RociFi - On-Chain Credit Risk Scoring

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1 Introduction

This whitepaper offers an overview of how credit risk score calculation using on-chain data along with Machine Learning can allow for effective and profitable under-collateralized lending on the blockchain. Furthermore, historical data from existing lending protocols like Aave and Compound is utilized to demonstrate the additional revenue these protocols could have generated by using RociFi's credit risk scoring system. As such, RociFi's innovative approach to calculating credit risk score in a distributed ledger setting is poised to usher in a new wave of capital efficiency.

2 Model

2.1 Data

Like traditional credit analysis, understanding a borrower's historical credit behavior is imperative to assessing creditworthiness. However, unlike traditional finance, a borrower's information, such as bank statements or FICO scores, is not readily available in a blockchain setting on account of the pseudonymous nature of identity. Nonetheless, one of the key benefits of public blockchain networks is that transaction data such as user addresses and their various interactions with protocols, other users and smart contracts, is publicly available to be consumed and analyzed. In this manner, a user's entire on-chain interaction can be utilized to create a credit risk profile with good accuracy.

An important element of on-chain behavior is past interaction with DeFi protocols, in particular loaning interactions; i.e. has an address taken out a loan from protocols like Aave or Compound previously? Were there any liquidations? How large were the loans?

Figure 1: Wallet address, 0x8d824f246edafd13f8539b7-c5495f94e8ed8757f, took out a loan of 35 ETH from Compound and repaid a portion, 29.36 ETH, 54 days later. Source: Metamask.io

Compared to traditional credit risk assessment, having access to such minute user activity offers a lot more granularity and insights - that is similar to the data available for traditional credit risk methodologies under open banking, e.g., wallet balance, flow of funds, etc. Having access to such data provides a holistic view of users which in turn allows for the development of a comprehensive credit risk profile. Furthermore, this Bayesian process is continually updated with new information in order to mitigate both direct (fraud) and indirect (missed interest payments or liquidations) defaults.

To-date, RociFi has analyzed over 13M transactions and 550k unique borrowing addresses, spanning over 6 DeFi protocols on Ethereum, Binance Smart Chain, and Polygon.

2.2 Model Construction

The raw, on-chain data for each address was also further transformed and processed to create new features with the aim of deriving additional insights, while being indicative of a user's implicit credit risk.

Using extensive statistical tests, collinear features are identified and removed. This is critical since the presence of multicollinearity implies that two or more features are correlated to each other. The presence of multicollinearity is not an issue where the objective is to simply make predictions, however, the essence of credit scoring is to understand the underlying data nuances affecting a user's credit score and to make reasonable inferences. Thus, having highly correlated features within the training data might result in unintended consequences where the effect of one feature on the model output is canceled by another, distorting the model coefficients, and compromising the model's interpretability. Variance Inflation Factor (VIF) and Pearson's correlation coefficient (r) have been used to identify collinear features.

$$VIF_i = \frac{1}{1-r_i^2} \tag{1}$$

$$r = \frac{\sum_{i=1}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}(x_i-\bar{x})^2 \sum_{i=1}(y_i-\bar{y})^2}} \tag{2}$$

In addition to the raw feature engineering referred to earlier, Weight of Evidence (WoE) and Information

Value (IV) have been utilized as well for further feature engineering and selection - both these concepts are extensively used in the traditional credit scoring domain. While WoE is a measure of the predictive or discriminatory power of an independent variable in relation to the target variable (the extent a specific feature can differentiate between the target classes), IV assists with ranking our features based on their relative importance. WoE feature engineering transforms all numerical and categorical variables into new WoE based features.

$$WoE = ln\left(\frac{Event\%}{Non\text{-}Event\%}\right) \tag{3}$$

$$IV = \sum(Event\% - Non\text{-}Event\%) \times WoE \tag{4}$$

WoE and IV analyses allow for consideration of each variable's independent contribution to the outcome while considering both linear and non-linear relationships together with ranking the independent variables in terms of their respective univariate predictive strength. Using discretized WoE engineered features allows the creation of an interpretable 'scorecard' for risk scoring whereby the specific reasons for low or high scores can be easily understood and explained to third parties.

