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Credit Where None Is Due? Authorized User Account Status and "Piggybacking Credit"

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Abstract: An "authorized user" is a person who is permitted by a revolving account holder to use an account without being legally liable for any charges incurred. The Federal Reserve's Regulation B, which implements the 1974 Equal Credit Opportunity Act, requires that information on spousal authorized user accounts be reported to the credit bureaus and considered when lenders evaluate credit history. Since creditors generally furnish to the credit bureaus information on all authorized user accounts, without indicating which are spouses and which are not, credit scoring modelers cannot distinguish spousal from non-spousal authorized user accounts. This effectively requires that all authorized user accounts receive similar treatment. Consequently, becoming an authorized user on an old account with a good payment history, may improve an individual's credit score, potentially increasing access to credit or reducing borrowing costs. As a result, the practice of "piggybacking credit" has developed. In a piggybacking arrangement, an individual pays a fee to be added as an authorized user on an account to "rent" the account's credit history. This paper provides the first comprehensive look at authorized user accounts in individual credit records and how their importance differs across demographic groups. Our analysis suggests that piggybacking credit can materially improve credit scores, particularly for individuals with thin or short credit histories. We also evaluate the effect that eliminating authorized user accounts from credit scoring models would have on individual credit scores. Our results suggest that removing this information has relatively little effect on credit scores, but may reduce model predictiveness.

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Introduction

Revolving account holders, such as credit card users, may designate other individuals as "authorized users" on their accounts. An authorized user is a person who is permitted to use an account without being legally liable for any charges incurred.

When an authorized user on an account is the spouse of an account holder, the Federal Reserve Board's Regulation B ("Reg. B"), which implements the 1974 Equal Credit Opportunity Act (ECOA), imposes two important requirements on creditors. First, when providing information to the credit bureaus, creditors are required to furnish information for the authorized user as well as for the account holders. Second, when using credit history to assess the creditworthiness of applicants, creditors are required to consider, when available, the history of accounts held by the applicant's spouse on which the applicant is an authorized user (as well as those accounts that are jointly held).[1] These requirements have been in place since Reg. B's inception in 1975.

In promulgating these provisions of Reg. B, the Federal Reserve Board pointed to complaints received from women who were unable to obtain credit because information on accounts jointly held with their husbands was reported to the credit bureaus in the husband's name alone. Additionally, the Board took the view that, since some state laws hold one spouse liable for debts incurred by the other, a spouse should have the "benefit or burden" of the credit history of their spouse's accounts that they were authorized to use. Further motivation was provided by the significant role that spousal authorized users were found to play in the maintenance of an account, such that the payment history on an account was often "as much the product of the user's contribution as that of the obligor."[2]

In addition to helping spousal authorized users build an independent credit history, granting authorized user status has been used to help young individuals learn to manage credit and build a credit history. This is possible because creditors generally have followed a practice of furnishing to credit bureaus information about all authorized users, whether or not the authorized user is a spouse, without indicating which authorized users are spouses and which are not. This practice does not violate Reg. B.

As a result, the information maintained in credit bureau records generally does not distinguish spousal from non-spousal authorized users. This prevents credit scoring modelers and

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[1] See Section 202.6(b) of Regulation B (12 CFR 202.6(b)).

[2] A discussion of the motivation behind the provisions of Regulation B can be found in the accompanying notice of final rulemaking in 40 Federal Register 205 (22 October 1975), pp. 49298-49310.

creditors that use credit reports from distinguishing spousal from non-spousal authorized user accounts. Since spousal authorized user tradelines must be considered in evaluating creditworthiness to comply with the requirements of Reg. B, but may not be identifiable in an applicant's credit record, creditors may have to consider all authorized user accounts on an individual's credit record, regardless of whether they reflect a spousal relationship to an account holder. For this reason, credit history scores, such as the FICO score,[3] have traditionally accorded authorized user accounts equal weight to the other accounts on an individual's credit record.

The practices described above have the unintended consequence of creating the opportunity for "piggybacking" credit to emerge. Piggybacking occurs when an individual becomes an authorized user on an account for the sole purpose of improving that person's credit history. Because of the manner in which authorized user information is reported to the credit bureaus, the full credit history of an account is reflected on the credit records of both an account holder and an authorized user, regardless of when the authorized user was added to the account. Consequently, a person's credit report may reflect several years of account history as soon as that person becomes an authorized user. If the account has desirable characteristics (such as a low utilization rate or a good payment history), this may improve the authorized user's credit risk profile and credit scores. The result may be enhanced access to credit and reduced borrowing costs.

Beginning in 2007, companies began to emerge to help borrowers with poor credit histories piggyback on the good credit history of others. Individuals pay a fee to these companies to locate an account holder who is willing to add this person to their account in exchange for a portion of the fee.[4] The person added to the account is an authorized user in name only, as the individual receives neither the account number nor an access device (such as a credit card) and consequently cannot use the account for purchases.[5] By piggybacking on someone else's account history, however, an authorized user may be able to improve their credit score in advance of a credit application,

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[3] FICO scores are a trademark of Fair Isaac Corporation. For more information on the FICO score, refer to http://www.myfico.com.

[4] Industry sources indicate that individuals pay between $1,000 and $2,000 to obtain an authorized user account and that the individual renting out an account can earn about $200 per month. Refer to Harney (2007), Yuille (2007), and Berney (2007).

[5] This approach is not without risks to the account holder. If the person added as an authorized user is able to obtain an access device directly from the lender, then they are legally permitted to run up charges on the account.

potentially resulting in lower borrowing costs or an ability to qualify for credit that otherwise would not be extended.

The practice of piggybacking credit has raised concerns that the credit scores of people with authorized user accounts may not accurately reflect their creditworthiness. For example, a study by Fitch Ratings (Pendley, Costello, and Kelsch, 2007) of mortgage defaults points to the presence of authorized user accounts on the credit records of high-FICO borrowers who defaulted on their loans as evidence of poor underwriting practice by the lender. In response to concerns about the role of authorized user accounts in credit scores, Fair Isaac, which has traditionally treated authorized users and account holders identically, has revised the FICO credit scoring model to place less weight on those accounts on which an individual is an authorized user. Despite these concerns, very little is known about the role played by authorized user accounts in credit history files and, to date, the Federal Trade Commission has not taken action against companies that offer piggybacking arrangements.

This study examines the role of authorized user accounts in credit scoring, with particular focus on the role of authorized user accounts in the credit records of married women, who whose treatment was a central motivating factor in the requirements of Reg. B, and consequences of piggybacking credit. We rely on a unique, nationally representative sample of credit records and a credit scoring model (the "FRB base model") constructed by staff of the Federal Reserve Board as part of a study of credit scoring mandated by Congress. Our analysis does three things. First, we provide a detailed profile of authorized users examining how the use of authorized user status differs across race or ethnicity, age, sex, and marital status in terms of its prevalence and importance to an individual's credit record. Using the FRB base model, we examine the contributions that authorized user accounts make to the credit scores of individuals in our sample. Particular focus is placed on the effect of authorized user accounts on the credit scores of married individuals.

Second, we evaluate the size of the potential gains an individual can achieve as a result of piggybacking credit. Using the FRB base model, we simulate the effect on an individual's credit score of being added as an authorized user to an established account with a good payment history. This allows us to identify the population whose scores are most likely to be affected by purchasing authorized user status and to estimate the potential harm that results from this practice. Our analysis reveals that these benefits are potentially quite large (particularly for people with thin or short credit histories), suggesting that the practice of piggybacking credit, in some cases, may artificially enhance an individual's access to credit without improving the individual's true creditworthiness.

Finally, we examine how credit scores change when authorized user accounts are not used in the construction and application of credit scoring models. This is done by re-estimating the FRB base model, using credit characteristics that exclude information from authorized user accounts, and generating scores based on this new model. The results of this analysis suggest there would be little impact on credit scores if a credit scoring model did not incorporate information on authorized user accounts. Nevertheless, the elimination of authorized user accounts slightly reduces the predictiveness of the FRB base model.

The remainder of the study documents the details of our analysis. The next section outlines the data used in this study and provides additional information on the development of the FRB base model. In the following section, we profile authorized user accounts and describe how FRB base scores are affected by the presence of this account information. In the two subsequent sections, we then describe how credit scores and model predictiveness are altered by the exclusion of authorized user trades and simulate the potential impact of piggybacking credit on individual credit scores. The final section summarizes our findings and discusses the public policy implications.

The Data and FRB Base Model

This study uses a large, nationally representative sample of individual credit records that has been augmented with personal demographic information on each individual. This dataset was assembled by staff of the Federal Reserve Board for use in its *Report to Congress on Credit Scoring and its Effects on the Availability and Affordability of Credit* (Board of Governors, 2007) and, as of this writing, is the only nationally representative dataset of its kind, since credit records do not include any personal demographic information, other than age (which is frequently missing).[6] The following briefly outlines the contents of this dataset.[7]

The dataset contains a nationally representative random sample of approximately 300,000 credit records from TransUnion, LLC, as of June 30, 2003 and updated as of December 31, 2004. These records include information on each individual's credit accounts or "tradelines," collection

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[6]This study was requested by Congress in Section 215 of the Fair and Accurate Credit Transaction Act, Public Law 108-159, enacted December 4, 2003. The study is available at http://www.federalreserve.gov/pubs/reports_other.htm.

[7]For more detail on the contents of this database, see Board of Governors (2007) or Avery, Brevoort, and Canner (2009).

accounts, monetary-related public records, and a complete record of inquiries made by creditors and others legally entitled to the information.[8] These data indicate whether a person individually holds, jointly holds, or is an authorized user on each of the tradelines in her credit record. The dataset also includes two commercially available credit scores, the TransRisk Account Management Score ("TransRisk score") and the VantageScore.[9]

The information provided by TransUnion included a file of 312 precalculated variables, referred to as "credit characteristics." These credit characteristics are summary measures of each credit record (for example, the age of an individual's oldest account, or the total number of serious delinquencies) and were created by TransUnion to facilitate the development of credit scoring models for themselves and for their customers. A subset of these credit characteristics comprise the inputs into the FRB base model.

As noted, the only personal demographic information included in credit records is date of birth (though this information was missing in about one-third of the credit records). However, credit records contain additional types of information (such as name, Social Security number, and current and previous addresses) that were used to obtain demographic information on each individual from the U.S. Social Security Administration (SSA) and from one of the nation's leading demographic information companies.[10]

The SSA collects demographic information when individuals apply for a Social Security card.[11] With the names and Social Security numbers provided by TransUnion, the SSA provided information on each individual including their citizenship, the date they filed for a Social Security card, their place of birth (state or country), race or ethnic description, sex, and date of birth. An

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[8] A detailed assessment of the contents of credit records is provided by Avery, *et al.* (2003).

[9] Approximately 23 percent of the sample population was unscoreable by at least one of the credit scoring models (the vast majority of whom were scoreable by neither). Generally, an individual credit record is unscoreable when it does not contain a sufficient amount of recent account activity.

[10] The matches involved a double-blind process between TransUnion and the other data providers so that the integrity and privacy of each party's records were maintained. No individually identifying information was provided to the Federal Reserve Board, no credit history information was received by the SSA or demographic company, and no demographic information was provided to TransUnion. The demographic information company has elected to remain anonymous.

[11] The application form for a Social Security card is SS-5 (05-2006). This form can be viewed online at http://www.ssa.gov/online/ss-5.html.

applicant for a Social Security card is required to supply all of this demographic information as part of their application, with the exception of race or ethnicity, which is requested by not required.[12]

Information on each individual's marital status was provided by the demographic information company. The company culls this information from thousands of public and private data sources and supplies it to creditors and other interested entities for use in marketing and solicitation activities.

As mentioned earlier, this study also makes use of the FRB base model, a credit history score developed by staff of the Federal Reserve. This credit scoring model was constructed using a model-building algorithm that was designed to mimic the process used by industry model-builders. The FRB base model was estimated using the same sample of credit records used in this study.

The FRB base model is comprised of three different scorecards. Individuals with two or fewer tradelines in their credit records are scored on the "thin" scorecard. People with more than two tradelines are placed on the "dirty" scorecard if they meet any of the following three conditions: (1) they have been 90 or more days past due on an account; (2) they have a monetary-related public record on their file (such as bankruptcy or garnishment); or (3) they have collection accounts totaling more than $50. Other individuals are placed on the "clean" scorecard. A separate equation, with a separate selection of right-hand-side credit characteristics, is used for each of these scorecards.

The model for each scorecard is designed to predict whether a person will have "bad" or "good" performance, measured as each individual's worst performance on a new or existing account during an 18 month performance window of July 2003 through December 2004.[13] Accounts that were 90 or more days past due exhibit "bad" performance and accounts that were not 30 or more days past due, but that have evidence of payments having been made, had "good" performance (other accounts had "indeterminate" performance). An individual's performance is "bad" if one or more of his accounts had bad performance during the performance period. Conversely, an individual's performance was "good" if he had good performance on at least one account without any accounts with bad or indeterminate performance. Otherwise, an individual's

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[12] For further discussion about the SSA data and how they were matched to the credit records, see Board of Governors (2007).

[13] New accounts are those that were opened during the first 6 months of the 18 month performance period. Existing accounts were those that were open as of June 2003 with no evidence of delinquency. This is a common definition of credit performance used by credit scoring model builders.

performance is classified as "indeterminate." The dependent variable in these estimations is a dichotomous indicator variable that takes on a value of 1 for good performance and 0 for bad performance. Individuals who have indeterminate performance are excluded from the estimation of the model, but are used in evaluating the model's effectiveness.

A separate linear probability model was estimated for each of the three scorecards.[14] The credit characteristics that comprised each model were selected using a forward stepwise selection process using the 312 credit characteristics supplied by TransUnion. Each credit characteristic entered the model as a step-function (or series of "credit attributes"), where the breakpoints of the individual steps were selected using statistical criteria used by industry model builders. Characteristics were selected until the marginal improvement in the divergence statistic from the addition of another characteristic fell below a specified threshold. This process was designed to mimic the process used by industry model builders (for example, each credit characteristic enters the model as a step function and the coefficients assigned to the steps of a characteristic, or the "credit attributes," were constrained to be monotonic). A detailed discussion of the model building process is provided by Board of Governors (2007).[15]

The fitted values from these estimated equations are then normalized to a rank-order scale. The normalization is constructed such that an individual's score represents the percentile of the distribution into which that score falls. In other words, 25 percent of the individuals in the sample had a score of 25 or less. These normalized scores range between 0 and 100.[16] Using two commercially available credit scores (the TransRisk Account Management score from TransUnion and the VantageScore) that had been normalized to an identical rank order scale, Board of Governors (2007) finds that the credit score patterns across demographic groups were very similar

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[14] The use of a linear probability model in the FRB base model was motivated by concerns about the additional computational burden of estimating a probit or logit model. Avery, Brevoort, and Canner (2009) use the same model-building process as the FRB base model but replace the linear probability model with a logit and find almost identical results to Board of Governors (2007).

[15] In some ways the process deviated from that used by industry model builders. Most importantly, this process was entirely algorithmic, whereas commercial model building generally involves greater use of art (*e.g.*, modeler experience and intuition). Additionally, the FRB base model was constructed using a linear probability model, rather than the more commonly used logit model. Avery, Brevoort, and Canner (2009) conduct a similar analysis to that of Board of Governors (2007) using a logit model and find that the results are qualitatively identical.

[16] As a frame of reference, a single point in the FRB base model is roughly equivalent to five points on a FICO or VantageScore scale.

across the three credit scoring models. This suggests that the FRB base model closely approximates score differences across demographic groups observed in commercially available models.

