# Potential Impacts of Credit Reporting Public Housing Rental Payment Data

U.S. Department of Housing and Urban Development | Office of Policy Development and Research

# Potential Impacts of Credit Reporting Public Housing Rental Payment Data


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**Policy and Economic Research Council**


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**Disclaimer**

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## Foreword

HUD subsidizes the rent of nearly one million very low-income households who live in public housing. Many of the households living in public housing have thin or invisible credit files or low credit scores, despite the fact that they generally pay 30 percent of their income towards rent each month. For many assisted households, rent payment constitutes the largest single expenditure on a monthly basis. In light of this information, this study examines the following question: what if public housing agencies provided the "full file" rental payment history of all tenants to credit reporting agencies, including histories of on-time, late, and omitted payments? This would put renters on par with homeowners with a mortgage, who almost universally have this full file payment history reported to the credit agencies each month. How would this affect the fraction of tenants who lack credit scores entirely, and how many tenants would have their credit scores improve relative to those who see decreases?

This study provides answers to these questions based on the experiences of the housing tenants of three public housing authorities in Seattle, Washington; Louisville, Kentucky; and Cook County, Illinois.

Thanks and gratitude go to the staff and leadership of the Seattle, Louisville and Cook County public housing authorities for their willingness to participate in this research. Thanks are also expressed to the Policy and Economic Research Council (PERC) for proposing this project through HUD's Research Partnerships program. PERC brought to the table resources and relationships with the credit reporting agencies that were invaluable to the outcome of the study. As a result of coupling PERC's resources and relationships with credit agencies with HUD's research resources and relationships with Public Housing Agencies, this report is a case study in the power of partnerships.

This study shows that public housing tenants currently have credit scores well below average. One-half to two-thirds of those with credit scores are rated as subprime (below 620). Up to half of all tenants studied were "credit invisible" to one or both of the consulted credit scoring systems.

It is a commonly accepted fact that credit invisibility and low credit ratings are a problem for those bearing these rankings. Landlords and property management groups regularly use credit checks to make determinations about renting to potential tenants and many employers incorporate credit checks in hiring decisions. A low credit score or credit invisibility can thusly limit housing choice and employment opportunity. It then stands to reason that a good credit score is part of the pathway to self-sufficiency and economic opportunity. As HUD's goal for work-able families is that they improve their incomes—through better employment—and move on from public housing to affordable private sector housing, finding answers to the questions posed by this study is of particular interest to HUD and its constituents.

This study offers an important insight to address a broader policy question of whether or not to provide full file rental history for public housing tenants to credit reporting agencies. The findings in this study show that, on average, full-file reporting is better for public housing tenants than the current system. The prevalence of credit invisibility is greatly reduced and the proportion of tenants with above-subprime credit scores increases substantially. That said, some are adversely impacted by the change as a smaller proportion of tenants experience decreases in credit scores, and a miniscule fraction fall into subprime status.

None of the tenants in this study had their actual credit scores change as a result of this "what if" research. The next step in this process would most likely be to find housing agencies willing to collaborate with their tenants and credit reporting agencies to see how this research might be effectively implemented in the real world. We look forward to the continuing conversation with tenants, public housing agencies, and the credit community on this topic.

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## Executive Summary and Key Findings

This study represents the first examination of how credit scores and traditional credit reports would be impacted if rent payments from public housing residents were fully reported, or positively-only reported, to nationwide consumer reporting agencies (CRAs), generally known as "credit bureaus." The tenant rental payment data used in this experiment come from three participating PHAs: (1) Housing Authority of Cook County (HACC); (2) Seattle Housing Authority (SHA); and (3) Louisville Metro Housing Authority (LMHA). Although data on as many as 16,626 tenants were examined, the sample sizes of most calculations were closer to 10,000 and under, depending on the period examined and calculation specifics. The rental data covers periods from late 2012 to late 2015, with specific dates depending on the particular PHA and tenant. The rental data was *full-file*, meaning it included both positive data (such as on-time payments) and negative data (such as late payments). The credit score models used in this research are the FICO® Score 9 and the VantageScore 3.0.

Key findings include:

- **The PHA sample examined is composed of relatively high credit-risk consumers**. Of the public housing residents with credit scores, 54 percent to 67 percent (depending on the scoring model) had a credit score of 620 or less (subprime) in the 2014 sample. This compares to a rate of 35 percent in the general population, using one of the credit-scoring models.

- **The PHA sample examined includes a large share of unscorable consumers.** The unscorability rate ranged between 11 percent and 49 percent of the 2014 sample, depending on the scoring model. This compares to the overall national rate of 19 percent and the low-income census tract rate of 45 percent found by the CFPB (CFPB, 2015).

- **Adding PHA rental data to credit file data only for those with on-time rental payment histories raised credit scores much more often than it lowered them.** In one credit-scoring model, over 16.5 times as many score rises occurred than score declines with the addition of the "positive" rental data. In the other model, over 2.5 times as many score rises occurred than score declines.

