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Economically Conditioned Credit Scores: An Example From Auto Loans

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Introduction

Consumer credit scores have become ubiquitous. Credit scores are used in everything from making loan decisions to setting insurance premiums to online dating applications. The reason behind this adoption lies in the power of credit scores to condense a variety of variables or metrics into a single number. Despite the widespread use of analytical tools such as machine learning in the development of scores, most credit scores lack features that would extend and enhance their utility across multiple users and applications. Specifically, the incorporation of detailed economic information in the credit scoring process could improve their accuracy and interpretation.

Economically Conditioned Credit Scores: An Example From Auto Loans

BY CRISTIAN DERITIS

Consumer credit scores have become ubiquitous. Credit scores are used in everything from making loan decisions to setting insurance premiums to online dating applications. The reason behind this adoption lies in the power of credit scores to condense a variety of variables or metrics into a single number. Despite the widespread use of analytical tools such as machine learning in the development of scores, most credit scores lack features that would extend and enhance their utility across multiple users and applications. Specifically, the incorporation of detailed economic information in the credit scoring process could improve their accuracy and interpretation.

In this study we examine how credit scores change and evolve over the business cycle. We discuss how credit scores may be influenced by external factors in addition to the internal or individual factors that they are designed to capture. We propose two methods for controlling these external risk factors across the business cycle in order to adjust credit scores for both the current and future states of the economy. Not only can economically conditioned credit scores provide a more complete picture of credit risk, but they also can provide a more accurate assessment of borrower-specific risks by teasing out external factors.

An adjusted credit score can provide a consistent measure of the absolute level of credit risk posed by a borrower across both time and space in addition to the relative rank-ordering that scores currently provide. The use of an economically adjusted credit score can permit lenders to maintain the same level of risk of default within their portfolios without having to constantly recalibrate their lending score cutoffs—an involved process that often occurs after risky loans have already been originated. Our research can also help explain the higher than expected losses experienced by some lenders recently. Lenders have been puzzled by rising losses despite having made no changes to their lending standards during a period of economic expansion. While their credit score cutoffs may not have changed, the meaning of the credit score itself may have led them to approve borrowers with higher than expected default risk.

What's in a score

The primary purpose of a credit score historically has been to combine disparate pieces of information about a borrower into a single, consistent, rank-ordering metric. Dealing with a single number facilitates lending operations and can improve communication with the individual borrower as well as with other stakeholders. A statistical approach to scorecard development imposes logic and consistency that go beyond the limits of human comprehension once more than a few credit risk factors are considered.

The two best known consumer credit scores in the United States are the FICO score produced by the Fair Isaac Corp. and the VantageScore produced by VantageScore Solutions, a limited liability corporation owned by the major consumer credit bureaus: Experian, Equifax and TransUnion.

Although FICO and VantageScore utilize different modeling technologies, the underlying algorithms are based on similar sets of information from consumer credit reports and produce roughly similar results in terms of rank-ordering. This should come as little surprise given that the primary factor in the determination of credit risk is a borrower's previous experience with credit. Borrowers who have been delinquent in the past are more likely to become delinquent in the future. Credit scores also consider utilization rates or the fraction of available credit that consumers have already borrowed against. This measures financial flexibility as borrowers with open credit lines may be better positioned to deal with unforeseen events than borrowers who are credit-constrained. Other factors include the length of experience with credit and credit mix or the relative mix of revolving and installment accounts held by a borrower.

In addition to these two generic scorecards, most large lenders have developed their own proprietary credit scores as well. Credit scores that are calibrated to specific lending products and portfolios will outperform generic credit scores within their specific applications by construction. While the specifics may differ, the methodology for developing scorecards tends not to differ dramatically across institutions.

Generally speaking, credit score models will seek to rank-order borrowers based on their delinquency performance within a given performance window. For example, the observance of a 90-day delinquency within a 24-month window is a common metric for estimating credit score models. The idea here is that a 90-day delinquency is severe enough that it captures true borrower behavior and not a randomly missed payment. Twenty-four months is also deemed a sufficient amount of time for such an event to be observed. Typically, logistic regression models have been applied to this problem with a variety of automated techniques utilized to comb through the thousands of credit variables collected by the consumer credit bureaus in order to find those that are most predictive of performance. In addition to out-of-sample model fit, developers will usually require that parameter estimates are intuitive and monotonic in order to facilitate communication and comply with fair lending regulatory requirements.

