Markov Process in Finance Group 2 Final Project

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1 Introduction

The objective for this project is to analyze the credit ratings phenomenon. In the following section, we will explore the single notch and multiple notch migrations by companies and sectors. We will also observe the changes over time and how it is affected during a financial crisis. The data we use for our analysis is the North America S&P credit ratings monthly data from WRDS.

2 Data Analysis from 1981 to 2017

2.1 Data Information

The target data is the S&P Long-Term Issue Credit Ratings (SPLTISRM), starting from January 1981 to February 2017. The credit ratings are classified from AAA (Highest) to D (Default, lowest) based on varying degrees of likelihood of payment, nature of the obligation, and protection afforded by the obligation in the event of bankruptcy.

Factors included in the data are:

2.1.1 gvkey

A unique six digit number assigned to each company issued by S&P Capital IQ Compustat.

2.1.2 datadate

The date of data. There is only monthly credit ratings data, hence the period is monthly.

2.1.3 gsector

GICS Sectors, the leftmost 2 digits of the total GICS code.

2.1.4 conm

The full name of each company.

2.1.5 tic

The ticker symbols.
(Note: We didn't use this as the classification method due to the possibility of some companies might have the same symbol)

2.2 Assumptions

2.2.1 Assumption 1

All data with credit rating available is used. Companies that have rating gaps during their lifetime are not dropped in this part and is assumed that the data is simply "missing". But the movements from a certain rating to missing does not count toward multi-notch movements. For example, a rating "AAA" to "missing" and back to "AAA" does not contribute to the multi-notch nor single-notch movements.

2.2.2 Assumption 2

Credit ratings of "SD" (Selective Default) and "D" (Default) are considered identical and is one notch away from the lowest non-default rating "C".

2.2.3 Assumption 3

Credit ratings of "N.M." (Not mentioned) has little to no data point and is neglected in this part.

2.2.4 Assumption 4

The birth and death of a company does not count toward multi-notch movements, same as assumption 1.

2.3 Observations

For the convenience for coding, the coding scheme for rating in this section is as followings:

AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+
22	21	20	19	18	17	16	15	14	13	12
BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	SD/D
11	10	9	8	7	6	5	4	3	2	1

Figure 1: Coding Scheme for Ratings

Since we have no prior intuition regarding this data, a straightforward approach is used to search for patterns or intuitions. In this approach, the data is wrangled into different companies' credit ratings over the whole time period of the dataset. The rows are set to be the datetime and columns are different companies.

2.3.1 Observation 1

The credit ratings are more concentrated toward the center, where "BBB" has the most data points. We can see from observe the number of each rating from Figure 2, whcih ranking from high to low.

	ratinglist	ratingcount
	Any	Float64
1	BBB	75748.0000
2	B+	69567.0000
3	BBB+	61873.0000
4	BBB-	58117.0000
5	BB-	56913.0000
6	A	56752.0000
7	A-	52823.0000
8	BB	45194.0000
9	B	43433.0000
10	A+	38430.0000
11	BB+	35605.0000
12	AA-	23763.0000
13	B-	21364.0000
14	AA	18569.0000
15	AAA	10311.0000
16	CCC+	8807.0000
17	D	8164.0000
18	AA+	5321.0000
19	CCC	4863.0000
20	CCC-	2042.0000
21	CC	1720.0000
22	C	42.0000

Figure 2: Number of Ratings

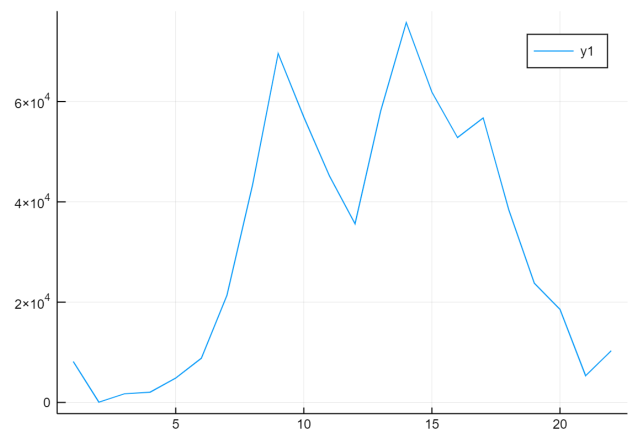

Figure 3: Distribution of Ratings

2.3.2 Observation 2

After plotting individual company's credit risk, it is clear that several companies have ratings gap in the data, which leads to our assumption 1 and the next part of our project – data censoring. The green line in the following plot is an example of missing data between ratings. (-2 means "missing")

