Stock Valuation Multiple & Drivers

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Abstract

Today, trillions dollars of assets are managed by investment managers in the U.S., with a majority utilizing traditional fundamental analysis. This study identifies valuation metrics (we will refer to this as “metric”) for different market sectors to assist equity analysts in valuing stocks within their industry. Statistical analysis were performed to discover the best valuation metric for each industry. We have also built statistic models to help predict the real/reasonable multiple of a company based on financial ratios (we will refer to this as “drivers”). A second test was conducted to verify the significance of these financial ratios in stock valuation. This information provides amateur investors a guide for applying multiples valuation techniques.

Introduction

Two most common approaches to calculate the fair value of a company are the Discounted Cash Flow (DCF) approach and the valuation multiples approach. While DCF is more complicated and thus might be more accurate, it is much less interpretable comparing to the valuation multiples approach. Moreover, the valuation multiples approach allows investors to directly compare the "cheapness" of two companies of the same industry. Generally, a lower Price-to-X, where X can be any financial value (e.g. Book Value Per Share, Revenue, etc.), indicates a cheaper stock and thus a stronger buy-signal. This approach consists of the following steps:

1. Identifying the best metric to be used for the stock based on its sector (Price-to-Earnings, Price-to-Sales, etc)
2. Using information from its financial statement, also known as drivers (Earnings Growth, Return on Assets, etc) to predict its reasonable multiple value.
3. Project a stock price with the reasonable multiple value

In this study, we will use statistical analysis to identify the most significant metric and the corresponding drivers for each industry to improve the interpretability of the valuation process and to predict a reasonable stock price.

Methodology

This project applies the valuation approach above to identify the best multiple for each sector and build models to predict reasonable multiples for each sector with a data mining approach. We used stock data spanning from 2011 to 2016. The analysis consists of:

1. For each market sector, we pick the best multiple out of the following with best subset selection:

   P/E, P/B, P/E, EV/EBIT, EV/EBITDA, EV/S, EV/FCF[1]

2. For each market sector, given its best multiple, we build linear models to predict the values of the metric using lasso regression.
3. For each market sector, we identify the important drivers (financial ratio) of the sector's metric using random forests.

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[1] P/E = Price-to-Earnings ratio; P/B = Price-to-Book-Value ratio; P/S = Price-to-Sales ratio; EV/EBIT = Enterprise-Value-to-EBIT ratio; EV/EBITDA = Enterprise-Value-to-EBITDA ratio; EV/S = Enterprise-Value-to-Sales ratio; EV/FCF = Enterprise-Value-to-Free-Cash-Flow ratio

Data Preparation

Data preparation was very tedious in this project. We used the dataset “Core US Fundamentals Data” from Quandl. This dataset provides 6 years of history for 123 fundamental indicators and financial ratios for 10,000~ US public companies. The 123 indicators fall under the categories of income statement, cash flow statement, balance sheet, metric & ratios etc.

Unfortunately, many of these “indicators” (or “predictors” in our case) have duplicated meanings. For example, both of the indicators “revenue” and “revenueusd” refer to the revenue of the stock, but in different currencies for foreign companies listed in the New York Exchange. Thus, many of them are highly correlated with each other. Collinearity will decrease the accuracy for our final linear model. Therefore, we used excel to create a covariance matrix of all predictors and for each highly correlated pair, we deleted one of the predictor. Luckily, it turned out that all correlated pairs of predictors have similar meaning, just like the case of “revenue” and “revenueusd”. Thus, we didn’t have to remove any meaningful predictor.

Next, we built a train dataset and a test dataset for each industry. We have 8 industries: Basic Materials, Consumer Goods, Financials, Healthcare Industrials, Services, Technology and Utilities. For each industry, we sample ¼ of the stocks in the industry to be the test dataset. Then, we began building datasets for step 1 and step 2 of our analysis. For each industry, we built 2 training datasets (one for step 1 and one for step 2) and 2 testing datasets (one for step 1 and one for step 2).

The step 1 datasets consist of the following columns:

Price, P/E, P/B, P/E, EV/EBIT, EV/EBITDA, EV/S, EV/FCF

where Price is the response variable and the metrics are the predictors. Recall that in step 1, we want to pick a metric that is the best for predicting stock price. More details about step 1 will be discussed later. P/E, P/B and P/E are included in the original dataset. We calculated EV/EBIT, EV/EBITDA, EV/S, EV/FCF by dividing Enterprise Value by EBIT, EBITDA, Revenue and Free Cash Flow, respectively, to obtain the other four metrics.

