MgtOp 519 Project: Analysis of Forbes 2000 Financial Data

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1 Introduction

1.1 Motivation

Each year, Forbes Global 2000 list measures the world's largest and most powerful public companies in terms of four equally weighted metrics: Sales, Profits, Assets, and Market Value (MV). The companies span across tens of countries and industries. The Forbes data is a reflection of the state of the world economy.

The Covid-19 pandemic resulted in months of unprecedented market turmoil and unfathomable human loss, which devastated the world economy. We are going to look at the state of the world economy by taking a closer look at the finances of top 2000 global companies in 2021 after they were hit by the pandemic. We will also compare the results with those of the pre-pandemic era (i.e., 2019).

1.2 The Data

The data was obtained from forbes.com and kaggle.com. The original data had seven variables: Rank, Company Name, Country, Sales, Profits, Assets, and Market Value. We added five new variables for deeper and more meaningful analysis.

1. Each company was assigned one of seven regions based on the Regional Classification in the International Telecommunications Union (Economy Classification).
2. Each of the first 250 companies was assigned a sector based on their activities. The sector data was obtained from 2017 data kaggle.com and cross-validated using the sectors from fortune 1000 companies and Wikipedia pages of the 250 companies.
3. The Assets to Sales ratio (A/S) was calculated and added as a variable. We believe this ratio helps in determining the efficiency of a company in managing its Assets to generate enough Sales for the company so as to make the Assets worthwhile.
4. The Profit to Asset ratio (P/A) was calculated and added as a variable. We believe this ratio is a good estimate of return on assets (ROA) and is an indicator of how Profitable a company is relative to its total Assets.
5. The Asset to market value ratio (A/MV) was calculated and added as a variable. We believe we can consider this ratio as a metric similar to Book-to-Market ratio.

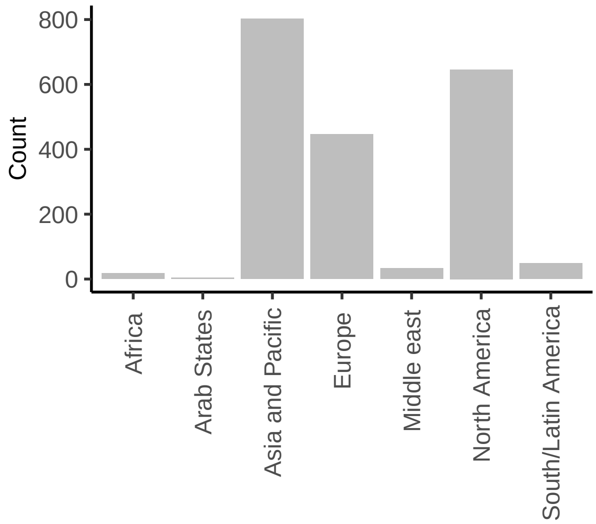
2 Statistical Analysis

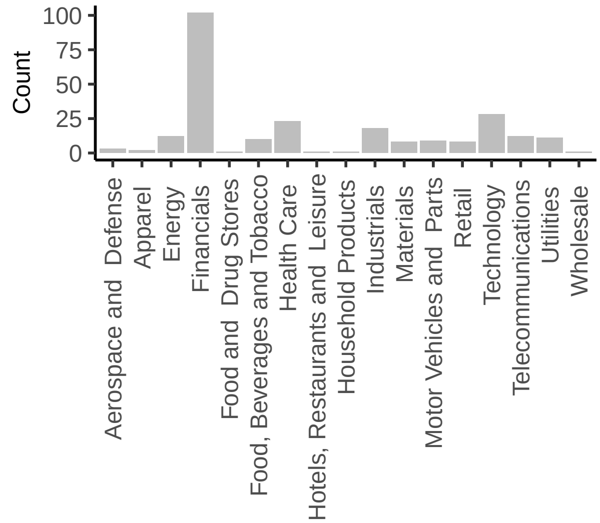
In this project, we utilized various methods of multivariate analysis.

2.1 Data Visualization

The first step in our analysis was to get a better sense of our data and the relationships among our variables.

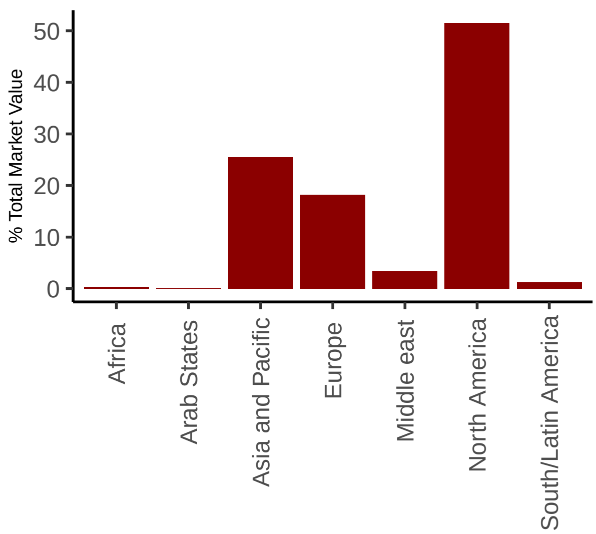
The breakdown of number of companies based on geographic region and sector (for the first 250 companies) are presented in the following plots.

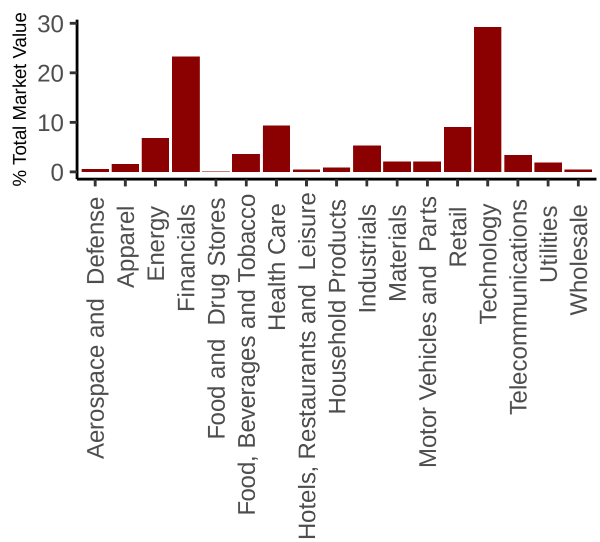


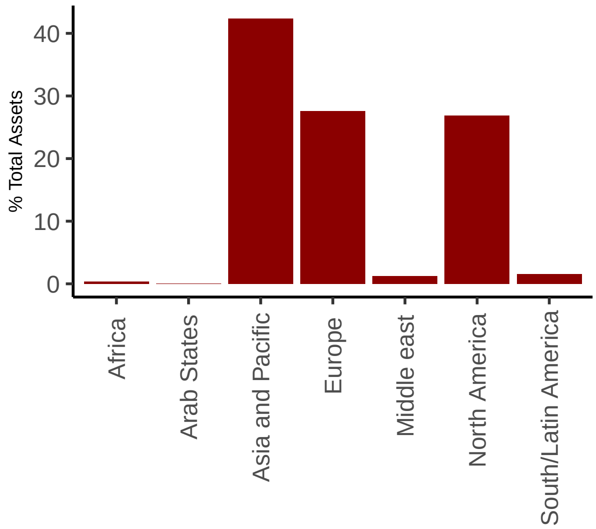


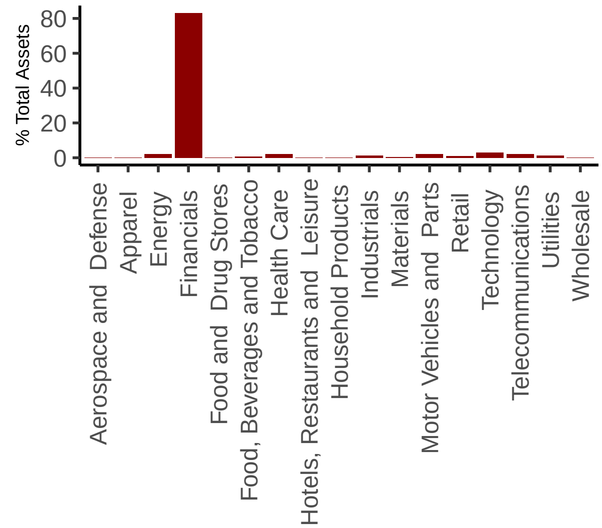
As evident by the plots and not surprisingly, Asia and Pacific, North America, and Europe regions dominated the world economy in terms of the number of companies present in the top 2000 companies of the world. The Finance sector companies dominated the list of top 250 companies, followed not so closely by Tech companies in 2021.

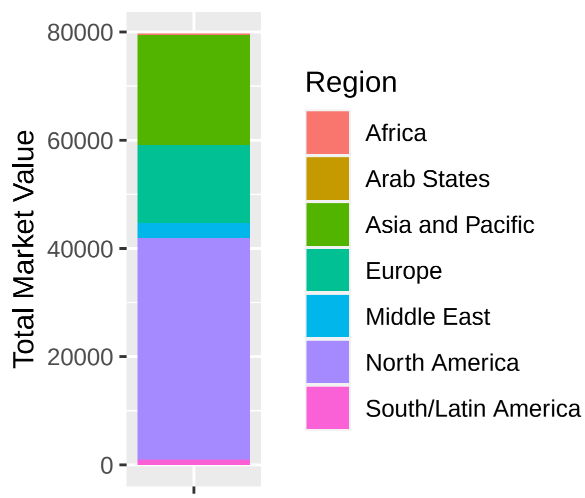
While the number of companies in each region/sector was important, we were more interested in the assets and market value held in each region/sector as a percentage of total asset and market value in possession of the top companies. The following plots depict this relationship.