Profile of Authorized User Accounts

This analysis focuses on the treatment of authorized user tradelines in credit scoring models and, consequently, we focus on the "scoreable" population, as defined by the FRB base model. In general, an individual credit record is considered to be "unscoreable" when it lacks sufficient information (such as information on at least one tradeline) or when there is no evidence of recent account activity.[17] Excluding the unscoreable population, for whom the treatment of authorized user tradelines in a credit scoring model is largely irrelevant, leaves a scoreable population of 232,467 credit records, all of which have at least one non-authorized user tradeline.

Authorized user accounts are not rare. As shown in table 1, over one-third of the scoreable population had one or more authorized user tradelines. Only a small fraction (1.3 percent), however, had more authorized user tradelines than non-authorized user tradelines (that is, tradelines on which the individual is an individual or joint account holder).[18] Across racial or ethnic groups, authorized user status was found more frequently among non-Hispanic whites than other groups, particularly blacks, only 19.9 percent of whom had authorized user accounts on their credit records. Authorized user accounts are also observed more frequently for married individuals than

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[17] The technical definition of a scoreable credit record for the FRB base model is that the record should have had both a TransRisk score and a VantageScore. This definition was largely equivalent to requiring each individual be scoreable under the TransRisk scoring model, as only 39 out of 301,536 records had a VantageScore but no TransRisk score. Approximately 23 percent of the sample population was unscoreable by at least one of the credit scoring models. Generally, an individual credit record is unscoreable when it does not contain a sufficient amount of recent account activity. For a detailed examination of the contents of the unscoreable credit records, see Board of Governors (2007).

[18] One reason this number is so small is that a credit record needs at least one non-authorized user tradeline to be scoreable. Consequently, credit records with only authorized user tradelines are excluded from the scoreable sample.

The term "non-authorized user tradeline" in this paper means that the individual whose credit record is being examined is not an authorized user on the account. This does not imply that there are no authorized users on that account. For example, if an account has a single account holder and an authorized user, that account information (which is reported on the credit records of both individuals) is considered an authorized user account for the authorized user and as a non-authorized user account for the account holder.

single individuals and less frequently for individuals under 30 years of age than for older individuals.

Table 1 also provides a detailed breakdown of the share of scoreable individuals with authorized user accounts that is based upon the contents of individual credit records. Generally, authorized user accounts are more likely to be found in credit records that are "thicker" (that is, that have more tradelines), older, or that have no evidence of delinquencies in the past 24 months. Overall there appears to be little relationship between credit card utilization and authorized user status.

Table 1 also indicates that across demographic and credit record groups, individuals with authorized user tradelines had higher VantageScores than individuals without authorized user accounts. Since the VantageScore does not use information on authorized user accounts, this difference reflects entirely differences in each individual's non-authorized user accounts. As shown in table 2, authorized user tradelines are generally higher quality than non-authorized user tradelines, in that they tend to be older, have lower utilization rates, and slightly lower delinquency rates. The differences between authorized user and non-authorized-user tradelines appear to hold for most demographic and credit record groups. Nevertheless, the characteristics of authorized user and non-authorized-user tradelines appear to be very similar across groups. For example, individuals under the age of 30 have younger tradeline ages for both their authorized user and non-authorized user accounts than do older individuals and people with more delinquencies on their non-authorized user accounts have higher delinquency rates on their authorized user accounts as well.

Particularly interesting from the standpoint of Reg. B is the difference in the presence of authorized user tradelines of the credit records of married men and women. As shown in table 1, the share of married women in the sample with authorized user tradelines was over 10 percentage points higher than the share of married men. Additionally, married women were twice as likely as married men to have authorized user tradelines constitute the majority of the tradelines on their credit record. These differences are much more pronounced than the differences between single women and men.

While these numbers appear consistent with the concerns originally used to motivate the authorized user provisions of Reg. B in the 1970s – that the credit accounts of married individuals tended to be reported in the husband's name – a closer look at the data suggests that these concerns may be less relevant today. While married women have more authorized user tradelines on their credit records than do married men (1.26 versus 0.90), there is only a slight difference between married men and married women in the number of non-authorized user tradelines on their credit record. Married women have, on average, 16.69 non-authorized user tradelines and married men have 16.72, a statistically insignificant difference. When the comparison is limited to open accounts, married women on average have more authorized user and non-authorized user accounts than married men.[19] This is consistent with the numbers provided in table 2, which show that married women have more authorized user and non-authorized user credit card tradelines than do married men. This analysis of the credit bureau record contents provides little evidence that the credit records of married women are less complete than those of married men.

Effects of Authorized User Accounts on Credit Scores and Access to Credit across Populations

To examine the contribution that the presence of authorized user accounts on an individual's credit record make to credit scores (in credit scoring models such as the FICO score that include them) and, consequently, access to credit for different populations, each of the credit characteristics that comprise the FRB base model was recalculated without the authorized user accounts. A new value for the FRB base score was computed based upon these recalculated credit characteristics. This new value represents the credit score that each individual would have received had their authorized user accounts not been in their credit record. The difference between each individual's FRB base score and this new value measures the contribution the authorized user accounts to each individual's credit score.

Table 3 provides the mean change in the FRB base score by demographic group resulting from the inclusion of authorized user accounts. A positive value indicates that an individual's score is higher when her authorized user accounts are factored into the calculation of the score than it would have been had these account not been reflected in her credit report. For individuals without authorized user accounts on their credit record, the score change will equal zero by definition. Therefore, the means presented in table 3 are calculated using only those individuals in each demographic group who have authorized user tradelines in their credit records. These changes are

[19] An account is considered to be open if it has not been reported as closed, has no comment codes indicating that it has been closed, and was verified after February 2003.

best interpreted as marginal contributions to an individual's credit score made by authorized user accounts and not as the changes that would result if credit scoring models were prohibited from using authorized user accounts, which is an exercise we conduct later in the paper.

Overall, the data suggest that people with authorized user accounts on their credit records experience an average score increase of 0.49 points and a median change of zero points because of the inclusion of this information in the score. Across different demographic groups, authorized user accounts appear to contribute very little to credit scores. The median score change for each of the demographic groups was zero, and the means, which were generally positive, were generally lower than 1. This suggests that none of the demographic groups examined appear to be substantially benefited or harmed, on average, by the authorized user tradelines in their credit records. For most demographic groups, a majority of individuals experienced score changes (positive or negative) of 2.5 points or less from the authorized user accounts on their credit record.

As discussed in the previous section, there are significant differences between married men and women in the number of authorized user tradelines in their credit records. These differences are reflected in their credit scores, as the increase in mean credit scores for married women (0.56 points) is larger than for married men (0.20). As with the other demographic groups, these differences are relatively small and suggest that the presence of authorized user tradelines can explain only slightly more than 10 percent of the average score difference between married women and men.[20] These results suggest that the credit scores of married women are marginally higher than married men, even without contribution made by authorized user tradelines.

Besides demographic groups, there may be other subsets of the population that are more likely to be helped or harmed by the presence of authorized user accounts. In particular, the importance to an individual of authorized user accounts in the calculation of a credit score may differ substantially depending upon the contents of an individual's credit record. In particular, those individuals with fewer non-authorized user accounts on their file, shorter credit histories, or higher utilization rates on their non-authorized user tradelines may stand to gain (or lose) the most from the inclusion of authorized user accounts in the calculation of a credit score. In contrast, those individuals with a large number of accounts or who are currently delinquent on one or more

[20] The mean FRB base score for married women is 3.3 points higher than for married men. Removing authorized user tradelines decreases the mean scores of married women by about 0.36 points more than married men. This suggests that the presence of authorized user account information in the FRB base model can explain 0.36/3.3 = 10.9 percent of the difference in credit scores between married men and women.

accounts may be the least susceptible to benefit or harm from the inclusion of authorized user tradelines.

To examine this possibility, table 3 also shows score changes for different groups based upon the contents of the each individual's credit record. The score changes suggest that some of the groups that were identified as being more likely to benefit from the inclusion of authorized user accounts experienced larger gains than other groups. In particular, those people with thin credit records (2 or fewer non-authorized user tradelines) or short credit histories (oldest non-authorized user account less than 24 months old) both experienced increases in credit scores of approximately 5 points on average because of authorized user accounts. This may reflect, in part, that these two groups have the highest share of individuals for whom authorized user accounts constitute at least half of the tradelines in their credit records (see table 1). In contrast there was a less consistent pattern of benefit or harm based upon past payment performance or utilization rates.[21]

On the whole, this analysis suggests that the inclusion of authorized user account information in computing an individual's credit score has only a modest effect. Furthermore, this inclusion does not appear to have a disproportionate impact on the members of any particular demographic group. However, there are some small subsets of the population (in particular, individuals with very thin or very short credit histories) for whom the inclusion of authorized user accounts has a relatively larger effect on scores. Consistent with our earlier findings about the relative quality of authorized user and non-authorized user tradelines, score changes from the inclusion of authorized user tradelines are generally positive.

The Effect of Piggybacking Credit on Credit Scores

The modest contribution that authorized user accounts appear to make, on average, to individual credit scores does not suggest that the potential change that can be achieved by buying authorized user status on an account is necessarily small. While authorized user accounts are generally higher-quality than non-authorized user accounts (in that they have lower utilization rates, older ages, and better payment histories) within most groups examined, the pattern of authorized user and non-authorized user accounts across groups is similar. For example, both the authorized user and non-

[21] There are two minor exceptions to this in table 3. Individuals with no observed performance on their accounts see their scores increase by 6.8 points and individuals with no revolving accounts on which utilization can be calculated experience increases of 2.8 points. Both of these groups tend to have very thin files.

authorized user accounts for young individuals (under age 30) are not as old on average, as the accounts of older individuals. Consequently, the estimates from the previous section may underestimate the gains in score that can be achieved from piggybacking on an even higher-quality account.

To evaluate the potential credit score boost that an individual might achieve by piggybacking on an additional high-quality account, we use the FRB base model to simulate the effect that the addition of an authorized user account would have on each individual's credit score. This process helps measure the magnitude that such changes are likely to have and helps identify which groups of individuals are the most likely to benefit from piggybacking credit.

The purpose of this exercise is to approximate the potential scope of the problem that piggybacking credit represents. If piggybacking credit has little or no impact on credit scores, or if the benefits are limited to a very small segment of the population, then the need for a remedy will be relatively smaller. In contrast, if piggybacking credit can increase credit scores substantially for a large share of the population, then the potential for harm from piggybacking credit may warrant a reconsideration of existing regulations, industry practices, or both to preserve the predictiveness of credit scoring models.

The simulation begins with the credit records of each of the 232,467 individuals in the 2003 sample and adds to their credit record an additional, authorized user credit card account. To provide an estimate of the maximum amount of benefit one could get by adding an authorized user tradeline to their record, we use values from the 90th percentile of the distributions for account age and credit limit (which translate into an account opening date of March 1987 and a credit limit of $15,000) and assume that the account has an unblemished payment history since opening.[22] Additionally, we assume that the current balance on the account is $1. We simulate what each borrower's FRB base score would have been after the addition of this account and compare this to the original FRB base score. The increase in score that results from the addition of this simulated authorized user account provides an estimate of the benefits to a consumer of piggybacking credit.

Table 4 shows a breakdown of score changes by the demographic characteristics and credit record classifications used earlier. On average, the addition of this simulated account increases credit scores by 6.9 points. Those segments of the population that were identified earlier as being

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[22] Carson and Becker (2007, p. 2) report that the intermediaries who facilitate piggybacking generally seek out accounts with ages ranging from "two years to decades" and that the credit limits on these accounts often exceed $50,000.

the most likely to benefit from an ability to purchase authorized user status, however, experienced much larger increases. The largest increase in score was experienced by individuals whose oldest tradeline was less than 2 years old. The addition of this simulated tradeline increased the credit scores for this group by an average of 22.4 points over the starting mean score of 37.9. As expected, individuals with thin credit files (2 or fewer non-authorized user tradelines) also experienced large increases in score, with their scores rising on average from 44.6 to 64.0.[23]

The importance of a change in credit score will depend crucially upon both the size of the change and the initial credit score. For example, a 20 point score increase might have a smaller effect for an already prime-quality borrower (who may already qualify for credit on the most favorable terms) than it would for a subprime borrower, who as a result might now appear to be near-prime or even prime-quality. To provide a better understanding of how credit score changes experienced after the addition of the simulated AU tradeline vary with the starting FRB base score level, figure 1 shows the mean change in score that resulted from the simulation against the beginning FRB base score.

As seen in that figure, there is substantial variation in the mean score change by credit score level. The smallest mean increases (and only decreases) are observed for individuals at the highest credit score levels. These are people who already are identified by the credit scoring model as having low default probabilities, such that the additional information provided by the simulated tradeline has little or no beneficial effect. The remainder of the population experienced larger increases on average, with a noticeable dip in the low 20s. The bottom of this dip occurs at a score

[23] The score changes summarized by table 4 also show that a small number of people (representing about 1 percent of the total population) experience a score decline following the addition of the simulated AU account to their credit record. While it may surprise some that a credit score can be reduced by adding information on an unambiguously "good" account, this result is not wholly unexpected. The reason is that while the simulated account will have increased or left unchanged the score of any individual who remained on the same scorecard, when the addition of an account alters the scorecard with which an individual is scored, unintuitive results can arise.

In the FRB base model, which contains only three scorecards, the addition of the simulated account can have the effect of moving people who would have been scored on the thin scorecard, without the simulated account, onto either the clean or dirty scorecards. People who were initially scored on the clean or dirty scorecards would not have changed scorecards. Because of this movement between scorecards, some individuals (particularly those who moved from the thin to the dirty scorecard) saw their credit scores decline as their profile appeared worse when evaluated using the model on their new scorecard. Since most credit scoring models make use of more than 3 scorecards (for example, the VantageScore is comprised of 12 different scorecards) this suggests that the FRB base model may understate the share of individuals who change scorecards as a result of the additional authorized user tradeline and who therefore may be subject to such counterintuitive score changes. For more information on the 12 scorecards that comprise the VantageScore, see VantageScore (2006).

of approximately 24, which roughly corresponds to the boundary between subprime and near-prime credit scores.[24]

An alternative method of evaluating the impact of the addition of the simulated tradeline is to look at threshold effects. In this case, we examine how many people with subprime-level credit scores experienced score increases that moved them into near-prime or even prime levels. The results of this analysis suggest that there is substantial potential for movement across these credit risk categories (table 5). More than one-quarter of the 56,000 subprime borrowers in our sample experienced credit score increases that moved their credit score into the near-prime range because of the simulated tradeline. Similarly, over one-third of near-prime borrowers had prime credit scores because of the simulated tradeline and 1.2 percent of these borrowers improved to super-prime credit scores.

While there are only small differences across demographic groups, the credit record population segments that we have already highlighted exhibit much larger threshold effects. Amongst the thin file population, for example, 46.8 percent of subprime borrowers are moved into the near-prime segment and an additional 3.6 percent become prime borrowers because of the simulated tradeline. Threshold effects are notably smaller, however, for individuals with past delinquency. For example, only 7.9 percent of subprime borrowers with two or more delinquencies in the past 24 months experience score increases into the near-prime segment and only 3.4 percent of near-prime borrowers with 2 delinquencies receive prime scores.

These numbers appear to indicate that the practice of piggybacking credit can increase credit scores to an economically-significant extent, if the account to which a non-prime borrower is being added is of sufficiently high quality. Furthermore, it appears that a large fraction of borrowers – particularly borrowers with thin or short credit histories – can obtain substantially higher credit scores as a result of this practice. This suggests that the practice of piggybacking credit offers substantial potential to increase the credit scores of individuals added as authorized users on existing accounts and consequently to enhance their access to credit at lower costs..

[24] The boundaries used to delineate subprime, near-prime, prime, and super-prime credit scores in this study are based on the VantageScore cutoffs for these groups (VantageScore, 2008) applied to the normalized 0-100 scale used for the FRB base model.

