CLO Portfolio Analysis

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August 23, 2021

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Data Source: Scott

Credit Data

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Credit	Facility	Modeled Par	Model Price	Spread	LIBOR Floor	1 year LIBOR	1 Year Income Rate	Maturity	Moody's CFR	Moody's Ratings Factor	S&P Industry	Recovery Rate
AAdvantage Loyalty IP Ltd	Term Loan	nan	0.9900	0.0475	0.0075	0.0019	0.0550	2028-03-10	Ba2	1350	Airlines	0.5000
Acrisure, LLC	2020 Term Loan (First Lien)	nan	0.9900	0.0350	0.0000	0.0019	0.0369	2027-02-15	B3	3490	Insurance	0.3000
Acuris Finance US, Inc.	Initial Dollar Term Loan	nan	0.9975	0.0400	0.0050	0.0019	0.0450	2028-02-16	B2	2720	Interactive Media and Services	0.4000
ADMI Corp.	Amendment No. 4 Refinancing Term Loan	nan	1.0000	0.0325	0.0050	0.0019	0.0375	2027-12-23	B2	2720	Healthcare Providers and Services	0.3000
Advantage Sales & Marketing Inc.	Initial Term Loan (First Lien)	nan	1.0086	0.0525	0.0075	0.0019	0.0600	2027-10-28	B2	2720	Media	0.4500

- ***Data Fields***: Credit, Facility, Modeled Par, Model Price, Spread, LIBOR Floor, 1 year LIBOR, 1 Year Income Rate, Maturity, Moody's CFR, Moody's Ratings Factor, S&P Industry, Recovery Rate
- ***No. of Credits***: 209
- ***No. of S&P Industries***: 50
- ***Existing Rating Categories*** : Baa2, Ba1, Ba2, Ba3, B1, B2, B3, Caa1

Constraint Data

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Constraint	Low Risk Portfolio	High Risk Portfolio
Minimum Weighted Average Income Rate	3.25%	4.35%
Maximum Weight per Credit	1.5%	2.5%
Maximum Weighted Average Price	100%	99.7%
Maximum Weight Per Industry	10%	15%
Maximum % in B3 or lower	15%	40%
Maximum % in Caa or lower	0%	2%
Minimum S&P WARR	43%	39%

- These constraints provide information about different sources of risk and return when constructing the portfolio

Default Rate Data

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Rating	WARF	Base Default Rate	Default Rate Sensitivity*
Baa2*	360	0.36%*	5*
Baa3	610	0.61%	10
Ba1	940	0.94%	20
Ba2	1350	1.35%	35
Ba3	1766	1.77%	50
B1	2220	2.22%	70
B2	2720	2.72%	100
B3	3490	3.49%	150
Caa1	4770	4.77%	250

- ***Default Rate Sensitivity***: Change in Default Rate per 100 bps Change in B2 Default Rate (bps)
- ***Data Processing***: Baa2 exists in credit data, but its base default rate and default rate sensitivity are not provided. By observing the pattern of other rating categories, I assigned Baa2 a base default rate of 0.36%, and default rate sensitivity of 5.

Portfolio Optimization Comparative Analysis

Portfolio Construction

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Low Risk Portfolio Example:

$$\min_{w_1,w_2,\ldots w_{209}} \quad \sum_{i=1}^{209} w_i \times RF_i$$

$$\text{s.t.} \quad \sum_{i=1}^{209} w_i = 100\%$$

$$0\% \leq w_i \leq 1.5\% \quad (\forall credit : i = 1, 2, ..., 209)$$

$$\sum_{i \in Sector_j} w_i \leq 10\% \quad (\forall sector : j = 1, 2, ..., 50)$$

