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Borrower Credit Access and Credit Performance After Loan Modifications

Abstract

While the preventive effect of loan modifications on mortgage default has been well-documented, evidence on the broad consequences of modifications has been fairly limited. Based on two unique loan-level data sets with borrower credit profiles, this study reports novel empirical evidence on how homeowners manage their credit before and after receiving modifications. The paper has several main findings. First, loan modifications improve borrowers' overall credit standing and access to credit. Modifications that provide principal reduction, rate reduction, or greater payment relief, as well as those received by borrowers not in financial catastrophe, lead to a larger improvement in borrowers' credit rating than others. Second, loan modifications lead to a slight increase in borrowers' debts, primarily on home equity line of credit (HELOC) accounts and auto loans. Third, borrowers' performance on nonmortgage accounts, however, has not been negatively impacted by modifications. This study demonstrates that interventions designed to improve household balance sheets could have a direct and sizable impact on borrower financial outcomes.

Keywords: loan modification, credit score, credit performance, mortgages

JEL Classification: D12, E20, E51, E65, G21

1. Introduction

A loan modification, which usually results in changes in a mortgage's contract terms not specified in the original contract,[1] is a loss mitigation practice aimed at helping troubled borrowers work out solutions and keep their homes. In the most recent housing cycle, many loan modification programs were developed in the U.S. to prevent financially struggling households from foreclosure, among which the federal government's Home Affordable Modification Program (HAMP) has been one of the most important modification programs. According to the Office of the Comptroller of the Currency (OCC) (2014), more than 3.6 million mortgages had been modified from 2008 to June 2014, about 1.4 million of which were modified under the HAMP program.

While prior empirical studies have provided generally consistent evidence on the preventive effect of loan modifications on mortgage default, evidence on the broad consequences of loan modifications has been fairly limited. One concern is the possible negative spillover effects of modifications on borrowers' future access to credit and performance on unsecured debt (Kim 2015). With a better chance of preserving their homes after receiving modifications, borrowers may be more likely to borrow more or to delay the payments on other debts, which could hurt the borrowers' creditability.

This study provides new evidence on borrowers' credit experience following loan modifications using two complementary loan-level data sets. The data sets provide a sufficiently large national sample with information on a rich array of consumer outcomes, such as credit scores and the quantity, balance, and performance of different outstanding credit accounts, in addition to the mortgage information. Such data sets allow for an examination of the full credit

[1] These changes may include one or more of the following: capitalization of arrears, extension of contract terms, interest rate freeze, reduction in mortgage interest rates, and principal reduction or forbearance.

portfolio of mortgage borrowers to detect even small effects of loan modifications in noisy consumer credit measures. The data sets also provide information for constructing two different loan modification measures: modifications that are identified by tracking changes to mortgage contract terms (*contract-change algorithm*) and those reported directly by servicers (*servicer-reported*). Such a cross-check improves the confidence in the robustness of the results. This study first identifies all modifications before 2013 out of a random sample of first-lien mortgages originated between 2005 and 2009. A comparison group has then been constructed by matching individuals with delinquent but not modified loans with individuals with modified loans based on the premodification characteristics.

No matter which measure is used, there is compelling evidence of a significant improvement in borrowers' overall credit standing after modification. Compared with those in the control group, a borrower's risk score, one widely used credit score, improves by an average of 40.7 points in 6 months, 36.4 points in 12 months, and 28.9 points in 24 months after receiving a modification. This is likely due to the curing of existing mortgage delinquencies and the potential spillover effects of loan modifications on the performance of other accounts. The improvement in borrowers' access to credit is also manifested by borrowers' ability to keep more credit cards and to have higher credit limits postmodification.

Furthermore, loan modifications slightly increase (about 8%) borrowers' debts on selected credit accounts, primarily on home equity line of credit (HELOC) accounts and auto loans. One possible explanation is that borrowers are more likely to slow down the speed of paying off their debts on these nonmortgage accounts to make their mortgage payments on time postmodification. Borrowers' performance on nonmortgage accounts, however, has not been negatively impacted by modifications, and one set of analyses based on contract-change modifications even suggests borrowers' performance on most nonmortgage accounts has been improved slightly after modification.

This study also finds significant heterogeneity in the effect different types of loan modifications have on credit rating and credit performance. Modifications with a reduction in the principal are the most effective ones in improving borrowers' access to credit and mortgage performance, followed by rate-reduction and term-extension modifications. Modifications that significantly reduce mortgage payments, thus providing more liquidity to troubled borrowers, lead to a larger improvement in borrowers' risk scores and mortgage performance as well. The finding is consistent with that of Keys et al. (2014), who find that lower mortgage payments (through refinancing into mortgages with lower rates) increase new auto financing and improve the overall household credit standing.

Financially troubled borrowers strived to keep their homes and to maintain or improve their access to credit during the housing crisis. While loan modifications were initially designed as a tool for foreclosure prevention, there could be significant ex post benefits on borrowers' access to credit and credit performance. Findings of this study are consistent with this contention and confirm a modest but significant improvement in borrowers' credit standing, although the generally positive effects depend on their financial situations and the intensity of the intervention. The results from this study support the view that interventions designed to improve household balance sheets could have a direct and sizeable impact on borrowers' financial outcomes.

The rest of the paper is organized as follows. Section 2 discusses how loan modifications may impact borrowers' credit experience and provides a brief review of the relevant literature. Section 3 describes the data and methodology in more detail. Section 4 presents the empirical results, and Section 5 concludes.

2. Background and Literature Review

As a tool for foreclosure avoidance, loan modifications could have a much broader impact on the borrowers' economic and financial life, such as on their credit scores and access to credit. For example, how a loan modification is reported by the lender may affect a borrower's credit score. Before loan modifications were implemented on a large scale, a credit inquiry and changes to the balance or the terms of a loan may have affected a borrower's credit score if the loan modification was reported as the same loan with changes or as an entirely new loan (VantageScore 2010). But more recent developments suggest that lenders that have standardized their reporting processes and modifications through large-scale intervention programs, particularly those endorsed by the U.S. government, may have no impact on credit scores at all. Comparatively, the reset of delinquency to current should have a far greater impact on credit scores than recording the loan modification itself.[2] So in a longer term, the effect of a loan modification on a borrower's credit score may largely depend on the curing of mortgage delinquency, the prevention of new mortgage defaults, and the potential spillover effect on other credit accounts.

The literature suggests two hypotheses on the impact of loan modifications on consumers' behavior on other nonmortgage accounts. The first hypothesis is that the potentially increased liquidity induced by modifications could help improve the performance on other accounts as well. Empirical studies have provided evidence that a loan modification, especially one that enhances a borrower's affordability (e.g., a modification that generates a lower monthly mortgage payment), is strongly associated with a lower postmodification redefault rate

[2] How recent a mortgage delinquency is has been an important factor in credit scoring models, and modifications automatically cure mortgage delinquencies by resetting existing delinquencies as current after modification.

(Haughwout, Okah, and Tracy 2010; Quercia and Ding 2009; Agarwal et al. 2012; Schmeiser and Gross 2014; Scharlemann and Shore 2015). Moreover, recent studies have also stressed the importance of liquidity on default behavior (Elul et al. 2010). A residential mortgage is usually the largest single debt in a homeowner's credit file, and housing expenditures are typically about 30% to 35% of total household income. As long as a loan modification can reduce the debt or payment significantly,[3] the increased liquidity could help improve a borrower's credit performance by curing existing delinquencies and preventing new defaults on credit cards and other accounts. So, if troubled borrowers can get some financial breathing room through modifications, the likelihood of default on either their mortgages or other debts should be reduced. However, two factors need to be considered here. First, most modifications programs, such as HAMP, only reduce mortgage payments to a more affordable level (e.g., 31% of debt-to-income (DTI) ratio), which may not provide much relief for payments on accounts other than mortgages, especially for borrowers with significant unsecured debt. Additionally, if borrowers start to make mortgage payments in a timely manner postmodification, they are less likely to benefit from the liquidity of delaying the mortgage payment before modification.

The second hypothesis is that, depending on the level of increased probability of keeping their homes gained from a loan modification, homeowners could be more likely to prioritize their home mortgages over payments on other credit accounts. Consumer finance literature has examined the choice between prioritizing mortgage payments or payments on other accounts (Cohen-Cole and Morse 2010; Jagtiani and Lang 2011; Andersson et al. 2013; Chan et al. 2015). If borrowers place their home mortgages at the top of their debt payment hierarchy after

[3] It has been reported that these programs resulted in lower monthly principal and interest payments on more than 90% of recently modified loans, with more than a half (58.6%) having payments reduced by 20% or more (OCC 2014). According to the OCC, modifications reduced payments by an average of $292 per month, while modifications made under HAMP reduced monthly payments by an average of $312.

modification, their performance on other debt could deteriorate as payments on various accounts compete for a limited budget. And, historically, homeowners had prioritized their mortgage payments over the payment of other unsecured debt and had been careful to pay their mortgages. Andersson et al. (2013), for example, find that nonprime borrowers are eight times more likely to default on their credit cards rather than their mortgage debt before the recent housing crisis. During the recent housing market recession, however, homeowners were often found to service other types of debt at the risk of losing their homes in an effort to preserve liquidity and access to credit. Cohen-Cole and Morse (2010) find that many individuals paid credit card bills even at the cost of mortgage delinquencies and foreclosures during the housing crisis likely because borrowers are more concerned about imminent individual-level liquidity (access to credit card borrowing) than the risk of losing their home in the longer term. Of course, servicers may also select borrowers who are more likely to prioritize mortgage payments over payments on other accounts during underwriting. As a result, a borrower's performance on credit accounts other than the mortgage may deteriorate after modification.

A few recent studies touched on the impact of loan modifications on the performance of other accounts. Calem, Jagtiani, and Lang (2016) focus on the impact of foreclosure delay on a borrower's access to credit. Using a sample of loans that entered foreclosure, their study explores the impact of loan modifications on the probability of curing borrowers' existing delinquencies on their credit card debts. The authors find that modifications generally improve the curing probability of credit card delinquencies and reduce the balance on credit cards for borrowers already in foreclosure. However, since the study focuses on loans already in the foreclosure process, whether their findings hold for the general population of loan modifications is still unknown.

Another recent study by Keys et al. (2014) does not focus on loan modifications directly but is relevant to this study. The authors find that a moderate decline in mortgage payments ($150 per month) induces a significant drop in mortgage defaults, a more than 10% increase in auto lending, and an increase of 5.7 points in borrowers' credit scores within 2 years. A theoretical work by Kim (2015) suggests that mortgage default rates decrease with modifications, but unsecured loan charge-off rates increase. The author suspects that when house price is persistently low, along with income shock, a household is more likely to default on its unsecured debt while preserving its home. Kim's (2015) work provides a useful theoretical framework to study the optimal borrowing and default decisions of households, but there is a lack of empirical tests of the theoretical model. In addition to the studies more closely related to consequences of loan modifications, this study on access to credit and credit performance in the context of loan modification relates to literature on credit experience following various shocks, such as foreclosure, bankruptcy, or unemployment (e.g., Han and Li 2011; Brevoort and Cooper 2013; Cohen-Cole, Duygan-Bump, and Montoriol-Garriga 2013; Jagtiani and Li 2014; Dobbie and Song 2015).

