

FINAL PROJECT PHYTON FOR FINANCE

PROJECT TITLE

*Exploring the Impact of Covid-19 on Financial Performance of
Health and Industrial Firms:
Evidence from Cross-Sectional Study of US Market*

GROUP 1

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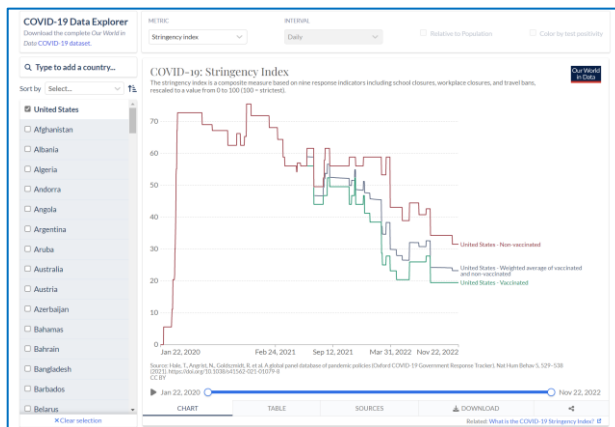
1. Project Overview
2. Data and Sample
3. Data Preparation
4. Python (brief coding) and Results
5. Discussion (all interpretations: hypotheses)
6. Conclusion
7. Recommendation
8. List of References

Project Overview

- **Project Topic:**
 - Analysing Impact of Covid-19 on quarterly firm performance in US
- **Time Horizon:**
 - COVID-19 and quarterly (continuous)
 - 2020 - 2022: Q1 – Q4
- **Research Method:**
 - CROSS SECTIONAL
- **Aim:**
 - To analyze the relationship between:
 - Firms' financial performance (Altman Z-score) in a sector in US
 - COVID-19 data in US
 - Macroeconomic variable: Federal Funds Effective Rate in US
 - With analysis on heterogeneity between 2 (two) industries/ sectors in US: HEALTH and INDUSTRIAL
- **Variables:**
 - **Dependent variable (DV)**
 - Altman Z-Score : *Z_Score*
 - **Independent variable**
 - Stringency Index : *SI*
 - Number of Cases : *NC*
 - Federal funds Effective Rate : *FF*
 - Size of firms : *size*
- **Data Processing**
 - **PART 0 Data Preparation**
 - 0.1. IV1 and IV2 csv in quarterly data
 - 0.2. Split WRDS csv data into two sectors
 - 0.3. For each sector, convert WRDS csv into DV csv (i.e. compute z-score, using excel)
 - **PART 1 Descriptive Statistics**
 - 1.1. Preliminary Data Visualization (# samples, etc.)
 - 1.2. Univariate Descriptive Statistics
 - 1.3. Histograms
 - 1.4. Winsorizing (if necessary)
 - 1.5. Correlation coefficients:
 - 1.5.1. Pearson
 - 1.5.2. Spearman's rank
 - **PART 2 Inferential Statistics**
 - 2.1 Classic assumption test
 - 2.1.1 Jarque Bera
 - 2.1.2 Kolmogorov-Smirnov
 - 2.2. Hypothesis Test:
 - 2.2.1. One Sample t-Test
 - 2.2.2. Two Sample t-Test
 - 2.2.3. Simple Regression
 - 2.2.4 Multiple Linear Regression
 - 2.2.5. Quantile Regression
 - **PART 3 Heterogeneity**

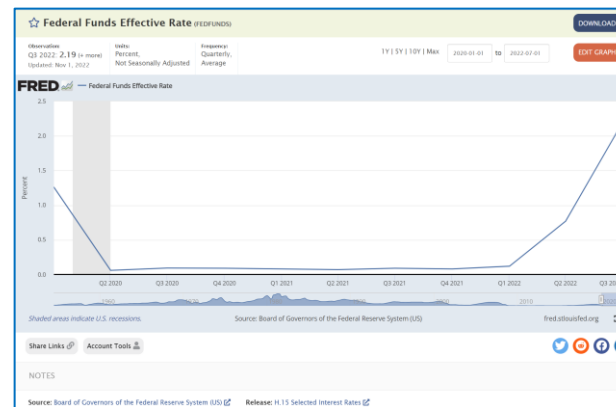
Data and Sample (1)

COVID 19 Data: Stringency Index (DAILY)



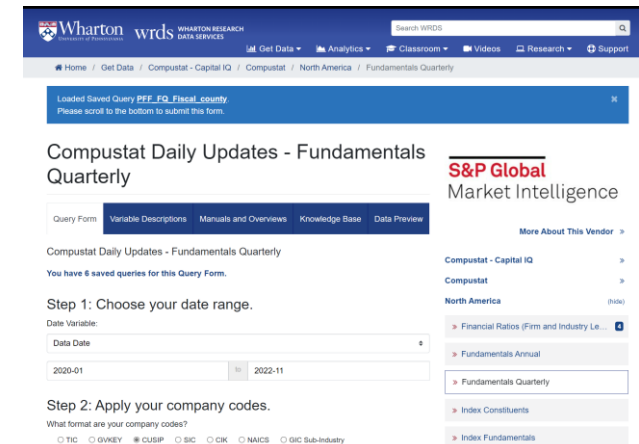
<https://ourworldindata.org/explorers/coronavirus-data-explorer?uniformYAxis=0&hideControls=true&Metric=Stringency+index&Interval=7-day+rolling+average&Relative+to+Population=true&Color+by+test+positivity=false&country=~USA>

Macroeconomic Data: Federal Funds ER (QUARTERLY)



<https://fred.stlouisfed.org/series/FEDFUNDS#0>

Financial Data – WRDS Fundamentals (QUARTERLY)



https://wrds-www.wharton.upenn.edu/pages/get-data/compustat-capital-iq-standard-poors/compustat/north-america-daily/fundamentals-quarterly/?saved_query=2316916