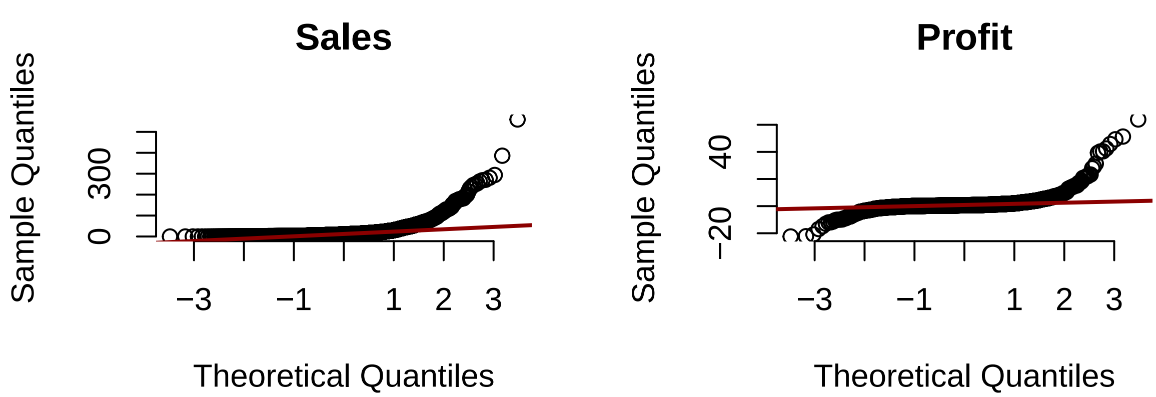


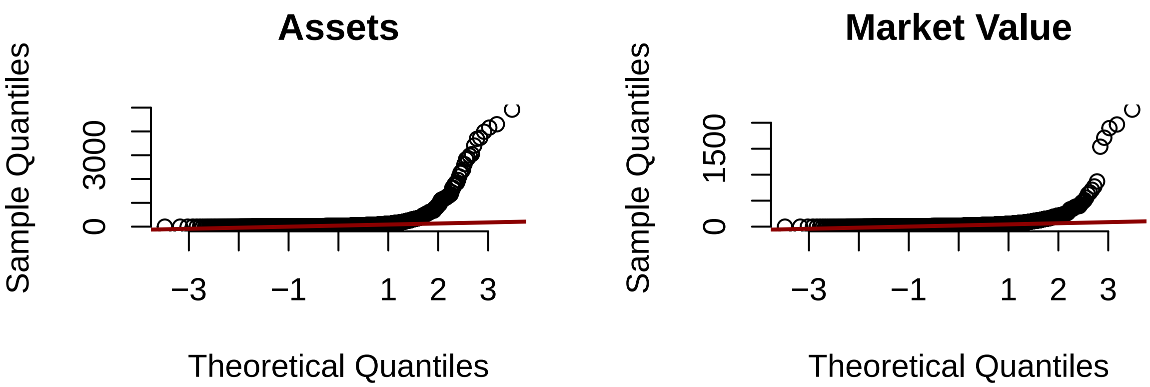




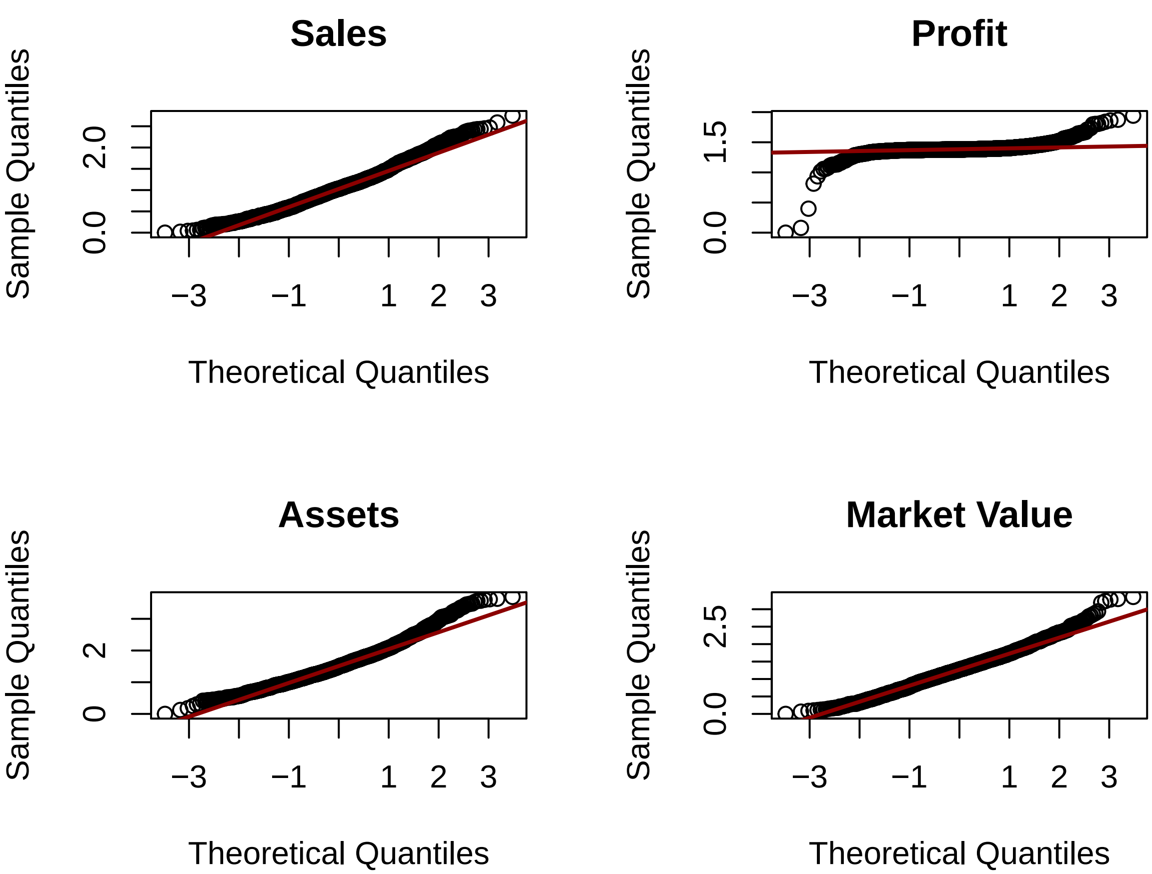


Next, we looked at QQ-plots to examine the normality of our data.

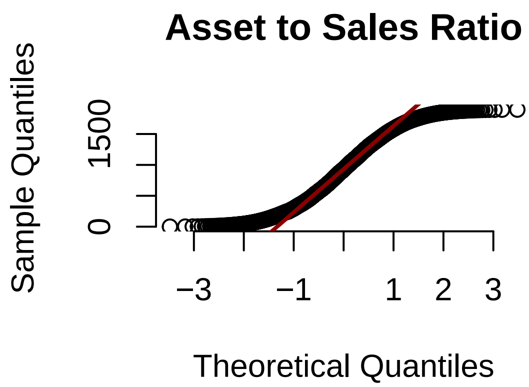


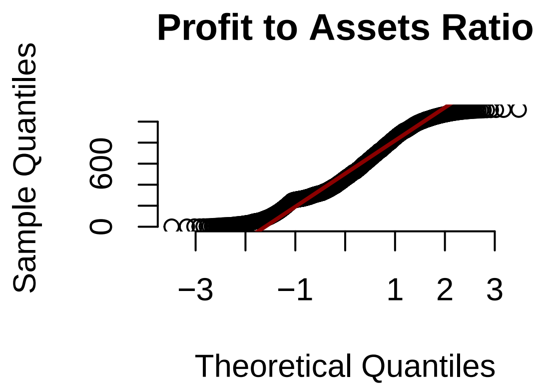


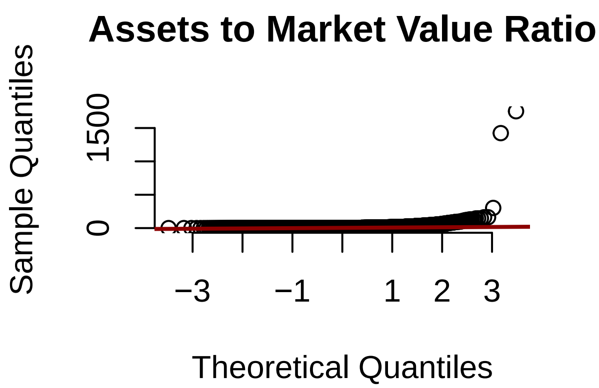
None of our four variables were normally distributed. They all had positive skews (range 5-12) so we used log transformation ($\log(X + a)$ where $a = 1 - \min(X)$) to normalize the variables. The QQ-plots (below) showed that three of the four transformed variables were normal (small deviations from the normality line). The profit values showed some abnormality, but for the purpose of this analysis, we assumed log-normality for all variables.



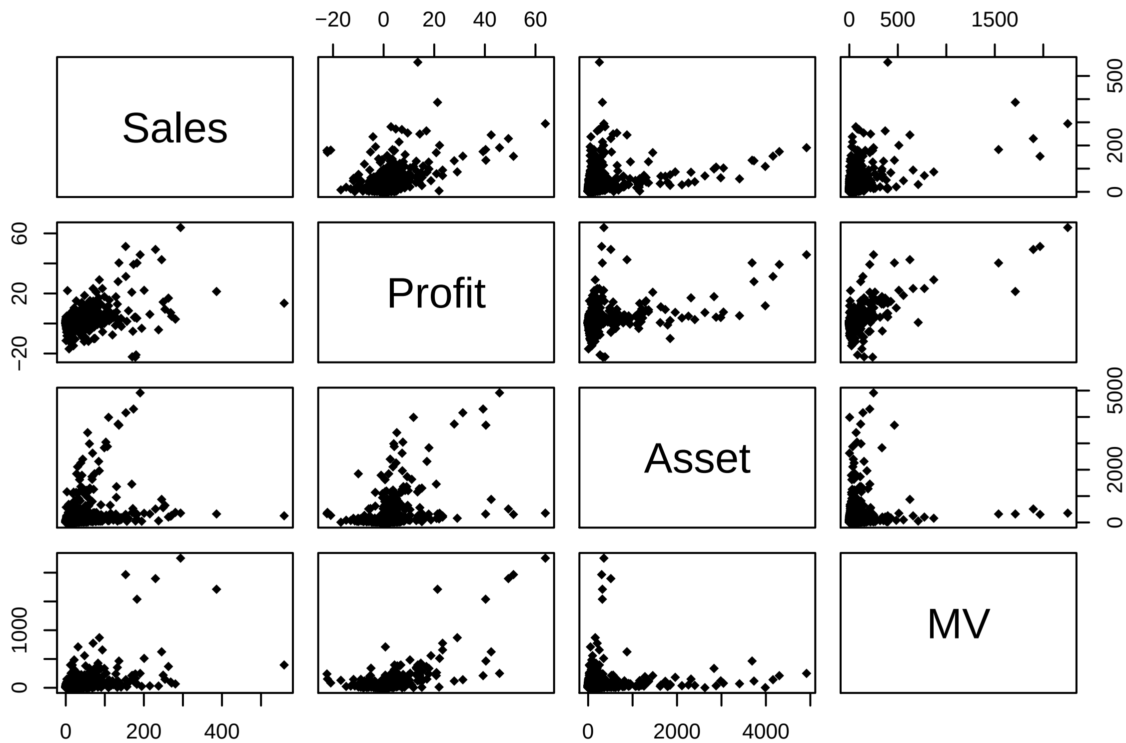
The ratios we defined looked more normal than our original variables, so we assumed normality for those as well.