The step 2 datasets consist of the following columns:

Asset Turnover, Debt/Equity, Dividend Yield, EBITDA Margin, Gross Margin, Net Margin, Payout Ratio, ROA, ROE, ROIC, ROS, Sales Growth, EPS Growth
plus the response variable, which is the metric we selected from step 1.

Note that the response variable for each industry in step 2 are different. It depends on the result from step 1.

The dataset built for step 2 is also used in step 3.

Lastly, for each predictor that we have to use (listed above), we deleted the rows with missing data. Moreover, since the original dataset does not provide sales growth and EPS growth, we calculated them using excel. For the first year (2011), we don't have the revenue and EPS data from 2010, so we used the average of the stock's EPS growth and sales growth for its observation in 2011.

Step 1: Identifying the Best Metric for each Sector with Best Subset Selection

One may wonder why we decided to pick one metric for each sector instead of building a valuation model that regresses all metrics. This is because valuation metrics serve a purpose other than calculating a reasonable price to buy a stock. Metrics are more often used to directly compare the cheapness/value of two stocks in the same industry. Therefore, we would like to find the most suitable valuation metric for each sector in a data mining approach.

Once the data was cleaned, we began step 1 of our analysis. We first applied best subset selection to find the most suitable metric for each sector. The response variables are the stock prices; the predictors are the 7 metrics presented in the introduction. Then, we built a one-variable linear regression model for each sector, where the variable is the selected metric, to obtain the p-value i.e. accuracy of the model. These linear regression models would be used to calculate the reasonable stock price in step 3 of the analysis.

The results are summarized in the table below. Screenshots of summary of each regression from R are attached in page 14.

Industry	Best Valuation Metric	β_0	β_1	p-value	Adjusted R^2
Basic Material	EV/EBIT	115.7406	0.0679	0.6639	- 0.001278
Consumer Goods	P/S	15.8512	14.6011	<2.2e-16	0.5212
Financials	P/B	31.5406	2.1454	1.66e_07	0.52302
Healthcare	EV/EBIT	2.174e2	8.493e-3	0.9457	-0.001273

Industrials	P/B	27.93716	0.06448	0.02426	0.6882
Services	EV/EBIT	2184e3	2696	0.5676	-0.005333
Technology	EV/S	16.7924	3.9707	<2.2e-16	0.7533
Utilities	EV/EBIT	34.9663	-0.0703	0.236	0.00216

The models for Basic Materials, Services, Utilities and Healthcare have high p-values, indicating that there is little to no relationship between stock prices and the proposed metric. In fact, none of the 7 metrics have strong relationship with stock prices of companies in these industries. We believe there are better ways to value stocks in these industries, but we will continue our analysis without these industries because we conclude that the metric approach is not suitable for Basic Materials, Services, Utilities and Healthcare.

As mentioned above, we split ¼ of the data set as the test data. Applying the one-variable linear regression models on the test datasets of Consumer Goods, Financials, Technology and Utilities, respectively, <u>the resulted test Mean Squared Errors are $28.23, $17.53, $10.28, $7.82</u>.

Step 2: Building a Linear Model to Project Reasonable Valuation Metric Values for each Sector from Financial Ratios of Companies

After selecting a suitable valuation metric for each sector, we built lasso regression models to predict a valuation metric that reflects the intrinsic value of a stock. <u>Thus, the response variables in step 2 are the metrics selected in step 1, while the predictors are the following set of financial ratios:</u>

1. Asset turnover
2. Dividend yield
3. EBITA Margin
4. Gross Margin
5. Net Income Margin
6. Payout ratio
7. Return on Asset
8. Return on Earning

9. Return on Invested Capital
10. Return on Sales
11. Earnings per Share Growth
12. Sales Growth
13. Debt to Equity ratio

Note that we are predicting the metric here. When we predict a stock price i.e. finding the true value of the stock, we do not use the metric given by the original dataset from Quandl because it only reflects current information rather than the intrinsic value of a stock (e.g. Price to Book Value is simply calculated by dividing the current stock price by its current asset value, but the stock price is the ultimate quantity we are trying to predict).