After applying the standard train-test data split and multi-fold, stratified cross-validation (model validation results are explained in detail in section 1b), the model's intercept and coefficients are then converted to credit scores within a range of 1-10 using simple arithmetic transformations.

A critical aspect that had to be taken care of during modeling was the identification of the independent target variable. Since the concept of default, in its traditional finance sense, is absent in over-collateralized lending, liquidations were instead used as a proxy for potential default. Accordingly, the target label represents whether the user was liquidated within 60 days from the cut-off date at which all its historical on-chain transactions were aggregated. Furthermore, we have set up the entire process so that our risk score calculations can be executed in real-time.

2.3 Model Results

Various alternative models were assessed and compared against each other using the following metrics:

2.3.1 Ranking Metrics

Area Under the Receiver Operating Characteristic Curve (*AUROC*): The Receiver Operating Characteristic curve plots a binary classifier's False Positive Rate (FPR) on the x-axis and True Positive Rate (TPR, *Recall*) on the y-axis. $AUROC$ ranges between 0 and 1, with 1 being the score of a perfectly skilled classifier, and $AUROC > 0.75$ considered quite strong in traditional credit analysis. RociFi model's $AUROC$ is 0.83.

$$TPR = \frac{TP}{TP+FN} \tag{5}$$

$$FPR = \frac{FP}{TN+FP} \tag{6}$$

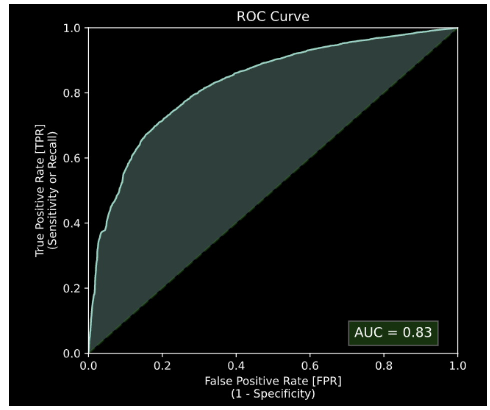

Figure 2: RociFi's model's $AUROC$ curve.

Area Under the Precision-Recall Curve: A Precision-Recall curve plots *Recall* on the x-axis against *Precision* on the y-axis (both defined below) for all the possible probability values. Since both *Precision* and *Recall* are concerned with true positives (the minority class), it makes it an effective tool for imbalanced classification problems. $PR\ AUC$ ranges between 0 and 1, with 1 being the score of a perfectly skilled model that makes no prediction errors. RociFi model's $PR\ AUC$ is 0.97.

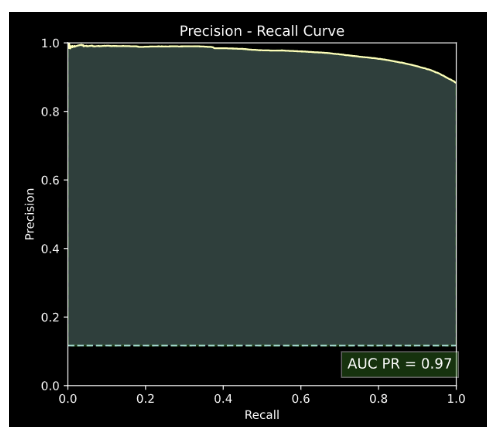

Figure 3: RociFi's model's $PR\ AUC$ curve.

2.3.2 Threshold Metrics

The ideal probability threshold for determining the following metrics was calculated using the *Youden's J* statistic - that minimizes the False Positive Rate while maximising the *True Positive Rate* (in other words, the top-left corner of the *Receiver Operating Characteristic curve*).

Recall: Also known as *Sensitivity* and *True Positive Rate* (*TPR*), *Recall* is the ratio of the count of true positives predicted to the ground-truth positives in the test data. *Recall* values range between 0 and 1, with 1 being the best. *Recall* aims to minimize the number of observations predicted as good where they were in fact bad. RociFi model's *Recall* is 0.72.

$$Recall = \frac{TP}{TP+FN} = TPR \tag{7}$$

Precision: Precision is the ratio of true positives to the total positives predicted by a model. Precision values range between 0 and 1, with 1 being the best. Precision aims to minimize the number of false positives only. However, we are also concerned with minimizing false negatives, thus we give less importance to Precision compared to *Recall* and the F_1-*Score*. RociFi model's Precision is 0.88.