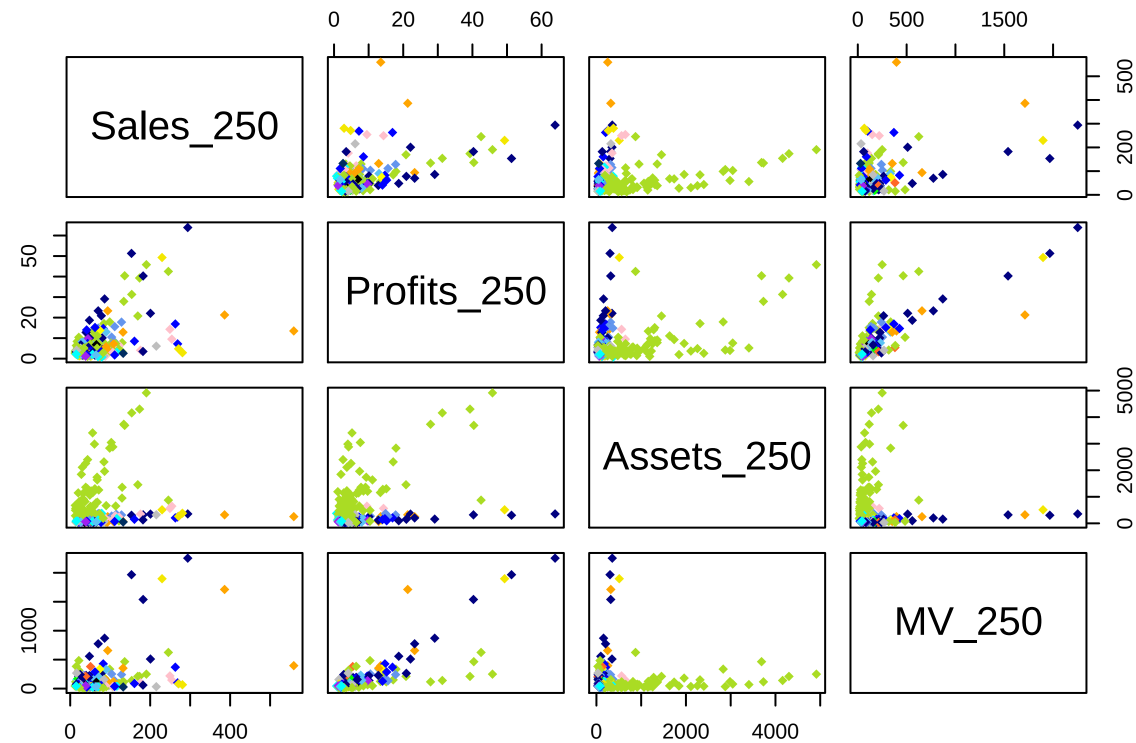


To examine the relationships among the variables, we looked at the scatter plots of each pair of our four variables (below) and then looked at the correlations.



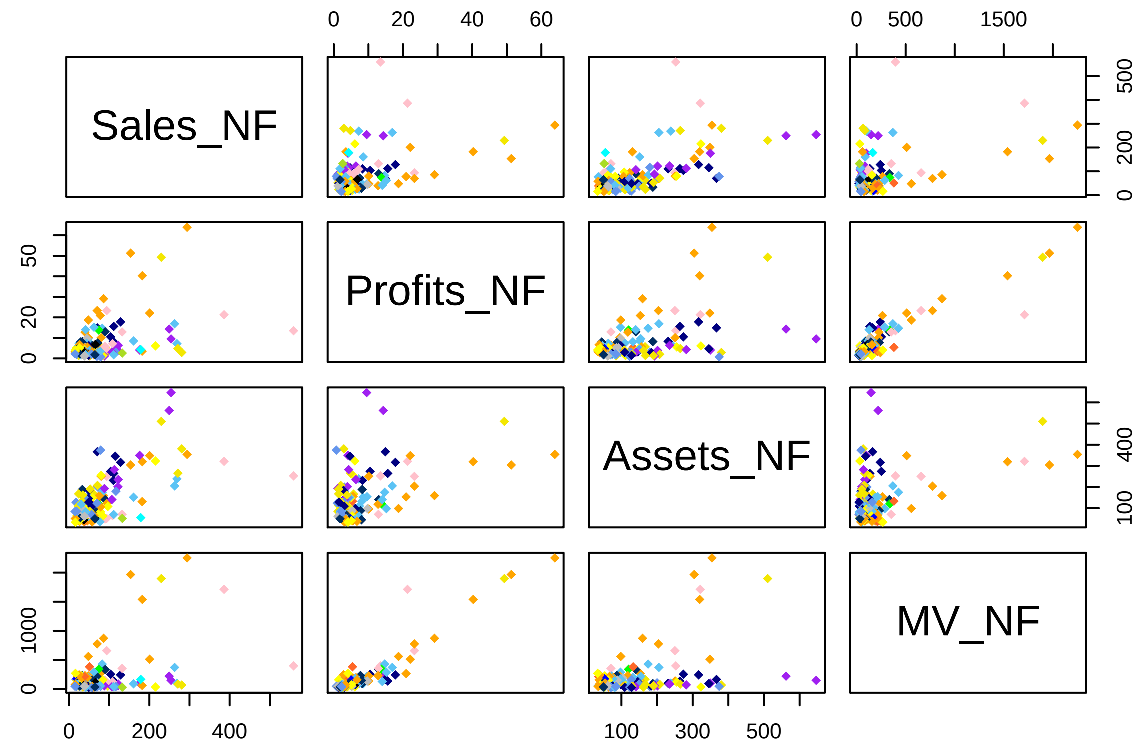

```
##                   Sales    Profit    Assets Market.Value
## Sales         1.0000000 0.4703200 0.3713174    0.5083093
## Profit        0.4703200 1.0000000 0.4428746    0.7014725
## Assets        0.3713174 0.4428746 1.0000000    0.1543442
## Market.Value  0.5083093 0.7014725 0.1543442    1.0000000
```

The scatter plots revealed a lot of irregularity in our data. It almost looked like we had two separate groups of companies. We then looked at the first 250 companies and separated them by sector to investigate the potential cause of the two-group behavior. Note that the green dots represent the companies from the financials sector (investment and insurance).




```
##                 Sales    Profit      Assets Market.Value
## Sales       1.0000000 0.5098062  0.16965668   0.45311429
## Profit      0.5098062 1.0000000  0.38619991   0.78786864
## Assets      0.1696567 0.3861999  1.00000000  -0.00974677
## Market.Value 0.4531143 0.7878686 -0.00974677   1.00000000
```

The companies in the financials sector seemed to act differently from others. The correlation values were interesting. There was almost no linear relationship between assets and market value (almost 0 correlation). To investigate further, we looked at the non-financial companies in the top 250 list. A total of 148 companies were identified and used for analysis.




```
##                   Sales    Profit    Assets Market.Value
## Sales        1.0000000 0.4455723 0.6536812    0.4384702
## Profit       0.4455723 1.0000000 0.4967563    0.9206140
## Assets       0.6536812 0.4967563 1.0000000    0.4141776
## Market.Value 0.4384702 0.9206140 0.4141776    1.0000000
```

The correlation values were very different, and moderate to strong linear relationships existed among all variables.