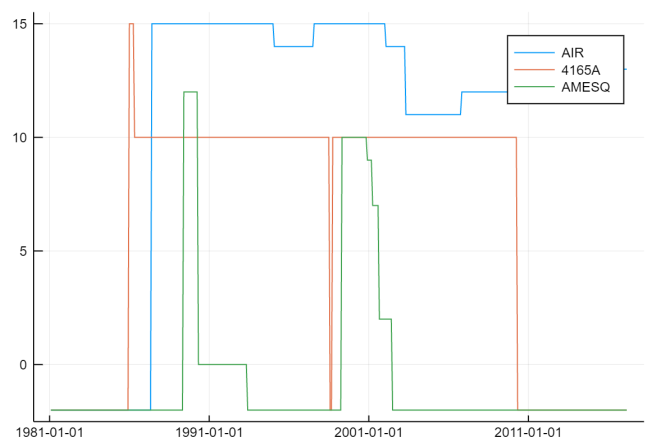

Figure 4: Individual Company Ratings Changes Sample

2.3.3 Observation 3

In this data set, there are more multi-notch movements (61%, total:18443) compared to single-notch movements (39%, total:11644). This contradicts with our hypothesis of there is more single-notch transitions than multi-notch transitions as companies are less likely to receive multi-notch downgrades or upgrades during non-recession periods.

The following result is the head of the notch change percentage DataFrame. A majority of the companies solely have multi-notch movements.

	single	multi	single_percentage	multi_percentage	tickername
	Any	Any	Any	Any	String?
1	5	2	0.714286	0.285714	AIR
2	0	5	0.0	1.0	4165A
3	0	3	0.0	1.0	5548C
4	0	2	0.0	1.0	AGS.2
5	3	6	0.333333	0.666667	ALO.2
6	0	2	0.0	1.0	UDI.

Figure 5: Single and Multiple Notch Percentage

2.3.4 Observation 4

Observing the transition matrix, an interesting thing to note is that the lower the credit rating of the company, the more possible it is to have a multi-notch movement

	ratinglist	multiprob	singprob		ratinglist	multiprob	singprob
1	D	0.0236	0.0000	12	BB+	0.0081	0.0202
2	C	0.0541	0.0541	13	BBB-	0.0057	0.0153
3	CC	0.1824	0.0134	14	BBB	0.0038	0.0143
4	CCC-	0.0721	0.0401	15	BBB+	0.0040	0.0153
5	CCC	0.0678	0.0200	16	A-	0.0041	0.0150
6	CCC+	0.0443	0.0295	17	A	0.0037	0.0118
7	B-	0.0212	0.0262	18	A+	0.0041	0.0127
8	B	0.0112	0.0234	19	AA-	0.0035	0.0144
9	B+	0.0075	0.0197	20	AA	0.0044	0.0118
10	BB-	0.0065	0.0203	21	AA+	0.0034	0.0151
11	BB	0.0075	0.0205	22	AAA	0.0030	0.0040

Figure 6: Single and Multiple Notch Percentage of Ratings

2.3.5 Observation 5

Taking the starting point from rating "AAA", running a 100 step transition would result in the "migration100" below, which tends to smooth out as the steps increase. We can observe that the first graph of our ratings count has a similar rank to the stationary distribution calculated by using matrix.

	ratinglist	migration_100	stationary		ratinglist	migration_100	stationary
1	D	0.0007	0.1244	12	BB+	0.0023	0.0538
2	C	0.0000	0.0003	13	BBB-	0.0037	0.0856
3	CC	0.0001	0.0075	14	BBB	0.0095	0.1015
4	CCC-	0.0001	0.0096	15	BBB+	0.0114	0.0750
5	CCC	0.0002	0.0183	16	A-	0.0194	0.0517
6	CCC+	0.0003	0.0293	17	A	0.0303	0.0408
7	B-	0.0006	0.0516	18	A+	0.0498	0.0191
8	B	0.0014	0.0762	19	AA-	0.0854	0.0090
9	B+	0.0024	0.0954	20	AA	0.1298	0.0044
10	BB-	0.0044	0.0782	21	AA+	0.1255	0.0013
11	BB	0.0043	0.0640	22	AAA	0.5185	0.0029

Figure 7: Single and Multiple Notch Percentage of Ratings (100 steps)

2.3.6 Observation 6

Grouping the As, Bs, Cs, and D up into buckets, it is hard to get from bucket A to multi-notch ratings, while the other ratings are more free to move up and down the ladder.