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

$\mathbf{F_1}$**-Score** : F_1-*Score* provides a single score to measure both Precision and Recall. Maximizing F_1-*Score* will mean that we would have maximized both Precision and Recall, and is widely used for imbalanced classification problems. Again, F_1-*Score* ranges between 0 and 1, with 1 being the best. RociFi model's F_1-*Score* is 0.77.

$$F_1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{9}$$

2.3.3 Probability Metric

***Brier Score*:** The Brier Score evaluates the accuracy of probabilistic predictions. The Brier Score ranges between 0 and 1, with 0 being the score of a perfectly calibrated model. The lower the score, the more accurate a model's predicted probabilities are accurate. RociFi model's *Brier Score* is 0.17.

$$BrierScore = \frac{1}{N}\sum_{t=1}^{N}\left(Predicted_t - Actual_t\right)^2 \tag{10}$$

3 Loan Parameters

3.1 *Loan-to-Value* (*LTV*) - *Aave* and *Compound*

The LTVs below for Aave and Compound, which were used for analyses and revenue comparisons, were selected using the loan parameter information from their respective sites[1,2].

Aave

	token	ltv
0	DAI	0.75
1	TUSD	0.75
2	USDC	0.80
3	AAVE	0.50
4	BAT	0.70
5	ENJ	0.55
6	ETH	0.80
7	KNC	0.60
8	LINK	0.70
9	MANA	0.60
10	MKR	0.60
11	REN	0.55
12	SNX	0.15
13	UNI	0.60
14	WBTC	0.70
15	YFI	0.40
16	ZRX	0.60
17	BAL	0.55
18	CRV	0.40
19	WETH	0.80
20	XSUSHI	0.25
21	USDT	0.75
22	BUSD	0.75

Figure 4: *Aave*'s *LTV*s for assets available to borrow.

Compound

	token	ltv
0	DAI	0.75
1	ETH	0.75
2	cDAI	0.75
3	USDC	0.75
4	BAT	0.65
5	ZRX	0.65
6	REP	0.50
7	cETH	0.75
8	WBTC	0.65
9	cUSDC	0.75
10	cBAT	0.65
11	cZRX	0.65
12	cWBTC	0.65
13	cREP	0.50
14	USDT	0.75
15	cUSDT	0.75
16	UNI	0.65
17	cUNI	0.65
18	cCOMP	0.60
19	COMP	0.60
20	TUSD	0.75
21	LINK	0.50
22	cLINK	0.50
23	cTUSD	0.75

Figure 5: *Compound*'s *LTV*s for assets available to borrow.

3.2 RociFi *Loan-to-Value* (*LTV*)

For RociFi, proper risk management in terms of loan parameters and assets available to borrow is as important as our CRS system. The LTVs chosen for both stable and non-stable coins were determined by an optimization process geared to maximize revenue and keep the loan default rate less than or equal to 10%.

[1]https://docs.aave.com/risk/asset-risk/risk-parameters#loan-to-value
[2]https://compound.finance/markets

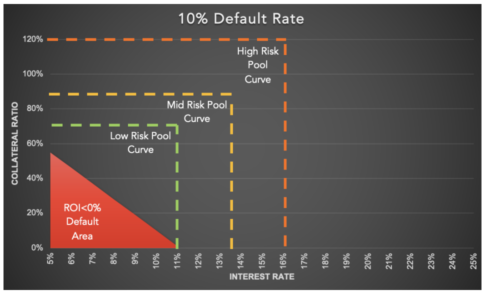

Figure 6: RociFi's lending pool risk curves and "bad" default area.

The chart above shows the area (scenarios) where RociFi lenders' *return on investment* (*ROI*) would be less than 0%. For example, assuming a 10% default rate, 5% average borrow rate, and 55% average collateral ratio, RociFi lender's *ROI* would equal 0%.

The default rate of 10% was chosen through trial and error as a way to evaluate CRS prediction risk under suboptimal circumstances. The results in this whitepaper reveal that a default rate of 10% is unlikely. Furthermore, RociFi's lending pools will be segmented by CRS with risk-adjusted borrow rates and *LTV*s for each pool. The estimated lending pool curves (Figure 6) show little risk of RociFi lender's *ROI* being less than 0%.