Removing Authorized User Accounts from Model Construction

We next consider the potential effect of eliminating consideration of authorized user tradelines in credit scoring models on the credit scores of individual borrowers (and hence their ability to access consumer credit) and the accuracy of credit scoring models, which may hinder the ability of consumer credit markets to allocate credit efficiently. Some credit scoring models in use today, including the VantageScore, exclude authorized user tradelines from their models and others, such as the FICO score, have altered the way authorized user tradelines are treated by their models. These policies, whether taken in response to abuse from piggybacking credit or not, can affect not only the credit scores of individual borrowers (and hence their ability to access consumer credit markets), but also the accuracy of credit scoring models, which may hinder the ability of consumer credit markets to allocate credit efficiently. In this section, we evaluate how removing authorized user accounts from credit score model construction affects both the credit scores of borrowers and the predictiveness of credit scoring models.

While the earlier analysis documented the contribution that authorized user accounts make to an individual's credit score, the results are not fully indicative of the effect that removing authorized user accounts from a credit scoring model would have on individual credit scores. This is because in the earlier exercise, we removed the authorized user tradelines but left the credit scoring model itself unchanged. If, however, authorized user tradelines were systematically excluded from credit scoring models, model builders would be expected to recalibrate their models to reflect this. The result would be a different credit scoring model that was optimized to predict future credit performance without using authorized user tradelines.

In this section, we examine how credit scores would change if authorized user tradelines were systematically excluded from the construction and application of credit scoring models. Using the credit characteristics that were calculated without authorized user accounts, we re-estimate the models for each of the three credit scorecards that comprise the FRB base model.[25] Fitted values from these new models are then normalized to the same rank-order scale used for the FRB base model (however, the mapping between fitted values and credit score differs from that of the FRB base model). This new score is then compared to the original FRB base score for each individual.

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[25]As part of the process of re-estimating each scorecard model, we recalculate the attributes constructed for each credit characteristic. This is done using the same algorithm used in generating the original FRB base model. For more information on the process used to construct attributes, see Board of Governors (2007).

The result of this process is an approximation of the credit scoring model that would have resulted had authorized user tradelines not been used in model development.[26] As such, it represents the outcome that would result if model developers excluded authorized user tradelines from their models.

Table 6 shows how credit scores change for each population group when the credit scoring model is re-estimated without authorized user accounts. The re-estimation of the credit scoring model will impact scores for almost all individuals, but because the effects of these changes are expected to be much larger for individuals with authorized user tradelines, we again focus on this subset of the population. The results indicate that the reestimated scoring model produces scores that are only 0.30 points lower, on average, for authorized users than the FRB base model. None of the demographic groups experience a score decline of more than 1 point. While the score decline was somewhat larger for married women than married men, credit scores remained higher for married women.

Across credit record groups, again it is the populations with thin or short credit histories that experience the largest declines. Mean scores for the thin file population and for the individuals whose oldest non-authorized-user tradeline was less than 2 years old both fell by 5.21 and 4.35 points respectively. These declines are somewhat lower than what would have been implied by our earlier exercise of removing authorized user account information while leaving the underlying scoring model unchanged. This may suggest that the within-group similarities in the characteristics of authorized user and non-authorized-user tradelines help capture some of the information provided by authorized user tradelines.

Evaluating the Predictiveness of Authorized User Account Information

We next consider what impact including, or alternatively excluding, authorized user account information in credit scoring models will have on the model's ability to predictive future credit performance. Since authorized users are not liable for any debt incurred, performance on these accounts may not reflect the authorized user's creditworthiness and consequently may have little relationship to the performance of authorized users on their own (non-authorized user) accounts

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[26]This approach is an approximation because we use the same set of credit characteristics on each scorecard as was used in the FRB base model. Reselecting credit characteristics would have required us to reverse engineer over 300 credit characteristics, a process that would have taken a prohibitive amount of time.

going forward. In such cases, including authorized user accounts in a credit score might reduce the predictiveness of a credit scoring model. However, if there is a close financial relationship between the account holder and the authorized user, in that the authorized user may rely on the account holder to provide financial support and to be a source of financial strength or may be the person who manages a household's finances, then both the account holder and the authorized user may have similar future loan performance. In this case, including authorized user accounts in the calculation of a credit score should increase the model's predictiveness.

To assess each model's predictiveness, we rely on credit performance on non-authorized user accounts that were opened in the six month period after the date for which the scores were calculated (July to December 2003). Credit performance is evaluated over the eighteen month performance window, running from July 2003 through December 2004 with performance on each account categorized as good, bad, or indeterminate using the same criteria described earlier in discussing model construction. All of an individual's accounts that exhibit performance are weighted equally with the sum of the weights summing to 1 for each individual. This is equivalent to measuring performance by selecting a random account from each credit record, which is a methodology commonly used in assessing credit scoring models.[27]

Using this performance measure, we calculate the credit scores produced by the FRB base model and by the re-estimated model without authorized user tradelines for the credit bureau records from June 2003. If authorized user accounts increase the predictiveness of a credit scoring model, we would expect the goodness-of-fit measures for the FRB base model to be higher than those for the re-estimated model. We rely on two commonly-used measures of goodness-of-fit to evaluate model predictiveness: the Kolmogorov-Smirnow ("KS") statistic and the divergence statistic.[28]

Both goodness-of-fit measures suggest that a credit scoring model that incorporates information on the authorized user accounts in a person's credit record has greater predictive power for new non-authorized user accounts than a model that does not consider this information. As shown in table 7, both the KS-statistic and the divergence statistic for the FRB base model (57.1 and 2.52, respectively) were higher than the values of these statistics for the versions of the FRB

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[27]The measure of performance used here is identical to the "modified new account" measure used in Board of Governors (2007) with the additional restriction that only non-authorized user accounts are evaluated.

[28]For additional information on these statistics and their use in credit scoring, see Mays (2004).

base model that was re-estimated without the information on each individual's authorized user accounts (57.0 and 2.51). However, both differences were small, suggesting that the increase in predictive power offered by authorized user accounts was marginal.

In addition to the overall change in score predictiveness, we can also evaluate how predictiveness is affected for specific subpopulations. Particularly interesting is the effect of including authorized user accounts in credit scoring models on predictiveness among individuals with short or thin credit histories based on their non-authorized user accounts. Since these are the individuals for whom non-authorized user accounts provide the least information, one might expect the additional information provided by authorized user accounts to be particularly effective at differentiating risk within these categories. Both goodness-of-fit measures suggest that the FRB base model has significantly greater predictiveness with the authorized user tradelines included than the model that excludes these tradelines. The improvements in fit for these populations are generally larger than for the other subpopulations examined.

Taken together, these results suggest that information provided by the authorized user accounts on an individual's credit record appear to provide additional information about the authorized user's future credit performance. The boost to credit score predictiveness, however, appears to be mild. Additionally, some of the decline in model predictiveness may be mitigated by altering the selection of credit characteristics included in the model. Nevertheless, authorized user account information does seem to add additional predictive power to the FRB base model.

Conclusions and Caveats

Regulation B, which implements the Equal Credit Opportunity Act (ECOA), contains several requirements about the treatment of spousal authorized user accounts. Among the requirements are that creditors who report information to credit bureaus must report the information in a manner that reflects the participation of both spouses and that information on spousal authorized user accounts must be considered, when available, in a evaluating credit history to assess creditworthiness.

Our analysis of authorized user tradelines in a random sample of credit records suggests that over one-third of individuals have one or more authorized user accounts. The characteristics of authorized user accounts are generally superior to non-authorized user accounts in that they tend to be older, have lower utilization levels, and less evidence of past delinquency. The usage of authorized user account status appears to differ across demographic groups with minorities, single individuals, and the young being less likely to have authorized user accounts than the rest of the population.

Married women, whose treatment was a central factor motivating the provisions of Reg. B, are more likely to have authorized user accounts on their credit records than are married men. The greater frequency with which married women are authorized users, however, does not appear to come at the expense of being an account holder. The credit records of married women also had the same or slightly more *non*-authorized user tradelines than the records of married men. This suggests that the concerns about a lack of credit history for married women as a result of accounts being reported to the credit bureaus in the husband's name that motivated the Reg. B provisions relating to spousal authorized user accounts may be less relevant today, possibly reflecting the success of ECOA in equalizing credit opportunity and credit reporting for married women.

Based on the analyses documented in this paper, authorized user accounts appear to provide only a modest boost on average to individual credit scores in a scoring model that incorporates authorized user account information. Despite the differences in usage patterns across groups, there is little evidence that authorized user accounts contribute meaningfully to score differences across demographic groups. While authorized user accounts increased the credit scores of married women more than married men, this difference explains only about 10 percent of the score difference between married women and men. For those individuals with thin or short credit histories, however, the incorporation of authorized user tradeline information may offer an economically-meaningful boost to scores.

Despite the minor differences observed in scores as a result of authorized user accounts, our results suggest that the practice of piggybacking credit can have a large effect on the scores of some individuals. Particularly for individuals with short or thin credit histories, the addition of a high-quality authorized user account can significantly improve an individual's credit score. In a substantial fraction of cases, these improvements are economically meaningful in that an individual with a subprime credit score can be moved to near-prime levels, or someone with a near-prime score can become prime. If an authorized user account is added in advance of a major credit transaction, such as a new mortgage, the individual may be able to access credit for which he would not have otherwise qualified or to obtain credit with much lower borrowing costs.

The potential distortions in credit scores that piggybacking credit may introduce suggest that a reconsideration of existing regulations, industry practices, or both may be warranted to preserve the predictiveness of credit scoring models. Our results suggest that eliminating authorized user accounts from a credit scoring model has only a modest effect on score differences across groups. Nevertheless, these same results suggest that the predictiveness of the credit scoring model without authorized user tradelines is somewhat diminished from that of the model that incorporates authorized user account information. This suggests that authorized user accounts provide useful information and there may be some downside to excluding this information from credit scoring models.

There are several caveats that go along with this analysis. First, the analysis here utilizes the FRB base model, instead of a commercially available credit scoring model. While we would have preferred to use one or more of the models actually used in credit underwriting, these models were not available and without the estimation sample used (along with demographic information on at least marital status) would not have been sufficient. Nevertheless, the FRB base model has been shown to produce very similar results to commercially available models (Board of Governors, 2007) and we believe that the results obtained from this model are broadly applicable.

Second, our analysis has examined the potential score improvement that an individual can achieve by piggybacking on a high quality account. The characteristics of the account used in our simulation were selected to provide, essentially, a reasonable upper bound on the benefit that an individual could achieve by buying authorized user status. The actual accounts available for piggybacking may result in smaller score improvements or even score declines (particularly if the account eventually becomes delinquent).

Third, the analysis presented in this paper has looked at a single possible response to piggybacking credit. Other possible responses, such as continuing to incorporate authorized user account information in credit scoring models but in a manner that is distinct from non-authorized-user accounts, have not been evaluated. This may be a useful area for further research to identify effective methods to minimize the potential harm from piggybacking credit while continuing to incorporate the predictive information provided by authorized user accounts.

Finally, our analysis has made no attempt to document the extent to which individuals are engaging in piggybacking credit. Because of the way data is reported to and stored by the credit bureaus, identifying such conduct is difficult if not impossible. Regardless of how often the practice is being used, however, we have shown that piggybacking credit has the potential to artificially improve credit scores at least for specific segments of the population.

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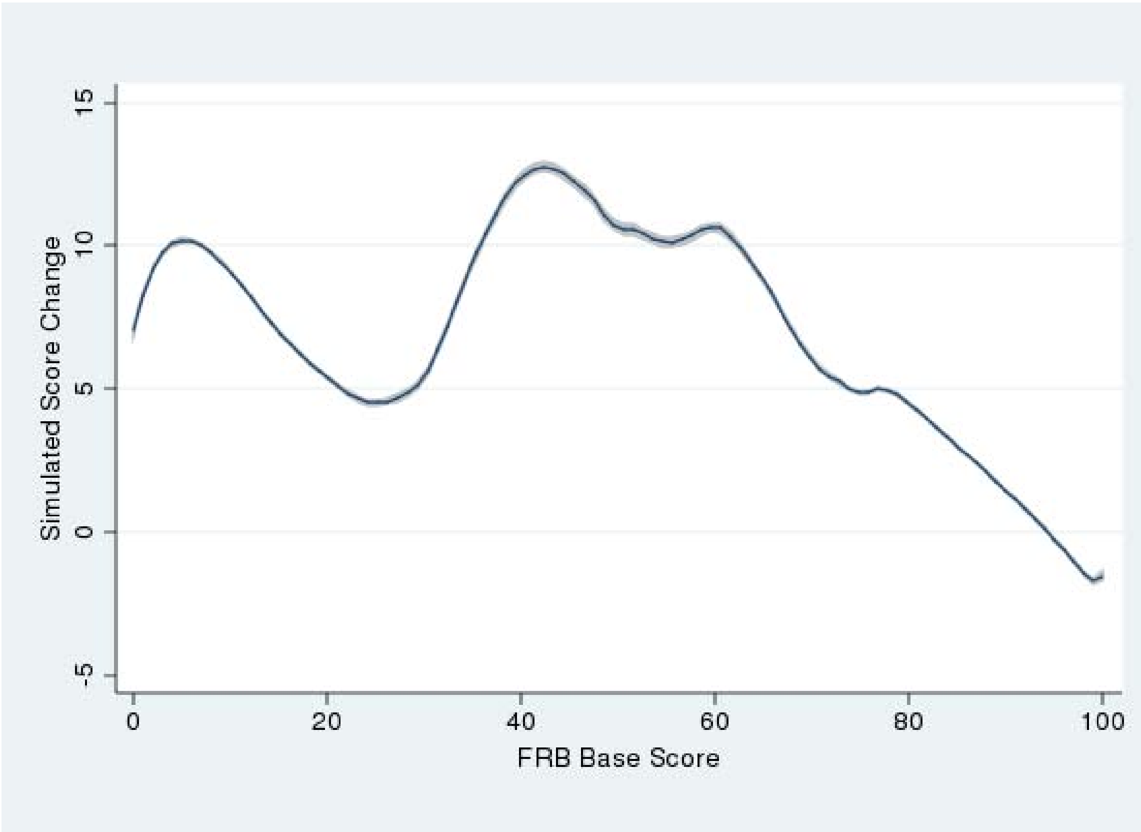

Figure 1: Simulated Score Change by Original FRB Base Score with 95 Percent Confidence Interval

