Impact of Local Economic Vitality on Residential Loan Portfolio Performance

Home building and remodeling—residential fixed investment—contributed 3.5% to US GDP in 2016[1]. As of December 2016, there is over $10 trillion in outstanding mortgage debt for one- to four-family residences[2]. Depository Institutions, Fannie Mae, and Freddie Mac hold over two-thirds of these residential mortgages. Any improvement in credit risk assessment of these mortgages would enhance investor capabilities for tuning their risk/reward profile and benefit consumers through improved pricing and greater availability.

Industry-wide, borrower (negative) equity in the property is accepted as a driver of default and, therefore, residential mortgage credit risk assessment typically incorporates a view on the trajectory of home prices. Analogously, we propose that credit risk assessment also incorporate a view on borrowers' future income prospects. Such a forward-looking view would supplement the currently used gauge of *income stability*.

WAIN Street's Local Economic Vitality is a monthly subnational ranking derived from macroeconomic factors such as labor market conditions, industrial production, sales, housing market conditions, and financial conditions. From a consumer credit risk perspective, it reflects a borrower's future economic prospects—a factor that influences consumer credit performance yet is not included in credit score construction[3]. Local economic vitality provides an additional factual, systematic, and timely perspective on borrower credit risk.

Predictive value of local economic vitality

To assess the advantage of using economic vitality as a predictor of loan defaults, we analyzed over twenty thousand re-performing residential loans (RPLs) closed during 2013-2014. The loans were purchased by an RPL investor. At end 2016 Q3, the RPL portfolio had experienced a 5.7% (equal-weighted) default rate.

We evaluated two Random Forest models for predicting loan defaults in the RPL portfolio.

1. Baseline model using FICO, LTV, Loan Type (fixed vs. adjustable), and RPL investor assigned PD.
2. Enhanced model that added WAIN Street Local Economic Vitality 1, 3, and 6 months prior to each loan's closing date based on the core-based statistical area (CBSA) of the property.

Both models relied on repeated cross-validation to ameliorate overfitting concerns and utilized a smoothed bootstrap approach to handle class imbalances.

Model performance

The enhanced model performed better on aggregate threshold-independent measures as summarized below.

Measure	Baseline model	Enhanced model
AUC	0.58	0.61
K-S statistic	0.11	0.16
H-measure	0.02	0.03

[1] https://www.bea.gov/national/index.htm
[2] https://www.federalreserve.gov/econresdata/releases/mortoutstand/current.htm
[3] http://www.wainstreet.com/blog/1926/

With some hand-waving, one can describe AUC and K-S statistic as quantifying the ability of a model to discriminate between loans that default and those that do not. The H-measure is a newer (circa 2009) alternative to AUC which traces its roots to WWII.

Cost sensitive performance

The cost of failing to predict a default is not the same as the cost of missing a non-default. We evaluated model performance recognizing this asymmetry. An intuitive starting point is to use the prevailing ratio of non-defaults to defaults. In the RPL portfolio, the value was 16.6 which translates to "missing a default is 16.6 times as grave a mistake as incorrectly identifying a default". This *misclassification cost* can be used to identify an optimal threshold for prediction. Using such an approach, the enhanced model performed better as summarized below.

Measure	Baseline model	Enhanced model
False negative rate	0.48	0.37
False discovery rate	0.93	0.93
Diagnostic odds ratio	1.55	1.92

The False negative rate gauges the extent to which we miss identifying a default—an expensive mistake that is less frequent in the enhanced model. The False discovery rate gauges the extent to which we incorrectly identify a default and thereby lose out on an opportunity—both models are similar in this aspect of performance. As an aside, there is a tradeoff between these two measures that must be understood in the context of the misclassification costs.

In medical testing, where the cost of missing a diagnosis is very high and the cost of raising a false alarm an expensive nuisance, the Diagnostic odds ratio is used as a single indicator of overall test accuracy. It is defined as the ratio of the odds of the test being positive if the subject has a disease relative to the odds of the test being positive if the subject does not have the disease. Its applicability to credit risk is immediate—missing a default negatively impacts the bottom line and being too restrictive denies portfolio opportunities. We prefer this measure as a succinct representation of a model's ability to identify defaults and note that the enhanced model performs better on this score.

Quantifying the advantage

The foregoing demonstrates that the enhanced model is more effective in identifying defaults. We can put a number on "how much better". An 11 percentage point improvement in False negative rate translates to missing 11% fewer defaults. In the RPL portfolio, the default rate was 5.7% and hence, the enhanced model would have decreased that default rate to 5.1%. Stated differently, the enhanced model could have prevented 120 defaults in the RPL portfolio of 20,000 loans.

Conclusion

WAIN Street's Local Economic Vitality provides granular and timely data that investors can incorporate into their credit risk assessment of residential loans to improve loan selection and pricing capabilities. In a sample portfolio of re-performing loans, using this data improved default prediction by over 10%.

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