	D	C	B	A
	Float64	Float64	Float64	Float64
1	0.9764	0.0119	0.0115	0.0001
2	0.0364	0.9450	0.0183	0.0003
3	0.0003	0.0024	0.9959	0.0013
4	0.0000	0.0000	0.0046	0.9954

Figure 8: Basket Transition Probability

With these observations, we could then discuss deeply the credit rating changes during financial crises and to use more assumptions in the second part.

3 Data Analysis from 1997 to 2017

This part of the report focuses on a shorter time period, starting in January 1997 to February 2017. We want to take a closer look and test out some time-dependent hypotheses in a shorter period that includes different economic cycles. During this twenty-one years of data, there are two significant economic downturns: the early 2000 internet bubble and the 2008 financial crisis.

The assumptions made during the following analysis is slightly different from other parts of this report. First of all, as stated earlier, due to the time difference, there is less data inputted into the code. After dropping missing data, the data set only contains 4981 companies which is significantly less than the amount of company analyzed in the full period. Secondly, data censoring in terms of length is used. Companies that don't have the complete data between 1997 and 2017 are dropped. It makes the analysis and transition matrix calculation easier and more consistent. Normally, this type of data length censoring allows for better accuracy and less noise. However, in this case, the data is skewed to the right. In other words, companies that have problems during this time period and end up in bankruptcy won't be reflected and at the same time, new companies created during this time period won't be included. Therefore, the remaining 529 companies after censoring are companies that are relatively stable and with moderate risk profiles. This bias is reflected in the percentage of multi-notch transitions which will be explained further in the following section. Another notable difference between this section and the rest of report also stems from the time period selection and potentially from the data censoring. The data set doesn't contain "not mentioned" (N.M) and "C" rating; as a result, these two ratings are not assigned a specific number in the coding scheme. Because of this difference, transition from a rating of "CC" to "D" or "SD" is considered to be single notch, not multiple notch.

The coding scheme for rating in this portion is as following:

AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-
21	20	19	18	17	16	15	14	13	12	11	10	9
B+	B	B-	CCC+	CCC	CCC-	CC	SD/D					
8	7	6	5	4	3	2	1					

Figure 9: Coding Scheme for Ratings

3.1 Single Notch, Multiple Notch Transition Percentage

3.1.1 Hypothesis 1

Hypothesis 1: There are more single notch transitions than multi-notch transitions as companies are less likely to receive multi-notch downgrades or upgrades during non-recession periods

This section is separated into two parts as the data is analyzed from two angles: company and time. The percentage of multi-notch transitions is first calculated by company. This allows us to error check and confirm our calculation in the time section. One subtlety that we find is that there is a significant amount of transitions in-between years. These cross-year transitions are included in the second year. For example, there are multiple transitions between December 1997 and January 1998; they are included in 1998 data. These transitions won't be taken into account if one simply looks at the transitions within the year. Therefore, there are two sets of calculations: one that includes cross-year transitions and one that doesn't.

When separating by company, it yields the following result (a portion of the DataFrame is attached)

	company	singlenotch	multinotch	perctmultinotch
	String	Int64	Int64	Float64
1	0141A	5	3	0.3750
2	0176A	1	0	0.0000
3	0191A	4	6	0.6000
4	1231B	6	3	0.3333
5	3NSRGY	0	1	1.0000
6	5672A	3	0	0.0000
7	5946B	6	2	0.2500
8	6120B	5	2	0.2857
9	8135A	8	0	0.0000
10	AAL	6	6	0.5000

Figure 10: Single and Multiple Notch Percentage of Companies

One can see that the percentage of multi-notch transition for each company is relatively low baring some exceptions. The total number of multi-notch transitions without accounting cross-year transitions is 468 while the number of single notch is 1963. When cross-year transitions are taken into account, the total number of multi-notch transitions amounts to 502 and the number of single notch is 2099. The percentage of multi-notch transition is approximately 24%. This supports hypothesis 1 that multi-notch transitions account for a relatively small percentage of all transitions.