Table 1: Sample Statistics by Demographic and Credit Record Group

Breakdown Category		Subgroup	Number of Obs.	Share of Individuals with Authorized User Tradelines	Share of Individuals with Majority Authorized User Tradelines	All Tradelines: Mean Number of Authorized User Tradelines	All Tradelines: Mean Number of Non-Authorized User Tradelines	Open Tradelines: Mean Number of Authorized User Tradelines	Open Tradelines: Mean Number of Non-Authorized User Tradelines	Mean VantageScore: Individuals with Authorized User Tradelines	Mean VantageScore: Individuals without Authorized User Tradelines
Demographic Groups	Race or Ethnicity	White	149,412	39.5	0.8	0.84	15.49	0.42	5.18	795.7	749.1
		Black	21,418	19.9	0.6	0.36	12.61	0.15	3.57	680.6	629.6
		Hispanic	17,003	31.3	1.2	0.63	13.08	0.31	4.54	732.5	683.2
		Asian	8,890	38.9	1.9	0.87	14.57	0.43	5.23	796.4	760.4
		American Indian	409	38.2	0.8	0.82	14.99	0.41	4.95	796.9	775.4
		Other	35,336	25.7	3.3	0.53	9.12	0.27	3.18	777.9	737.4
	Individual Age	Under 30	33,827	20.1	1.8	0.33	8.77	0.18	3.34	703.8	658.4
		30 to 39	40,669	36.3	0.7	0.75	16.25	0.34	4.65	744.6	685.3
		40 to 49	46,462	42.2	0.6	0.94	17.62	0.45	5.61	777.5	719.1
		50 to 61	43,488	44.1	0.6	1.00	17.90	0.51	6.10	806.1	757.5
		62 or older	44,075	36.2	1.0	0.74	12.66	0.39	4.68	838.4	814.6
		Age missing	23,946	20.8	4.4	0.41	6.34	0.21	2.27	769.7	738.6
	Marital Status by Gender	Married male	54,711	42.9	0.6	0.90	16.72	0.43	5.47	797.6	768.3
		Single male	29,184	21.0	0.6	0.36	13.47	0.16	4.32	743.0	715.2
		Married female	55,443	53.6	1.2	1.26	16.69	0.66	5.77	806.4	756.0
		Single female	32,992	23.5	0.8	0.45	14.25	0.20	4.82	750.6	716.6
		Unknown	60,137	23.7	2.4	0.45	9.34	0.22	3.07	748.3	700.4
Credit Record Groups	Number of Tradelines	2 or fewer	31,944	11.0	7.3	0.17	1.38	0.10	0.79	719.2	691.3
		3 to 5	30,071	20.5	1.6	0.34	3.98	0.19	1.66	754.2	700.3
		6 to 10	44,303	30.3	0.2	0.55	7.96	0.29	3.04	777.7	727.3
		More than 10	126,149	46.2	0.0	1.05	21.79	0.50	6.97	791.9	755.3
	Credit Card Utilization	No accounts	70,643	20.7	2.6	0.37	7.27	0.16	1.34	702.9	651.2
		None (0 percent)	22,719	39.4	1.8	0.89	11.24	0.48	3.64	846.6	817.1
		Less than 25 percent	75,243	43.7	0.5	0.96	17.75	0.49	6.67	862.7	851.4
		25 to 49 percent	19,905	43.4	0.4	0.98	19.81	0.49	7.22	764.5	747.4
		50 to 74 percent	15,086	40.2	0.5	0.87	18.68	0.44	6.72	708.9	689.5
		75 percent or more	28,871	35.3	0.5	0.72	16.78	0.33	5.68	649.5	626.2
	Age of Oldest Tradeline	Less than 24 months	11,920	13.5	6.9	0.21	2.07	0.15	1.54	688.2	663.8
		24 to 59 months	24,552	16.3	2.8	0.27	5.28	0.15	2.48	693.5	652.8
		60 to 119 months	44,278	26.1	1.3	0.49	10.82	0.23	3.47	707.5	665.1
		120 or more months	151,717	42.3	0.5	0.93	17.34	0.45	5.64	805.3	778.2
	Number of Delinquencies in Past 24 Months	No performance	3,922	6.8	3.9	0.09	1.94	0.03	0.12	592.3	568.9
		0	174,226	38.2	1.5	0.83	14.30	0.43	5.21	817.6	784.0
		1	24,467	26.3	0.8	0.50	12.32	0.21	3.48	669.7	615.5
		2 or more	29,852	27.1	0.1	0.49	15.55	0.14	3.19	599.6	576.8
Total			232,467	35.0	1.3	0.74	14.04	0.36	4.68	783.6	728.8

NOTE: Credit record group information is based upon non-authorized-user account information only. "Open Tradelines" include tradelines that have not been reported as having been closed, have no comment codes indicating closure, and have been verified to the credit bureau no earlier than March 2003.

Table 2: Characteristics of Authorized-User and Non-Authorized-User Accounts by Demographic and Credit Record Group

Breakdown Category		Subgroup	Number of Individuals with AU Trades	Mean Credit Card Trades Per Person		Average Account Age (in months)		Credit Card Utilization Rate		Delinquency Rate	
				Authorized User Trades	Non-Authorized User Trades	Authorized User Trades	Non-Authorized User Trades	Authorized User Trades	Non-Authorized User Trades	Authorized User Trades	Non-Authorized User Trades
Demographic Groups	Race or Ethnicity	White	59,047	2.0	10.2	103.8	43.7	10.5	13.8	1.0	1.2
		Black	4,268	1.7	9.0	93.0	23.3	31.4	43.4	3.4	3.7
		Hispanic	5,322	1.9	9.6	87.3	32.1	18.0	21.8	1.9	2.2
		Asian	3,456	2.2	11.2	86.8	38.3	8.9	14.7	0.6	0.9
		American Indian	156	2.0	9.4	113.2	45.5	13.7	17.2	0.7	1.1
		Other	9,098	2.0	8.7	102.5	40.1	9.8	17.5	1.2	1.6
	Individual Age	Under 30	6,814	1.6	6.6	59.4	12.3	19.9	26.6	1.8	2.5
		30 to 39	14,779	2.0	10.0	74.8	32.3	13.4	17.3	1.6	2.2
		40 to 49	19,616	2.1	11.0	93.4	42.5	13.1	17.2	1.5	1.5
		50 to 61	19,181	2.1	11.2	111.5	49.7	10.9	15.0	0.9	1.1
		62 or older	15,967	1.9	9.5	137.3	50.6	5.8	10.6	0.5	0.7
		Age missing	4,989	1.9	7.2	102.9	38.9	9.9	18.3	1.2	1.7
	Marital Status by Gender	Married male	23,497	2.0	10.2	85.2	49.4	10.4	12.4	1.0	1.1
		Single male	6,119	1.6	9.2	84.3	22.5	17.3	21.8	2.0	1.9
		Married female	29,705	2.2	10.7	117.2	54.5	8.9	13.4	0.9	1.1
		Single female	7,748	1.8	10.2	107.9	22.9	15.5	23.7	1.8	2.0
		Unknown	14,277	1.8	8.1	93.1	31.0	16.7	21.8	1.7	2.1
Credit Record Groups	Number of Tradelines	2 or fewer	3,520	1.5	1.1	91.6	9.5	16.8	31.1	1.9	1.9
		3 to 5	6,171	1.6	2.6	109.8	19.1	13.9	25.5	1.4	2.1
		6 to 10	13,413	1.7	4.8	109.3	28.7	12.6	23.0	1.3	1.9
		More than 10	58,242	2.1	12.5	99.7	43.6	10.9	15.1	1.1	1.3
	Credit Card Utilization	No accounts	14,628	1.7	4.5	96.3	25.6	26.1	42.7	2.4	3.5
		None (0 percent)	8,943	2.2	8.1	103.8	48.4	3.3	9.8	0.5	0.3
		Less than 25 percent	32,876	2.1	11.9	107.8	47.4	2.0	2.9	0.2	0.2
		25 to 49 percent	8,631	2.2	12.6	97.7	43.0	7.7	9.6	0.8	0.7
		50 to 74 percent	6,068	2.1	11.5	95.4	39.1	19.1	23.7	1.4	1.4
		75 percent or more	10,200	1.9	9.9	90.6	32.7	45.6	49.8	4.3	7.1
	Age of Oldest Tradeline	Less than 24 months	1,610	1.5	1.8	48.2	1.9	20.1	46.6	1.9	2.7
		24 to 59 months	4,005	1.6	4.5	57.7	5.7	24.7	40.9	2.2	3.2
		60 to 119 months	11,537	1.8	7.3	71.7	16.9	24.9	31.3	2.1	3.0
		120 or more months	64,194	2.1	11.0	109.0	47.0	9.3	13.8	1.0	1.1
	Number of Delinquencies in Past 24 Months	No performance	265	1.3	0.9	70.1	5.2	73.4	64.4	4.8	N/A
		0	66,579	2.1	10.1	103.8	44.5	4.6	5.3	0.4	0.2
		1	6,425	1.8	9.0	92.8	31.8	32.2	29.4	3.4	3.3
		2 or more	8,077	1.7	9.5	86.0	26.0	65.4	63.9	10.7	16.3
Total			81,346	2.0	10.0	101.4	40.6	11.4	15.8	1.2	1.4

NOTE: N/A = not available. Credit record groups are based on information on non-authorized-user account information only.

Table 3: Marginal Improvement in the FRB Base Score Because of Authorized User Accounts by Demographic and Credit Record Group

Breakdown Category		Subgroup	Number of Obs.	Mean FRB Base Score	Score Change: Mean	Score Change: Mean Standard Error	Score Change: Median	Share of Individuals: Change < -7.5	Share of Individuals: -7.5 ≤ Change < -2.5	Share of Individuals: -2.5 ≤ Change ≤ 2.5	Share of Individuals: 2.5 < Change ≤ 7.5	Share of Individuals: Change > 7.5
Demographic Groups	Race or Ethnicity	White	59,047	60.0	0.47 ***	0.023	0.00	5.21	7.48	68.65	11.65	7.02
		Black	4,268	33.1	-0.24 ***	0.020	0.00	5.23	9.04	73.17	8.47	4.10
		Hispanic	5,322	45.0	0.01	0.022	0.00	5.27	9.50	70.02	10.00	5.21
		Asian	3,456	59.2	0.67 ***	0.026	0.00	4.94	8.27	66.61	12.21	7.97
		American Indian	156	60.3	0.79 ***	0.023	0.00	4.50	6.17	71.05	10.94	7.34
		Other	9,098	57.0	1.21 ***	0.036	0.00	7.79	7.08	62.39	11.44	11.30
	Individual Age	Under 30	6,814	41.0	0.97 ***	0.090	0.00	5.94	10.30	59.64	13.85	10.26
		30 to 39	14,779	48.7	-0.05	0.049	0.00	5.31	9.52	70.86	9.12	5.20
		40 to 49	19,616	55.3	-0.01	0.045	0.00	5.46	8.22	71.55	9.46	5.32
		50 to 61	19,181	61.3	0.27 ***	0.046	0.00	5.04	7.41	70.65	10.71	6.18
		62 or older	15,967	69.6	1.23 ***	0.059	0.00	4.71	4.82	65.79	15.54	9.15
		Age missing	4,989	56.8	1.95 ***	0.177	0.00	9.72	6.78	57.03	11.39	15.09
	Marital Status by Gender	Married male	23,497	59.4	0.20 ***	0.041	0.00	4.93	7.83	71.73	9.81	5.70
		Single male	6,119	47.6	0.34 ***	0.076	0.00	4.20	7.47	72.81	10.03	5.49
		Married female	29,705	62.7	0.56 ***	0.041	0.00	5.63	7.53	65.99	12.99	7.86
		Single female	7,748	49.6	0.30 ***	0.075	0.00	5.37	7.71	69.82	10.91	6.20
		Unknown	14,277	50.2	1.01 ***	0.077	0.00	6.74	7.84	64.10	11.39	9.94
Credit Record Groups	Number of Tradelines	2 or fewer	3,520	54.2	4.77 ***	0.324	2.40	21.85	6.99	21.28	13.72	36.17
		3 to 5	6,171	53.9	2.77 ***	0.107	1.00	4.83	7.33	49.83	20.58	17.44
		6 to 10	13,413	56.3	1.23 ***	0.059	0.00	4.40	6.98	62.84	16.37	9.42
		More than 10	58,242	57.9	-0.18 ***	0.022	0.00	4.82	7.93	74.21	9.10	3.95
	Credit Card Utilization	No accounts	14,628	40.7	2.79 ***	0.091	0.20	6.71	7.47	56.08	11.61	18.14
		None (0 percent)	8,943	68.4	0.39 ***	0.083	0.00	6.87	6.80	62.59	15.26	8.49
		Less than 25 percent	32,876	73.5	0.17 ***	0.031	0.00	4.34	5.03	74.09	11.87	4.68
		25 to 49 percent	8,631	55.3	-0.51 ***	0.063	0.00	7.15	10.24	68.31	10.29	4.01
		50 to 74 percent	6,068	42.3	-0.40 ***	0.069	0.00	5.95	12.84	67.60	9.43	4.19
		75 percent or more	10,200	29.0	-0.28 ***	0.048	0.00	4.55	12.11	71.72	8.10	3.53
	Age of Oldest Tradeline	Fewer than 24 months	1,610	45.6	5.09 ***	0.345	3.20	11.12	9.13	26.46	22.17	31.12
		24 to 59 months	4,005	39.7	0.92 ***	0.161	0.00	8.74	10.09	53.76	15.03	12.39
		60 to 119 months	11,537	40.6	0.73 ***	0.070	0.00	5.39	9.61	64.83	11.54	8.63
		120 or more months	64,194	61.6	0.31 ***	0.026	0.00	5.16	7.15	70.75	10.84	6.10
	Number of Delinquencies in Past 24 Months	No performance	265	25.0	6.84 ***	0.762	3.20	4.15	6.79	36.98	17.74	34.34
		0	66,579	65.7	0.60 ***	0.030	0.00	6.20	7.47	65.58	12.40	8.35
		1	6,425	25.7	-0.17 ***	0.043	0.00	3.32	9.77	76.97	7.46	2.49
		2 or more	8,077	13.2	-0.09 ***	0.028	0.00	1.37	7.81	83.76	5.83	1.23
Total			81,346	57.2	0.49 ***	0.025	0.00	5.49	7.68	68.19	11.37	7.27

NOTE: *,**,*** represent statistical significance at the 5, 1, and 0.1 percent leveles, respectively. Credit record groups are based on non-authorized-user account information only.

Table 4: Score Changes from the Addition of a Simulated Authorized-User Tradeline by Demographic and Credit Record Group

Breakdown Category		Subgroup	Number of Obs.	Mean FRB Base Score	Score Change: Mean	Score Change: Mean Standard Error	Score Change: Median	Share of Individuals: Change < -7.5	Share of Individuals: -7.5 ≤ Change < -2.5	Share of Individuals: -2.5 ≤ Change ≤ 2.5	Share of Individuals: 2.5 < Change ≤ 7.5	Share of Individuals: Change > 7.5
Demographic Groups	Race or Ethnicity	White	149,412	54.0	5.53 ***	0.015	4.00	0.58	0.17	40.15	35.54	23.56
		Black	21,418	25.8	7.45 ***	0.014	5.80	0.11	0.05	19.54	45.38	34.92
		Hispanic	17,003	38.2	7.07 ***	0.017	5.20	0.36	0.17	28.34	39.80	31.34
		Asian	8,890	54.8	6.38 ***	0.018	4.20	0.73	0.17	38.39	32.98	27.73
		American Indian	409	57.3	4.59 ***	0.013	3.40	0.97	0.28	43.84	36.51	18.41
		Other	35,336	52.1	12.69 ***	0.033	6.20	2.15	0.54	25.40	26.96	44.95
	Individual Age	Under 30	33,827	33.6	10.06 ***	0.052	7.00	0.36	0.12	13.37	39.36	46.78
		30 to 39	40,669	40.8	6.11 ***	0.032	4.80	0.18	0.05	31.72	40.43	27.63
		40 to 49	46,462	48.2	5.06 ***	0.029	3.60	0.17	0.07	42.29	35.51	21.95
		50 to 61	43,488	55.4	4.38 ***	0.029	2.60	0.28	0.12	49.14	32.34	18.13
		62 or older	44,075	66.0	4.93 ***	0.037	3.60	1.54	0.42	42.08	37.22	18.75
		Age missing	23,946	53.0	15.93 ***	0.115	9.60	2.98	0.71	19.06	22.86	54.39
	Marital Status by Gender	Married male	54,711	56.3	4.99 ***	0.030	3.20	0.50	0.15	44.79	34.12	20.44
		Single male	29,184	43.5	6.57 ***	0.045	4.80	0.58	0.20	31.20	38.06	29.96
		Married female	55,443	57.6	4.85 ***	0.029	3.40	0.47	0.15	44.56	35.39	19.44
		Single female	32,992	44.4	6.26 ***	0.040	4.80	0.56	0.17	31.00	40.89	27.38
		Unknown	60,137	43.5	11.20 ***	0.055	6.40	1.50	0.37	21.63	32.12	44.39
Credit Record Groups	Number of Tradelines	2 or fewer	31,944	44.6	19.42 ***	0.098	15.80	5.53	1.37	5.94	10.67	76.50
		3 to 5	30,071	42.8	9.64 ***	0.039	7.80	0.02	0.02	11.52	36.16	52.28
		6 to 10	44,303	48.1	6.00 ***	0.025	5.20	0.01	0.03	24.79	49.13	26.03
		More than 10	126,149	53.7	3.47 ***	0.012	2.20	0.01	0.04	51.69	36.58	11.69
	Credit Card Utilization	No accounts	70,643	31.6	12.74 ***	0.047	9.00	0.89	0.29	8.94	35.17	54.70
		None (0 percent)	22,719	66.1	5.53 ***	0.064	3.40	2.50	0.45	42.18	33.68	21.20
		Less than 25 percent	75,243	72.4	2.87 ***	0.018	1.00	0.72	0.22	61.55	26.56	10.94
		25 to 49 percent	19,905	53.5	4.15 ***	0.042	2.20	0.12	0.08	52.90	31.34	15.56
		50 to 74 percent	15,086	40.3	5.36 ***	0.052	3.60	0.07	0.04	33.75	46.46	19.68
		75 percent or more	28,871	26.6	7.20 ***	0.039	5.80	0.03	0.02	12.88	57.04	30.03
	Age of Oldest Tradeline	Less than 24 months	11,920	37.9	22.36 ***	0.145	19.00	0.79	0.35	2.25	12.95	83.66
		24 to 59 months	24,552	32.8	11.26 ***	0.070	8.40	1.22	0.28	8.98	34.98	54.55
		60 to 119 months	44,278	34.1	8.20 ***	0.040	6.00	0.66	0.14	17.42	44.24	37.54
		120 or more months	151,717	58.4	4.66 ***	0.019	2.80	0.73	0.22	47.04	34.59	17.43
	Number of Delinquencies in Past 24 Months	No performance	3,922	14.0	15.66 ***	0.101	14.60	0.10	0.03	0.18	1.79	97.91
		0	174,226	61.5	7.05 ***	0.026	4.00	1.01	0.26	40.32	30.35	28.05
		1	24,467	21.0	6.11 ***	0.031	5.20	0.04	0.12	26.69	43.10	30.06
		2 or more	29,852	11.3	5.84 ***	0.021	5.40	0.02	0.03	15.95	62.65	21.35
Total			232,467	50.0	6.94 ***	0.020	4.60	0.77	0.22	35.08	35.36	28.58