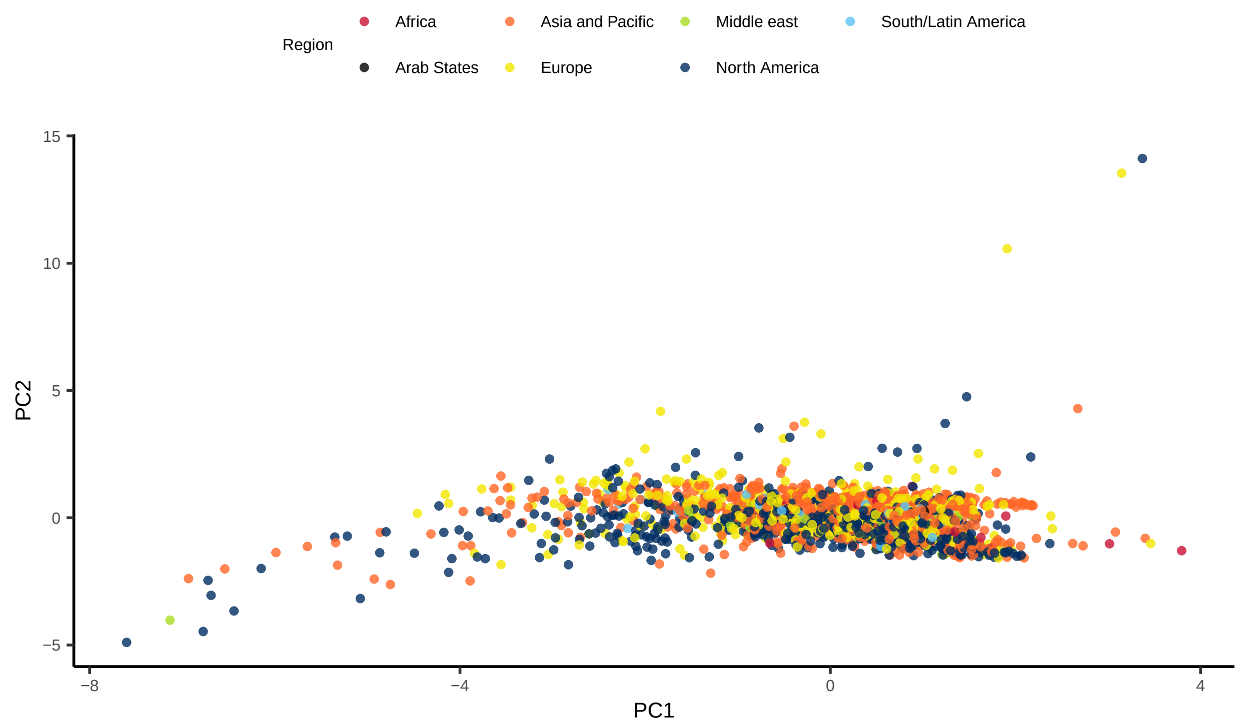
2.2 Principal Component Analysis

We performed PCA on the normalized data to reduce the dimension and get an insight on the general structure of our data. We started by running PCA on all our data (2000 rows).

```
## Importance of components:
##                           PC1    PC2    PC3    PC4
## Standard deviation     1.3870 0.9523 0.8734 0.6376
## Proportion of Variance 0.4809 0.2267 0.1907 0.1016
## Cumulative Proportion  0.4809 0.7077 0.8984 1.0000
```

```
## Standard deviations (1, .., p=4):
## [1] 1.3869732 0.9523146 0.8734021 0.6376291
##
## Rotation (n x k) = (4 x 4):
##                     PC1        PC2        PC3        PC4
## Sales        -0.5926079  0.3211873 -0.1591564  0.7213347
## Profit       -0.3802033 -0.7250060  0.5585125  0.1336995
## Assets       -0.5169031  0.4970014  0.4254418 -0.5520871
```

```
## Market.Value -0.4869010 -0.3524126 -0.6940694 -0.3962329
```

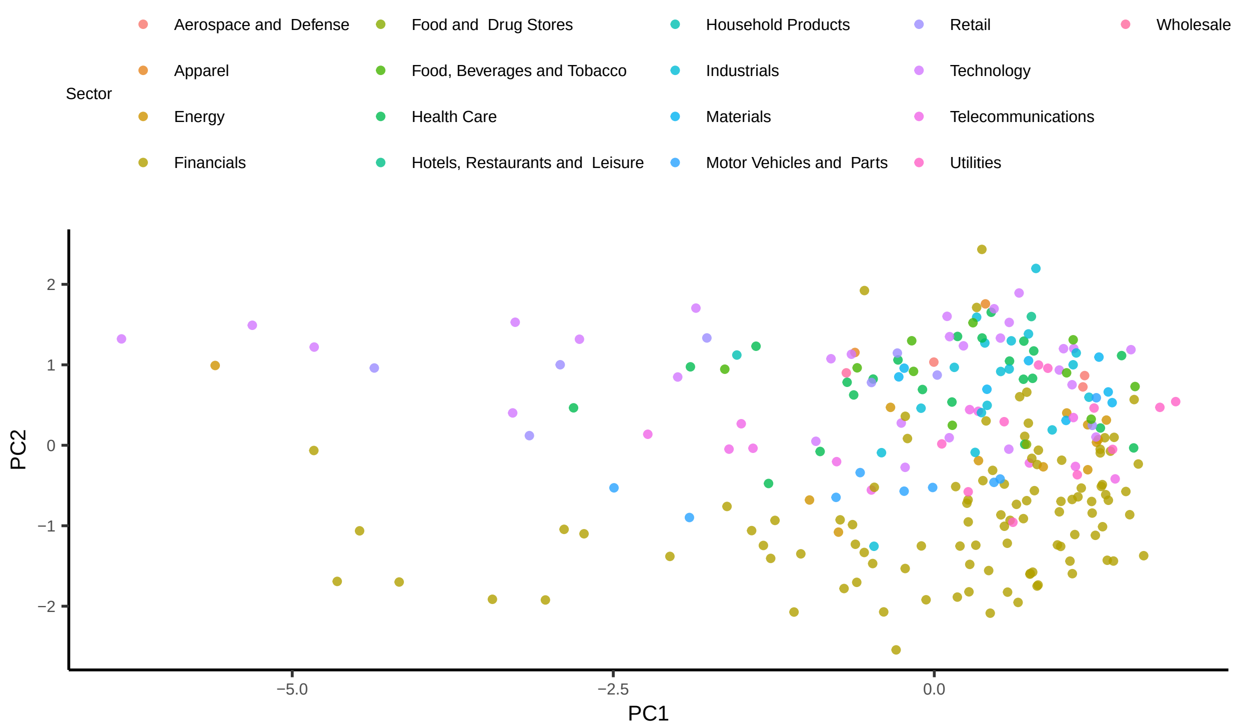


About 71% of the variation in data could be explained using the first two principal components. PC1 was a weighted sum of all four variables, which may have been an index that indicated the financial health of a company. Profit dominated PC2. Also, PC2 contrasted profit and market value with sales and assets (opposite signs). Region did not seem to be a discriminating factor on the biplot.

We then performed PCA on our top 250 list to investigate whether sector is a discriminating factor.

```
## Importance of components:
##                           PC1    PC2    PC3     PC4
## Standard deviation     1.4584 1.0439 0.7890 0.40113
## Proportion of Variance 0.5317 0.2724 0.1556 0.04023
## Cumulative Proportion  0.5317 0.8041 0.9598 1.00000
```

```
## Standard deviations (1, .., p=4):
## [1] 1.4583568 1.0439128 0.7890099 0.4011294
##
## Rotation (n x k) = (4 x 4):
##                     PC1         PC2        PC3        PC4
## Sales        -0.4933826 -0.20742941  0.8333335  0.1382097
## Profit       -0.6411216  0.06207967 -0.2438863 -0.7250025
## Assets       -0.2609678 -0.82234783 -0.4085952  0.2978083
## Market.Value -0.5267187  0.52617791 -0.2812910  0.6054582
```



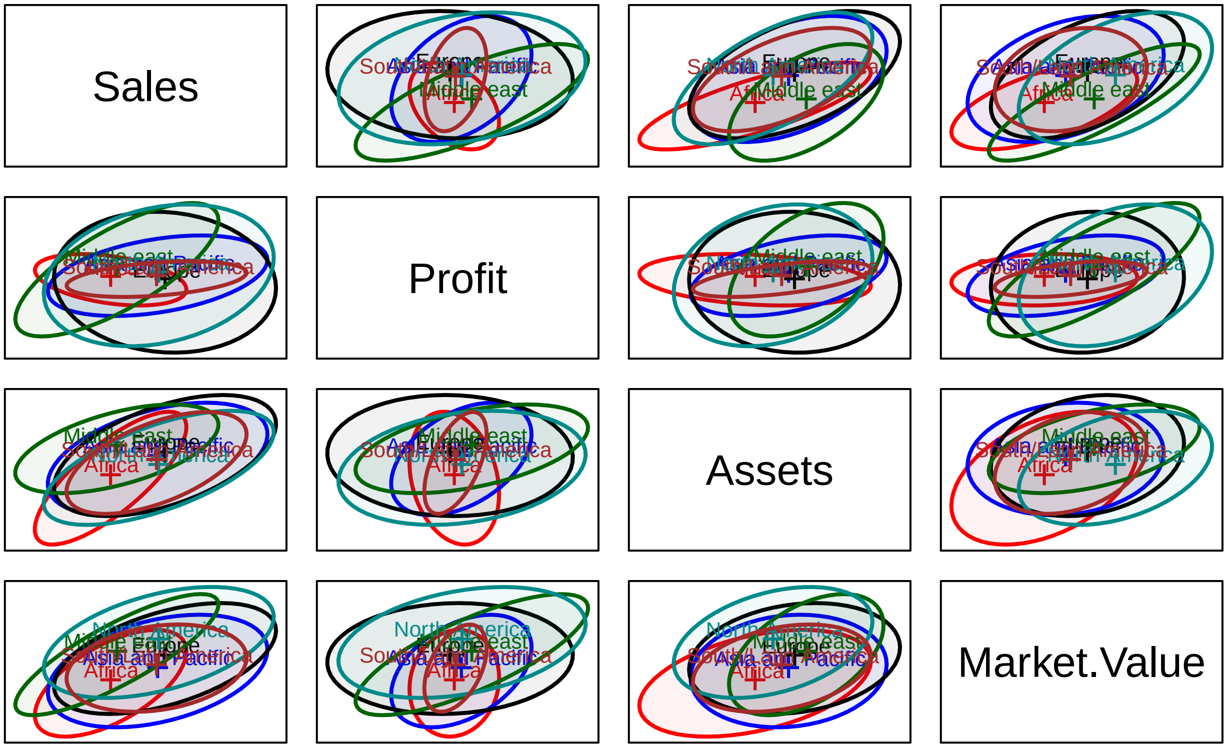
About 80% of the variation in data can be explained using the first two principal components. Here, PC2 is dominated by assets, however, we still see the same sign difference. Consistent with our previous findings, finance sector companies seem to act differently from others. They tend to score lower on PC2.

