WHAT FINANCIAL CHARACTERISTICS DO COMPANIES EXHIBIT WHEN GOING BANKRUPT?

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Question/The Data/Preprocessing

The Question

I chose my question “What financial characteristics do failing companies exhibit?” to describe information that will help inform external users of what key metrics change as the company is going bankrupt. Data visualization was an essential part of answering this question because raw financial information is difficult to understand, but thanks to Python we can transform this information into an illustration explaining what is going on over time with a company or with failed companies in particular.

The key metrics to answering our question are profit margin and debt-to-equity. *Profit margin* is a metric that describes how much profit was generated by each sale and will help us answer the question of “How does profit change if a company is failing?”. *Debt-to-equity* is a measure of how a company finances through debt compared to stock financing and helps us answer the question “How does a falling company's balance sheet change?”. These two questions are connected through an account on the balance sheet known as *retained* earnings representing the profit that a company carries over to reinvest into a company or to distribute to shareholders. Specifically, the net income at the end of an income statement is transferred to the retained earnings account, and net income is a value that is used to find the profit margin – Profit margin = Net Income/Total Sales.

The Data

The data we are using is a data set pulled from Kaggle. The data set includes a set of 8,262 companies that were listed on the NYSE and the NASDAQ along with their financials. Both "failed”, and "alive" companies are in the data; failed means that they have filed for bankruptcy, and alive means that from 1999 - 2018 they did not file for bankruptcy. When a company goes bankrupt, it does not mean that it shuts down entirely - although it could mean that, rather, it means that the company cannot pay its obligations and as such will either restructure to pay off its debts ("Chapter 11") or sell off its asset ("Chapter 7")

The data includes 21 characteristics. The first three are the company number, the year of operations, and lastly the company status (Bankrupt or alive). The other 18 include financial data, like total revenue, expenses, total assets, total liabilities, etc.

Limitations

The data does not include the name, the sector, if the company recovered, or what year they went bankrupt, and it does not specify the measurement of the currency in the data. This limits how much categorization I can do with the data: for example, if I want to research if tech companies are more susceptible to bankruptcy than financial companies. The lack of information on recovery is especially limiting since we won’t know if it was Chapter 7 or Chapter 11 bankruptcy. Lastly, I am assuming that the data is in U.S. dollars because it's on the NYSE and NASDAQ and that it is being measured in millions of dollars because most companies report their financials in millions of dollars.

Secondly, there are limits on external events. The data provides insight into what is going on financially, and inferences can be made on some things, however, we are left in the dark about factors like the economy, the health of the company’s sector, reputation, bad publicity, and other non-financial data. This limit is the reason our scope is on financials and describing what is going on rather than addressing what caused financials to be like this.

Lastly, the size of the data for failing companies is concerning as well. I realized that two approaches can be taken, a micro and a macro point of view. The micro point of view provides a more in-depth investigation into what goes on with a company that is failing and the macro with characteristics that bankrupt companies exhibit as a category. The problem is bankrupt companies make up only 3000 of the 78000 companies and as a result, we have much more information and variety than non-bankrupt companies.

Pre-processing

My dataset includes a total of 78,000 entries. With this large amount, there were a couple of preprocessing steps I took. All code is provided within this document.

1. Column Names

Initially, my column names were just numbers, and the data set included a legend. For convenience, I renamed the columns to their appropriate financial account names.

2. Nulls

Luckily my dataset did not have any null values.

3. Data Types

My dataset was formatted correctly for all the data types.

4. Adjusting measurement for dollars

For convenience, I adjusted the measurement for dollars from millions of dollars to thousands of dollars. For example, 1,000,000.000 is 1 billion dollars.