However, this contradicts with the result from the whole period. As stated in the first portion of the report, there are more multi-notch transitions than single notch transitions. This can be explained as an effect of data censoring. The companies in this section have lower risk and are relatively stable. Thus, they have a lower possibility of receiving a multi-notch upgrade or downgrade. Other sections don't have the same data censoring process and companies are more likely to receive multi-notch transitions and default.

3.1.2 Hypothesis 2

Hypothesis 2: There are more multi-notch transitions during crisis period as companies face harsher economic conditions

After calculating the percentage of multi-notch transitions for each company, one can move on to the time non-homogeneous portion of the calculation. For each year, the number of single notch and multi-notch transitions are amassed, resulting in the following table:

	year	singlenotch	multinotch	perctmultinotch
	Int64	Int64	Int64	Float64
1	1997	84	9	0.0968
2	1998	90	17	0.1589
3	1999	83	22	0.2095
4	2000	75	33	0.3056
5	2001	87	36	0.2927
6	2002	117	38	0.2452
7	2003	113	29	0.2042
8	2004	72	14	0.1628
9	2005	103	16	0.1345
10	2006	106	17	0.1382
11	2007	108	31	0.2230
12	2008	116	35	0.2318
13	2009	110	53	0.3252
14	2010	97	24	0.1983
15	2011	116	17	0.1278
16	2012	90	19	0.1743
17	2013	104	11	0.0957
18	2014	80	12	0.1304
19	2015	101	13	0.1140
20	2016	101	22	0.1789

Figure 11: Single and Multiple Notch Percentage of Years

The DataFrame above confirms our hypothesis that during financial downturns, the percentage of multi-notch transitions is significantly higher. The first recession during this period happened in 2000 which is known as the internet bubble. The percentage of multi-notch transition spikes from 21% to 31%, which is a 46% increase. The following year 2001 also had a high percentage of 29%. Moving onto the most recent 2008 financial crisis, one can also observe a similar pattern. At the end of 2008 and the height of the crisis, Lehman Brothers filed for bankruptcy. The market went into deep recession in the following year. This can be observed from the data as the percentage spiked in percentage in 2009. The percentage shots up by 40%, going from 23% to 33%

3.2 Transition Probability Matrix and Stationary Distribution

After accumulating the transitions, one can look to fit a Markov chain to each time period and compute the transition probability matrix. The transition matrix is computed using maximum likelihood. The calculation process is very similar to the one mentioned in class and it is annotated with markdowns in the code. The transition probability matrix for each year is stored inside an array; each element in the array is a 21-by-21 matrix. We won't be going through the process in detail in the report and instead will be focusing on some observations obtained from the analysis.

From observing the array of transition probability matrices, one can see that single notch transitions account for the majority of the transitions. All the transition probability matrices are essentially tridiagonal matrix with the diagonals being close to one. This is consistent with the result from earlier section. Another observation is that multi-notch transitions are cluster around default and CC. This is due to that fact that default is not an absorbing state in this model. Companies that go into default or have lower ratings tend to go into chapter 11 to restructure or selective default some of their debts. Instead of chapter 7 bankruptcy, these companies survive and their ratings are reevaluated, hence the clustering of multi-notch upgrades and downgrades. The final observation we can make is that ratings above BB- tend to have fatter right tails, indicating that there is a higher probability of upgrading. On the other hand, ratings lower than BB- have fatter left tails. A possible explanation for this dichotomy is that companies that have ratings lower than BB- might be facing escalating managerial or financial problems while companies that are close to investment grade or close to investment grade have the comparative advantage or market share to stay in that region. Aside from the transition probability matrix, stationary distribution for each Markov chain can be computed. One can see that the stationary distribution is centered around the ratings in the middle with a maximum at BBB.

This concludes the analysis on this period between 1997 2017. A closer examination of this period provides a lot of insights on the credit rating transitions across time and also across companies. Now, we can take a deeper dive into how sector affects credit rating transitions.