Data and Sample (2)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	
1	gvkey	datadate	yearq	fqtr	indfmt	consol	popsrc	datafmt	tic	cusip	conm	curcdq	datacqr	datafqr	cogsq	niq	req	revqt	txtq	wcapq	xintq	xoprq	costat	mkvalqt	busdesc	gsector	
2	1004	20200229	2019	3	INDL	C	D	STD	AIR	361105	AAR CORP USD	2020Q1	2019Q3	461.9	2.3	685.2	562.9	0.2	672.8	2.4	518.7	A	1212.74	AAR Corp.	2C		
3	1004	20200531	2019	4	INDL	C	D	STD	AIR	361105	AAR CORP USD	2020Q2	2019Q4	353.7	-16.5	661.4	424	-4	1055.6	2.8	397.7	A	707.9065	AAR Corp.	2C		
4	1004	20200831	2020	1	INDL	C	D	STD	AIR	361105	AAR CORP USD	2020Q3	2020Q1	341.3	-14.5	648.3	402.7	-3.8	679.9	1.7	383.7	A	712.3742	AAR Corp.	2C		
5	1004	20201130	2020	2	INDL	C	D	STD	AIR	361105	AAR CORP USD	2020Q4	2020Q2	332.2	8.2	656.6	401.7	5.2	633.5	1.3	376.4	A	1001.234	AAR Corp.	2C		
6	1004	20210228	2020	3	INDL	C	D	STD	AIR	361105	AAR CORP USD	2021Q1	2020Q3	336.8	28.1	685.3	411.8	12	640.7	1.1	383.4	A	1404.99	AAR Corp.	2C		
7	1004	20210531	2020	4	INDL	C	D	STD	AIR	361105	AAR CORP USD	2021Q2	2020Q4	354.3	14	723.4	435.2	4.8	600.2	0.9	406.1	A	1476.906	AAR Corp.	2C		
8	1004	20210831	2021	1	INDL	C	D	STD	AIR	361105	AAR CORP USD	2021Q3	2021Q1	373.7	11.5	734.6	456.1	3.9	620.7	0.7	422	A	1200.693	AAR Corp.	2C		
9	1004	20211130	2021	2	INDL	C	D	STD	AIR	361105	AAR CORP USD	2021Q4	2021Q2	352.5	20.8	751.8	434.1	7.9	626.5	0.5	398.3	A	1158.418	AAR Corp.	2C		
10	1004	20220228	2021	3	INDL	C	D	STD	AIR	361105	AAR CORP USD	2022Q1	2021Q3	365.3	22.5	776.4	452	8.2	634.1	0.6	412.7	A	1581.753	AAR Corp.	2C		
11	1004	20220531	2021	4	INDL	C	D	STD	AIR	361105	AAR CORP USD	2022Q2	2021Q4	378.8	23.9	800.8	474.9	6.6	659	0.6	434.8	A	1706.554	AAR Corp.	2C		
12	1004	20220831	2022	1	INDL	C	D	STD	AIR	361105	AAR CORP USD	2022Q3	2022Q1	358.7	22.7	820.4	446.4	8.1	677.3	1.1	408.1	A	1504.359	AAR Corp.	2C		
13	1019	20200331	2020	1	INDL	C	D	STD	AFAP	1038108	AFA PROT USD	2020Q1	2020Q1									A		AFA Prote	2C		
14	1019	20200630	2020	2	INDL	C	D	STD	AFAP	1038108	AFA PROT USD	2020Q2	2020Q2									A		AFA Prote	2C		
15	1019	20200930	2020	3	INDL	C	D	STD	AFAP	1038108	AFA PROT USD	2020Q3	2020Q3									A		AFA Prote	2C		
16	1019	20201231	2020	4	INDL	C	D	STD	AFAP	1038108	AFA PROT USD	2020Q4	2020Q4	55.673	2.603	10.262	82.679	1.2	15.525	0.109	76.909	A		28.188	AFA Prote	2C	
17	1045	20200331	2020	1	INDL	C	D	STD	AAL	02376R10	AMERICA USD	2020Q1	2020Q1	7541	-2241	-6501	8515	-649	-12038	257	9196	A		5154.993	American	2C	
18	1045	20200630	2020	2	INDL	C	D	STD	AAL	02376R10	AMERICA USD	2020Q2	2020Q2	4538	-2067	-8551	1622	-592	-4211	255	5195	A		6646.827	American	2C	
19	1045	20200930	2020	3	INDL	C	D	STD	AAL	02376R10	AMERICA USD	2020Q3	2020Q3	5191	-2399	-10963	3172	-696	-4244	339	5986	A		6250.743	American	2C	
20	1045	20201231	2020	4	INDL	C	D	STD	AAL	02376R10	AMERICA USD	2020Q4	2020Q4	5237	-2178	-13767	4028	-631	-5474	376	5982	A		9800.74	American	2C	
21	1045	20210331	2021	1	INDL	C	D	STD	AAL	02376R10	AMERICA USD	2021Q1	2021Q1	5820	-1250	-14931	4008	-323	756	371	6687	A		15328.84	American	2C	
22	1045	20210630	2021	2	INDL	C	D	STD	AAL	02376R10	AMERICA USD	2021Q2	2021Q2	6697	19	-14873	7478	-10	1126	485	7932	A		13732.33	American	2C	
23	1045	20210930	2021	3	INDL	C	D	STD	AAL	02376R10	AMERICA USD	2021Q3	2021Q3	7448	170	-14664	8969	37	257	476	8875	A		13286.23	American	2C	
24	1045	20211231	2021	4	INDL	C	D	STD	AAL	02376R10	AMERICA USD	2021Q4	2021Q4	8004	-932	-14580	9427	-259	-1670	468	9567	A		11633.19	American	2C	
25	1045	20220331	2022	1	INDL	C	D	STD	AAL	02376R10	AMERICA USD	2022Q1	2022Q1	8276	-1635	-16189	8899	-451	-4104	463	9893	A		11853.34	American	2C	
26	1045	20220630	2022	2	INDL	C	D	STD	AAL	02376R10	AMERICA USD	2022Q2	2022Q2	9933	476	-15687	13422	127	-4245	469	11827	A		8239.198	American	2C	
27	1045	20220930	2022	3	INDL	C	D	STD	AAL	02376R10	AMERICA USD	2022Q3	2022Q3	10064	483	-15176	13462	176	-4593	498	11921	A		7824.351	American	2C	
28	1050	20200331	2020	1	INDL	C	D	STD	CECO	1.25E+08	CECO ENV USD	2020Q1	2020Q1	51.723	3.412	-59.705	80.486	0.779	109.905	1.023	73.699	A		164.384	CECO Envi	2C	
29	1050	20200630	2020	2	INDL	C	D	STD	CECO	1.25E+08	CECO ENV USD	2020Q2	2020Q2	48.688	3.258	-55.28	75.17	0.564	73.997	0.944	67.095	A		232.996	CECO Envi	2C	
30	1050	20200930	2020	3	INDL	C	D	STD	CECO	1.25E+08	CECO ENV USD	2020Q3	2020Q3	52.087	-0.239	-54.155	77.425	0.206	74.055	0.772	71.07	A		257.8254	CECO Envi	2C	
31	1050	20201231	2020	4	INDL	C	D	STD	CECO	1.25E+08	CECO ENV USD	2020Q4	2020Q4	56.073	1.78	-52.637	82.93	2.123	74.129	0.796	73.633	A		246.1543	CECO Envi	2C	
32	1050	20210331	2021	1	INDL	C	D	STD	CECO	1.25E+08	CECO ENV USD	2021Q1	2021Q1	46.841	1.181	-51.401	71.892	0.551	75.434	0.725	66.295	A		280.9599	CECO Envi	2C	
33	1050	20210630	2021	2	INDL	C	D	STD	CECO	1.25E+08	CECO ENV USD	2021Q2	2021Q2	53.235	0.293	-50.818	78.68	0.199	75.305	0.705	73.746	A		254.9819	CECO Envi	2C	
34	1050	20210930	2021	3	INDL	C	D	STD	CECO	1.25E+08	CECO ENV USD	2021Q3	2021Q3	56.564	-1.25	-52.317	79.979	0.063	71.299	0.722	77.493	A		247.456	CECO Envi	2C	
35	1050	20211231	2021	4	INDL	C	D	STD	CECO	1.25E+08	CECO ENV USD	2021Q4	2021Q4	64.514	1.202	-48.785	93.589	1.878	72.326	0.8	85.417	A		218.2244	CECO Envi	2C	
36	1050	20220331	2022	1	INDL	C	D	STD	CECO	1.25E+08	CECO ENV USD	2022Q1	2022Q1	65.172	2.792	-46.524	92.436	1.112	79.248	0.822	86.324	A		192.5672	CECO Envi	2C	
37	1050	20220630	2022	2	INDL	C	D	STD	CECO	1.25E+08	CECO ENV USD	2022Q2	2022Q2	72.768	4.388	-45.105	105.375	1.86	74.69	1.098	95.756	A		206.5133	CECO Envi	2C	
38	1050	20220930	2022	3	INDL	C	D	STD	CECO	1.25E+08	CECO ENV USD	2022Q3	2022Q3	75.086	1.942	-49.052	108.414	0.315	82.867	1.569	100.252	A		303.8205	CECO Envi	2C	
39	1062	20200229	2020	1	INDL	C	D	STD	ASA	G3156P10	ASA GOLD USD	2020Q1	2020Q1	0.886	-8.931	256.285	0.157	0	0	0.886	A		237.8457	ASA Gold	4C		
40	1062	20200531	2020	2	INDL	C	D	STD	ASA	G3156P10	ASA GOLD USD	2020Q2	2020Q2	0.842	87.373	343.466	0.503	0	0	0.842	A		295.137	ASA Gold	4C		
41	1062	20200831	2020	3	INDL	C	D	STD	ASA	G3156P10	ASA GOLD USD	2020Q3	2020Q3	1.201	158.462	501.927	0.243	0	0	1.201	A		449.0712	ASA Gold	4C		
42	1062	20201130	2020	4	INDL	C	D	STD	ASA	G3156P10	ASA GOLD USD	2020Q4	2020Q4	1.045	-58.461	443.274	0.43	0	0	1.045	A		384.0639	ASA Gold	4C		
43	WRDS FundQuart NorthAmerica Q1-2022																										

10 Energy	3694	
15 Materials	4346	
20 Industrials	7773	
25 Consumer Discretionary	7099	
30 Consumer Staples	2806	
35 Health Care	14558	
40 Financials	10833	
45 IT	8696	
50 Communication Services	3305	
55 Utilities	2492	
60 Real estates	2677	
Total	68279	TRUE

GCSI Structure

<https://www.msci.com/documents/1296102/11185224/GICS+Methodology+2022.pdf/f9910041-6127-17d2-1246-4052926adaf7?t=1645738126436>

Data Preparation

1. Altman Z-Score computation
2. Creation of COVID- and FederalFunds Quarterly Data
3. Duplication of Stringency Index Quarterly Data
4. Duplication of Covid and Federal Funds Quarterly Data
5. Merging data and using the common Sample Period

Sample Period:

2020Q1 to 2022Q3 (Covid period)

$$Z\ score = 1.2 \times \frac{WC}{TA} + 1.4 \times \frac{RE}{TA} + 3.3 \times \frac{EBIT}{TA} + 0.6 \times \frac{ME}{TL} + 1.0 \times \frac{SALE}{TA}$$

```
#EBIT calculation
FundQ_sector["EBIT"] = FundQ_sector["Total Revenue"] - FundQ_sector["COGS"] - FundQ_sector["Total Operating Expense"]
```

