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

"Piggybacking credit" is a new practice that helps consumers improve their credit scores by paying to become "authorized users" on established accounts. Authorized users are not liable for paying an account, but because of Regulation B (which implements the 1974 Equal Credit Opportunity Act), the account's history factors into their credit scores. As a result piggybacking can be used to manipulate the signal of creditworthiness that scores provide and may help borrowers obtain credit for which they would not have otherwise qualified. This article investigates the policy questions raised by piggybacking. First, we evaluate whether the credit history disparities that motivated these provisions of Regulation B have persisted since they were written. Then, we assess the potential for score improvement through piggybacking. Finally, we evaluate the likely score effects of allowing credit scoring models to exclude authorized-user accounts, the most widely proposed policy response to the emergence of piggybacking.

INTRODUCTION

"Credit scoring," or the use of statistical techniques to quantify credit risk, comes in different varieties but arguably the most important scoring models rely entirely on the credit history information collected by credit bureaus. The quantitative assessments that such models produce, called "credit scores," are widely used in all aspects of consumer lending as well as in noncredit areas such as insurance.

As credit scoring has become more pervasive, the importance of having a higher score has grown. Particularly for people with low

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"subprime" scores, who are generally considered too risky to qualify for credit on the best terms, score increases can substantially improve access to credit. Score improvement, however, can be a slow and difficult process.[1] Borrowers may have to pay down their revolving accounts, refrain from opening new accounts, or, for borrowers with past delinquencies, wait for time to elapse without missing any new payments.

To shortcut this process, some credit repair companies in the United States facilitate a practice called "piggybacking credit" (sometimes referred to as "tradeline renting"). This practice involves an individual paying a fee to the credit repair company to locate a third party who, for a portion of the fee, makes the payer an "authorized user" on a revolving account.[2] An "authorized user" is someone who is permitted to use a revolving account without being legally liable for any charges incurred. Traditionally, authorized-user status has been used to provide family members with access to credit or to help teach children how to manage credit. When piggybacking, the payer is an authorized user in name only, as he receives neither the account number nor an access device (such as a credit card) and consequently cannot use the account for purchases.[3] However, by becoming an authorized user, the account's history will be reflected on the payer's credit report. If the account has favorable characteristics (such as a long history of on-time payments or a low utilization rate), this can improve the payer's credit score. As a result, when undertaken in advance of a credit application, piggybacking can allow applicants to obtain credit for which they would not otherwise have qualified.

The reason that authorized-user accounts can improve credit scores, even though authorized users are not liable for paying these accounts, is that until recently credit scoring models have treated the accounts on which an individual is an authorized user ("authorized-user accounts") the same as the accounts for which the person is contractually liable ("nonauthorized-user accounts"). This equal treatment results from Regulation B ("Reg. B"), which implements the 1974 Equal Credit Opportunity Act (ECOA).[4] Since its inception in 1975, Reg. B has

1. For example, Brevoort and Cooper (2013) show credit score recovery can take a decade or more for borrowers whose mortgage enters foreclosure.

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

3. This is not without risks to the account holder. If the person added as an authorized user manages to obtain an access device from the lender, then they are legally permitted to incur charges on the account.

4. On July 21, 2011, ECOA rule-writing authority transferred from the Federal Reserve to the Consumer Financial Protection Bureau (CFPB).

imposed two important requirements on creditors when an authorized user is the spouse of an account holder. First, when reporting to the credit bureaus, creditors are required to furnish information for the authorized user as well as for all account holders. Second, when using credit history to assess an applicant's creditworthiness, 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).[5]

In promulgating these provisions, the Federal Reserve Board was responding to complaints received from women who were unable to obtain credit because information about the accounts jointly held with their husbands were being reported in the husband's name alone. The Board took the view that, since some state laws hold one spouse liable for debts incurred by the other, both spouses should have the "benefit or burden" of the credit history of any of their spouse's accounts they were authorized to use. Moreover, spouses were found to play a significant role in maintaining accounts, such that an account's payment history was often "as much the product of the user's contribution as that of the obligor."[6]

Though Reg. B's requirements only apply when an authorized user is an account holder's spouse, in practice they are more broadly applied. Reg. B explicitly permits over-compliance with these requirements and creditors have followed a practice of furnishing information about all authorized users, without indicating which users are spouses. Consequently, when evaluating credit history lenders cannot distinguish other authorized-user accounts from the spousal authorized-user accounts Reg. B requires them to consider.

As lenders cannot distinguish spousal authorized-user accounts, an argument can be made that Reg. B requires lenders to afford equal treatment to all authorized-user accounts.[7] For this reason, credit scores, such as the FICO score, have traditionally treated authorized-user accounts like any other account on an individual's credit record. Piggybacking

5. These requirements are set forth in Section 202.6(b) of Regulation B (12 CFR 202.6(b)).

6. 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 (October 22, 1975), pp. 49298–49310.

7. This interpretation of Reg. B is not universally accepted. Reg. B requires spousal authorized-user accounts be evaluated *when available*. VantageScore Solutions, LLC, and others argue that because spousal authorized-user accounts are not identifiable in credit records, they are not "available" and therefore need not be incorporated in a credit scoring model. Others believe that Reg. B effectively requires consideration of all authorized-user accounts. We take no position in this article on which legal interpretation is correct.

is an unintended and unforeseen consequence of this situation, and its emergence has raised concerns about how credit scoring models treat authorized-user accounts. For example, a study of mortgage defaults by Fitch Ratings (Pendley, Costello, and Kelsch 2007) uses the presence of authorized-user accounts on the credit records of high-FICO-score borrowers as evidence of poor underwriting by the lender.

Because of such concerns, FICO announced plans to revise its scoring model to exclude authorized-user accounts (Fair Isaac Corporation 2007). These plans were abandoned when regulators and others suggested that the new model might not comply with Reg. B. Instead, FICO altered its model to place less weight on authorized-user accounts (Fair Isaac Corporation 2008). Similarly, VantageScore Solutions, LLC has opted to exclude authorized-user accounts because of concerns about piggybacking (Experian 2007); however, lender concerns about Reg. B compliance caused VantageScore to introduce authorized-user accounts in version 2.0 of its model. In both cases, concerns about Reg. B compliance appear to have restricted adjustments to the characteristics of scoring models available for underwriting.

The emergence of piggybacking has reopened questions about whether scoring models should be required to consider authorized-user accounts. Yet, despite the policy importance of these issues, very little is known about the role that authorized-user accounts play in credit records or scoring models. This article seeks to fill this gap using a unique dataset that combines a nationally representative sample of anonymous credit records with demographic information from other sources. We use this dataset to address three questions that need to be answered to evaluate whether credit scoring models should be required to include authorized-user accounts.

