FICO® Score 10 and FICO® Score 10 T model assessment

A Milliman Report Commissioned by FICO

July 25, 2023

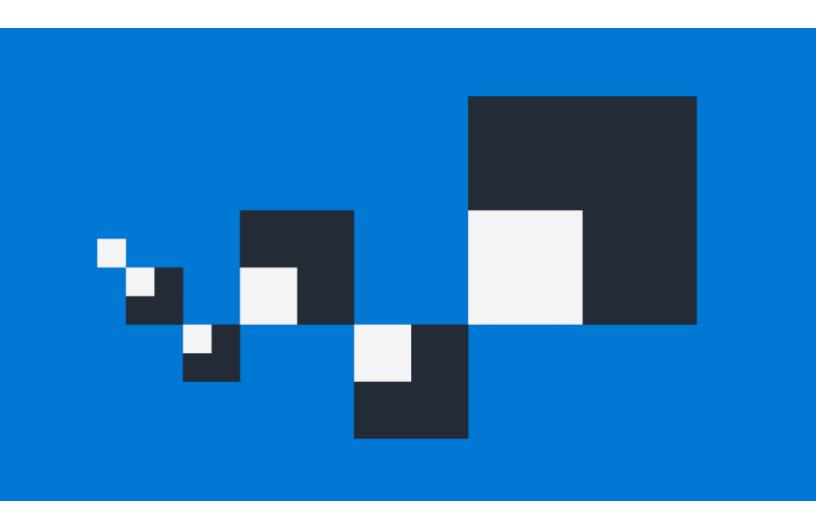




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Introduction

Credit scores are commonly used by lenders such as banks and credit card companies to assess the risk associated with extending credit to an individual or granting them a loan. The mortgage market utilizes credit scores for credit underwriting, setting the interest rate on the loan, estimating future mortgage cash flows, and to monitor credit trends. This paper is going to focus on the use of credit scores in the mortgage market. Credit scores are numerical values developed using mathematical models that represent a borrower's creditworthiness. The goal is to rank their likelihood to repay debts and manage credit responsibly. These models analyze various factors related to an individual's credit history and financial behavior to generate a score. The specific components and weightings used in credit score models may vary depending on the model being employed.

FICO is a leading analytics software company, and its namesake model is used by mortgage originators to underwrite borrowers. The FICO scoring system calculates credit scores based on various factors in an individual's credit history, such as payment history, amounts owed, length of credit history, credit mix, and new credit, etc. FICO periodically updates its scoring models to incorporate new information and improve predictive accuracy. These updates are often referred to as "versions." Each new version typically includes refinements and adjustments to the scoring algorithm based on updated data and trends. Currently, mortgage originators underwrite and deliver mortgages to investors as required utilizing FICO® Score 2 (FICO 2) or otherwise known as Classic FICO®. It is important to note that a score can only be generated for individuals with sufficient data and credit history to calculate the credit score.

In 2018, through the enactment of the Economic Growth, Regulatory Relief and Consumer Protection Act (Section 310) and the Validation and Approval of Credit Score Models Rule (12 CFR Part 1254), the Federal Housing Finance Agency (FHFA) committed to improving the accuracy and inclusivity in credit scoring, as well as improving the safety and soundness of the Government Sponsored Enterprises (GSEs), Fannie Mae and Freddie Mac. To that end, FHFA and the GSEs are currently implementing key updates to their credit score model requirements. In 2022, FHFA announced the validation and approval of FICO® Score 10 T (FICO 10 T) for use by the GSEs.

The FICO® Score 10 (FICO 10) and FICO 10 T credit scoring models were developed to leverage up to date machine learning techniques and include additional consumer data that was previously unavailable. FICO 10, although a model upgrade, stays true to previous reason codes and remains backwards compatible to existing operational systems. FICO 10 T is a variation of FICO 10 that includes additional predictive characteristics based on trended credit bureau borrower data within 24 months of the scoring date to capture behavioral patterns underlying borrower default

This report, authored by Milliman, Inc. (Milliman), provides an assessment of FICO 10 and FICO 10 T when compared to FICO 2. Specifically, this report:

- Evaluates if FICO 10 and FICO 10 T provide an improvement relative to FICO 2
- Highlights how the model improvements to FICO 10 and FICO 10 T may impact various borrower segments
- Evaluates the impact to investors that rely on credit scores for underwriting and pricing decisions when it comes to managing mortgage delinquencies

Executive summary

Milliman's analysis concludes that the credit scores produced by the FICO 10 and FICO 10 T models provide an improvement over the FICO 2 model in several key areas.

