FDIC
Federal Deposit Insurance Corporation
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Legal Division

June 27, 2012

TO: Executive Secretary

FROM: Phillip E. Sloan, Counsel
Legal Division

SUBJECT: Meeting with Fair Isaac Corporation to Discuss the Notice of Proposed Rulemaking Related to Section 941 of the Dodd-Frank Wall Street Reform and Consumer Protection Act

Please include this memorandum in the public file on the Notice of Proposed Rulemaking relating to Credit Risk Retention (RIN 3064-AD74), 76 Fed. Reg. 24090 (the "NPR").

On June 19, 2012 FDIC staff (George Alexander, Kathy Russo and Phil Sloan) met with representatives of Fair Isaac Corporation (Joanne Gaskin and Daniel Nestel) and Peck, Madigan, Jones & Stewart (Drew Cantor) to receive comments on the NPR.

The primary focus of the discussion was on the proposal of Fair Isaac Corporation to use credit scoring models in lieu of the derogatory factors included in the NPR as one of the factors for determining whether a residential mortgage satisfies the conditions for qualified residential mortgage status.

The documents distributed at the meeting by Fair Isaac Corporation, as well as two documents submitted after the meeting, are attached to this memorandum.

In the matter of: Credit Risk Retention Proposed Rule

Federal Register / Vol. 76, No. 83 / Friday, April 29, 2011 / Proposed Rules

DEPARTMENT OF THE TREASURY
Office of the Comptroller of the Currency
12 CFR Part 43
[Docket No. OCC–2011–0002]
RIN 1557–AD40

FEDERAL RESERVE SYSTEM
12 CFR Part 244
[Docket No. 2011–1411]
RIN 7100–AD–70

FEDERAL DEPOSIT INSURANCE CORPORATION
12 CFR Part 373
RIN 3064–AD74

FEDERAL HOUSING FINANCE AGENCY
12 CFR Part 1234
RIN 2590–AA43

SECURITIES AND EXCHANGE COMMISSION
17 CFR Part 246
[Release No. 34–64148; File No. S7–14–11]
RIN 3235–AK96

DEPARTMENT OF HOUSING AND URBAN DEVELOPMENT
24 CFR Part 267
RIN 2501–AD53

Proposal: Require the use of credit scoring models in the QRM Definition in place of the proposed "derogatory factors" to assess credit risk

On April 29, 2011, the OCC, Board, FDIC, Commission, FHFA, and HUD (the "Agencies") proposed rules to implement the credit risk retention requirements of section 15G of the Securities Exchange Act of 1934, as added by section 941 of the Dodd-Frank Wall Street Reform and Consumer Protection Act (the "Proposed Rule"). In response to the Agencies' request for comments on the Proposed Rule, Fair Isaac Corporation (FICO) respectfully submitted comments, which presented comprehensive research that demonstrated the Agencies' "derogatory factors", included in the definition of qualified residential mortgage (QRM), are not sufficiently predictive to accurately assess a mortgage borrower's credit risk for purposes of qualifying for the QRM exemption. The research revealed that the derogatory factors are not an adequate substitute for the use of a credit risk score, which is the method used currently by all mortgage lenders to assess credit risk in the mortgage underwriting process.

In its comment letter, FICO proposed a different approach: mandate the use of credit scoring models on a vendor-neutral basis, within the existing regulatory structure. We recommended that regulators require the use of credit risk models to make the critical credit risk analysis of mortgage applicants, subject to certain constraints. In response to our comment letter, FICO was asked by several of the Agencies to suggest practical ways to implement this approach.

Below are four potential credit history rule solutions, each with its own advantages. Any one of the four solutions would be considerably more predictive than the "derogatory factors" approach in the Proposed Rule, and would therefore be fairer to consumers and lenders alike. By assuring that the QRM exemption applies only to those mortgage originations that present the least credit risk, each of these solutions helps achieve Congress's goal of protecting the securitization market and its investors.

Guiding Principles

The proposed solutions are guided by five principles:

- *Reliable analytics* – the model must accurately rank order credit risk;
- *Vendor neutral* – the solution cannot prefer one credit scoring model builder;
- *Regulatory oversight* – regulators should have the power to assure compliance, but they should not need to frequently calibrate the compliance process;
- *Simple way to comply* – creditors should be able to comply with minimal burden; and
- *Minimize market disruption* – the credit model approach works today.

Each proposed solution requires the use of a credit risk model that is "empirically derived, demonstrably and statistically sound" ("EDDSS"), as that phrase is defined in Regulation B, which implements the Equal Credit Opportunity Act. This approach assures quality, consistency, and objective standards by which to judge the effectiveness of the model. EDDSS requirements are well-established, so there would be no need to invent a new test or determine how the regulatory oversight would work. EDDSS requires model validation at inception and "within a reasonable period of time" thereafter.

Such credit scoring models could be subject to standards similar to the Supervisory Guidance on Model Risk Management, OCC 2011-12 and SR Letter 11-7 ("Guidance"), published by Federal Reserve Board and the Office of the Comptroller of the Currency on April 4, 2011. The Agencies could incorporate the Guidance by reference into its rule, or propose a variation of it. The Guidance explains the role of risk models and sets compliance standards; prescribes the need for banks that rely on quantitative analysis and models to demonstrate expertise in model development, implementation, use, and validation; and requires banks to establish a process of governance, policies, and controls over its own models, and those it uses from third party vendors and contractors. The Guidance, which is a compilation and update of past statements by the OCC on model risk management, would not impose new burdens on banks or require a new regulatory structure by the bank regulators and the Consumer Financial Protection Bureau (CFPB) to administer and audit for compliance.

Two Distinct Approaches

The Proposed Rule should use credit scoring models to more accurately determine which mortgage loans qualify for the QRM exemption from the 5% skin-in-the-game retention requirements. First, however, the Agencies must determine: (1) whether the QRM exemption should apply to all mortgage borrowers whose credit risk profile represents a predetermined **level of credit risk**, irrespective of how many borrowers qualify under that test; or (2) whether the QRM exemption should apply to a predetermined **percentage** of all mortgage borrowers whose credit risk profiles are the least risky of all such borrowers, irrespective of the actual level of credit risk presented by those who qualify for the acceptable percentage. The use of either approach would result in a considerably more accurate assessment of the borrower's credit risk, which would permit the QRM definition to rely less heavily on certain non-credit history criteria such as the borrower's debt-to-income [§(d)(8)], loan-to-value [§(d)(9)], and amount of downpayment [§(d)(10)].

Setting a Level of Credit Risk (Options 1-3). The Agencies would predetermine a specific credit risk *default rate* that would qualify a mortgage loan for QRM status. The default rate would be a permissible ratio that indicated the borrower's *odds-of-default* on the mortgage. The mortgage lender would use an EDDSS credit scoring model that, when the mortgage borrower's credit profile is an input to the model, is capable of rank ordering the credit risk presented by each mortgage borrower over the spectrum of all mortgage borrowers. In order for a certain mortgage loan to qualify for the QRM exemption, a securitizer would be required to demonstrate that the credit risk score on that mortgage borrower produced by the model indicated an odds-of-default ratio that was less than or equal to the Agencies' predetermined odds-of-default ratio.

- The creditor would be required to use a qualified third party's EDDSS model in Option #1, which would be certified annually by the third party.
- The creditor could use either a qualified third party's model or its own proprietary model in Option #2, but the creditor would have to annually validate whatever model it selected on its own book of business.
- The creditor could use either a qualified third party's model or its own proprietary model in Option #3; if the creditor selected the third party model, the creditor could rely on the annual certification by the third party, but if the creditor selected its own proprietary model, that model would have to be annually validated on the creditor's own book of business.

Setting a Percentage of Loans (Option 4). The Agencies would predetermine a specific *percentage of loans* that qualifies for QRM status—say the least credit risky 20% of all residential mortgages issued by mortgage originators would be targeted for QRM status. The mortgage lender would be required to use a qualified third party's EDDSS credit scoring model that, when the mortgage borrower's credit profile is an input to the model, is capable of rank ordering the credit risk presented by each mortgage borrower over the spectrum of all mortgage borrowers. In order for a certain mortgage loan to qualify for the QRM exemption, a securitizer would be required to demonstrate that the borrower has a credit risk score that places the borrower in the least credit risky 20% of mortgage borrowers.

There is no option presented herein that would allow a mortgage originator to comply with the QRM exemption by relying on its own proprietary EDDSS model. This is because the percentage approach would result in significantly different results among creditors using their own models, even if the models were EDDSS, due to the regional and lender-by-lender variances in the quality of mortgage loans written by such creditors. Therefore, the only option presented under the percentage approach is to require all mortgage securitizers to use credit scoring models built using data from a consumer reporting agency that compiles and maintains files on consumers on a nationwide basis.

Proposed Credit History Rule Options 1– 3

Option #1 (Setting a Level of Credit Risk): Odds-of-default, certification on national database

A borrower's loan would qualify for the QRM exemption if the borrower's credit score indicated an acceptable odds-of-default credit risk. The mortgage lender would comply by using a qualified third party's EDDSS credit risk model. For QRM purposes, the creditor need not validate the model on its own database, but may rely on the third party's annual certification that the model is still EDDSS and accurately rank orders mortgage credit risk. A recent example of this approach is the Federal Reserve's Risk-Based Pricing Rule, 12 CFR Part 222, which requires credit bureaus and credit scoring model developers to provide the content for certain mandated consumer notices (providing information about the national distribution of credit scores) on an annual basis, and entitles lenders to rely on that information.

This option does not allow creditors to develop and use their own credit scoring models for QRM purposes (see Option #2), but does relieve creditors from their burden of validation and annual revalidation of the models for QRM purposes. Since all mortgage securitizers under this option must use credit scoring models built by third party credit score developers using data from a consumer reporting agency that compiles and maintains files on consumers on a nationwide basis, this option also adds consistency to the odds-of-default approach.

- » The creditor must use a model that:
  - » accurately rank orders mortgage credit risk
  - » is built on a nationwide database of consumers
  - » assigns a cut-off score that represents the predetermined odds-of-default ratio (established by the Agencies) for that model
  - » is periodically revalidated to preserve its status as EDDSS and to determine if the cut-off score needs to change to meet the predetermined odds-of-default ratio
  - » is subject to examination by the CFPB
- » Agencies may reset the qualifying odds-of-default ratio

For guidance, the following table generally matches a borrower's odds-of-default with the corresponding FICO 8 score (calculated on performance from Oct 2008 - Oct 2010):

Odds-of Default	*FICO 8 Score*
5:1	610
10:1	645

20:1	685
30:1	705
40:1	720
50:1	735
100:1	770

Option #2 (Setting a Level of Credit Risk): Odds-of-default, validation on creditor's own database

Like Option #1, a borrower's loan would qualify for the QRM exemption if the borrower's credit score indicated an acceptable odds-of-default credit risk. Unlike Option #1, Option #2 would allow creditors to develop and use their own credit scoring models for QRM purposes. A creditor would comply either by developing and using its own EDDSS credit risk model or by using a qualified third party's EDDSS credit risk model. In either case, however, the creditor would be required to validate and annually revalidate on its own book of business that the credit risk model selected (either a proprietary model or a model created by the third party) is EDDSS. Unlike Option #1, the creditor cannot rely on the third party's annual certification that the model is still EDDSS and accurately rank orders mortgage credit risk.

» The creditor must assure that the model it uses:

  » accurately rank orders mortgage credit risk

  » assigns a cut-off score that represents the predetermined odds-of-default ratio (established by the Agencies) for that model based on a validation on the creditor's own book of business

  » is periodically revalidated to preserve its status as EDDSS and to determine if the cut-off score needs to change to meet the predetermined odds-of-default ratio

  » is subject to examination by CFPB

» Agencies may reset the qualifying odds-of-default ratio

For guidance, the following table generally matches a borrower's odds-of-default with the corresponding FICO 8 score (calculated on performance from Oct 2008 - Oct 2010). Of course, the range of scores and odds-of-default will vary with each model as creditors develop and validate their own credit scoring models.

Odds-of Default	***FICO 8 Score***
5:1	610
10:1	645
20:1	685
30:1	705
40:1	720
50:1	735
100:1	770

Option #3 (Setting a Percentage of Loans): Odds-of-default, validation or certification depending on the option selected by creditor

Like Options #1 and #2, a borrower's loan would qualify for the QRM exemption if the borrower's credit score indicated an acceptable odds-of-default credit risk. Unlike Option #1, but like Option #2, Option #3 would allow creditors to develop and use their own credit scoring models for QRM purposes. A creditor would comply either by developing and using its own EDDSS credit risk model or by using a qualified third party's EDDSS credit risk model. If the creditor chose to use a qualified third party's EDDSS credit risk model, for QRM purposes, the creditor would not need to validate the model on its own database, but could rely on the third party's annual certification that the model is still EDDSS and accurately rank orders mortgage credit risk. If the mortgage lender chose to use it own credit scoring model for compliance, the creditor would be required to validate and annually revalidate on its own book of business that the credit risk model used is EDDSS.

For guidance, the following table generally matches a borrower's odds-of-default with the corresponding FICO 8 score (calculated on performance from Oct 2008 - Oct 2010). Of course, the range of scores and odds-of-default will vary with each model as creditors develop and validate their own credit scoring models.