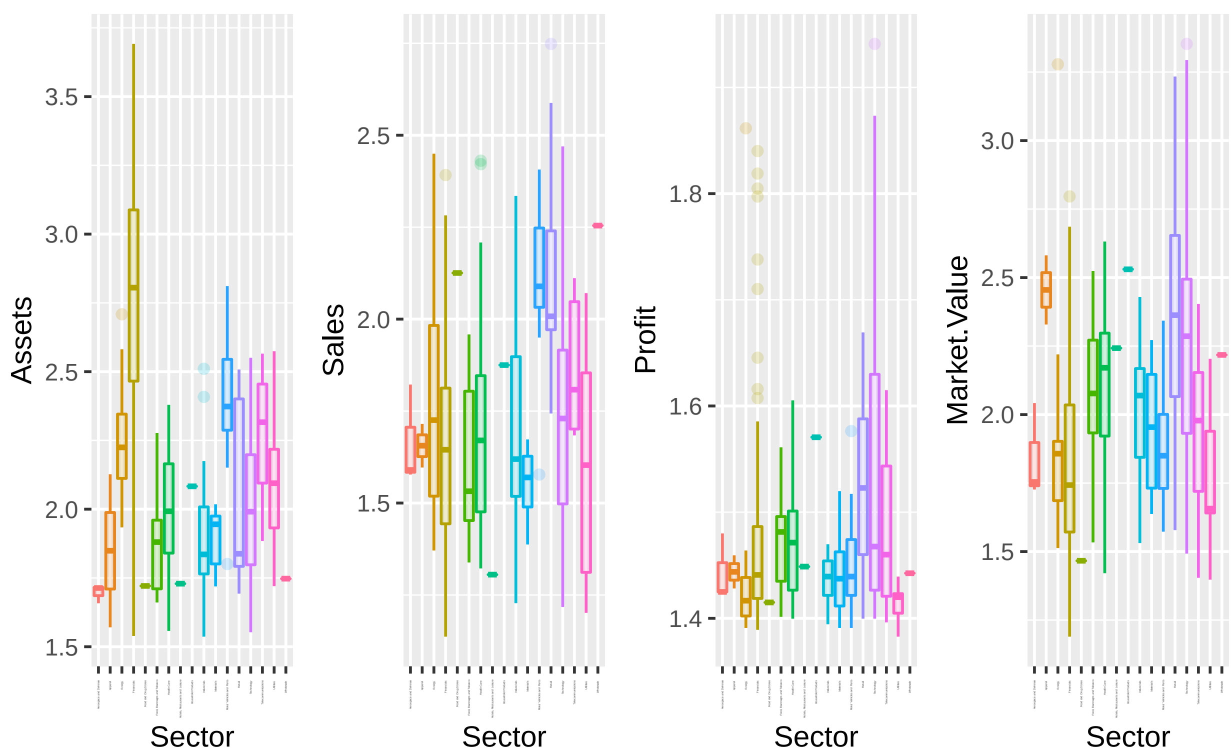
We ranked the companies on the list based on our PCA results (performed on both original data and normalized data). The rankings were different from Forbes ranking. The results are available in Appendix A.

2.3 Discriminant Analysis

Both LDA and QDA assume the the predictor variables are drawn from a multivariate normal distribution. LDA assumes equality of covariances among the predictor variables X across each all levels of Y. This assumption is relaxed with the QDA model.

We ran some analysis to examine the equality of covariances among our variables among different regions and sectors. The different size ellipses in the first plot below suggested that the equality of covariance did not hold for our normalized variables across regions. The different sizes of boxplots also suggested that the equality of covariance did not hold for our normalized variables across sectors, so LDA was not a good option.





We ran quadratic discriminant analysis on our data. The accuracy of prediction for the region was about 47%. We ran the analysis on financials vs non-financials sector companies and found it to be about 93% accurate in predicting whether a company belonged to the financials sector or not.

```
## [1] 46.74
```

```
## [1] 92.62
```

2.4 Logistic Regression

Because our initial discriminant analysis allowed us to identify whether our a company belonged to the financials sector or not, we attempted to define key characteristics and metrics that impacted companies exclusively in the financials and technology sectors (our two most common and impactful industries from the dataset). We did this using logistic regression, which utilized key independent variables and subsequently identified whether a company is a member of the respective sector (a binary variable). First, we looked at the financials sector.

Upon initial analysis of the financials sector, we identified two key indicators (Sales and Assets), and we removed the two insignificant variables: Profit and Market Value (p-value > 0.1). After doing so, we observed that Sales and Assets p-values were still very significant with little change in the residual deviance. This indicated that while these two independent variables were very significant, the maximum likelihood method was still effective in making this assumption.

Similarly, we observed that Profit and Assets were the two most significant variables when identifying a company in the technology sector. Neither was as significant as the metrics for the financials sector (p-values of 0.008 and 0.002, respectively). Removing Sales and Market Value from the analysis, we observed a more statistically significant Profit variable and maintained our residual deviance.

We then asked the question: how could our key metrics (Assets/Sales, Profits/Assets, Assets/Market Value) describe these given sectors? Not surprisingly, the P/A ratio was the least important in identifying companies in the financials sector. An important finding was that the residual deviance among our calculated metrics was substantially less than that of our previous raw variables in this similar analysis (residual deviance of metrics and raw variables: 95.644 and 113.35, respectively), indicating a better fitting model. We saw in this same analysis with respect to the technology sector that initially no metrics were significant. Using our intuition, we removed all metrics except for profit from our analysis and witnessed a significant ratio: P/A.

Naturally, in these measurements we encountered some multicollinearity. Still, we were able to extract some key descriptors of the financials and technology sectors.

```
##
## Call:
## glm(formula = Is.Financial ~ Sales + Profit + Assets + Market.Value,
##     family = "binomial", data = data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9190  -0.4300  -0.1235   0.0034   3.5525
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.617843   0.462931  -3.495 0.000474 ***
## Sales        -0.050700   0.012016  -4.219 2.45e-05 ***
## Profit       -0.024660   0.089849  -0.274 0.783728
## Assets        0.019660   0.003527   5.574 2.48e-08 ***
## Market.Value -0.001440   0.003585  -0.402 0.687861
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 338.06  on 249  degrees of freedom
## Residual deviance: 113.35  on 245  degrees of freedom
## AIC: 123.35
```

```
##
## Number of Fisher Scoring iterations: 9

##
## Call:
## glm(formula = Is.Financial ~ Sales + Assets, family = "binomial",
##     data = data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9255  -0.4476  -0.1321   0.0031   3.6726
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.753095   0.442134  -3.965 7.34e-05 ***
## Sales       -0.055417   0.011773  -4.707 2.51e-06 ***
## Assets       0.019995   0.003427   5.834 5.42e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 338.06  on 249  degrees of freedom
## Residual deviance: 114.39  on 247  degrees of freedom
## AIC: 120.39
##
## Number of Fisher Scoring iterations: 9

##
## Call:
## glm(formula = Is.Tech ~ Sales + Profit + Assets + Market.Value,
##     family = "binomial", data = data)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.21301  -0.53322  -0.24555  -0.00199   2.39700
##
## Coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.4152786  0.3985180  -3.551 0.000383 ***
## Sales        -0.0009185  0.0051402  -0.179 0.858180
## Profit        0.2030897  0.0769347   2.640 0.008296 **
## Assets       -0.0129572  0.0043507  -2.978 0.002900 **
## Market.Value -0.0009378  0.0019028  -0.493 0.622107
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 175.34  on 249  degrees of freedom
## Residual deviance: 125.72  on 245  degrees of freedom
## AIC: 135.72
##
## Number of Fisher Scoring iterations: 9
```

```
##
## Call:
## glm(formula = Is.Tech ~ Profit + Assets, family = "binomial",
##     data = data)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.28112  -0.53560  -0.23303  -0.00182   2.46441
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.384726   0.376440  -3.678 0.000235 ***
## Profit       0.170056   0.041117   4.136 3.54e-05 ***
## Assets      -0.013244   0.004168  -3.178 0.001484 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 175.34  on 249  degrees of freedom
## Residual deviance: 126.03  on 247  degrees of freedom
## AIC: 132.03
##
## Number of Fisher Scoring iterations: 9
```

```
##
## Call:
## glm(formula = Is.Financial ~ A.S + P.A + A.MV, family = "binomial",
##     data = data)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.93310  -0.35231  -0.20951   0.00002   2.95241
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -6.2804     1.0455  -6.007 1.89e-09 ***
## A.S           0.7829     0.1681   4.658 3.19e-06 ***
## P.A          17.0226     7.4641   2.281 0.022572 *
## A.MV          0.5010     0.1331   3.765 0.000166 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 338.061  on 249  degrees of freedom
## Residual deviance:  95.644  on 246  degrees of freedom
## AIC: 103.64
##
## Number of Fisher Scoring iterations: 9
```