Note: RociFi intends to implement a zero-collateral pool with a borrow rate of 8%, which falls within the ROI < 0% default area. However, it will be a private, invite-only pool for the highest quality borrowers and lenders, e.g. funds, protocols, and blockchain entities. (Figure 7)

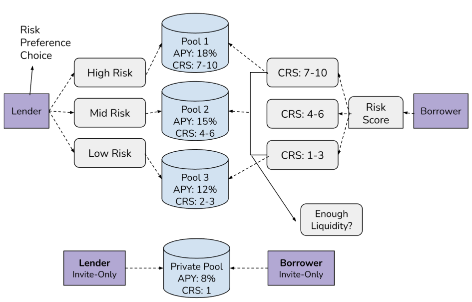

Figure 7: RociFi's lending pool architecture.

Despite the margin of safety shown in Figure 6, RociFi's initial *LTV*s and assets supported will be conservative, being gradually relaxed over time. Furthermore, the loan parameters will be updated on a continuous basis given borrow dynamics and market conditions.

Below are RociFi's *LTV*s for both revenue comparison to *Aave* and *Compound*, and projected revenue simulations.

Stable Coins

	score	ltv_roci
0	1	1.300
1	2	1.200
2	3	1.100
3	4	1.000
4	5	0.900
5	6	0.875
6	7	0.875
7	8	0.850
8	9	0.850
9	10	0.850

Non-Stable Coins

	score	ltv_roci
0	1	0.90
1	2	0.90
2	3	0.90
3	4	0.90
4	5	0.85
5	6	0.85
6	7	0.85
7	8	0.80
8	9	0.80
9	10	0.80

Figure 8: RociFi's *LTV*s for stable and non-stable assets available to borrow.

4 *Aave* Simulations

Assumptions

1. Analysis period, 1 Dec 2020 to 31 July 2021.
2. *Total protocol revenue* = *Average borrow rate* × *total net loans outstanding.*
3. Average borrow rate is 4% per annum.
4. No issues with liquidators that could have prevented a timely liquidation of at-risk loans.

4.1 *Aave* Historical Revenue

Aave's gross total revenue, *average borrow rate* (4%) × *total net outstanding loans*, from 1 Dec 2020 to 31 July 2021, was ∼ \$21M, which included 1,351 liquidation events.

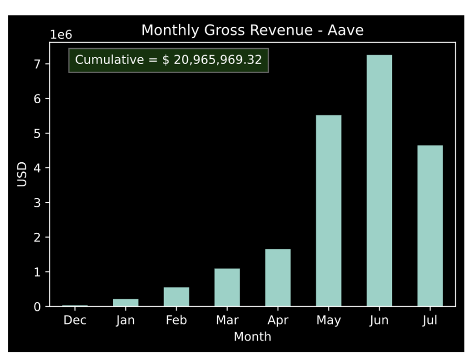

Figure 9: *Aave*'s cumulative monthly simulated revenue.

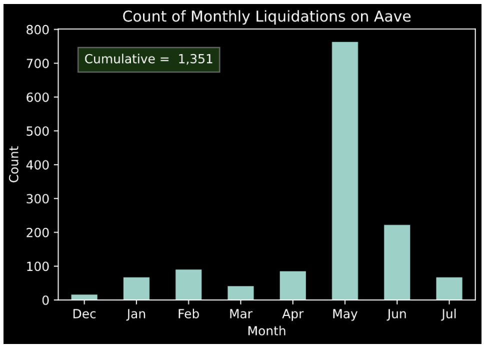

Figure 10: *Aave*'s cumulative monthly liquidation count.

4.2 *Aave* Revenue using RociFi

Assumptions

1. Analysis period, 1 Dec 2020 to 31 July 2021.
2. *Total protocol revenue* = *Average borrow rate* × *total net loans outstanding*.
3. Average borrow rate is 4% per annum.
4. No issues with liquidators that could have prevented a timely liquidation of at-risk loans.
5. All historical borrowers would choose to take the maximum loan amount afforded by RociFi's higher *LTV*.
6. No fraud, i.e. users who were granted under-collateralized loans did not simply run away with the funds.

