]
  DAret[[i]] <-  as.matrix(DAAA[[i]])
  ERodBeta[[i]] <- data(DA[[i]],SP)
  maxdd[[i]] <- maxDrawdown(DAret[[i]])
  aunnalret[[i]] <- Return.annualized(DAret[[i]])
  standBeta[[i]] <- CAPM.beta(DAAA[[i]],SPret)
}

# dataframe of ERoD beta, standard Beta, annual return, and max drawdown
ERodBetalist <- as.matrix(ERodBeta)
standBetalist <- as.matrix(standBeta)
aunnalretlist <- as.matrix(aunnalret)
maxddlist <- as.matrix(maxdd)
all <- data.frame()
all <- cbind(ERodBetalist,standBetalist)
all <- cbind(all,aunnalretlist)
all <- cbind(all,maxddlist)
all2 <- as.data.frame(all)
names(all2) <- c('ERod_Beta','Standard_Beta','Annual Return','Max Drawdown')

# output the all ERoD beta, standard Beta, annual return, and max drawdown data into csv
df <- apply(all2,2,as.character)
write.csv(df,"alldata.csv")
```

```python
import pandas as pd
import numpy as np
import yfinance as yf
import requests
import matplotlib.pyplot as plt
import pandas_datareader as pdr
import datetime as dt
```

```python
from pandas.core.frame import DataFrame

wikiPg = requests.get("https://en.wikipedia.org/wiki/List_of_S%26P_500_companies").text
tickerList = pd.read_html(wikiPg)[0]["Symbol"].tolist()
len(tickerList)

# find all stocks with the ESG ratings
esgData = pd.DataFrame()
for ii in tickerList[:]:
    print(ii)
    objY = yf.Ticker(ii)
    try:
        if objY.sustainability is not None:
            v = objY.sustainability.T
            v["ticker"] = str(objY.ticker)
            esgData = esgData.append(v)
    except Exception as e:
        print(e)

es = esgData.reset_index(drop = True)
esg = es[['ticker']]
esg.to_csv("sustainability_scores.csv", encoding="utf-8")

# get sp500 Adj Close price data
sp500 = "^GSPC"
start = dt.datetime(2016, 11, 1)
end = dt.datetime(2022, 11, 1)
spdata = pdr.get_data_yahoo(sp500, start, end)
spdata = spdata.loc[:,('Adj Close')]

# calculate the CDaR Beta
def CDar_beta(X,Y):

```

```
    x_cumret = np.cumsum(X)
    sp_cumret = np.cumsum(Y)
    DD_sp = np.maximum.accumulate(sp_cumret.values) - sp_cumret.values
    dd = np.zeros((len(x_cumret)))
    for i in range(0, len(x_cumret)):
        dd[i] = x_cumret[np.argmax(sp_cumret[0:i+1])]-x_cumret[i]
    cdar_x = dd[DD_sp >= np.sort(DD_sp)[::-1][int(len(DD_sp)*0.1)]]
    cdar_sp = np.sort(DD_sp)[::-1][:(int(len(DD_sp)*0.1)+1)]
    cdar_beta = np.mean(cdar_x)/np.mean(cdar_sp)

    return cdar_beta

# Maximum drawdown calculation function
def maxdrawdown(X):
    i = np.argmax(np.maximum.accumulate(X) - X.values) # end of the
    period
    j = np.argmax(X.values[:i]) # start of period
    maxdrawdown =abs(100.0*(X[i]-X[j]))
    return maxdrawdown

pd_reader = pd.read_csv("/Users/dazhiyi/Downloads/
    sustainability_scores.csv")
pd_reader = pd_reader[['ticker','totalEsg']]

# take all stock tickers name
x = []
for row , index in pd_reader.iterrows():
     x.append(index[0])

# calculate CDaR Beta for all stocks with ESG rating
cdardata = []
for i in x:
    data = pdr.get_data_yahoo(i, start, end)
    data1 = data.loc[:,('Adj Close')]
```

```
    X = data1.pct_change().dropna()
    cdar = CDar_beta(X,Y)
    cdardata.append(cdar)

c={"ticker" : x,
   "CDaR_beta" : cdardata,
   "TotalEsg" : esg}
alldata=DataFrame(c)

# read ERoD beta, standard Beta, annual return, and max drawdown calculate in R
reader_data = pd.read_csv("/Users/dazhiyi/Downloads/alldata.csv")
reader_data = reader_data.drop(['Unnamed: 0'],axis=1)

# combine CDaR beta into ERoD beta, standard Beta, annual return, and max drawdown calculate
data2 = alldata.join(reader_data)
d = data2.pop('TotalEsg')
data2.insert(6,'TotalEsg', d)
data3 = data2

# correlation table
data3.corr()
data3.corr(method="spearman")
# esg rank 5 group
data4 = data3[(0 <= data3.TotalEsg) &(data3.TotalEsg <= 9.9)]
data5 = data3[(10 <= data3.TotalEsg) &(data3.TotalEsg <= 19.9)]
data6 = data3[(20 <= data3.TotalEsg) &(data3.TotalEsg <= 29.9)]
data7 = data3[(30 <= data3.TotalEsg) &(data3.TotalEsg <= 39.9)]
data8 = data3[data3.TotalEsg >= 40]
# average all beta function
def findaverage(data):
    datanew = data.drop('ticker',axis=1)

```

```
    datanew.loc["Average"] = datanew.apply(lambda x: x.mean())
    return datanew[len(datanew)-1:len(datanew)]

findaverage(data3)
findaverage(data4)
findaverage(data5)
findaverage(data6)
findaverage(data7)
findaverage(data8)

# correlation graph
def display_correlation(df):
    r = df.corr(method="spearman")
    plt.figure(figsize=(10,6))
    heatmap = sns.heatmap(df.corr(), vmin=-1,
                          vmax=1, annot=True)
    plt.title("Spearman Correlation")
    return(r)
def display_corr_pairs(df,color="cyan"):
    s = set_title = np.vectorize(lambda ax,r,rho: ax.title.set_text("r = " +
                                        "{:.2f}".format(r) +
                                        '\n $\\rho$ = ' +
                                        "{:.2f}".format(rho)) if ax!= None else None)
    r = display_correlation(df)
    rho = df.corr(method="pearson")
    g = sns.PairGrid(df,corner=True)
    g.map_diag(plt.hist)
    g.map_lower(sns.scatterplot,s=6)
    set_title(g.axes,r,rho)
    plt.subplots_adjust(hspace = 0.6)
    plt.show()
display_corr_pairs(data3)
```