Odds-of Default	***FICO 8 Score***
5:1	610
10:1	645
20:1	685
30:1	705
40:1	720
50:1	735
100:1	770

Option #4 (Setting a Percentage of Loans): Percentage of least risky borrowers, certification on national database

A borrower's loan would qualify for the QRM exemption if the borrower's credit score placed the borrower in the acceptable percentage of least credit risky borrowers. The mortgage lender would comply by using a qualified third party's EDDSS credit risk model to determine the borrower's credit score. For QRM purposes, the creditor need not validate the model on its own book of business, but may rely on the third party's annual certification that the model is still EDDSS and accurately rank orders credit risk. A recent example of this approach is the Federal Reserve's Risk-Based Pricing Rule, 12 CFR Part 222, which requires credit bureaus and credit scoring model developers to provide the content for certain mandated consumer notices (providing information about the national distribution of credit scores) on an annual basis, and entitles lenders to rely on that information.

Like Option #1 above, this option does not allow creditors to develop and use their own credit scoring models for QRM purposes, but does relieve creditors from their burden of validation and annual revalidation of the models for QRM purposes. Since all mortgage securitizers under this option must rely on credit scoring models built by third party credit score developers using data from a consumer reporting agency that compiles and maintains files on consumers on a nationwide basis, this option also adds consistency to the odds-of-default approach.

- The creditor must use a model that:
    - accurately rank orders mortgage credit risk
    - is built on a nationwide database of consumers
    - assigns a cut-off score that represents the acceptable percentage of least credit risky borrowers (established by the Agencies) for that model
    - is periodically revalidated to preserve its status as EDDSS and to determine if the cut-off score needs to change to meet the acceptable percentage of least credit risky borrowers for that model
    - is subject to examination by CFPB
- Agencies may reset the qualifying percentage of least risky borrowers

For guidance, the following table generally matches the percentage of mortgage borrowers who achieved certain FICO 8 scores, calculated on performance from Oct 2008 - Oct 2010):

Percentage of Population	***FICO 8 Score***
10%	815
20%	795
30%	770
40%	740
50%	710
60%	675
70%	625
80%	570
90%	520

Proposed Credit History Rule -- Option #1

DELETE:
Subpart D—Exceptions and Exemptions, §__.15 *Exemption for qualified residential mortgages,* subsection (d)(5):

(d)(5) *Credit history*—(i) *In general.* The creditor has verified and documented that within ninety (90) days prior to the closing of the mortgage transaction:
(A) The borrower is not currently 30 days or more past due, in whole or in part, on any debt obligation;
(B) Within the previous twenty-four (24) months, the borrower has not been 60 days or more past due, in whole or in part, on any debt obligation; and
(C) Within the previous thirty-six (36) months:
(*1*) The borrower has not been a debtor in a case commenced under Chapter 7, Chapter 12, or Chapter 13 of Title 11, United States Code, or been the subject of any Federal or State judicial judgment for the collection of any unpaid debt;
(*2*) The borrower has not had any personal property repossessed; and (*3*) No one-to-four family property owned by the borrower has been the subject of any foreclosure, deed-in-lieu of foreclosure, or short sale.
(ii) *Safe harbor.* A creditor will be deemed to have met the requirements of paragraph (d)(5)(i) of this section if:
(A) The creditor, no more than 90 days before the closing of the mortgage transaction, obtains a credit report regarding the borrower from at least two consumer reporting agencies that compile and maintain files on consumers on a nationwide basis;
(B) Based on the information in such credit reports, the borrower meets all of the requirements of paragraph (d)(5)(i) of this section, and no information in a credit report subsequently obtained by the creditor before the closing of the mortgage transaction contains contrary information; and
(C) The creditor maintains copies of such credit reports in the loan file for the mortgage transaction.

REPLACE subsection (d)(5) with the following:

(d)(5) *Credit history*—(i) *In general.* The creditor has verified and documented within ten (10) days prior to the closing of the mortgage transaction that the borrower has a credit risk score that indicates the borrower's odds-of-default on the mortgage are [X] to 1 or higher. The credit risk score shall be the product of an empirically derived, demonstrably and statistically sound credit scoring model based on data from a consumer reporting agency that compiles and maintains files on consumers on a nationwide basis, as defined in 15 U.S.C. 1681a(p). The credit scoring model shall be capable of rank ordering the credit risk presented by a borrower over the spectrum of all mortgage borrowers.

(A) *Empirically derived and other credit scoring models.* A credit scoring model is a model that evaluates a borrower's creditworthiness mechanically, based on key attributes of the borrower and aspects of the transaction, and that determines, alone or in conjunction with an evaluation of additional information about the borrower, whether the borrower is deemed creditworthy. To qualify as an empirically derived, demonstrably and statistically sound, credit scoring model for purposes of this section (d)(5), the model must be:
(I) based on data that are derived from an empirical comparison of sample groups or the population of creditworthy and noncreditworthy applicants who applied for credit within a reasonable preceding period of time;
(II) developed for the purpose of evaluating the creditworthiness of consumer applicants for credit, and applicable to mortgage applicants;
(III) developed and validated using accepted statistical principles and methodology; and
(IV) periodically revalidated by the use of appropriate statistical principles and methodology and adjusted as necessary to maintain predictive ability.

(B) *Odds-of-default.* The odds-of-default shall be defined as the ratio of non-delinquent borrowers to delinquent borrowers. Delinquent borrowers shall be defined as those with a mortgage delinquency of 90 days past due or worse over the 24 month period following the origination of the loan; non-delinquent borrowers shall be defined as those with no mortgage delinquency of 90 days past due or worse over the same 24 month period following the origination of the loan.

(C) *Annual Certification.* For purposes of compliance with subsection (d)(5)(i), a creditor may rely on the annual written certification of the person that developed the empirically derived, demonstrably and statistically sound credit scoring model that the model has been validated within a reasonable period of time on a national database of scoreable individuals with recent data from a consumer reporting agency that compiles and maintains files on a nationwide basis, as defined in 15 U.S.C. 1681a(p), and that the [X] to 1 odds-of-default credit risk threshold is represented by a specific credit score produced by such model, as determined through the validation process.

(D) *Model Risk Management.* The credit scoring models used by creditors pursuant to this section (d)(5) shall be developed and actively managed in accordance with the Supervisory Guidance on Model Risk Management promulgated by the Federal Reserve Board and the Office of the Comptroller of the Currency (SR Letter 11-7 and OCC 2011-12). The credit scoring model developers shall verify their methodology for calculating the relationship between their credit scoring model and the scoreable individuals' odds-of-default, as defined in this section (d)(5). Creditors shall retain satisfactory evidence of compliance with these requirements for examination purposes.

(ii) *Resetting the Minimum Odds-of-Default.* The Agencies shall have the authority to alter or amend the definition of odds-of-default, or adjust the minimum acceptable odds-of-default, in order to effect the purposes of the QRM exemption.

Proposed Credit History Rule -- Option #2

DELETE:

Subpart D—Exceptions and Exemptions, §__.15 *Exemption for qualified residential mortgages,* subsection (d)(5):

(d)(5) *Credit history*—(i) *In general.* The creditor has verified and documented that within ninety (90) days prior to the closing of the mortgage transaction:
(A) The borrower is not currently 30 days or more past due, in whole or in part, on any debt obligation;
(B) Within the previous twenty-four (24) months, the borrower has not been 60 days or more past due, in whole or in part, on any debt obligation; and
(C) Within the previous thirty-six (36) months:
(*1*) The borrower has not been a debtor in a case commenced under Chapter 7, Chapter 12, or Chapter 13 of Title 11, United States Code, or been the subject of any Federal or State judicial judgment for the collection of any unpaid debt;
(*2*) The borrower has not had any personal property repossessed; and (*3*) No one-to-four family property owned by the borrower has been the subject of any foreclosure, deed-in-lieu of foreclosure, or short sale.
(ii) *Safe harbor.* A creditor will be deemed to have met the requirements of paragraph (d)(5)(i) of this section if:
(A) The creditor, no more than 90 days before the closing of the mortgage transaction, obtains a credit report regarding the borrower from at least two consumer reporting agencies that compile and maintain files on consumers on a nationwide basis;
(B) Based on the information in such credit reports, the borrower meets all of the requirements of paragraph (d)(5)(i) of this section, and no information in a credit report subsequently obtained by the creditor before the closing of the mortgage transaction contains contrary information; and
(C) The creditor maintains copies of such credit reports in the loan file for the mortgage transaction.

REPLACE subsection (d)(5) with the following:

(d)(5) *Credit history—(i) In general.* The creditor has verified and documented within ten (10) days prior to the closing of the mortgage transaction that the borrower has a credit risk score that indicates the borrower's odds-of-default on the mortgage are [X] to 1 or higher. The credit risk score shall be the product of an empirically derived, demonstrably and statistically sound credit scoring model. The credit scoring model shall be capable of rank ordering the credit risk presented by a borrower over the spectrum of all mortgage borrowers.

(A) *Empirically derived and other credit scoring models.* A credit scoring model is a model that evaluates a borrower's creditworthiness mechanically, based on key attributes of the borrower and aspects of the transaction, and that determines, alone or in conjunction with an evaluation of additional information about the borrower, whether the borrower is deemed creditworthy. To qualify as an empirically derived, demonstrably and statistically sound, credit scoring model for purposes of this section (d)(5), the model must be:
(I) based on data that are derived from an empirical comparison of sample groups or the population of creditworthy and noncreditworthy applicants who applied for credit within a reasonable preceding period of time;
(II) developed for the purpose of evaluating the creditworthiness of consumer applicants for credit, and applicable to mortgage applicants;
(III) developed and validated using accepted statistical principles and methodology; and
(IV) periodically revalidated by the use of appropriate statistical principles and methodology and adjusted as necessary to maintain predictive ability.

(B) *Odds-of-default.* The odds-of-default shall be defined as the ratio of non-delinquent borrowers to delinquent borrowers. Delinquent borrowers shall be defined as those with a mortgage delinquency of 90 days past due or worse over the 24 month period following the origination of the loan; non-delinquent borrowers shall be defined as those with no mortgage delinquency of 90 days past due or worse over the same 24 month period following the origination of the loan.

(C) *Model Validation and Compliance.* A creditor may use an empirically derived, demonstrably and statistically sound, credit scoring model obtained from another person, if such model is based on a national database of scoreable individuals with recent data from a consumer reporting agency that compiles and maintains files on a nationwide basis, as defined in 15 U.S.C. 1681a(p); or a creditor may develop its own credit risk model if the model is capable of rank ordering the credit risk presented by each borrower over the spectrum of the creditor's mortgage borrowers, and the model satisfies the criteria set forth in paragraphs (A)(I) through (IV) of this section (d)(5). The creditor shall validate the model it uses at least annually, based on its own credit experience in accordance with paragraphs (A)(I) through (IV). A model that fails this validity test is no longer an empirically derived, demonstrably and statistically sound, credit scoring model for that creditor.

(D) *Model Risk Management.* The credit scoring models used by creditors pursuant to this section (d)(5) shall be developed and actively managed by creditors in accordance with the Supervisory Guidance on Model Risk Management promulgated by the Federal Reserve Board and the Office of the Comptroller of the Currency (SR Letter 11-7 and OCC 2011-12). Pursuant to these regulatory standards, creditors shall validate the accuracy of their credit scoring models and verify their methodology for calculating the relationship between their credit scoring model and their borrowers' odds-of-default, as defined in this section (d)(5). Creditors shall retain satisfactory evidence of compliance with these requirements for examination purposes.

(ii) *Resetting the Minimum Odds-of-Default.* The Agencies shall have the authority to alter or amend the definition of odds-of-default, or adjust the minimum acceptable odds-of-default, in order to effect the purposes of the QRM exemption.

Proposed Credit History Rule -- Option #3

<u>DELETE</u>:
Subpart D—Exceptions and Exemptions, §__.15 *Exemption for qualified residential mortgages,* subsection (d)(5):

(d)(5) *Credit history*—(i) *In general.* The creditor has verified and documented that within ninety (90) days prior to the closing of the mortgage transaction:
(A) The borrower is not currently 30 days or more past due, in whole or in part, on any debt obligation;
(B) Within the previous twenty-four (24) months, the borrower has not been 60 days or more past due, in whole or in part, on any debt obligation; and
(C) Within the previous thirty-six (36) months:
(*1*) The borrower has not been a debtor in a case commenced under Chapter 7, Chapter 12, or Chapter 13 of Title 11, United States Code, or been the subject of any Federal or State judicial judgment for the collection of any unpaid debt;
(*2*) The borrower has not had any personal property repossessed; and (*3*) No one-to-four family property owned by the borrower has been the subject of any foreclosure, deed-in-lieu of foreclosure, or short sale.
(ii) *Safe harbor.* A creditor will be deemed to have met the requirements of paragraph (d)(5)(i) of this section if:
(A) The creditor, no more than 90 days before the closing of the mortgage transaction, obtains a credit report regarding the borrower from at least two consumer reporting agencies that compile and maintain files on consumers on a nationwide basis;
(B) Based on the information in such credit reports, the borrower meets all of the requirements of paragraph (d)(5)(i) of this section, and no information in a credit report subsequently obtained by the creditor before the closing of the mortgage transaction contains contrary information; and
(C) The creditor maintains copies of such credit reports in the loan file for the mortgage transaction.