- At a distributional level, credit scores indicate more differentiation near the upper and lower ends of the score population distribution. Despite FICO being an ordinal measure in nature, improved performance modeling applications appreciate the increased distance between low- and high-risk borrowers. Many individuals also shifted upward to higher scores, such as from a score between (750, 799) to a score between (800, 850), while still maintaining the same overall delinquency rate within the cohort. Score migration through the assignment of a more accurate score suggests that borrowers will receive a more accurate underwriting evaluation, leading to a wider choice of potential lenders, an improved chance of loan approval, and more appropriate terms of the loan such as interest rates, down payments, and fees.
- An analysis of opportunity cost reveals that FICO 10/FICO 10 T provide improved segmentation across the credit score range, including the lower end of the range. This means that the relative default rate for borrowers above score cutoffs was lower under FICO 10/FICO 10 T when compared to FICO 2. The implication for this conclusion is that mortgage originators and investors may be able to adjust underwriting requirements to expand automated approval to include borrowers with a lower credit rating relative to existing requirements.
- Performance metrics indicate FICO 10/FICO 10 T display a stronger capability to ordinally rank borrowers relative to their level of risk when compared to FICO 2. This is observable both at the aggregate level and for select segments of interest including first-time home buyers and FHA-insured borrowers. Relative model improvement for FHA borrowers is about three times the gain experienced when using the data sample provided for this analysis. Across the credit score range, FICO 10 T produces a lift superior to FICO 10, according to our criteria. This is attributable to the inclusion of trended data in 10 T, the main source of difference between the methodology underlying these models.
- The distribution of scores does change from FICO 2 to FICO 10 and FICO 10 T; however, for any individual borrower, the change is not extreme, on average. When grouping by 50-point-wide cohorts, just under 50% of borrowers do not see significant movement. When movement is observed, it is generally only one cohort above or below their initial score. The FICO 10 and FICO 10 T score very similarly; however, the FICO 10 T is more likely to put individuals in the highest grouping (800-850), displaying the benefit of trended data.

Methodology

FICO provided Milliman with a set of scores for this model assessment. The sample included data on 1.85 million consumers who were funded for a mortgage loan within six months of the FICO score being provided. The sample data covered calendar months April 2018 to April 2020, where scores were assigned as of April 2018. Milliman was also provided with additional credit attribute data and actual delinquency performance from Experian to identify borrower segments and measure delinquency performance within the 24-month period following loan origination. The credit attribute data and delinquency data covered calendar months April 2018 to April 2020. Due to unprecedented policy actions taken during the COVID-19 pandemic, Milliman's analysis mostly focused on the 24-month observation period beginning April 2018 to compare modeled scores and subsequent borrower defaults. This analysis focuses on the difference in ability to segment borrowers by the actual incidence rate of 90-day delinquencies at any point during the 24-month period; credit scores are not designed to estimate a given level of the default rate as the level of defaults are dependent upon other factors such as economic conditions.

The analysis first looks to understand differences in the distributions of credit scores across the data sample and the delinquency dispersion within the data. Implicit costs are addressed across a continuous set of cut-offs by identifying relative scores that produce the same level of risk in the sample and calculating trade-off curves. A swap set analysis is conducted to measure the relative shift in the borrower sample above and below the cut-off scores at the margins. The percentage lift in the Gini coefficient from FICO 2 to FICO 10/FICO 10 T is also evaluated to quantify performance improvement. The Gini coefficient, also referred to as Somers' D in this context, is a statistical measure to describe the ordinal relationship between two variables. In this case, it is the extent to which the FICO score rank orders borrowers based on their probability of 90-day delinquency, within a population. This is done both in aggregate and for select segments of the population where expanding access to mortgage credit may be of interest to mortgage lenders. Finally, score migration is addressed (i.e., the difference in score across the same individual) to identify possible implications of switching from one model methodology to another. This also enables some comparison between FICO 10 and FICO 10 T.

On a technical note, the results of Milliman's assessment may be impacted by underlying sampling bias in the data. Because FICO 2 was used to approve the mortgages contained in the data, there will be certain restrictions on the score distribution. Specifically, borrowers that were not approved are not included in the data. Therefore, improvements from FICO 10/FICO 10 T within the data have the potential to be overstated. This issue is pervasive within model validation across the *entire* credit industry. Data on the entire universe of potential mortgage borrowers is inherently cost prohibitive and therefore not available to this study, which if made available could be used for bias correction in further analysis.

¹ The CARES Act law passed in late March 2020 is intended to help provide funding for economic relief related to temporary shutdowns and job losses. As part of the CARES Act, Congress gave Americans impacted by COVID-19 the option to request up to a year of mortgage payment forbearance.