Using RociFi's CRS system, *Aave* would have generated ∼\$24M in gross total revenue, an increase in gross incremental revenue of ∼ \$3M. Loan losses were ∼ \$1.1M, which equates to ∼ \$1.9M in incremental revenue, net of loan losses; representing a ∼ 9% boost in *Aave*'s net revenue. Loan losses as percentage of total revenue generated using RociFi's CRS system were ∼ 4.6%.

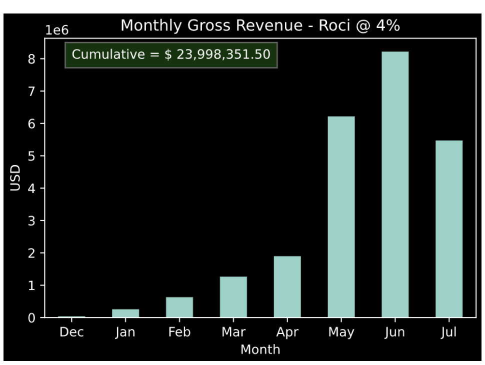

Figure 11: Aave's cumulative monthly simulated revenue using RociFi CRS.

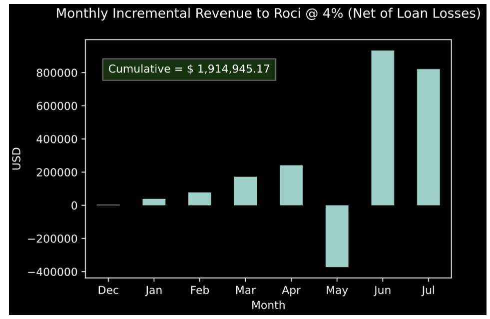

Figure 12: *Aave*'s cumulative monthly simulated revenue using RociFi CRS, net of loan losses.

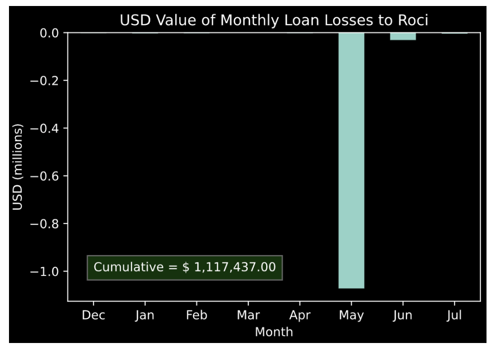

Figure 13: *Aave*'s cumulative monthly loan losses (\$USD Value) using RociFi CRS.

For clarity, the magic behind RociFi's revenue results compared to *Aave*'s is that for any given collateral type, *Aave* offers a fixed *LTV* for any borrower, regardless of their credit history. This means that more creditworthy borrowers receive less loans than they should relative to less creditworthy borrowers. RociFi's CRS system allows borrowers to receive different *LTV*s based on their credit history, which results in higher capital efficiency and revenue.

5 Compound Simulations

Assumptions

1. Analysis period, 8 May 2019 to 31 July 2021.
2. *Total protocol revenue* = *Average borrow rate* × *total net loans outstanding*.
3. Average borrow rate is 4% per annum.
4. No issues with liquidators that could have prevented a timely liquidation of at-risk loans.

5.1 *Compound* Historical Revenue

Compound's gross total revenue, *average borrow rate* (4%)× *total net outstanding loans*, from 8 May 2019 to 31 July 2021, was ∼ \$60M, which included 1,172 liquidation events.

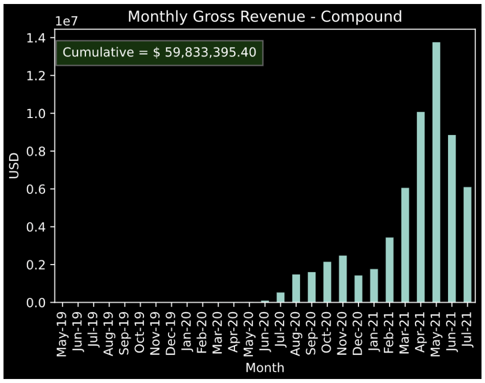

Figure 14: Compound's cumulative monthly simulated revenue.