Overall, the existing literature on loan modifications primarily focuses on the incidence of loan modifications and the preventive effects of loan modifications on mortgage redefault. To date, there is limited knowledge on the credit experience of troubled borrowers following loan modifications. This study examines this issue empirically.

3. Data and Methodology

This study primarily relies on the Equifax Credit Risk Insight Servicing McDash (CRISM) database, which contains credit bureau data from Equifax on individual consumers matched to mortgages in the Black Knight Financial Services data (also known as McDash data). The McDash data provide information collected at loan origination and subsequent payment activity in each month after origination. To create the CRISM database, Equifax used anonymous fields, such as original and current mortgage balance, origination date, zip code, and payment history, to match each loan in the McDash data to a particular consumer's mortgage records.[4] For McDash loans that can be matched with Equifax mortgage records, the CRISM data provide additional information on the credit history of mortgage holders in each month 6 months before origination to 6 months after termination of the mortgage. The CRISM data also contain monthly information on borrowing and the payment of various accounts, such as credit cards, retail cards, auto loans, student loans, HELOC loans, and others, for the primary borrowers and co-borrowers. CRISM further provides estimated personal income[5] and a DTI score, which is based on a borrower's debt obligations and estimated income and predicts a consumer's ability to pay.[6] More general information available in the data includes the residential location of the borrower at the zip code level and the borrower's year of birth. Put together, the CRISM data allow for a comprehensive look at an individual mortgage borrower's overall credit portfolio. The second data set used in this study is the McDash Loss Mitigation (MLM) data, which provide information on loss mitigation activities (including loan modifications) collected by selected servicers that report data to the McDash core data set. The MLM data set is one of a few large data sets that provide information on loan modifications reported by servicers. The Appendix provides more details about the MLM data and a comparison of the loan modification measures that are constructed using these two data sets.

[4] According to Equifax, approximately 90% of the mortgage loans have a good match, which have match confidence scores above a threshold.
[5] The estimated annual personal income is based on credit file attributes and behaviors. Actual income information is not available for the proprietary data set because of use restrictions.
[6] The DTI score is not a real DTI ratio. It is a credit score that uses the DTI framework to determine a consumer's ability to pay. The score ranges from 1 to 990, with 990 indicating the highest debt risk.

Loan modifications are identified based on a contract-change algorithm similar to the one developed by Foote et al. (2010) and Adelino, Gerardi, and Willen (2013), which identifies loan modifications based on the changes in the mortgage's terms that are not stipulated by the initial terms of the contract. These changes include capitalization of arrears, interest rate reductions, principal balance reductions, and term extensions (see a detailed description of the algorithm in Adelino, Gerardi, and Willen 2013). This study further uses a sample of servicer-reported loan modifications in the MLM data as a robustness check. This study primarily relies on the contract-change algorithm, instead of servicer-reported data, for two considerations. First, the contract-change algorithm provides a more consistent estimate of loan modifications than do servicer-reported data (Adelino, Gerardi, and Willen 2013). Many servicer-reported modifications do not involve meaningful changes in loan terms. My own evaluation suggests that almost 28% of servicer-reported modifications fail to change the loan terms in a way that can be identified as modifications by the contract-change algorithm (see more details in the Appendix). They could involve small or no changes in any of the loan terms (e.g., interest rates, principal, term, or payment). As such, it is questionable to consider all servicer-reported modifications as interventions that would have a meaningful impact on a borrower's financial life. Second, the number of modifications identified by the contract-change algorithm and the number reported by servicers had converged over time, especially after 2008 (Adelino, Gerardi, and Willen 2013). This study confirms that the time trends in the volume of modifications identified by either method are extremely similar during the study period (Figure 1).

The CRISM data set, which has been updated monthly, goes back to June 2005. This study, therefore, starts with a 5% random sample of all first-lien originations between 2005 and 2009 in CRISM and then uses the contract-change algorithm to identify loan modifications during the 2005 to 2012 period. Borrowers' credit scores, credit limits, credit uses, and credit performances have been tracked until the end of 2014. Recent loan modifications (those modified after 2012) are not included to allow a reasonable amount of time to observe the impact of loan modifications. The results, therefore, may not represent the experience of borrowers with older originations or those with loans that were modified before or after our study periods. Loans that have received modifications multiple times and borrowers with multiple first-lien mortgages were excluded from the sample because it is difficult to isolate the impact of each individual loan modification. This study has a total of 65,504 unique loan modifications (individuals) for the match.

Analysis Sample

After identifying loan modifications using the contract-change algorithm, this study uses a cell match algorithm similar to the one used by Molloy and Shan (2013)[7] to construct a comparison group in which troubled borrowers with modified loans are matched with those who are at least moderately delinquent (60+ days) on their first-lien mortgages but who have not received modifications. The control group focuses on 60+ day delinquencies because modified loans usually experience at least a moderate delinquency before receiving modifications.[8] Also, focusing on moderately delinquent mortgages helps distinguish between individuals who face a shock and those who casually miss payments. The premodification characteristics that are considered in the matching include the risk score of the primary borrower (<550, 550–679, and ≥680), mortgage loan balance (<$200k, $200k–$399k, and >$400k), estimated DTI score (<650,

[7] Molloy and Shan (2013) matched troubled borrowers who ended up in foreclosure with those who did not based on a set of borrower and loan characteristics as well as the location of the property.

[8] Delinquent loans already in a later stage of foreclosures (post sale or real estate owned) were excluded because they are usually less likely to receive modifications and may have characteristics significantly different from loans that could be considered for modifications.

650–749, and ≥750), whether the borrower has any credit cards, and the level of mortgage default before modification (30–60 days delinquency, 90+ days delinquency, or in foreclosure). Furthermore, for each loan modification, I search for all loans that became moderately delinquent roughly in the same period (within 6 months from the initial delinquency of the modified loan), with borrowers living in the same geographic area (zip code), and that have characteristics that fell into the same cell but did not receive a loan modification during the sample period. If I could not match any delinquent loans in the same zip code with a modification, I broaden the geographic area to the county. To make borrowers in the matched group more comparable, I add the following factors for the match at the county level:[9] borrower age (≤35, 36–50, and ≥51), mortgage cohort (2005 to 2006 or 2007 to 2008), and estimated borrower income (≤$35k, $36k–$75k, and ≥$76k).[10]

The matched data set has 14,718 unique borrowers with modified loans (out of the total of 65,504 modifications identified by the contract-change algorithm; with a match rate of 23%), which are matched by 20,812 unique borrowers with delinquent loans. Approximately 42.7% of loan modifications are matched at the zip code level, and 57.3% are matched at the county level. Because there are some one-to-many or many-to-many matches, the total number of observations is 49,388.[11] Following the standard procedure in matching estimation, I weight borrowers to give equal weight to the modification and comparison groups. Modifications that do not have matches even at the county level are excluded from the analysis (50,786 out of the initial sample of 65,504 modifications). Although a significant share of modifications could not be matched, a

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[9] The three additional matching variables have been introduced to reduce the number of duplicates in a relatively large geography (county). Additional analysis suggests the results generally do not change qualitatively when both matches use the same set of matching variables.

[10] Borrower income is the sum of the estimated annual personal income for primary borrowers and coborrowers.

[11] The total number of observations is 42,006 for the match sample using the servicer-reported modifications, with a total of 9,123 servicer-reported loan modifications and 16,262 delinquent loans. The number of matched loans is smaller because not all servicers (about 3 out of 4) have reported their loan modifications.

rough comparison based on the observables suggests the matched sample does not show sharp differences from the full sample: The differences for mean risk scores, age, and borrower income are insignificant, while the differences are generally small for most other characteristics. So the representation of the matched sample should not be a major concern here.

Table 1 reports a number of summary statistics for the modification group and the matched group, which are all measured in the month just before modification (or the month being matched with a modification). For the matching variables, the differences between these two groups are either insignificant (such as risk score and borrower income) or quite small (such as principal balance). Figure 2 shows the distributions of risk scores for the treatment group and the control group. The distributions of both groups are extremely similar. Of course, there are systematic differences between the two groups in terms of many variables not considered in the match. For example, borrowers in the control group generally have slightly larger unsecured debts and higher delinquency rates on accounts other than mortgages, which should be controlled in the regression analysis. Overall, borrowers in the matched sample generally have similar risk scores, DTI scores, estimated borrower incomes, principal balances, ages, number of credit cards, and levels of mortgage delinquency before modification, although they have slightly different levels of debts and delinquency on credit accounts other than mortgages. They also live in the same geographic area and experience mortgage delinquency roughly during the same time period.

It needs to be noted that there are many matching algorithms other than the cell match algorithm used here. However, the challenge for the mortgage study is that a panel data set (payment history) is used in the match. While the timing of treatment for borrowers who have received modifications can be easily identified, the timing of the matching for individuals in the control group is hard to determine (in which month they should be matched with one with a modified loan). And to better isolate the impact of local market conditions on various outcomes, this study wants to match borrowers in the same geography. So this study has chosen the cell match to have more precise matches.

Key Outcomes

The following is a list of variables (or groups of variables) used in this study to measure borrowers' access to credit, credit use, and credit performance (see Table 2 for detailed definitions of the variables used in the model):

- *Credit score*: The primary borrower's risk score is used as the summary measure of an individual's creditworthiness and the ability to obtain credit.
- *Credit limit*: Credit limit, which captures the amount of credit that lenders are willing to offer, serves as an important indicator of a borrower's access to credit. The credit limits of credit cards, HELOC accounts, retail cards, and consumer finance accounts[12] are used as measures of access to credit. The number of credit cards the primary borrower has is also used as an alternative measure of access to credit.
- *Credit balance*: The balances on all revolving accounts, as well as balances on credit card accounts, HELOC loans, auto loans, retail accounts, student loans, and consumer finance accounts, respectively, are used to capture the credit use and borrowing pattern of a borrower before and after modification.
- *Utilization rate*: Credit card utilization rate, which is the ratio between credit balance and the total credit limit, is another important measure of both credit use and access to credit.

[12] Consumer finance loans, which often bear high interest rates, are usually granted to people with poor credit histories who often cannot get loans from traditional lending companies, such as banks or credit unions.

- *Credit delinquency*: This term indicates whether the payment on a credit account is late at the end of a particular month (30+ days delinquent). The delinquency status of borrowers on first-lien mortgages, credit cards, HELOC loans, auto loans, retail accounts, student loans, and consumer finance accounts has been tracked in this study.