A typical scorecard may have anywhere from five to 20 individual risk factors, although some will have many more or use segmentation to develop unique scorecards on specific subpopulations. The specification of the individual factors in a scorecard model may be linear, categorical, polynomial, or some other nonlinear transformation depending on this specific nature of the variable in consideration and its correlation to the delinquency or default outcome.

As they are highly tuned to an individual borrower's previous credit history, credit scores tend to do a very good job in rank-ordering the probability of nonpayment across individuals. Common measures of rank-ordering accuracy include the Kolmogorov-Smirnov or K-S statistic. Typically, credit score models will have a K-S statistic in the range of 0.5-0.8, indicating that the scorecard accurately assigns low scores to high-risk borrowers and high scores to low-risk borrowers.

We live in a society

While internal characteristics are the most important factors in determining a borrower's future payment performance, clearly the external economic environment has an impact on performance as well. It is simply much easier to meet monthly debt payments if jobs are plentiful and wages are rising. The reverse is true in an economic recession or depression. Even the most cautious, careful consumers may have trouble making payments if they have the misfortune of being laid off.

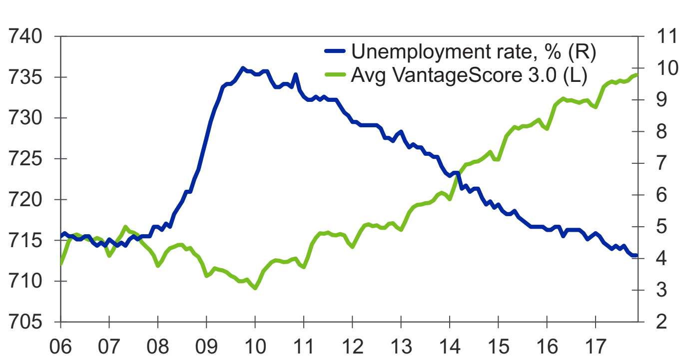
As a result, it is necessary to consider the impact of the external economic environment when either constructing or using credit scores. For example, there is a clear inverse relationship between the average credit score in the population and the overall unemployment rate (see Chart 1). The relationship with house price growth is much less pronounced but positive (see Chart 2).

We observe two phenomena related to credit scores during economic expansions. First, overall credit scores rise given declines in delinquency rates across consumer credit categories (see Chart 3). Not only does the average credit score in the population rise, but the number and percentage of individuals with lower or subprime credit tends to decline. At present, the number of subprime consumers with VantageScores below 620 is at a record low.

Second, the relative risk of default between borrowers with different credit scores tends to widen during economic expansions. Many borrowers will be classified as subprime during an economic contraction due to external reasons such as general joblessness that may be difficult to distinguish from individual-specific factors. However, borrowers who are still classified as subprime during an economic expansion will tend to pose a much higher relative risk of default. As a result, lenders should be particularly cautious in targeting subprime borrowers during expansions. Though the absolute default rate on subprime loans will be lower during expansions, lenders may be surprised to find that performance is not even better. This group of borrowers is also particularly vulnerable to any type of future slowdown in the economy, warranting extra caution on the part of lenders.

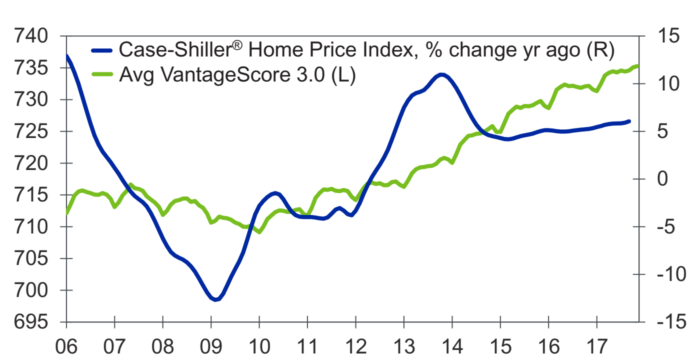
While the distinctions between prime and subprime borrowers may be more pronounced during expansions, the differences within credit score bands may be less