Discussion of analysis

FICO SCORE DISTRIBUTIONS

Exhibit 1 depicts the distribution across different credit scoring methodologies for all borrowers in the 2018 - 2020 sample set.

40%

30%

20%

10%

0%

ERC 208

ERC 20

EXHIBIT 1: DISTRIBUTION OF FICO SCORE - SAMPLE SCORED APRIL 2018

The data sample used for this analysis was developed to assess the relative performance of FICO 10 and FICO 10 T relative to FICO 2. The data sample is filtered to borrowers who were approved for and obtained a mortgage within six months of receiving the FICO 2 score. In general, this population of borrowers will have a higher credit score relative to the entire population given the underwriting requirements for being approved for a mortgage. Therefore, the distribution of credit scores used in this analysis is skewed toward borrowers with higher credit scores.

When compared to FICO 2, FICO 10/FICO 10 T score a higher proportion of individuals in the highest cohort (800, 850). The ideal classifier would perfectly separate low- and high-risk individuals; therefore, the observed outward movement of scores when compared to the FICO 2 could be considered a functional improvement, assuming that the default rate within each credit score band is generally consistent and monotonically decreasing with higher credit score ranges.

A table of counts is provided below:

Record Count by FICO Cohort Sample Scored April 2018

FICO Score	FICO 2	FICO 10	FICO 10 T
(300, 549)	11,345	13,305	13,415
(550, 599)	40,915	48,247	50,089
(600, 649)	146,734	137,143	139,777
(650, 699)	301,729	272,503	270,590
(700, 749)	435,440	396,837	390,336
(750, 799)	653,213	462,727	454,367
(800, 850)	265,032	523,646	535,834
Total			1.854.408

While the FICO score is used to rank order borrowers by their credit risk, higher scores may impact the underwriting process. Many of the individuals in the highest credit score cohort for FICO 10/FICO 10 T migrated from the (750, 800) grouping for FICO 2.

DELINQUENCY RATE DISTRIBUTIONS

Exhibit 2 presents the 90-day delinquency rates within credit score bands across methodologies. The 90-day delinquency rate is defined as the number of borrowers that went delinquent in the 24-month period following loan origination divided by the number of borrowers with a given credit score range. The total 90-day delinquency rate for the sample is 1.4%.



EXHIBIT 2: 90-DAY DELINQUENCY RATE BY FICO COHORT - SAMPLE SCORED APRIL 2018

Delinquency rates are higher for FICO 10/FICO 10 T on the lower end of the distribution (300, 599] when compared to FICO 2 and generally consistent on the higher end of the distribution (600,850]. These results demonstrate that for the sample provided, FICO 10 and FICO 10 T provide improved segmentation of borrowers relative to FICO 2.

From Exhibit 1, the number of borrowers scored in the (800, 850) cohort roughly doubles from FICO 2 to FICO 10/FICO 10 T. The delinquency rate within this group is unchanged, meaning that more individuals can score higher without any change in relative risk. If the score migration was a net negative, the expectation would be that the quality of the cohort would decline. Instead, the quality has been held constant while the number of individuals has increased.

ASSESSMENT OF MARGINAL RISK ACROSS SCORE

Differences in marginal risk as a cut-off score is applied to the sample to highlight the ability of FICO 10/FICO 10 T to produce stronger pools of borrowers relative to the same score under FICO 2. To demonstrate this, Exhibit 3 shows the 90-day delinquency rate of the sample above the cut-off score across methodology. In the exhibit, the x-axis shows the cut-off score. The y-axis shows the delinquency rate for all borrowers above the cut-off score. For example, the delinquency rate for all borrowers in the sample is 1.4% or greater when using a cut-off of 564. At 700, the delinquency rate for FICO 2 is 0.39% (meaning the delinquency rate for all borrowers with a credit score of 700 or greater under FICO 2 was 0.39% or less), and the delinquency rate for FICO 10 and FICO 10 T was 0.34% or less.

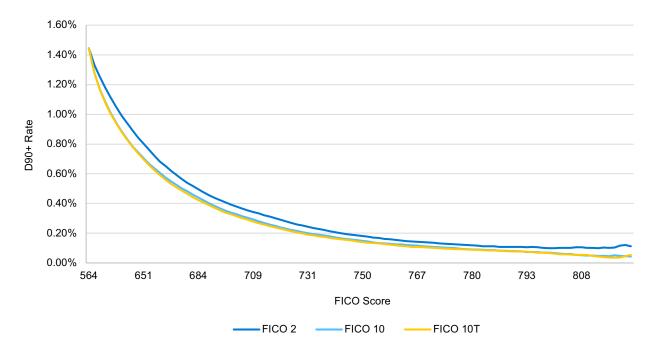


EXHIBIT 3: 90-DAY DELINQUENCY RATE ABOVE SCORE CUT-OFF - SAMPLE SCORED APRIL 2018

Holding score constant, the FICO 10 and FICO 10 T was associated with a lower 90-day delinquency rate when compared to the FICO 2 across the credit score range. Defaults rates under FICO 10 and FICO 10 T were consistent across the credit score range.