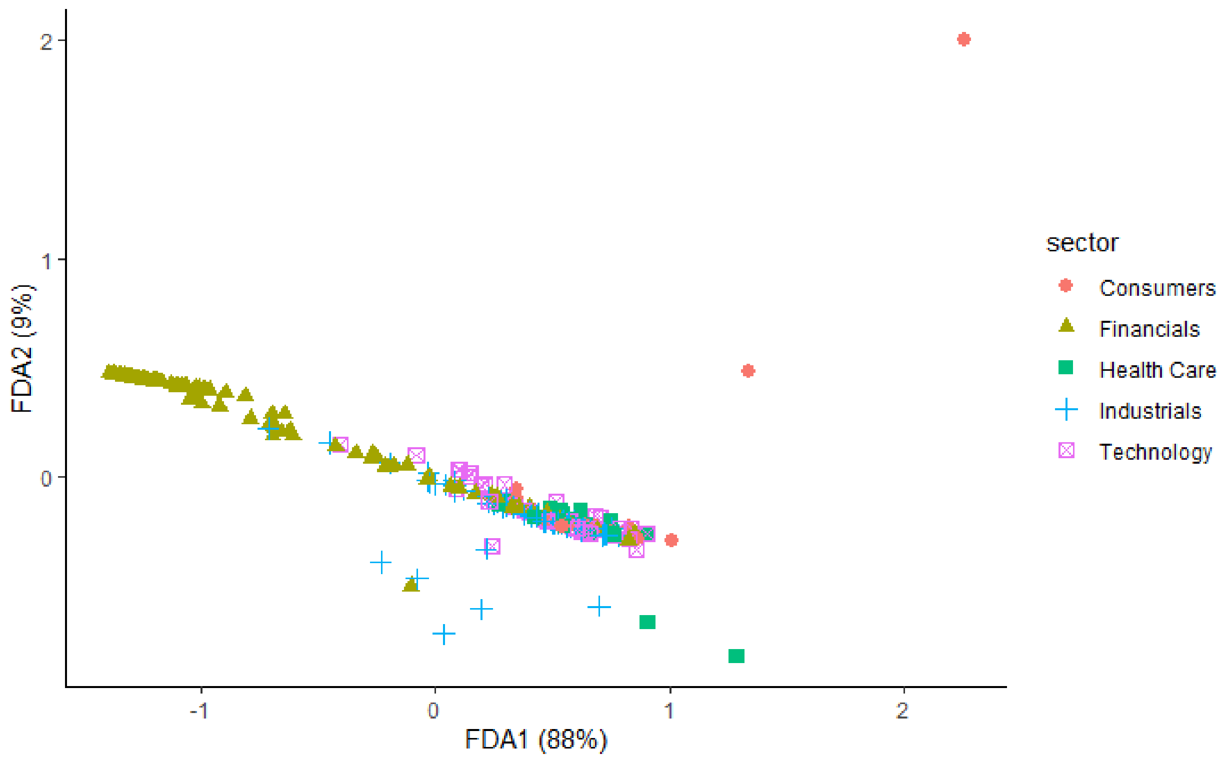
```
##
## Call:
## glm(formula = Is.Financial ~ A.S + A.MV, family = "binomial",
##     data = data)
```

```
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.84906  -0.34406  -0.22958   0.00015   2.79326
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -4.7087     0.6129  -7.682 1.57e-14 ***
## A.S           0.6558     0.1414   4.639 3.51e-06 ***
## A.MV          0.3677     0.1015   3.622 0.000292 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 338.06  on 249  degrees of freedom
## Residual deviance: 100.24  on 247  degrees of freedom
## AIC: 106.24
##
## Number of Fisher Scoring iterations: 9
```

```
##
## Call:
## glm(formula = Is.Tech ~ A.S + P.A + A.MV, family = "binomial",
##     data = data)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.30037  -0.54250  -0.22813  -0.00253   2.28309
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.5343     0.8371  -1.833   0.0668 .
## A.S          -0.1418     0.1907  -0.743   0.4574
## P.A          10.9076     5.9998   1.818   0.0691 .
## A.MV         -0.4909     0.3308  -1.484   0.1378
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 175.34  on 249  degrees of freedom
## Residual deviance: 130.63  on 246  degrees of freedom
## AIC: 138.63
##
## Number of Fisher Scoring iterations: 10
```

```
##
## Call:
## glm(formula = Is.Tech ~ P.A, family = "binomial", data = data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6170  -0.4240  -0.3016  -0.2650   2.4101
##
```

```
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -3.4628     0.3874  -8.939  < 2e-16 ***
## P.A          23.3844     4.2796   5.464 4.65e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 175.34  on 249  degrees of freedom
## Residual deviance: 141.25  on 248  degrees of freedom
## AIC: 145.25
##
## Number of Fisher Scoring iterations: 5
```



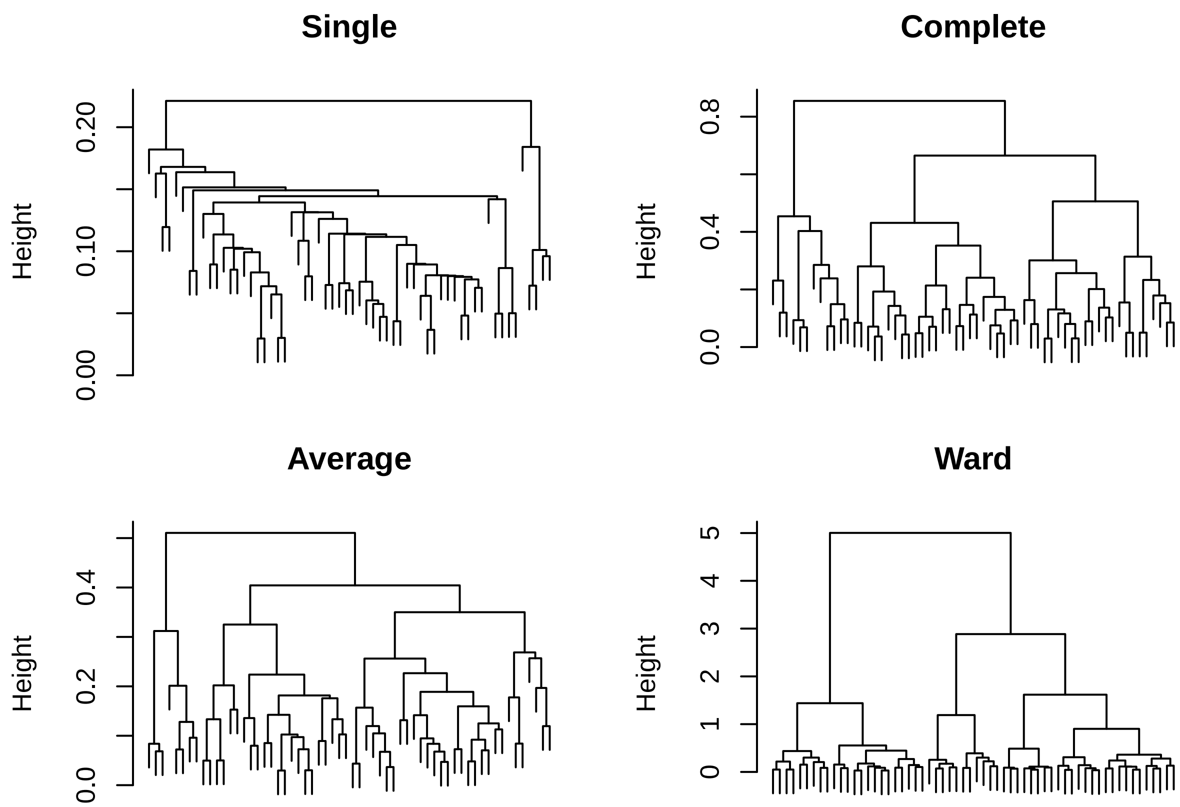
2.5 Flexible Discriminant Analysis

Earlier, we ran into the issues and limitations that were unavoidable with Linear Discriminant Analysis (LDA). Flexible Discriminant Analysis (FDA) is a flexible extension of LDA that uses non-linear combinations of predictors such as splines. FDA should not be confused with Mixed Discriminant Analysis (MDA), which is similar but assumes each class to be a Gaussian mixture of variables.

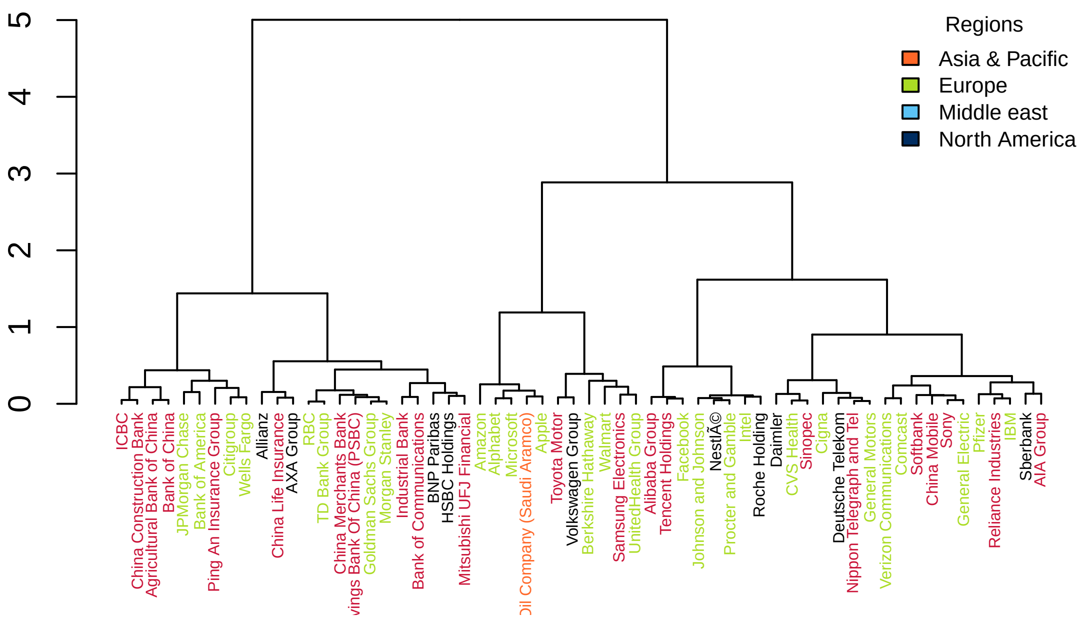
We performed FDA, which is useful in modeling multivariate non-normality or non-linear relationships among variables within each group and allows for a more accurate classification. In order to understand the discriminant variables best, we arbitrarily reduced our sectors from 17 in total to 5, combing several less represented industries into one (e.g., "Food & Drug Stores" and "Food, Beverages & Tobacco" became "Consumers"). These 5 reduced sectors more equally distributed our top 250 companies across industries. However, as evident in our results below, there was still much correlation between these reduced sectors. Visualizing the results, we could see that the Financials sector was again the most distinct among the five, even as FDA1 accounted for 88% of the explained variation.