- **The addition of the full-file PHA rental payment data both raised and lowered credit scores, with more score increases than decreases.** In one scoring model the score changes were nearly symmetric with 23 percent of tenants having score increases and 20 percent having score decreases. For the second model, 61 percent had credit score increases while only 22 percent had score decreases.

- **The addition of the full-file PHA rental payment data tended to dramatically reduce unscorability.** With the 2014 credit scores, the rate of unscorability fell from 49 percent to 7 percent in one model and fell from 11 percent to 0 percent in the other model with the addition of full-file rental payment data. The addition of PHA rental data among those with only positive payment histories also lowered the unscorability rates, though to a lesser degree, to 23 percent and 3 percent, respectively.

- **The share of consumers who were scorable and had credit scores above 620 noticeably increased with the addition of the full-file rental payment data.** With the 2014 credit scores, using the first credit-scoring model, the share of consumers who had a score over 620 increased 65 percent, increasing from 23 percent of the sample to 38 percent of the sample with the addition of the full-file PHA rental data. The addition of PHA rental data among those with only positive payment histories raised this to a slightly lower 37 percent. For the second model, this rate rose 54 percent, from 28 percent of the sample to 43 percent of the sample. The addition of positive-only data also raised this to 43 percent. Credit scores above 620 are typically considered some type of prime and are accepted for conventional mortgage loans by Fannie Mae and Freddie Mac and generally yield more affordable credit.

## Introduction

The Consumer Financial Protection Bureau (CFPB) estimated that some 45 million Americans either have no credit file with an consumer reporting agency (CRA) or have insufficient information in their credit file to generate a traditional credit score (CFPB, 2015). In an environment of pervasive automated credit underwriting, individuals who either have no credit file or are otherwise unscorable (known as "credit invisibles"), can face considerable obstacles in improving their financial opportunities. Lenders that use credit-scoring models to help determine a person's creditworthiness often reject an unscorable applicant or offer them credit on less than favorable terms.

For "credit invisibles," escaping the "Catch-22" of credit is no easy proposition: in order to qualify for credit, one must already have credit. Consequently, many credit invisibles have limited options to meet their real credit needs, including payday lenders, pawn shops, check cashing services, or other higher-cost lenders. In addition to those who are credit invisible, there are many consumers who have a credit score but, due to a lack of data ("thin file"), have lower scores than they otherwise could have if they had additional accounts reported to the CRAs.

An established body of empirical economic research demonstrates that including fully reported (timely and late) nonfinancial payment data in consumer credit reports has immediate and dramatic positive impacts on the credit profiles of the credit invisible and thin-file populations, which are disproportionately composed of lower-income persons, immigrants, younger and elderly Americans, and members of minority populations (Turner, Varghese, and Walker, 2015).[1] Much of the established research has focused on energy utility and media payment information. However, research from Experian, a credit reporting company, on the impacts of positive rental payment data in traditional credit files suggests that there are good reasons to believe that including rental payment data could have significant impacts on the credit invisible and renter populations (Experian RentBureau, 2014). Given that many credit invisibles are renters, research that examines whether and how rental payments should be reported to CRAs is needed to assess if and how public policy can support rental reporting and investment in its collection.

For renters, the rental payment is often the single largest credit/contractual obligation. One of the blind spots of conventional consumer credit reports involves inadequate reporting of this major monthly payment (unlike mortgage payments which are typically reported to the CRAs). As such, prospective borrowers who are renters likely will not have their credit standing benefit from their on-time rental payments but may be penalized from very late payments or unpaid balances (for instance, if the account goes to collections).

Although the value of the rental data for credit risk assessment has long been understood, early attempts to collect the data were viewed as quixotic owing to the highly fragmented

[1] See also Afshar, 2005; Turner et al., 2006; Turner and Lee, 2008; Turner and Varghese, 2009.

nature of the rental market. Most landlords are people who are renting a room in their home, a single home, or an apartment above their garage.

One pioneering business model—Pay Rent Build Credit (Singletary, 2004)—attempted to introduce rental payment data into the origination process by charging consumers a fee to verify their rental payment data and then make it available to lenders, at the data subject's request. This approach failed to solve the overall lack of rental payment reporting owing to a lack of acceptance in the market—too few consumers signed up, and too few end-users embraced the solution. Another later business model—Rental Kharma[2]—employed a similar approach, but rather than providing the data to lenders, it instead made rental payment data available to nationwide credit bureaus. This approach, however, still has to contend with the limitations of an opt-in and fee approach, which tends to reduce uptake.

Traditional credit reporting directly from property managers of apartment complexes or other rental units (including public housing agencies) is now also possible. This can be facilitated by accessing and uploading needed data from the accounting software used by the property manager (property managers typically utilize a limited number of types of accounting software). Smaller property managers or landlords can also have rental account payment data reported to the nationwide CRAs via online platforms and services. All these developments have greatly reduced the hurdles of rental payment reporting.

Along with these advancements in *collecting* nonfinancial data, credit scoring models have also been advancing in their ability to use this data. For instance, both the FICO® Score 9 and the VantageScore 3.0 (which are used in this research) are designed to accept and use rental payment data.