The first question is "do the credit history disparities that motivated the requirements of Reg. B regarding authorized-user accounts persist today?" These provisions were motivated by concerns that the credit records of married women were less complete than those of their husbands and that this was reducing their access to credit. We evaluate whether this credit history disparity has dissipated in the decades since Reg. B was originally written. As part of this analysis, we also explore whether any other protected classes have credit histories that are sufficiently dependent on authorized-user accounts so that the treatment of these accounts will affect their credit access.

Like lenders, we are unable to determine with our data which authorized-user accounts are the result of piggybacking and, therefore, are unable to measure the extent to which piggybacking is occurring.

Nevertheless, we can evaluate the extent to which consumers can increase their credit scores by piggybacking, thereby distorting the quality of the signal of creditworthiness that credit scoring provides to lenders. So, the second question we ask is "can piggybacking materially improve credit scores?" Credit repair companies stress the large positive effects that piggybacking can have on credit scores, but very little is known about the true size of such effects. While some borrowers (particularly those with thin or short credit histories) might expect a large score increase from adding a seasoned account, the benefits for other borrowers are less clear. Yet, the size and pervasiveness of credit score effects from piggybacking is important. If the score effects are small, then there is little potential for harm. But, if the gains are large, piggybacking may lower the quality of the signal that credit scoring provides and, consequently, reduce the efficiency with which credit is allocated. We use simulation to estimate the potential for credit score improvement through piggybacking to ascertain the extent to which people can materially improve their credit profile through its use.

The third question that we ask is "how does excluding authorized-user accounts from credit scoring models affect credit scores?" Excluding authorized-user accounts from scoring models has been the most commonly proposed solution to the challenge posed by piggybacking. We re-estimate the scoring model used in this study without using any information from authorized-user accounts and generate new scores using this re-estimated model. With these new scores, we determine how excluding authorized-user accounts affects the scores of married women and other protected classes. Moreover, by comparing the predictiveness of the re-estimated scores and the original scores, we ascertain whether authorized-user accounts provide useful information about creditworthiness, as the Federal Reserve Board suggested (at least for spousal authorized users) when promulgating Reg. B.

The plan for the remainder of the article is as follows. The next section reviews the existing literature on credit scoring models, followed by a review of the data used in this study. Subsequent sections present our analysis regarding the three questions posed in this paper, and the final section of the paper discusses the conclusions that can be drawn.

BACKGROUND AND LITERATURE REVIEW

The imperfect information that lenders have about the probability that a loan will be repaid causes them to screen applicants and ration credit (Stiglitz and Weiss 1981). As shown by Pagano and Jappelli

(1993), lenders can improve these screens by sharing information among themselves, thus reducing credit risk and increasing loan volumes. Information sharing can also improve loan performance by introducing reputation effects and giving borrowers an additional incentive to repay (Padilla and Pagano 2000). In the United States, such information sharing is facilitated by private credit bureaus.

Credit bureaus collect information from lenders and compile it into a "credit record" for each borrower. These records, which contain information about the accounts the borrower is or has been associated with, are sold to lenders who use the information to derive signals about creditworthiness. Credit reports may be sold along with credit-bureau-based scores or may be used by lenders in their own internal scoring models.

The quality of signal provided by credit scoring has been established by a significant literature. This literature compares outcomes when credit scoring is used in underwriting to outcomes from underwriting without statistical techniques, commonly called "judgmental underwriting." Most of the studies in this literature find that credit scoring is a superior predictor of loan performance (Chandler and Coffman 1979; Hand and Henley 1997; Rosenberg and Gleit 1994; Straka 2000; Thomas 2000). Chandler and Parker (1989) also show that credit-bureau-based scoring models are more predictive than models built using data from loan applications. Consistent with theory, the use of credit scoring has also been found to increase lending (Gates, Perry, and Zorn 2002; Jeong 2003). This evidence suggests that credit scoring increases the efficiency with which consumer credit is allocated.

The potential danger from piggybacking, and perhaps authorized-user credit accounts in general, is that its use might distort the quality of the signal that credit scoring provides. By and large, the provisions of Reg. B governing authorized-user accounts were predicated on the belief that they will be predictive of future performance, at least for spousal authorized-user accounts. But outside of a spousal relationship, the value of this information is less clear since the authorized user is not responsible for paying the account. In the case of a piggybacked account, in particular, there is little reason to believe that the account's history conveys any information about the authorized user's creditworthiness. If authorized-user accounts are treated identically to nonauthorized-user accounts in a credit scoring model, but are less predictive of future performance, the resulting score may provide a less informative signal about creditworthiness. This would be expected to reduce both the efficiency with which credit is allocated and the volume of credit extended (Jeong 2003; Pagano and Jappelli 1993).

DATA AND THE FRB BASE MODEL

This study uses a large, nationally representative sample of anonymous individual credit records that has been augmented with 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.[8]

The dataset includes a random sample of 300,000 anonymous credit records from TransUnion, LLC, as of June 30, 2003. The credit records for these same consumers from December 31, 2004 were also provided.[9] Each record provides information about an individual's credit accounts (also called "tradelines"), collection agency accounts for noncredit-related debts (such as unpaid medical or cell phone bills), monetary-related public records, and a list of inquiries made by lenders in connection with a credit application.[10]

The information on each tradeline includes each account's opening date, the date it was closed (if applicable), its balance, original loan amount, credit limit (for revolving accounts), and up to 48 months of payment history. Each tradeline record also indicates whether the person individually holds, jointly holds, or is an authorized user of that account. Authorized users are only found on revolving accounts, not on installment accounts, collection agency accounts, public records, or inquiries. We refer to those revolving tradelines that indicate the individual is an authorized user as "authorized-user accounts" and the individually or jointly held (installment or revolving) accounts as "nonauthorized-user accounts." These designations are specific to each individual record, in that an account held by one person with a second person associated as an authorized user will generate a nonauthorized-user tradeline on the credit record of the account holder, and an authorized-user tradeline on the record of the authorized user. Like lenders, we cannot identify which authorized-user tradelines involve spousal relationships.

8. Other datasets combine credit and demographic information for specific populations. For example, the Freddie Mac Consumer Credit Survey combines credit records with demographic information from survey responses, but is limited to people aged 20 to 40 with household incomes under $75,000 (Courchane and Zorn 2005).

9. For more detail on the dataset, see Board of Governors (2007) or Avery, Brevoort, and Canner (2013).

10. A detailed assessment of the contents of credit records is provided by Avery, Brevoort, and Canner (2003).

The only demographic information included in the credit records is the date of birth, though this information was missing for about one third of the sample. Demographic information was obtained from two other sources. The first was the US Social Security Administration (SSA), which provided information collected on applications for Social Security cards, including each individual's citizenship, race or ethnicity, sex, and date of birth.[11] The second source, a demographic information company that provided data under the condition that it remain anonymous, supplied each individual's marital status, which was culled from thousands of public and private data sources.