Chart 1: Credit Scores and Unemployment



Sources: CreditForecast.com, BLS, Moody's Analytics

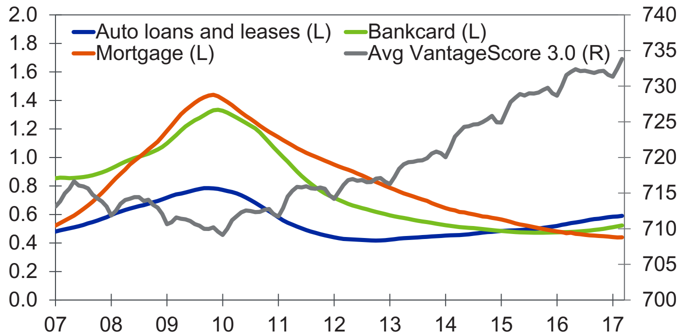
Chart 2: Credit Scores and House Prices



Sources: CreditForecast.com, BLS, CoreLogic, Moody's Analytics

Chart 3: Scores Mirror Delinquencies

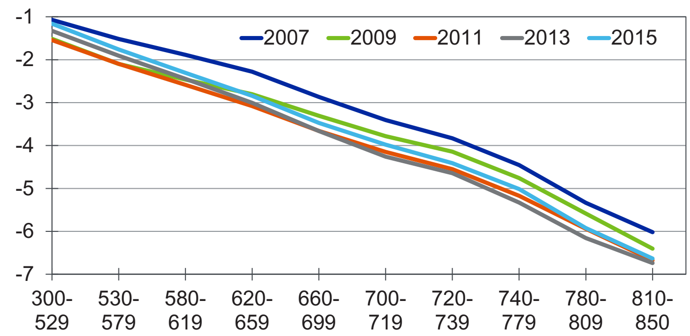
60 days delinquent, % of outstanding balance, 12-mo MA



Sources: CreditForecast.com, Moody's Analytics

Chart 4: Odds Ratios Vary by Vintage

Log odds ratios by VantageScore 3.0 and origination yr



Sources: CreditForecast.com, Moody's Analytics

pronounced, as the rising economic tide can influence borrower behavior, particularly at the higher end of the credit spectrum. Some borrowers will find it easier to make their payments and to control their spending levels in order to increase their credit scores. The Hawthorne effect is a well-known concept in psychology whereby individuals who know that they are being observed will adjust their behavior to maximize a favorable measurement. As monthly payments are either made or they are not, it is difficult to distinguish between those borrowers who are able to pay because the economy is favorable from those who are resilient across economic environments. As a result, a credit score based solely on individually observed factors may not fully capture differences in the risk of individual borrowers.

Catching the credit drift

These observations have led to the development of a theory of credit score drift. The default risk of borrowers with the same credit score may change across the economic cycle due to the influence of both internal and external forces. For example, we may observe increases in delinquency rates in loan portfolios even after we control for credit score, geography, and other observable borrower characteristics due to shifts in the population of eligible and approved borrowers.

In the sections that follow, we propose two methods for adjusting credit scores to take into account or control for the impact of externally driven events. Conceptually we may think of adding points to borrowers' credit scores during times of conservative lending such as that which occurs during economic contractions and subtracting credit score points from borrowers during periods of aggressive lending as might occur during a boom or credit expansion.

Option 1: An absolute credit risk score

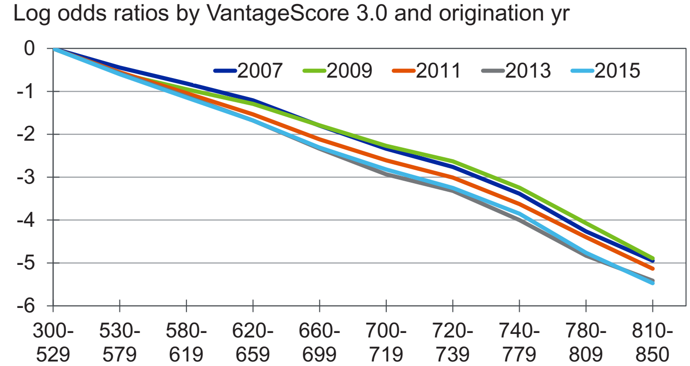
For the purpose of exposition, we focus on the performance and credit scores of auto loans originated by banks. However, the methods described can be generalized to any loan product category as well as a generic credit score. We utilize consumer credit performance data from CreditForecast.com for our analytics. The data consist of volume and performance information aggregated across all of the consumer credit reports in the Equifax database. The data are updated monthly back to July 2005 and are broken out by product, geography, origination quarter, loan term, and 10 Vantage credit score bands.