As an extension to evaluating the equivalent default rate for a given value of FICO 2, it is also important to evaluate the percent of borrowers that exceed a given credit score. This type of analysis can be used as one consideration in evaluating how access to credit could change under FICO 10 and FICO 10 T relative to FICO 2. The table below provides the results of this analysis by select levels of the FICO 2 cut-off value.

Increase in Number of Borrowers under Selected Cut-Off Score Sample Scored April 2018

	FIC	O 10	FICO 10 T			
FICO 2 Cut-Off	Risk Equivalent Score	Percent Increase in Number of Borrowers	Risk Equivalent Score	Percent Increase in Number of Borrowers		
681	673	3.8%	673	3.8%		
702	696	5.5%	695	5.5%		
721	714	7.7%	711	9.2%		
731	726	8.3%	724	10.0%		

For a FICO 2 cut-off score of 721, a 90-day delinquency rate of 0.38% is obtained. The same delinquency rate can be observed for cut-off scores of 714 and 711 under FICO 10 and FICO 10 T, respectively. At the same time, the volume above the cut-off increases by 7.7 percentage points for FICO 10, and 9.2 percentage points for FICO 10 T. While only a few examples are shown in the table, this result is generally consistent across the entire distribution of FICO 2 scores. This observation can also be demonstrated using trade-off curves, which show the relative increase in the cumulative percentage of delinquent borrowers relative to the cumulative percentage of all borrowers as the cut-offs score moves across the sample. For example, at a FICO 2 score of 712, 84.1% of all 90-day delinquencies fall below this cut-off. At the same time, 32% of all borrowers in the sample have been accounted for below the cut-off.

These are shown in exhibit 4 below:

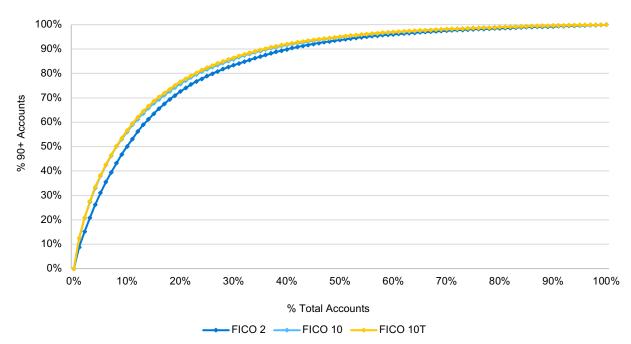


EXHIBIT 4: TRADE OFF CURVES: FICO 2, FICO 10, FICO 10T - SAMPLE SCORED APRIL 2018

Trade-off curves can be used to measure the opportunity cost associated with reaching any target delinquency rate. The y-axis charts the percent of 90-day delinquency rates, and the x-axis charts the percent of total accounts. The cost of removing delinquencies is the possibility that borrowers who would have otherwise been timely (i.e., not delinquent) are removed from the population. For instance, a cut-off to remove 50% of delinquent borrowers from the sample would also remove 10% of the total volume. For FICO 10 and FICO 10 T, only 8% of accounts would be required to achieve the same volume of identified delinquencies. To remove 90% of the delinquent borrowers, 41% of the sample would have needed to be denied credit under FICO 2, compared to only 37% under FICO 10 and FICO 10 T. Therefore, it can be interpreted that the opportunity cost under FICO 10 and FICO 10 T is lower compared to the FICO 2. That is, a larger share of borrowers can be approved without altering the risk level with the newer models.

SWAP-SET ANALYSIS

Changing credit score methodologies could have implications for those who lie on the boundaries of common credit score cut-offs. The swap-set analysis focuses on the relative performance and volume of individuals swapped above and below the cut-off under the different score methodologies. The tabular results from this analysis can be found in the Appendix. Exhibit 5 displays the proportion of the sample that appears above and below the cut-off from FICO 2 to FICO 10 and FICO 10 T, respectively.