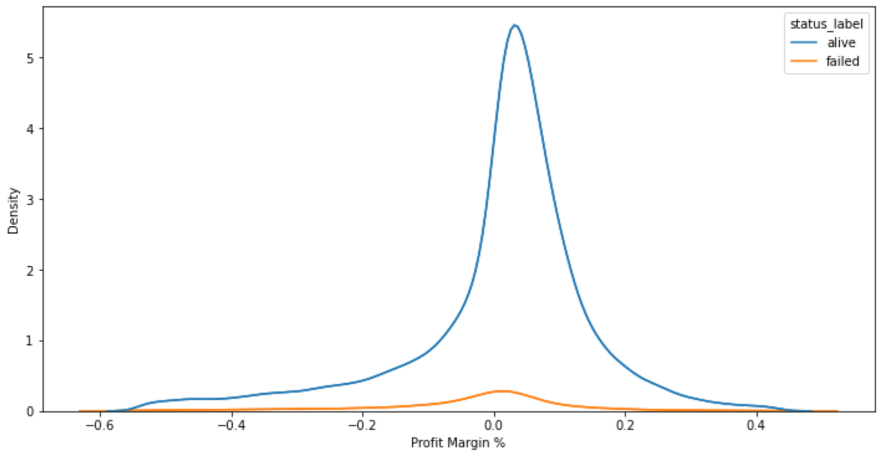
5. Outliers

Some major outliers with my dataset offset the means. To deal with this, I created a removeOutliers function that removes the outliers and keeps only those values within the 1st and 3rd quartile, but I did this based on certain columns because there are some financial ratios I want to use, and I only want to remove outliers for those specific ratios.

Visualizing & Story Telling

Fig 1.1 & 1.2 Profit Margin for Failed Companies

Profit margin is a measure of how much profit a company makes compared to its total sales. The profit margin is important because it is a measure of how much profit a company is generating from its sales. A low-profit margin could indicate low sales or high expenses. According to our statistics, bankrupt companies had an average profit margin of -3.34% (not including outliers) while successful companies had an average profit margin of 1.13%.



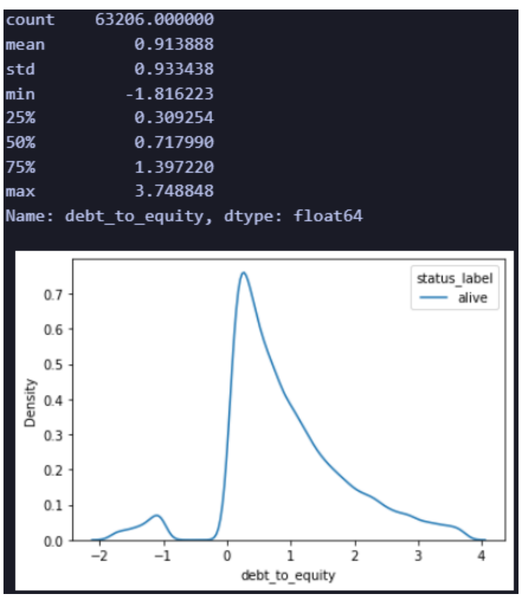
count	60533.000000
mean	0.011343
std	0.142739
min	-0.541677
25%	-0.024328
50%	0.032759
75%	0.081965
max	0.437576

count	3898.000000
mean	-0.033395
std	0.156265
min	-0.541090
25%	-0.090627
50%	0.000991
75%	0.045526
max	0.433946

Figure 1: Profit Margin for companies

Fig 2/3. Debt-to-equity ratio

The debt-to-equity ratio measures how much debt a company has relative to the amount of equity. It's important because it can signal the probability that a company may go bankrupt. The statistic that stands out the most is when a company has a negative ratio. This means that the company may have negative equity typically resulting from the company carrying over negative profits from prior periods. On average, failed companies tend to have a slightly higher debt-to-equity ratio, 1.03 vs .91, but both failed and alive companies have similar distributions illustrating that there is no right debt-to-equity ratio. Rather, we want to look out for the outliers that have extremely high debt-to-equity ratios of more than 2.0. Very high could mean that they have high amounts of debt, declining profits, or lowering market values.