As a first step we went back historically and calculated the cumulative two-year default rate for each origination vintage by loan term by state by credit score band segment. We defined this probability of default, or PD, rate as the sum of outstanding balances on default loans divided by the origination balance for each cohort. Defining losses from origination permits us to control for maturation of individual loan portfolios. Younger portfolios will tend to have higher default probabilities than more seasoned portfolios where most of the default events may have already occurred.

We converted the two-year default rates to log odds ratios, log(PD/(1-PD)), in order to examine the variation in performance by credit score (see Chart 4). The data show significant variation by vintage. For example, a log odds ratio of -4 (with a PD rate of 1.8%) was associated with a 720-739 credit score for 2007 originations but only a 700-719 credit score for the 2011 and 2013 vintages with stronger credit quality. Shifting the log odds curves to a common level or anchor point reveals that significant variation in performance by credit score remains even after we account for level differences (see Chart 5). That is, a 720 VantageScore originated in

Chart 5: Slopes of Odds Ratios Vary, Too

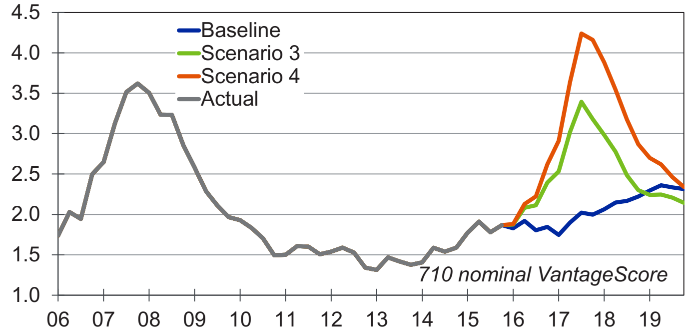
Log odds ratios by VantageScore 3.0 and origination yr



Sources: CreditForecast.com, Moody's Analytics

Chart 6: Auto Loan PDs Vary With Cycle

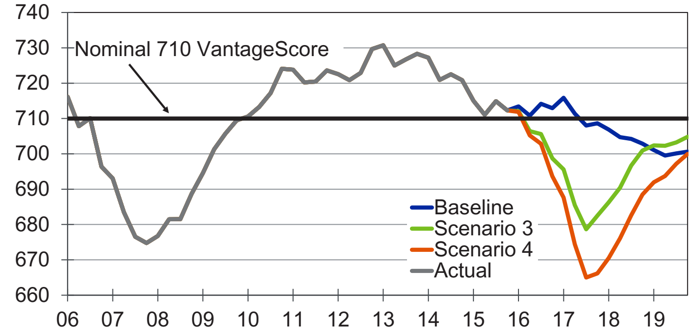
Cumulative probability of default over 24 mos by orig. vintage, %



Sources: CreditForecast.com, Moody's Analytics

Chart 7: Scenario Conditioned Scores

Economic outlook adjusted VantageScore 3.0 by orig. vintage, %



Sources: CreditForecast.com, Moody's Analytics

2007 still performed relatively worse than a 720 VantageScore originated in 2013. Not only did the odds ratio curves shift across vintages, they also tilted.

Chart 6 provides an example of these cohort-level default rates for auto loans originated to borrowers with a VantageScore between 700 and 719. Based on this example, we observe that the two-year default rates were highest for loans underwritten in 2007. The cohort default rates fell dramatically right after the recession ended, with 2013 loan originations having a default rate that was 60% lower than the 2007 cohort.

Repeating this exercise for all cohorts produced a dataset with which to examine the relationship between credit scores and loan performance. We used the 24-month cumulative default rate as a proxy for the state of the economy in our credit score normalization exercise. Not only is the probability of default of greatest importance to lenders, it is also highly correlated with key economic indicators such as GDP growth and the unemployment rate.

We estimated a series of models that regress the VantageScore on a logarithmic transformation of the 24-month cumulative probability of default, or PD. The logarithmic transformation of the rate expands the range of the probability of default from the [0,1] interval and is more highly correlated with the VantageScore than the untransformed default rate. We tested a variety of log and logistic specifications for robustness and found minor variation in model fit (see Table 1). Specification [6] provided the best fit at the U.S. level and was used to generate our new credit score based on the absolute level of credit risk. We tested variations of the analysis on different performance windows (12-month, 36-month and 48-month) and found little change in the qualitative results.