The Z-Score is then calculated the same way like we did in Class

Index	il Quarter by	new cases	rindcncv indi	Index	DATE	FEDFUNDS	il Quarter by
0	2020Q1	192078	17.0476	0	1/1/2020	0.0126	2020Q1
1	2020Q2	2.45658e+06	72.0304	1	4/1/2020	0.0006	2020Q2
2	2020Q3	4.59754e+06	66.5305	2	7/1/2020	0.000933333	2020Q3
3	2020Q4	1.29711e+07	68.5199	3	10/1/2020	0.0009	2020Q4
4	2021Q1	1.03601e+07	67.6377	4	1/1/2021	0.0008	2021Q1
5	2021Q2	3.20289e+06	56.6393	5	4/1/2021	0.0007	2021Q2
				6	7/1/2021	0.0009	2021Q3
				7	10/1/2021	0.0008	2021Q4

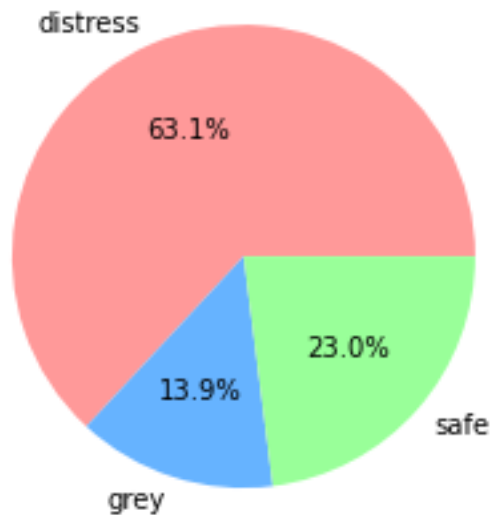
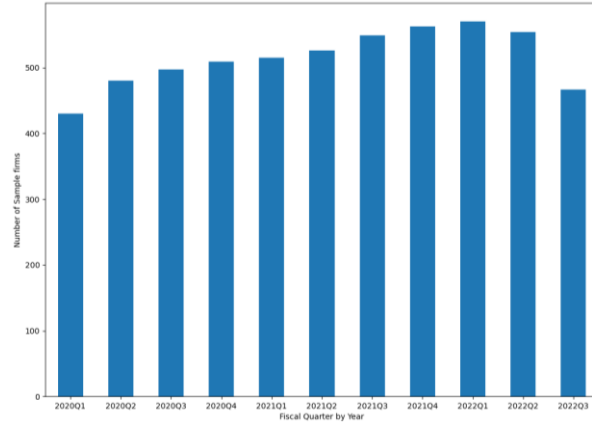
- Only 11 values for the COVID Data → We needed to merge them with the firm data such that the values are duplicated and matched to the respective quarter
- Selection of the columns we needed for the statistical analysis.



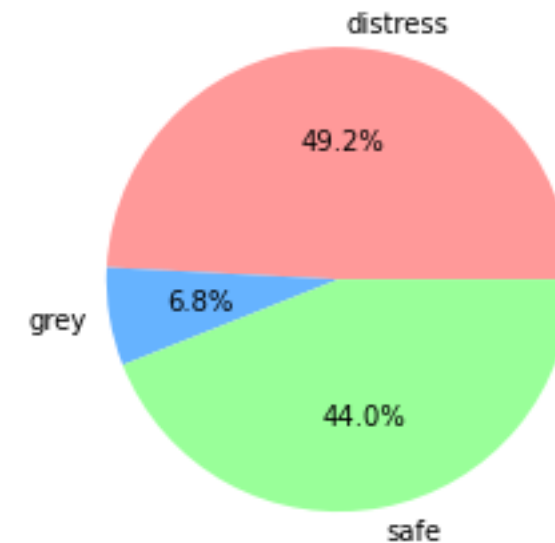
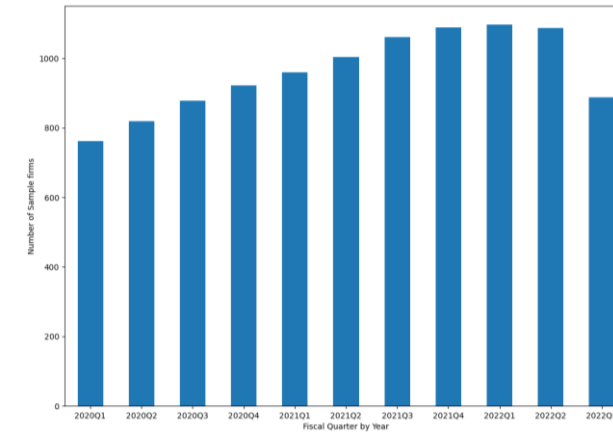
Index	Firm	Year	EBIT	WC	RE	ME	SALE	distress	safe	grey	
0	360626	2020Q1	17.0476	0.0126	2514.77	18.2697	7.82994	safe	12.1657	2.09301	0.0125215
1	361105	2020Q1	17.0476	0.0126	712.378	1.11025	6.5686	distress	12.1657	2.09301	0.0125215
2	957100	2020Q1	17.0476	0.0126	2545.96	0.36081	7.84226	distress	12.1657	2.09301	0.0125215
3	1088182	2020Q1	17.0476	0.0126	2537.23	0.00073	8.1711	distress	12.1657	2.09301	0.0125215
4	2474104	2020Q1	17.0476	0.0126	829.334	1.81137	6.72062	grey	12.1657	2.09301	0.0125215
5	4816184	2020Q1	17.0476	0.0126	67.7018	1.82042	8.21511	grey	12.1657	2.09301	0.0125215
6	7737189	2020Q1	17.0476	0.0126	1.546	0.0219159	0.435671	distress	12.1657	2.09301	0.0125215
7	7808185	2020Q1	17.0476	0.0126	3246.01	0.006652	8.00318	distress	12.1657	2.09301	0.0125215
8	8073188	2020Q1	17.0476	0.0126	1845.24	26.4038	7.50536	safe	12.1657	2.09301	0.0125215
9	9207181	2020Q1	17.0476	0.0126	31.8635	0.311576	5.12234	distress	12.1657	2.09301	0.0125215
10	11111107	2020Q1	17.0476	0.0126	1036.86	1.5988	6.94795	distress	12.1657	2.09301	0.0125215
11	11659189	2020Q1	17.0476	0.0126	3489.99	0.320884	8.15766	distress	12.1657	2.09301	0.0125215
12	12348108	2020Q1	17.0476	0.0126	1529.75	1.9928	7.11288	grey	12.1657	2.09301	0.0125215
13	13130109	2020Q1	17.0476	0.0126	230.151	1.61733	5.43873	distress	12.1657	2.09301	0.0125215
14	23586100	2020Q1	17.0476	0.0126	5925.34	0.820626	8.48099	distress	12.1657	2.09301	0.0125215
15	39111207	2020Q1	17.0476	0.0126	187.275	-0.52394	5.23258	distress	12.1657	2.09301	0.0125215
16	39586109	2020Q1	17.0476	0.0126	1369.57	-0.00835	7.22225	distress	12.1657	2.09301	0.0125215
17	11180180	2020Q1	17.0476	0.0126	10523.7	2.82231	8.71253	grey	12.1657	2.09301	0.0125215
18	37598109	2020Q1	17.0476	0.0126	544.52	0.625187	6.2999	distress	12.1657	2.09301	0.0125215