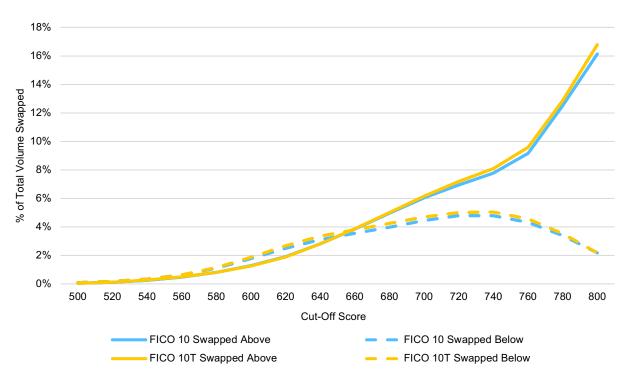


EXHIBIT 5: TOTAL VOLUME SWAPPED ABOVE/BELOW CUT-OFF - SAMPLE SCORED APRIL 2018

For example, the values for FICO 10 at 800 are 16.8% for swapped above and 2.2% for swapped below. These are calculated as follows:

$$Volume Swapped Above = \frac{\# of Borrowers where FICO \ 2 < Cut \ Off \le FICO \ 10}{\# of Borrowers}$$

$$Volume\ Swapped\ Below = \frac{\#\ of\ Borrowers\ where\ FICO\ 10 < Cut\ Off \le FICO\ 2}{\#\ of\ Borrowers}$$

For cut-off scores less than ~650, more volume shifts below the cut-off than above the cut-off for both FICO 10 and FICO 10 T relative to FICO 2. For cut-off scores greater than 650, more volume shifts above the cut-off (meaning more borrowers are assigned a higher value under FICO 10 and FICO 10 T relative to FICO 2). In most cases, at least as many scores swap above the threshold for FICO 10 T as they do under FICO 10.

To determine the quality of the swap, the ratio of performing to delinquent borrowers can be calculated within both those who are swapped above and below the cut-off across score type. The 90-day delinquency odds for those swapped below for FICO 10 are calculated using the following formula:

$$Swapped \ Below \ Odds = \frac{\% \ of \ borrowers \ that \ do \ not \ go \ delinquent, where \ FICO \ 10 < Cut \ Off \le FICO \ 2}{\% \ of \ borrowers \ 90 \ days + delinquent, \ where \ FICO \ 10 < Cut \ Off \le FICO \ 2}$$

The delinquency odds for those swapped above are calculated similarly:

$$Swapped\ Above\ Odds\ \frac{\%\ of\ borrowers\ that\ do\ not\ go\ delinquent, where\ FICO\ 2 < Cut\ Off \le FICO\ 10}{\%\ of\ borrowers\ 90\ days\ +\ delinquent,\ where\ FICO\ 2 < Cut\ Off\ \le FICO\ 10}$$

These measures can be interpreted as the number of performing borrowers below/above the cut-off for every one delinquent borrower. If the swapped above odds were 100, this implies 100 'good' borrowers are swapped in for every one delinquent borrower. Therefore, if the odds are greater for those swapped above the cut-off relative to those swapped below, the new score is an improvement. Odds are calculated across the cut-off interval in Exhibit 6.

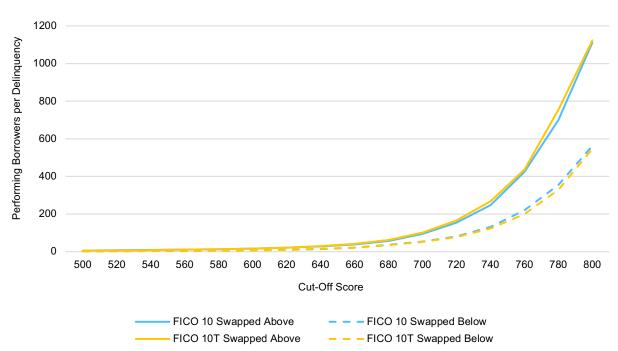


EXHIBIT 6: 90-DAY DELINQUENCY ODDS FOR BORROWERS SWAPPED ABOVE/BELOW CUT-OFF - SAMPLE SCORED APRIL 2018

In all cases, the swapped above odds are greater than the swapped below odds across the range of cut-off scores. This means that both FICO 10 and FICO 10 T can identify higher-quality borrower pools relative to FICO 2. All else equal and based on the data in this sample, the new scores could result in approval for more borrowers at a lower delinquency rate.

ASSESSMENT OF MODEL LIFT

As a broader assessment of model performance, the Gini coefficient provides a metric to evaluate the extent to which borrowers are ordered appropriately relative to the signal in the data (i.e., 90-day delinquency within 24 months for this analysis). Comparing the relativity from one Gini coefficient to another produces the calculated lift. Exhibit 7 demonstrates the Gini lift for the entire sample period on predicting 90-day delinquencies within 24 months of loan origination.