Next, we re-centered the resulting credit scores from this model to ensure that the average score within each credit score band matched the nominal credit score across the business cycle. For example, a stated (or nominal) credit score of 710 would have been reduced to 680 in 2007 to capture the heightened risk of that cohort and increased to 730 for 2013 originations given their lower probabilities of default (see Chart 7). However, the average adjustment to credit scores from 2006 to 2015 is 0 by construction. Alternatively, users could choose not to re-center the scores or to create their own rating scale (say from 0 to 100) if they wish to make a clear distinction between the nominal VantageScore and this economically conditioned score.

As this score is forward-looking, it requires a set of economic forecasts in order to generate the score for future originations. Assumptions on key economic indicators such as GDP growth, unemployment rates, initial unemployment insurance claims, and interest rates will impact forecast PDs and the adjusted credit score by extension. The PD model used for this analysis comes from the CreditForecast.com forecasting service and incorporates the state of the economy at the time of origination, consistent with our observation that poorer quality loans tend to be originated during times of eco-

Table 1: VantageScore Regression Models

	Vintage-state-term level					Vintage level	
VantageScore=	[1]	[2]	[3]	[4]	[5]	[6]	[7]
logp	-42.2613		-47.8347			-46.1996	
log(1-p)	171.7636		176.0563			385.4053	
log(p/(1-p))		-45.0497		-50.5957	-52.6207		-59.0754
State dummies			X	X	X		
Term dummies			X	X	X		
Vintage dummies					X		
constant	485.3633	468.8210	449.4638	433.3702	427.4179	530.1075	461.5088
R-squared	0.6239	0.6205	0.7357	0.7324	0.7607	0.9721	0.9530
N observations	140,403	140,403	140,403	140,403	140,403	560	560

Source: Moody's Analytics

nomic expansion when competition among lenders leads to a race to the bottom in underwriting standards.

Under a baseline economic scenario, we observe that the credit quality of auto loans is expected to remain relatively stable over the next few years (see Chart 7). Continued improvements in the economy under the baseline scenario should put downward pressure on defaults, as low unemployment and wage growth make it easier for borrowers to make their payments. However, the growing economy will also lead to the aforementioned drift in credit scores, putting upward pressure on default rates as the population of 710 score borrowers will not be constant. The latter effect will eventually overwhelm the former such that the 710 VantageScore loans originated at the end of 2018 will perform more like loans with a 700 economically adjusted credit score.

The credit score adjustments become larger under expectations of an economic contraction. Under the mild recession scenario represented by the Moody's Analytics Scenario 3, we observe that the performance of loans originated in 2017 would be on par with that of loans originated in 2007. Although the economic outlook for Scenario 3 is not as severe as the Great Recession, the presumption is that the inherent credit quality of auto loan borrowers has diminished as a result of more aggressive lending over the past five years. Lenders should require borrowers to have higher VantageScores in 2017 and 2018 if they wish to maintain the same level of risk.

The Moody's Analytics Scenario 4, which represents a severe economic downturn even worse than the Great Recession in terms of the magnitude of the decline and length of recovery, would increase PDs thereby causing our adjusted credit scores to fall even further.

For lenders currently relying primarily on generic off-the-shelf credit scores, Option 1 provides a quick and effective method for either adjusting the credit scores of their applicants or the credit score cutoffs in the lending policies. For example, a lender comfortable with "average 710 credit score" risk should start to subtract credit score points from individuals as they review loan applications in 2018. Alternatively, the lender could leave applicants' reported credit scores alone while adjusting their credit score cutoffs upward such that they will require applicants to have scores of 720 or higher in 2018.

Option 2: Credit score drift quantification

A credit score based on the absolute level of credit risk represented by a borrower is insightful, but it may not be a reasonable solution for lenders who have already developed their own probability of default models. PD models conditioned on economic drivers along with other factors such as credit score, loan-to-value ratio, and loan age may already capture some of the variation in default rates across origination vintages. Utilizing the adjusted credit score from Option 1 in place of the observed (nominal) credit score in these models could result in the "double-counting" of risk factors and lead to an overprediction of credit risk.

The impact of credit score drift will vary across specific PD models. In some instances the models may already capture the implicit impact of the drift through the interaction of credit scores with economic factors. If this is the case, then the models may be checked to ensure that they back-test well across a variety of positive and negative economic environments. If they back-test well, then no further external credit score adjustments may be needed.