1.1. Preliminary Data Visualization (Number of.)

SECTOR 1: INDUSTRIAL



SECTOR 2: HEALTH



1.2. Univariate Descriptive Statistics

SECTOR 1: INDUSTRIAL

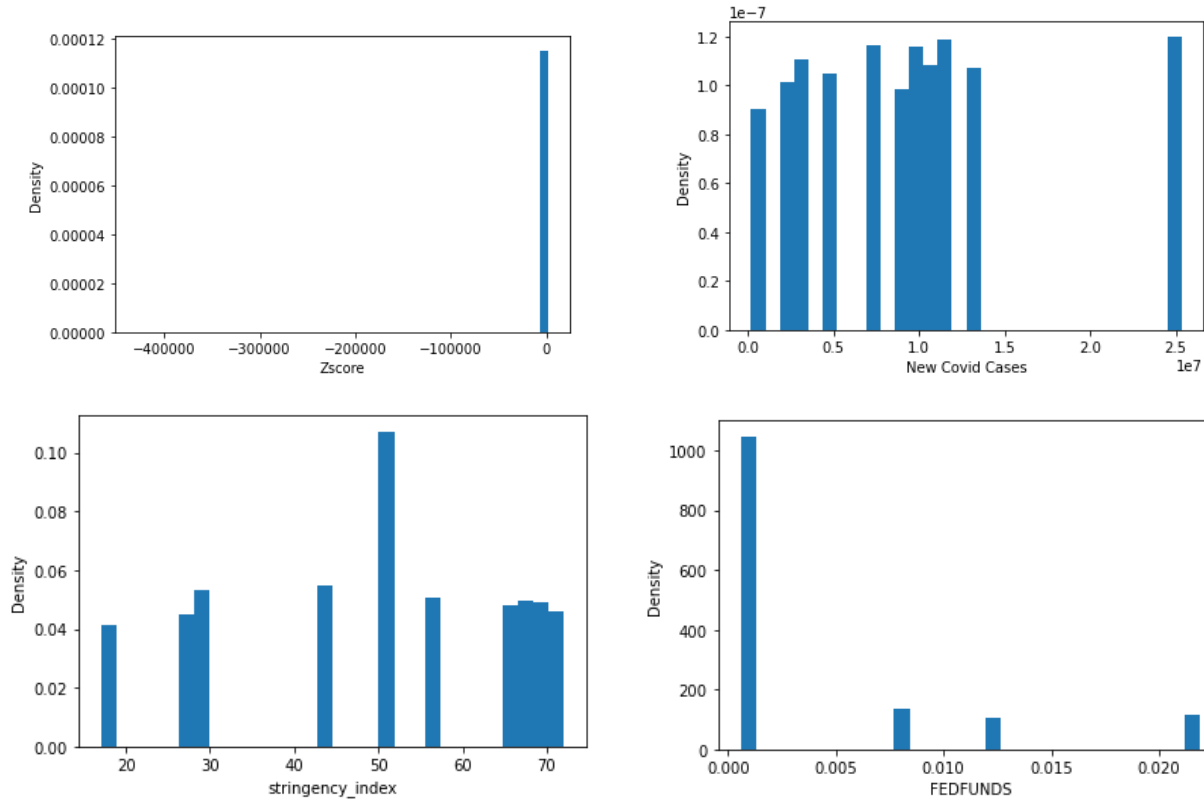
	new_cases	stringency_index	FEDFUNDS	Z_Score
count	5.660000e+03	5660.000000	5660.000000	5660.000000
mean	9.108190e+06	50.307819	0.004157	-114.186900
std	6.607299e+06	17.299089	0.006382	5821.615094
min	1.920780e+05	17.047597	0.000600	-430411.821234
25%	3.202890e+06	29.152842	0.000800	0.228439
50%	8.686982e+06	51.214645	0.000900	1.189588
75%	1.136729e+07	67.637665	0.007700	2.776037
max	2.533413e+07	72.030444	0.021900	2492.176716
	logNC	logSI	logFF	
count	5660.000000	5660.000000	5660.000000	
mean	15.614944	3.864351	0.004129	
std	1.174522	0.411697	0.006319	
min	12.165662	2.893013	0.000600	
25%	14.979564	3.406279	0.000800	
50%	15.977336	3.955363	0.000900	
75%	16.246250	4.228841	0.007671	
max	17.047663	4.290876	0.021664	

SECTOR 2: HEALTH

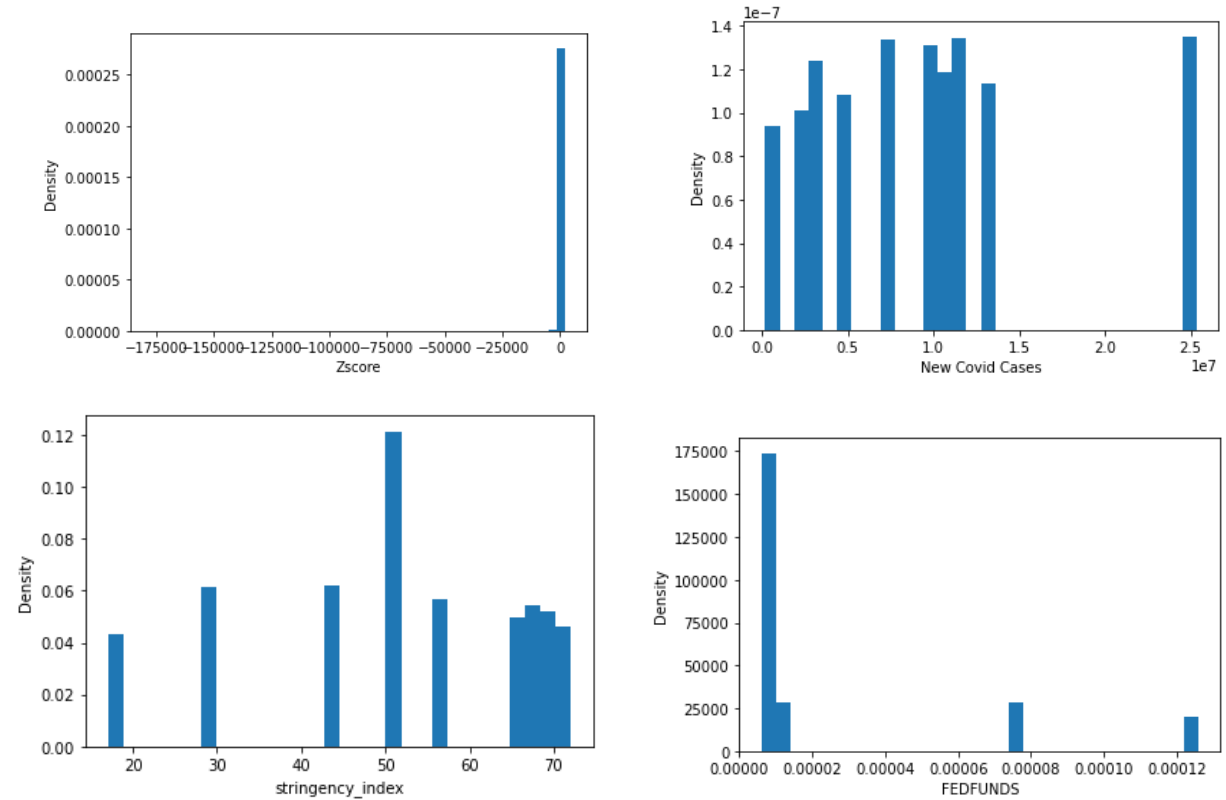
	new_cases	stringency_index	FEDFUNDS	Z_Score
count	1.056200e+04	10562.000000	10562.000000	10562.000000
mean	9.240568e+06	50.008811	0.004179	-174.501036
std	6.617038e+06	17.104406	0.006398	4089.558398
min	1.920780e+05	17.047597	0.000600	-177398.552000
25%	4.597537e+06	29.152842	0.000800	-2.007426
50%	8.686982e+06	51.214645	0.000900	1.808619
75%	1.136729e+07	67.637665	0.007700	9.108121
max	2.533413e+07	72.030444	0.021900	2300.534229
	logNC	logSI	logFF	
count	10562.000000	10562.000000	10562.000000	
mean	15.642457	3.860041	0.004150	
std	1.155428	0.406362	0.006334	
min	12.165662	2.893013	0.000600	
25%	15.341032	3.406279	0.000800	
50%	15.977336	3.955363	0.000900	
75%	16.246250	4.228841	0.007671	
max	17.047663	4.290876	0.021664	

1.3. Histograms

SECTOR 1: INDUSTRIAL

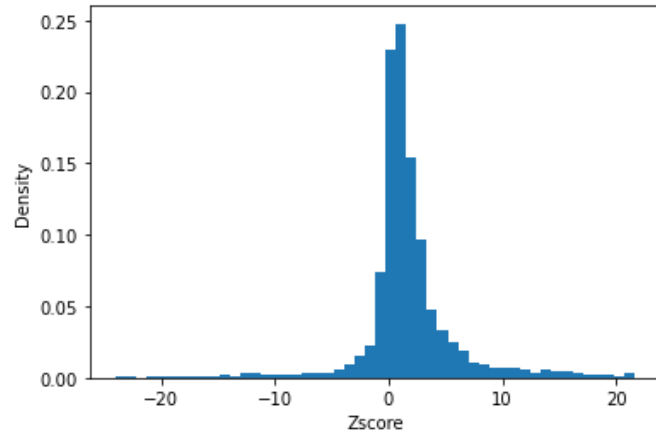
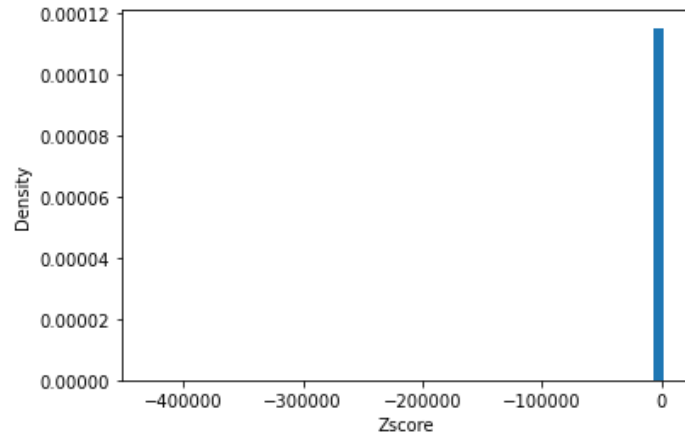