Lasso regression was used because not only that we want to avoid overfitting, but also that we would like to identify important drivers to each metric. As such, we would use Random Forests later in our analysis to identify important drivers and compare the results. While building our lasso regression models, we used Cross Validation to tune the parameter λ for each model i.e. each sector.

For consistency, the data that we use for step 2 are corresponding to those for step 1. The splitting proportion of the training and testing data sets are also equivalent. Since we have to scale the data in the pre-processing phrase for lasso regression, in order to predict the value accurately using the beta coefficients that we obtained, we have to unscaled the data after performing lasso regression.

The results are summarized in the table below. Screenshots of plots on lasso regression from R are attached in page 13.

	Consumer goods	Financial	Industrial goods	Technology
Intercept	6.60220e-18	-3.72671e-17	-4.868433e-17	4.148546e-17
Asset turnover	-1.050787e-01	4.186060e-01	0	-1.911773e-01
Debt/Equity	0	6.814763e-04	9.285767e-01	0
Dividend yield	0	0	-2.315864e-03	-5.155058e-02
EBITDA margin	1.900462e-01	9.292609e-04	0	3.533316e-01
Gross margin	4.799017e-01	4.657095e-02	1.207317e-02	2.988093e-01
Net margin	0	0	0	-6.553070e-01
Payout ratio	0	0	0	7.151913e-03
ROA	0	3.984200e-01	1.607174e-02	8.528043e-02

ROE	0	1.317299e-02	-3.917249e-02	-9.375288e-03
ROIC	5.941937e-02	-9.395115e-03	0	0
ROS	0	0	0	0
Sales growth	0	0	0	1.072097e-01
EPS growth	0	0	0	0

Note that the intercept terms in the table above are all extremely close to 0. This is because normalization been done to all predictors prior to running Lasso Regressions.

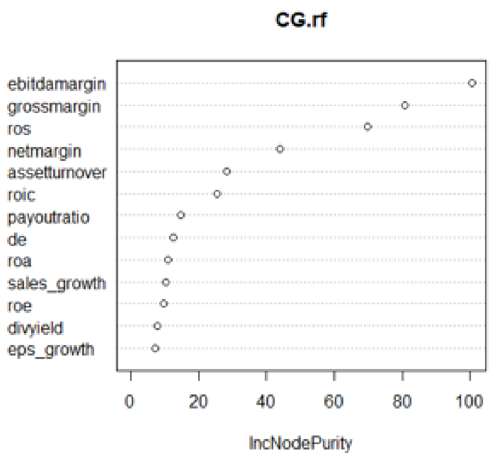
After performing Lasso regression on the 13 predictors, we are hoping to opt out the insignificant predictors in order to enhance the prediction accuracy and interpretability of this statistical model. From the table above, we can interpret that the predictors with a beta of 0 are insignificant and thus omitted from the model. Note that the coefficients have the similar values due to the normalization of the data sets in the pre-processing phrase. Normalization is necessary for Lasso Regression because Lasso Regression penalize for overfitting caused by using excessive predictors. The non-zero coefficients indicate that the corresponding predictors will be used. For instance, in the consumer goods industry, Asset turnover, EBITDA margin, Gross margin and ROIC will be used in the model. Notice that for the technology industry, the majority of the predictors have non-negative beta. However, only Asset turnover, EBITDA margin, Gross margin, Net margin, and Sales growth are significant in this model since the absolute values of their coefficients are over 0.01 and larger than that of other drivers.

With the optimal tuning parameter, we can calculate the mean squared prediction error on the test set on the predicted values. As mentioned previously, we split ¼ from the data as the test set to verify our model. Using the predict function in R and the actual values from the test set, we calculated the mean squared test error to be 0.4611606, 0.547454, 0.1840327, and 0.5361655, corresponding to the Consumer goods, Financial, Industrial goods and technology industry. These MSE are totally acceptable, as valuation metrics typically range from -5 to 5.