In general, PD models may fail to fully capture the impact of credit score drift for a variety of reasons, including the lack of robust historical data. We propose a relatively straightforward method for estimating the impact of the drift through various stages of the business cycle by examining the historical prediction errors of the PD models in use and computing the credit score adjustments necessary to bring these prediction errors to zero.

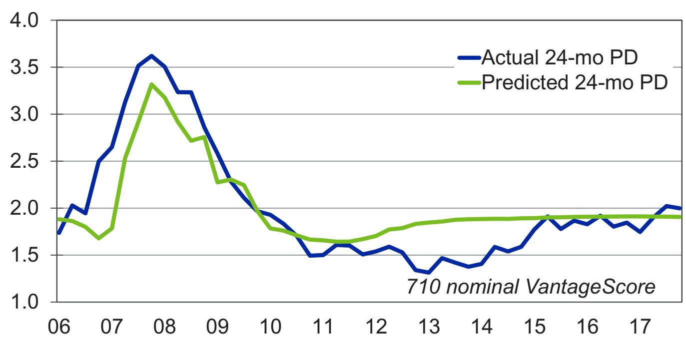
For the purpose of our exposition, we estimate a simplified model of the log odds transformation of the 24-month default rate for each of our auto loan cohorts as a function of origination credit score, loan term and geographic location (that is, state), as well as the unemployment rate 24 months from origination. Although this model could be refined further, it performs relatively well with a high in-sample R-squared value (see Table 2). In-sample predictions based on the realized unemployment rate show a reasonable fit that captures the sharp rise in defaults during the recession as well as the rapid decline in default rates throughout the recovery period (see Chart 8).

Although the model performed well, we observe that it did not fit the data perfectly. Predicted default rates fell short of the recession peak and were higher than actual values for the 2013 and 2014 vintages. While the model's shortcomings may be addressed by altering the specification and/or introducing additional factors, some residual error will likely remain. By definition the specific nature or reason for this error cannot be known, but to the extent it is systematic in the sense of leading to under-prediction during times of stress and over-prediction in times of strength, it is consistent with our credit score drift hypothesis.

We convert these prediction errors to credit score adjustments by dividing the error for each cohort by the value of -0.016, the parameter estimate on the credit score vari-

Chart 8: Forecasting PD

Cumulative probability of default over 24 mo by orig. vintage, %



Sources: CreditForecast.com, Moody's Analytics

Table 2: PD Regression Models

	log(PD/(1-PD))=					
	[1]	[2]	[3]	[4]	[5]	[6]
VantageScore	-0.0161		-0.0161		-0.0161	
VantageScore categories						
300-529				0.0000		0.0000
530-579				-0.5394		-0.5394
580-619				-1.0033		-1.0033
620-659				-1.4748		-1.4748
660-699				-2.0642		-2.0642
700-719				-2.5607		-2.5607
720-739				-2.9365		-2.9365
740-779				-3.5399		-3.5399
780-809				-4.4669		-4.4669
810-850				-5.1737		-5.1737
Unemployment rate, 24 mo from origination		0.0543	0.0543	0.0543	2.6303	2.6303
Vintage dummies					X	X
constant	7.2695	-4.0610	6.9324	-1.6851	-5.8663	-14.4837
R-squared	0.9530	0.0045	0.9575	0.9819	0.9705	0.9949
N observations	560	560	560	560	560	560

Source: Moody's Analytics

able in our estimated PD model. Essentially, we are examining the error in each period for each cohort and asking ourselves the question, "How much higher or lower would borrowers' credit scores have to be in order to eliminate the observed prediction error?" In the case of under-prediction, the credit score would have to decline to compensate. For over-prediction, the credit score would need to rise.

Based on our analysis for this particular PD model, we find that scores for 2007Q1 originations should have been adjusted downward by about 20 points while originations in 2013Q1 should have had their credit scores adjusted upward by 20 points to compensate for their better-than-expected performance (see Chart 9). Analysts looking to stress their loss forecasting models may wish to use the factors proposed in Table 3 to account for credit score drift in their analysis. Although specific drift values will be model dependent, the score adjustments provided should serve as reasonable approximations for most models.