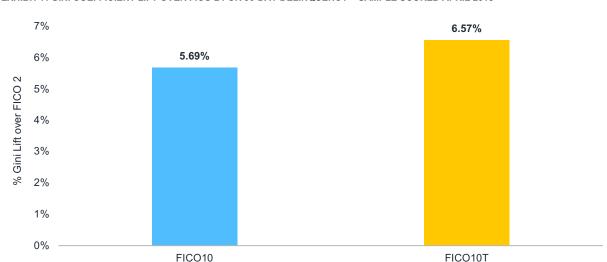


EXHIBIT 7: GINI COEFFICIENT LIFT OVER FICO 2 FOR 90-DAY DELINQUENCY - SAMPLE SCORED APRIL 2018

When compared to FICO 2, both the FICO 10 and the FICO 10 T produce a Gini coefficient that is 5.7% and 6.6% greater, respectively. This suggests that there has been an improvement in the extent to which individuals are ordered by delinquency risk under both new models. The Gini coefficient lift is about a percentage point greater for the FICO 10 T, meaning that the FICO 10 T is marginally superior to the FICO 10 under this evaluation metric in this sample.

Of interest to mortgage lenders are borrowers who may have had limited access to credit and traditionally lower credit scores. Specifically, first-time home buyers and/or mortgages insured by the Federal Housing Administration (FHA) on average are typically shown to have shorter credit histories and lower credit scores when compared to the general population of mortgage applicants. To provide further access to homeownership, mortgage lenders often devise special credit and underwriting programs that specifically focus on these groups. Because the identifiers for these groups were present in the data and understanding the baseline risk for these characteristics is important, segment-specific model lift is calculated to evaluate if the new scores will more accurately assess credit risk for these borrower groups. The model lift for first-time homebuyers and FHA borrowers is displayed in Exhibit 8:

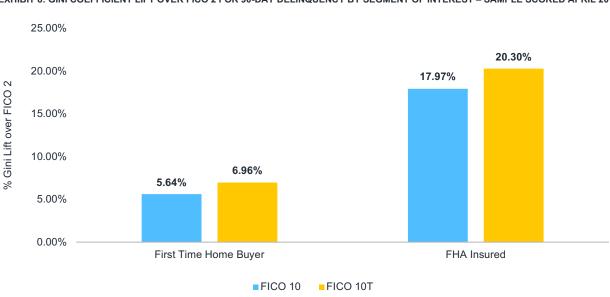


EXHIBIT 8: GINI COEFFICIENT LIFT OVER FICO 2 FOR 90-DAY DELINQUENCY BY SEGMENT OF INTEREST - SAMPLE SCORED APRIL 2018

The Gini coefficient lift for first-time home buyers is relatively consistent with what is recognized at the aggregate level, though the relative lift is slightly less for FICO 10 and slightly greater for FICO 10 T. FICO 10 T uses trended data, which contains more data that can be used to analyze the borrower.

Relative to the lift realized at the aggregate level, the ordinal capabilities of the model improve by a factor of roughly three times for FHA-insured borrowers. The difference between the lift from the FICO 10 and FICO 10 T is further explained by the trended component. Like first-time home buyers, a shorter credit history means that the trended data on the 24-month period prior to scoring should, on average, represent a greater share of that borrower's entire credit history relative to a market average borrower. For FHA-insured mortgages, FICO 10 T was able to provide greater segmentation within the sample data.

SCORE MIGRATION

Adopting the FICO 10 or FICO 10 T may cause the same borrower to be scored differently, relative to FICO 2, at the same point in time. Understanding the migration of scores can provide insight into explaining why the new models may be performing better and get an appreciation for the relative difference that may be incurred from one score to the other. Exhibit 9 shows a heatmap of scores from FICO 2 to FICO 10 and FICO 10 T for the sample data. Note that percentages run row-wise.