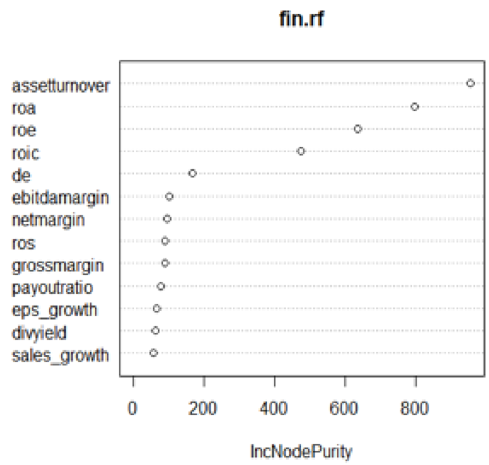
Step 3: Identifying the important drivers (financial ratio) of the sector's valuation metric using random forests

Random forest models are not as easily interpretable as linear regression models. However, the plots below provide insights into which drivers (predictors) were most important for predicting the intrinsic value of the metric for each industry (Consumer Goods, Industrials, Technology, Financials).

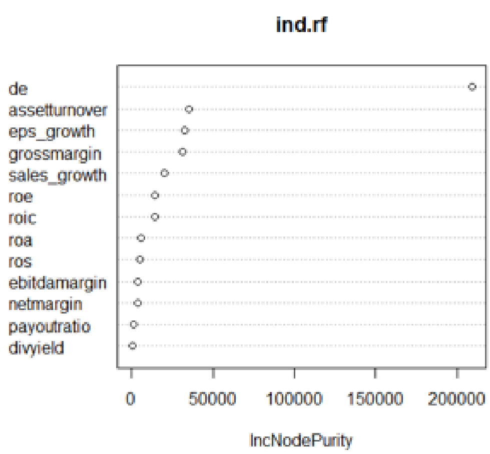
Consumer Goods



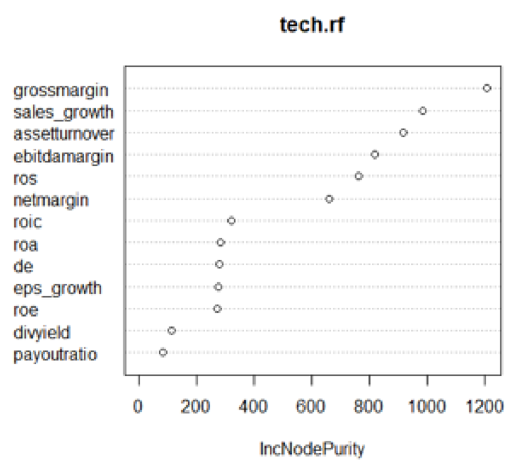
Financials



Industrials



Technology



From the plots, we can summarize that the significant drivers for the valuation metric of each industry are:

Industry	Metric	Significant Drivers (The order of importance is left to right)			
Consumer Goods	P/S	EBITDA Margin	Gross Margin	Return on Sales	Net Margin

Financials	P/B	Asset Turnover	Return on Asset	Return on Earnings	Return on Invested Capital
Industrials	P/B	Debt/Equity Ratio			
Technology	EV/S	Gross Margin	Sales Growth	Asset Turnover	EBITDA Margin

The plots above show how much the node purity increases when a given predictor is present in the tree. Node purity is measured by the Gini Index, which captures how similar the observations that fall under the same branch are.
These results are consistent with what we found in step 2. Therefore, we are confident to use the lasso regression models in step 2 to predict the metric for each industry. Theses

These results are consistent with what we found in step 2. Therefore, we are confident to use the lasso regression models in step 2 to predict the valuation metrics for each stock in the test data sets of each industry. Investors should also pay attention to these statistically significant drivers when analyzing companies that fall under the industries above.

Conclusion

Our findings are somewhat different from the usual approach of equity research analysts in the investment industry. For example, analysts usually use P/E or P/S to value stocks in the Industrials sector. However, our analysis found that stock prices of Industrials companies are statistically significant related to its P/B ratio, rather than P/E or P/S.

Let's say you are deciding whether you should buy/sell the stock of a financials company. How should you utilize our results to help make your decision? First, based on our findings in step 1, you should use P/B to value your stock. This aligns with the insights of equity research analysts in the investment industry.[2] Then, you can compare the stock you are considering with other stocks that fall under the Financials sector to see if your stock is relatively "cheaper". A small P/B indicates that the value of the stock (valued by its Book Value Per Share) has not yet been revealed in its stock price, showing that it's a buy.

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[2] Schreiner, Andreas. Equity valuation using multiples: an empirical investigation. Springer Science & Business Media, 2009.