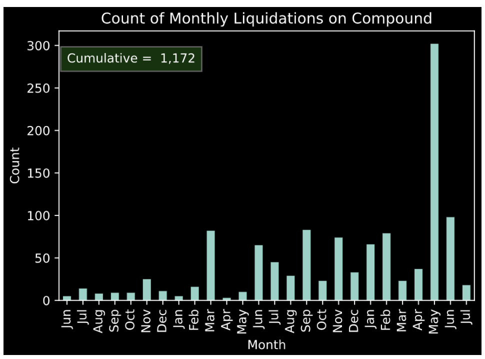

Figure 15: *Compound*'s cumulative monthly liquidation count.

5.2 *Compound* Revenue using RociFi

Assumptions

1. Analysis period, 8 May 2019 to 31 July 2021.
2. Total protocol revenue = Average borrow rate total net loans outstanding
3. Average borrow rate is 4% per annum.
4. No issues with liquidators that could have prevented a timely liquidation of at-risk loans.
5. All historical borrowers would choose to take the maximum loan amount afforded by RociFi's higher *LTV*.
6. No fraud, i.e. users who were granted under-collateralized loans did not simply run away with the funds.

Using RociFi's CRS system, *Compound* would have generated $\sim$ \$70M in gross total revenue, an increase in gross incremental revenue of $\sim$ \$10M. Loan losses were $\sim$ \$65k, which equates to $\sim$ \$10M in incremental revenue, net of loan losses; representing a $\sim$ 17% boost in *Compound*'s net revenue. Loan losses as percentage of total revenue generated using the RociFi CRS system were $\sim$ 0.09%.

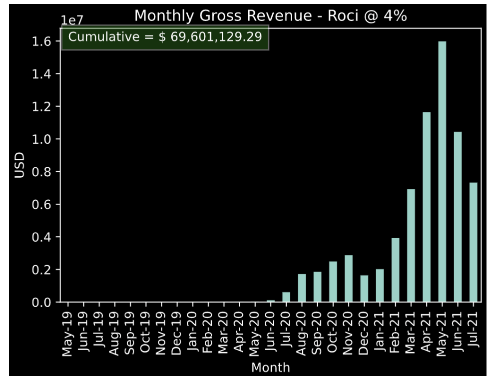

Figure 16: *Compound*'s cumulative monthly simulated revenue using RociFi CRS.

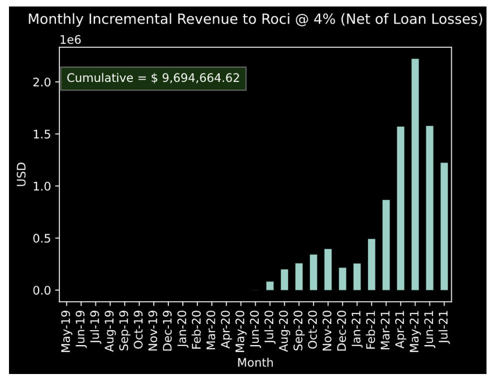

Figure 17: Compound's cumulative monthly simulated revenue using RociFi CRS, net of loan losses.

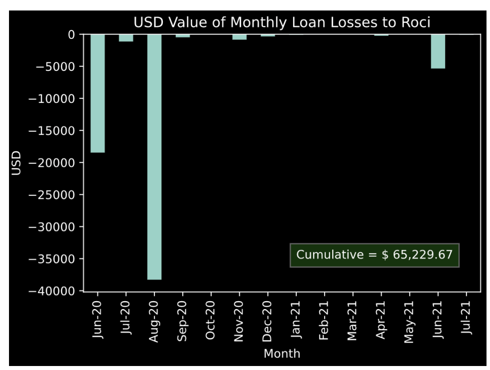

Figure 18: *Compound*'s cumulative monthly loan losses (\$USD Value) using RociFi CRS.

For reference, the stark contrast in CRS loan losses on *Compound* versus *Aave* provides an interesting insight around protocol loan parameters. Using the number of liquidations and CRS loan losses as risk proxies, *Compound* appears to be a less risky platform compared to *Aave*. This makes intuitive sense given *Compound* lends less volatile assets, which can be seen in Figures 4 and 5. Interestingly, after analyzing the risk score distributions of both protocols (Figures 21 and 22 in Appendix), *Aave* actually has slightly "less risky" borrowers compared to Compound, but still has higher liquidations.