SECTOR 2: HEALTH



1.4. Winsorizing of the Z-Score

SECTOR 1: INDUSTRIAL



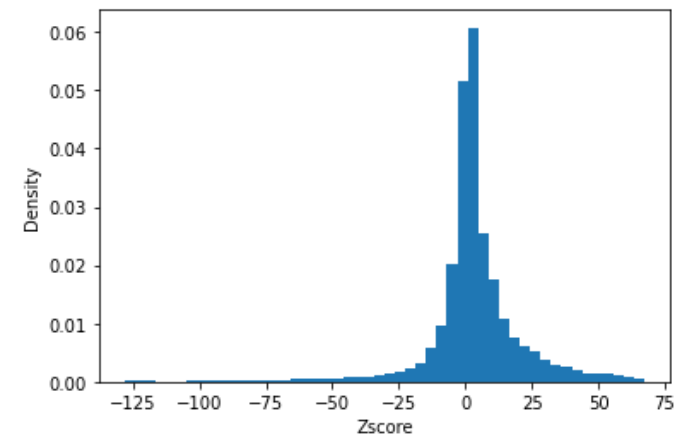
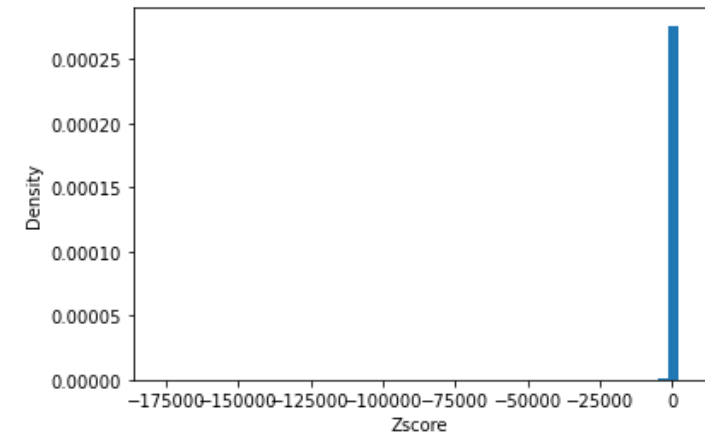
- Values that exceeded the 2.5% or 97.5% percentile were replaced with the percentile
- Makes the distribution more normalized
- And the mean has a value that is in the range of the actual Z-Score

For example for the Industrial sector we get the following Statistics:

Before: After:

	Z_Score	Z_Score
count	5660.000000	5376.000000
mean	-114.186900	1.699561
std	5821.615094	4.347951
min	-430411.821234	-24.034667
25%	0.228439	0.285224
50%	1.189588	1.189588
75%	2.776037	2.654219
max	2492.176716	21.648497

SECTOR 2: HEALTH



1.5. Correlation Coefficients: Pearson

SECTOR 1: INDUSTRIAL

	logNC	logSI	logFF	Z_Score	size
logNC	1.000000	0.451678	-0.295122	0.069025	0.078571
logSI	0.451678	1.000000	-0.783331	0.056297	0.030001
logFF	-0.295122	-0.783331	1.000000	-0.059580	-0.013437
Z_Score	0.069025	0.056297	-0.059580	1.000000	0.349764
size	0.078571	0.030001	-0.013437	0.349764	1.000000



SECTOR 2: HEALTH

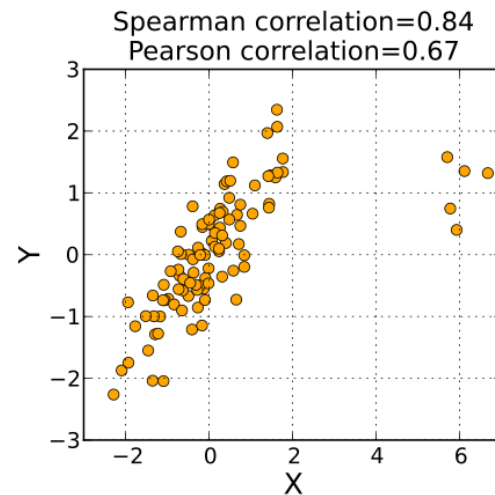
	logNC	logSI	logFF	Z_Score	size
logNC	1.000000	0.510591	-0.671029	0.051455	0.043267
logSI	0.510591	1.000000	-0.928709	0.091064	0.096937
logFF	-0.671029	-0.928709	1.000000	-0.098879	-0.098745
Z_Score	0.051455	0.091064	-0.098879	1.000000	0.400855
size	0.043267	0.096937	-0.098745	0.400855	1.000000



1.5. Correlation Coefficients: Spearman's Rank

SECTOR 1: INDUSTRIAL

	logNC	logSI	logFF	Z_Score	size
logNC	1.000000	0.049512	0.043613	0.089391	0.060635
logSI	0.049512	1.000000	-0.789485	0.034115	0.004085
logFF	0.043613	-0.789485	1.000000	-0.071404	-0.026252
Z_Score	0.089391	0.034115	-0.071404	1.000000	0.404897
size	0.060635	0.004085	-0.026252	0.404897	1.000000

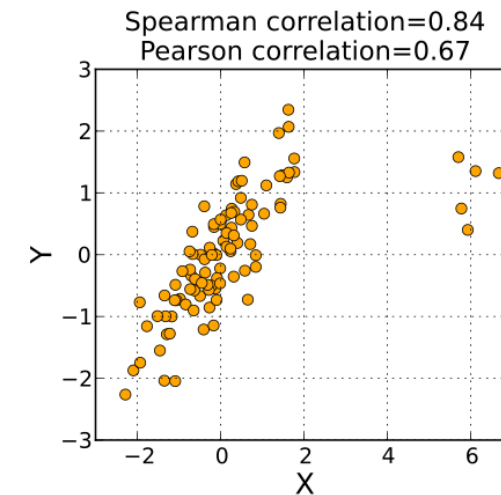


Predicted graphs

$$r_s = \rho_{R(X), R(Y)} = \frac{\text{cov}(R(X), R(Y))}{\sigma_{R(X)} \sigma_{R(Y)}},$$

SECTOR 2: HEALTH

	logNC	logSI	logFF	Z_Score	size
logNC	1.000000	-0.012001	0.084017	0.038203	0.023209
logSI	-0.012001	1.000000	-0.731064	0.096633	0.091844
logFF	0.084017	-0.731064	1.000000	-0.119743	-0.101599
Z_Score	0.038203	0.096633	-0.119743	1.000000	0.492085
size	0.023209	0.091844	-0.101599	0.492085	1.000000



Predicted graphs

2.1.1 Classic assumption test: Jarque Bera

SECTOR 1: INDUSTRIAL

The Jarque-Bera test stat of New Cases is 4600.01
The p value of Jarque-Bera test is 0.0

The Jarque-Bera test stat of Stringency-index is 845.67
The p value of Jarque-Bera test is 0.0

The Jarque-Bera test stat of FEDFUNDS is 3933.99
The p value of Jarque-Bera test is 0.0

The Jarque-Bera test stat of Z-score is 13620.47
The p value of Jarque-Bera test is 0.0

The Jarque-Bera test stat of size is 109.41
The p value of Jarque-Bera test is 0.0

Reject H_0
Non-normal distribution

SECTOR 2: HEALTH

The Jarque-Bera test stat of New Cases is 6789.91
The p value of Jarque-Bera test is 0.0

The Jarque-Bera test stat of Stringency-index is 2882.59
The p value of Jarque-Bera test is 0.0

The Jarque-Bera test stat of FEDFUNDS is 6806.68
The p value of Jarque-Bera test is 0.0

The Jarque-Bera test stat of Z-score is 35725.88
The p value of Jarque-Bera test is 0.0

The Jarque-Bera test stat of size is 156.81
The p value of Jarque-Bera test is 0.0

Reject H_0
Non-normal distribution

2.1.2. Classic assumption test: Kolmogorov-Smirnov

SECTOR 1: INDUSTRIAL

The KS test stat of New Cases is 1.0
The p value of KS test is 0.0

The KS test stat of Stringency is 1.0
The p value of KS test is 0.0

The KS test stat of FEDFUNDS is 0.5
The p value of KS test is 0.0

The KS test stat of Z_Score is 0.39
The p value of KS test is 0.0

The KS test stat of size is 0.96
The p value of KS test is 0.0

Reject H_0
Non-normal distribution

SECTOR 2: HEALTH

The KS test stat of New Cases is 1.0
The p value of KS test is 0.0

The KS test stat of Stringency is 1.0
The p value of KS test is 0.0

The KS test stat of FEDFUNDS is 0.5
The p value of KS test is 0.0

The KS test stat of Z_Score is 0.48
The p value of KS test is 0.0

The KS test stat of size is 0.96
The p value of KS test is 0.0

Reject H_0
Non-normal distribution

2.1.3 Justification on Parametric Test on Non-Normal

PARAMETRIC TESTS CAN PERFORM WELL WITH SKEWED AND NONNORMAL DISTRIBUTIONS

Parametric tests can perform well with continuous data that are nonnormal if you satisfy the sample size guidelines in the table below. These guidelines are based on simulation studies conducted by statisticians here at Minitab.