Methodology

With the matched sample, I use a difference-in-differences (DID) framework to estimate the treatment effect of loan modifications by comparing the average change in an outcome variable for the treatment group (borrowers with modified loans) before and after the modification with the average change for the control group (borrowers with delinquent but not modified loans). In order to track the outcomes in three different periods (6 months, 12 months, or 24 months after modification), this study considers two groups (treatment and control) and four periods (one premodification period and three postmodification periods). The model can be specified as:

$$Y_{it} = \beta_0 + \beta_1 * POST_{it} + \beta_2 * MODIFY_i * POST_{it} + \beta_3 * D_i + \varepsilon_{it}$$

where:

- Y_{it} is the value of the outcome measure Y for the primary borrower i (the experience of co-borrowers not considered here) at the end of month t (the month before modification as the reference group, and 6 months, 12 months, or 24 months after modification). This study focuses on the short-term impact of loan modifications to up to 2 years afterward.[13]
- $POST_{it}$ represents different study periods for individual i (the month before modification, and 6 months, 12 months, or 24 months after modification).

[13] Considering the relatively lengthy foreclosure process and the extended observation period on borrower credit information (6 months immediately preceding origination and 6 months following termination), a 24-month follow-up period should not suffer from serious censoring issues.

- $MODIFY_i$*$POST_{it}$ represents three interaction terms (borrowers receiving modifications and three postmodification dummies). The loan modification dummy is not included since the individual fixed effect has been controlled.
- D_i represents the individual fixed effect for individual *i*, which helps control for individual-level unobserved heterogeneity.

To correct for serial correlation within individual markets, the standard errors are clustered at the county level. For selected outcome variables, the regressions are run separately for borrowers with or without delinquent credit card accounts. Borrowers who are delinquent on both mortgages and other accounts before modification are likely facing more serious liquidity problems and probably in a shock large enough to force a financial catastrophe. Consequently, the impact of loan modifications may be different for borrowers with more serious financial troubles.

4. Empirical Results

Descriptive Analysis of the Matched Sample

The discussion of empirical results that follows focuses on those based on the contract-change algorithm, as mentioned earlier. A few observations stand out from the descriptive analysis that illustrates the change of a variety of outcome measures before and after loan modifications for the matched group (Figures 3–6). First, the risk scores for borrowers with modified loans start to recover immediately after modification, while borrowers in the control group see their risk scores continue to decline for another 4 months on average (Figure 3). Second, there is a decline in the number of credit cards and the total amount of credit limits for both groups, but, compared with the control group, the decline is relatively less for borrowers with modified loans (Figure 4). In other words, delinquent borrowers in the control group experience sharper declines in their credit limits and the quantity of credit cards than do those who receive modifications. Borrowers in the control group also have higher utilization rates on credit cards, relative to borrowers receiving modifications. This could be explained by a more significant decline in the credit limits on their credit cards or selection effects: Those less likely to utilize credit cards are more likely to seek loan modifications. Third, with respect to credit balances, borrowers in the control group experience a sharper decline in the balances on their credit cards, auto loans, and HELOC loans than do those in the treatment group (Figure 5). Finally, the delinquency rates (30+ days) of credit cards, HELOC loans, consumer finance loans, and mortgages are relatively lower for the treatment group postmodification (Figure 6). Results from the descriptive analysis, however, are suggestive only, and more concrete conclusions can be drawn from the regression analyses discussed in the following section.

Impact of Loan Modifications on Borrowers' Credit Scores

Regression results confirm that loan modifications are linked to a significant increase in borrowers' risk scores (Table 3). A typical modification leads to an increase of 40.7 points in the primary borrower's risk score in 6 months, about 7.2% relative to the premodification mean. The positive effect fades slightly over time, decreasing to an improvement of 36.4 points (6.5% of the premodification mean) in 12 months and 28.9 points (5.1% of the premodification mean) in 24 months postmodification. This narrower gap between these two groups over time is consistent with the notion of mean reversion of credit scores documented in the literature, which suggests that the impact of the negative or positive events an individual experiences (e.g., foreclosure or a loan modification) on the individual's credit score decreases over time (i.e., time decay of information) and that the score differences between borrowers with good credit and bad credit tend to cluster around the mean credit score (Anderson 2007). The ability to keep a relatively higher risk score has important implications for troubled borrowers' access to credit and their economic and job opportunities. For example, recent studies suggest that a 100-point increase in credit score is associated with an average reduction in interest rate of 100 to 300 basis points (e.g., Agarwal et al. 2015).

This study further explores the heterogeneity in the effects of loan modifications on borrowers' risk scores across different types of modifications (Table 3). Among various types of modifications, principal-reduction modifications lead to the largest increase in risk scores (an increase of 39.9 points in 12 months), higher than rate-reduction modifications (38.8 points), term-extension modifications (31.0 points), and other types of modifications (23.2 points) that usually lead to unchanged or increased mortgage payments. All the changes are significant at the 0.01 level. The level of risk score improvement also depends on the level of payment relief gained from loan modifications. In 12 months, modifications that result in an unchanged or increased mortgage payment lead to an average increase of 25.0 points in borrowers' risk scores, whereas modifications that induce a payment reduction are associated with larger increases in risk scores (about 33.9 to 46.4 points).

For these borrowers who have more financial challenges (e.g., being late on their credit card payments before modification), loan modifications lead to an average increase of 26.0 points in their risk scores in 6 months and 13.9 points in 12 months, much lower than the average increases of 40.7 points (6 months) and 36.4 points (12 months) for all matched borrowers with modified loans (Table 3). The positive effect of loan modifications on borrowers' risk scores becomes much less for borrowers who are likely to have more serious financial troubles.

Impact of Loan Modifications on Other Measures of Credit Access

The increase in borrowers' access to credit after modification is also reflected by borrowers' ability to keep more credit cards and to retain a higher level of credit limit postmodification (Table 4). Relative to the control group, borrowers with modified loans are able to keep slightly more credit cards (0.07, 0.12, or 0.23 more in 6 months, 12 months, or 24 months). To put this in context, these increases are about 2.6%, 4.8%, or 9.2% relative to the premodification mean of 2.5 credit cards per borrower. These borrowers are able to keep higher credit limits as well: The credit limits on credit cards for borrowers with modified loans are on average \$383 higher in 6 months, \$1,132 higher in 12 months, and \$1,839 higher in 24 months (or 2.3%, 6.8%, or 11.1% relative to the premodification mean) than that of a borrower in the control group. As to other credit accounts, 12 months later, the credit limit is on average \$5,116 higher on HELOC loans (or about 6.8% relative to the premodification level), \$283 higher on retail cards (7.9% of the premodification mean), and \$251 higher on consumer finance accounts (3.4% of the premodification mean) for borrowers with modified loans. This is consistent with the finding of a greater improvement in risk scores for the treatment group: Borrowers receiving loan modifications have higher risk scores, and consequently lenders are less likely to close their credit accounts or lower their credit limits. Of course, the ability to keep higher credit limits or more credit accounts can positively impact risk scores as well.

Impact of Loan Modifications on Borrowers' Credit Use

Assuming a mortgage borrower's budget is constrained, the speed with which the borrower pays off debts on other accounts could be slower when the borrower prioritizes the mortgage payment over other payments. The results suggest loan modifications lead to a slight increase in the balances of revolving accounts, with an average increase of $1,819 in 6 months, $3,050 in 12 months, and $3,884 in 24 months (Table 5). More specifically, loan modifications are associated with increases in borrowers' balances on their HELOC loans ($5,230 larger, or 8.2% of the mean), auto loans ($1,290 larger, or 7.9% of the mean), and retail accounts ($96 larger, or 7.0% of the mean). The coefficients are insignificant for credit cards, consumer finance accounts, and student loans. The larger balances on various credit accounts are consistent with the contention that budget-constrained borrowers have to borrow short-term debt from or slow the speed of paying off the balance on other accounts after modification. But it may also reflect the improved ability to access credit for troubled borrowers after they receive modifications. In fact, while borrowers with modified loans have a slightly higher level of credit card debt ($226 higher though not significant), their credit card utilization rates become even lower relative to that of the control group (about 2.4 percentage points lower in 12 months). This could be explained by the finding that borrowers in the treatment group are able to retain a much higher credit limit than borrowers in the control group, and consequently they are able to hold a relatively higher level of debt. Borrowers in the control group, in contrast, hold a lower level of debt likely because they have more constraints to accessing credit.

Impact of Loan Modifications on Borrowers' Credit Performance

Loan modifications lead to lower delinquency rates on various credit accounts (e.g., credit cards, HELOC, retail cards, and consumer finance accounts; see Table 6). A loan modification is associated with a decrease of 2.8 percentage points in the probability of being late on credit cards (or 8.3% relative to the premodification mean) in 12 months. Loan modifications are also associated with significant decreases in the risk of delinquency for HELOC loans (a reduction of 11.3 percentage points in 12 months, or 36.7% of the premodification mean), retail cards (a reduction of 3.0 percentage points in 12 months, or 13.6% of the mean), and consumer finance accounts (a reduction of 4.4 percentage points in 12 months, or 17.3% of the mean). The impact of modifications on the performance of auto loans and student loans is insignificant. Overall, results suggest loan modifications help improve borrowers' performance on most nonmortgage credit accounts. However, the generally positive effect of loan modifications becomes insignificant for borrowers who are already delinquent on their credit card accounts before modification (only significant in a longer term of 24 months after modification; see Table 6). The results suggest loan modifications are more effective in improving a borrower's performance on credit cards if the borrower has not been in serious financial trouble (reflected by the existence of delinquencies on credit cards).

Because a loan modification cures an existing mortgage delinquency automatically by resetting the delinquency status back to current, a direct comparison of the mortgage delinquency rates between the treatment and control groups does not make sense. But using the control group as a benchmark, I can compare the relative effectiveness of different types of modifications in preventing new mortgage delinquencies. Among the different types of modifications, the principal-reduction modification is the most effective in preventing new delinquencies (a reduction of 80.3 percentage points in 12 months). Rate-reduction modification is the second most effective (a reduction of 68.7 percentage points in 12 months), and term-extension modification is the third (a reduction of 62.3 percentage points in 12 months). The level of payment relief is also negatively associated with the probability of mortgage delinquency, which is consistent with findings in the earlier studies on the relationship between the level of payment relief from loan modifications and the reduced risk in mortgage redefault (e.g., see Quercia and Ding, 2009).

Identifying Assumption and Robustness Check

There are important assumptions for the DID approach. Most importantly, the DID approach assumes parallel trends prior to the treatment. One way to assess this identifying assumption is to look at the trends in outcomes leading up to the loan modification. The descriptive charts based on the matched sample (see Figures 3–6) suggest that the trends for borrowers with modified loans and those in the control group are quite similar for most outcome variables during the premodification period.[14] For example, as Figure 3 shows, the risk scores for the treatment and the control group followed extremely similar time trends (and even with similar means) in the 4-year period leading to modifications. Equality of premodification trends lends confidence for the use of DID as the identification strategy here. Of course, it needs to be acknowledged that, while the matching process mitigates the selection bias significantly, there might still be unobservable heterogeneity between the modified and control groups (Ding, 2013; Mayer et al., 2014),[15] which should be taken into consideration when interpreting the empirical results.

