A Simple Top-Down Perspective to Risk Management for Affirm

Objective

I will present here the ideas for using two very simple metrics – one a credit risk one and the other a profitability calculation. Though very basic, they can prove to be very powerful in the context of risk modelling of Affirm's loan portfolios and thus in turn assist in pricing strategies as well. Both build up on Affirm's advanced analytical tools and thus I think should be simple additions to the current modelling infrastructure.

The suggested credit risk metric is Probability of Default (PD) based on the proprietary Affirm credit quality scoring tool – *ITACs* classes and the profitability metric is a simple profit calculation as revenue minus costs, computed with the help of the confusion matrix obtained from Affirm's loan default prediction models.

Motivation

Affirm has been growing at a very ambitious pace and this has in turn led to a huge increase in proportion of relatively subprime borrowers over the last couple of years, as is reflected from it's own credit scoring methodology in the financial statements -;

The following table presents an analysis of the credit quality, by ITACs score, of the amortized cost basis by fiscal year of origination on loans held for investment and loans held for sale (in thousands) as of December 31, 2021:

	Amortized Costs Basis by Fiscal Year of Origination						
	2022	2021	2020	2019	2018	Prior	Total
96+	$ 950,760	$ 378,657	$ 61,263	$ 2,316	$ 1	$ —	$ 1,392,997
94 – 96	433,536	96,220	2,221	129	2	—	532,108
90 – 94	194,066	35,571	203	4	—	—	229,844
<90	87,498	96	—	—	—	—	87,594
No score(1)	140,972	41,598	7,178	875	167	7	190,797
Total loan receivables	$ 1,806,832	$ 552,142	$ 70,865	$ 3,324	$ 170	$ 7	$ 2,433,340

That's an origination of "<90" scored loans of 87,498/1,806,832 = 4.84% in 2022, up from <1% in the previous year (computed from financial statements of previous year) – a 5x increase in proportion, and similar sizeable increase in "No score" quality loans as well. The need for an appropriate measure of credit risk for these increasingly riskier loans is the need of the hour for Affirm, both for decision making in risk management (approval rate of new loan applications) and for pricing (charging the right surplus in interest rates). The PD should be an essential metric in the credit risk management toolbox for Affirm.

Additionally for future predicted PD by Affirm's loan default models (binary classification ML), for deciding the approval/denial of the loan application and thus the classification threshold, the simple profit calculation could be a useful metric. From running the models on the past training data and obtaining the corresponding confusion matrix and AUC-ROC curve, we can alter the classification threshold in such a way so as to maximize the profit metric (more on the computation in the following 'Methodology' section).

Methodology

Pang and Hou suggest classification of various approved loans using a ML technique of clustering using user level and transaction level features (Pang, Hou and Xia, 2021) but Affirm already has that in hand with it's ITACs credit scoring tool. We can compute the PD in each of these 5 given classes as -;

PD(i) = D(i) / N(i)

Where 'i' is the subscript of the loan class, PD the Probability of Default, D the number of defaults and N the total number of sample loans classified for the particular loan class. The progression of these PDs over the years for each class can then be assessed against the tolerance criterion (of how much risk can Affirm afford) for each of the loan class samples and can thus assist in portfolio risk allocation strategy.

The profitability metric can be calculated with the help of the confusion matrix, based on the concept that the 'True Positives' would be the past loans that Affirm approved and managed to pay off the principal with interest in a timely manner, whereas the 'False Positives' would measure the Predicted Defaults that actually did manage to pay off in time without delinquency. Similarly the True and False negative would apply for the vice versa as can easily be seen in the diagram below-;

Confusion matrix.

		Predicted class Default	Non-default
Actual class	Default	TN	FN
	Non-default	FP	TP

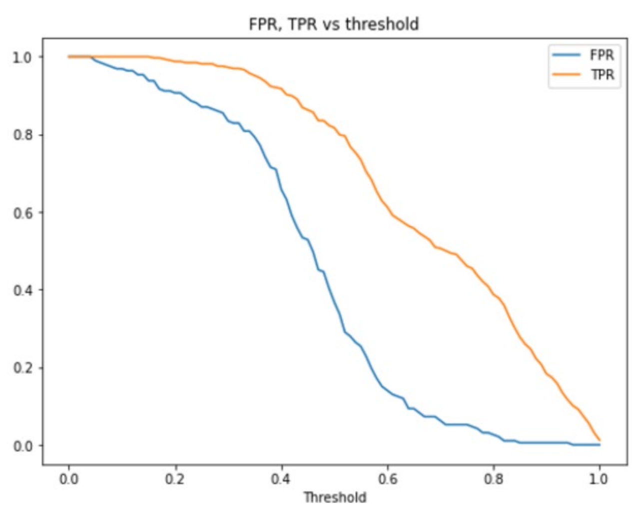
The actual Profit calculation could look something like-;

Profit = Revenue – Cost,

where Revenue = Σ(i) L(i) *TP(i),

Cost = Σ(i) L(i) *(FP(i) + FN(i)) and 'i' is the subscript of the particular loan transaction ,'L' represents Loan Amount and TP, FP and FN are all Booleans representing the success/failure of each loan classification and the summation thus acts over all loan transactions

Thus there is a cost associated with both failing to correctly predict a default and an opportunity cost with predicting a default even when there is none. This should give us a graph like below -;



And using any simple optimization methods, it should be easy to optimize for the profit metric mentioned here using historical loans data.

Pitfalls

Of course, the simplicity of the calculation of these metrics could be deceiving and the following limitations should be kept in mind-;

- The calculation for PD does not take into account any external macroeconomic factors and the changes in interest rates. These factors could cause massive differences between PDs of even the same loan class over different economic climates. For instance, the PDs in the recent Covid period can be expected to be on the higher end, and making pricing decisions based on the assumption that these stressed PDs will carry forward in normal times too may be incorrect.
- Seasonality of the loan default data is also not considered in the computation of these metrics. It is a well-known fact that due to the nature of this time series data, there is cyclical behavior in loan default patterns.
- Insufficient historical data – In the past, there have not been too many loans approved in the low ITACs score and unscored credit classes. Computing PDs on such short time series data with few data points may give incorrect results.

Conclusion

The reasoning for suggesting the two metrics presented here was twofold- first to offer effectiveness in making risk management decisions for Affirm's loan portfolio from a **top-down perspective** and second, to leverage Affirm's powerful analytics toolkit (ITACs scoring and ML default prediction).

The first metric PD is a fundamental credit risk metric that should be gauged against the tolerance threshold and interest rates/merchant fees of each credit class (segmented by ITACs score) – if found favorable, Affirm can look to more aggressively seek borrowers from this segment, and if not then it can look to either de-risk from that segment or to increase interest rates/merchant fees for transactions in that credit class.

Moving from the portfolio level to a more granular level of decision making for each particular loan application, the profitability metric can be resorted to. Drawing from the confusion matrix of Affirm's expert binary classification models, it can help in delineating a very clear threshold boundary in predicting defaults, thus assisting in making a very simple automated approve/deny decision for future loan applications.

References

Pang, P., Hou, X. and Xia, L., 2021. Borrowers' credit quality scoring model and applications, with default discriminant analysis based on the extreme learning machine. *Technological Forecasting and Social Change*, 165, p.120462.

Volk, M., 2014. Estimating probability of default and comparing it to credit rating classification by banks. *Economic and Business Review*, 12(4).