<u>REPLACE</u> subsection (d)(5) with the following:

(d)(5) *Credit history*—(i) *In general.* The creditor has verified and documented within ten (10) days prior to the closing of the mortgage transaction that the borrower has a credit risk score that indicates the borrower's odds-of-default on the mortgage are [X] to 1 or higher. The credit risk score shall be the product of an empirically derived, demonstrably and statistically sound credit scoring model. The credit scoring model shall be capable of rank ordering the credit risk presented by a borrower over the spectrum of all mortgage borrowers.

(A) *Empirically derived and other credit scoring models.* A credit scoring model is a model that evaluates a borrower's creditworthiness mechanically, based on key attributes of the borrower and aspects of the transaction, and that determines, alone or in conjunction with an evaluation of additional information about the borrower, whether the borrower is deemed creditworthy. To qualify as an empirically derived, demonstrably and statistically sound, credit scoring model for purposes of this section (d)(5), the model must be:
(I) based on data that are derived from an empirical comparison of sample groups or the population of creditworthy and noncreditworthy applicants who applied for credit within a reasonable preceding period of time;
(II) developed for the purpose of evaluating the creditworthiness of consumer applicants for credit, and applicable to mortgage applicants;
(III) developed and validated using accepted statistical principles and methodology; and
(IV) periodically revalidated by the use of appropriate statistical principles and methodology and adjusted as necessary to maintain predictive ability.

(B) *Odds-of-default.* The odds-of-default shall be defined as the ratio of non-delinquent borrowers to delinquent borrowers. Delinquent borrowers shall be defined as those with a mortgage delinquency of 90 days past due or worse over the 24 month period following the origination of the loan; non-delinquent borrowers shall be defined as those with no mortgage delinquency of 90 days past due or worse over the same 24 month period following the origination of the loan.

(C) Annual Certification; Model Validation; and Compliance. A creditor may use an empirically derived, demonstrably and statistically sound, credit scoring model obtained from another person, if such model is based on a national database of scoreable individuals with recent data from a consumer reporting agency that compiles and maintains files on a nationwide basis, as defined in 15 U.S.C. 1681a(p). For purposes of compliance with subsection

(d)(5)(i), a creditor may rely on the annual written certification of such other person that the [X] to 1 odds-of-default credit risk threshold is represented by a specific credit score produced by such model, as determined through the validation process.

For purposes of compliance with subsection (d)(5)(i), a creditor may develop its own credit model if that model is capable of rank ordering the credit risk presented by each borrower over the spectrum of the creditor's mortgage borrowers, and the model satisfies the criteria set forth in paragraphs (A)(I) through (IV) of this section (d)(5). The creditor shall validate the model it uses at least annually, based on its own credit experience in accordance with paragraphs (A)(I) through (IV). A model that fails this validity test is no longer an empirically derived, demonstrably and statistically sound, credit scoring model for that creditor.

(D) *Model Risk Management*. The credit scoring models used by creditors pursuant to this section (d)(5) shall be developed and actively managed in accordance with the Supervisory Guidance on Model Risk Management promulgated by the Federal Reserve Board and the Office of the Comptroller of the Currency (SR Letter 11-7 and OCC 2011-12). The credit scoring model developers shall verify their methodology for calculating the relationship between their credit scoring model and the scoreable individuals' odds-of-default, as defined in this section (d)(5). Creditors shall retain satisfactory evidence of compliance with these requirements for examination purposes.

(ii) *Resetting the Minimum Odds-of-Default*. The Agencies shall have the authority to alter or amend the definition of odds-of-default, or adjust the minimum acceptable odds-of-default, in order to effect the purposes of the QRM exemption.

Proposed Credit History Rule -- Option #4

DELETE:
Subpart D—Exceptions and Exemptions, §__.15 *Exemption for qualified residential mortgages,* subsection (d)(5):

(d)(5) *Credit history*—(i) *In general.* The creditor has verified and documented that within ninety (90) days prior to the closing of the mortgage transaction:
(A) The borrower is not currently 30 days or more past due, in whole or in part, on any debt obligation;
(B) Within the previous twenty-four (24) months, the borrower has not been 60 days or more past due, in whole or in part, on any debt obligation; and
(C) Within the previous thirty-six (36) months:
(*1*) The borrower has not been a debtor in a case commenced under Chapter 7, Chapter 12, or Chapter 13 of Title 11, United States Code, or been the subject of any Federal or State judicial judgment for the collection of any unpaid debt;
(*2*) The borrower has not had any personal property repossessed; and (*3*) No one-to-four family property owned by the borrower has been the subject of any foreclosure, deed-in-lieu of foreclosure, or short sale.
(ii) *Safe harbor.* A creditor will be deemed to have met the requirements of paragraph (d)(5)(i) of this section if:
(A) The creditor, no more than 90 days before the closing of the mortgage transaction, obtains a credit report regarding the borrower from at least two consumer reporting agencies that compile and maintain files on consumers on a nationwide basis;
(B) Based on the information in such credit reports, the borrower meets all of the requirements of paragraph (d)(5)(i) of this section, and no information in a credit report subsequently obtained by the creditor before the closing of the mortgage transaction contains contrary information; and
(C) The creditor maintains copies of such credit reports in the loan file for the mortgage transaction.

REPLACE subsection (d)(5) with the following:

(d)(5) *Credit history*—(i) *In general.* The creditor has verified and documented within ten (10) days prior to the closing of the mortgage transaction that the borrower has a credit risk score that places that borrower in the least credit risky [X]% of mortgage borrowers. The credit risk score shall be the product of an empirically derived, demonstrably and statistically sound credit scoring model, based on data from a consumer reporting agency that compiles and maintains files on consumers on a nationwide basis, as defined in 15 U.S.C. 1681a(p). The credit scoring model shall be capable of rank ordering the credit risk presented by a borrower over the spectrum of all mortgage borrowers.

(A) *Empirically derived and other credit scoring models.* A credit scoring model is a model that evaluates a borrower's creditworthiness mechanically, based on key attributes of the borrower and aspects of the transaction, and that determines, alone or in conjunction with an evaluation of additional information about the borrower, whether the borrower is deemed creditworthy. To qualify as an empirically derived, demonstrably and statistically sound, credit scoring model for purposes of this section (d)(5), the model must be:
(I) based on data that are derived from an empirical comparison of sample groups or the population of creditworthy and noncreditworthy applicants who applied for credit within a reasonable preceding period of time;
(II) developed for the purpose of evaluating the creditworthiness of consumer applicants for credit, and applicable to mortgage applicants;
(III) developed and validated using accepted statistical principles and methodology; and
(IV) periodically revalidated by the use of appropriate statistical principles and methodology and adjusted as necessary to maintain predictive ability.

(B) *Odds-of-default.* The odds-of-default shall be defined as the ratio of non-delinquent borrowers to delinquent borrowers. Delinquent borrowers shall be defined as those with a mortgage delinquency of 90 days past due or worse over the 24 month period following the origination of the loan; non-delinquent borrowers shall be defined as those with no mortgage delinquency of 90 days past due or worse over the same 24 month period following the origination of the loan.

(C) *Annual Certification.* For purposes of compliance with subsection (d)(5)(i), a creditor may rely on the annual written certification of the person that developed the empirically derived, demonstrably and statistically sound credit scoring model that the model has been validated within a reasonable period of time on a national database of scoreable individuals with recent data from a consumer reporting agency that compiles and maintains files on a nationwide basis, as defined in 15 U.S.C. 1681a(p), and that the [X]% credit risk threshold is represented by a specific credit score produced by such model.

(D) *Model Risk Management*. The credit scoring models used by creditors pursuant to this section (d)(5) shall be developed and actively managed in accordance with the Supervisory Guidance on Model Risk Management promulgated by the Federal Reserve Board and the Office of the Comptroller of the Currency (SR Letter 11-7 and OCC 2011-12). The credit scoring model developers shall verify their methodology for calculating the relationship between their credit scoring model and the percentage of individuals who qualify under this section (d)(5). Creditors shall retain satisfactory evidence of compliance with these requirements for examination purposes.

(ii). *Resetting the Percentages of Qualifying Mortgages*. The Agencies shall have the authority to adjust the percentage of loans that qualify under this section (d)(5) for the QRM exemption.

Summary of FICO's Comment Letter

The Dodd-Frank Wall Street Reform and Consumer Protection Act amended the securities laws to require securitizers of asset-backed securities to retain five percent of the credit risk of the assets collateralizing the securities. The Proposed Rule would include an exemption from this credit risk retention requirement in the form of a "qualified residential mortgage" (QRM). FICO is generally supportive of the legislative intent behind the Proposed Rule's QRM standard, based on the notion that some securities are relatively risk-free, and thus risk retention is unnecessary.

However, FICO believes the Proposed Rule is fundamentally flawed in one significant respect: the credit history standards incorporated into the proposed definition of QRM are not sufficiently predictive of the risk of delinquency or default. The proposed credit history standards shift away from the use of the most predictive measurement of default risk (credit scores) and instead adopt a narrow set of "derogatory factors" found in credit reports. In addition, the Proposed Rule takes a similarly flawed approach to defining a Qualifying Auto Loan (QAL): the Proposed Rule would include credit history standards very similar to those incorporated into the QRM definition, and the QAL credit history standards would also fail to adequately predict credit risk.

Key Problems

- **Proposed credit history standards select the wrong population of risks**. FICO believes the proposed credit history standards exclude too many borrowers who are good credit risks, while at the same time failing to identify too many borrowers who are bad credit risks – that is, a significant number of low risk borrowers fail to meet the QRM standards while high risk borrowers satisfy the QRM standards. FICO conducted extensive research analyzing the effectiveness of the proposed QRM credit history standards compared to analytically derived credit scores. The research revealed the following:
  - The proposed credit history standards would include borrowers qualifying under the QRM with FICO scores as low as 472, which is very high risk.
  - Many low-risk borrowers would inadvertently be denied access to QRM loans, some with scores as high as 845 on a 300- 850 FICO Score range.
  - Sharp discrepancies in the proposed QRM rule's treatment of consumers within a range of FICO Scores that would impact more than 25 percent of the US population. For example, at any given score level within this range some consumers would qualify and others would not qualify under the proposed QRM credit history rules.
- **A return to manual underwriting**. The proposed credit history standards will mark an unwelcome return to manual underwriting while also proving to be difficult to implement. Requiring originators to conduct a manual review of the proposed credit history standards, i.e., the —derogatory factors, in the credit file will signal a shift away from automated underwriting, and will likely be accompanied by added costs, delays, errors and transparency concerns.
- **Some data is unavailable or may be stale**. Some of the credit history information relied upon in the proposed standards, such as the timing of short sales and repossessions, is not readily available to lenders at the time of underwriting and, because the proposed standards permit lenders to determine QRM status on data that is up to 90 days old, many of these important decisions will be based on stale information.
- **Imposes a check-the-box solution**. As FICO has seen in other recent rulemakings where already overburdened financial institutions with scarce compliance resources are driven

toward adopting check-the-box solutions in order to comply with an ineffective regulatory requirement, the proposed QRM standards could result in some institutions taking the disastrous step of substituting the proposed standards for sound underwriting practices.

- **May Imperil the securitization market**. The purpose of the risk retention provisions is to protect the securitization and credit markets, and the clear solution is to require the use of credit scoring models to accurately predict the credit risk that is being assumed by securitizers.

Benefits of Credit Scoring

The benefits derived from the use of credit scores have been well documented in a number of government studies. Most notably, the following reports confirmed that credit scoring:

- **Increases accuracy, access to credit, and market efficiency**. The Federal Reserve Board underscored these points in its 2007 Report to Congress on *Credit Scoring and Its Effects on the Availability and Affordability of Credit*.
- **Decreases the possibility of bias.** The 2010 Federal Reserve Staff Report titled —*Does Credit Scoring Produce a Disparate Impact?* recognized the benefits derived from the use of an objective measurement of credit risk and concluded that there was no evidence that credit scoring yields a disparate impact by race or gender.

FICO's QRM Solution

The Agencies (OCC, FRB, FDIC, SEC, FHFA, HUD) should mandate the inclusion of credit scores as a QRM underwriting standard. This can be done under their existing regulatory authority and oversight power and in a vendor-neutral way.

- Credit scores are the product of credit scoring models, which are built with depersonalized data pursuant to the rigorous requirements of Regulation B, which implements the Equal Credit Opportunity Act.

- Credit scores are already validated, revalidated and subject to comprehensive regulatory oversight, as evidenced by the recently published Federal Reserve/OCC Supervisory Guidance on Credit Risk Management, to ensure that they are fully predictive, and do not result in impermissible discrimination or exposure to unwarranted credit risk.

- All credit scoring models that meet these regulatory requirements can easily be calibrated to a standard set by regulators based on a specified percentage of the national population of residential mortgage loans that qualify under QRM or, alternatively, a specified national default rate.