We also make use of the "FRB base model," a credit scoring model developed by staff of the Federal Reserve from the same dataset used in this study. FRB base scores are normalized to a 0-to-100 rank-order scale, such that each score represents the percentile of the distribution into which the score falls.[12] As a result, for example, one quarter of our sample has an FRB base score of 25 or less. To avoid confusion with the better known scoring ranges used by FICO and VantageScore, for the remainder of this paper we refer to the numerical scores produced by the FRB base model as "percentile point" scores. Board of Governors (2007) shows that the percentile point scores generated by the FRB base model closely approximate several commercially available scores, which the Consumer Financial Protection Bureau (2012) shows are highly correlated with FICO and VantageScore.

As our focus is on the role of authorized-user accounts in credit scoring, we restrict our analysis to the "scorable" population defined by the FRB base model. A credit record is considered "unscorable" when it lacks sufficient information (such as at least one tradeline) or when there is no evidence of recent account activity.[13] The resulting sample has 232,467 credit records, all of which have at least one nonauthorized-user tradeline. Summary statistics for the scorable sample and the subset of the sample with authorized-user accounts (the "authorized-user sample") are provided in Table 1. More than one third of the scorable sample has an authorized-user account and is part of the authorized-user sample.

11. The SSA data and the matching process are discussed in detail by Board of Governors (2007).

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

13. The FRB base model defines a scorable record as one with a TransRisk score and a VantageScore, the two commercial scores that were available to staff of the Federal Reserve. This is largely equivalent to requiring that each record have a TransRisk score, as only 39 records had a VantageScore alone.

TABLE 1
Summary Statistics

	Scorable Sample[a]		Authorized User Sample[b]	
	Mean (1)	SD (2)	Mean (3)	SD (4)
Demographic characteristics				
Race or ethnicity				
Non-Hispanic White	0.64	0.47	0.73	0.43
Black	0.09	0.29	0.05	0.22
Hispanic White	0.07	0.25	0.07	0.23
Asian	0.04	0.18	0.04	0.19
Other	0.15	0.36	0.11	0.31
Gender and Marital Status				
Married male	0.24	0.42	0.29	0.45
Younger	0.12	0.32	0.15	0.35
Older	0.12	0.32	0.14	0.35
Married female	0.24	0.43	0.37	0.48
Younger	0.12	0.33	0.18	0.38
Older	0.12	0.32	0.19	0.39
Single male	0.13	0.33	0.08	0.26
Single female	0.14	0.35	0.10	0.29
Unknown	0.26	0.44	0.18	0.38
Age group				
Under 30	0.15	0.35	0.08	0.28
30 to 39	0.17	0.38	0.18	0.39
40 to 49	0.20	0.40	0.24	0.43
50 to 61	0.19	0.39	0.24	0.42
62 or older	0.19	0.39	0.20	0.40
Unknown	0.10	0.30	0.06	0.24
Credit characteristics				
Number of tradelines				
2 or fewer	0.14	0.34	0.04	0.20
3 to 5	0.13	0.34	0.08	0.26
6 to 10	0.19	0.39	0.16	0.37
More than 10	0.54	0.50	0.72	0.45
Utilization rate				
No accounts	0.30	0.46	0.18	0.38
None (0%)	0.10	0.30	0.11	0.31
<25%	0.32	0.47	0.40	0.49
25% to 49%	0.09	0.28	0.11	0.31
50% to 74%	0.06	0.25	0.07	0.26
75% or more	0.12	0.33	0.13	0.33
Dependent variables				
Age of oldest account				
Less than 24 months	0.05	0.22	0.02	0.14
24 to 59 months	0.11	0.31	0.05	0.22
60 to 119 months	0.19	0.39	0.14	0.35
120 or more months	0.65	0.48	0.79	0.41

TABLE 1
continued

	Scorable Sample[a]		Authorized User Sample[b]	
	Mean (1)	SD (2)	Mean (3)	SD (4)
Number of delinquencies				
No observed performance	0.02	0.13	0.00	0.06
No delinquencies	0.75	0.43	0.82	0.39
1 Delinquency	0.11	0.31	0.08	0.27
2 or More delinquencies	0.13	0.33	0.10	0.30
Credit record contents				
Authorized user tradelines	0.74	1.39	2.11	1.62
Non-authorized-user tradelines	14.04	11.10	18.18	11.38
Open authorized-user tradelines	0.36	0.83	1.04	1.12
Open non-authorized-user tradelines	4.68	4.15	6.02	4.32
Has authorized user accounts	0.35	0.48	1.00	0.00
Has majority authorized user accounts	0.01	0.11	0.04	0.19
FRB base score	49.99	28.86	57.20	27.60
Performance (1 = good performance)	0.96	0.20	0.98	0.15
Score changes relative to FRB base score				
From AU accounts	0.17	4.25	0.49	7.17
From simulated piggyback account	6.94	9.57	3.88	5.10
From re-estimating model	0.02	5.18	−0.30	7.62
Number of observations	232,467	232,467	81,346	81,346

Notes: The omitted group for each set of demographic or credit record characteristics are shown in bold.
[a]Scorable sample includes people for whom an FRB base score can be calculated.
[b]Authorized user sample includes people in the scorable sample who have one or more authorized user tradelines on their credit record.

QUESTION 1: HAVE CREDIT HISTORY DISPARITIES PERSISTED?

As discussed earlier, Reg. B's requirements regarding authorized-user accounts were motivated by concerns that the credit records of married women were less complete than those of their husbands. In this section, we explore whether this disparity in credit history has been maintained in the decades since Reg. B was originally authored.

We begin by examining how the credit records of married women and men differ in terms of the presence of authorized-user accounts. Columns 1 and 2 of Table 2 present the estimation results from regressions of the number of authorized- and nonauthorized-user accounts, respectively, on the demographic characteristics listed in Table 1. These characteristics include an interaction of gender and marital status that allows us to explicitly compare married women and men without conflating either with single individuals.

The results suggest that the disparity in credit history between married women and men has been substantially reduced if not eliminated. The average number of nonauthorized-user accounts on the credit records of married women is not significantly different than for comparable men. Married women also have 0.4 more authorized-user accounts. While the equality in nonauthorized-user accounts could be a carryover from their premarital years (when single women have 1.2 more nonauthorized-user accounts on average), additional analyses suggest this is not the case. When the number of open accounts is used as the dependent variable, shown in Columns 3 and 4, married women have 0.2 more open authorized-user accounts and 0.3 more nonauthorized-user accounts on average than married men.

While the credit records of married women appear no less complete overall, disparities may persist for older married women. Older married women are likely to have been married longer, giving them more time to become dependent on their husbands for credit. Additionally, the early credit experiences of older married women are more likely to have occurred in the years before the passage of ECOA. While accounts from before the passage of ECOA are unlikely to be on an individual's credit record (for men or women) these early experiences may continue to influence perceptions about the importance of married women maintaining credit in their own names.