$$\sum_{i=1}^{209} w_i \times IR_i \geq 3.25\%$$

$$\sum_{i=1}^{209} w_i \times P_i \leq 100\%$$

$$\sum_{i=1}^{209} w_i \times RR_i \geq 43\%$$

$$\sum_{i \in \{B3, Caa1\}} w_i \leq 15\%$$

$$\sum_{i \in \{Caa1\}} w_i \leq 0\%$$

Portfolio Metrics

Portfolio Optimization
Comparative Analysis

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Portfolio Metric	Low Risk Portfolio	High Risk Portfolio
Weighted Average Spread	2.86%	3.8%
Weighted Average Income Rate	3.25%	4.35%
Weighted Average Maturity	2026-12-06 03:29:42	2027-03-12 15:25:44
Weighted Average Ratings Factor	1785.9	2132.1
Weighted Average Recovery Rate	46.96%	41.78%
Weighted Average Price	100%	99.7%

	Low Risk Portfolio	High Risk Portfolio
Skewness	1.60	1.16

Table 4: Sector Skewness

- The metrics of constructed portfolios are consistent with the constraints.
- Low Risk Portfolio has lower risk and lower return than the High Risk Portfolio.
- Both portfolios are positively/right skewed (mode>median>mean), which means they're more diversified than concentrated.
- The Low Risk Portfolio has more significant skewness than the High Risk Portfolio, which means the weights of the Low Risk Portfolio is more diversified into sectors.

Top Allocations by Size*

Portfolio Optimization Comparative Analysis

Portfolio Construction

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Low Risk Portfolio

	Credit	Modeled Par
0	AAdvantage Loyalty IP Ltd	$7,575,762
25	Asurion, LLC	$7,575,762
58	Enviva Holdings, LP	$7,575,762
103	LogMeIn, Inc.	$7,556,679
64	Froneri International Limited	$7,552,874

High Risk Portfolio

	Credit	Modeled Par
58	Enviva Holdings, LP	$12,626,261
0	AAdvantage Loyalty IP Ltd	$12,626,261
130	PetSmart LLC	$12,626,258
25	Asurion, LLC	$12,626,257
103	LogMeIn, Inc.	$12,594,454

Low Risk Portfolio

S&P Industry	Modeled Par
Commercial Services and Supplies	$49,859,621
Specialty Retail	$25,322,643
Food Products	$22,560,209
Insurance	$22,557,228
Capital Markets	$22,483,032

High Risk Portfolio

S&P Industry	Modeled Par
Commercial Services and Supplies	$50,071,573
Specialty Retail	$25,189,162
Trading Companies and Distributors	$25,157,173
Chemicals	$25,125,561
Building Products	$25,062,788

- *Modeled Par is used to represent Size in our analysis

Rating Category Distribution

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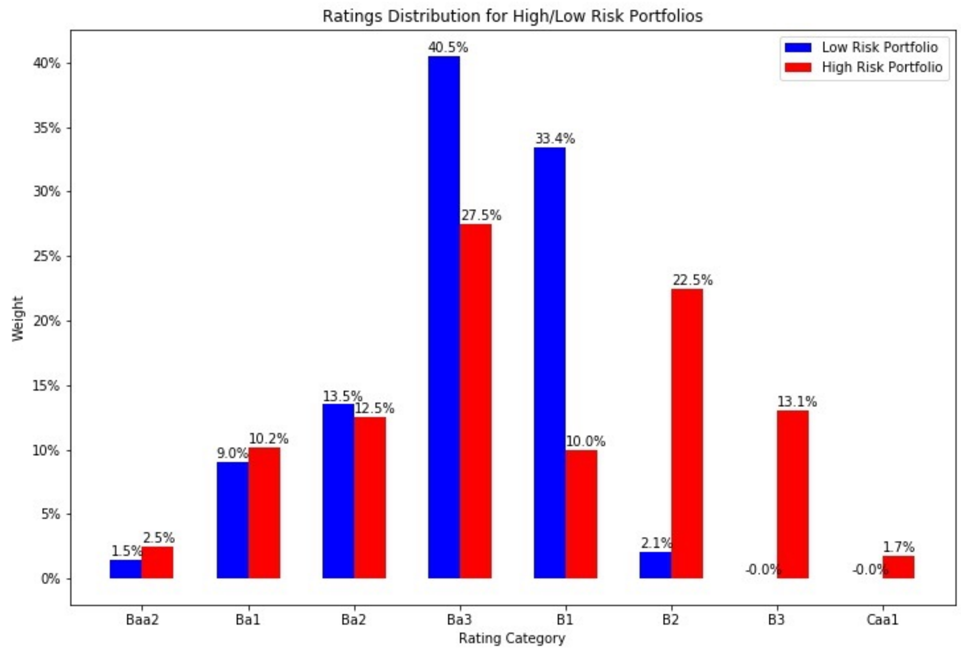