NOTE: *,**,*** represent statistical significance at the 5, 1, and 0.1 percent leveles, respectively. Credit record groups are based on non-authorized-user account information only.

Table 5: Subprime and Near-prime Credit Score Transitions following the Addition of a Simulated Authorized User Account by Demographic and Credit Record Group

Breakdown Category		Subgroup	Share of Subprime Borrowers That				Share of Near-Prime Borrowers That			
			Remain Subprime	Become Near-Prime	Become Prime	Become Super-Prime	Become Subprime	Remain Near-Prime	Become Prime	Become Super-Prime
Demographic Groups	Race or Ethnicity	White	71.6	27.8	0.6	0.0	0.1	67.9	31.7	0.3
		Black	76.8	22.8	0.4	0.0	0.1	68.6	30.9	0.5
		Hispanic	73.3	26.0	0.7	0.0	0.1	65.9	33.4	0.7
		Asian	71.5	27.7	0.8	0.0	0.2	65.6	33.9	0.3
		American Indian	66.9	32.5	0.6	0.0	0.0	71.7	28.1	0.1
		Other	64.1	34.0	1.9	0.0	0.1	49.7	44.1	6.1
	Individual Age	Under 30	74.3	25.2	0.5	0.0	0.2	54.8	44.0	1.0
		30 to 39	74.4	25.1	0.5	0.0	0.1	68.8	30.8	0.3
		40 to 49	73.8	25.8	0.4	0.0	0.1	72.8	27.0	0.2
		50 to 61	72.3	27.1	0.5	0.0	0.0	72.4	27.4	0.2
		62 or older	64.6	33.9	1.5	0.0	0.1	67.7	31.9	0.4
		Age missing	57.9	39.4	2.7	0.0	0.2	40.7	50.1	8.9
	Marital Status by Gender	Married male	72.4	27.2	0.4	0.0	0.0	69.9	29.8	0.3
		Single male	71.5	27.8	0.8	0.0	0.1	65.9	33.5	0.4
		Married female	75.5	24.1	0.4	0.0	0.0	70.2	29.5	0.2
		Single female	75.4	24.1	0.4	0.0	0.1	67.8	31.7	0.3
		Unknown	68.7	30.1	1.2	0.0	0.1	55.4	40.9	3.6
Credit Record Groups	Number of Tradelines	2 or fewer	49.6	46.8	3.6	0.0	0.4	25.9	64.5	9.3
		3 to 5	66.7	32.8	0.5	0.0	0.1	50.2	49.8	0.0
		6 to 10	75.2	24.8	0.1	0.0	0.0	65.1	34.8	0.0
		More than 10	81.3	18.6	0.0	0.0	0.0	76.6	23.4	0.0
	Credit Card Utilization	No accounts	68.2	30.8	1.1	0.0	0.2	50.7	45.8	3.3
		None (0 percent)	78.2	21.7	0.1	0.0	0.1	76.6	22.8	0.4
		Less than 25 percent	83.4	16.4	0.2	0.0	0.1	90.3	9.5	0.0
		25 to 49 percent	81.2	18.7	0.1	0.0	0.1	81.8	18.1	0.1
		50 to 74 percent	74.4	25.6	0.1	0.0	0.0	71.7	28.3	0.0
		75 percent or more	79.6	20.2	0.1	0.0	0.0	57.3	42.1	0.6
	Age of Oldest Tradeline	Less than 24 months	57.1	41.0	2.0	0.0	0.2	26.0	65.8	8.0
		24 to 59 months	74.4	24.7	0.8	0.0	0.3	52.1	45.9	1.7
		60 to 119 months	71.6	27.7	0.7	0.0	0.0	65.2	34.2	0.7
		120 or more months	72.9	26.5	0.6	0.0	0.1	73.0	26.6	0.4
	Number of Delinquencies in Past 24 Months	No performance	47.4	51.1	1.5	0.0	0.0	13.3	82.8	3.9
		0	34.3	62.6	3.1	0.0	0.0	55.7	42.5	1.7
		1	67.0	32.8	0.2	0.0	0.1	83.3	16.6	0.0
		2 or more	92.1	7.9	0.0	0.0	0.7	95.9	3.4	0.0
Total			72.1	27.2	0.7	0.0	0.1	65.0	33.7	1.2

NOTE: Credit record groups are based on non-authorized-user account information only.

Table 6: Score Changes Resulting from Excluding Authorized User Account Information from the Credit Scoring Model by Demographic and Credit Record Group

Breakdown Category		Group	Number of Obs.	Mean FRB Base Score	Score Change: Mean	Score Change: Mean Standard Error	Score Change: Median	Share of Individuals: Change < -7.5	Share of Individuals: -7.5 ≤ Change < -2.5	Share of Individuals: -2.5 ≤ Change ≤ 2.5	Share of Individuals: 2.5 < Change ≤ 7.5	Share of Individuals: Change > 7.5
Demographic Groups	Race or Ethnicity	White	59,047	60.0	-0.24 ***	0.025	0.00	9.32	15.47	52.70	15.39	7.11
		Black	4,268	33.1	0.09 ***	0.021	-0.20	5.75	11.70	64.23	12.21	6.11
		Hispanic	5,322	45.0	0.09 ***	0.024	0.00	6.76	13.71	58.03	14.24	7.26
		Asian	3,456	59.2	-0.45 ***	0.027	0.00	9.31	15.44	54.90	13.82	6.53
		American Indian	156	60.3	-0.56 ***	0.026	-0.20	9.44	15.54	53.67	14.56	6.80
		Other	9,098	57.0	-1.10 ***	0.037	-0.20	13.18	15.21	48.49	13.94	9.18
	Individual Age	Under 30	6,814	41.0	-0.93 ***	0.091	-0.40	10.93	16.57	53.10	12.40	7.00
		30 to 39	14,779	48.7	0.27 ***	0.054	0.00	6.96	13.21	56.85	15.53	7.46
		40 to 49	19,616	55.3	0.16 **	0.050	0.00	8.01	14.19	54.72	15.52	7.55
		50 to 61	19,181	61.3	-0.10 *	0.051	0.00	8.80	15.32	53.76	15.25	6.87
		62 or older	15,967	69.6	-0.87 ***	0.062	-0.40	10.95	17.42	50.55	14.79	6.29
		Age missing	4,989	56.8	-1.95 ***	0.178	-0.20	17.24	14.47	44.20	13.35	10.74
	Marital Status by Gender	Married male	23,497	59.4	-0.04	0.045	0.00	8.38	14.39	54.16	16.16	6.92
		Single male	6,119	47.6	-0.20 *	0.082	-0.20	7.21	14.14	58.87	13.71	6.08
		Married female	29,705	62.7	-0.28 ***	0.044	0.00	9.88	16.57	50.79	15.25	7.50
		Single female	7,748	49.6	-0.13	0.079	-0.20	7.99	14.33	57.27	13.32	7.10
		Unknown	14,277	50.2	-0.94 ***	0.079	-0.20	11.74	14.21	52.46	13.59	8.01
Credit Record Groups	Number of Tradelines	2 or fewer	3,520	54.2	-5.21 ***	0.314	-3.20	36.71	17.07	15.94	9.46	20.82
		3 to 5	6,171	53.9	-2.30 ***	0.109	-1.20	17.10	19.64	45.36	12.36	5.54
		6 to 10	13,413	56.3	-0.86 ***	0.061	-0.40	10.13	16.59	54.32	13.20	5.76
		More than 10	58,242	57.9	0.33 ***	0.026	0.00	6.76	14.20	56.14	15.92	6.99
	Credit Card Utilization	No accounts	14,628	40.7	-2.49 ***	0.091	-0.40	18.06	12.84	50.90	10.52	7.68
		None (0 percent)	8,943	68.4	-0.04	0.086	0.00	10.16	16.75	49.19	15.72	8.17
		Less than 25 percent	32,876	73.5	0.20 ***	0.036	0.20	7.77	16.30	52.50	17.03	6.40
		25 to 49 percent	8,631	55.3	0.14 *	0.071	-0.20	8.33	16.49	52.06	14.54	8.59
		50 to 74 percent	6,068	42.3	0.37 ***	0.076	0.00	5.67	14.73	55.22	15.95	8.42
		75 percent or more	10,200	29.0	0.20 ***	0.053	-0.20	4.65	12.32	62.67	13.43	6.93
	Age of Oldest Tradeline	Less than 24 months	1,610	45.6	-4.35 ***	0.334	-2.60	29.13	21.24	27.14	10.00	12.48
		24 to 59 months	4,005	39.7	-1.20 ***	0.159	-0.80	13.66	17.60	48.84	10.59	9.31
		60 to 119 months	11,537	40.6	-0.66 ***	0.072	-0.20	9.48	13.91	57.75	12.22	6.63
		120 or more months	64,194	61.6	-0.08 **	0.028	0.00	8.62	15.04	53.41	15.80	7.13
	Number of Delinquencies in Past 24 Months	No performance	265	25.0	-7.07 ***	0.761	-3.60	34.34	18.87	38.49	5.28	3.02
		0	66,579	65.7	-0.34 ***	0.032	0.00	10.68	16.47	48.63	16.14	8.07
		1	6,425	25.7	-0.10	0.055	-0.40	5.00	11.91	66.18	11.18	5.74
		2 or more	8,077	13.2	0.07 *	0.031	0.00	1.46	6.53	81.81	8.13	2.07
Total			81,346	57.2	-0.30 ***	0.027	0.00	9.39	15.13	53.28	14.92	7.28

NOTE: *,**,*** represent statistical significance at the 5, 1, and 0.1 percent leveles, respectively. Credit record groups are based on non-authorized-user account information only.

Table 7: Goodness-of-Fit Measures for FRB Base Model Estimated With and Without Authorized User Accounts

Breakdown Category		Group	With Authorized User Accounts		Without Authorized User Accounts	
			KS Statistics	Divergence Statistic	KS Statistics	Divergence Statistic
Demographic Groups	Race or Ethnicity	White	59.0	2.62	58.2	2.62
		Black	44.8	1.21	44.3	1.18
		Hispanic	45.1	1.39	45.1	1.38
		Asian	58.1	2.03	56.9	2.06
		American Indian	62.5	2.65	61.2	2.63
		Other	55.2	2.26	55.1	2.27
	Individual Age	Under 30	47.9	1.69	48.0	1.69
		30 to 39	61.4	2.68	61.1	2.66
		40 to 49	59.9	2.86	60.1	2.80
		50 to 61	62.6	2.96	62.3	2.92
		62 or older	57.3	2.19	56.7	2.25
		Age Missing	46.6	1.42	47.5	1.47
	Marital Status	Married	61.0	2.91	59.8	2.89
		Single	52.9	2.02	53.9	2.05
		Unknown	50.9	1.79	51.3	1.74
	Gender	Male	56.2	2.37	56.5	2.37
		Female	59.3	2.80	59.5	2.76
		Unknown	46.7	1.43	47.6	1.47
	Marital Status by Gender	Married Male	60.4	2.84	59.5	2.85
		Single Male	51.6	1.82	52.8	1.87
		Married Female	63.5	3.06	62.1	3.02
		Single Female	55.8	2.32	56.6	2.31
		Unknown	50.6	1.79	51.2	1.76
Credit Record Groups	VantageScore	Less than 700	23.0	0.28	23.4	0.29
		700 - 799	12.8	0.11	14.5	0.11
		800 - 899	37.9	0.77	36.8	0.76
		900 - 990	32.4	0.16	31.3	0.12
	Number of Tradelines	2 or Fewer Tradelines	42.7	0.95	40.2	0.92
		3 to 5 Tradelines	51.6	1.80	53.6	1.80
		6 to 10 Tradelines	58.8	2.48	58.9	2.51
		More than 10 Tradelines	59.3	2.73	59.4	2.73
	Credit Card Utilization	No Revolving Accounts	44.1	1.21	43.8	1.19
		No Utilization	61.9	2.73	60.7	2.75
		Utilization less than 25%	47.4	1.39	47.2	1.42
		25 to 49 percent	47.8	1.55	48.3	1.59
		50 to 74 percent	35.3	0.82	35.6	0.81
		75 percent or more	33.7	0.65	33.4	0.68
	Age of Oldest Tradeline	Less than 24 months	37.7	0.69	36.7	0.68
		24 to 59 months	49.7	1.52	50.5	1.56
		60 to 119 months	56.0	2.13	56.1	2.16
		120 or more months	60.7	2.82	60.1	2.79
	Months Since Most Recent Delinquency	Never Delinquent	61.2	2.89	60.0	2.89
		Less than 3 months	33.5	0.51	32.7	0.48
		4 to 11 months	37.4	0.84	38.4	0.89
		12 - 23 months	40.7	0.95	40.1	0.94
		24 or more months	47.6	1.32	47.0	1.30
	Number of Delinquencies in Past 24 Months	No observed Performance	32.0	0.42	29.2	0.34
		No delinquencies	54.1	1.96	53.6	1.96
		1 Delinquency	40.7	1.06	41.1	1.05
		2 or more delinquencies	31.6	0.56	32.6	0.59
Total			57.1	2.52	57.0	2.51

NOTE: Credit record groups are based on non-authorized user account information only.