Comparing P/B between companies with similar business might help you find another (or better) investment opportunity. Next, you can use our lasso regression model to find the "reasonable P/B" of the stock you are considering, using the information of its financial statements we calculate:

Reasonable P/B =
(4.186060e-01)(Asset Turnover) + (6.814763e-04)(D/E) + (9.292609e-04)(EBIT Margin) + (4.657095e-02)(Gross Margin) + (3.984200e-01)(ROA) + (1.317299e-02)(ROE) + (-9.395115e-03)(ROIC).

Then,

Fair stock price =
$\boldsymbol{\beta_0}$ of the one-variable linear regression model for financials in step 1
+
Reasonable P/B * BVPS[3]

If the fair stock price is higher than the current stock price, you can consider buying the stock. Otherwise, you can consider shorting the stock. You should obviously consider other factors while using our model, such as the case presented in the paragraph right below.

The random forest model could also be used for evaluating an investment opportunity. It could be used when you are deciding whether you should buy/sell the same stock of a financials company. From our random forest model, ROA and Asset Turnover are the two most important drivers for P/B of financial stocks. This again aligns with the insights of equity research analysts in the investment industry.[4] If the stock's P/B looks attractive comparing to other stocks in the same industry, you might consider buying the stock. However, if it's Return on Asset and Asset Turnover have been decreasing for years, the company might be experiencing a downturn. As such, you might want to reconsider your buy decision.

We have stopped our analysis for Basic Materials, Healthcare, Services, Utilities after step 1 because we found that even the best valuation were not statistically useful for predicting the stock price. This might due to scarcity of data for these industries or that the valuation multiple approach is not suitable for evaluating stocks in these industries.

On the other hand, our results for Consumer Goods, Industrials, Technology and Financials aligned with our hypothesis. P-values for these industries in step 1 were very small.

[3] BVPS = Book Value Per Share
[4] Schreiner, Andreas. Equity valuation using multiples: an empirical investigation. Springer Science & Business Media, 2009.

MSE of our Lasso Regression models in step 2 were small relative to the typical range of valuation metrics of stocks in the New York Exchange (e.g. P/B € [-5.5]). The important drivers of each industry found with random forests models in step 3 mostly align with insights of equity research analysts in the investment industry.[3] Therefore, we concluded that models built in this study is useful for investors to evaluate their investment opportunities.

Bibliography

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Liu, Jing, Doron Nissim, and Jacob Thomas. "Equity valuation using multiples." Journal of Accounting Research 40.1 (2002): 135-172.

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Schreiner, Andreas. Equity valuation using multiples: an empirical investigation. Springer Science & Business Media, 2009.

Step1: Best subset selection R printout

Basic material:

```
Subset selection object
Call: regsubsets.formula(price ~ ., BMdata, nvmax = 1)
7 Variables  (and intercept)
        Forced in Forced out
pb          FALSE      FALSE
pe          FALSE      FALSE
ps          FALSE      FALSE
evebit      FALSE      FALSE
evebita     FALSE      FALSE
evs         FALSE      FALSE
evfcf       FALSE      FALSE
1 subsets of each size up to 1
Selection Algorithm: exhaustive
         pb  pe  ps  evebit evebita evs evfcf
1  ( 1 ) " " " " " " "*"    " "     " " " "
```

Consumer goods:

```
Subset selection object
Call: regsubsets.formula(price ~ ., CGdata, nvmax = 1)
7 Variables  (and intercept)
        Forced in Forced out
pb          FALSE      FALSE
pe          FALSE      FALSE
ps          FALSE      FALSE
evebit      FALSE      FALSE
evebita     FALSE      FALSE
evs         FALSE      FALSE
evfcf       FALSE      FALSE
1 subsets of each size up to 1
Selection Algorithm: exhaustive
         pb  pe  ps  evebit evebita evs evfcf
1  ( 1 ) " " " " "*" " "    " "     " " " "
```

Financials:

```
Subset selection object
Call: regsubsets.formula(price ~ ., findata, nvmax = 1)
7 Variables  (and intercept)
        Forced in Forced out
pb          FALSE      FALSE
pe          FALSE      FALSE
ps          FALSE      FALSE
evebit      FALSE      FALSE
evebita     FALSE      FALSE
evs         FALSE      FALSE
evfcf       FALSE      FALSE
1 subsets of each size up to 1
Selection Algorithm: exhaustive
         pb  pe  ps  evebit evebita evs evfcf
1  ( 1 ) "*" " " " " " "    " "     " " " "
```