FICO

THE IMPORTANCE OF PREDICTIVE ANALYTICS vs. MANUAL REVIEW IN CREDIT HISTORY STANDARDS

THE PROPOSED CREDIT RISK RETENTION RULE WILL NOT IMPROVE THE SECURITIZATION MARKET

QRM CREDIT HISTORY STANDARDS NEED TO BE PREDICTIVE AND RELY ON CREDIT SCORES

OVERVIEW:

Starting in the late 1950s, Fair Isaac sparked a revolution by pioneering credit risk scoring for the financial services industry. This new approach to lending enabled financial institutions to improve their business performance and expand consumers' access to credit. While the FICO score provides the most reliable and objective evaluation for a borrower's repayment risk, it is only one risk factor among many that lenders consider when making decisions about consumer credit – the three C's – 1) credit score, 2) capacity and 3) collateral. FICO believes that, in order to get our economy back on track and ensure a properly functioning securitization market, there must be transparent, reliable and objective criteria by which credit risk is determined. Sound underwriting standards must include analytically derived, statistically sound credit scores that provide predictive and objective measurements of credit risk across all market cycles.

THE ISSUE:

The proposed credit risk retention rule, recently issued in accordance with Section 941 of the Dodd-Frank Act, contains an exemption from risk retention requirements for those loans that meet the standards of a "Qualified Residential Mortgage" (QRM). However, the proposed QRM credit history standards, if adopted as proposed, would undermine Congress' legislative intent to create a pool of high quality loans that merit exclusion from risk retention requirements. The credit history requirements fail to include the accepted industry standard (the use of predictive analytics in the form of FICO® scores) in favor of a manual review of derogatory factors in the borrower's credit file that research has shown is not sufficiently predictive of credit risk and that will have significant negative unintended consequences.

As outlined in the Federal Reserve Board's 2007 Report to Congress on *"Credit Scoring and Its Effects on the Availability and Affordability of Credit,"* credit scoring not only is accurate and promotes a more efficient marketplace but it also provides valuable benefits to consumers:

"Credit scoring...increases the consistency and objectivity of credit evaluation and thus may diminish the possibility that credit decisions will be influenced by personal characteristics or other factors prohibited by law, including race or ethnicity. In addition, quicker decision-making also promotes increased competition because, by receiving information on a timelier basis, consumers can more easily shop for credit. Finally, credit scoring is accurate; that is, individuals with lower (worse) credit scores are more likely to default on their loans than individuals with higher (better) scores. [p. O-5]"

FICO

WHY THE PROPOSED QRM CREDIT HISTORY STANDARDS WILL NOT WORK:

1. ***The proposed credit history standards are not sufficiently predictive***. FICO has conducted research examining:
   a. the proposed QRM derogatory factors (no 60+ day delinquency within past 24 months, no current 30+ day delinquency and no bankruptcies, foreclosures, deed-in-lieu of foreclosures or judgments of any unpaid debt) as well as
   b. the proposed QRM derogatory factors (same as above) coupled with the proposed non-credit QRM criteria.

   FICO reviewed the performance of mortgage origination data between the years of 2005 and 2008 and compared the QRM criteria to analytically derived credit scores. The research revealed that the minimum FICO score that met the proposed QRM delinquency standards was as low as 472 and the maximum FICO score that failed to meet the proposed QRM delinquency standards was as high 845 – a distorted outcome allowing consumers with low FICO scores in and leaving consumers with high FICO scores out. In addition, when studying both the proposed derogatory factors in combination with the other non-credit QRM criteria, FICO saw the same distorted outcomes with borrowers qualifying for QRM with FICO scores as low as 493 while those with scores up to 827 being denied a QRM loan. To place this in perspective, the FICO score range is 300 to 850, with lower scores indicating higher risk. The median FICO score of the US consumer today is 713 and the minimum FICO score threshold for an FHA loan is 580. This demonstrates that the proposed approach of using derogatory credit history standards for QRM loans could lead to the inclusion of many high-risk borrowers as well as the exclusion of excellent credit risks – precisely the wrong result on both counts.

2. ***A manual review of credit files raises costs, delays, errors and transparency concerns.***
   The proposed method of examining the credit file for derogatory factors represents a shift away from automated underwriting to a manual approach that will impose increased expense on lenders, slower loan processing times, less accuracy and decreased transparency in the securitization market where credit scores today are shared seamlessly between originators, issuers and investors for decision making.

3. ***A "check the box" solution may have unintended consequences for small and medium lenders.***
   Requiring a new and ineffective set of QRM credit history standards will not only impose additional compliance costs on lenders but also likely force many small and medium banks to choose the "check the box" requirement over the continued use of predictive analytics – exposing the lender and the potential investor to greater credit risk exposure.

4. ***QRM credit history standards will face implementation challenges.*** The credit history standards include a requirement that lenders ensure that a borrower has not had a short sale or repossession in the past three years. However, today the credit report does not provide dates for these actions. In addition, allowing credit reports to be verified as far out as 90 days from the closing date exposes investors unnecessarily to increased credit risk exposure compared to current requirements where

credit scores are pulled just days prior to the funding date of the loan to assure the highest degree of accuracy in assessing consumer credit risk.

5. **"Empirically Derived, Demonstrably and Statistically Sound" vs. Subjective Decision-Making.** Regulation B (implementing the provisions of the Equal Credit Opportunity Act) details lenders' use of approved credit scoring models that are "empirically derived, demonstrably and statistically sound." The proposed rules fall far short of this standard. Under the proposed rules, there would be a shift away from credit scores, which threatens a return to the days marked by subjective decision-making. The mortgage industry's adoption of credit scores not only served as an advanced method of predicting credit risk but removed the subjectivity and bias that too often was associated with the lending process. Compliance with Regulation B standards is evidence of an objective assessment of a borrower's credit risk. The mortgage industry has complied with Regulation B through the widespread adoption of FICO® scores which are also the credit risk underwriting standard for FHA-insured loans as well as loans sold to Fannie Mae and Freddie Mac. The proposed QRM credit history standards will bring an element of subjectivity back into the process, once again creating an environment that in the past has fostered discrimination.

CONCLUSION:

Credit scores are not only the market standard among lenders for assessing consumer credit risk but their use is supported by a large body of research that concludes that they are the most accurate predictors of default. Reliance on predictive analytics is already the accepted practice in the marketplace and has helped transform an industry that relied on manual underwriting decades ago to an automated system today that is marked by efficiency, objectivity and accuracy. As a result, credit scores should be part of the credit history standards in the final rule and can be implemented in a vendor-neutral manner leveraging existing federal regulatory oversight.

QRM CREDIT PROFILES

FICO

While the derogatory payment factors in the proposed QRM rule may be indicators of risky credit behavior, these factors represent less than 35% of the analytical inputs used by FICO in its credit risk scoring models. Other factors not considered by the QRM credit history standards include amounts owed, length of credit history, recent credit-seeking activity, types of credit used, and positive payment history. As a result, reliance on derogatory payment factors results in an inaccurate measurement of credit risk.

Relocated Father with Lost Bank Bill

I am a middle-aged married father of three. My job requires me to travel several times a month. I've had credit since I was in college 27 years ago. My company is moving my job to an adjacent state to cut down on travel expenses. I'm selling our home and have moved my family into an apartment in our new city. I'm hoping to buy a house here soon. I have no history of collections and no adverse public records. My wife and I are careful with money. I have successfully repaid two car loans, have two bank credit cards and a retail card, and keep my card balances low. I am currently reported as 30 days past due on my retail card because the card issuer didn't send my last bill to our new address and the post office didn't forward it. **My FICO score is around 700, but I am not eligible for a QRM.** Now, we'll have to pay a significantly higher interest rate on our new home.

Elderly Woman with Health Problems

I am a 62-year-old woman with an almost pristine credit history. With one exception, I've never had a reported late payment. I've had no collections accounts, no adverse public records, and never missed a payment on a mortgage account. I have a well-documented history of successfully paying a variety of different types of credit obligations (revolving, auto, mortgage); low revolving balances; very low revolving utilization ratio; long credit history (25+ years); and few recently opened accounts. Recently I had an unexpected health problem that caused me to be 60 days delinquent 23 months ago, which I paid off in full a few days thereafter. **My FICO score is above 800, but I would not be eligible for a QRM.**

Bachelor with Bad Credit History

I am a 35-year-old bachelor. I haven't held a steady job in 10 years and stay afloat through get-rich-quick ventures and borrowing from friends. A little over three years ago I had three foreclosures at nearly the same time. I now have five separate accounts in collection. A little over two years ago my finances forced me to stop paying the balances on four credit cards for six months, resulting in 180-days past-due delinquencies before I was able to resume making the minimum payments. All four cards are currently maxed out. Because I am tapped out, in the past two months I have applied for three new credit cards. **My FICO score is about 550, but I would be eligible for a QRM.**

Credit-Worthy College Professor

I am a woman in my late 30s, am unmarried, and a college professor. I have no history of collections and no adverse public records. I've paid off both my student loan and an auto loan. I bought the car new and it has over 230,000 miles because I am meticulous about routine maintenance. I have carefully managed a bank credit card for 17 years and have a retail store card. A year and a half ago I bought an electric mixer with my retail store card. When its motor immediately burnt out, I tried to return it to the store. Both the store and the manufacturer refused to accept the return, so I refused to pay my retail card bill for that purchase for two months. I finally gave up my fight and paid the past-due amount. I have not been late with a payment since. **My FICO score is around 700, but I would not be eligible for a QRM.**

Recent College Grad Careless with Credit

I am a 23-year-old recent college graduate. Very recently I became 30 days past-due on several accounts, but I'm now paid-up. Those were my only delinquencies within the past 2 years. However, just over 2 years ago I became 3-6 months delinquent on three other credit accounts. I also now have numerous 3rd party collections accounts and I'm maxed out on several credit cards. I have a relatively short credit history (far less than 10 years). Recently I applied for a number of new credit cards and opened quite a few new accounts, although I could only qualify for accounts with small credit limits and high interest rates. **My FICO score is below 500, but I would be eligible for a QRM.**

FICO

Analysis of Proposed QRM Risk Criteria

The Dodd-Frank Wall Street Reform and Consumer Protection Act includes regulations designed to encourage responsible lending and protect credit markets from unreasonable risk. One important mechanism for providing such protection is a rule that requires lenders to hold onto 5% of the credit risk on residential mortgages they underwrite.

A proposed exception to this rule would enable lenders to securitize and sell 100% of mortgages that meet a yet-to-be-finalized Qualified Residential Mortgage (QRM) standard. This standard is meant to ensure that qualifying mortgages are of extremely high quality and low risk.

Determining which loans earn QRM status

- To help gauge the riskiness of a mortgage, the proposed QRM standard includes several criteria related to the credit history of a borrower.
- Unfortunately, no research was conducted by regulators to determine the predictive value of the criteria that were included in the proposed QRM credit history standard.
- The proposed standard does not use credit scores, which are the most accurate measures of credit risk and are used to underwrite nearly every mortgage in the U.S.

Instead of empirically derived credit scores, the proposed judgmental criteria include a hodgepodge of items from a borrower's credit history, including 30-day payment delinquencies, short sales, and other derogatory factors. These factors make up less than one-third of the predictive information assessed by the FICO® Score. And unlike credit scores, this judgmental approach does not allow for compensating factors or the careful weighting of data points.

The danger of using arbitrary and unproven criteria to assess risk

FICO analyzed over 10 million consumer credit files* for mortgage loans originated from 2005-2008 to understand how the proposed QRM risk criteria would have performed. The results of this study indicate that the current QRM proposal would bring more risk into mortgage securitization than regulators and legislators intended, while preventing highly qualified buyers from entering the housing market.

- Buyers with FICO scores up to 827 (on a scale of 300-850) could be denied QRM loans. The scientifically validated creditworthiness of these people is in the top 5% of U.S. borrowers.
- Buyers with FICO scores as low as 493 could qualify for QRM loans. The creditworthiness of these buyers is only in the lowest 6% of U.S. borrowers.

Working toward a specific goal

A logical way to determine the QRM standard is to define the desired outcome, and then establish rules to achieve that outcome. Such an approach would be vendor-neutral and not rely on credit scores from any specific vendor to ensure lender compliance.

- As one approach, regulators could set a specific targeted national default rate for loans that qualify under QRM.
- Alternatively, regulators could set a specific targeted percentage of the national population of residential mortgage loans which would qualify under QRM.

Provided with such a target, lenders could use credit scores to quickly determine which mortgages should be given QRM status. It is impossible to achieve this level of precision and control with an unscientific approach that relies on isolated data points such as a 30-day delinquency on a credit report.

A simple, inexpensive and highly accurate solution

Lenders already generate credit scores for every person who applies for a mortgage. Based on those credit scores, lenders know the probability that a borrower will default. And while these probabilities may shift over time, lenders routinely review the correlation between default rates and credit scores in their mortgage portfolios so they can adjust their minimum score requirements for new loans and thereby maintain desired risk levels. In this way lenders could comply consistently and routinely with a national risk standard established for QRM.

FICO's analysis of mortgages originated from 2005-2008 found that:

- The default rate on such mortgages could have been limited to 2% if lenders had required a minimum FICO score of 650.
- Alternatively, setting a 25% volume standard for such mortgages would correspond to a minimum FICO score of 650 for successful applicants.
- When only the derogatory factors of the proposed QRM credit risk standard are used to judge risk, the resulting default rate is closer to an equivalent FICO® Score of 620 than to the FICO® Score of 690 targeted by regulators.