- ***Observation***: a trend of decentralization when going from Low Risk Portfolio to High Risk Portfolio
- ***Intuition***: when going from Low Risk Portfolio to High Risk Portfolio, the optimizer tried to increase the weights of low rating categories to meet the increased ”Income Rate Constraint”, and, at the same time, it tried to assign more weights to the high rating categories to maintain the overall credit quality as required by the objective function.

Theory

Portfolio Performance Analysis under Various Default Scenarios

Scenario Analysis

03

$$
\begin{cases}
Ret_{ptf} = \dfrac{\sum_{i=1}^{209} PnL_i}{Cost_{ptf}} = \dfrac{\sum_{i=1}^{209} (Profit_i - Loss_i)}{Cost_{ptf}} \\
Profit_i = Par_i \cdot IR_i \\
Loss_i = PD_i \cdot EAD_i \cdot LGD_i
\end{cases}
$$

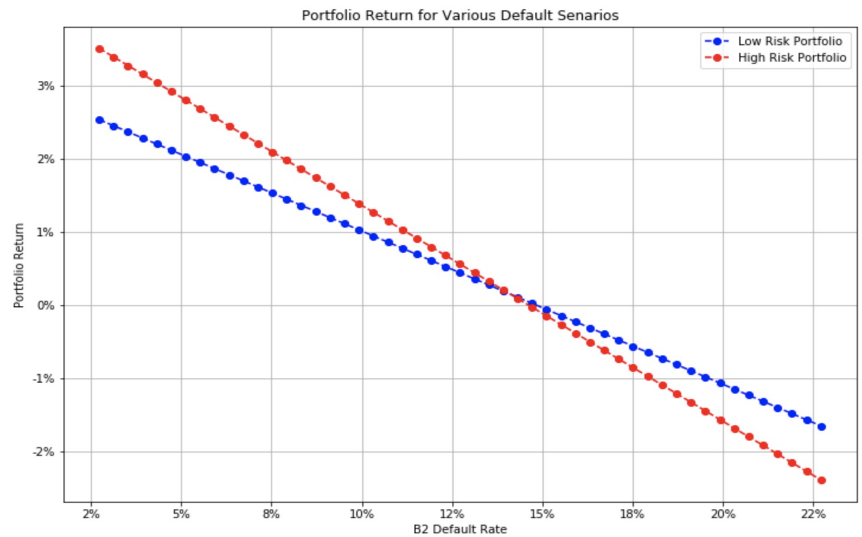
$$
\begin{cases}
PD_i = BasePD_i + PDSensi_i^{B2} \cdot (CurPD_{B2} - BasePD_{B2}) \\
EAD_i = Cost_i = w_i \cdot Cost_{ptf} \\
LGD_i = 1 - RR_i
\end{cases}
$$

Result and Analysis

Portfolio Performance Analysis under Various Default Scenarios

Scenario Analysis

03



Scenario	B2 Default Rate	Low Risk Portfolio Return	High Risk Portfolio Return
Base Scenario	2.72%	2.54%	3.51%
High > Low	[2.72%, 14.10%)	[2.54%,0.15%)	[3.51%, 0.15%)
High = Low	14.10%	0.15%	0.15%
High < Low	>14.10%	<0.15%	<0.15%

- ***Observation***: lower base return and lower risk from default for the Low Risk Portfolio
- ***Conclusion***: if the expected future default rate is high, choose the Low Risk Portfolio because of lower risk; if the expected future default rate is low, choose the High Risk Portfolio because of higher return.
- ***Other analyses and Factors***: 1) Non-linear default rate relationship; 2) heterogenous recovery rate upon default, etc.