Healthcare:

```
Subset selection object
Call: regsubsets.formula(price ~ ., HCdata, nvmax = 1)
7 Variables  (and intercept)
        Forced in Forced out
pb          FALSE      FALSE
pe          FALSE      FALSE
ps          FALSE      FALSE
evebit      FALSE      FALSE
evebita     FALSE      FALSE
evs         FALSE      FALSE
evfcf       FALSE      FALSE
1 subsets of each size up to 1
Selection Algorithm: exhaustive
         pb  pe  ps  evebit evebita evs evfcf
1  ( 1 ) " " " " " " " "    "*"     " " " "
```

Industrials:

```
Subset selection object
Call: regsubsets.formula(price ~ ., inddata, nvmax = 1)
7 Variables  (and intercept)
        Forced in Forced out
pb          FALSE      FALSE
pe          FALSE      FALSE
ps          FALSE      FALSE
evebit      FALSE      FALSE
evebita     FALSE      FALSE
evs         FALSE      FALSE
evfcf       FALSE      FALSE
1 subsets of each size up to 1
Selection Algorithm: exhaustive
         pb  pe  ps  evebit evebita evs evfcf
1  ( 1 ) "*" " " " " " "    " "     " " " "
```

Services:

```
Subset selection object
Call: regsubsets.formula(price ~ ., serdata, nvmax = 1)
7 Variables  (and intercept)
        Forced in Forced out
pb          FALSE      FALSE
pe          FALSE      FALSE
ps          FALSE      FALSE
evebit      FALSE      FALSE
evebita     FALSE      FALSE
evs         FALSE      FALSE
evfcf       FALSE      FALSE
1 subsets of each size up to 1
Selection Algorithm: exhaustive
         pb  pe  ps  evebit evebita evs evfcf
1  ( 1 ) " " " " " " "*"    " "     " " " "
```

Technology:

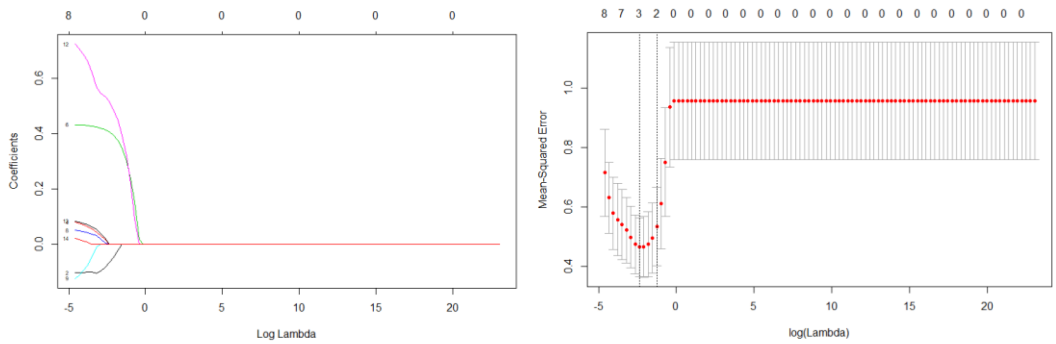
```
Subset selection object
Call: regsubsets.formula(price ~ ., techdata, nvmax = 1)
7 Variables  (and intercept)
        Forced in Forced out
pb          FALSE      FALSE
pe          FALSE      FALSE
ps          FALSE      FALSE
evebit      FALSE      FALSE
evebita     FALSE      FALSE
evs         FALSE      FALSE
evfcf       FALSE      FALSE
1 subsets of each size up to 1
Selection Algorithm: exhaustive
         pb  pe  ps  evebit evebita evs evfcf
1  ( 1 ) " " " " " " " "    " "     "*" " "
```

Utility:

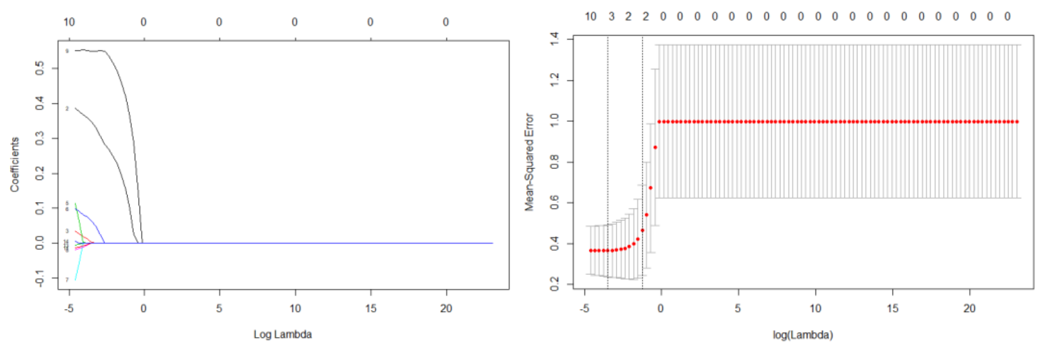
```
Subset selection object
Call: regsubsets.formula(price ~ ., utildata, nvmax = 1)
7 Variables  (and intercept)
        Forced in Forced out
pb          FALSE      FALSE
pe          FALSE      FALSE
ps          FALSE      FALSE
evebit      FALSE      FALSE
evebita     FALSE      FALSE
evs         FALSE      FALSE
evfcf       FALSE      FALSE
1 subsets of each size up to 1
Selection Algorithm: exhaustive
         pb  pe  ps  evebit evebita evs evfcf
1  ( 1 ) " " " " " " " "    "*"     " " " "
```

Step 2: Lasso regression R printout

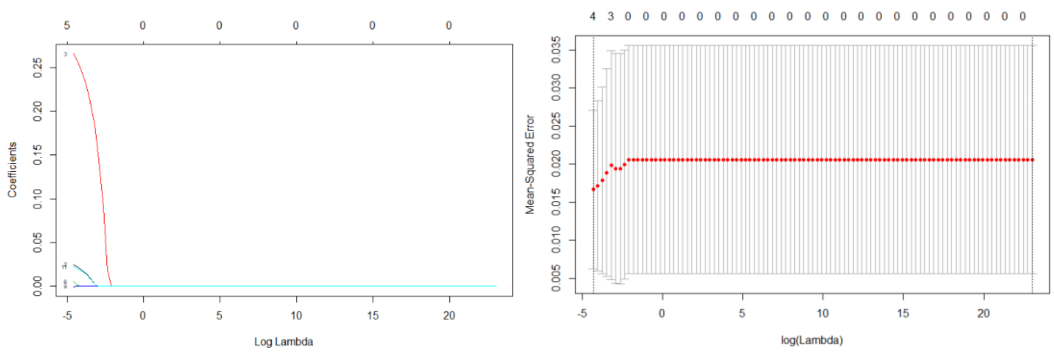
Consumer goods industry lambda: 0.09326033



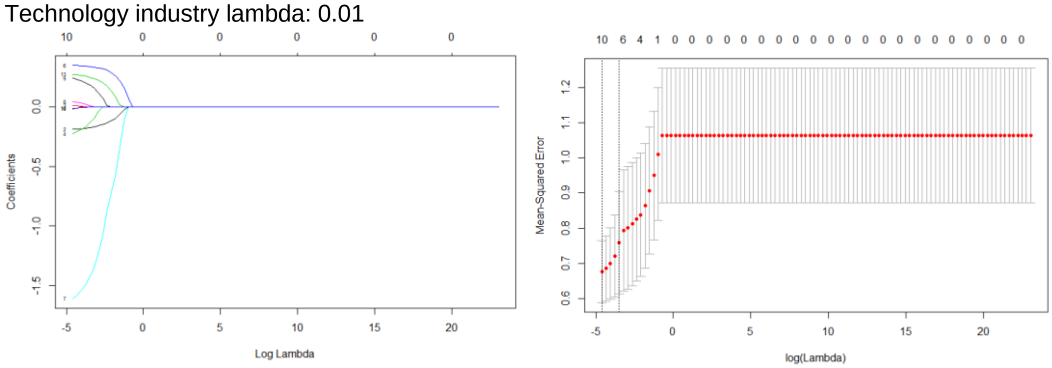
Financial industry lambda: 0.03053856



Industrial industry lambda: 0.01321941



Technology industry lambda: 0.01



ORIE 4740 Final Project

Step 1: Linear regression summaries

Basic material:

```
Call:
lm(formula = price ~ evebit, data = Healthcare)

Residuals:
   Min     1Q Median     3Q    Max
  -231   -212   -202   -177 109991

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.170e+02  1.440e+02   1.507    0.132
evebit      6.254e-03  2.609e-01   0.024    0.981

Residual standard error: 4031 on 782 degrees of freedom
Multiple R-squared:  7.348e-07, Adjusted R-squared:  -0.001278
F-statistic: 0.0005746 on 1 and 782 DF,  p-value: 0.9809
```