To evaluate whether disparities persist for older married women, we divide the married population into "older" and "younger" groups, depending on whether they are 50 years old or older and estimate regressions of the number of authorized-user and nonauthorized-user tradelines. While these estimations suggest that older married women have more authorized-user accounts on average than older married men, there is a disparity in the number of nonauthorized-user accounts.[14] Older married women have one fewer nonauthorized-user accounts on their credit record on average (Column 5). While this disparity suggests that the credit records of older married women are thinner than older married men, older married women and men have about the same number of open nonauthorized-user accounts (Column 6), suggesting that older married women do not maintain fewer accounts.

14. The estimation results for authorized-user accounts are not shown in the tables but are available upon request. Estimated coefficients indicate that older married women have 0.48 more authorized-user accounts and 0.31 more open accounts, both of which are significant at the 1% level.

TABLE 2
Estimations of Credit Record Contents by Demographic Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	OLS	OLS	OLS	OLS	OLS
Sample Used	Scorable	Scorable	Scorable	Scorable	Scorable	Scorable
Dependent Variable	AU Tradelines	NAU Tradelines	Open AU Tradelines	Open NAU Tradelines	NAU Tradelines	Open NAU Tradelines
Constant	1.04***	19.35***	0.48***	6.08***	19.35***	6.08***
	(0.008)	(0.061)	0.00	(0.023)	(0.06)	(0.02)
Race or ethnicity (omitted group: non-Hispanic White)						
Black	−0.34***	−2.15***	−0.19***	−1.29***	−2.15***	−1.29***
	(0.010)	(0.076)	(0.006)	(0.029)	(0.08)	(0.03)
Hispanic White	−0.10***	−1.88***	−0.05***	−0.31***	−1.88***	−0.31***
	(0.011)	(0.087)	(0.007)	(0.034)	(0.09)	(0.03)
Asian	0.16***	−0.44***	0.09***	0.38***	−0.44***	0.38***
	(0.015)	(0.118)	(0.009)	(0.045)	(0.12)	(0.05)
Gender and marital status (omitted group: married males or younger married males in Columns 5 and 6)						
Single male	−0.49***	−2.81***	−0.25***	−0.92***	−2.67***	−0.80***
	(0.01)	(0.074)	(0.006)	(0.029)	(0.09)	(0.03)
Single female	−0.38***	−1.59***	−0.19***	−0.33***	−1.47***	−0.21***
	(0.009)	(0.072)	(0.006)	(0.028)	(0.09)	(0.03)
Married female	0.36***	−0.10	0.23***	0.30***		
	(0.008)	(0.061)	(0.00)	(0.024)		
Younger					0.71***	0.51***
					(0.09)	(0.03)
Older					−0.75***	0.31***
					(0.11)	(0.04)
Older married male					0.21	0.24***
					(0.11)	(0.04)

TABLE 2
continued

	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	OLS	OLS	OLS	OLS	OLS
Sample Used	Scorable	Scorable	Scorable	Scorable	Scorable	Scorable
Dependent Variable	AU Tradelines	NAU Tradelines	Open AU Tradelines	Open NAU Tradelines	NAU Tradelines	Open NAU Tradelines
Age group (omitted group: aged 40 to 49)						
Under 30	-0.47^{***}	-7.99^{***}	-0.20^{***}	-1.96^{***}	-7.93^{***}	-1.96^{***}
	(0.010)	(0.074)	(0.006)	(0.028)	(0.07)	(0.03)
30 to 39	-0.11^{***}	-0.92^{***}	-0.07^{***}	-0.80^{***}	-0.88^{***}	-0.80^{***}
	(0.009)	(0.069)	(0.005)	(0.027)	(0.07)	(0.03)
50 to 61	0.04^{***}	0.05	0.05^{***}	0.40^{***}	0.43^{***}	0.39^{***}
	(0.009)	(0.068)	(0.005)	(0.026)	(0.09)	(0.03)
62 and over	-0.23^{***}	-5.35^{***}	-0.08^{***}	-1.07^{***}	-4.97^{***}	-1.09^{***}
	(0.009)	(0.068)	(0.005)	(0.026)	(0.09)	(0.03)
Number of observations	232,467	232,467	232,467	232,467	232,467	232,467
Mean of dependent variable	0.74	14.04	0.36	4.68	14.04	4.68
Log likelihood	−396,378	−869,118	−277,648	−646,622	−869,003	−646,580
R^2	0.08	0.16	0.07	0.11	0.16	0.11

*,**, and *** denote statistical significance at the 10, 5 and 1% levels.

Differences in the presence of authorized-user accounts alone may not fully reflect the importance of these accounts to credit scores and credit access. Accounts have different characteristics that affect how they are evaluated. If the characteristics of the accounts maintained by married women and men differ in material ways, then looking at account totals alone may be misleading. To gauge the effect of these accounts, we measure the contribution that authorized-user accounts currently make to credit scores by removing the authorized-user tradelines from the credit records in our sample, recalculating the credit characteristics that comprise the FRB base model using only the remaining items in each credit record, and rescoring each record using the FRB base model's mapping of fitted values to scores (rather than creating a new mapping to reflect the percentiles of these new scores). The difference between this new score and the FRB base score, which we calculate so that a positive value indicates the score is higher when authorized-user accounts are included, represents the marginal contribution of the authorized-user accounts.

Overall, the contribution of authorized-user accounts is surprisingly nuanced. Since authorized-user accounts provide a more extensive credit history and tend to have other characteristics that are positively related to credit scores (e.g., authorized-user accounts tend to be older and have lower delinquency rates than nonauthorized-user accounts), we would have expected the additional information to increase scores broadly. But only 38% of people with authorized-user accounts have higher scores as a result. Almost an equal number (36%) experience no change, and scores are reduced for the remaining 26%. Additionally, while people with authorized-user accounts are more likely to be helped than hurt, the magnitude of the score changes appears to be slightly larger for people experiencing score declines. The mean and median decrease (−5.4 and −2.6, respectively) are larger than the mean and median increase (5.0 and 2.4).

To assess how these score changes differ across demographic groups, we regress score changes on the demographic characteristics used earlier. Results from this estimation are provided in Column 2 of Table 3, with the results of a regression of the FRB base score on demographics presented in Column 1 for reference. An alternative approach to this analysis would be to focus on the average score effects around an arbitrary score threshold. As shown in Board of Governors (2007), loan denial rates tend to decline monotonically with credit scores across the entire score range without obvious discontinuities at any single score threshold. Moreover, even for borrowers who qualify for prime credit, a higher score can lower interest rates or increase loan amounts. This suggests that the benefits of score improvement are more widely experienced than evaluating a single score threshold would imply. For this reason, we believe average effects provide the best available metric of benefit or harm and we focus on these effects. However, we also estimate probit models showing the likelihood of a score decline or increase of at least five percentile points (Columns 3 and 4), which is our definition of a large effect. Since the score change for people who have no authorized-user accounts will always be zero, we estimate these models using the authorized-user sample.