FICO 08 AND OTHER DEVELOPMENTS IN THE CREDIT SCORING INDUSTRY

Consumer Finance
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1. Trouble Brewing

The Fair Isaac Corporation developed the FICO score to give credit issuers an analytical tool to determine a borrower's likelihood of default. Since its development,[1] the FICO score product has become the standard consumer credit score used by creditors to make more informed lending decisions. However, as the consumer finance market has evolved in recent years, the FICO score's predictive power has suffered. According to a 2001 Fitch study,[2] the FICO scores of borrowers who stopped making home-loan payments differed on average by just 31 points from those paying on time. By 2006, this gap had shrunk to only 10 points. At the same time that its predictive power for evaluating borrowers is declining, FICO scores are being used in an ever-growing multitude of applications that seem far removed from the function these scores were designed to serve. For example, credit reports are not only used to prescreen credit card offers, but also to set insurance premiums, and to evaluate prospective candidates for jobs. According to BusinessWeek magazine, retailers even use FICO scores when deciding on where to place new locations for their stores.[3]

Compounding the problems arising from the use of credit scores in these new applications, some entrepreneurial businesses have discovered techniques to manipulate FICO scores based on loopholes in the FICO formula. In fact, an entire cottage-industry has developed, consisting of companies offering to boost consumers' credit scores through a technique known as "credit piggybacking."[4] The Fair Isaac Corporation has routinely redeveloped its formula since the initial release of FICO in 1989; however, under pressure from its customers (creditors) due to the worsening problem of score manipulation, it has recently released an upgrade for its credit scoring formula: FICO 08.

[1] History, http://www.fairisaac.com/fic/en/company/history.htm
[2] Foust, D. and Pressman, A. "Credit Scores: Not-So-Magic Numbers," Feb. 2008, http://www.businessweek.com/print/magazine/content/08_07/b4071038384407.htm
[3] Id.
[4] BoostMyScore.net - Your Credit Advisor - Home Page, http://boostmyscore.net/

2. BoostMyScore.net and Other Credit-Boosting Companies

Although the detailed mechanics of the FICO algorithm are not known outside of the Fair Isaac Corporation, a few flaws have been observed by the public, leading to the development of the credit boosting industry, which targets consumers with poor or non-existent credit histories. One such company, BoostMyScore.net was founded in 2007.[5] The company could be termed an innovator in the "credit piggybacking" industry, providing what is essentially a matching service that connects people with a strong credit history, called "credit-lenders" to customers with poor credit scores, who are willing to pay a price to boost their scores. The key to the piggybacking business is how authorized user accounts are incorporated into the FICO score calculation. From BoostMyScore.net's website:

> **CREDIT PIGGYBACKING**
> "'Credit Piggybacking' is when one person is listed as an authorized user on someone else's credit card, someone with a healthy credit rating. The authorized user does not typically use the card, but the credit history of that card appears on their credit report. When the new history appears in the authorized user's credit reports, their credit score is immediately recalculated to show an increase as a result of the new card's presence in the report. While the authorized user does not receive the physical card or account number, they do receive the benefit of having that particular credit card's entire credit history - limit, balance, payments - in essence "copied and pasted" onto their credit report, looking as though it were there the entire time. Having a higher FICO (c) Credit score means lower interest rates, easier loan approvals, higher credit limits and better terms for consumers."[6]

The company's founder explained that he discovered the piggybacking effect by accident while applying for an auto loan with his wife.[7] At the time his wife, a South African citizen, had only recently received a social security number, so they were considering whether including her name in the credit application would raise the cost of their loan. The dealership ran a credit check, and they were surprised to learn that she had a credit score of 785—a score better than his own.[8] Previously, he had added her as an authorized user on his credit cards, and due to what seems to be a logical flaw in the FICO algorithm, she received the benefit of

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[5] BoostMyScore.net - Your Credit Advisor - About Us, http://boostmyscore.net/about.html
[6] Id.
[7] Interview with Company Owner (April 2009).
[8] Id.

the full payment history associated with that credit card account, giving her a rating that classified her within the top 40% of the US population, despite having no personal credit history.[9]

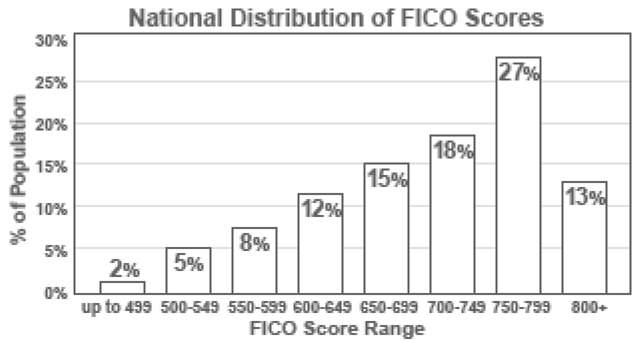

Figure 1 National distribution of FICO scores[10]

From this experience, the Company Owner realized the significant impact this technique could have on consumers with poor credit scores, and how valuable a service based on this effect could be. On its website, BoostMyScore.net clearly identifies the value proposition for consumers: a higher FICO score will lower the interest rate on a loan, saving thousands of dollars in interest expense each year for consumers planning a large purchase, such as a house.[11] For some consumers, using a quick fix method to boost their FICO score seems like a winning proposition, even at the cost of several hundred, or thousands of dollars in upfront charges.

According to Instantcreditbuilders.com, "one borrowed credit card account can increase a score between 30 and 45 points, two between 60 and 90 points, and five between 150 and 205 points."[12] Although others in the industry dispute the precision of these estimates, given the FICO score's range of between 300 and 850, and the score distribution in the figure above, this effect can be substantial.[13]

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[9] Id.
[10] Liz Pulliam Weston, What Is a Good Score, Your Credit Score, Your Money & What's at Stake (Updated Edition): How to Improve the 3-Digit Number That Shapes Your Financial Future. "How Credit Scoring Works," 2009.
[11] BoostMyScore.net - Your Credit Advisor - Secret, http://boostmyscore.net/secret.html
[12] "Credit Card 'Piggybacking' Worries Lending Industry," June 2007, http://www.foxnews.com/story/0,2933,277874,00.html
[13] The Owner of BoostMyScore.net contests the numbers offered by ICM as an overgeneralization, arguing that the boost for an individual consumer will have far more variation, depending on what is initially in their credit report. According to the Company Owner, the size of the boost depends on 1) the number of tradelines added; 2) the number of credit cards currently in the report; and 3) the quality of the tradelines added. In his experience, The Company Owner has seen boosts from single credit cards ranging from 12 points to hundreds.

Savings Example

The higher your FICO® scores the less you can expect to pay for your loan. For example, on a $216,000 30-year, fixed-rate mortgage:

If your FICO score is	Your interest rate is	and your monthly payment is
760 - 850	5.8%	$1,267
700 - 759	6.02%	$1,298
680 - 699	6.2%	$1,323
660 - 679	6.41%	$1,353
640 - 659	6.84%	$1,414
620 - 639	7.39%	$1,494

Actual National Interest Rates

As you can see in this example using today's national rates, a person with a FICO® score of 760 or better will pay $227 less per month for a $216,000 30-year, fixed-rate mortgage than a person with a FICO® score of 620 □□□ **that's a savings of $2,724 per year**. You can see how essential improving your credit scores can be if they are low, and also how important it is to keep them high if they are good.

- MyFICO.com

Figure 2 Savings Example from BoostMyScore. Net's website[14]

Before opening, BoostMyScore.net hired a law firm to research the legality of credit piggybacking, from which it received assurance that "the practice is legal under current federal regulations and law."[15] The lawyer analyzed whether the company was in compliance with the Truth in Lending Act, the Fair Credit Reporting Act, and the Fair and Accurate Credit Transaction Act, and concluded that none of these regulations apply to its business.[16]

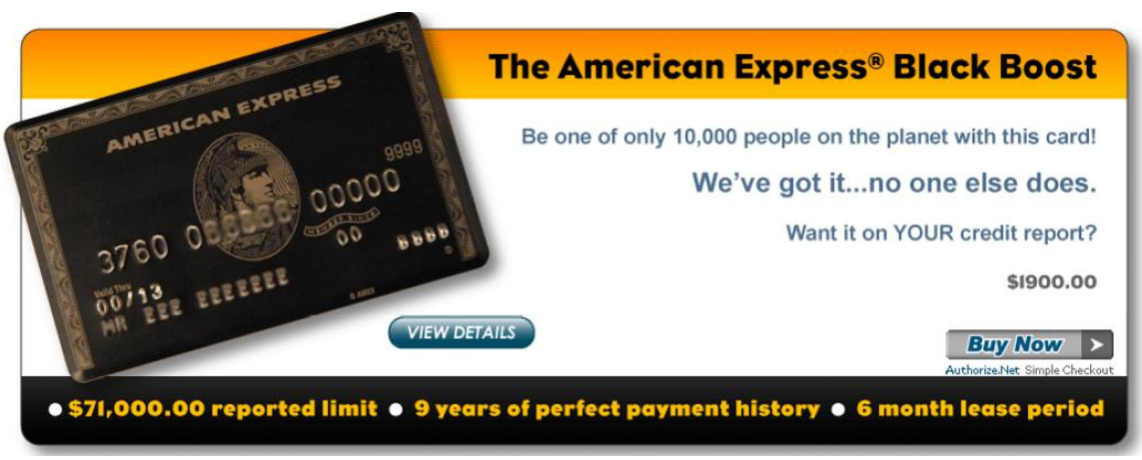

Figure 3 The premier credit boosting product offered by BoostMyScore.net[17]

[14] Supra note 10.
[15] See Appendix for a copy of the opinion letter by counsel to BoostMyScore.net.
[16] It is worth noting that the lawyer's opinion does not mention compliance with the Credit Repair Organizations Act (CROA). The copy of the letter from counsel did not include a date, but it is the author's belief that it predated the passage of this act. See the Appendix for a later legal opinion issued to client, asserting that BoostMyScore.net is not a credit repair organization.
[17] BoostMyScore.net - Your Credit Advisor - Decide, http://boostmyscore.net/decide.html

On its website, BoostMyScore.net offers a shopping list of credit card accounts, boasting high credit limits and years of perfect payment history. For each offering, the website lists such details as the card type, limit, duration of perfect history, balance, reporting date, along with the corresponding cost to "rent" a space as an authorized user of the card. Most credit cards limit the number of authorized users that can be added, so each of the cards has limited availability of authorized user accounts to rent. Figure 3 shows a listing from the website for one of the premier credit card offerings, "The American Express® Black Boost," and Figure 4 displays several other card listings.

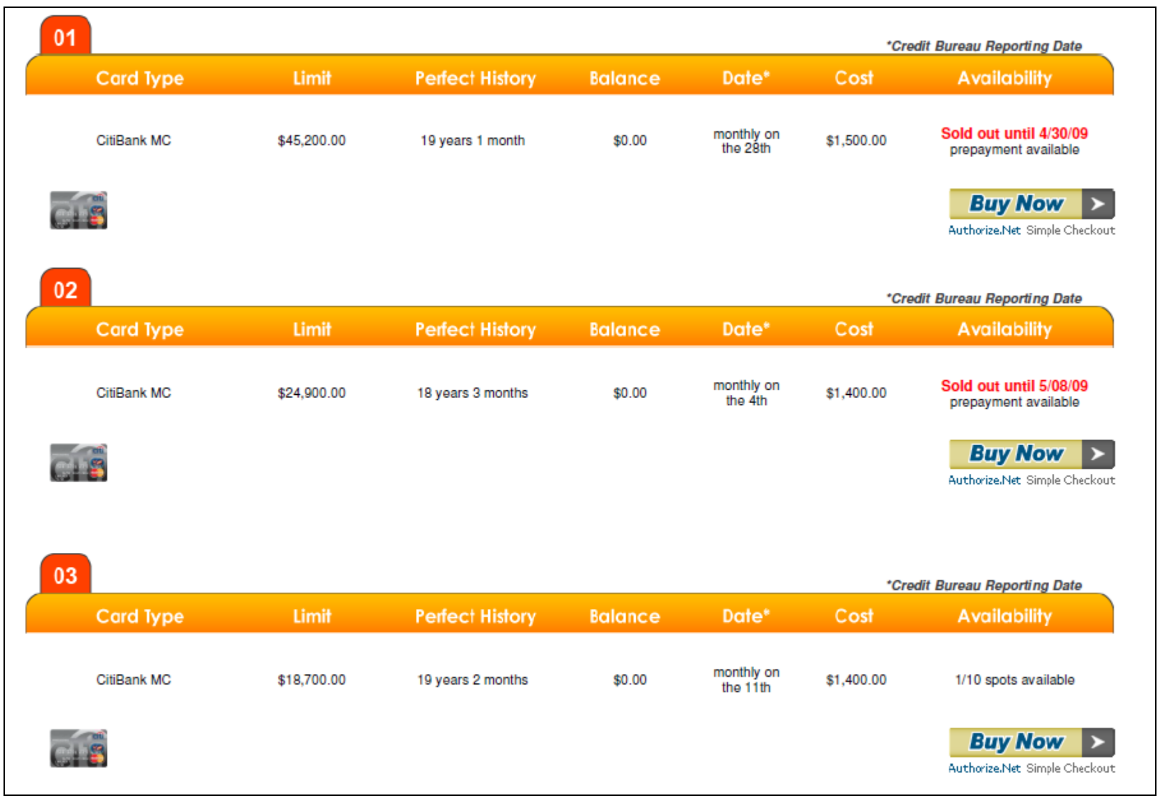

Figure 4 Other score boosting products from BoostMyScore.net`[18]

3. <u>The Introduction of FICO 08</u>

The effect of credit piggybacking is most directly felt by creditors. In the modern credit system, lending decisions are based on elaborate actuarial models that focus on quantitative

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[18] Id.

measures of consumer creditworthiness. Since creditors are the customer-base for Fair Isaac Corporation, the company quickly became aware of the credit piggybacking practice. However, it was unable to efficiently retrofit its product to solve the piggybacking problem for existing clients.[19] Instead, the company opted to address the problem by issuing a new version of the FICO score. This new version would fix the credit piggybacking loophole by excluding authorized user accounts, and incorporate various other upgrades expected to improve the formula's predictive power.[20] In the words of Tom Quinn, a Fair Isaac Corporation Vice President—in newer versions of FICO "[t]he entire [authorized user] account will be bypassed," eliminating the benefit of credit piggybacking.[21]

However this all or nothing treatment of authorized user accounts would not be able to differentiate between the legitimate uses of authorized accounts and illegitimate credit piggybacking. The Fair Isaac Corporation even acknowledged that such a change would impact a large segment of the consumer population: "[o]ur analysis during development showed that 30% of the population has an account on their report that lists them as an authorized user."[22] Although the full extent of the piggybacking problem is unknown, it is likely that the overwhelming majority of authorized user accounts are legitimate.

The Fair Isaac Corporation publicly announced its planned changes for the FICO 08 formula in June 2007. According to the company's original timetable, the new formula would be available to the credit reporting bureaus as early as September 2007.[23] And despite the antitrust litigation that was ongoing at the time between Fair Isaac Corporation and the three major credit bureaus regarding competition from VantageScore (discussed below), all three bureaus were planning to adopt FICO 08 between late 2007 and early 2008.[24]

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[19] J. Ulzheimer and E. Davidson. "Consumer Alert: FICO Scores Dropping Authorized User Accounts," http://www.credit.com/credit_information/credit_report/Consumer-Alert-FICO-Formula-Changes.jsp
[20] Id.
[21] Id.
[22] Id.
[23] "Understanding FICO 08," http://www.money-zine.com/Financial-Planning/Debt-Consolidation/Understanding-FICO-08/
[24] Supra note 18.

The apparent Fair Isaac Corporation's victory over the credit piggybackers was embraced by the media with headlines such as "Putting a Stop to a Credit Ruse"[25] and "Credit-Rating Standard Tightens."[26] However unforeseen problems with the upgrade would emerge.