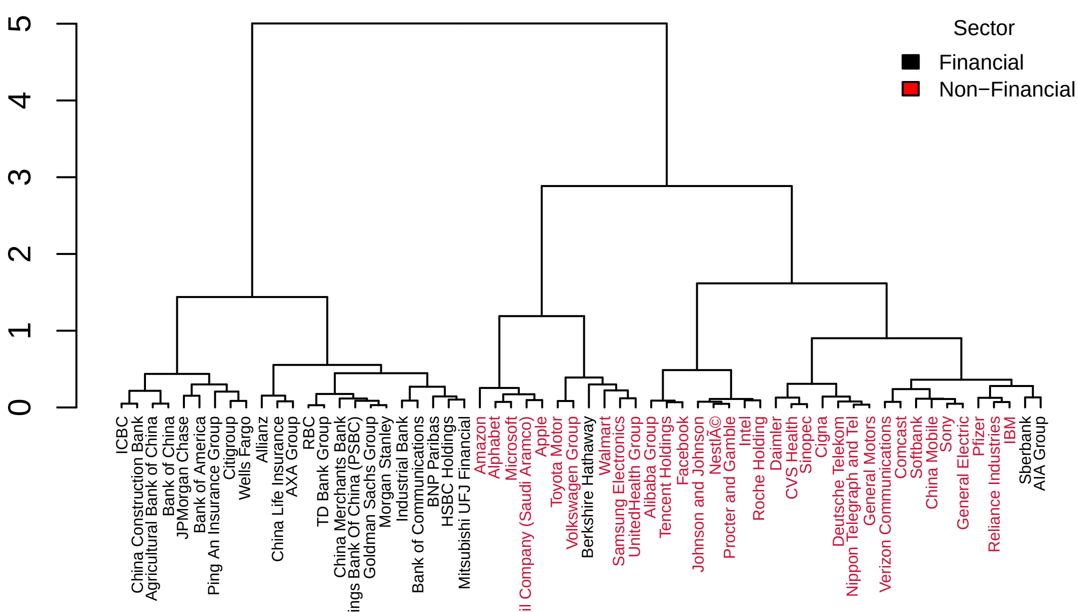
2.6 Hierarchical Clustering

We performed hierarchical clustering on the first 60 companies to investigate their natural grouping. We started by looking at different methods. Below you can see the dendrograms generated using the four methods of clustering.



We felt that the Ward method generated a more balanced dendrogram and decided to use that method to explore the natural groupings further.





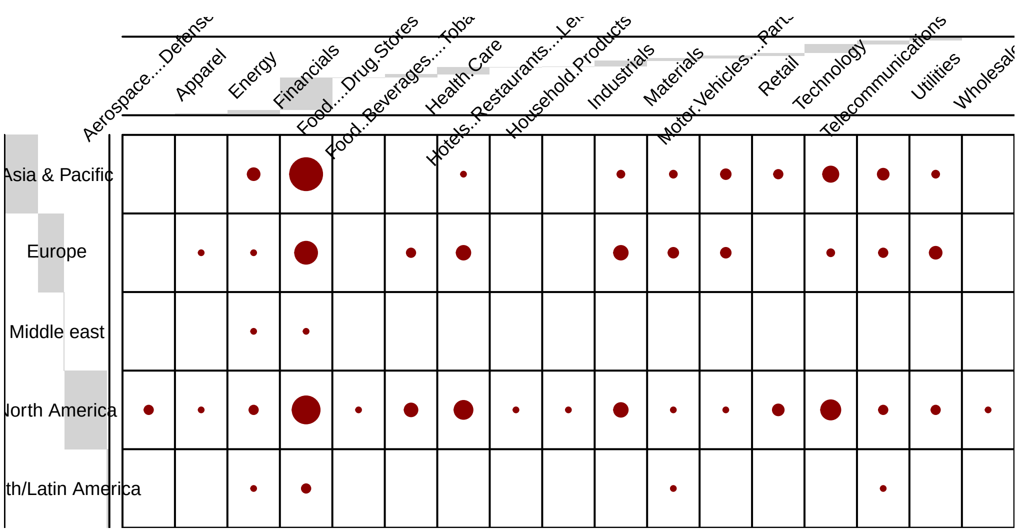
Once again, we can see that the region is not a discriminating factor, however, sector is.

2.7 Correspondence Analysis

To identify potential associations between region and sector in the top 250 companies, we ran a correspondence analysis.

Null Hypothesis (H_0): There is no association between region and sector in the top 250 companies.

```
## **Results of the Correspondence Analysis (CA)**
## The row variable has  5  categories; the column variable has 17 categories
## The chi square of independence between the two variables is equal to 83.6132 (p-value =  0.05047562 )
## *The results are available in the following objects:
##
##    name               description
## 1  "$eig"             "eigenvalues"
## 2  "$col"             "results for the columns"
## 3  "$col$coord"       "coord. for the columns"
## 4  "$col$cos2"        "cos2 for the columns"
## 5  "$col$contrib"     "contributions of the columns"
## 6  "$row"             "results for the rows"
## 7  "$row$coord"       "coord. for the rows"
## 8  "$row$cos2"        "cos2 for the rows"
## 9  "$row$contrib"     "contributions of the rows"
## 10 "$call"            "summary called parameters"
## 11 "$call$marge.col" "weights of the columns"
## 12 "$call$marge.row" "weights of the rows"
```



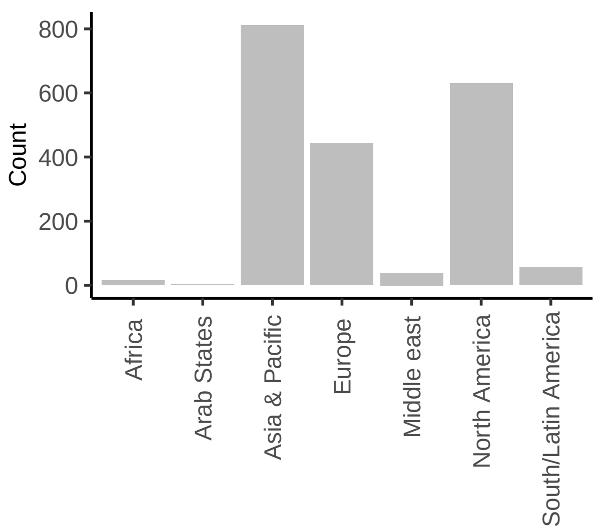
The correspondence analysis results showed that the p-value was <0.1, therefore, this distribution could not have been due to chance and we could safely reject the null hypothesis. There was an association between the region that a company belonged to and the sector in which it operated.

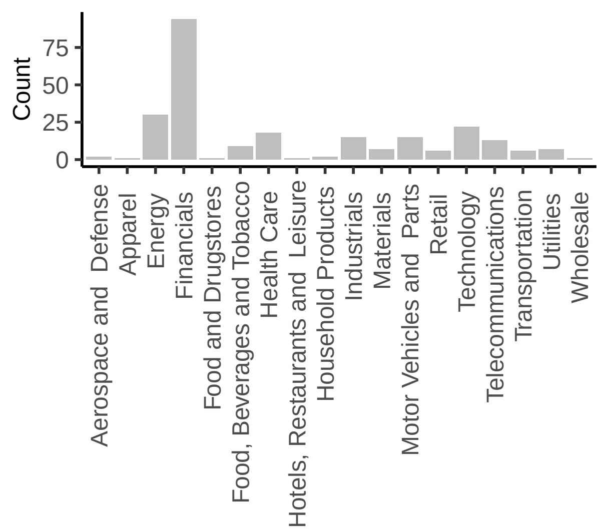
3 Pre-Pandemic vs. Post-Pandemic

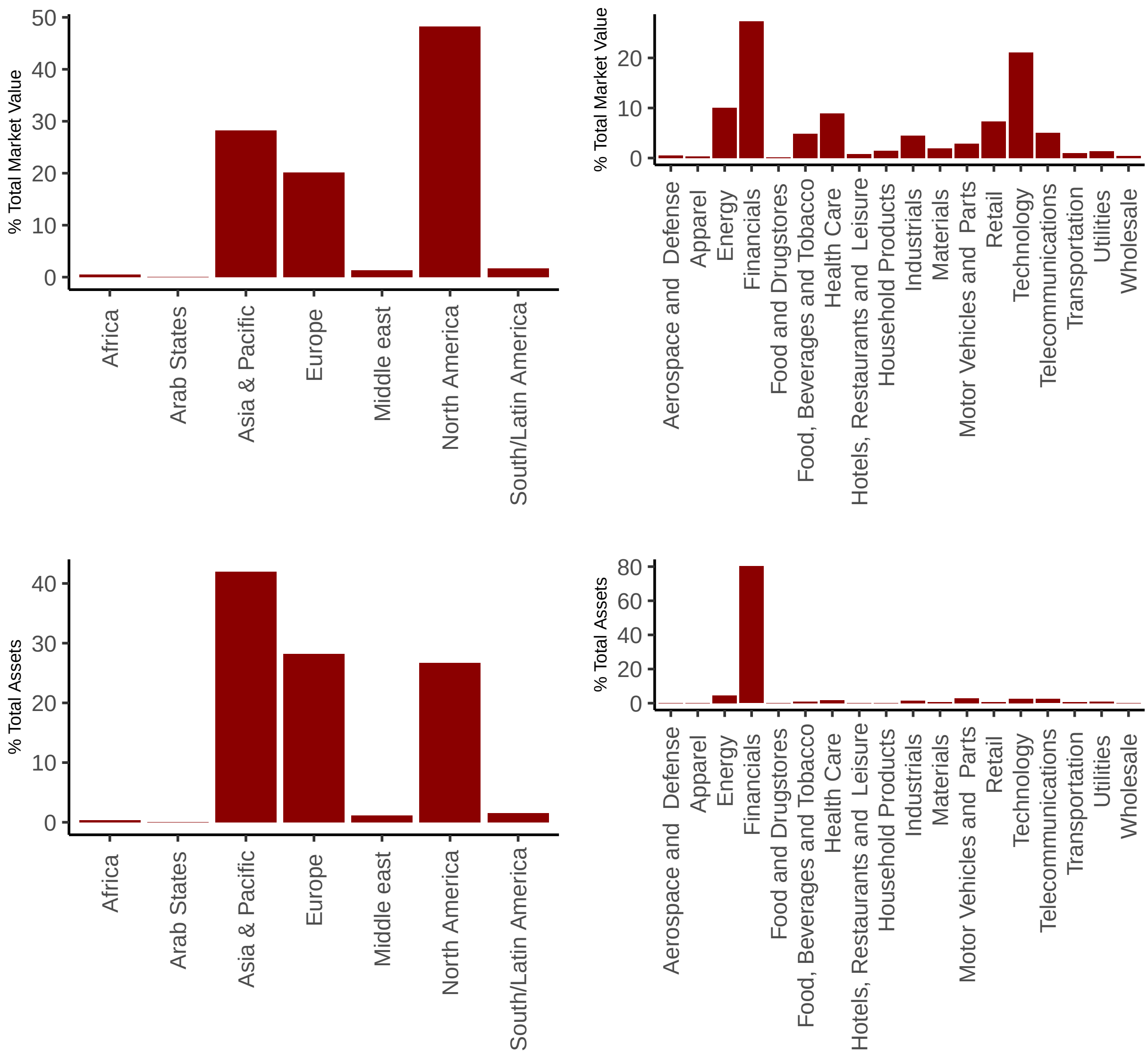
It is no surprise that, given the Covid-19 Pandemic's global reach, many things have changed among the Forbes top 2,000 companies of 2019 and 2021. Industries have adapted and global demand has shifted. Some things that once seemed resolute or permanent have been disbanded. Similarly, some ideas that seemed impractical before are now commonplace necessities. Of course, this forced adaptation can be measured in many ways, but we try to examine how the worlds best businesses have changed.