The importance of smart public policy

A QRM standard pegged to a default rate of 2.4% (which corresponds to a FICO Score of 620) would have resulted in the same general default rate as the proposed QRM risk criteria, but with the added benefit of allowing approximately 830,000 more mortgages to qualify for QRM status.

It also would prevent significant losses. Industry experts have estimated that each mortgage default costs an average of $50,000. Based on that estimate, the elimination of just 20,000 defaults would save $1 billion in losses. A QRM standard based on a default rate of 2% (which corresponds to a FICO Score of 650) would have prevented 48 thousand more defaults than the proposed QRM risk criteria when applied to mortgages originated between 2005-2008. That translates into a loss prevention of $2.4 billion.

This analysis showed that by allowing lenders to use credit scores to satisfy the risk assessment of any proposed QRM standard, regulators can:

- Confidently control the volume of QRM loans that default;
- Significantly increase the number of mortgages that qualify for QRM status.

FICO examined data from real mortgages to assess the effectiveness of possible QRM standards. The results are clear and unambiguous. The most reliable, convenient and objective way to set a risk threshold for the QRM standard is either through the use of default rates tied to credit scores, or by setting a percentage of the national population of residential mortgage loans which would qualify under QRM based on credit scores. Such regulation can be vendor-neutral because different commercial credit scoring models could be used to comply with such a standard, just as businesses comply today with Reg B of the Equal Credit Opportunity Act.

*CoreLogic provided loan characteristics and performance data for this study. The CoreLogic LoanPerformance databases contain information on more than 85% of all outstanding mortgage loans. The study dataset was constructed by identifying the loans within CoreLogic's databases that had sufficient information to calculate default rates based on the proposed QRM standard.

Parameters of Proposed QRM Study

FICO

- Examined pool of new mortgages opened between 2005-2008
- Merged loan-level information with Credit Bureau files to more fully explore the outcomes of the proposed QRM definition
- QRM "non-credit" criteria applied to dataset
  - Back-end DTI <= 36%
  - Origination Loan-to-Value
    - Purchase <= 80%
    - Refinance <= 75%
    - Cash out Refinance <= 70%
  - Owner occupied
  - First lien
- <u>After applying QRM "non-credit" criteria, ~29% new mortgages originated between 2005-2008 remained</u>
- <u>Files with new mortgage that satisfy all aspects of QRM criteria ~25%</u>
- All subsequent analyses are based on the new mortgages which satisfied the QRM "non-credit" criteria

QRM Criteria and Comparable FICO Score Cut-off (volume held fixed)

FICO™

Corresponding FICO Score Cut-off Analysis

QRM/Score	Score Cut-off	Above Cut-off	Below Cut-off
QRM Criteria	-	86%	14%
FICO 8	650	86%	14%
FICO 8 Mortgage	635	86%	14%
Prior FICO	645	86%	14%

90+ Bad Rate on New Mortgage Accounts

QRM/Score	Score Cut-off	Above Cut-off	Below Cut-off
QRM Criteria	-	2.4%	9.5%
FICO 8	650	2.0%	11.8%
FICO 8 Mortgage	635	1.7%	13.4%
Prior FICO	645	2.0%	12.0%

Overall 90+ Bad Rate on New Mortgage Accounts – 3.4%

Data Summary: The proposed QRM credit criteria allowed for 86% of the new mortgage population to qualify for the QRM exemption. The corresponding FICO® Score that would allow for the same percentage of population to qualify for QRM is a 650. The resulting 90+ dpd rate for the QRM credit criteria is 2.4% vs 2.0% for the FICO® 8 650 Score.

Applying a Score rather than the QRM criteria on the ~47.8 million new mortgages booked between 2005-2008 would have resulted in ~48,000 fewer 90+ dpd accounts qualified for the QRM exemption. Assuming ~$50k loss per bad mortgage, <u>use of a Score would correspond to a reduction in losses of ~$2.4 billion within the QRM qualified loans.</u>

QRM Criteria and Comparable FICO Score Cut-off (bad rate held fixed)

FICO

90+ Bad Rate on New Mortgage Accounts

QRM/Score	Score Cut-off	Above Cut-off	Below Cut-off
QRM Criteria	-	2.4%	9.5%
FICO 8	620	2.4%	15.2%
FICO 8 Mortgage	580	2.4%	20.1%
Prior FICO	620	2.4%	14.0%

Overall 90+ Bad Rate on New Mortgage Accounts – 3.4%

Resulting Volumes by FICO Scores

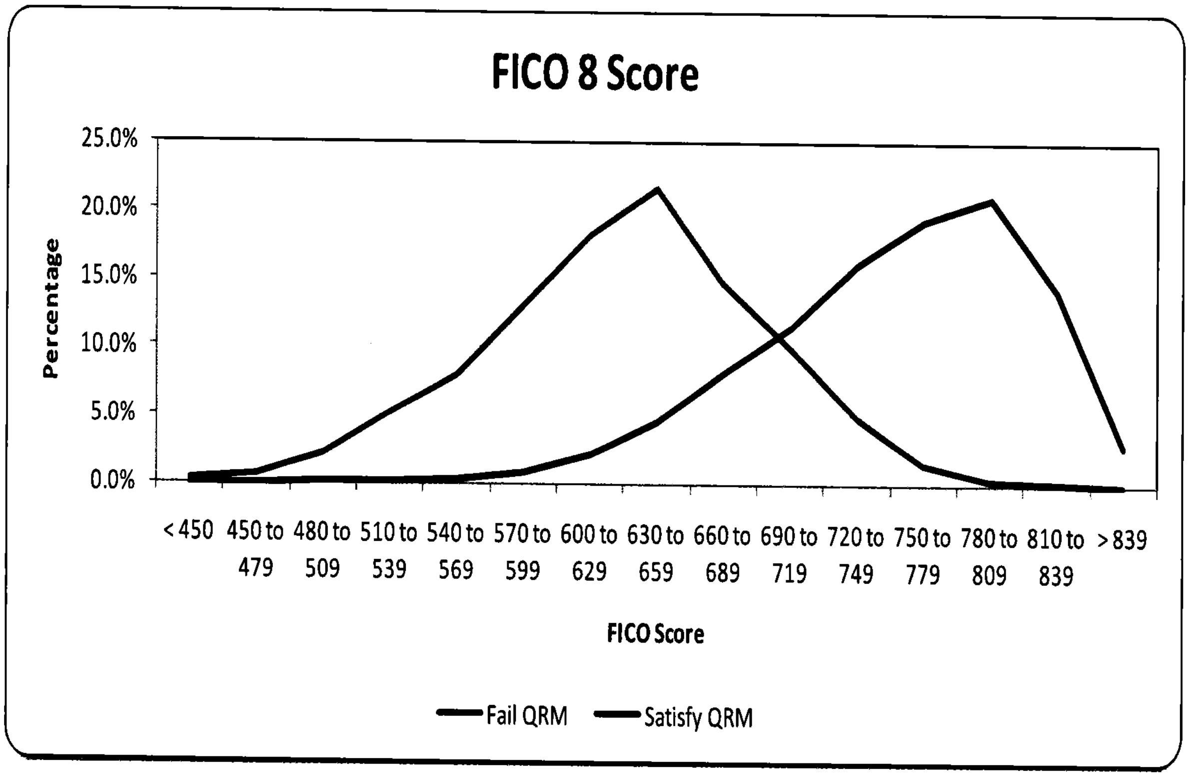
QRM/Score	Score Cut-off	Above Cut-off	Below Cut-off
QRM Criteria	-	86%	14%
FICO 8	620	92%	8%
FICO 8 Mortgage	580	95%	5%
Prior FICO	620	91%	9%

Data Summary: The proposed QRM standards would result in an overall 2.4% 90+ dpd rate for the QRM qualified population. The corresponding FICO 8 score that would result in the same 90+ dpd rate is a 620.

Applying FICO® 8 score of 620 instead of the QRM criteria on the ~47.8 million new mortgages booked between 2005-2008 would have resulted in <u>~832,000 more QRM qualified consumers</u> while still holding the bad rate of the QRM qualified population fixed at 2.4%.

Proposed QRM Score Distribution

FICO



FICO Score Stats – a wide range of credit both qualifies and fails under the proposed rules

FICO

	Files that Fail QRM "Credit" Criteria							
					Percentiles			
Score Version	*Min*	*Max*	*Mean*	*Median*	*1st*	*5th*	*95th*	*99th*
FICO 8	438	827	630	634	481	523	727	760
FICO 8 Mortgage	332	850	624	630	409	475	749	791
Prior FICO	396	782	619	625	470	509	710	738

	Files that Satisfy QRM "Credit" Criteria							
					Percentiles			
Score Version	*Min*	*Max*	*Mean*	*Median*	*1st*	*5th*	*95th*	*99th*
FICO 8	493	850	752	761	598	644	833	848
FICO 8 Mortgage	407	850	752	761	561	616	850	850
Prior FICO	492	818	746	760	599	642	809	816

The proposed QRM rules will result in consumers with good credit not qualifying for the QRM exemption while those with poorer credit qualifying, potentially resulting in disparate pricing and terms.

ABOUT FICO:

FICO is a leading provider of analytics and decision management technology. The company offers a wide range of market leading products and services including the FICO® score that was first introduced in 1989. FICO® scores are the most widely used credit bureau risk scores, powering approximately 9 billion decisions a year. In addition, FICO scores are the required credit risk underwriting standard for all FHA-insured loans sold to Fannie Mae and Freddie Mac. Headquartered in Minneapolis, Minnesota, FICO also has U.S. offices in California, Colorado, Delaware, New York, and Virginia.

FICO's COMMITMENT TO CONSUMER EDUCATION:

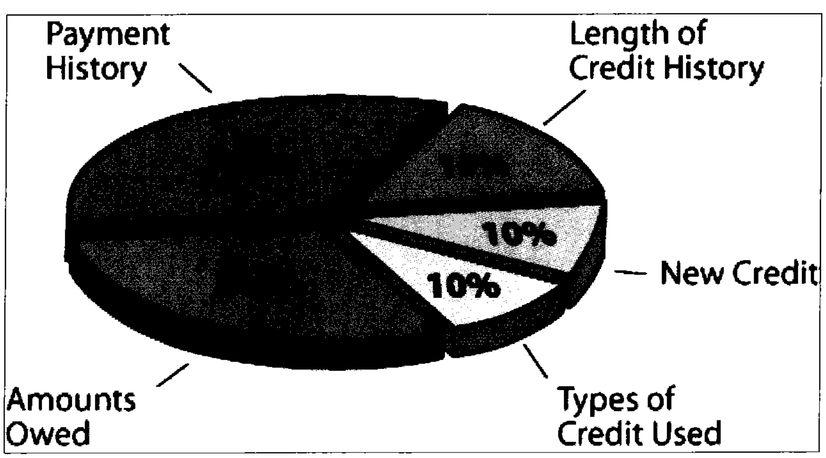
About myFICO®:

myFICO® is the consumer division of Fair Isaac, the company that invented the FICO® credit risk score more widely used by lenders.

Through myFICO.com, FICO offers informative credit-information projects along with consumer financial education materials that help people understand actions they can take to achieve and protect their overall financial health. Over 23 million FICO® scores have been sold to U.S. consumers since FICO launched its consumer service in March of 2001.

About ScoreInfo:

ScoreInfo.org is a non-commercial website launched by FICO to help consumers understand and benefit from the risk-based pricing and credit score disclosure notices they receive in the mail from U.S. lenders in accordance with federal regulations (Risk-Based Pricing Rule) effective January 1, 2011. Many lenders have chosen to comply with this new regulation by providing all consumers with a notice that contains their credit score and other related information shortly after they apply for credit. As most credit decisions include FICO® scores, the ScoreInfo.org website aims to help consumers understand how the FICO® scores they receive in their disclosure notices are calculated and how they can manage their credit and their scores over time.



FICO® credit scores are calculated from a wide range of information from the consumer's credit report. Just 35% of the score is based on payment history including reported delinquencies.

Adapting Credit Scores to Evolving Consumer Behavior and Data

By Frederic Huynh[1], Principal Scientist, FICO

April 2012

Abstract: Credit scores have become an integral component of the credit landscape. As that landscape shifts, credit score algorithms should adapt to changes in consumer behavior that are reflected in the information that creditors share with the credit reporting agencies. In addition to adjusting the algorithm's mix of characteristics and associated score weights over time, model developers should also evolve the predictive characteristics—those building blocks of the score algorithm—in order to account both for changes in the ways consumers seek and use credit and for the introduction of new financial products. Through such advances, scientists can develop increasingly predictive scores based on credit information, and they can develop more sophisticated logic that recognizes consumers who manage credit responsibly. This paper discusses three different research studies. The first study focuses on changes made while redeveloping an earlier generation of the FICO® Score algorithm. FICO scientists introduced logic to improve the way the algorithm evaluated credit inquiry information, making it more appropriate to consumers who were rate shopping for the best loan. The second research study discusses how credit utilization calculations were modified to account for flexible spending accounts, a new type of credit card that possesses both a charge and revolve feature. This enhancement was incorporated into the current suite of FICO® Scores. The final research study examines whether, in future versions of the FICO® Score algorithm, mortgage short sales should penalize scores less than foreclosures do.