EXHIBIT 9: SCORE MIGRATION FROM FICO 2 TO FICO 10 & FICO 10T - SAMPLE SCORED APRIL 2018

FICO 2 to FICO 10	(300, 549)	(550, 599)	(600, 649)	(650, 699)	(700, 749)	(750, 799)	(800, 850)
(300, 549)	42.5%	37.2%	17.7%	2.5%	0.1%	0.0%	0.0%
(550, 599)	12.4%	35.8%	38.2%	12.3%	1.3%	0.0%	0.0%
(600, 649)	2.1%	15.9%	44.0%	31.8%	5.8%	0.4%	0.0%
(650, 699)	0.1%	1.9%	16.4%	47.7%	28.7%	4.4%	0.8%
(700, 749)	0.0%	0.1%	1.2%	15.9%	51.3%	28.4%	3.2%
(750, 799)	0.0%	0.0%	0.1%	1.1%	11.4%	44.2%	43.3%
(800, 850)	0.0%	0.0%	0.0%	0.2%	1.3%	13.7%	84.7%
FICO 2 to FICO 10T	(300, 549)	(550, 599)	(600, 649)	(650, 699)	(700, 749)	(750, 799)	(800, 850)
(300, 549)	40.00/						
(300, 343)	42.0%	37.3%	17.7%	2.8%	0.2%	0.0%	0.0%
(550, 599)	42.0% 12.4%	37.3% 36.0%	17.7% 37.7%	2.8% 12.4%	0.2% 1.5%	0.0% 0.1%	0.0% 0.0%
,							
(550, 599)	12.4%	36.0%	37.7%	12.4%	1.5%	0.1%	0.0%
(550, 599) (600, 649)	12.4% 2.1%	36.0% 16.6%	37.7% 43.2%	12.4% 31.3%	1.5% 6.2%	0.1% 0.5%	0.0% 0.0%
(550, 599) (600, 649) (650, 699)	12.4% 2.1% 0.1%	36.0% 16.6% 2.1%	37.7% 43.2% 17.3%	12.4% 31.3% 46.2%	1.5% 6.2% 28.5%	0.1% 0.5% 4.9%	0.0% 0.0% 0.8%

Across the diagonal when comparing the migration of FICO 2 to both FICO 10 and FICO 10 T respectively, 35% to 50% of borrowers stay within their original credit score cohort, with the exception for the 800-850 bucket. A fair degree of movement occurs at the lower end of the distribution, where 17.7% of borrowers who were in the 300-549 FICO 2 cohort increase their score up to the 600-649 bucket for both FICO 10 and FICO 10 T.

The score shift is generally not that extreme, as individuals mostly rescore within one credit score cohort relative to where they appeared with FICO 2. Borrowers at the highest end of the distribution are more likely to stay in their assigned cohort, which suggests that the criteria that determines the predicted strongest borrowers across models is consistent. As expected by looking at the distribution of credit score, a number of the entrants to the 800-850 bucket from FICO 2 to FICO 10 and FICO 10 T come from the 750-799 FICO 2 cohort. Additionally, it can be seen that more individuals enter the top cohort than those who exit it.

This same process can be repeated to highlight differences between FICO 10 and FICO 10 T. Exhibit 10 presents the score migration heatmap below:

EXHIBIT 10: SCORE MIGRATION FROM FICO 10 TO FICO 10T - SAMPLE SCORED APRIL 2018

FICO 10\FICO10 T	(300, 549)	(550, 599)	(600, 649)	(650, 699)	(700, 749)	(750, 799)	(800, 850)
(300, 549)	84.8%	15.2%	0.0%	0.0%	0.0%	0.0%	0.0%
(550, 599)	4.4%	79.5%	16.1%	0.0%	0.0%	0.0%	0.0%
(600, 649)	0.0%	7.0%	79.1%	13.8%	0.0%	0.0%	0.0%
(650, 699)	0.0%	0.0%	8.6%	78.7%	12.7%	0.0%	0.0%
(700, 749)	0.0%	0.0%	0.0%	9.4%	78.9%	11.7%	0.0%
(750, 799)	0.0%	0.0%	0.0%	0.0%	9.2%	78.5%	12.3%
(800, 850)	0.0%	0.0%	0.0%	0.0%	0.0%	8.5%	91.4%

As anticipated, individuals are mostly scored consistently between the FICO 10 and FICO 10 T. There are no individuals in the sample that fall two credit score cohorts away from the diagonal. Exhibit 10 indicates that the FICO 10 T model tends to score slightly higher on average than the FICO 10. The proportion of individuals moving up a credit cohort tends to be slightly greater than the proportion of individuals moving down, though on the whole, the FICO 10 T is more willing to allocate on the ends of the distribution.

Conclusion

The FICO 2 or Classic FICO has proven itself as an invaluable tool for assessing credit risk in the mortgage lending industry for over two decades. However, the introduction of FICO 10 and FICO 10 T marks a meaningful advancement, harnessing the power of trended data and cutting-edge analytical techniques. As demonstrated in this analysis, the impact of these updates is evident in the improvement of raw scores, the notable shift towards a more pronounced distribution, and the enhancement of performance overall to crucial segments of the borrower population.

Qualifications and distribution

QUALIFICATIONS AND LIMITATIONS

This report was commissioned by FICO.

The authors and/or peer reviewers of this analysis have significant expertise in the evaluation of mortgage credit risk using statistical methods.