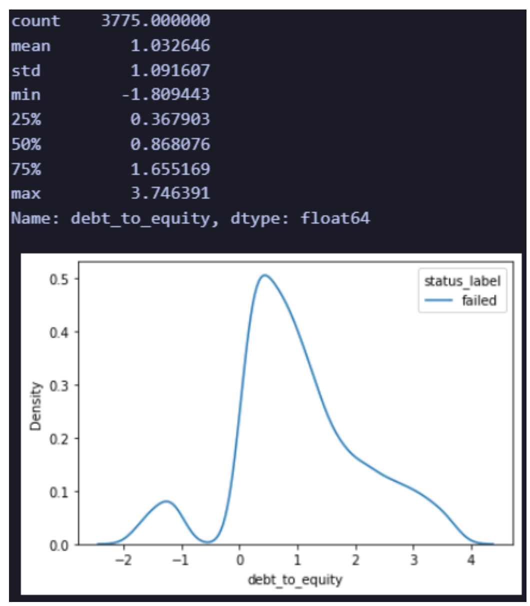
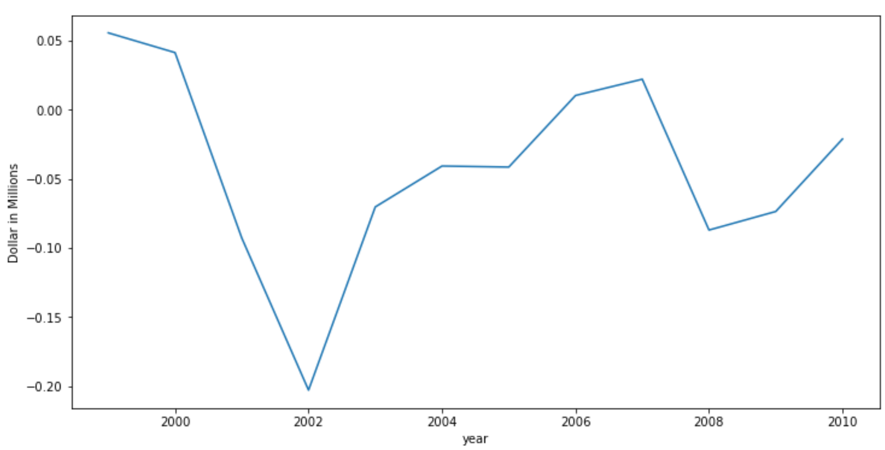


Fig 4/5/6 - Going more in-depth: C_6

With our new benchmarks, we can go into depth to a singular company, company six. We will look at its profit margin and debt-to-equity ratio and try to answer our question.

Company six had an average profit margin of -4.19% and this can be seen in the line plot in Figure 4. They spent a lot of their time after 1999 in this range. I also plotted their total revenue and cost of goods sold. These two figures are important because when you subtract them you get the gross profit. Gross profit is a measure of how much money a company has after covering the cost to generate revenue. If gross profit is negative, then the company is losing money when generating sales. Company six experienced negative gross profits from 2001 through 2002 (Fig. 5) which could have resulted in a massive -20% profit margin. When we add the debt-to-equity ratio into the picture we get a much more in-depth look at how these two years of unprofitability affected the company's balance sheet. It looks like the following year they had a massive spike in the debt-to-equity ratio to 636.00, meaning they had $636 of debt for each $1 in equity. As aforementioned, this probably resulted from the decrease in retained earnings from negative profits. This measure signals that company six is a risky investment, and the company may go bankrupt. Additionally, it's a signal that the company is relying heavily on debt for financing since they are not generating profits.