4. Compliance with Regulation B of the ECOA

BoostMyScore.net and other credit building companies were vocal in their criticism of the FICO 08 changes.[27] In January 2008, attorneys working for BoostMyScore.net were asked to research whether the elimination of authorized user accounts in FICO 08 could put creditors in violation of Regulation B of the Equal Credit Opportunity Act (ECOA).[28] The attorneys found a Regulation B compliance issue, and BoostMyScore.net promptly brought this matter to the attention of the FTC and other government regulatory bodies that interact with the Fair Isaac Corporation.[29]

Regulation B,[30] was issued by the Board of Governors of the Federal Reserve System under authority granted by the ECOA (15 U.S.C. 1601 *et seq*). The goal of the regulation is to provide more detailed guidance on how to implement the anti-discriminatory goals of the ECOA. Section 202.6(b) lists rules about what specific pieces of information should be used "in any system of evaluating the creditworthiness of applicants."[31] One of the requirements is listed in §202.6(b)(6) which is reproduced below:

[25] Kenneth R. Harney. "Putting a Stop To a Credit Ruse," June 2007, http://www.washingtonpost.com/wp-dyn/content/article/2007/06/15/AR2007061500917_pf.html
[26] Jaclyne Badal. "Credit-Rating Standard Tightens," June 2007, http://online.wsj.com/article/SB118118471927527461.html
[27] "FICO 08 Arrives in '09," Feb. 2009, http://boostmyscore.net/FICO_08_Arrives_in_09.html; Jeremy M. Simon. "'Piggybacking' gets clemency from FICO,"July 2008, http://www.creditcards.com/credit-card-news/piggybacking-fico-credit-score-authorized-user-1265.php
[28] Supra note 7.
[29] Id.
[30] 12 C.F.R. 202
[31] 12 C.F.R. 202.6(b)

AUTHORIZED USER ACCOUNTS

"§202.6(b)(6) Credit history. To the extent that a creditor considers credit history in evaluating the creditworthiness of similarly qualified applicants for a similar type and amount of credit, in evaluating an applicant's creditworthiness a creditor shall consider:

(i) The credit history, when available, of accounts designated as accounts that the applicant and the applicant's spouse are permitted to use or for which both are contractually liable" [32]

The ECOA, passed in 1974 prohibits any discrimination by creditors, at any point within the lending process, against several protected classes. By its terms, all persons defined as creditors under §202.2(l) fall within its regulatory scope. Under its definition, "[c]reditor means a person who, in the ordinary course of business, regularly participates in a credit decision, including setting the terms of the credit."[33] Although the Fair Isaac Corporation does not fall within the definition of a creditor, the majority of its customers—who typically use its formula to evaluate consumers' credit worthiness—are creditors under the ECOA. If FICO 08 does not satisfy the ECOA's required criteria in its evaluation of credit applicants, those creditors who want to use FICO to make lending decisions would be unable to do so without risking a violation of the ECOA—a risk no prudent lender would take.

One surprising caveat to this incident, is that public awareness of the compliance issue may have been avoided if Fair Isaac's public relation team had been less forthcoming in explaining how it planned to eliminate credit piggybacking in FICO 08. If the Regulation B issue had not reached the attention of the FTC and Federal Reserve, these changes to the formula may slipped through the cracks, due to the secrecy with which the Fair Isaac Corporation holds its proprietary information. But ultimately since this issue did become public, the Fair Isaac Corporation was forced to take a step back and acknowledge its mistake.

[32] 12 C.F.R. 202.6(b)(6)
[33] 12 C.F.R. 202.2(l)

5. Fair Isaac Corporation Admits its Mistake

In July 2008, before the U.S. House of Representatives Subcommittee on Oversight and Investigations, the Fair Isaac Corporation issued a written statement explaining that the proposed FICO 08 changes that eliminated authorized user accounts had been an attempt "to protect lenders and consumers from a new type of credit repair practice known as 'piggybacking' or 'tradeline renting', which has received national attention from news media since March 2007."[34] The statement continued with the line reproduced below:

> **FAIR ISAAC'S REVERSAL**
> "After consulting with the Federal Reserve Board and the Federal Trade Commission earlier this year, Fair Isaac has decided to include consideration of authorized user tradelines present on the credit report in the FICO 08 model. Our scientists have devised a method to consider these tradelines while materially reducing the negative impact that could arise from piggybacking"[35]

Despite this setback, the Fair Isaac Corporation claims it has found another way to eliminate piggybacking, though this time they have been less forthcoming with the details of the new technique. According to a Fair Isaac press release, the "FICO® 08 score also incorporates new, patent-pending technology that protects lenders from authorized user (AU) abuse, while still supporting regulatory compliance."[36] Since lenders want continued ECOA compliance, the new technology "includes [authorized user] data in the calculation of scores, while reducing potential impact from tampering."[37] This solution allows the "more than 50 million US consumers [who] are legitimate authorized users" to continue to benefit, and at the same time stops credit piggybackers.[38]

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[34] "Credit Scoring Models and Credit Scores." Before the U.S. House of Representatives, Committee on Financial Services, Subcommittee on Oversight and Investigations, Washington, D.C. July 29. 2008.
[35] Id.
[36] "FICO 08 score delivers predictive boost where lenders need it most," http://www.fairisaac.com/NR/exeres/E098C595-545F-4DDD-A6CF-449EA685E8E1,frameless.htm
[37] Id.
[38] Id.

Although Fair Isaac Corporation has not explained how it intends to count authorized user accounts while excluding piggybackers, The Company Owner has contemplated how they may be able to differentiate piggybackers from other authorized users.[39] According to The Company Owner, when a credit card company reports a credit card's history to the bureaus, the date that a user was authorized is reported. If this piece of information were factored into the score calculation, a newly authorized user would not receive the benefit of an account's long credit history, which provides much of the boost of credit piggybacking. Furthermore, credit scores suffer a 15 point hit for having a new account with no payment history, so for most consumers, piggybacking could initially harm their score. The only people who would still benefit from piggybacking are those who have maxed out all of their lines of credit. For these users, the decrease in their utilization ratio would likely outweigh the new account penalty.[40]

When FICO announced its plans to eliminate credit piggybacking, Mr. Airy's business took a substantial hit—many customers were discouraged by Fair Isaac's claim that piggybacking was over. Through the ups and downs of his business, The Company Owner has maintained a pragmatic outlook. He recognizes that with the upcoming changes to the FICO scoring algorithm,

BoostMyScore.net's business model is winding down. At the time that FICO 08 was initially announced, he anticipated that he would remain in business for another year and a half; however, that time has already elapsed, due to the compliance issues that emerged. But since adoption of FICO 08 is still proceeding at a slow pace, the piggybacking business may continue to defy expectations.

6. About the Fair Isaac Corporation

The Fair Isaac Corporation traces its beginning to the 1950s, when a partnership was created between mathematician, Bill Fair and engineer, Early Isaac.[41] The two proposed that the use of data analysis could improve the decision-making processes of businesses, particularly

[39] Supra note 7.
[40] Id.
[41] Supra note 1.

those in the credit industry. At that time, Fair was developing statistical techniques to build predictive models of behavior. He understood that credit decisions involve hundreds of factors, creating a vast number of possible outcomes. But he recognized that with the use of multivariate analysis, a scoring algorithm could be developed that greatly simplify the analysis.[42] This task was aided by concurrent developments in the computer industry, which allowed increasingly complex calculations to be performed at quicker speeds.

During the 1950s, credit and loan making decisions were generally made on a subjective basis. Banks and other lenders were usually based locally, and the lending process was more personal in nature. This personalized system, in addition to being less consistent, allowed the biases of bank agents to influence their decisions. Bill Fair saw a better way to manage credit risk, though it took creditors some time to realize it. In 1958, the company's first credit scoring system was only able to attract a single customer among the fifty largest credit-granting businesses in the United States.

Although Fair Isaac Corporation is today best known for its credit scoring applications, the company received its first big break in 1972 for a different application: developing an auditing algorithm for the Internal Revenue Service. The company was contracted to produce a program to more accurately identify tax evaders, thus allowing the IRS to more efficiently choose which taxpayers to audit. Shortly thereafter, the IRS was able to reduce audits by a third, while posting a higher level of uncovered payments.[43] The unifying theme underlying all of Fair Isaac Corporation's endeavors is the incorporation of statistical data analysis techniques to create predictive models of behavior. This specialized focus led the company to develop scoring systems for employee hiring practices, insurance scoring systems,[44] strategic decision making,[45]

[42] "Fair, Isaac and Company – Company History," http://www.fundinguniverse.com/company-histories/Fair-Isaac-and-Company-Company-History.html
[43] Id.
[44] "Insurance," http://www.fico.com/en/Industries/Insurance/Pages/default.aspx
[45] "HSBC Adopts Fair Isaac Strategy Science Framework to Fuel Growth in Asia-Pacific Region," Aug. 2006, http://www.fairisaac.com/fic/en/news/press-releases/HSBC-Adopts-Fair-Isaac-Strategy-Science-Framework-to-Fuel-Growth-in-Asia-Pacific-Region.htm

as well as more sophisticated credit scoring products, which have evolved into the present day FICO score.[46]

A variety of factors contributed to Fair Isaac's dominance of the credit scoring industry. During the 1970s the use of credit cards increased dramatically. Evaluating credit limits took on greater importance for lenders trying to manage risk. Furthermore, with the passage of the Equal Credit Opportunity Act (ECOA) in 1974, creditors had to be careful about any discriminatory practices that their traditional lending system may have enabled. As a consequence, lenders were forced to abandon many of their old practices, which had long disguised discriminatory biases. Another advantage of the Fair Isaac algorithms was their use of objective metrics, which avoided the risk of discrimination through disparate treatment.

During the 1970s, many creditors adopted credit scoring formulas. Initially, a custom-tailored formula was developed for each company to meet their desired risk profile.[47] However, custom-designed credit risk systems are far more expensive, and these early embodiments only used the customer data from individual companies. In the mid-1980s, the national credit bureaus arose as repositories for vast amounts of consumer information, from which Fair Isaac developed a generic scoring system. Rather than relying on the experience of just one lender, the experiences of millions of lenders could be mined in search of patterns of consumer behavior. Thus, the FICO score was positioned to become the dominant metric for evaluating consumer credit.

7. <u>The Market for Credit Scoring</u>

It is important to understand the distinctions between the different entities that form the backbone of the credit system. The credit bureaus and Fair Isaac Corporation are not themselves creditors, and are not directly subject to the authority of the Equal Credit

[46] "FICO® score," http://www.fico.com/en/Products/Scoring/Pages/FICO-score.aspx
[47] Supra note 10 at "How Credit Scoring Came into Being."

Opportunity Act (ECOA).[48] However, these businesses are providing a service for creditors, who are under the regulation of the ECOA and other laws, and if they want their products to meet the needs of their customers, they need to ensure that use of their credit scoring products will comply with all anti-discriminatory laws.

a. FICO's Dominance

The Fair Isaac Corporation developed, and closely controls the formula used to calculate the FICO score. Although the details of the algorithm used to calculate FICO scores are the proprietary information of the Fair Isaac Corporation, the following information has been disclosed to the public to help consumers better understand their scores.

DEVELOPMENT OF THE FICO SCORING MODEL

"Creating the FICO scoring model requires two samples of credit reports two years apart for the same randomly selected depersonalized set of consumers, provided by one of the national credit reporting agencies. Our analytic scientists then analyze the data in the earlier data set to isolate and prioritize factors that consistently predict the credit account performance noted two years later in the later data set. Those factors found to be most powerful and consistent in predicting credit performance, individually and in combinations, form the basis for a complex mathematical algorithm which becomes the predictive scoring model."[49]

The figure below lists the five types of information that factor into the score, along with the approximate contribution of each to a typical consumer's FICO score.

[48] §202.2(l). "Creditor means a person who, in the ordinary course of business, regularly participates in a credit decision, including setting the terms of the credit. The term creditor includes a creditor's assignee, transferee, or subrogee who so participates. For purposes of §202.4(a) and (b), the term creditor also includes a person who, in the ordinary course of business, regularly refers applicants or prospective applicants to creditors, or selects or offers to select creditors to whom requests for credit may be made. A person is not a creditor regarding any violation of the Act or this regulation committed by another creditor unless the person knew or had reasonable notice of the act, policy, or practice that constituted the violation before becoming involved in the credit transaction. The term does not include a person whose only participation in a credit transaction involves honoring a credit card."

[49] Supra note 33.

Table 1 FICO Factors[50]

Payment history	35%
Outstanding debt	30%
Length of credit history	15%
Pursuit of new credit	10%
Mix of types of credit	10%

Negative marks on a consumer's payment history are evaluated based on the recency, frequency, and severity of any incidents. The outstanding debt metric weighs the total amount owed on all credit lines against the available credit limits—using a high percentage of their limit will hurt a borrower's score.[51] The age of the oldest account, as well as the average account age is also considered. The number of times and how recently a consumer has applied for, or opened new lines of credit, and in this way, "shopping around" for credit could potentially harm a borrower's score.[52] The remaining factor considers whether a consumer has a mix of different types of credit, though the benefit of having such a mix is not clear.[53]

b. Competition From VantageScore

In March 2006, the three major credit bureaus announced their participation and ownership in a joint venture to create an alternative generic credit scoring system called VantageScore. The motivation for the project is clear: each time the bureaus calculate a credit score using the FICO model, they are required to pay a fee to the Fair Isaac Corporation. This business is highly profitable for Fair Isaac, consisting of approximately 65% of its operating profits, according to analysts.[54] The credit bureaus had previously attempted to devise proprietary scoring models; however these initiatives were uncoordinated and poorly received because each agency used a different system with a different range.[55] The companies realized that to create a viable alternative to FICO, they would need to collaborate.

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[50] Id.
[51] Supra note 10 at "The Five Most Important Factors."
[52] Id.
[53] Id.
[54] Id at "VantageScore—A Revolution or Just More of the Same?"
[55] Damon Darlin. "The Credit Game Is Getting a Second Scorekeeper," July 2006, http://www.nytimes.com/2006/07/08/business/yourmoney/08money.html?pagewanted=all

Table 2 VantageScore Factors[56]

Payment history	32%	Whether your payments are satisfactory, delinquent, or derogatory
Utilization	23%	The percentage of credit that you have used or that you owe on your accounts
Balances	15%	The amount of recently reported balances, both current and delinquent
Depth of credit	13%	The length of your credit history and the types of credit you have
Recent credit	10%	The number of recently opened accounts and credit inquiries
Available credit	7%	The amount of available credit on all your accounts

The ranges of each scoring model differ slightly: FICO scores run from 300 to 850, while VantageScores are between 501 and 990. The factors used to calculate a consumer's VantageScore substantially overlap with the FICO factors, but with different weights assigned. Payment history is counted approximately the same in each system, but FICO assigns greater weight to the length of credit history, while VantageScore gives more consideration to the amount and usage of available credit (compare the chart for VantageScore with that for FICO).

Regardless of whether or not VantageScore is a better predictive model than FICO, the Fair Isaac Corporation holds a substantial competitive advantage because of the high barriers to entry in the credit scoring industry. FICO scores "are deeply embedded in the complex, highly automated formulas that lenders use to evaluate current and potential borrowers."[57] Credit scoring expert, John Ulzheimer compares switching models to "spending $10,000 to replace a $1 part, and the $1 part isn't even broken."[58] FICO scores have become the standard metric for evaluating credit quality, not just for lenders, but for the Wall Street institutions participating in transactions on secondary markets for commoditized debt obligations.