Finally, this study replicates most of the analysis discussed previously using the binary loan modification variable based on the servicer-reported loan modifications in the MLM data as a robustness check. The results on the impact of loan modifications on risk scores, various credit

[14] A few exceptions include the credit limit and credit balance on revolving accounts, where borrowers in the control group experience sharper declines in these outcomes than those in the treatment group premodification. But debt level and credit limits have been quite close at the time of modification (or being matched to a modification).

[15] For example, servicers may have targeted modifications for households that would have more stable incomes to make mortgage payments under the new terms by requiring full documentation of their incomes, by requiring more stable employment in their underwriting, or both. The inclusion of the estimated income and debt ratios in the match should help mitigate this concern.

access measures (number of credit cards and credit limits), and credit use measures are quite consistent with those based on the contract-change algorithm in terms of the sign and significance of the coefficients (Table 7). Some noticeable differences include a slightly lower improvement in borrowers' risk scores over a longer period: A loan modification is associated with an increase of 29.9 points in risk scores in 12 months and an increase of 22.1 points in 24 months based on the servicer-reported sample, lower than the increase of 36.4 points and the increase of 28.9 points in the corresponding periods based on the contract-change algorithm sample. Borrowers also experience a larger increase (about 28% larger in 12 months) in the level of debt on revolving accounts postmodification when using the servicer-reported modifications.

The robustness check, however, suggests that the impact of loan modifications on borrowers' performance on various credit accounts other than mortgages is generally insignificant (Table 8). The coefficients of the interaction variables are generally insignificant. The only exception is a lower risk of being late on the HELOC loan for the borrower with a modified loan (a decrease of 9.4 percentage points in 12 months, or 30.6% relative to the premodification mean). None of the impact of loan modifications on the performance of other nonmortgage credit accounts, including credit cards, auto loans, retail cards, consumer finance accounts, and student loans, is significant. These results are slightly different from those based on the contract-change algorithm, which show a generally positive impact of loan modifications on the performance of various credit accounts. One possible explanation is that servicer-reported modifications include additional modifications that provide no or little relief for troubled borrowers and, consequently, provide fewer financial benefits to borrowers. In any case, the results generally do not support the hypothesis reviewed earlier: that modifications lead to increased default risk on borrowers’ debt other than mortgages because of the changed priority in debt payment hierarchy.

Overall, the robustness check based on the servicer-reported sample confirms a significant improvement in borrowers’ overall credit standing as well as a slight increase in borrowers’ debts on selected credit accounts postmodification. The robustness check, however, suggests slightly fewer financial benefits from loan modifications for borrowers’ financial health as manifested by a slightly lower improvement in borrowers’ risk scores, a larger increase in total debt other than mortgages, and a generally insignificant impact on the performance of most credit accounts.

5. Conclusions

This study provides a comprehensive look at the consequences that loan modification as an important foreclosure prevention effort may have on borrowers in terms of credit performance and future access to credit. A loan modification, especially one that helps address liquidity issues, is expected to alter a borrower’s financial circumstances in a manner that makes future default on a mortgage less likely. Such loan modifications could have significant spillover effects on unsecured accounts and borrowers’ overall financial health as well.

Overall, loan modifications increase borrowers’ access to credit. Modifications — especially those that reduce principal balances or address liquidity issues of troubled borrowers — help improve borrowers’ credit ratings, reduce the likelihood of losing credit cards, and help borrowers keep higher credit limits. Modifications lead to a slight increase in borrowers’ other debts, primarily HELOC accounts and auto loans. One possible explanation is that certain budget-constrained borrowers need to borrow short-term debt from the HELOC accounts or slow down the speed of paying off these debts to make timely mortgage payments.

Loan modifications help prevent new mortgage delinquencies. Modifications also improve the performance of selected credit accounts slightly, although analyses based on servicer-reported modifications suggest a generally insignificant impact of loan modifications on credit performance. The inclusion of the modifications reported by servicers that do not significantly change the terms of mortgages may help explain the discrepancy in these results. The bottom line is that the performance on borrowers' nonmortgage credit accounts has not been negatively impacted by modifications.

Borrowers receiving modifications are troubled borrowers facing significant financial challenges. Their credit histories and credit scores had been negatively affected by mortgage delinquencies and possible late payments on other accounts. Loan modifications cure mortgage delinquencies and improve borrowers' credit ratings, thereby increasing their access to credit, decreasing their costs of access, and improving their capacity to handle financial challenges in the aftermath of the housing crisis. Given the greater prominence of credit scores, the extra benefits of increases in credit scores should not be overlooked when estimating the benefits of loan modifications. Of course, a comprehensive cost-benefit analysis is needed to evaluate the successfulness of loan modifications, and the optimal loss mitigation solution should be in the collective interests of borrowers, investors, and other stakeholders, which is beyond the scope of this study.

Appendix

The McDash Loss Mitigation (MLM) data set, including data from January 2008 on, provides information on whether a loan was modified, the month in which a loan was modified, modification type, and other loss mitigation activities such as short sales and deeds in lieu of foreclosure. This is one of a few large data sets that are able to identify loan modifications directly. Unfortunately, not all servicers presently provide loss mitigation data to McDash (about three out of four first-lien loans in McDash are covered by the MLM data as of the end of 2015), even though they are contributing data to the core McDash mortgage database. And some of the key loan modification variables are not well-populated, such as the modification dates or the modification types.[16] The modification types are often unavailable because servicers failed to provide information on specific types for many reported modifications.[17]

To evaluate the likelihood of false negatives and false positives for the contract-change algorithm, I compare the number of loan modifications identified based on either the contract-change algorithm measure or the servicer-reported measure. This was done by focusing on the 5% random sample of 2005 to 2009 first-lien originations in both the McDash and the MLM data sets. In terms of the incidence of misidentification, the contract-change algorithm generally identifies fewer loan modifications than the servicer-reported measure because the latter includes additional modifications that do not necessarily involve significant changes in loan terms, such as rate-freezing modifications. But the contract-change algorithm produces fewer false positives, in which a modification identified by the algorithm is not reported by the servicer as such. About 93% of the modifications identified by the contract-change algorithm are also reported by

[16] The vendor derived the loan modification identifier for modifications with more complete information on modification types and modification date; however, excluding the records with missing values on certain variables may lead to an underestimate of the actual number of modifications.

[17] More than half of the servicer-reported modifications were coded as "*Proprietary Other*," which means servicers failed to provide information on specific loan modification types.

servicers as loan modifications (in other words, only about 7% of the modifications identified by the contract-change algorithm are false positives). Likely because there were no consistent conventions in reporting loan modifications across institutions until very recently (Adelino, Gerardi, and Willen 2013), the contract-change algorithm only identifies about 72% of servicer-reported ones as modifications. The contract-change algorithm, therefore, generates about 28% false negatives and 7% false positives for this study sample. To check the possible bias due to the misidentifications inevitably introduced by the contract-change algorithm, this study replicated most of the analysis using the new MLM data as a robustness check, while primarily relying on the loan modifications identified by the contract-change algorithm.

References

Adelino, Manuel, Kristopher Gerardi, and Paul S. Willen. 2013. "Why Don't Lenders Renegotiate More Home Mortgages? Redefaults, Self-Cures and Securitization." *Journal of Monetary Economics*, 60(7): 835–853.

Agarwal, Sumit, Gene Amromin, Itzhak Ben-David, Souphala Chomsisengphet, Tomasz Piskorski, and Amit Seru. 2012. "Policy Intervention in Debt Renegotiation: Evidence from the Home Affordable Modification Program." NBER Working Paper 18311.

Agarwal, Sumit, Souphala Chomsisengphet, Neale Mahoney, and Johannes Stroebel. 2015. "Do Banks Pass Through Credit Expansions? The Marginal Profitability of Consumer Lending During the Great Recession." NBER Working Paper 21567.

Anderson, Raymond. 2007. *The Credit Scoring Toolkit: Theory and Practice for Retail Credit Risk Management and Decision Automation*. New York: Oxford University Press.

Andersson, Fredrik, Souphala Chomsisengphet, Dennis Glennon, and Feng Li. 2013. "The Changing Pecking Order of Consumer Defaults." *Journal of Money, Credit, and Banking*, 45(2–3): 251–275.

Brevoort, Kenneth P., and Cheryl R. Cooper. 2013. "Foreclosure's Wake: The Credit Experiences of Individuals Following Foreclosure." *Real Estate Economics*, 41(4): 747–792.

Calem, Paul S., Julapa Jagtiani, and William W. Lang. 2016. "Foreclosure Delay and Consumer Credit Performance." Working Paper 15-24/R. Federal Reserve Bank of Philadelphia. Available at www.philadelphiafed.org/-/media/research-and-data/publications/working-papers/2015/wp15-24r.pdf?la=en.

Chan, Sewin, Andrew Haughwout, Andrew Hayashi, and Wilbert van der Klaauw. 2015. "Determinants of Mortgage Default and Consumer Credit Use: The Effects of Foreclosure Laws and Foreclosure Delays." Staff Report 732. Federal Reserve Bank of New York. Available at www.newyorkfed.org/research/staff_reports/sr732.pdf.

Cohen-Cole, Ethan, Burcu Duygan-Bump, and Judit Montoriol-Garriga. 2013. "Who Gets Credit After Bankruptcy and Why? An Information Channel." *Journal of Banking & Finance*, 37(12): 5101–5117.

Cohen-Cole, Ethan, and Jonathan Morse. 2010. "Your House or Your Credit Card, Which Would You Choose? Personal Delinquency Tradeoffs and Precautionary Liquidity Motives." Working Paper QAU09-5. Federal Reserve Bank of Boston. Available at www.bostonfed.org/bankinfo/qau/wp/2009/qau0905.pdf.

Ding, Lei. 2013. "Servicer and Spatial Heterogeneity of Loss Mitigation Practices in Soft Housing Markets." *Housing Policy Debate*, 23(3): 521–542.

Dobbie, Will, and Jae Song. 2015. "Debt Relief and Debtor Outcomes: Measuring the Effects of Consumer Bankruptcy Protection." *American Economic Review*, 105(3): 1272–1311.

Elul, Ronel, Nicholas S. Souleles, Souphala Chomsisengphet, Dennis Glennon, and Robert Hunt. 2010. "What 'Triggers' Mortgage Default?" *American Economic Review*, 100(2): 490–494.

Foote, Christopher, Kristopher Gerardi, Lorenz Goette, and Paul Willen. 2010. "Reducing Foreclosures: No Easy Answers," *NBER Macroeconomics Annual*, 24: 89–138.

Han, Song, and Geng Li. 2011. "Household Borrowing After Personal Bankruptcy." *Journal of Money, Credit, and Banking*, 43(2–3): 491–517.

Haughwout, Andrew, Ebiere Okah, and Joseph Tracy. 2010. "Second Chances: Subprime Mortgage Modification and Re-Default." Staff Report 417. Federal Reserve Bank of New York. Available at www.newyorkfed.org/research/staff_reports/sr417.pdf.