Better credit decisions

The widespread adoption of consumer credit scoring over 30 years ago brought about a host of benefits. Lenders were able to utilize the wide variety of information available on consumer credit reports in a consistent and easily digestible fashion. Statistical modeling of borrower characteristics made the lending process more transparent and less susceptible to racial or other biases. Credit scores favored the development of the mortgage-backed securities market permitting banks and other lenders to sell their assets to raise capital for additional lending rather than being locked into long-term contracts. Credit scores provided investors in these securities with a tool to gauge the credit risk of one pool of loans versus another and adjust their pricing accordingly.

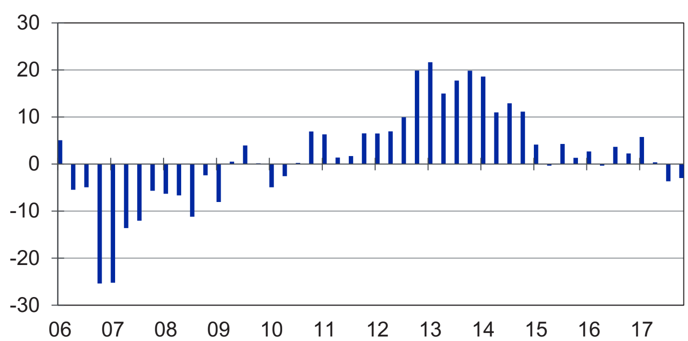
We propose to build off the successes of credit scoring models through the formal introduction of external economic factors and forward-looking scenarios. While rank-ordering borrowers within a particular timeframe and geography is beneficial, the incorporation of economic indicators in the credit scoring process can allow us to compare the default risk of borrowers across different parts of the business cycle and across varying local economies.

We explored two options for conditioning credit scores on economic scenarios. In the first, we proposed a model that related the nominal credit score to the absolute level of default risk over a two-year horizon from origination. We calibrated the resulting score to ensure that it was neutral across the business cycle for each score band. The estimated score adjustments are useful for lenders and investors who wish to evaluate the absolute level of credit risk across different geographies and origination cohorts with a single score.

In the second option we considered the case where a lender may be using a probability of default model that does not fully capture changes in default behavior across the business cycle. In this case we estimate the change in credit scores that would be needed to improve the historical model fit under the presumption that the model errors are driven by changes in the relative meaning of reported credit scores across the business cycle (that is, credit score drift).

Chart 9: Implied Credit Score Adjustments

Score adjustment implied by forecast model, VantageScore points



Sources: CreditForecast.com, Moody's Analytics

The result of both of these options is a set of models or tables that permit lenders to dynamically adjust either the reported credit scores of their applicants or their own lending standards in order to maintain a consistent level of risk tolerance throughout the business cycle. Scenario-conditioned credit scores also provide a mechanism for lenders to communicate changes in risk profile more effectively to auditors, regulators and other stakeholders as well as individual borrowers.

As the consumer credit industry continues to evolve, new tools and data services will permit lenders to more accurately assess the credit risk of individual borrowers. Controlling for economic factors in the credit score process can provide key insights and allow lenders to disentangle credit risk due to borrower idiosyncratic factors from broader external trends in the economy.

Table 3: VantageScore Adjustments by Economic Scenario

VantageScore category	Baseline*	Adverse***	Severely Adverse**
Missing	-2	-16	-31
300-529	4	-9	-22
530-579	2	-11	-25
580-619	3	-13	-29
620-659	4	-14	-32
660-699	2	-15	-31
700-719	-5	-15	-25
720-739	-11	-17	-22
740-779	-14	-18	-22
780-809	5	-9	-23
810-850	6	-13	-32

*Baseline is based on projected performance for 2018Q1 loans
**Severely Adverse is based on historical performance for 2007Q1 loans
***Adverse is a simple average of the Baseline and Severely Adverse scenarios

Source: Moody's Analytics

About the Author

Cristian deRitis is a senior director at Moody's Analytics, where he leads a team of economic analysts and develops econometric models for a wide variety of clients. His regular analysis and commentary on consumer credit, policy and the broader economy appear on the firm's Economy.com web site and in other publications. He is regularly quoted in publications such as the Wall Street Journal for his views on the economy and consumer credit markets. Currently he is spearheading efforts to develop alternative sources of data to measure economic activity more accurately than traditional sources of data.

Before joining Moody's Analytics, Cristian worked for Fannie Mae and taught at Johns Hopkins University. He received his PhD in economics from Johns Hopkins University and is named on two U.S. patents for credit modeling techniques.

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