Profit Margin



count	12.000000
mean	-0.041808
std	0.071388
min	-0.202960
25%	-0.077065
50%	-0.041193
75%	0.013182
max	0.055556

Figure 4 Profit Margin line plot - C_6

Total Revenue & Cost of Goods Sold

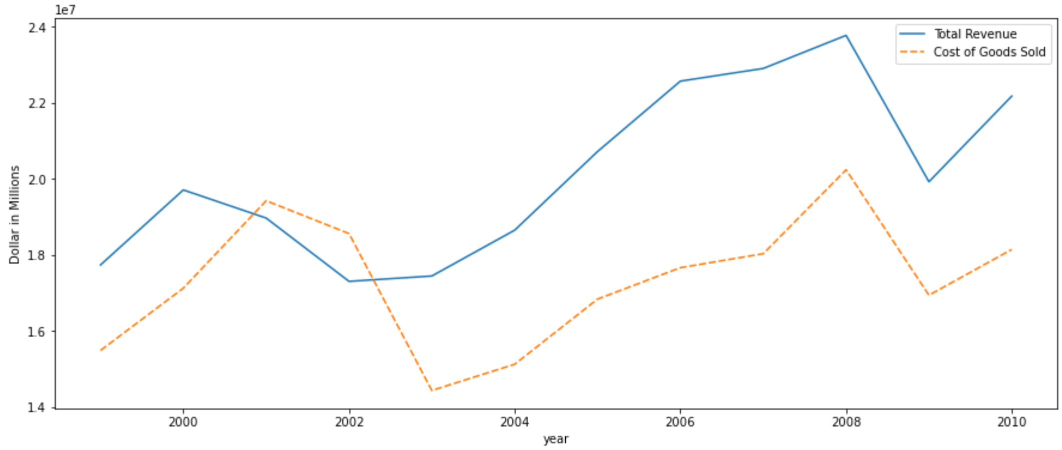
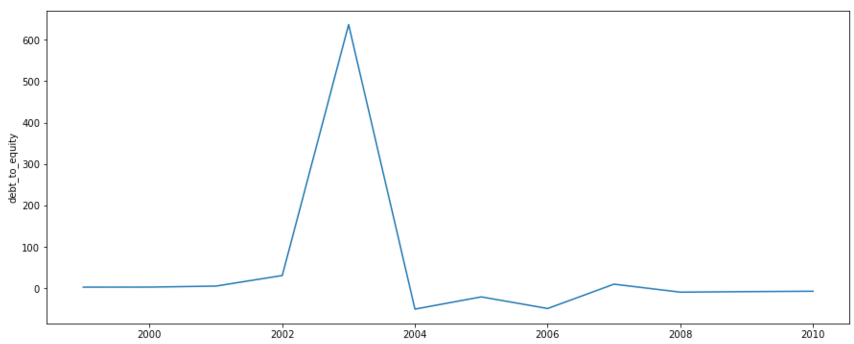


Figure 5: Line plot - Total Revenue & COGS

Debt-to-Equity ratio



count	12.000000
mean	45.125564
std	187.695176
min	-50.523236
25%	-12.422140
50%	-2.402672
75%	6.272447
max	636.608696

Figure 6: C_6 debt-to-equity ratio line plot

Story Telling/Impact

Storytelling

From our analysis, we can conclude that on average, failing companies tend to have a lower and negative profit margin of -3.34% and a slightly higher debt-to-equity ratio of 1.03. Additionally, through our illustrations of profit margin and the debt-to-equity ratio from company six, we observe that failing companies' negative profit margins are exacerbated by negative gross profits which then lead to high/negative debt-to-equity ratios. We learn that failing companies with large losses rely heavily on debt and that we can see an illustration of this with the spike in the debt-to-equity ratio and then the drastic move to the negative range. Overall, we learn that the profit margin, gross profit, and debt-to-equity are effective tools in telling the story of what happens to a failing company's financials.

Impact

My concern about my dataset and analysis is that I did not go into depth for more companies. This is concerning because we are limiting our scope. The information I provide does not take into consideration outliers and paints the picture that negative profit margins are bad and companies with high debt-to-equity ratios will fail. This is not true; companies can have negative profit margins and succeed, and debt-to-equity can vary between different industries. Additionally, there are thousands of companies we have not analyzed that could have drastically different stories compared to the average or company six. Overall, our analysis is here to provide a big picture view and it does a good job at this.