We will have performed a limited review of the data used directly in our analysis for reasonableness and consistency. If there are material defects in the data, it is possible that they would be uncovered by a detailed, systematic review and comparison of the data to search for data values that are questionable or relationships that are materially inconsistent. Such a review is beyond the scope of our assignment.

The analysis and any conclusions provided in Milliman's deliverables will be based on data provided to Milliman by third-party sources. Milliman does not warrant the accuracy or completeness of any third-party data, and Milliman disclaims any and all liability in connection with such third-party data. Any errors in the data provided may affect the results of Milliman's analysis. Milliman shall not be liable for the results of its analysis to the extent that errors are contained in third-party data sources.

Any study of future operating results involves estimates of future contingencies. While our analysis will represent our best professional judgment, arrived at after careful analysis of the available information, it is important to note that a significant degree of variation from our projections is not only possible, but is in fact probable. The sources of this variation are numerous: Future national or regional economic conditions, mortgage prepayment speeds, mortgage modifications, and legislative changes are examples.

The uncertainty associated with our estimates is also magnified by the nature of mortgage credit risk. Mortgage credit forecasting results are sensitive to external factors such as unemployment, housing market conditions, etc. Past experience may not be indicative of future conditions. A mortgage underwritten in a given year is generally active over several calendar years. Therefore, adverse economic conditions in a given calendar year could affect results not only for the current underwriting year but also for prior underwriting years.

Our estimates make no provision for extraordinary future emergence of new classes of delinquencies and losses or types of delinquencies not sufficiently represented in FICO's historical databases or that are not yet quantifiable, including the potential impact of the emerging situation regarding the COVID-19 pandemic.

There is substantial uncertainty regarding the impact of COVID-19 on the level and nature of business activity. Exposures, delinquencies, and severity of loss will likely be affected in ways we cannot currently estimate. It is important to recognize that results may emerge significantly higher or lower than the estimates in this analysis.

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Appendix

SWAP-SET TABLE

Sample Scored April 2018

	FICO 2		FICO 10				FICO 10 T			
Cut-Off Score	% of Total Volume Above Cut-Off	% of Total Volume Below Cut-Off	% of Total Volume Swapped Above Cut-Off	% of Total Volume Swapped Below Cut-Off	90-Day Delinquen cy Odds Swapped Above Cut-Off	90-Day Delinquen cy Odds Swapped Below Cut-Off	% of Total Volume Swapped Above Cut-Off	% of Total Volume Swapped Below Cut-Off	90-Day Delinquen cy Odds Swapped Above Cut-Off	90-Day Delinquen cy Odds Swapped Below Cut- Off
500	99.9%	0.1%	0.0%	0.1%	5.80	2.62	0.0%	0.1%	5.67	2.68
520	99.8%	0.2%	0.1%	0.2%	7.21	3.50	0.1%	0.2%	6.94	3.33
540	99.6%	0.4%	0.3%	0.3%	8.76	4.02	0.3%	0.3%	8.38	4.02
560	99.1%	0.9%	0.5%	0.6%	11.15	4.78	0.5%	0.6%	10.88	4.68
580	98.4%	1.6%	0.8%	1.1%	13.63	5.86	0.8%	1.1%	13.48	5.87
600	97.2%	2.8%	1.3%	1.8%	16.47	7.56	1.3%	1.9%	17.08	7.52
620	95.1%	4.9%	1.9%	2.5%	22.10	10.22	1.9%	2.7%	22.14	10.27
640	91.6%	8.4%	2.8%	3.1%	28.90	14.41	2.8%	3.3%	29.39	14.44
660	86.6%	13.4%	3.8%	3.5%	39.22	22.20	3.9%	3.8%	41.87	21.74
680	80.4%	19.6%	5.0%	4.0%	57.70	36.04	5.0%	4.2%	62.59	34.42
700	73.0%	27.0%	6.0%	4.5%	95.30	54.34	6.1%	4.7%	100.73	51.46
720	64.5%	35.5%	6.9%	4.8%	153.70	80.72	7.2%	5.0%	166.43	76.99
740	54.9%	45.1%	7.8%	4.8%	247.57	132.23	8.1%	5.0%	268.01	123.95
760	43.6%	56.4%	9.2%	4.3%	425.28	220.32	9.6%	4.6%	435.54	200.09
780	29.5%	70.5%	12.5%	3.4%	699.56	355.10	12.9%	3.5%	754.29	328.65
800	14.3%	85.7%	16.1%	2.2%	1111.22	562.50	16.8%	2.2%	1122.81	546.22

^{*}Odds are measured as the ratio between the probability a borrower is performing to the probability a borrower goes 90-days delinquent within 24 months



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