4 Sector Data Analysis

For this part of report, we will focus on the sector rather than a individual company. The analysis uses all time data, starting from 1981 to 2017. The objective for this part is to discuss the volatility of each industry.

We use the same coding scheme for rating as the section 2 does in this portion, which is as followings:

AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+
22	21	20	19	18	17	16	15	14	13	12
BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	C	SD/D
11	10	9	8	7	6	5	4	3	2	1

Figure 12: Coding Scheme for Ratings

4.1 Single Notch, Multiple Notch Transitions Percentage

Hypothesis 1: There are more multiple notch transitions in the volatile industry than in the stable industry

```
sector_10_num
single notch percentage: 0.4694
multi  notch percentage: 0.5306
sector_15_num
single notch percentage: 0.4305
multi  notch percentage: 0.5695
sector_20_num
single notch percentage: 0.4234
multi  notch percentage: 0.5766
sector_25_num
single notch percentage: 0.4699
multi  notch percentage: 0.5301
sector_30_num
single notch percentage: 0.4286
multi  notch percentage: 0.5714
sector_35_num
single notch percentage: 0.3987
multi  notch percentage: 0.6013
sector_40_num
single notch percentage: 0.4920
multi  notch percentage: 0.5080
sector_45_num
single notch percentage: 0.3708
multi  notch percentage: 0.6292
sector_50_num
single notch percentage: 0.3880
multi  notch percentage: 0.6120
sector_55_num
single notch percentage: 0.5590
multi  notch percentage: 0.4410
sector_60_num
single notch percentage: 0.7584
multi  notch percentage: 0.2416
```

Figure 13: Single and Multiple Notch Percentage of Sectors

This section is aimed to analyze the for different sector. The percentage of multi-notch and single-notch transitions are first calculated by sector. There are totally 11 sectors, which are Energy (Sector 10), Materials (Sector 15), Industrial (Sector 20), Consumer Discretionary (Sector 25), Consumer Staple (Sector 30), Health Care (Sector 35), Financials (Sector 40), Information Technology (Sector 45), Communication Services (Sector 50), Utilities (Sector 55), and Real Estate (Sector 60).

It is intuitive for us to assume that when the sector is more risky, the multi notch transitions is more likely to be higher than the single notch transitions. From the Figure 13, we can see taht for different sectors, the single notch and multiple notch transition ratio vary. Let's take a look on the Figure 13, it is easy to observe that the highest single notch percentage is 75.84% in sector 60, which is also known as real estate. On the other hand, the lowest single notch percentage is 37.08% in sector 45, which is also known as the Information Technology. These two data indeed verifies our hypothesis. The information technology industry is often considered as a more volatile industry and thus the multiple notch percentage is higher compared with other industry. On the other hand, real estate is considered more stable and thus has a quite high percentage in single notch percentage.

4.2 Transition Probability Matrix and Stationary Distribution

After accumulating the transitions, we can look to fit a Markov chain to compute the transition probability matrix. From the observing the array of transition probability matrices, we can see that for different sectors as the previous section shows. As a result, unlike the previous two part analysis, single notch transitions may not account for the majority of the transitions. Also, the transition probability matrices are "similar" to tridiagonal matrix with the diagonals being close to one. The reason we use similar here is because that some ratings do not exist in certain sectors and thus we can't guarantee for the diagonals to be close to one, which can be observed easily from Figure 14.

	x1	x2	x3	x4	x5	x6
	Float64	Float64	Float64	Float64	Float64	Float64
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0000	0.9756	0.0000	0.0244	0.0000	0.0000
3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
4	0.0000	0.0270	0.0000	0.9189	0.0270	0.0270
5	0.0000	0.0000	0.0000	0.1111	0.7778	0.0000
6	0.0000	0.0109	0.0000	0.0109	0.0000	0.9239

Figure 14: Part of Transition Probability Matrix of Sector 60

5 Future Potential Research

The analysis we've done provide a good guide to understand properties for credit ratings. There are some potential area to be explored deeper. For example, we believe it is possible to implement Hidden Markov Model to this problem. The transition probability matrices for financial crisis state and non-financial crisis state should be different and the Hidden Markov Model might be able to help us solve the problem by maximizing the expectation. Thanks to Professor Atteson, we've had a summary of the HMM model for this problem. However, due to the limitation of the time, we aren't able to finish the last part and hopefully we can finish it in the future.