Jagtiani, Julapa, and William W. Lang. 2011. "Strategic Default on First and Second Lien Mortgages During the Financial Crisis." *Journal of Fixed Income*, 20(4): 7–23.

Jagtiani, Julapa, and Wenli Li. 2014. "Credit Access After Consumer Bankruptcy Filing: New Evidence." Working Paper 14-25. Federal Reserve Bank of Philadelphia. Available at http://philadelphiafed.org/research-and-data/publications/working-papers/2014/wp14-25.pdf.

Keys, Benjamin J., Tomasz Piskorski, Amit Seru, and Vincent Yao. 2014. "Mortgage Rates, Household Balance Sheets, and the Real Economy." NBER Working Paper 20561.

Kim, Jiseob. 2015. "Household's Optimal Mortgage and Unsecured Loan Default Decision." *Journal of Macroeconomics*, 45(C): 222–244.

Mayer, Christopher, Edward Morrison, Tomasz Piskorski, and Arpit Gupta. 2014. "Mortgage Modification and Strategic Behavior: Evidence from a Legal Settlement with Countrywide." *American Economic Review*, 104(9): 2830–2857.

Molloy, Raven, and Hui Shan. 2013. "The Postforeclosure Experience of U.S. Households." *Real Estate Economics*, 41(2): 225–254.

Office of the Comptroller of the Currency. 2014. "OCC Mortgage Metrics Report: Third Quarter 2014." Available at www.occ.treas.gov/publications/publications-by-type/other-publications-reports/mortgage-metrics/mortgage-metrics-q3-2014.pdf.

Quercia, Roberto G., and Lei Ding. 2009. "Loan Modifications and Redefault Risk: An Examination of Short-Term Impacts." *Cityscape*. 11(3): 171–193.

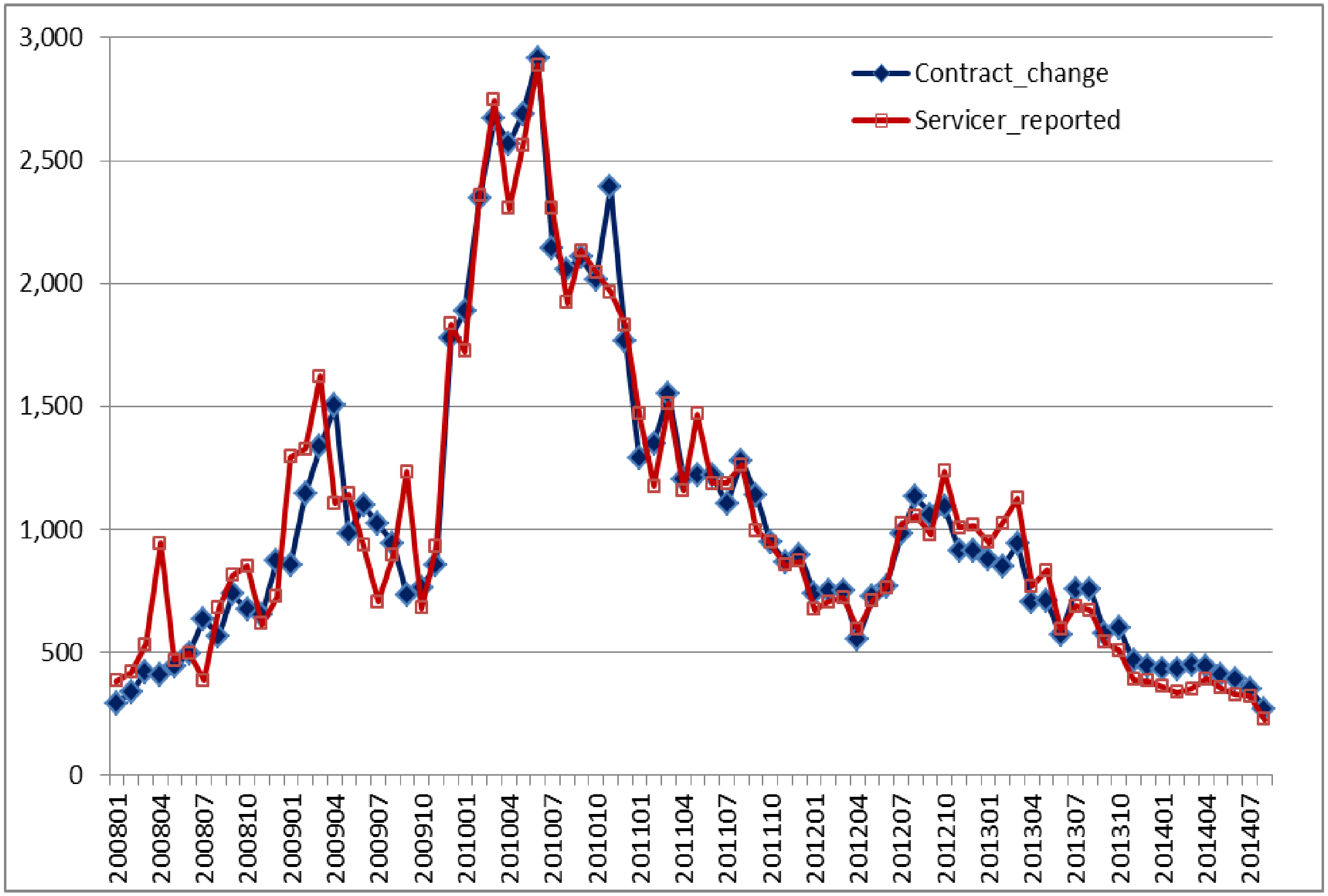
Scharlemann, Therese C., and Stephen H. Shore. 2015. "The Effect of Negative Equity on Mortgage Default: Evidence from HAMP PRA." Working Paper 15-06. Office of Financial Research. Available at https://financialresearch.gov/working-papers/files/OFRwp-2015-06_Effect-of-Negative-Equity-on-Mortgage-Default.pdf.

Schmeiser, Maximilian D., and Matthew B. Gross. 2014. "The Determinants of Subprime Mortgage Performance Following a Loan Modification." Finance and Economics Discussion

Series 2015-006. Board of Governors of the Federal Reserve System. Available at www.federalreserve.gov/econresdata/feds/2015/files/2015006pap.pdf.

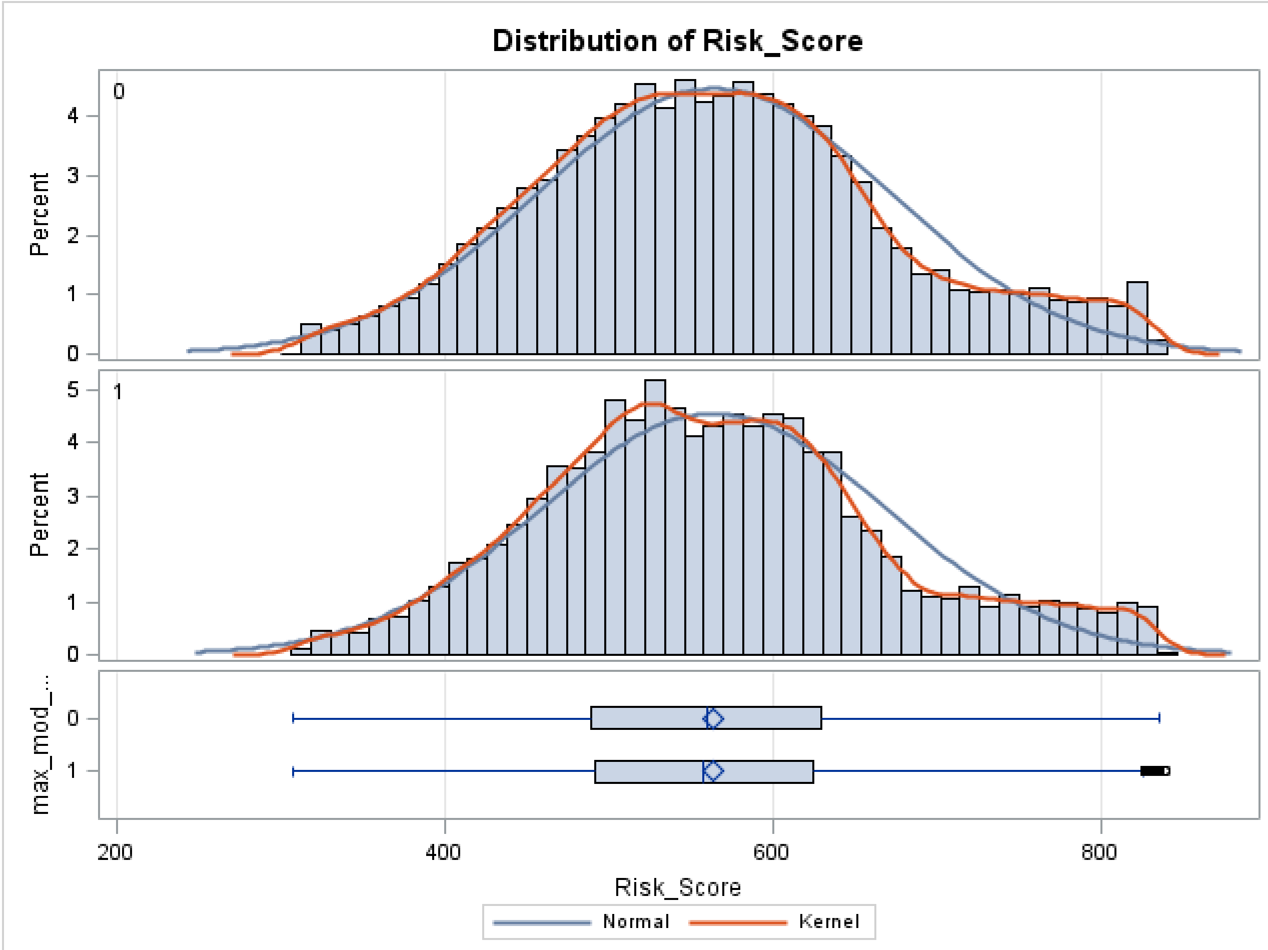
VantageScore. 2010. “Impact on Consumer VantageScore Credit Scores Due to Various Mortgage Loan Restructuring Options.” Available at www.vantagescore.com/images/resources/loan_restructuring_options.pdf.