These estimations suggest that authorized-user accounts are a net positive for married women. On average, authorized-user accounts increase the scores of married women by 0.3 percentile points more than for otherwise identical married men. Married women are also significantly more likely to experience large score changes, either positive or negative, and these differences can be meaningful. For example, a married White woman in her 40s has a 10.8% chance of experiencing a score increase of at least 5 percentile points, compared to a 7.7% chance for a similar married man. But while authorized-user accounts appear to contribute more to the scores of married women on average, they explain only a portion of the 3-percentile-point average score difference between married women and men.

To evaluate the contribution that authorized-user accounts make to the scores of older married women, we re-estimate the regressions in the first two columns with separate effects for older and younger married people (Columns 5 and 6). The results of those estimations show that authorized-user accounts have equal effects on the scores of younger married women and men. The result for older married women, in contrast, is consistent with the score effects that we observed for all married women. Authorized-user accounts add 0.63 percentile points more to the scores of older married women than they do to older married men, though this again explains only a portion of the overall 3.51-percentile-point average score difference.

While married women provided the primary motivation for the equal treatment of authorized-user accounts, our results show that other demographic groups are also affected. The largest score effects are experienced by people aged 62 or older, whose scores are increased by 1.2 percentile points on average. Like individuals younger than 30, whose scores also increase by about a percentile point, this likely reflects their thinner credit files (as shown in Column 2 of Table 2, both age groups have substantially fewer nonauthorized-user accounts). These score improvements are likely much less important for the older individuals, as their scores tend to be higher than younger individuals even without their authorized-user accounts.

TABLE 3
Effect of Authorized User Account Information on Credit Scores by Demographic Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	OLS	Probit	Probit	OLS	OLS
Sample Used	Authorized Users	Authorized Users	Authorized Users	Authorized Users	Authorized Users	Authorized Users
			Change from AU Trades			
Dependent Variable	FRB Base Score	Change from NAU Accounts	<−5 points	>5 points	FRB Base Score	Change from NAU Accounts
Constant	58.30***	−0.14*	−1.40***	−1.42***	58.60***	0
	(0.229)	(0.065)	(0.017)	(0.016)	(0.26)	(0.07)
Race or ethnicity (omitted group: non-Hispanic White)						
Black	−24.15***	−0.67***	0.02	−0.25***	−24.15***	−0.67***
	(0.406)	(0.115)	(0.029)	(0.03)	(0.41)	(0.11)
Hispanic White	−11.83***	−0.43***	0.03	−0.13***	−11.83***	−0.43***
	(0.387)	(0.110)	(0.027)	(0.027)	(0.39)	(0.11)
Asian	4.43***	0.32*	−0.02	0.11***	4.44***	0.31*
	(0.471)	(0.133)	(0.034)	(0.030)	(0.47)	(0.13)
Gender and marital status (omitted group: married males or younger married males in Columns 5 and 6)						
Single male	−7.65***	0.2	−0.08**	−0.02	−7.98***	0.10
	(0.365)	(0.103)	(0.027)	(0.026)	(0.42)	(0.12)
Single female	−6.04***	0.10	−0.00	0.05*	−6.38***	0.01
	(0.334)	(0.095)	(0.024)	(0.023)	(0.40)	(0.11)
Married female	3.01***	0.33***	0.04**	0.19***		
	(0.220)	(0.062)	(0.016)	(0.015)		
Younger					2.50***	0.03
					(0.31)	(0.09)
Older					2.82***	0.46***
					(0.47)	(0.13)

TABLE 3
continued

	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	OLS	Probit	Probit	OLS	OLS
Sample Used	Authorized Users	Authorized Users	Authorized Users	Authorized Users	Authorized Users	Authorized Users
			Change from AU Trades			
Dependent Variable	FRB Base Score	Change from NAU Accounts	<−5 points	>5 points	FRB Base Score	Change from NAU Accounts
Older married male					−0.69	−0.17
					(0.48)	(0.14)
Age group (omitted group: aged 40 to 49)						
Under 30	−11.26***	0.98***	0.08***	0.38***	−11.24***	0.96***
	(0.360)	(0.102)	(0.025)	(0.023)	(0.36)	(0.10)
30 to 39	−5.31***	−0.03	0.04	0.01	−5.31***	−0.04
	(0.276)	(0.078)	(0.020)	(0.019)	(0.28)	(0.08)
50 to 61	5.29***	0.27***	−0.04*	0.08***	5.38***	0.15
	(0.256)	(0.073)	(0.019)	(0.018)	(0.40)	(0.11)
62 and over	13.21***	1.23***	−0.13***	0.31***	13.31***	1.11***
	(0.270)	(0.076)	(0.020)	(0.018)	(0.41)	(0.12)
Number of observations	81,346	81,346	81,346	81,346	81,346	81,346
Mean of dependent variable	57.20	0.49	0.08	0.12	57.20	0.49
Log likelihood	−377,923	−275,300	−23,029	−28,862	−377,921	−275,288
R^2	0.17	0.01			0.17	0.01

*,**, and *** denote statistical significance at the 10, 5 and 1% levels.

But perhaps most notable is that Blacks and Hispanic Whites both appear to benefit significantly less from the inclusion of authorized-user accounts than non-Hispanic Whites. Both groups have lower average score changes and are significantly less likely to experience score increases of at least 5 or 10 percentile points than the baseline group. This is somewhat surprising given that minorities tend to have thinner credit records and might have been expected, *ex ante*, to benefit the most from considering this information.[15] This suggests that the authorized-user accounts of minorities tend to provide less positive information than they do for other groups.

QUESTION 2: CAN PIGGYBACKING MATERIALLY IMPROVE CREDIT SCORES?

The modest contribution that authorized-user accounts make, on average, to credit scores does not by itself imply that the score increases from piggybacking will be small, or that its effects on creditworthiness assessments will be immaterial. In part, authorized-user accounts have modest effects because they have similar profiles to nonauthorized-user accounts for most individuals. For example, the authorized-user accounts of young people, like their nonauthorized-user accounts, tend to have shorter-than-average histories. But, if a young person can piggyback on an older account, the estimates from the previous section will underestimate the score gains that can be achieved.

The size of the potential score gains is important for gauging the dangers posed by piggybacking. If piggybacking has little effect on scores, or if the benefits are limited to a small portion of the population, then the harm that piggybacking might cause is small. In contrast, if piggybacking yields large score increases, the dangers may be substantial and a reconsideration of existing regulations or industry practices warranted.