I. Introduction:

Credit scores are a vital element of the lending ecosystem, providing lenders with an objective means to assess a consumer's creditworthiness. Broad based credit scores[2], such as the FICO® Score, are redeveloped periodically to capture changes in consumer risk patterns, leverage improvements in the reporting of information in the Credit Reporting Agencies (CRAs) and incorporate new technological enhancements into the score algorithm.

To demonstrate how consumer risk patterns have changed over time, we might consider the number of credit cards a consumer has. The earliest incarnations of the FICO® Score typically incorporated a predictive variable that measured the number of credit cards a consumer possessed. In the nascent

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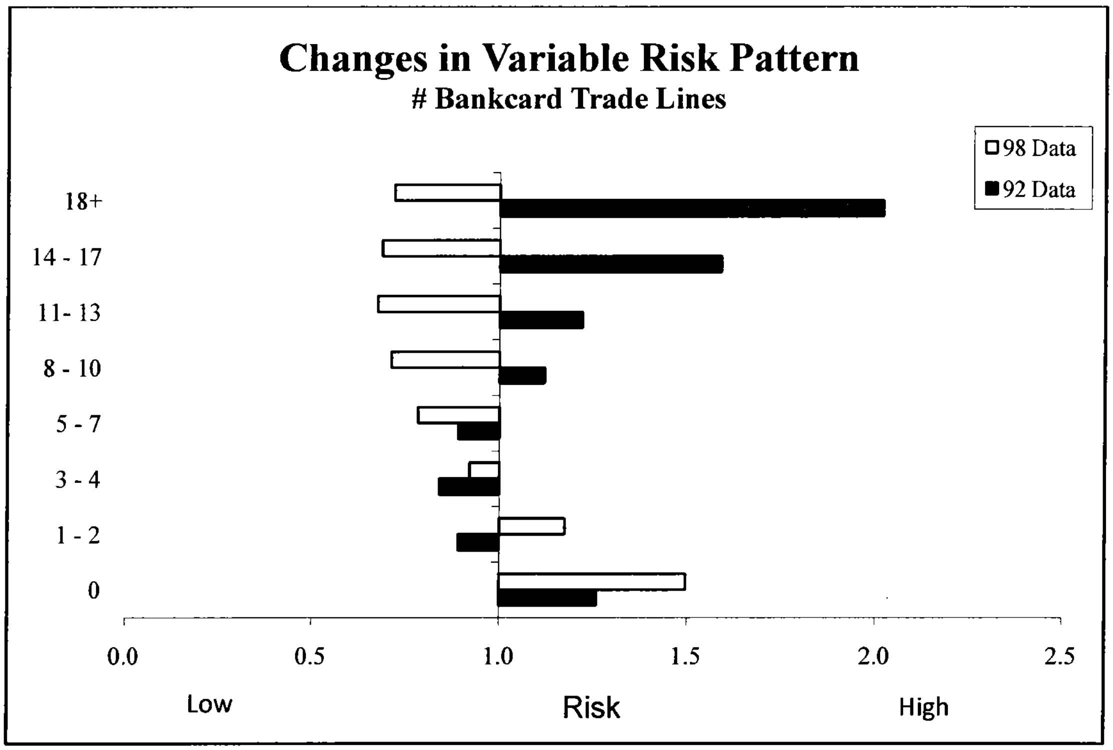
[1] The author thanks the numerous analysts who contributed to the research that was referenced in this study: Heidi Kotani, Tommy Lee, SinYing Li, Sumeet Patel, Christine Shih, and Bradley Vancho. He is also thankful for the analytic counsel of Luke van Dijk and the support of Craig Watts.

[2] Broad based, or generic, credit scores like the FICO® Score are designed to be used across a wide variety of applications and products. On the other hand, custom credit scores are frequently designed with a more specific or narrow focus – for example, originations for a specific type of credit product. Custom credit scores can also be developed for a specific lender's portfolio.

days of FICO® Scores, having many credit cards was very risky and having very few credit cards actually represented good risk. Over time, the risk pattern associated with that variable fundamentally changed.

In Figure 1, we see that the relationship the number of credit cards has with risk has changed noticeably. In 1992, having many credit cards indicated a high level of credit risk; in fact, a consumer with 18 or more credit cards was twice as risky as the total population. In 1998, consumers with many credit cards were actually slightly better credit risks than the total population. In both time periods, having no credit cards indicated a greater degree of credit risk, but elsewhere the risk pattern fundamentally changed. While most predictive characteristics employed by credit scores demonstrate more stable risk patterns, this is one example that demonstrates the benefit of redeveloping scores periodically in order to account for changing risk patterns.

Figure 1 – Risk Pattern for # Bankcard Trade Lines Over Time



The vertical axis represents the number of bankcard trade lines on consumer credit reports. The horizontal axis measures normalized risk. Risk values are calculated by taking the bad rate observed for a given attribute and dividing that by the bad rate observed for the total population. Risk values greater than 1 indicate that the attribute is riskier than that of the total population. For example, consumers who have 0 bankcards in 1998 are 1.5 times *riskier* than the total population. But in 1998, consumers with 8 to 10 bankcards are 0.71 times *less risky* than the general population.

In addition to redeveloping the scores to accommodate for changing risk patterns, the building blocks of the score—the characteristics and the treatment of the primitive data elements—should also evolve. This paper presents three different examples of how the predictive characteristics of the score evolved to adapt for changes in the credit landscape. The first study focuses on enhancements introduced to an earlier generation of the FICO® Score, released in the early 2000's. The second study focuses on enhancements that were incorporated into the FICO 8 models. The last study focuses on research that determines whether short sales and other codes signifying different types of mortgage stress events should be treated less harshly by the FICO® Score.

II. Changing Inquiry Assessment To More Effectively Accommodate Rate Shopping

Credit inquiries have long served as predictors in credit scoring models. Although they contribute a relatively small percentage to the predictiveness of the final score, they often attract a disproportionate amount of attention from consumers. This presumably has been due to the prominence they receive on credit reports. Since the mid 1990s, FICO® Scores have employed logic in the treatment of inquiries that recognizes the presence of rate shopping behavior. There are two components of this logic, a buffer and a de-duplication or "deduplication" window. The purpose of the buffer is to bypass any auto or mortgage inquiries made within the last 30 days. This prevents very recent auto or mortgage inquiries from influencing any current application for credit. The deduplication window is a rolling timeframe in which multiple auto or mortgage inquiries posted to the credit report during the deduplication window will be counted as a single inquiry.

The following table illustrates the general concepts behind the earlier inquiry logic. In this example, all of the auto inquiries occur within the last 30 days and are ignored. The two mortgage inquiries fall outside of the 30 day buffer, and are eligible to be counted. However, since both mortgage inquiries fall within 14 days of each other, only one inquiry will be counted. Even though the department store inquiry occurs with 14 days of the first mortgage inquiry, it is counted separately; only auto and mortgage inquiries are deduplicated. In this example, an earlier version of the FICO® Score would count 2 inquiries.

Figure 2 – Example of Earlier Inquiry Logic

Type of Inquiry	Number of Days Ago	Treatment
Department Store	68	Counted as 1 inquiry
Mortgage	65	Counted as 1 inquiry (deduplicated within 14 days)
Mortgage	56	
Auto	17	Not counted (ignored within 30 days)
Auto	9	
Auto	8	

With the beginning of consumer score disclosure in 2000, the launch of MyFICO.com in the early 2000's, and the increase in financial advice to consumers through news media and the internet, consumers became more aware of the benefits of shopping for the best rate. At the same time lenders offered a wider array of credit products enabled by risk-based pricing[3]. As consumers became more financially savvy, their search for the best interest rates on a mortgage or auto loan often took longer than 14 days. FICO suspected that consumers who were attempting to find the best rate could be penalized and that the inquiry logic could be improved upon. The company's scientists revisited the model's inquiry logic to

[3] The practice of setting credit terms according to a consumer's credit risk profile.

determine if a 14 day deduplication window remained ideal for risk prediction. If the 14 day window was too short, too many inquiries were being counted – excessively penalizing the consumer and yielding slightly less predictive characteristics.

To investigate the merits of broadening the deduplication window, FICO varied the length of the window and measured the resulting impact to predictiveness. In general, a longer deduplication window was proven to be more effective in evaluating inquiry information. Information value[4] – a statistic that measures how well a given characteristic separates goods from bads – was used to determine if a change in the deduplication window was merited.

The tables in Figures 3 and 4 demonstrate that by expanding the length of the deduplication window, the characteristic is marginally better at predicting risk. Figure 3 is based on the performance of all credit accounts on the consumer's file. Figure 4 is based on the performance of new accounts. Inquiries can be more relevant in an originations context, so the same analysis was repeated based on the performance of new accounts, that is, accounts opened within the 6 months following the scoring date. The patterns are fairly consistent in both contexts.

Figure 3 –Varying the Length of the Deduplication Window (Performance on All Accounts)

Information Value Calculation

Length of Deduplication Window

	14	21	30	45	60	90
Total	0.466	0.469	0.472	0.475	0.476	0.476
Derog	0.200	0.202	0.204	0.208	0.208	0.211
Clean	0.304	0.307	0.308	0.308	0.308	0.306

The column headings indicate the length in days of the potential deduplication window. The rows indicate values for three different populations: the total population, the population of people with derogatory events on their credit files, and the population with clean credit files (no derogs). In the table itself, larger values indicate a more predictive characteristic based on consumers' performance on all categories of credit accounts.

[4] For a characteristic with bins i = 1,...q, factored counts are defined by:
n_g = Number of Goods in the population; n_b = Number of Bads in the population
n_{gi} = Number of Goods in bin i; n_{bi} = Number of Bads in bin i
Empirical frequency distribution versions of these counts are defined by:
$f_g(i) = 100\frac{n_{gi}}{n_g}$; $f_b(i) = 100\frac{n_{bi}}{n_b}$
Information value of a binned variable is defined as:
$IV = \sum_{i=1}^{q} \frac{f_g(i)-f_b(i)}{100} log\left[\frac{f_g(i)}{b(i)}\right]$

Figure 4 –Varying the Length of the Deduplication Window (Performance on New Accounts)

Information Value Calculation

Length of Deduplication Window

	14	21	30	45	60	90
Total	0.369	0.373	0.373	0.376	0.377	0.379
Derog	0.163	0.167	0.167	0.169	0.171	0.176
Clean	0.291	0.294	0.294	0.297	0.296	0.294

In this second table, larger values indicate a more predictive characteristic based on consumers' performance only on new credit accounts.

For the total population, increasing the deduplication window leads to a slightly stronger characteristic. However we found there is an upper limit to the length of the deduplication window. The improvement gained in using a 60 or 90 day deduplication window is marginal. For the clean population (roughly 70% of all consumers), the ideal deduplication window is approximately 45 days when looking at performance metrics for both all accounts and new accounts separately. Interestingly, we see that the ideal deduplication window for the rest of the population—those who have at least one derogatory event on their credit history—may be greater than 45 days. This is intuitive since consumers with blemished credit history may require more time to find and secure credit.

Only one deduplication window could be selected – it would be impractical and confusing to consumers if differing deduplication windows were used to assess inquiries. Ultimately, a 45 day window was selected. The 45 day window was more predictive than the status quo window of 14 days. The information value associated with a 60 and 90 day window was not discernibly stronger than the 45 day window. Additionally, for subpopulations with no credit blemishes, a slight reversal in the predictiveness of the characteristic was observed with a 60 and 90 day window. This observation was notable because inquiry information is slightly more predictive for this pocket of the population.

In this way FICO was able to introduce an enhancement to the FICO® Score that provided a more effective methodology to evaluate inquiry information. Given that this characteristic is designed to measure the true number of unique searches for credit by the consumer, it is not surprising that increasing the deduplication window to better reflect how long it takes a consumer to shop for a loan can make the characteristic more predictive.

III. Adapting To New Credit Products

As the credit card industry becomes more competitive, issuers introduce new products in an effort to grow their portfolios. As an example, they introduced flexible spending cards in the mid-2000s. Flexible spending accounts are hybrid accounts with a revolving component as well as a charge component. These accounts have no preset spending limits but do have revolving limits. Thus, amounts charged in excess of the revolving limit need to be paid in full at the next billing cycle. Flexible spending accounts have also been referred to as no-preset spending limit accounts, Signature Cards, or World Accounts[5].

From a credit reporting perspective, flexible spending accounts represent a challenge as they carry both revolving and charge features. Reporting guidelines from the Consumer Data Industry Association (CDIA) indicate that flexible spending accounts should be reported as a revolving card, and that the limit reported should reflect the revolving limit component of the card. Since utilization characteristics[6] can have significant importance for FICO® Scores, issuers of flexible spending accounts were concerned that FICO® Scores should evaluate flexible spending accounts appropriately in characteristics measuring credit card utilization. In particular, they were concerned about instances where the balance exceeds the limit for the revolving portion of these accounts. They felt that the risk associated with the over-utilized flexible spending account is not reflective of traditional revolving accounts that are over limit. This suggested that flexible spending accounts should be treated differently by the FICO® Score, or should be represented on the credit report in a different manner. This hypothesis is supported by the observation that users of flexible spending accounts are encouraged and authorized to exceed the credit limit assigned, whereas traditional revolving products are not allowed to go over limit without an authorization.