Figure 1. Comparison of Different Loan Modifications Measures: Number of Modifications Based on Contract-Change Algorithm Versus Servicer-Reported Modifications



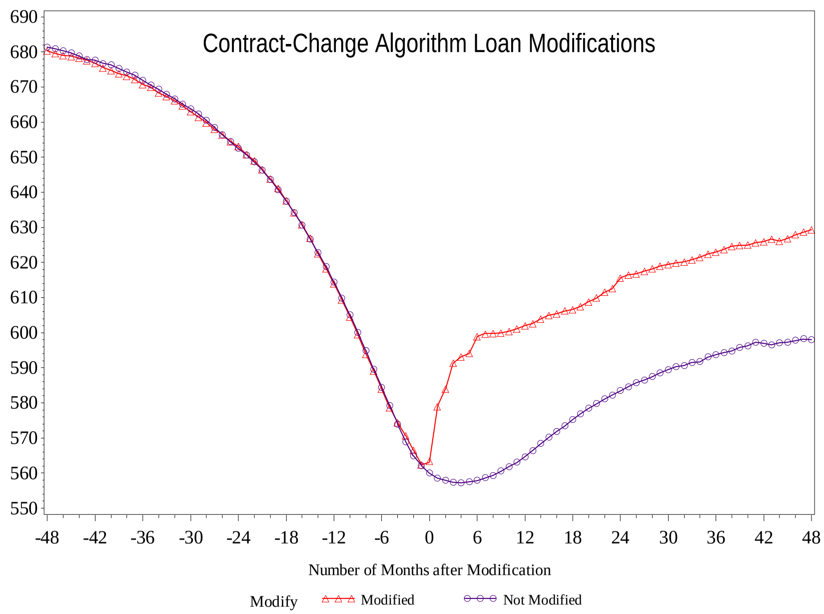
Notes: Based on a 5% random sample of loans that were originated between 2005 and 2009 and were covered by the McDash Loss Mitigation data set. Servicer-reported loan modifications that do not report modification dates are not included here. Source: Author's calculation using McDash data and McDash Loss Mitigation data set.

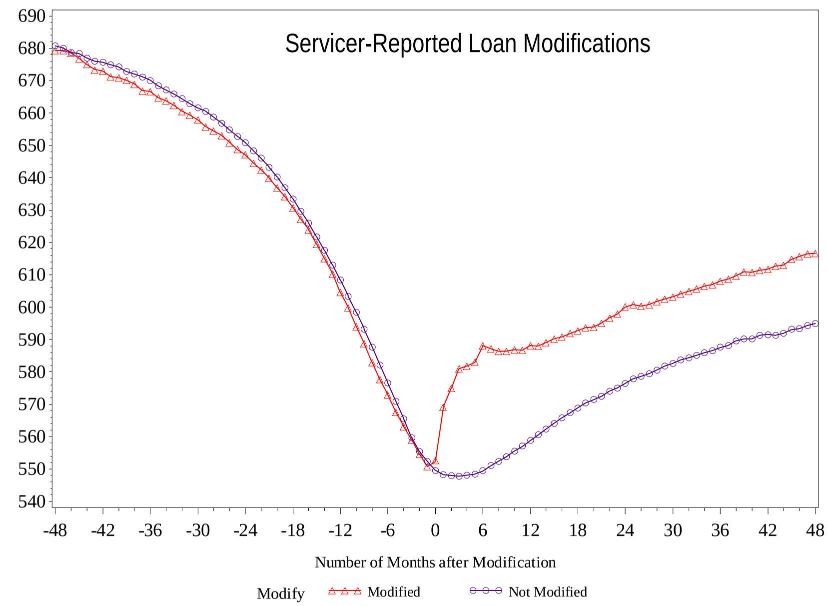
Figure 2. Distributions of Borrower Risk Scores: Matched Sample (Top Panel) and Modified Sample (Bottom Panel)



Notes: Based on 14,718 individuals with modified loans and 20,812 individuals with delinquent but not modified loans. Loan modifications were identified based on the contract-change algorithm. The matching variables include risk score; loan balance; estimated debt-to-income score; whether the borrower has credit cards; the level of default before modification; timing of initial delinquency; geography (zip code or county); and borrower age, mortgage cohort, and estimated borrower income when matching at the county level. Source: Author's calculation using the Equifax Credit Risk Insight Servicing McDash database.

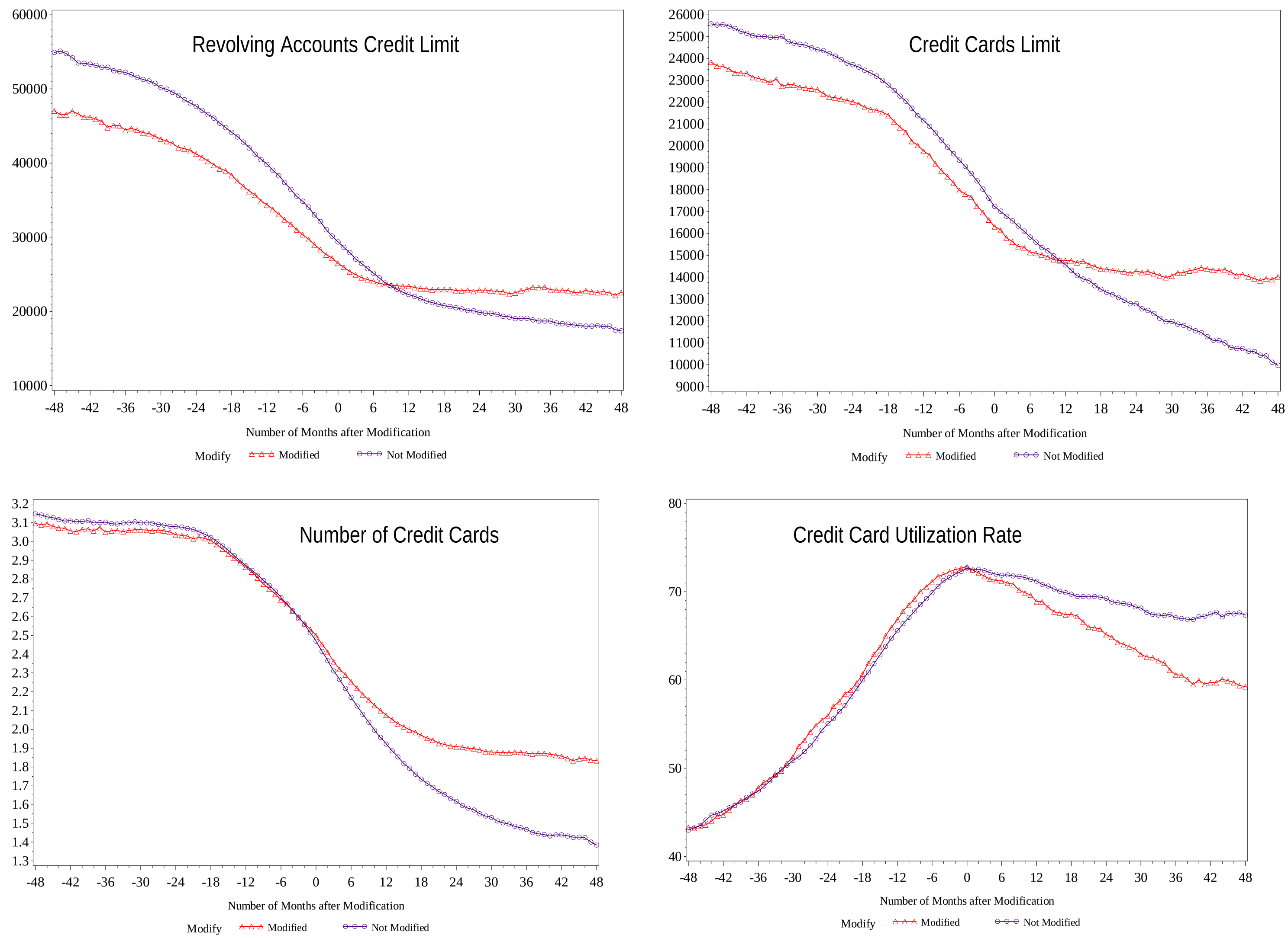
Figure 3. Borrower Risk Score Changes Pre- and Postmodification (Modified and Matched)





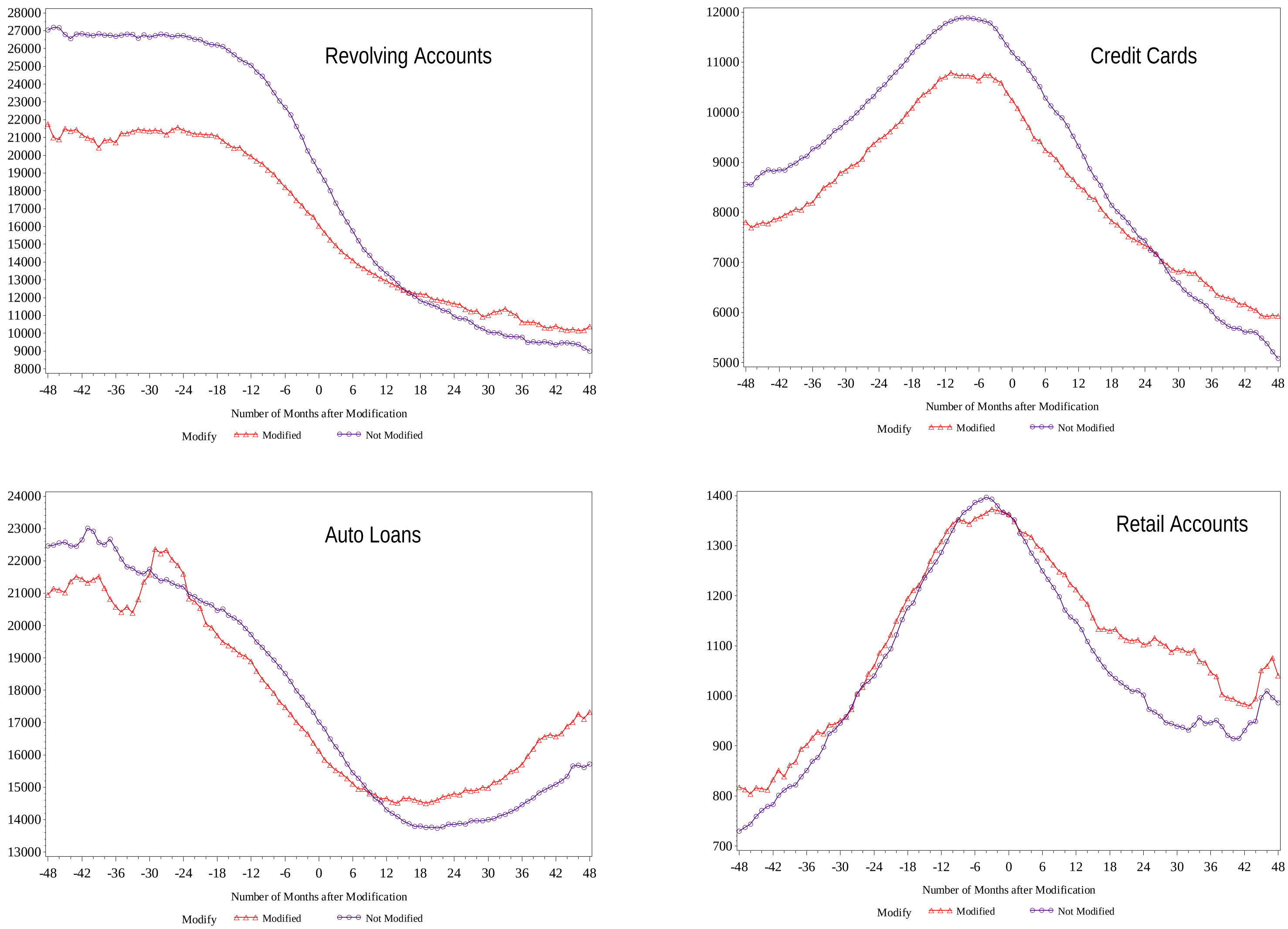
Notes: Sample sizes are different for different charts. Observations were weighted to give equal weight to the modification and comparison groups. The matching variables include risk score; loan balance; estimated debt-to-income score; whether the borrower has credit cards; the level of default premodification; timing of initial delinquency; geography (zip code or county); and borrower age, mortgage cohort, and estimated borrower income when matching at the county level.
Source: Author’s calculation using the Equifax Credit Risk Insight Servicing McDash database and the McDash Loss Mitigation data set.