To do so, we reviewed some of our summary statistics with which we initially analyzed our 2021. While a combination of non-linearity and some multicollinearity among our independent variables made this task difficult at a granular level, some things were apparent with little rumination. Below, we can see the results of the sector analysis of our top 250 companies. Not surprisingly, some institutions left this list and some entered. While the number of companies per region has not changed drastically, the industry sectors represented in the top 250 companies have certainly changed. The number of energy and motor vehicle companies has decreased significantly in 2021 data compared to 2019. Also, substantially more market value is now held by technology companies compared to 2019.

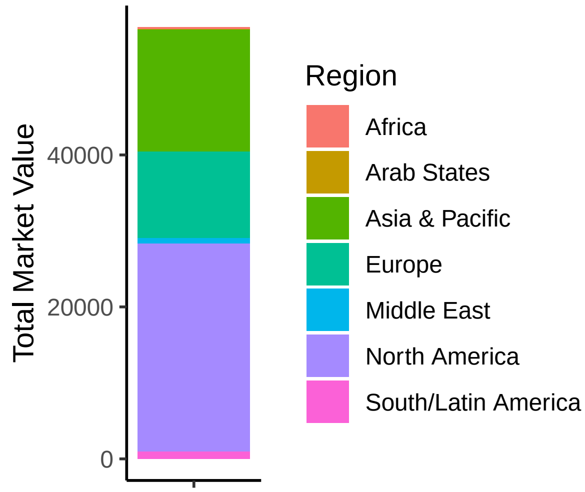
Perhaps most notably, the overall market value of all 2,000 companies that Forbes included in their lists dropped considerably. Between the years of 2019 and 2021, the overall market value of the Forbes Top 2,000 dropped from a resounding $79.710 trillion to mere $56.816 trillion.







% Total Market Value
50
40
30
20
10
0
Africa
Arab States
Asia & Pacific
Europe
Middle east
North America
South/Latin America
% Total Market Value
20
10
0
Aerospace and Defense
Apparel
Energy
Financials
Food and Drugstores
Food, Beverages and Tobacco
Health Care
Hotels, Restaurants and Leisure
Household Products
Industrials
Materials
Motor Vehicles and Parts
Retail
Technology
Telecommunications
Transportation
Utilities
Wholesale
% Total Assets
40
30
20
10
0
Africa
Arab States
Asia & Pacific
Europe
Middle east
North America
South/Latin America
% Total Assets
80
60
40
20
0
Aerospace and Defense
Apparel
Energy
Financials
Food and Drugstores
Food, Beverages and Tobacco
Health Care
Hotels, Restaurants and Leisure
Household Products
Industrials
Materials
Motor Vehicles and Parts
Retail
Technology
Telecommunications
Transportation
Utilities
Wholesale



4 Conclusion

The visual inspection of our data showed that Asia and Pacific, North America, and Europe regions dominated the world economy in terms of the number of companies present in the top 2000 companies of the world. The Finance sector companies dominated the list of top 250 companies, followed by Tech companies in 2021.

Interestingly, even though more than 40% of the assets are held in the Asia and Pacific region, North American companies are more valuable. This is possibly because companies in finance sector hold more assets and are abundantly present in Asia and Pacific region. In contrast to finance sector companies, tech companies hold less assets but have high market values and are abundantly present in North America.

We used a log transformation to normalize our variables. Correlation analysis indicated the existence of two separate groups: financials sector companies and non-financials sector companies. This was not surprising, because the former hold a lot of assets and generally function differently from the latter. Looking at the non-financials sector companies, we found moderate to strong linear relationships among all variables. The strongest correlation belonged to that of profit and market value.

Biplot of our PCA showed no discrimination by region for companies. Again, sector seemed to be a discriminating factor. Our rankings based on PCA did not match Forbes ranking either. Interestingly, airlines ranked really high on the list we created by using original variable PCA data.

We found that the equality of covariances among our variables among different regions and sectors did not hold, so we performed QDA, which classified our financial and non-financial companies correctly about 93% of the time. Our logistic regression results suggested that sales and assets were key metrics that impacted companies in the financials sector, and profit and assets were key metrics that impacted companies in the technology sector. The impact of profit and assets on technology companies was not as significant as that of sales and assets on financial companies. This was not surprising - intuitively, we know that the technology sector does not require the immense assets under management (AUMs) that the financials sector needs to be successful. In fact, anecdotally, we know that much of the technology industry is made up of intangibles and intellectual property rights. Looking at our ratios, we found no significant variable for the companies in the technology sector. Again, we understand that the technology sector is more diverse than the financials - technology is only a description of many companies that may transcend industries and manifest in many different use cases. As a part of our own intuition, we suspected that profit is the most important metric to these asset-less entities, and we were right. After removing all variables but profit, we found a low p-value for profit that, in conjunction with the higher residual deviance (141.25), was a testament to the diversity of the technology sector.

Our FDA results complimented our earlier QDA results. There was much correlation between the reduced sectors. This was not surprising, as top performing companies possess similar qualities, regardless of industry. Once again, we found that companies in the financials sector are more distinct. The distinction of financials sector companies was further confirmed by our hierarchical clustering results.

Our correspondence analysis results suggested that there was an association between the region that a company belonged to and the sector in which it operated. For example, Asia and Pacific region seemed to have more companies in the financials sector.

Comparing pre-pandemic data with post-pandemic data, we found some significant changes in the makeup of Forbes 2000 list. A number of companies in the financials sector departed from the top 250 list of 2019 (e.g., Banco do Brasil). Many of the companies in the financials sector that were not removed from the list were demoted in rank (e.g., Itau Unibanco Holding, Value , Banco Bradesco, and Petrobras were all Brazilian companies in the financials sector that dropped rank by more than 50 points in this time span possibly due to Brazil's poor response to Covid). The industory sector makeup has also changed significantly because of the pandemic. The number of energy and motor vehicle companies in the top 250 companies has decreased significantly in 2021 compared to 2019. Also, substantially more market value is now held by technology companies compared to 2019, which is expected as Covid-19 necessitated the use of technology across all fronts of our lives, from education to shopping. We also found that the overall market value of all 2,000 companies that Forbes included in their lists dropped considerably. Between the years of 2019 and 2021, the overall market value of the Forbes Top 2,000 dropped from a resounding $79.710 trillion to mere $56.816 trillion. This depreciation of nearly $23 trillion quantifies our altered global economy. While the Covid-19 Pandemic has brought rise to many things and offered new solutions for cohabitation, it has also cause unprecedented destruction to global financial economy.

Appendix A

PCA-Based Rankings

PCA was done using normalized variables and companies were ranked based on their PCA scores. Table below shows the first 20 companies on the list.

	Company	rank
1	RMB Holdings	3.79516169818486
2	Bank of Greece	3.46102186197555
3	Fareast Islami Life Insurance Company	3.4025702979712
4	ExxonMobil	3.37155667334845
5	Royal Dutch Shell	3.14701629703405
6	First Heartland Jusan Bank	3.08034734326256
7	PSG Group	3.01638952408808
8	Iluka Resources	2.73062978691541
9	Kuaishou Technology	2.67378225270095
10	Ruchi Soya Industries	2.61871645120013
11	Sparebanken Nord-Norge	2.39863618366968
12	Heimstaden AB Pref. Shs	2.38218936599674
13	Cannae Holdings	2.37174078772631
14	Brilliance China Automotive Holdings	2.22687119281044
15	Bank of Nagoya	2.19122813780401
16	Hyakujushi Bank	2.17389296878834
17	Musashino Bank	2.1723024821217
18	Carnival	2.16531941537478
19	Keiyo Bank	2.133012933986
20	Senshu Ikeda Holdings	2.09711510978408

Showing 1 to 20 of 2,000 entries

PCA was done using original variables and companies were ranked based on their PCA scores. Table below shows the first 20 companies on the list.

	Company	rank
1	Kuaishou Technology	2.26208225145875
2	Occidental Petroleum	2.23953661228648
3	Delta Air Lines	2.08264519060508
4	Carnival	2.05733676012854
5	Baker Hughes Company	1.66280824241221
6	Unibail-Rodamco	1.64176129558352
7	Air France-KLM	1.60380686308198
8	Schlumberger	1.59433245307567
9	International Airlines	1.57600763185937
10	American Airlines Group	1.55946981370764
11	Vodafone Idea	1.50803573012676
12	Deutsche Lufthansa	1.47186381268282
13	Royal Caribbean Group	1.3656421995549
14	United Airlines Holdings	1.32562306688034
15	Bayer	1.2039547357864
16	Sasol	1.17777577483044
17	Woodside Petroleum	1.16020734740667
18	Link REIT	1.10065876248154
19	Renault	1.0352431958554
20	All Nippon Airways	1.021192086852

Showing 1 to 20 of 2,000 entries