During the development of the FICO® 8 Score, research was conducted to determine the best way to factor flexible spending accounts into utilization characteristics. To better understand the relationship between risk and utilization characteristics, the analysis population was narrowed to only those consumers who possessed at least one flexible spending account. The study was performed on a database consisting of approximately 4 million consumer records. The database was based on two archives: April 2005 and April 2007. As of April 2005, consumers with a flexible spending account represented approximately 0.2% of the scoreable population.

The focus of the study was to evaluate alternative treatments for flexible spending accounts and utilization characteristics. Utilization characteristics are variables used by the FICO® Score to evaluate the indebtedness dimension of a consumer credit report. The research focused on the following utilization characteristics: highest utilization on bankcard[7], highest utilization on credit card[8], bankcard utilization, and credit card utilization.

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[5] It is important to note that in the context of credit scores, the flexible spending accounts referenced here are not the tax exempt healthcare spending accounts that companies offer to their employees.

[6] Utilization characteristics measure outstanding balances in relation to credit limits, or loan amounts. Within the FICO® Score, credit card utilization calculations are very influential predictors. Credit card utilization can be calculated by taking the sum of the credit card balances and dividing that by the sum of the credit card limits.

[7] Other variations of utilization calculations look at the highest utilized credit card on file. For example, if a consumer has a credit card with a 500 balance and a 1000 limit, and another credit card with a 9000 balance and a 10,000 limit, the highest utilization for that consumer will be 90%.

[8] Bankcards are a subset of credit cards. Bankcards are credit cards issued by a bank. Credit cards can also be issued finance companies, credit unions, and other financial institutions.

For each of these utilization characteristics, five different versions were generated. Each version represented a specific treatment for flexible spending accounts.

Version 1 – Benchmark; No special treatment for flexible spending accounts
Version 2 – Bypass flexible spending accounts from utilization calculation
Version 3 – Use the high balance as the limit for flexible spending accounts
Version 4 – Use the high balance as the limit for flexible spending accounts when the balance is greater than the limit
Version 5 – Use the maximum of the balance and the limit for flexible spending accounts

To evaluate the predictive merit associated with each variation, information value was calculated across each version for each characteristic. Because of the smaller proportion of flexible spending accounts relative to 'traditional' credit cards, analyzing the predictiveness on the aggregate level would dilute the impact of each variation. For that reason, the analysis population focused on consumers with flexible spending accounts.

As summarized in Figure 5, Version 2 yields a lower information value than Version 1 for three of the four utilization characteristics. This indicates that bypassing flexible spending accounts from utilization characteristics generally results in a weaker predictive characteristic. The result is intuitive as it illustrates the potential loss in predictiveness from indiscriminately removing valuable information from the characteristic calculation. The results also suggest that versions of the characteristics show promise when they mitigate utilization calculations in scenarios where the balance exceeds the credit limit.

Figure 5 – Measuring Predictiveness for Different Utilization Calculations (CRA #1)

	Information Value				
	Version 1	Version 2	Version 3	Version 4	Version 5
Highest Utilization on Bankcard Trade Line	1.308	1.285	1.373	1.407	**1.411**
Highest Utilization on Credit Card Trade Line	1.367	1.308	1.409	1.443	**1.446**
Bankcard Utilization	1.262	1.183	1.318	**1.331**	1.328
Credit Card Utilization	1.308	1.189	1.397	1.406	**1.407**

This table measures how predictive each version of the characteristic is based on our analysis of data provided by a major consumer reporting agency. Higher values indicate a stronger, more predictive characteristic.

The results of the analysis indicate that changing the treatment of flexible spending accounts could lead to a more predictive way of assessing utilization for this population. In three of four characteristics, version 5 yields the greatest information value, indicating that it is the most predictive variation. These results suggest that utilization characteristics that mitigate over-utilized flexible spending accounts are more predictive than the current methodology.

Of particular interest are the results associated with the information value for characteristics that measure highest utilization. Highest utilization is calculated by identifying the highest utilization level for each credit card separately. For purposes of illustration, consider a consumer who has two credit cards, one with a balance of $750 and a limit of $1,000, and the other with a balance of $5,000 and a limit of $10,000. The highest utilization on a credit card for this consumer is 75%. Comparing versions 2 through versions 5 to versions 1, the difference in predictiveness in the highest utilization characteristics are more pronounced. This should not come as a surprise because these variations are the ones that will have the largest impact caused by flexible spending accounts where the balance is greater than the reported credit limit. Unlike the variations that look at utilization across the sum of all credit card balances and credit card limits, the highest utilization characteristics cannot be watered down by multiple accounts, so the impact is more noticeable.

This research was repeated at another major credit reporting agency and the conclusions outlined in Figure 6 were similar: utilization characteristics employed by the FICO® Score can be modified to better assess flexible spending accounts.

Figure 6 – Measuring Predictiveness for Different Utilization Calculations (CRA #2)

	Information Value				
	Version 1	Version 2	Version 3	Version 4	Version 5
Highest Utilization on Bankcard Trade Line	1.418	1.35	1.502	**1.524**	1.521
Highest Utilization on Credit Card Trade Line	1.485	1.487	1.556	1.583	**1.586**
Bankcard Utilization	1.479	1.294	1.564	**1.578**	1.536
Credit Card Utilization	1.500	1.393	1.581	**1.586**	1.554

Fig. 6 is similar to Fig. 5 but represents a separate analysis of data from a different consumer reporting agency. As before, higher values indicate a stronger, more predictive characteristic.

Ultimately, version 5 was selected. Though both version 4 and version 5 represent improvements over the status quo, version 5 was selected because Version 4 calculations can be susceptible to an isolated spike in the high balance. When the new scoring model encountered an over-utilized flexible spending account, for scoring purposes the utilization would be capped at 100%. It is important to note that this treatment assumes that the account is reported according to CDIA guidelines. If the account is not reported appropriately, then it is possible for the account not to receive the specialized treatment associated with this particular type of account.

IV. The Mortgage Crisis and Revisiting the Classification of Short Sales

The aftermath of the mortgage crisis created an unprecedented wave of stress in the housing market. Depressed housing values and increased unemployment continue to strain homeowners. When home owners find they have no choice but to default on their mortgages, they may consider various options from loan modifications to foreclosures, short sales, and deeds in lieu of foreclosure. Some want to better understand the credit scoring consequences of their options. In general, foreclosures, short sales, and deeds in lieu are all treated in a similar manner by the FICO® Score. As a result, there is no substantial difference in the impact to the FICO® Score between a foreclosure, short sale, and a deed in lieu. Each of these events, in and of itself, is considered derogatory by the FICO® Score and the specifics of how the event is reported can lead to subtle differences in its treatment by the score. For example, short sales without a reported deficiency balance could have a slightly smaller impact than a foreclosure.

Observers sometimes ask whether it remains appropriate for a short sale to be treated in a manner similar to a foreclosure. Some critics assert that a short sale should be substantially less punitive than a foreclosure because short sales do not cost the bank as much money as foreclosures and the penalty to a credit score should be commensurate with the financial impact on a lender. Some also suggest that a willingness of the borrower to work with the lender should have a positive effect on the borrower's credit risk.

Additionally, as the mortgage crisis evolved many lenders used loan modifications as a remediation strategy for distressed homeowners. From a credit reporting perspective, no existing codes were available to lenders for clearly differentiating loan modifications from other events. The Consumer Data Industry Association (CDIA) introduced new reporting codes to allow lenders to accurately account for those events. All newly introduced loan modification codes received no special treatment by the FICO® Score. Until an empirical study can determine the relationship between the presence of these new codes and credit risk, the FICO® Score cannot provide them with any special treatment.

Figure 7 documents the frequency of various mortgage stress-related events over time. Each column represents the number of consumers whose credit report contains a reporting code for a specific event (foreclosure, short sale, deed in lieu, etc.) on a mortgage trade line for a given year. The table is based on a random sample of 10 million consumer credit reports over time. The descriptions in the table are self-explanatory but two merit additional commentary. Events such as "paying under a partial payment agreement" are typically reported for mortgages that are in the trial period of renegotiated or refinanced loans, or are referenced in Making Home Affordable and Fannie Mae/Freddie Mac and loan forbearance programs. Events that are reported as "account paid for less than the full balance" are typically associated with the reporting of short sales.

Figure 7 – Frequency of Mortgage Reporting Codes Over Time

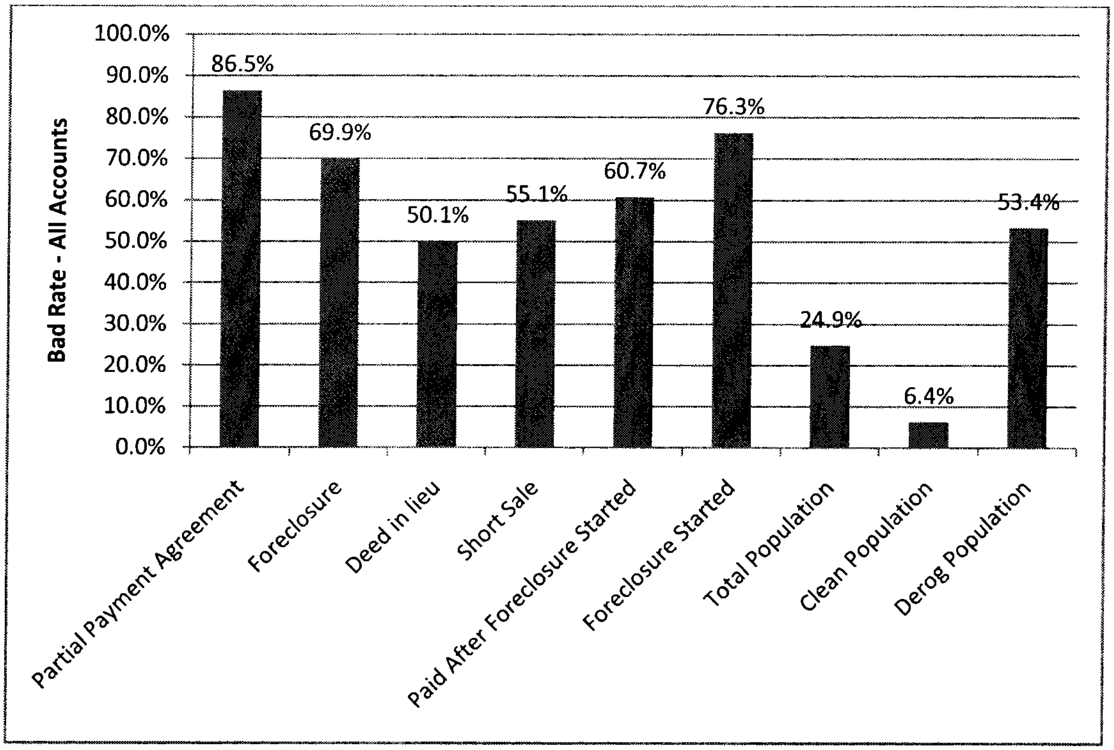
Event:	# of Consumers with Specific Mortgage Trade Line 2005	2007	2009	2011
Paying under a partial payment agreement	9,771	13,449	48,368	23,022
Foreclosure	43,907	47,721	66,328	96,796
Forfeit of deed in lieu of foreclosure	461	787	1,682	3,223
Account paid for less than the full balance	5,346	6,934	22,187	52,436
Account paid after foreclosure started	4,320	6,021	8,107	9,725
Making payment - foreclosure was initiated	2	3	1	1
Foreclosure process started	38,498	60,824	12,9043	140,356
Loan modified under a federal govt plan	0	0	0	43,968
Loan modified	0	0	0	52,447
Account in forbearance	0	0	0	0

Not surprisingly, there is a dramatic increase in the number of consumers who experienced a distressful event regarding their mortgage between 2005 and 2011. In particular, reported short sales are nearly ten times more prevalent in 2011 than they were in 2005. Deeds in lieu are seven times more common than they were in 2005. When it comes to foreclosures, codes indicating that a foreclosure process has started are more than 3.5 times more common in 2011 than they were in 2005.

As noted, loan modification codes were introduced in the wake of the mortgage crisis, and were not observed on credit report data available to FICO until 2010. In terms of scale, it is interesting to observe that nearly twice as many loan modifications, government and non-government, were reported in 2011 compared to short sales. All of the listed events demonstrate a consistent increase over time, with the exception of "paying under a partial payment agreement."

The next phase of the analysis is to understand the risk associated with each of these reported events. The analysis population was based on an observation snapshot of October 2009 and a performance snapshot of October 2011. For each of the events in question, the borrowers' subsequent payment behavior over the two-year performance window was observed. Figure 8 depicts the "bad rates" observed following each of the events. A "bad" is defined as any consumer who experienced a delinquency of 90 days past due or greater on any of their reported credit obligations during the two-year performance window.

Figure 8 – Bad Rates for Mortgage Related Codes (Performance on All Accounts)



This chart displays the percentage of people with different events on their credit reports who go on to default on one of their credit obligations during the two-year performance window. For example, people with evidence of a short sale on their credit report go on to default on one of their credit obligations 55.1% of the time.