To assess the possible effects, we simulate the score changes that result when a high-quality account is added to each credit record in our sample. We approximate the characteristics of the type of account that might be available for piggybacking using values from the 90th percentile of the distribution for account age and credit limit, which translate into a credit limit of $15,000 and an account age of about 16

15. Unconditional on other factors, the mean and median score changes experienced by Hispanic Whites with authorized-user accounts were 0.01 and 0 percentile points respectively. While the median unconditional score change for Blacks was also zero, Blacks experienced an average score *decline* of 0.24 percentile points.

years. Furthermore, we assume that the account has an unblemished payment history and an outstanding balance of \$1.[16] The resulting score increases approximate what piggybacking can achieve.

Our simulation results suggest that piggybacking can increase scores significantly. The mean and median score changes in our sample were 4.6 and 6.9 percentile points, respectively; moreover, scores increased 10 percentile points or more for 20% of our sample. But while these changes appear substantial, by themselves they may not be meaningful. A subprime borrower who experiences a 10-percentile-point increase from piggybacking may see no improvement in credit access if her score remains subprime. Alternatively, even a small score increase may substantially improve credit access for someone with a score just below the prime threshold.

To assess the extent to which piggybacking can increase a person's credit risk profile, we divide the score range into four segments: subprime, near-prime, prime, and super-prime. We delineate these segments using the VantageScore cutoffs for these groups (VantageScore 2009) applied to the FRB base model's score range. Adding the piggybacked account moves 28% of subprime and 35% of near-prime borrowers into a higher-credit-quality segment. As a result, access to credit for these borrowers would likely be notably improved.

Such average changes for the whole population will overestimate the gains for some groups and underestimate them for others. Acquiring a seasoned account will likely have the largest effect for people with thin or short credit histories, as these are conditions that an additional account can alleviate. In contrast, people who are delinquent on an account remain so after piggybacking and therefore are less likely to benefit.

To evaluate how the potential score increases from piggybacking vary across credit records characteristics, we regress the simulated score changes on the number of tradelines on file, the utilization rate on revolving trades, the age of the oldest account on file, and the number of accounts that have been 90 or more days past due in the previous 24 months. Since relationships between credit characteristics and scores are often highly nonlinear, these explanatory variables enter as step functions (which is also the functional form used in the FRB base model and most other scoring models). Within each of these credit characteristics, the modal group is used as the omitted category. We also

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

estimate probit models for large score changes, focusing exclusively on large positive changes because only a negligible share of the sample experiences a score decline from our simulated account.

The estimation results, provided in Table 4, are consistent with our expectations. The largest increases are found for people with thin or short credit histories. Indeed, for someone with two or fewer tradelines and a credit history of less than two years, the expected score increase from piggybacking will be around 20 percentile points. For the rest of the population, people with thicker or longer credit histories, the potential gains are more modest. Nevertheless, these results suggest that piggybacking can potentially increase scores substantially for a sizable portion of the population.

QUESTION 3: HOW DOES EXCLUDING AUTHORIZED-USER ACCOUNTS AFFECT CREDIT SCORES?

One response to the threat piggybacking poses is to exclude authorized-user accounts from scoring models. Because the usage of these accounts differs across demographic groups, excluding these accounts may adversely affect some groups more than others and run afoul of ECOA's goal of promoting equal access to credit. In this section, we evaluate how different demographic groups are affected by excluding these accounts.

Our earlier analysis of the marginal contribution that authorized-user accounts make to scores is insufficient to address this question because that analysis left the underlying credit scoring model unchanged. Were model builders to exclude authorized-user accounts, they would recalibrate their models so that they were optimized to predict credit performance without these accounts. Because we have the dataset that generated the FRB base model, we can conduct the same exercise and re-estimate the FRB base model with authorized-user accounts excluded. Specifically, we remove all authorized-user tradelines from the credit records in our sample and recalculate the credit characteristics that comprise the FRB base model using only the remaining information in each credit record. Using these new credit characteristics, we re-estimate the model coefficients, generate fitted values, and create a new mapping from fitted values to the percentile scores used by the FRB base model.[17] The

17. When re-estimating the FRB base model, attributes for each credit characteristic are reconstructed using the same algorithm that generated the FRB base model, which is discussed in Board of Governors (2007).

TABLE 4
Simulated Effect of Adding an Authorized User Account on Credit Scores by Credit Record Characteristics

	(1)	(2)	(3)	(4)
Method	OLS	OLS	Probit	Probit
Sample Used	Authorized Users	Authorized Users	Authorized Users	Authorized Users
			Change from Piggybacking	
Dependent Variable	FRB Base Score	Change from Piggybacking	<−5 Points	>5 Points
Constant	75.28***	1.93***	−3.47***	−1.05***
	(0.064)	(0.029)	(0.072)	(0.006)
Number of tradelines (omitted group: 10 or more tradelines)				
2 or fewer	6.99***	10.65***	3.08***	0.75***
	(0.139)	(0.063)	(0.077)	(0.012)
3 to 5	0.75***	3.55***	0.47***	0.88***
	(0.117)	(0.053)	(0.131)	(0.010)
6 to 10	0.96***	1.40***	0.19	0.47***
	(0.094)	(0.043)	(0.128)	(0.008)
Utilization rate (omitted group: between 1 and 24%)				
No accounts	−24.31***	6.31***	−0.96***	1.02***
	(0.106)	(0.048)	(0.033)	(0.009)
None (0%)	−3.81***	0.74***	−0.21***	0.12***
	(0.126)	(0.057)	(0.037)	(0.011)
25% to 49%	−14.59***	1.48***	−0.76***	0.15***
	(0.130)	(0.059)	(0.095)	(0.011)
50% to 74%	−23.55***	2.73***	−1.00***	0.36***
	(0.147)	(0.067)	(0.123)	(0.012)
75% or more	−29.40***	4.85***	−1.33***	1.00***
	(0.120)	(0.054)	(0.119)	(0.010)
Age of oldest account (omitted group: 120 or more months)				
<24 months	−17.12***	7.47***	−1.06***	1.06***
	(0.179)	(0.081)	(0.042)	(0.020)
24 to 59 months	−12.63***	1.27***	−0.48***	0.51***
	(0.125)	(0.057)	(0.033)	(0.011)
60 to 119 months	−10.40***	1.10***	−0.38***	0.39***
	(0.093)	(0.042)	(0.034)	(0.008)
Number of delinquencies (omitted group: observed performance without delinquencies)				
No observed performance	−32.00***	−3.27***	−1.29***	1.24***
	(0.276)	(0.126)	(0.155)	(0.063)
1 Delinquency	−28.91***	−3.79***	−0.77***	−0.26***
	(0.116)	(0.053)	(0.080)	(0.010)
2 or More delinquencies	−35.56***	−2.74***	−0.24*	0.05***
	(0.114)	(0.052)	(0.118)	(0.010)
Number of observations	232,467	232,467	232,467	232,467
Mean of dependent variable	49.99	6.94	0.01	0.46
Log likelihood	−978,150	−795,234	−6149	−119,605
R^2	0.68	0.40		

*, **, and *** denote statistical significance at the 10, 5 and 1% levels.

scores that result from this process approximate what would result if authorized-user accounts were excluded from model development. This is an approximation because we hold the selection of credit characteristics in the model fixed, since reselecting characteristics would have been prohibitively difficult (requiring us to reverse-engineer over 300 variables).