Parametric analyses	Sample size guidelines for nonnormal data
1-sample t test	Greater than 20
2-sample t test	Each group should be greater than 15
One-Way ANOVA	<ul style="list-style-type: none">• If you have 2-9 groups, each group should be greater than 15.• If you have 10-12 groups, each group should be greater than 20.

<https://blog.minitab.com/en/adventures-in-statistics-2/choosing-between-a-nonparametric-test-and-a-parametric-test>

2.2.1. One Sample and 2.2.2. Two Sample t-Test

SECTOR 1: INDUSTRIAL

One Sample t-test:

The t-test stat of Z_Score against 1.81 is -1.86
The p value of t-test is 0.063

Two Sample t-test:

The t-test stat of the diff between two groups is -6.63
The p value of t-test is 0.0

The t-test stat of the diff between two groups is -5.88
The p value of t-test is 0.0

The t-test stat of the diff between two groups is 6.41
The p value of t-test is 0.0

The t-test stat of the diff between two groups is -18.09
The p value of t-test is 0.0

SECTOR 2: HEALTH

One Sample t-test:

The t-test stat of Z_Score against 1.81 is 7.92
The p value of t-test is 0.0

Two Sample t-test:

The t-test stat of the diff between two groups is -5.33
The p value of t-test is 0.0

The t-test stat of the diff between two groups is -10.24
The p value of t-test is 0.0

The t-test stat of the diff between two groups is 10.99
The p value of t-test is 0.0

The t-test stat of the diff between two groups is -39.61
The p value of t-test is 0.0

2.2.3. Simple Regression

```
NC_zscore_reg = smf.ols(formula='Z_Score ~ 1 + logNC', data = Total_df).fit()
print(NC_zscore_reg.summary())

SI_zscore_reg = smf.ols(formula='Z_Score ~ 1 + logSI', data = Total_df).fit()
print(SI_zscore_reg.summary())

FF_zscore_reg = smf.ols(formula='Z_Score ~ 1 + logFF', data = Total_df).fit()
print(FF_zscore_reg.summary())

Size_zscore_reg = smf.ols(formula='Z_Score ~ 1 + size', data = Total_df).fit()
print(Size_zscore_reg.summary())

# visualizing simple linear regression
# binscatter plot with fitted line

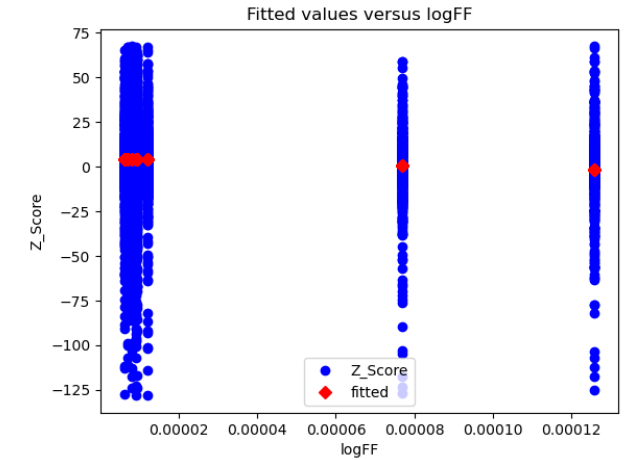
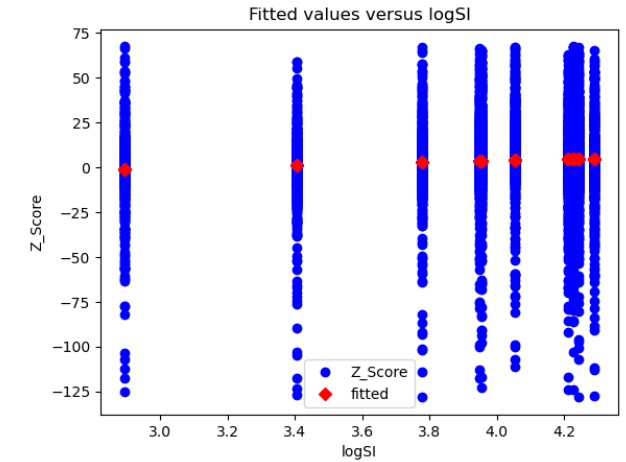
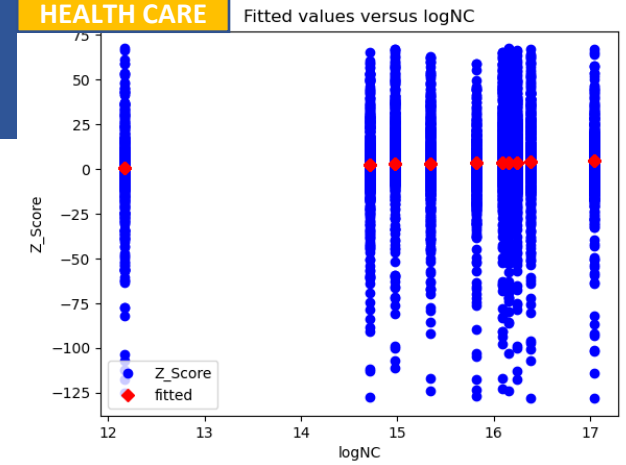
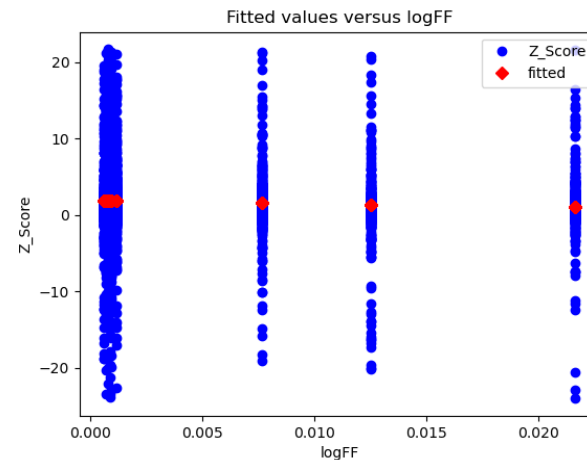
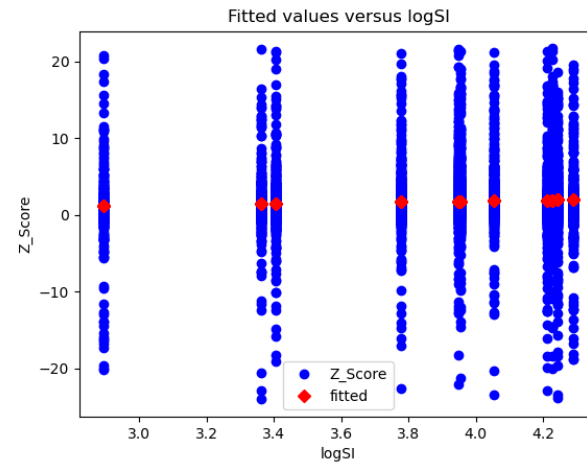
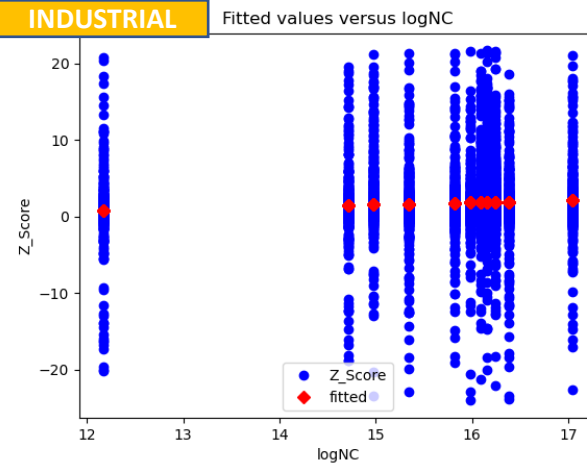
#model = sm.OLS(Y, X, missing='drop')
#model_result = model.fit()
sm.graphics.plot_fit(NC_zscore_reg,1, vlines=False)
sm.graphics.plot_fit(SI_zscore_reg,1, vlines=False)
sm.graphics.plot_fit(FF_zscore_reg,1, vlines=False)
```

OLS Regression Results

Dep. Variable:	Z_Score	R-squared:	0.008
Model:	OLS	Adj. R-squared:	0.008
Method:	Least Squares	F-statistic:	31.70
Date:	Tue, 29 Nov 2022	Prob (F-statistic):	1.92e-08
Time:	21:07:15	Log-Likelihood:	-11654.
No. Observations:	3865	AIC:	2.331e+04
Df Residuals:	3863	BIC:	2.332e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-3.8067	0.981	-3.879	0.000	-5.731	-1.882
logNC	0.3591	0.064	5.631	0.000	0.234	0.484

Omnibus:	888.944	Durbin-Watson:	1.949
Prob(Omnibus):	0.000	Jarque-Bera (JB):	16610.218
Skew:	-0.604	Prob(JB):	0.00
Kurtosis:	13.084	Cond. No.	191.