This paradox will play a strong factor in determining what non-stable assets RociFi will lend and when to relax loan parameters. The *Compound* analysis has shown that more conservative loan parameters and assets can still generate higher revenue.

5.3 RociFi Revenue Simulations

RociFi's lending protocol will be riskier than both *Aave* and *Compound* given the under-collateralization, and fixed term and rate of loans issued. Given that, the average borrow rate used to calculate total protocol revenue was 8% per annum versus 4%. This adjustment makes logical sense given additional risk commands a higher borrow rate.

Assumptions

1. Analysis period, 8 May 2019 to 31 July 2021 for *Aave*.
2. Analysis period, 8 May 2019 to 31 July 2021 for *Compound*.
3. *Total protocol revenue* = *Average borrow rate* × *total net loans outstanding*.
4. Average borrow rate is 8% per annum.
5. No issues with liquidators that could have prevented a timely liquidation of at-risk loans.
6. All historical borrowers would choose to take the maximum loan amount afforded by RociFi's higher *LTV*.
7. No fraud, i.e. users who were granted under-collateralized loans did not simply run away with the funds.

5.3.1 Revenue Simulation 1 - *Aave* Loan Volume

Assuming *Aave*'s historical loan volume and borrower profiles, RociFi would have generated ∼ \$48M in gross total revenue from 1 Dec 2020 to 31 Jul 2021 with loan losses of ∼ \$1.1M.

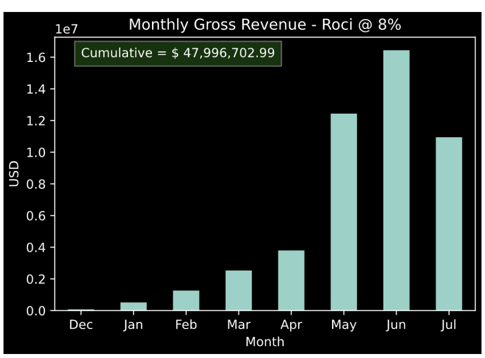

Figure 19: RociFi's cumulative monthly simulated revenue using *Aave*'s loan volume.

5.3.2 Revenue Simulation 2 - *Compound* Loan Volume

Assuming Compound's historical loan volume and borrower profiles, RociFi would have generated ∼ \$140M in gross total revenue from 8 May 2019 to 31 Jul 2021 with loan losses of ∼ \$65k.

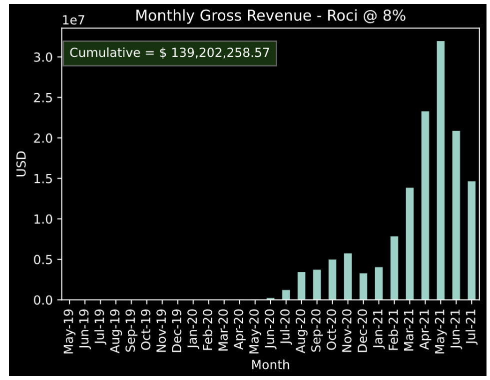

Figure 20: RociFi's cumulative monthly simulated revenue using *Compound*'s loan volume.

5.3.3 Revenue Simulation 3 - Combined Loan Volume

Assuming both *Aave* and *Compound*'s historical loan volume and borrower profiles, RociFi would have generated ∼ \$190M in gross total revenue with ∼ \$1.1M in loan losses.

6 Conclusion

In this whitepaper, a novel approach to credit risk scoring is demonstrated; one that combines on-chain data, Machine Learning and loan risk-management to effectively and profitably facilitate under-collateralized loans. Furthermore, despite the assumptions and limitations of the backtest results, RociFi's modeling approach, out-of-sample results, and continual model upgrades provide high confidence that these results will hold in the real-world once RociFi's lending protocol is launched.