We use multivariate analysis to assess how excluding authorized-user accounts affects the scores of different demographic groups. We regress these score changes on the demographic characteristics used earlier. Because excluding these accounts alters the scoring model, everyone's score may be affected. We therefore conduct this estimation both for the scorable sample (Column 1 of Table 5) and the authorized-user sample (Column 2). We also estimate probit models of the likelihood of large positive or negative score changes (Columns 3 through 6).

The results of these estimations suggest that, even among people with authorized-user accounts, the score effects are mild on average. The largest changes are observed by younger and older age groups, with people under 30 or 62 and older experiencing score declines (relative to middle-age people) of over 1 percentile point. As with our earlier analysis, this likely reflects the greater tendency of these age groups to have thin credit files. Scores for Blacks and Hispanic Whites appear to increase when authorized-user accounts are excluded; however, these results should be treated with caution since both populations are more likely to be young or single and these characteristics are associated with smaller increases. On net, these competing effects appear to balance out: unconditional on factors other than race or ethnicity, score changes for Blacks and Hispanic Whites are very small (−.01 and .07, respectively) and not statistically significant.

Excluding authorized-user accounts appears to decrease the scores of married women. The average decline is small (0.2 percentile points), but significant at the 0.1% confidence level. Married women are also significantly more likely to experience large score declines than otherwise identical men. The score declines for married women likely reflect the fact that married women tend to have more authorized-user accounts on their credit records. While the relative score decline experienced by married women reduces the average score difference with married men, married women continue to have higher scores on average when authorized-user accounts are excluded. When the analysis is conducted separately for older married women (shown in Columns 5 and 6), similar results are observed though the magnitudes are larger. Excluding authorized-user accounts decreases the scores of older married women by an average

TABLE 5

Effects of Excluding Authorized User Account Information from Credit Scoring Models by Demographic Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Method	OLS	OLS	Probit	Probit	OLS	OLS
Sample Used	Scorable	Authorized Users	Authorized Users	Authorized Users	Scorable	Authorized Users
			Change from Re-estimation			
Dependent Variable	Score Change from Re-estimation	Score Change from Re-estimation	<−5 Points	>5 Points	Score Change from Re-estimation	Score Change from Re-estimation
Constant	0.22***	0.27***	−1.13***	−1.16***	0.17***	0.13
	(0.031)	(0.069)	(0.014)	(0.015)	(0.04)	(0.08)
Race or ethnicity (omitted group: non-Hispanic White)						
Black	−0.06	0.30*	−0.23***	−0.07*	−0.06	0.30*
	(0.039)	(0.122)	(0.027)	(0.027)	(0.04)	(0.12)
Hispanic White	0.04	0.32**	−0.15***	0.00	0.05	0.32**
	(0.044)	(0.117)	(0.025)	(0.025)	(0.04)	(0.12)
Asian	−0.08	−0.29*	0.02	−0.08*	−0.07	−0.28*
	(0.06)	(0.142)	(0.029)	(0.032)	(0.06)	(0.14)
Gender and marital status (omitted group: married male or younger married male in Columns 5 and 6)						
Single male	−0.08*	−0.19	−0.03	−0.07**	−0.10*	−0.11
	(0.038)	(0.11)	(0.023)	(0.025)	(0.05)	(0.13)
Single female	−0.02	−0.05	−0.03	−0.04	−0.05	0.02
	(0.037)	(0.101)	(0.021)	(0.022)	(0.05)	(0.12)
Married female	−0.18***	−0.22**	0.10***	0.02		
	(0.031)	(0.066)	(0.013)	(0.014)		
Younger					0.01	0.07
					(0.04)	(0.09)
Older					−0.46***	−0.37**
					(0.06)	(0.14)

TABLE 5
continued

Method	(1) OLS	(2) OLS	(3) Probit	(4) Probit	(5) OLS	(6) OLS
Sample Used	Scorable	Authorized Users	Authorized Users	Authorized Users	Scorable	Authorized Users
			Change from Re-estimation			
Dependent Variable	Score Change from Re-estimation	Score Change from Re-estimation	<−5 Points	>5 Points	Score Change from Re-estimation	Score Change from Re-estimation
Older married male					−0.08	0.13
					(0.06)	(0.15)
Age group (omitted group: aged 40 to 49)						
Under 30	-0.23^{***}	-1.07^{***}	0.22^{***}	−0.04	-0.20^{***}	-1.05^{***}
	(0.037)	(0.108)	(0.021)	(0.024)	(0.04)	(0.11)
30 to 39	0.03	0.12	-0.04^{*}	0.02	0.05	0.12
	(0.035)	(0.083)	(0.018)	(0.018)	(0.04)	(0.08)
50 to 61	-0.11^{**}	-0.26^{***}	0.07^{***}	-0.05^{**}	0.05	−0.12
	(0.035)	(0.077)	(0.016)	(0.017)	(0.04)	(0.12)
62 and over	-0.21^{***}	-1.03^{***}	0.20^{***}	-0.15^{***}	−0.05	-0.88^{***}
	(0.035)	(0.081)	(0.016)	(0.018)	(0.04)	(0.12)
Number of observations	232,467	81,346	81,346	81,346	232,467	81,346
Mean of dependent variable	0.018	−0.304	0.154	0.114	0.02	−0.30
Log likelihood	−712,337	−280,369	−34,515	−28,850	−712,301	−280,359
R^2	0.00	0.01			0.00	0.01

*,**, and *** denote statistical significance at the 10, 5 and 1% levels.

0.46 percentile points, though the scores of older married women remain about 3 percentile points above those of older married men.

An additional consideration in deciding whether authorized-user accounts should be included in credit scoring models is the predictive power of the information. Reg. B's requirements were predicated in part on the belief that the information would be predictive, at least for spousal authorized users. However, since an authorized user is not liable for debts incurred, one might expect these accounts to be less informative about whether he will make timely payments on his own accounts. We assess the predictive value of authorized-user accounts by comparing the FRB base scores to the scores generated by the re-estimated model, in terms of how well they predict future credit performance.