Figure 4. Credit Limits, Number of Credit Cards, and Credit Card Utilization Rate Pre- and Postmodification



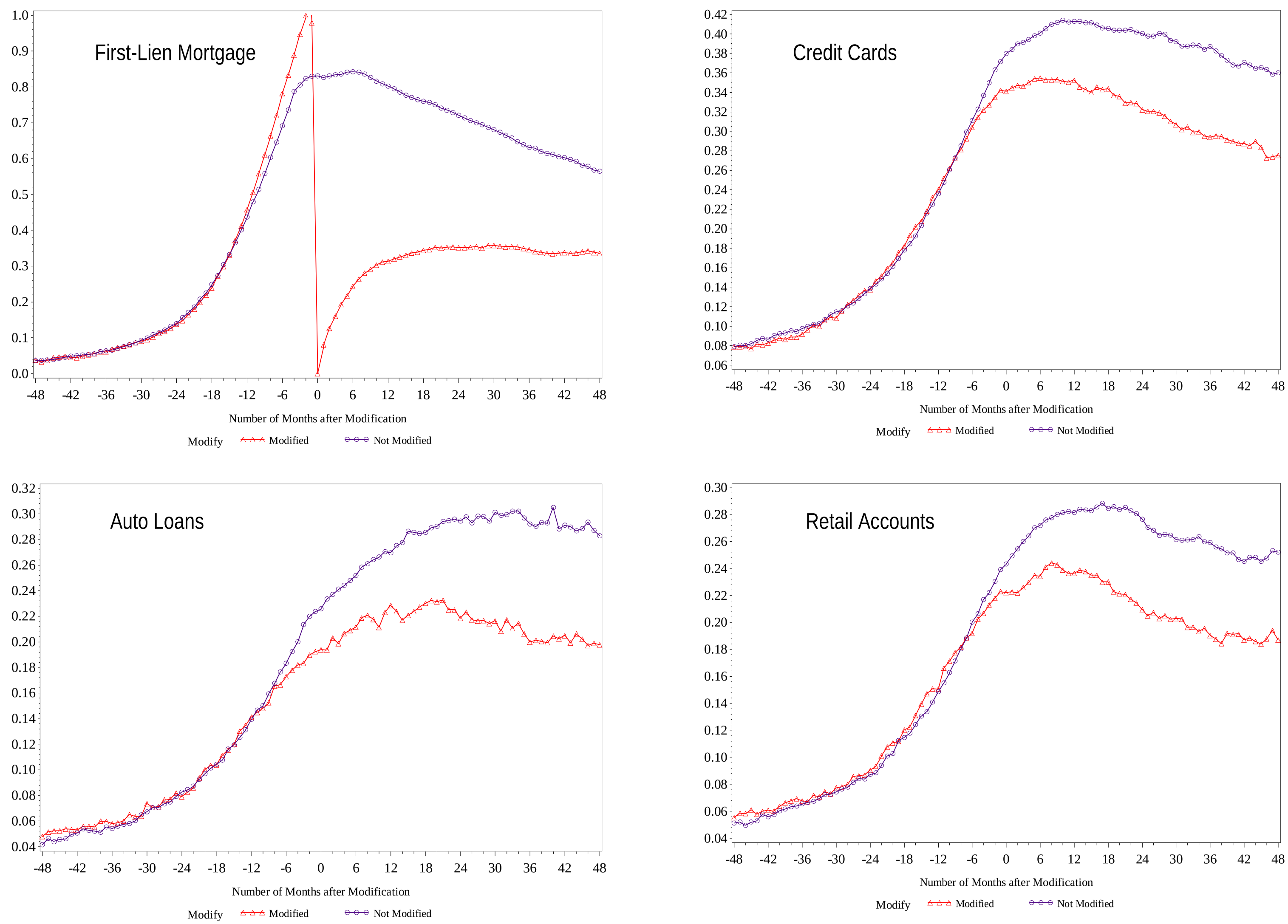
Notes: Based on 14,718 individuals with modified loans and 20,812 individuals with delinquent but not modified loans. Sample size may vary for different charts. Loan modifications were identified based on the contract-change algorithm. Observations were weighted to give equal weight to the modification and comparison groups. Source: Author's calculation using the Equifax Credit Risk Insight Servicing McDash database.

Figure 5. Credit Balance Pre- and Postmodification: Revolving Accounts, Credit Cards, Auto Loans, and Retail Accounts



Notes: Based on 14,718 individuals with modified loans and 20,812 individuals with delinquent but not modified loans. Sample size may vary for different charts. Loan modifications were identified based on the contract-change algorithm. Observations were weighted to give equal weight to the modification and comparison groups. Source: Author's calculation using the Equifax Credit Risk Insight Servicing McDash database.

Figure 6. Performance on Mortgages and Other Credit Accounts Pre- and Postmodification



Notes: Based on 14,718 individuals with modified loans and 20,812 individuals with delinquent but not modified loans. Sample size may vary for different charts. Loan modifications were identified based on the contract-change algorithm. Observations were weighted to give equal weight to the modification and comparison groups. Source: Author's calculation using the Equifax Credit Risk Insight Servicing McDash database.

Table 1. Summary Statistics of All Loan Modifications and the Matched Sample

Variable	Contract-Change Algorithm: All Loan Modifications	Contract-Change Algorithm: Modified	Contract-Change Algorithm: Delinquent but Not Modified	Contract-Change Algorithm: Significance of Difference	Servicer-Reported: Modified	Servicer-Reported: Delinquent but Not Modified	Servicer-Reported: Significance of Difference
Risk score (mean)	562	562	562		551	552	
Risk score (median)	553	557	559		544	549	
FICO score	575	575	576		567	571	***
Borrower age (mean)	46	46	45	***	46	45	***
Borrower age (median)	45	45	44		45	44	
Debt-to-income score	634	640	635	***	663	655	***
Estimated individual income ($k)	41	43	43	***	42	43	***
Estimated borrower income ($k)	58	58	58		56	56	
Principal balance amount ($)	235,769	256,826	261,384	***	268,037	269,800	
Credit card dummy	0.742	0.884	0.883		0.878	0.877	
Number of credit cards	2.008	2.533	2.513		2.468	2.521	
Credit card limit ($)	15,971	16,619	17,611	***	15,891	17,629	***
Credit card balance ($)	9,799	10,396	11,348	***	10,455	11,899	***
Credit card utilization rate	73.137	72.692	72.297		75.184	73.644	***
Late on credit cards	0.274	0.342	0.372	***	0.353	0.392	***
HELOC dummy	0.118	0.144	0.159	***	0.146	0.159	***
HELOC limit ($)	77,161	74,786	89,321	***	80,652	95,429	***
HELOC balance ($)	64,549	63,610	77,261	***	68,790	82,851	***
Late on HELOC	0.315	0.308	0.422	***	0.317	0.469	***
Auto loan dummy	0.485	0.513	0.532	***	0.522	0.531	
Auto loan balance ($)	15,632	16,374	17,320	***	16,564	17,392	***
Late on auto loans	0.220	0.192	0.224	***	0.186	0.226	***
Retail card dummy	0.543	0.621	0.600	***	0.604	0.594	
Retail card limit ($)	3,234	3,570	3,431	***	3,567	3,329	***
Retail card balance ($)	1,280	1,368	1,366		1,512	1,390	***
Late on retail cards	0.238	0.223	0.239	***	0.229	0.254	***
Consumer finance dummy	0.363	0.411	0.391	***	0.423	0.392	***
Consumer finance account limit ($)	7,443	7,379	7,645		8,474	7,659	
Consumer finance account balance ($)	4,518	4,168	4,543		5,511	4,739	
Late on consumer finance accounts	0.282	0.254	0.291	***	0.272	0.314	***
Student loan dummy	0.171	0.174	0.175		0.176	0.173	
Student loan balance ($)	29,510	29,471	30,237		30,140	29,551	
Late on student loan	0.170	0.138	0.158	***	0.143	0.166	***
Number of loans	65,504	14,718	20,812		9,123	16,262	

*** represents significant at 0.01 level.

Notes: Statistics indicate one month prior to modification (or being matched to a modification). Mortgage balance, credit balance, credit limit, and delinquency status are conditional on having such accounts. All statistics except the number of observations are weighted to give equal weight to the modification and the comparison groups. Source: Author's calculation using the Equifax Credit Risk Insight Servicing McDash database and the McDash Loss Mitigation data.

Table 2. Variable Definitions

Variable	Definition
modify	Indicator variable = 1 for borrowers receiving a modification
mod_type	Principal reduction (prin_red)
	Rate reduction and no principle reduction (rate_red)
	Term extension (term_ext)
	Other modifications (othermods)
pay_red_cat	No reduction, 1%–10% reduction, 11%–20% reduction, 21%–30% reduction, 31%–40% reduction, 41%–50% reduction, or >50% reducation
post	Premodification; 6, 12, or 24 months postmodification
riskscore	Equifax risk score
cc_lim	Credit card limit
heloc_lim	HELOC account limit
retail_lim	Retail account limit
cf_lim	Credit finance account limit
cc_num	Number of credit cards
re_bal	Revolving account balance
cc_bal	Credit card account balance
heloc_bal	HELOC account balance
auto_bal	Auto loan account balance
retail_bal	Retail account balance
stu_bal	Student loan account balance
cf_bal	Consumer finance account balance
utilization_rate	Credit card utilization ratio
mort_del	Indicator variable = 1 for a borrower who is late on first-lien mortgage payment
re_del	Indicator variable = 1 for a borrower who is late on revolving account payment
cc_del	Indicator variable = 1 for a borrower who is late on credit card payment
heloc_del	Indicator variable = 1 for a borrower who is late on HELOC account payment
auto_del	Indicator variable = 1 for a borrower who is late on auto loan payment
retail_del	Indicator variable = 1 for a borrower who is late on retail account payment
stu_del	Indicator variable = 1 for a borrower who is late on student loan payment
cf_del	Indicator variable = 1 for a borrower who is late on credit card payment

Note: *Premodification* refers to the month immediately before a loan modification (or being matched with a loan modification).