2.2.4. Multiple Linear Regression

```
Covid_zscore_reg = smf.ols(formula='Z_Score ~ 1 + logNC + logSI + logFF + size', data = Total_df).fit()
print(Covid_zscore_reg.summary())

sm.graphics.plot_fit(Covid_zscore_reg,1, vlines=False)
```

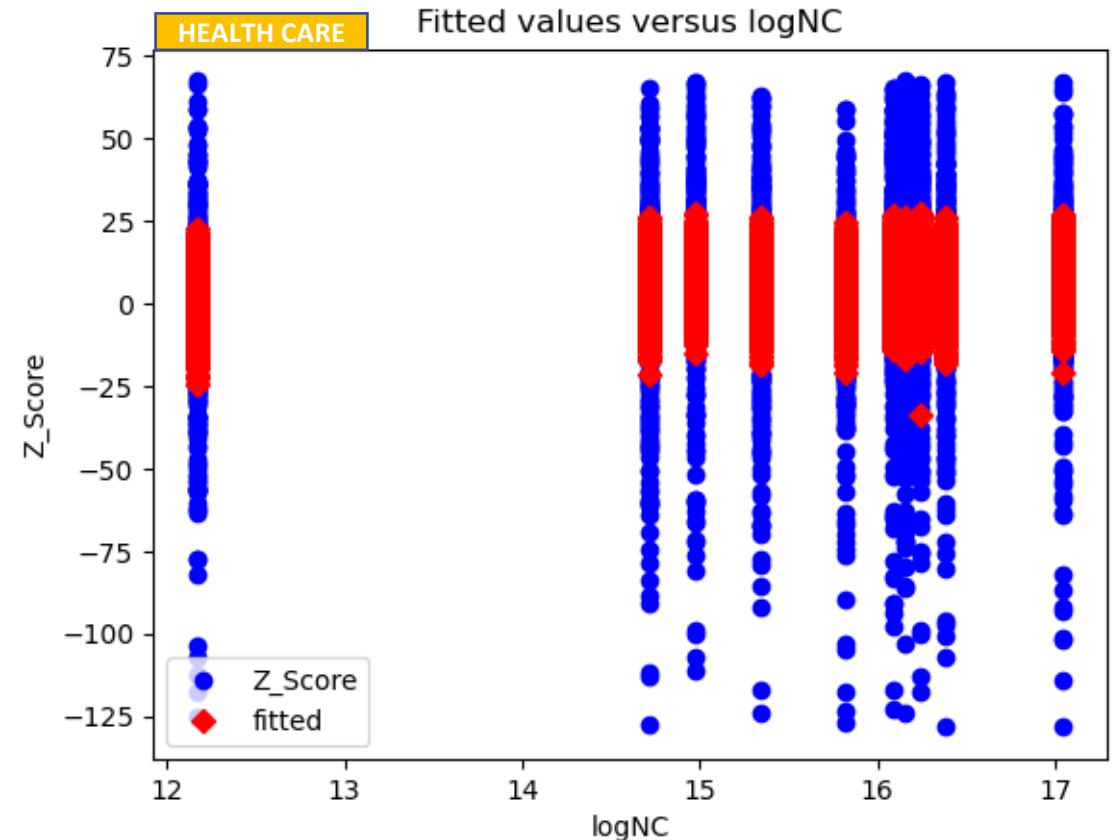
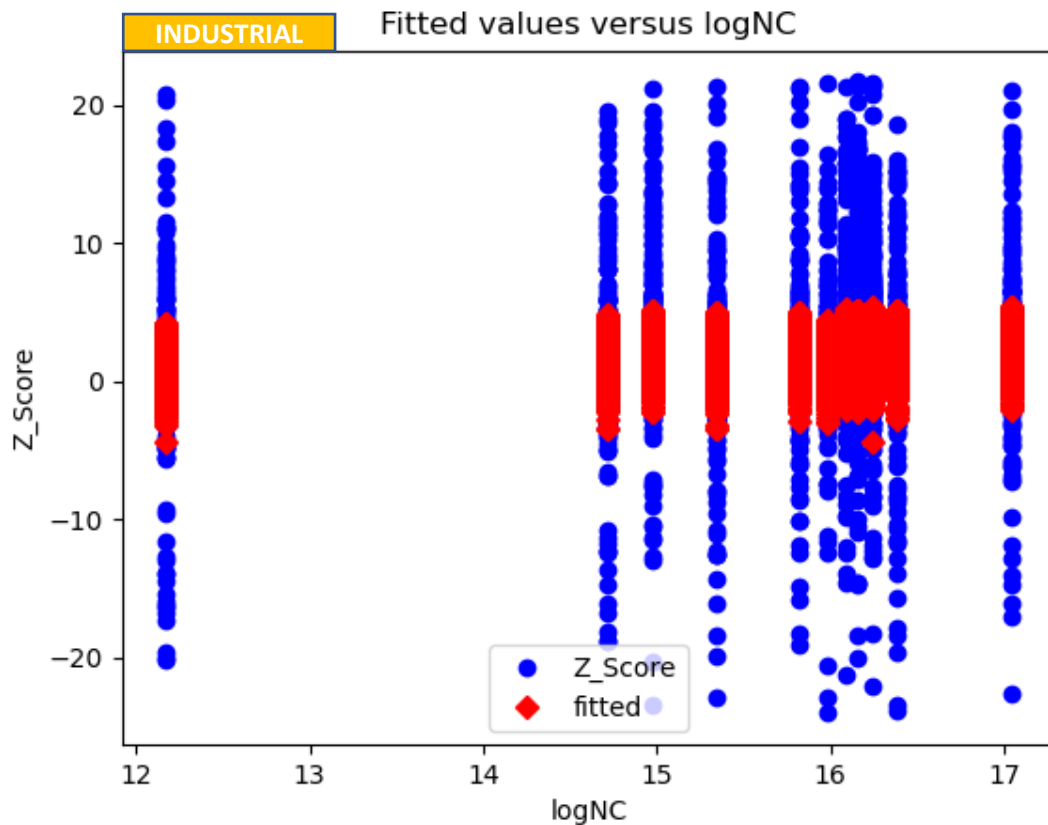
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

OLS Regression Results

Dep. Variable:	Z_Score	R-squared:	0.130
Model:	OLS	Adj. R-squared:	0.129
Method:	Least Squares	F-statistic:	143.8
Date:	Tue, 29 Nov 2022	Prob (F-statistic):	9.57e-115
Time:	21:07:15	Log-Likelihood:	-11401.
No. Observations:	3865	AIC:	2.281e+04
Df Residuals:	3860	BIC:	2.284e+04
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	0.2776	3.686	0.075	0.940	-6.949	7.504
logNC	0.1332	0.127	1.049	0.294	-0.116	0.382
logSI	-1.3325	0.616	-2.164	0.030	-2.539	-0.125
logFF	-1.723e+08	8.51e+07	-2.024	0.043	-3.39e+08	-5.37e+06
size	0.7377	0.032	22.943	0.000	0.675	0.801

Omnibus:	650.696	Durbin-Watson:	1.949
Prob(Omnibus):	0.000	Jarque-Bera (JB):	13555.067
Skew:	0.033	Prob(JB):	0.00
Kurtosis:	12.174	Cond. No.	1.99e+10