Additionally, our comparative analysis uncovered certain insights regarding *Compound* and *Aave*'s loan parameters and borrower profiles. *Compound* appears to be slightly more conservative than *Aave*, which has higher liquidations. Interestingly, *Aave*'s risk score distribution (Figure 21) is slightly less risky than *Compound*'s (Figure 22), but 54% of *Aave*'s total loan volume was rated as CRS 7-8 (Figure 23). Comparatively, 60% of Compound's total loan volume was rated as CRS 5-6 (Figure 24).

The above insights will play a strong factor in determining which non-stable assets RociFi will lend and when to relax loan parameters. RociFi's Compound analysis has shown that optimized loan parameters and asset selection can generate higher revenue while minimizing losses.

A Supplementary Calculations

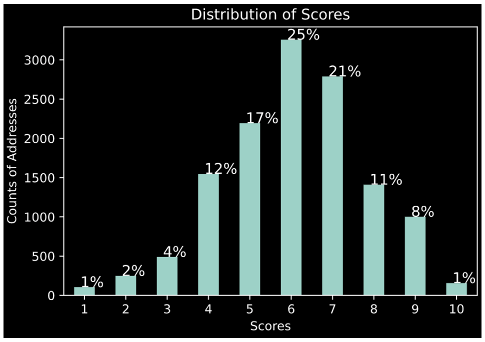

Figure 21: RociFi's CRS distribution of *Aave* borrowers.

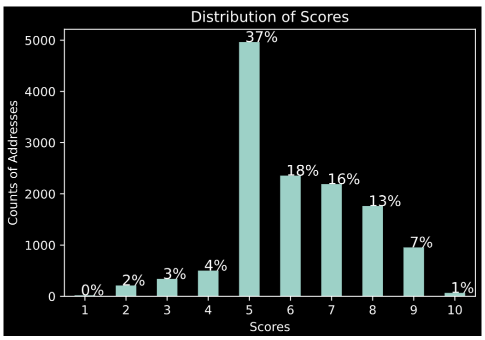

Figure 22: RociFi's CRS distribution of *Compound* borrowers.

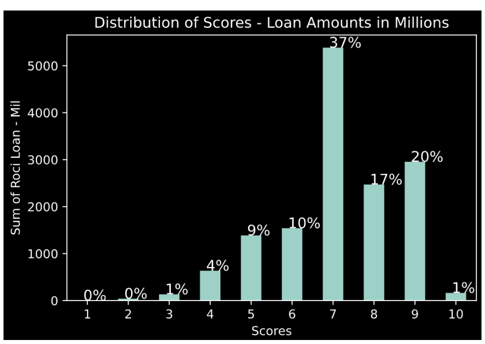

Figure 23: *Aave* total loan amount distribution by RociFi CRS.

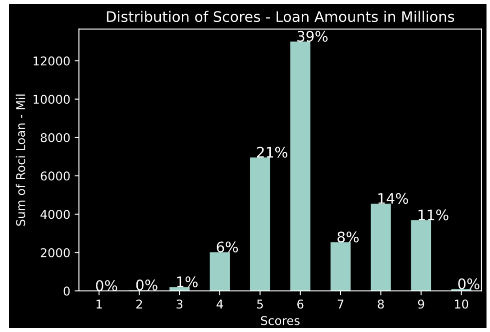

Figure 24: *Compound* total loan amount distribution by RociFi CRS.

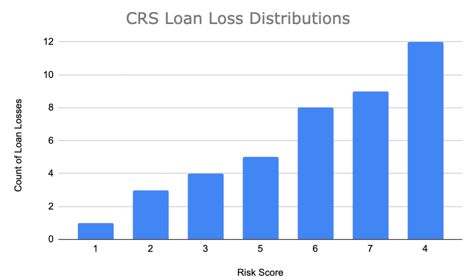

Figure 25: RociFi loan loss distribution by CRS for *Aave*.

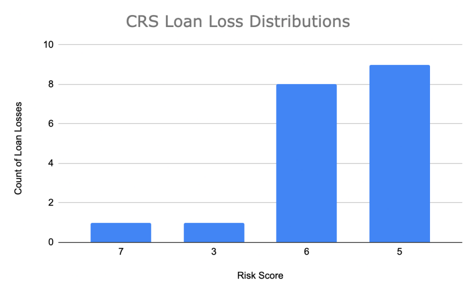

Figure 26: RociFi loan loss distribution by CRS for *Compound*.