Table 3. Impact of Loan Modifications on Borrowers' Risk Scores: Summary of Coefficients from Different Linear Regressions

	Coefficients	*SEs*	*Number of Observations*	*R2*
Risk Score				
modify & 6-month	40.738***	1.206		
modify & 12-month	36.412***	1.150		
modify & 24-month	28.913***	1.206	184,680	0.037
Risk Score & Modification Type				
prin_red & 12-month	39.889***	2.373		
rate_red & 12-month	38.757***	1.275		
term_ext & 12-month	31.049***	4.525		
othermods & 12-month	23.171***	2.800	96,521	0.018
Risk Score & Payment Reduction				
no reduction & 12-month	24.964***	2.836		
1%–10% reduction & 12-month	39.957***	2.689		
11%–20% reduction & 12-month	33.910***	2.992		
21%–30% reduction & 12-month	34.407***	2.174		
31%–40% reduction & 12-month	35.179***	1.942		
41%–50% reduction & 12-month	39.472***	1.871		
>50% reduction & 12-month	46.395***	2.291	96,294	0.029
Risk Score (delinquent on credit cards before loan modification)				
modify & 6-month	26.035***	1.156		
modify & 12-month	13.906***	1.465		
modify & 24-month	10.021***	1.842	50,964	0.111

SEs = standard errors (clustered at county level); ***, **, * represent significant at the 0.01, 0.05, or 0.1 level, respectively.

Notes: Loan modifications were identified based on the contract-change algorithm. Individual fixed effect has been controlled. The sample may include multiple records for the same borrower for one-to-many or many-to-many matches. Source: Author's calculation using the Equifax Credit Risk Insight Servicing McDash database.

Table 4. Impact of Loan Modifications on Borrowers' Access to Credit: Summary of Coefficients from Different Linear Regressions

	Coefficients	*SEs*	*Number of Observations*	*R2*
Number of Credit Cards				
modify & 6-month	0.066***	0.009		
modify & 12-month	0.123***	0.013		
modify & 24-month	0.233***	0.022	184,689	0.020
Credit Card Limit ($)				
modify & 6-month	382.5***	119.1		
modify & 12-month	1,131.6***	206.5		
modify & 24-month	1,839.3***	162.5	146,641	0.004
Credit Limit (modify & 12-month, $)				
credit card	1,131.6***	206.5	146,641	0.004
HELOC	5,115.9***	836.3	21,685	0.001
retail account	282.6***	63.6	100,354	0.004
consumer finance account	250.5	161.8	61,327	0.000

SEs = standard errors (clustered at county level); ***, **, * represent significant at the 0.01, 0.05, or 0.1 level, respectively.

Notes: Loan modifications were identified based on the contract-change algorithm. Individual fixed effect has been controlled. Sample size may be different for different outcome variables, and the sample may include multiple records for the same borrower for one-to-many or many-to-many matches. Source: Author's calculation using the Equifax Credit Risk Insight Servicing McDash database.

Table 5. Impact of Loan Modifications on Borrowers' Credit Use: Summary of Coefficients from Different Linear Regressions

	Coefficients	*SEs*	*Number of Observations*	*R2*
Revolving Account Balance ($)				
modify & 6-month	1,819.2***	386.9		
modify & 12-month	3,049.5***	451.3		
modify & 24-month	3,883.9***	715.0	138,180	0.004
Credit Card Balance ($)				
modify & 6-month	-52.7	95.3		
modify & 12-month	226.0	180.1		
modify & 24-month	601.3***	159.0	146,641	0.006
Utilization Rate				
modify & 6-month	-1.044***	0.293		
modify & 12-month	-2.394***	0.379		
modify & 24-month	-3.212***	0.645	146,450	0.002
Credit Balance (modify & 12-month, $)				
revolving account	3,049.5***	451.3	138,180	0.004
credit card	226.0	180.1	146,641	0.006
HELOC	5,230.0***	1,008.9	21,685	0.000
auto loan	1,289.8***	208.3	89,920	0.006
retail account	96.1***	32.9	100,354	0.002
student loan	-3.7	342.2	32,492	0.001
consumer finance account	114.5	159.7	61,327	0.000

SEs = standard errors (clustered at county level); ***, **, * represent significant at the 0.01, 0.05, or 0.1 level, respectively.

Notes: Loan modifications were identified based on the contract-change algorithm. Individual fixed effect has been controlled. Sample size may be different for different outcome variables, and the sample may include multiple records for the same borrower for one-to-many or many-to-many matches. Source: Author's calculation using the Equifax Credit Risk Insight Servicing McDash database.

Table 6. Impact of Loan Modifications on Borrowers' Credit Performance (30+ Days Delinquent): Summary of Coefficients from Different Linear Probability Regressions

	Coefficients	*SEs*	*Number of Observations*	*R2*
Credit Delinquency (modify & 12-month)				
credit cards	-0.028***	0.005	148,914	0.001
HELOC	-0.113***	0.020	22,699	0.011
auto loans	-0.007	0.007	83,593	0.005
retail account	-0.030***	0.006	99,879	0.002
student loans	-0.018	0.012	30,739	0.006
consumer finance	-0.044***	0.008	58,420	0.005
Credit Card Delinquency				
modify & 6-month	-0.022***	0.006		
modify & 12-month	-0.028***	0.005		
modify & 24-month	-0.038***	0.006	148,914	0.001
Credit Card Delinquency (delinquent on credit cards before loan modification)				
modify & 6-month	-0.015	0.010		
modify & 12-month	-0.008	0.008		
modify & 24-month	-0.037***	0.009	48,865	0.080
Mortgage Delinquency by Modification Type				
prin_red & 12-month	-0.803***	0.023		
rate_red & 12-month	-0.687***	0.005		
term_ext & 12-month	-0.623***	0.012		
othermods & 12-month	-0.284***	0.018	90,245	0.327
Mortgage Delinquency by Mortgage Payment Relief				
no reduction &12-month	-0.307***	0.014		
1%–10% reduction &12-month	-0.522***	0.021		
11%–20% reduction &12-month	-0.571***	0.013		
21%–30% reduction &12-month	-0.654***	0.014		
31%–40% reduction &12-month	-0.740***	0.014		
41%–50% reduction &12-month	-0.806***	0.014		
>50% reduction &12-month	-0.840***	0.013	90,048	0.340

SEs = standard errors (clustered at county level); ***, **, * represent significant at the 0.01, 0.05, or 0.1 level, respectively.

Notes: Loan modifications were identified based on the contract-change algorithm. Individual fixed effect has been controlled. Sample size may be different for different outcome variables, and the sample may include multiple records for the same borrower for one-to-many or many-to-many matches. Source: Author's calculation using the Equifax Credit Risk Insight Servicing McDash database.

Table 7. Robustness Test of Loan Modifications' Impact on Borrowers' Credit Access and Credit Use: Servicer-Reported Versus Contract-Change Algorithm Modifications

	Servicer-Reported		Contract-Change Algorithm	
	Coefficients	*SEs*	*Coefficients*	*SEs*
Risk Score				
modify & 6-month	40.342***	1.417	40.738***	1.206
modify & 12-month	29.943***	1.421	36.412***	1.150
modify & 24-month	22.099***	1.392	28.913***	1.206
Number of Credit Cards				
modify & 6-month	0.085***	0.016	0.066***	0.009
modify & 12-month	0.176***	0.023	0.123***	0.013
modify & 24-month	0.272***	0.028	0.233***	0.022
Credit Card Limit ($)				
modify & 6-month	612.1***	135.0	382.5***	119.1
modify & 12-month	1,498.4***	144.3	1,131.6***	206.5
modify & 24-month	2,134.3***	341.3	1,839.3***	162.5
Credit Limit (modify & 12-month, $)				
credit card	1,498.4***	144.3	1,131.6***	206.5
HELOC	4,703.2***	1,363.9	5,115.9***	836.3
retail account	174.7**	86.4	282.6***	63.6
consumer finance	446.8*	249.5	250.5	161.8
Revolving Account Balance ($)				
modify & 6-month	2,547.7***	480.1	1,819.2***	386.9
modify & 12-month	3,905.4***	575.7	3,049.5***	451.3
modify & 24-month	5,418.5***	944.9	3,883.9***	715.0
Credit Card Balance ($)				
modify & 6-month	93.1	108.8	-52.7	95.3
modify & 12-month	564.9***	150.4	226.0	180.1
modify & 24-month	613.3***	292.3	601.3***	159.0
Utilization Rate				
modify & 6-month	-1.145**	0.451	-1.044***	0.293
modify & 12-month	-1.865***	0.574	-2.394***	0.379
modify & 24-month	-2.907***	0.904	-3.212***	0.645
Credit Balance (modify & 12-month, $)				
revolving account	3,905.4***	575.7	3,049.5***	451.3
credit card	564.9***	150.4	226.0	180.1
HELOC	6,115.3***	1,645.4	5,230.0***	1,008.9
auto loan	1,232.2***	228.4	1,289.8***	208.3
retail account	48.7**	23.6	96.1***	32.9
student loan	126.5	437.7	-3.7	342.2
consumer finance account	191.1	204.8	114.5	159.7

SEs = standard errors (clustered at county level); ***, **, * represent significant at the 0.01, 0.05, or 0.1 level, respectively.

Notes: Sample size for different regressions may be different (N = 157,004 for the servicer-reported risk score model). Individual fixed effect has been controlled. The sample may include multiple records for the same borrower for one-to-many or many-to-many matches. Source: Author's calculation using the McDash Loss Mitigation data set.

Table 8. Robustness Test of Loan Modifications' Impact on Borrowers' Credit Performance: Servicer-Reported Versus Contract-Change Algorithm Modifications

	Servicer-Reported		Contract-Change Algorithm	
	Coefficients	*SEs*	*Coefficients*	*SEs*
Credit Delinquency (modify & 12-month)				
credit card	-0.010	0.013	-0.028***	0.005
HELOC	-0.094**	0.038	-0.113***	0.020
auto loan	0.008	0.010	-0.007	0.007
retail account	-0.007	0.008	-0.030***	0.006
student loan	-0.013	0.016	-0.018	0.012
consumer finance	-0.014	0.015	-0.044***	0.008
Credit Card Delinquency				
modify & 6-month	-0.014	0.013	-0.022***	0.006
modify & 12-month	-0.010	0.013	-0.028***	0.005
modify & 24-month	-0.006	0.010	-0.038***	0.006
Credit Card Delinquency (delinquent on credit cards before loan modification)				
modify & 6-month	-0.025*	0.014	-0.015	0.010
modify & 12-month	0.006	0.014	-0.008	0.008
modify & 24-month	-0.001	0.012	-0.037***	0.009

SEs = standard errors (clustered at county level); ***, **, * represent significant at the 0.01, 0.05, or 0.1 level, respectively.

Notes: Sample sizes for different regressions may be different (N = 124,582 for the servicer-reported credit card delinquency model). Individual fixed effect has been controlled. The sample may include multiple records for the same borrower for one-to-many or many-to-many matches. Source: Author's calculation using the McDash Loss Mitigation data set.