Code

Code for Renaming Columns

```
my_data.rename(columns={'X1': 'Current Assets'}, inplace=True)
my_data.rename(columns={'X2': 'Cost of Goods Sold'}, inplace=True)
my_data.rename(columns={'X3': 'Depreciation and Amortization'}, inplace=True)
my_data.rename(columns={'X4': 'EBITDA'}, inplace=True)
my_data.rename(columns={'X5': 'Inventory'}, inplace=True)
my_data.rename(columns={'X6': 'Net Income'}, inplace=True)
my_data.rename(columns={'X7': 'Total Receivables'}, inplace=True)
my_data.rename(columns={'X8': 'Market Value'}, inplace=True)
my_data.rename(columns={'X9': 'Net Sales'}, inplace=True)
my_data.rename(columns={'X10': 'Total Assets'}, inplace=True)
my_data.rename(columns={'X11': 'Total Long-term Debt'}, inplace=True)
my_data.rename(columns={'X12': 'EBIT'}, inplace=True)
my_data.rename(columns={'X13': 'Gross Profit'}, inplace=True)
my_data.rename(columns={'X14': 'Total Current Liabilities'}, inplace=True)
my_data.rename(columns={'X15': 'Retained Earnings'}, inplace=True)
my_data.rename(columns={'X16': 'Total Revenue'}, inplace=True)
my_data.rename(columns={'X17': 'Total Liabilities'}, inplace=True)
my_data.rename(columns={'X18': 'Total Operating Expenses'}, inplace=True)
```

Code for Null Values

```
my_data.isnull().sum()
```

Code for Adjusting Measurement of Dollars

```
#Adjusting values back to thousands
for n in my_data:
    if n != "company_name" and n != "status_label" and n != "year":
        my_data[n] = my_data[n] * 1000

my_data #Just to make sure that the values are adjusted
```

Outliers Function

```
# function to handle outliers
def removeOutliers(df, columnName):
    Q1 = df[columnName].quantile(0.25)
    Q3 = df[columnName].quantile(0.75)
    IQR = Q3 - Q1

    dfFilter = (df[columnName] >= Q1 - 1.5 * IQR) & (df[columnName] <= Q3 + 1.5 *IQR)

    return df.loc[dfFilter]
```

Fig 1 Code

```
plt.figure(figsize=(12,6))
failed_comp_dist = sns.kdeplot(data=failed_comp_No_out, x="profit_margin", hue="status_label")
failed_comp_No_out["profit_margin"].describe()
```

Fig 2 Code

```
failed_companies_FL = financial_Leverage_dist_no_out[financial_Leverage_dist_no_out["status_label"] == "failed"]

failed_financial_Leverage_dist = sns.kdeplot(data=failed_companies_FL, x="debt_to_equity", hue="status_label")
failed_companies_FL["debt_to_equity"].describe()
```

Fig 3 Code

```
sns.kdeplot(data=succ_comp, x="debt_to_equity", hue="status_label")
succ_comp["debt_to_equity"].describe()
```

Fig 4 Code

```
plt.figure(figsize=(12,6))
plt.ylabel("Dollar in Millions")
sns.lineplot(data=failed_comp1["profit_margin"])
failed_comp1["profit_margin"].describe()
```

Fig 5 Code

```
plt.figure(figsize= (15, 6))
plt.ylabel("Dollar in Millions")
sns.lineplot(data = failed_comp1[["Total Revenue", "Cost of Goods Sold"]]) #Gross Profit  #Cost of goods sold
```

Fig 6 Code

```
plt.figure(figsize = (15,6))
failed_comp1FinancialLeverage = failed_comp1["debt_to_equity"]
sns.lineplot(data = (failed_comp1FinancialLeverage))

failed_comp1["debt_to_equity"].describe()
```

References

- Kaggle Data Base: https://www.kaggle.com/datasets/utkarshx27/american-companies-bankruptcy-prediction-dataset