Both scores were generated using credit records from June 30, 2003. As our measure of future performance, we identify nonauthorized-user accounts that were opened during the subsequent six months (July to December 2003) and evaluate performance on these accounts over the same 18-month performance window, and using the same definition of performance, as was used in estimating the FRB base model. Since these accounts were opened after the date for which the scores were calculated, nothing about these accounts affects the scores themselves.

Predictiveness is measured using the Kolmogorov-Smirnov ("KS") statistic, a commonly used measure of goodness of fit for credit scoring models (Mays 2004). The KS for the FRB base scores (.582) is slightly higher than the KS for the re-estimated model (.578), but the Krzanowski and Hand (2011) test suggests that this difference is not statistically significant ($p = .326$).[18] This suggests that authorized-user accounts provide little additional predictive value.[19]

Similarly, when we evaluate the predictive value that authorized-user accounts provide for specific demographic and credit characteristic groups, the results suggest that for most groups including authorized-user accounts has an insignificant effect on the KS statistic. This includes married women ($p = .106$) and many other groups whose scores were most affected by including authorized-user accounts, such as people

18. Because both scores come from the same sample of credit records, they are not independent and most common significance tests are inapplicable. The Krzanowski and Hand test evaluates the significance of differences when scores come from the same sample. Reported p-values are based on 10,000 draws.

19. Since we required the model that was re-estimated without authorized-user accounts to contain the same selection of credit characteristics as the FRB base model, the KS statistic for the re-estimated model likely underestimates what model builders can achieve by reselecting characteristics. As a result, our estimate of the value of authorized-user account information is likely overstated.

with credit histories shorter than 24 months ($p = .218$) and the young ($p = .644$). People with two or fewer nonauthorized-user tradelines provide a notable exception. For this group, the KS from the FRB base model (.643) is higher than the KS from the re-estimated scores (.629), a statistically significant difference ($p = .015$) that implies including authorized-user accounts enhances the predictiveness of credit scoring models for people with thin files.

Taken together, these results suggest that authorized-user accounts provide little additional information about future credit performance. However, it is also notable that including information about these accounts did not decrease the KS statistic, an outcome that might have been expected if authorized-user accounts were completely uninformative. While this information does not appear to increase the accuracy of the creditworthiness signal that scores provide, it also does not appear to decrease it.

CONCLUSIONS

The existence of piggybacking credit raises important questions about how authorized-user accounts should be treated when assessing creditworthiness. These questions are particularly acute in the context of credit scoring models, where some interpret Reg. B as requiring equal treatment for authorized-user accounts.

Our analysis suggests that concerns about the potential harm from piggybacking are warranted. Piggybacking appears to be an effective means of increasing credit scores, particularly for people with thin or short credit histories. Score increases are often sufficient to materially improve the credit profile of borrowers, potentially allowing them to obtain credit for which they would not otherwise have qualified. Though we cannot determine how often this occurs, piggybacking represents a vulnerability in the credit granting process that, if exploited often enough, can be expected to reduce the quality of the signal that scoring provides. As a result, it would reduce the efficiency of credit allocation and the availability of credit.

Some lenders have responded to the dangers posed by piggybacking by reducing or eliminating the consideration of authorized-user accounts in their credit scoring models. Such models, however, may not comply with Reg. B. This raises the question of whether the requirements of Reg. B should be amended to allow credit scoring models to ignore authorized-user accounts. Doing so would remove the potential harm from piggybacking, but might adversely affect credit access for some consumers.

Among the demographic groups that might be affected by such a change are married women whose circumstances in the 1970s motivated the provisions of Reg. B governing authorized-user accounts. Our analysis suggests that these circumstances have changed in the years since Reg. B was originally drafted. We find little evidence that married women have less complete credit records than married men. While older married women have fewer nonauthorized-user accounts on average, married women generally tend to have more open accounts and credit scores that are significantly above those of married men even when authorized-user accounts are excluded. Nevertheless, authorized-user accounts appear to be a net positive for the credit scores of married women and excluding these accounts lowers their credit scores.

For most other demographic groups, authorized-user accounts make a surprisingly nuanced contribution to credit scores. The scores of these groups, notably including Blacks and Hispanic Whites, are little changed when authorized-user accounts are excluded. Nevertheless, some demographic groups, particularly people younger than 30 or 62 and older, experience significant score declines from excluding authorized-user accounts. For people 62 and older, the score declines should have less effect on credit access as their scores tend to be well above average and most will likely continue to qualify for prime credit. The consequences for people younger than 30 will likely be more substantial, as their scores tend to be lower, principally reflecting their shorter account histories.

The large score effects for people younger than 30 are also notable because these may reflect one of the traditional uses of authorized-user account status, helping children build credit histories. Parent–child authorized-user relationships lie somewhere between the extremes of spousal authorized-user accounts and piggybacking on the accounts of strangers, in that considering these accounts may not adversely affect the quality of the signal that scoring provides. Parents with good credit histories may be more likely to teach good financial management practices to their kids or be more likely to have the resources (and willingness) to help their children pay credit obligations. While Reg. B does not require the consideration of parent–child authorized-user accounts, any decision about Reg. B's requirements should also explicitly consider how these accounts should be evaluated and the effects the decision will have on access to credit for the young.

While our analysis has evaluated a single response to piggybacking—excluding authorized-user accounts—there are other possible responses. Allowing partial consideration of these accounts might mitigate the threat posed by piggybacking while retaining some of the benefits these accounts provide. Our analysis has not examined these partial approaches because evaluating the myriad different ways they might be operationalized is well beyond the scope of this article, particularly given that some of these methods, such as FICO's, are proprietary and have not been publicly disclosed. We expect that partial consideration approaches will produce score effects in between the extremes that we evaluate. Nevertheless, before any of these alternatives could be widely adopted, the requirements of Reg. B that we discuss in this paper would have to be altered or clarified.

Another potential response, which we also do not evaluate, is to require that lenders identify which authorized users are spouses when furnishing information to the credit bureaus. Such an approach could provide equal treatment to spousal authorized-user accounts without requiring it for all authorized-user accounts (including piggybacked accounts). However, this approach would likely entail significant compliance costs. To comply with such a requirement, lenders would have to know the relationship not only when the authorized user is added to the account but also on an on-going basis to account for marriages and divorces. Since these compliance costs cannot be estimated from our data, we have not focused on this option.

A third potential response is to outlaw the practice of piggybacking itself. This may be the least effective solution. Even if federal laws were enacted to shut down the intermediaries that facilitate this practice, the underlying problem would remain. Many credit counselors routinely recommend that people looking to repair their credit or build a credit history piggyback on the accounts of friends or relatives. Fundamentally, this is exactly the same conduct in that it allows people to acquire the credit history of others but without the need for a middleman. While getting rid of the intermediaries could restrict the number of credit lines available for piggybacking to those possessed by willing relatives and friends, piggybacking would remain an option for many.

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