All of the mortgage-stress events represent a substantially greater degree of risk than that posed by the total population. All of these events are currently classified as derogatory items by the FICO® Score, and could result in a negative impact to a consumer's score. The three columns on the far right on Figure 8 represent different benchmark populations. One represents the aggregate population, the second represents "clean" consumers with no severe derogatory information[9], and the third column represents consumers with some severe derogatory information on file. Reporting codes associated with short sales (account paid for less than full balance) remain extremely risky; they are slightly better risks than foreclosures, but are at least twice as risky compared to the total population. Consumers with short sales also perform no better when compared to consumers who have the presence of a derogatory item on file.

Figure 8 looks at the performance on any trade line, including any mortgage trade lines opened at the time of scoring. What if we examined the consumers' subsequent payment behavior on bankcards alone, a credit obligation far removed from the consumers' mortgage obligations? Figure 9 indicates that there remains a strong link between poor bankcard payment behavior and consumers who experience one of the mortgage-stress events.

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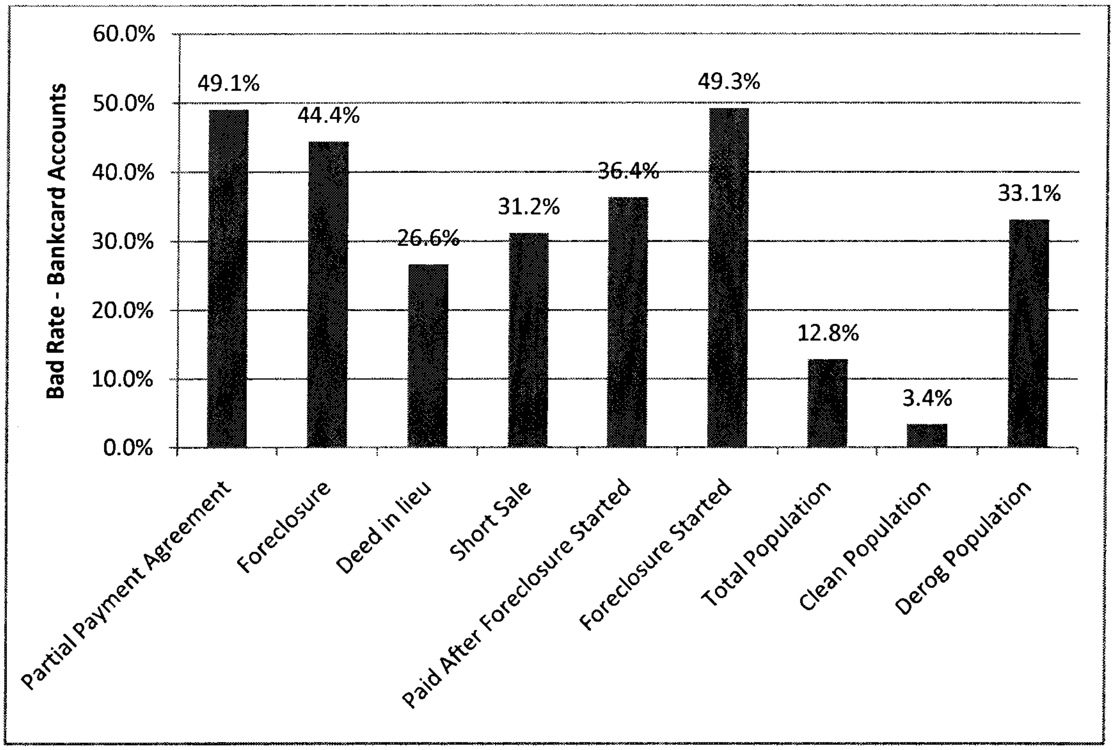
[9] A derogatory file is a credit report with the presence of severe delinquency (90+ days past due), a collection, or a derogatory public record.

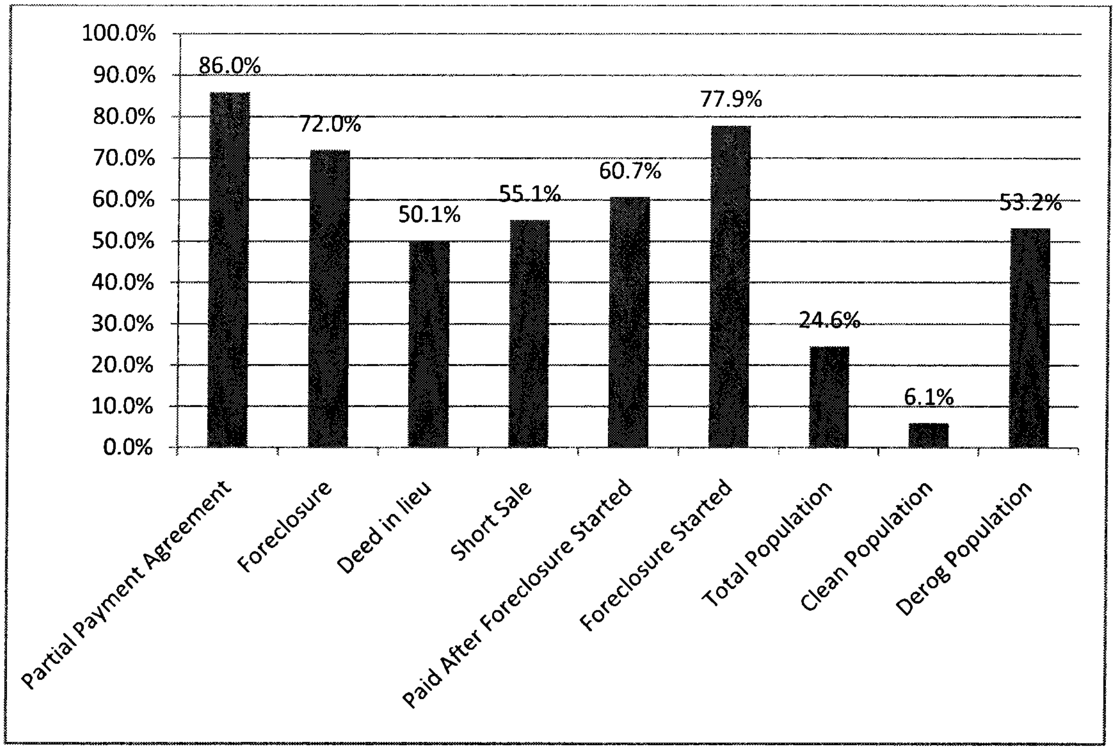
Figure 9 – Bad Rate for Mortgage Related Codes (Performance on Bankcard Accounts)



Unlike the previous chart, this chart displays the percentage of people who go on to default specifically on one of their bankcard obligations. The previous chart addressed those who default on any of their credit obligations, including auto loans, student loans, bankcards, and so on. For example, people with evidence of a foreclosure starting on their credit report go on to default on one of their bankcards 49.3% of the time.

One of the arguments for revisiting the scoring model's treatment of these mortgage-stress events is that the mortgage crisis was unprecedented; consumers who would have otherwise paid responsibly, were now making decisions that theoretically were not representative of their true risk. This premise was tested by isolating more recent occurrences of these events by identifying records that contained one of these reporting codes in 2009, but did not contain it in 2007. For example, of the 66,328 records with a reported foreclosure in 2009, the analysis focused on the 18,607 records (66,328 – 47,721) with a foreclosure in 2009, but not in 2007. This analysis produced the results in Figure 10. Comparing it to Figure 8 yields no discernible difference. The same conclusion is drawn: all of the reported mortgage stress events represent a greater degree of credit risk when compared with the general population.

Figure 10 – Bad Rate for Mortgage Related Codes (Performance on All Accounts)



This chart displays the percentage of people whose mortgage-stress events first appeared on their credit reports between 2007-2009, who go on to default on one of their credit obligations. For example, people with recent evidence of a deed in lieu on their credit report go on to default on one of their credit obligations 50.1% of the time.

Not quite enough time has passed to provide a 24 month performance window for analyzing the predictiveness of the codes representing loan modification. If there is empirical evidence demonstrating that consumers with a reported loan modification perform substantially worse in repaying their credit obligations, future credit scoring models will be modified to appropriately classify those codes.

V. Conclusion

Credit scoring models are periodically redeveloped to account for changing risk patterns. To build the most effective credit scores, scientists may need to go beyond re-optimizing the scorecard weights given to predictive characteristics based on recent data. The building blocks of the credit scores, the predictive characteristics themselves, may need to evolve with the model as well. This evolutionary innovation insures the components of the model adapt to changes in consumer credit behavior and produce the most consistently predictive score.

Various market forces can influence how consumer repayment behavior relates to the predictive characteristics used in calculating credit scores. For example, the combination of making scores available to consumers, plus a wealth of financial literacy information on the Internet, has made consumers more aware of the benefit of shopping for the best interest rates. Research demonstrated that the logic used in assessing the predictive value of inquiry information could be updated to better recognize the actual risk associated with rate-shopping behavior.

New credit products can also create the need for predictive characteristics to evolve. In the mid 2000s, flexible spending accounts that incorporated revolving and charge properties for the cards were introduced. Because of the properties of the card and the lenders' target markets, the risk associated with flexible spending accounts when the balance was greater than the revolving limit was not great, when compared to the risk of traditional revolving products. Mitigating the treatment of utilization rates for flexible spending accounts improved the model's ability to assess indebtedness.

Lastly, the mortgage crisis raised interest in how the FICO® Score treated various events relating to mortgage stress. Of particular interest was whether it remained appropriate for short sales to be classified as derogatory items, similar to foreclosures. Evaluating the credit performance following these various mortgage events validated the derogatory classification by the scoring model. Consumers with short sales on their credit reports continue to represent considerable credit risk, and scoring models need to continue representing that risk appropriately.

Reporting codes for loan modification are relatively new to the databases of consumer reporting agencies. Currently, these codes are not classified as derogatory indicators by the FICO® Score. As time passes and the credit risk associated with these consumers over a 24-month performance window can be evaluated, their classification in the scoring model may change. If it is determined that the credit risk associated with these accounts is substantially greater than that of the total population, it is possible that future scoring models will treat these events as negative items. As credit data evolves and reflects changing consumer behavior, FICO® Scores will continue to evolve to adapt to the ever changing credit landscape.

FICO Banking Analytics Blog

Research looks at how mortgage delinquencies affect scores

How much impact does a short sale have on FICO® Scores? How about a foreclosure? Since I frequently hear these questions from clients and others, I thought I'd share new FICO research that sheds light on this very subject.

The FICO study simulated various types of mortgage delinquencies on three representative credit bureau profiles of consumers scoring 680, 720 and 780, respectively. I say "representative profiles" because we focused on consumers whose credit characteristics (e.g., utilization, delinquency history, age of file) were typical of the three score points considered. All consumers had an active currently-paid-as-agreed mortgage on file.

Results are shown below. The first chart shows the impact on the score for each stage of delinquency, and the second shows how long it takes the score to fully "recover" after the fact.

Impact to FICO® Score

	Consumer A	Consumer B	Consumer C
Starting FICO® Score	~680	~720	~780
FICO® Score after these events:			
30 days late on mortgage	600–620	630–650	670–690
90 days late on mortgage	600–620	610–630	650–670
Short sale / deed-in-lieu / settlement (no deficiency balance)	610–630	605–625	655–675
Short sale (with deficiency balance)	575–595	570–590	620–640
Foreclosure	575–595	570–590	620–640
Bankruptcy	530–550	525–545	540–560

Source: FICO® Banking Analytics Blog. © 2011 Fair Isaac Corporation.

Estimated Time for FICO® Score to Fully Recover

	Consumer A	Consumer B	Consumer C
Starting FICO® Score	~680	~720	~780
Time for FICO® Score to recover after these events:			
30 days late on mortgage	~9 months	~2.5 years	~3 years
90 days late on mortgage	~9 months	~3 years	~7 years
Short sale / deed-in-lieu / settlement (no deficiency balance)	~3 years	~7 years	~7 years
Short sale (with deficiency balance)	~3 years	~7 years	~7 years
Foreclosure	~3 years	~7 years	~7 years
Bankruptcy	~5 years	~7–10 years	~7–10 years

Note: Estimates assume all else held constant over time (e.g., no new account openings, no new delinquency, similar outstanding debt).

Source: FICO® Banking Analytics Blog. © 2011 Fair Isaac Corporation.

All in all, we saw:

- The magnitude of FICO® Score impact is highly dependent on the starting score.
- There's no significant difference in score impact between short sale/deed-in-lieu/settlement and foreclosure.
- While a score may *begin* to improve sooner, it could take up to 7-10 years to *fully* recover, assuming all other obligations are paid as agreed.
- In general, the higher starting score, the longer it takes for the score to fully recover.
- Even if there's minimal difference in score impact between moderate and severe delinquencies, there may be

significant difference in time required for the score to fully recover.

This study provides good benchmarks of score impact from mortgage delinquencies. However, it is important to note that research was done only on select consumer credit profiles. Given the wide range of credit profiles that exist, results may vary beyond what's in the charts above.

If you have questions about this research, I encourage you to post them here on the blog.

Posted by Joanne Gaskin on 03/24/2011 at 09:56 AM in Collections, Consumer Issues, Credit Risk, Credit Trends, Economic Trends, Mortgage , Risk Management | Permalink