Further Improvements Framework

Break the Assumptions
Improve the Optimization

Further Improvements

04

Break the Assumptions

Improve the Optimization Process

The "What-Why-How" Format

Break the Assumptions
Improve the Optimization

Further Improvements
04

- ***What***: What's the assumption?
- ***Why***: Why do you think that it doesn't depict the reality accurately? What are the anomalies?
- ***How***: How to improve the assumption and the process to be closer to the real situation?

Break the Assumption Example

Break the Assumptions
Improve the Optimization

Further Improvements

04

1. ***What***
   - All credits in the same rating category have the same credit quality as measured by the rating factor.
2. ***Why***
   - Different credits within the same rating category can have different rating factors, which are related to e.g., their fundamentals. Example, B2 (2220) -> 2100/2300.
3. ***How***
   - Increase the granularity of the credit rating factor data, i.e., from rating-category-level to credit-level.
   - Potentially apply machine learning models to historical data and learn a relationship between companies' rating factors and their features (e.g., fundamentals, sector, country).
   - $RF_{\mathrm{i}} = f(country_i,\ sector_i,\ fundamentals_i, \dots)$

Note: sectors could matter because credits in same sector tend to have positively correlated credit quality changes, which could result from bottom-up or top-down forces that hit the credits in the same sector similarly.

Current Assumptions

Break the Assumptions
Improve the Optimization

Further Improvements

04

- Recovery rate upon default is 60% of par for all credits.
- Linear default rates relationship, i.e., changes in default rates for B2 and changes in default rates for other rating categories have linear relationship.
- Single period (one year horizon), all defaults occur at the end of the one year, and we would have received a full year of income prior to the default.
- No tax and transaction cost.
- All loans are fully divisible.
- Fully invested, i.e., invest all money to construct the loan portfolio.
- Long only, i.e., all the loans have non-negative weights.
- …

Improve the Portfolio Optimization Specification

Break the Assumptions
Improve the Optimization

Further Improvements

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Optimization Specification

- ***Objective Function***: Incorporate more risk and return sources into the objective function, e.g., risk as measured by ex ante volatility, return as measured by statistical return predictions. See below the example of risk adjusted weighted average rating factor:

$$\max_{w_1, w_2, \ldots, w_{209}} \frac{-\sum_{i=1}^{209} w_i \cdot RF_i}{\sqrt{\sum_{i=1}^{209} \sum_{i=1}^{209} w_i \cdot w_j \cdot \sigma_{ij}}}$$

- ***Constraints***: Incorporate more risk and return sources into the constraints, e.g., interest rate risk, pre-payment risk etc. These risk factors and return sources reflect the view of the portfolio manager in terms of what kind of risk and return to incorporate into the portfolio. For example, if we want to manage the interest rate risk of the portfolio, we could add a “Maturity Constraint” to limit the portfolio’s interest risk.

Improve the Portfolio Optimization Process

Break the Assumptions
Improve the Optimization

Further Improvements

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Optimization Process

- ***Linear Programming***: Currently the process is modeled as a linear programming problem, where the objective function and constraints are all linear w.r.t. weights, and the weights can take any positive real values.
- ***Integer Programming***: Consider the fact that there are smallest unit of currency, the feasible set is discrete and finite. If we keep the objective function and constraints linear, the process should be modeled as an Integer Programming problem, which is more difficult to solve.
- ***Combinatorial Optimization***: We could also add non-linear components (e.g., higher-order statistics such as variance and skewness) to the objective function or constraints of the optimization problem. Considering the smallest unit of currency which means the feasible set is discrete, the process should be modeled as a Combinatorial Optimization problem.