Consumer goods:

```
Call:
lm(formula = price ~ ps, data = Consumer_Goods)

Residuals:
    Min      1Q  Median      3Q     Max
-66.322 -16.102  -6.305  11.758 155.927

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)    15.85       1.74   9.109   <2e-16 ***
ps             14.60       1.14  12.812   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 26.34 on 483 degrees of freedom
Multiple R-squared:  0.2537,	Adjusted R-squared:  0.5212
F-statistic: 164.2 on 1 and 483 DF,  p-value: < 2.2e-16
```

Financials:

```
Call:
lm(formula = price ~ pb, data = Financials)

Residuals:
   Min     1Q Median     3Q    Max
-33.12 -20.27 -11.09   5.41 391.89

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  31.5406     1.4236  22.156  < 2e-16 ***
pb            2.1454     0.4021   5.335 1.17e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 41.98 on 1060 degrees of freedom
Multiple R-squared:  0.02615,	Adjusted R-squared:  0.52302
F-statistic: 28.47 on 1 and 1060 DF,  p-value: 1.166e-07
```

Healthcare:

```
Call:
lm(formula = price ~ evebita, data = Healthcare)

Residuals:
   Min     1Q Median     3Q    Max
  -218   -213   -203   -177 109991

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.174e+02  1.442e+02   1.508    0.132
evebita     8.493e-03  1.247e-01   0.068    0.946

Residual standard error: 4031 on 782 degrees of freedom
Multiple R-squared:  5.928e-06, Adjusted R-squared:  -0.001273
F-statistic: 0.004636 on 1 and 782 DF,  p-value: 0.9457
```

Industrials:

```
Call:
lm(formula = price ~ pb, data = Industrials)

Residuals:
    Min      1Q  Median      3Q     Max
-28.002 -18.900  -8.515  11.546 120.160

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 27.93716    1.08015  25.864   <2e-16 ***
pb           0.06448    0.02855   2.259   0.0243 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 26.26 on 591 degrees of freedom
Multiple R-squared:  0.008559,	Adjusted R-squared:  0.6882
F-statistic: 5.102 on 1 and 591 DF,  p-value: 0.02426
```

Services:

```
Call:
lm(formula = price ~ evebit, data = Services)

Residuals:
      Min        1Q    Median        3Q       Max
-19266777  -2228995  -2215376  -2202018 1379548202

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2184053    1270525   1.719   0.0859 .
evebit          2696       4715   0.572   0.5676
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 45120000 on 1262 degrees of freedom
Multiple R-squared:  0.0002589, Adjusted R-squared:  -0.0005333
F-statistic: 0.3269 on 1 and 1262 DF,  p-value: 0.5676
```

Technology:

```
Call:
lm(formula = price ~ evs, data = technology)

Residuals:
     Min       1Q   Median       3Q      Max
-144.100  -15.606   -8.794    6.925  243.748

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  16.7764     1.1385   14.73   <2e-16 ***
evs           3.9729     0.2772   14.33   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 28.95 on 1128 degrees of freedom
  (18 observations deleted due to missingness)
Multiple R-squared:  0.1541,	Adjusted R-squared:  0.7533
F-statistic: 205.5 on 1 and 1128 DF,  p-value: < 2.2e-16
```

Utilities:

```
Call:
lm(formula = price ~ evebita, data = Utilities)

Residuals:
    Min      1Q  Median      3Q     Max
-36.401 -15.536  -3.375  15.422  64.291

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 34.96627    1.73345  20.172   <2e-16 ***
evebita     -0.07030    0.05913  -1.189    0.236
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 21.58 on 190 degrees of freedom
Multiple R-squared:  0.007385,	Adjusted R-squared:  0.00216
F-statistic: 1.414 on 1 and 190 DF,  p-value: 0.236
```