Despite these substantial structural advantages, the Fair Isaac Corporation was still threatened by this collaboration among its rivals. In October 2006, Fair Isaac brought suit in the U.S. District Court in Minnesota against VantageScore Solutions and the three credit bureaus that own it, alleging multiple counts of unfair competition, trademark infringement, deceptive

[56] Supra note 53.
[57] Id.
[58] Id.

trade practices, and illegal attempts to monopolize.[59] Among other claims, Fair Isaac pleads that the overlap in the score ranges was an attempt to confuse customers, to unfairly profit from its goodwill, and violate its trademark.[60]

In early 2007, Fair Isaac served discovery requests on VantageScore, seeking the details of the VantageScore algorithm.[61] Worried that the secrets of their proprietary formula may be revealed to their main competitor, the defendants moved for a protective order shielding these specific items from discovery, and requested a protective order generally shielding highly confidential information from discovery.[62] In July 2007, the magistrate judge ruled against the defendant's motion and granted the plaintiff's motion to compel discovery. The defendants appealed to the district court, which agreed to stay the order to prevent the defendants' objections from becoming moot. In its ruling in September 2007, the district court went on to overrule the defendant's objections, sustaining the magistrate's ruling. In March 2008, the case again came before the district court, which denied the defendants' motions for partial summary judgment on the pleadings and for partial summary judgment on the antitrust claims.[63]

During the ongoing litigation over VantageScore, the conflict between the companies expanded when Equifax announced a halt to its plan to implement FICO 08.[64] The company directly attributed this decision to the litigation over VantageScore. According to Equifax spokesman, David Rubinger, "[o]ur relationship with FICO remains strained as long as FICO is suing over VantageScore."[65] While discussing the company's decision not to implement FICO 08, Equifax chief marketing officer, Paul Springman conceded that "[Fair Isaac wasn't] happy

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[59] Complaint. 2006 WL 6201833 (D.Minn.)
[60] "FICO Creator Sues National Credit Agencies Over VantageScore," Oct. 2006, http://www.foxnews.com/story/0,2933,220155,00.html
[61] 2007 WL 2791168 at *1 (D.Minn.).
[62] Id.
[63] 2008 WL 623120 (D.Minn.).
[64] Pamela Yip. "No more free rides," Feb. 2008, http://www.signonsandiego.com/uniontrib/20080217/news_lz1b17score.html
[65] Id.

about it and our customers weren't happy about it, but we decided this was our stake in the ground."[66]

Despite the parties' tenacity in this dispute, business interests took priority over the litigation. In June 2008, Fair Isaac and Equifax announced "that they have established a partnership to develop and sell advanced analytics and scoring solutions for businesses and consumers."[67] Furthermore, in a reversal from Equifax's earlier statements, the two companies planned to "accelerate testing and roll-out of the FICO 08 model for Equifax customers."[68] In the same press release, Fair Isaac made the announcement that it would "separately" drop Equifax from its VantageScore lawsuit.[69]

Since then, the case has been proceeding through an excruciatingly slow discovery phase. Both sides seem determined to use the full arsenal of legal weapons available through the discovery process to compel disclosure of each others' valuable trade secrets. In the latest court opinion in January 2009, another set of discovery motions came before the district judge.[70] The subject of this latest disagreement is whether two Fair Isaac employees can be compelled during deposition to answer questions relating to the new business initiative with Equifax. The two employees were preparing analyses and projections "comparing what Fair Isaac's scoring business would look like depending on whether or not the company entered into" the partnership with Equifax.[71] The magistrate judge ruled against the defendants' motion to compel, and the defendants objected.[72] In this latest motion, the district judge overruled each of the defendants' objections.[73]

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[66] Russell Grantham. "Equifax, partner call truce," June 2008, http://www.ajc.com/services/content/business/stories/2008/06/12/equifax.html?cxntlid=inform_sr
[67] "Equifax and Fair Isaac Enter Partnership to Accelerate Development and Delivery of New Analytic Solutions," June 2008, http://www.fairisaac.com/fic/en/news/press-releases/fair-isaac-and-equifax-enter-partnership.htm
[68] Id.
[69] Id.
[70] 2009 WL 161247 (D.Minn.).
[71] Id. at *1.
[72] Id.
[73] Id. at *3.

8. Regulatory Landscape for Credit Scoring

a. "Disparate Impact"

Regulation B of the ECOA contemplates two main types of credit evaluations: traditional judgment-based decisions, and credit-score-based decisions. In the modern credit system, lending decisions are typically made through a process that relies heavily on quantitative factors, such as credit scores, rather than subjective evaluations. For lenders, this reduces the possibility that an applicant will be denied credit as a result of direct discrimination that treats applicants different based on one of the ECOA's prohibited factors, a practice sometimes referred to as "disparate treatment."[74] The more probable ECOA compliance issue for modern lenders arises under the "disparate impact theory." See the box below for a more detailed explanation of disparate impact. When the lending transaction involves residential real estate, the Fair Housing Act (FHA) prohibitions on discrimination apply, along with those of the ECOA.[75]

DISPARATE IMPACT

"Most fair lending cases present claims of 'disparate treatment,' which is a form of intentional discrimination. A more controversial legal theory contends that even policies and practices that are adopted and implemented without a discriminatory purpose can be unlawful if they have a discriminatory impact. A plaintiff can thus challenge a racially neutral policy and, to support the claim, present statistical evidence demonstrating that the policy detrimentally impacts a significantly greater percentage of a particular racial or ethnic group than it does Whites. To avoid a finding of liability, the defendant can show that, notwithstanding this differential impact, the policy is based on sound business reasons or, as sometimes is said, a 'business necessity.' A plaintiff can still prevail if she can demonstrate that the business purpose can be achieved by policies that have a significantly smaller differential impact."[76]

[74] "Report to the Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit," Federal Reserve Board. August 2007, http://www.federalreserve.gov/boarddocs/rptcongress/creditscore/creditscore.pdf at 51. The ECOA prohibits discrimination on the basis of race, color, religion, sex, national origin, age, and marital status.

[75] Id. at 50.

[76] http://www.klgates.com/newsstand/Detail.aspx?publication=4009

b. Credit Scoring System Criteria

Section 202.2(p) of Regulation B of the ECOA established several criteria for the development of a credit scoring system.[77] First, the data set used to derive the formula must consist of both creditworthy and non-creditworthy applicants who recently applied for credit.[78] Second, the system must be designed to serve the legitimate business interests of the creditor using the system.[79] Third, accepted statistical methods must be used to develop the formula. And fourth, the system must be periodically revalidated and adjusted to maintain its predictive capacity.[80]

c. Credit Scoring and Its Effects on the Availability and Affordability of Credit

As the use of credit scores has expanded beyond just the traditional lending markets and into other fields such as the insurance industry, there are growing concerns that minorities are impacted unfairly by the methodologies of credit-scoring models. With the passage of The Fair and Accurate Credit Transactions Act of 2003 (FACTA), the Federal Reserve Board (FRB) and the Federal Trade Commission (FTC) were required to study how credit scoring was affecting the cost of credit and insurance for minorities populations, and whether these predictive models were accurate for these groups.[81] Section 215 of FACTA further directed the FRB and FTC to study whether credit scoring has a differential impact on the groups protected under the Equal Credit Opportunity Act (ECOA).[82] Few studies have been conducted into the potential disparate impact of credit scoring, in part because it is illegal for creditors to collect the demographic information on race or national origin that would be needed to conduct this analysis.[83]

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[77] 12 C.F.R. 202.2(p).
[78] Supra note 73 at 52.
[79] Id.
[80] Id.
[81] Section 215 of The Fact Act, Public Law 108-159, enacted December 4, 2003.
[82] Supra note 73.
[83] Hancock, P. and Brody, M. "Disparate Credit Scores Not a Proxy for Unlawful Discrimination Says FRB," Aug. 2007, http://www.klgates.com/newsstand/Detail.aspx?publication=4009

To conduct this study, the FRB collected the full credit records of over 300,000 people as of June 2003, along with their credit records eighteen months later.[84] Since the FRB did not have access to the algorithms underlying the proprietary scoring models, it created its own simplified credit model for use in this study. After creating this model, its predictive success was evaluated with respect to different breakdowns of the population, to consider whether use of these factors in forming a credit score was having a disparate effect on any protected groups. In effect, the FRB was subjecting its credit model to the disparate impact analysis described above. After conducting this study, the FRB found that the credit scores were not mere proxies for race, and actually served as good indicators of loan performance.[85]

<u>STRONGER CORRELATION TO PERFORMANCE THAN TO RACE</u>

"For race and ethnicity, almost all of the credit characteristics . . . are more correlated with performance than with demographic characteristic . . . regardless of the specific group considered." Report at 101. 'Indeed, most credit characteristics are only minimally correlated with race and ethnicity, many are not correlated at all, and none are highly correlated. . . . [T]he characteristics that are most correlated with both performance and race are all related to past payment history. Each of these characteristics is also highly correlated with performance.' *Id*. at 102."[86]

Going through the logical steps required to prove a disparate impact claim under the ECOA, as described above, the first prong of the test asks whether credit scoring detrimentally impacts a protected group. The empirical data clearly indicates that, blacks and hispanics have significantly lower scores than non-hispanic whites, satisfying the first part of the test.[87] Notwithstanding this showing of detrimental impact, a lender can avoid liability by showing that the allegedly discriminatory policy—in this case, using credit scores to make lending decisions—is a business necessity. Since the study indicates that the models are actually accurate predictors of behavior that are not mere proxies for race, a lender would likely meet this

[84] Id.
[85] Id.
[86] Id. (quoting Federal Reserve Board Report)
[87] Id.

burden.[88] A plaintiff would still have the chance to argue that the business policies could be achieved in a manner that has a smaller differential impact. However, after contemplating this issue the FRB was unable to identify an alternative manner that could be a viable alternative.[89] Thus the FRB's analysis indicates that credit scoring models would likely be found compliant with disparate impact analysis under the ECOA.

CREDIT SCORING BIASES

"Consistently, across all three credit scores and all five performance measures, blacks, single individuals, individuals residing in lower-income or predominantly minority census tracts show consistently higher incidences of bad performance than would be predicted by the credit scores. Similarly, Asians, married individuals, foreign-born (particularly, recent immigrants), and those residing in higher-income census tracts consistently perform better than predicted by their credit scores."[90]

The report concluded that "there is little evidence from the analysis here that any of the credit characteristics included in the FRB base model embeds negative differential effects for any racial or ethnic group."[91] However, "[u]nlike race and ethnicity . . . there is some evidence that the FRB base model credit characteristics may embed some disparate effects by age, but the effect appears small."[92] Surprisingly, the FRB's conclusion from this study is that a litigant bringing a disparate impact claim would find a stronger basis in alleging age discrimination than race discrimination. However, given the study's other finding that the models were strongly predictive of performance, even for the age-based claim the disparate impact would probably be considered justifiable as a business necessity with no clear alternative.[93]

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[88] Id.
[89] Id.
[90] Supra note 73 at 89.
[91] Id. at 113.
[92] Id. at 115.
[93] Supra note 82.

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Piggyback can lift your credit score

He suggests that consumers who do decide to try piggybacking read the fine print, find out if there's a money-back guarantee, frequently pull their credit report to make sure the account was reported, ask for names and contact information for previous customers of the service and don't assume that everything you read on the Web site is true.

Deborah Kennedy, whose husband is a co-owner of Instant Credit Builders, says authorized users at her company never get the card nor does it get activated. The new card comes to her home and is shredded.

Kennedy says she and her husband support eight to 10 authorized users on each of their three credit cards. She claims the thief would have to know both her and her husband's names, account numbers, Social Security numbers, dates of birth and pass codes to use the card.

Still, Kennedy says she encourages the company's cardholders to put a pass code on their account and has added a privacy guard to her account anytime there's a new user so she can receive e-mail alerts regarding activity on the account.

Solutions

Roberts believes the three major credit bureaus should address the piggybacking technique.

"They're the ones that we look for to get content of information," Roberts says. "They're giving us information that's being manipulated. Their situation is being manipulated to enhance lenders' money."

Norm Magnuson, spokesman for the Consumer Data Industry Association, which represents consumer credit reporting associations, says only, "We are aware of the issue and are engaged in a dialogue with several lenders on it. However, that's all we can say at this point."

Terry Clemans, executive director of the National Credit Reporting Association, which represents the mortgage credit reporting industry, says that based on conversations he has had with the mortgage lending community, a consumer who is found to have used the credit programs to obtain better credit to close a mortgage loan could have that note canceled or called due for falsely misrepresenting their credit history.

Dorman says the FTC advises consumers to be very careful entering an arrangement that purports to result in improved credit scores.

"If a consumer appears to be more creditworthy than they really are, they might be able to secure a loan they cannot afford."

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Bank Lawyer's Blog

June 13, 2007

Piggyback My FICO

If you're a subprime borrower with a low credit score, don't despair, and don't settle for an Option ARM or other exotic mortgage loan. *Dallas Morning News* business columnist Pamela Yip profiles the latest and greatest ~~fraudulent~~ innovative scheme to artificially boost that score: piggyback the high FICO score of a "prime" borrower.

The latest strategy is a real doozy. It lets those with poor scores "piggyback" on – or mooch off – someone else's good credit record.

These companies say they can boost your credit score by having you added as an authorized user on the credit cards of strangers with stellar credit, for a fee. This raises your credit score.

The strangers get paid based on the quality of their credit, with the promise that the new "authorized users" won't actually be able to buy anything on their cards or even get any of their personal information.

The bottom line: People with bad credit can pay a fee to get better credit. If they have a history of late payments, they can get the same low interest rate as someone who always pays on time.

Sounds like it ought to be illegal, doesn't it? The regulators aren't certain that it is.

"We're still trying to get a good fix on what this is and how it works, and what the issues are," said Steve Baker, director of the Midwest region of the Federal Trade Commission, which enforces the nation's credit laws. "One concern is whether this might violate the Credit Repair Organizations Act."

Under that law, it's illegal to charge consumers money before performing the promised credit repair services.

Lenders think that it's just GOT to be fraudulent.

"Someone is artificially elevating their credit score beyond the risk level they deserve based on their own payment history and payment patterns," said Ginny Ferguson, a member of the Credit Scoring Committee of the National Association of Mortgage Brokers. "If we can't trust the credit score to give us a good indicator of the likelihood of someone repaying their loan, the score isn't good to any of us."

It might be tough to prove fraud, however. There's the practical problem of discovering the existence of the piggybacking in the first place. Moreover, if the rules of the credit score providers don't prohibit the practice of adding "authorized users" to your credit accounts, then this tactic appears to be a "loophole" that you could drive a tank through. After all, the loan applicant isn't forcing the lender to rely on a FICO score in underwriting a loan nor to assign it any particular weight versus other factors, nor is he or she determining what factors are used by the credit scoring companies in establishing the score. The fact that the score might not be any good to the lender is not the same thing as the borrower committing fraud against the lender. It smells like fraud to me, but I could argue with gusto either way, depending on who was paying my monthly invoices.

Traditionally, Ms. Yip has been no fan of lenders, and she's not shedding any crocodile tears in this case.

[L]enders' single-minded focus on credit scores and the fact that they've become so pervasive – even being used by insurance companies to determine what premiums to charge – has forced consumers to take desperate measures to raise their score.

That sounds like an "ends-justify-means" argument, which is less than persuasive. Nevertheless, her conversations with representatives of "score renting" companies about their "services" and how they price them make you shake your head in begrudging admiration at the enterprising skill of folks for whom the word "ethics" has no meaning.

This all appears to be an academic discussion for the long-term, however. Fair Isaac, the "dominant" credit score provider, intends to hobble this one-trick pony.

In response to credit renting, Fair Isaac says that starting in September, authorized users on someone else's account will no longer benefit from the account holder's good payment history.

"We will do whatever it takes to protect the reliability and accuracy of FICO credit scores for lenders, and to ensure lenders can continue to use FICO scores with confidence when making their most important customer decisions," said Mark Greene, Fair Isaac chief executive. "We will continue working with lenders, regulators and others in the credit reporting industry to end deceptive practices that fraudulently misrepresent consumer credit histories for profit."

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