2.2.5. Quantile Regression

```
# the 60% unconditional quantiles of Z_score
Z_Score_p60=Total_df['Z_Score'].quantile(0.6)
print("The 60% (and below) percentile of Z_Score is 1.61.")

# quantile regression for 80% quantile
e_qreg = smf.quantreg(formula='Z_Score ~ 1 + logNC + logSI + logFF + size', data = Total_df).fit(q=0.8)
print(e_qreg.summary())

# plot the quantile regression coefficient and confidence intervals
q_start=0.7
q_end=0.98
q_inc=0.02
n=(q_end-q_start)/q_inc+1
n=int(n)
q_forplot=np.linspace(q_start,q_end,n)
beta_forplot=np.zeros(n)
se_forplot=np.zeros(n)
for i in range(n):
    e_qreg = smf.quantreg(formula='Z_Score ~ 1 + logNC + logSI + logFF + size', data = Total_df).fit(q=q_forplot[i])
    beta=e_qreg.params
    beta_forplot[i]=beta[1]
    se=e_qreg.bse
    se_forplot[i]=se[1]

e_reg_control = smf.ols(formula='Z_Score ~ 1 + logNC + logSI + logFF + size', data = Total_df).fit()
beta=e_reg_control.params
beta_ols=beta[1]

fig = plt.figure()
ax = fig.add_subplot(111)
ax.plot(q_forplot,beta_forplot,label='Quantile Reg')
ax.fill_between(q_forplot,beta_forplot-1.96*se_forplot,
               beta_forplot+1.96*se_forplot,color='b',
               alpha=0.1)
ax.plot(q_forplot,beta_ols*np.ones(n),color='r',
        linestyle='dashed',linewidth=0.8,
        label='OLS Reg')
ax.legend(loc='lower left')
ax.set_xlabel('Quantile')
ax.set_ylabel(r'$\beta_{\log NC, \log SI, \log FF, size}$')
plt.show()
```

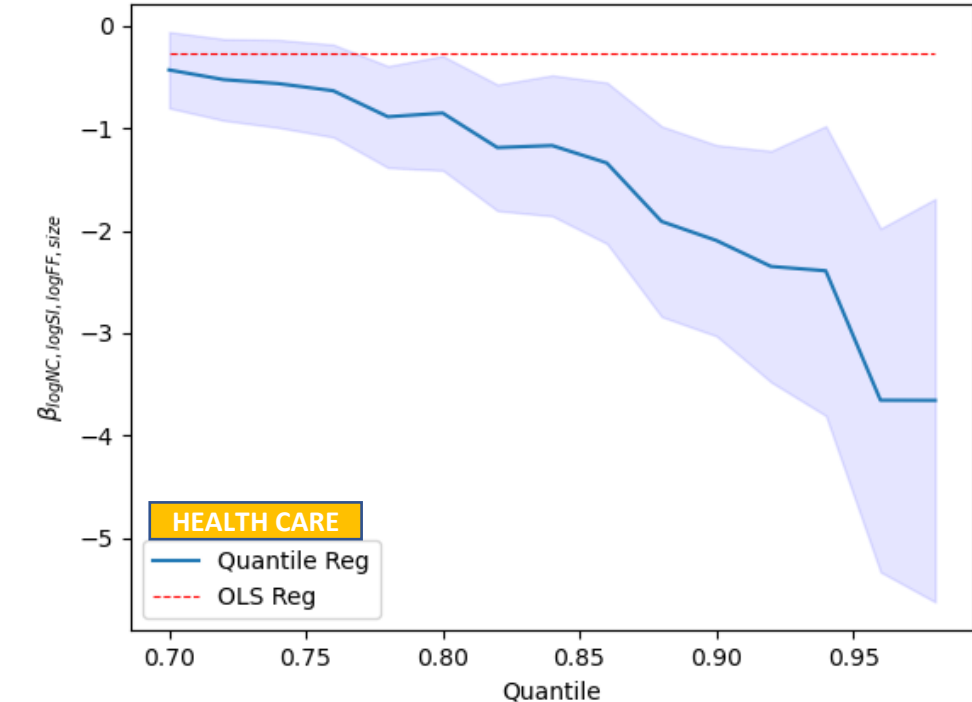
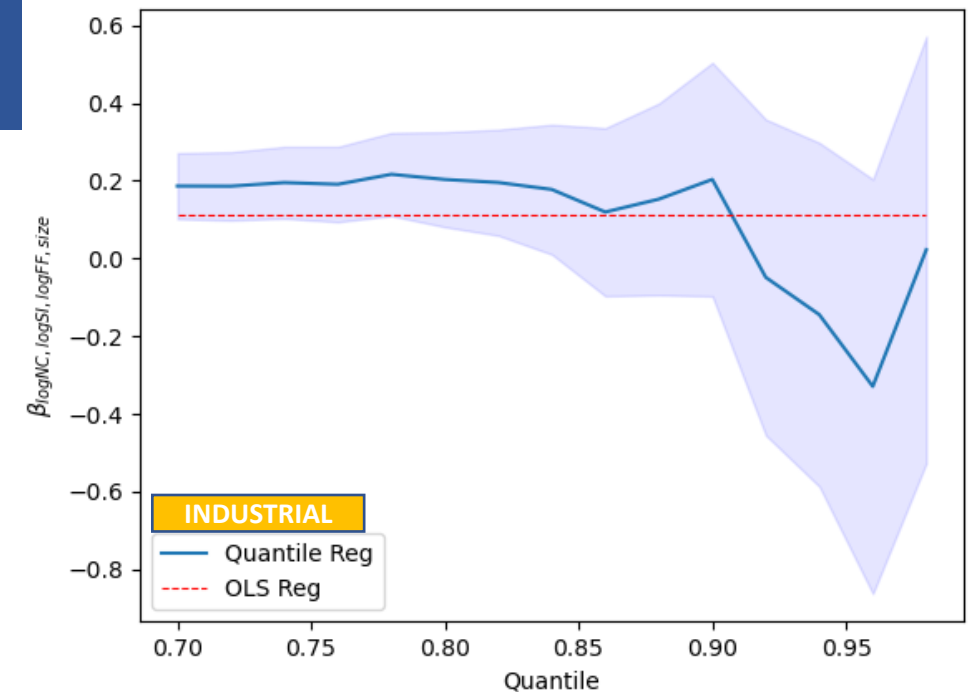
Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.95e-15. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.
The 60% (and below) percentile of Z_Score is 1.61.

QuantReg Regression Results

Dep. Variable:	Z_Score	Pseudo R-squared:	0.02713			
Model:	QuantReg	Bandwidth:	0.4887			
Method:	Least Squares	Sparsity:	13.23			
Date:	Tue, 29 Nov 2022	No. Observations:	3865			
Time:	21:07:15	Df Residuals:	3860			
		Df Model:	4			
	coef	std err	t	P> t	[0.025	0.975]
Intercept	-4.8938	1.049	-4.666	0.000	-6.950	-2.837
logNC	0.5436	0.112	4.853	0.000	0.324	0.763
logSI	-0.7514	0.344	-2.181	0.029	-1.427	-0.076
logFF	-1.96e-07	4.41e-08	-4.446	0.000	-2.82e-07	-1.1e-07
size	0.3984	0.036	11.163	0.000	0.328	0.468

The smallest eigenvalue is 6.48e-15. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.



Discussion: Hypotheses Test, Results and Interpretation

No.	Hypotheses	Test	Sector 1: Industrial	Sector 2: Health
H1	Z is significantly different from 1.81	One-sample t-test	Do not reject H_0	Reject H_0
H2	$SI_{\text{distressed}}$ is significantly different from $SI_{\text{non-distressed}}$	Two-sample t-test	Reject H_0	Reject H_0
H3	$FF_{\text{distressed}}$ is significantly different from $FF_{\text{non-distressed}}$	Two-sample t-test	Reject H_0	Reject H_0
H4	$Size_{\text{distressed}}$ is significantly different from $Size_{\text{non-distressed}}$	Two-sample t-test	Reject H_0	Reject H_0
H5	There is a significant relationship between Z and logNC	SRA (p-value)	Reject H_0	Reject H_0
H6	There is a significant relationship between Z and logSI	SRA (p-value)	Reject H_0	Reject H_0
H7	There is a significant relationship between Z and logFF	SRA (p-value)	Reject H_0	Reject H_0
H8	There is a significant relationship between Z and size	SRA (p-value)	Reject H_0	Reject H_0
H9	At least one of the independent variables is related to Z	MRA (p of F)	Reject H_0	Reject H_0
H10	At least one of the independent variables is related to Z	QRA (p-value)	Reject H_0	Reject H_0

Observations based on our analysis : -

- Industrial sector performed better during the Covid period. During pandemic FED kept on reducing the interest rate thereby, the debt burden on industrial sector diminished.
- Health sector performed even better than industrial sector during the same tenure. With the reduced debt burden and in anticipation of vaccine development the health sector performed as per the expectation.
- Industrial sector and Health sector both are in positive co-relation with increase in number of covid cases. Both these sector were inversely propotional to the FED rate.

Limitation

- This analysis measured the impact of COVID-19 using the growth rate of all confirmed cases and the stringency index. However, other measures, such as the net growth rate (i.e., numbers subtracting recovered cases from confirmed cases), may capture net declines in active confirmed cases which may help avoid unnecessarily inflating the negative impact of global pandemic.
- It should be also noted that there is much uncertainty in calculating recovered cases due to questionable data source reporting recovered cases in many countries, including U.S.

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