## Study Objectives

This study examines the relationship between consumer credit profiles, as measured by credit scores, and the inclusion of public housing agency (PHA) rental payment data in consumer credit reports maintained by nationwide CRAs. Congressional interest in the credit reporting of rental payment data and other such payments for nonfinancial services dates back to the enactment of the Fair and Accurate Credit Transactions Act (FACT Act) in 2003. Interest has been rising steadily, indicated by an increasing frequency of hearings and the growing bipartisan support for legislation that would enable and promote this practice.[3] The Credit Access and Inclusion Act of 2015, 2017, and 2019 are examples of the bi-partisan support.

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[2] A list of a number of similar services to Rental Kharma can be found here: https://www.nerdwallet.com/blog/finance/credit-report-rent-payments-incorporated/.

[3] Since 2005, Congress has considered legislation regarding alternative data. Rep. Mike Castle (R-DE) held several hearings and floated draft bills. In 2012, Reps. Keith Ellison (D-MN) and Jim Renacci (R-OH) introduced the "Credit Access and Inclusion Act." The bill was reintroduced in the following Congress and garnered considerable bipartisan support. See Ellison and Renacci, 2012.

This research is also consistent with HUD's stated strategic objectives to "increase economic security and self-sufficiency" and "[find] ways that are safer for both borrowers and lenders to extend mortgage credit to first-time homebuyers and homeowners with less-than-stellar credit."[4]

This study helps determine whether HUD's strategic objective of helping creditworthy first-time homebuyers access affordable sources of mortgage credit could be advanced with more rental payment data of all varieties being fully reported to nationwide CRAs. Given the well-established link between homeownership and many positive social and economic outcomes, advancing this objective through credit-reporting rental payment data would be highly likely to contribute directly to increased economic security and self-sufficiency for would-be homeowners.

Furthermore, this study also adds to the existing body of theoretical and empirical economic literature on this topic by examining the credit profile impacts resulting from the inclusion of subsidized rental payment data from public housing tenants. Currently, there is only one publicly released study on credit reporting rental payment data (Experian RentBureau, 2014), and this study examined only positive payment reporting for the subset of tenants with only positive (paid-as-agreed) payment data. PHAs, with millions of lower-income tenants, represent perhaps one of the largest potential sources of rental payment data for credit invisibles. The results of this study can inform Congress, HUD, PHAs, and other stakeholders about the value of promoting credit reporting by PHAs.

The results can also make a strong test case for the value of rental payment data more broadly as a potential tool for driving financial inclusion by adding more full-file data to the main consumer credit databases, which the mainstream, lower-cost financial institutions use. Unfortunately, and perversely, negative-only account data are the most common way nonfinancial services (that is, utilities, telecoms, and rentals) report to the main consumer credit databases (for instance, via collection accounts).

## Approach

To test whether public housing rental payment data can help public housing residents enter the credit system and access mainstream, affordable credit, we conducted a series of simulations to measure the impact of that data on credit scores, credit file thickness,[5] and the no-score rates. The analysis compares credit files *without* rental payment data (status quo) to credit files *with* rental data added for a group of current and former PHA tenants. To create

[4] "Specifically, the Department is interested in how HUD-provided housing assistance can be used to accomplish such things as …*increase economic security and self-sufficiency"* (ital. added); and "HUD is interested in research in many areas of homeownership and housing finance, which include, but are not limited to, finding ways that are safer for both borrowers and lenders to extend mortgage credit to first-time homebuyers and homeowners with less-than-stellar credit" (HUD, 2014).

[5] Credit file thickness refers to how many accounts are reported to a person's credit file, such as auto loan accounts, mortgage accounts, credit card accounts, or other such accounts. A file with two or fewer reported accounts is typically referred to as a "thin file" while credit files with three or more reported accounts are typically referred to as "thick files."

the credit files with rental data, the following was performed: in a research database, rental payment data for tenants in public housing was combined with their traditional credit file data (for those that have files with other accounts reported). Both sets of files (with and without rental data) were then scored by the two credit-scoring models we selected. This allowed for a clear assessment of the impact of adding PHA rental payment data to consumer credit files.

## Methodology

The PHA tenant rental payment data used in this experiment come from three participating PHAs: Housing Authority of Cook County (HACC), Seattle Housing Authority (SHA), and Louisville Metro Housing Authority (LMHA). While data on as many as 16,626 tenants were examined, the sample sizes of most calculations were closer to 10,000, depending on the period examined. The rental data covers a period from late 2012 to late 2015, though specific dates depended on the particular PHA and tenant. The data request to the PHA was that all data be returned on persons who were tenants at any point between October 1, 2012, to September 30, 2014, with data continuing until October 1, 2015, if possible. IT and data retention constraints, however, meant that data, in many cases, did not cover this entire period.

The data cover only PHA-owned buildings. It did not include participants in the Housing Choice Voucher (Section 8) program. However, some results from separate, earlier Experian analysis that do examine subsidized housing (presumably including Section 8) are included in this report.

The rental data was full file, and the credit scores used in this research are the FICO® Score 9 and the VantageScore 3.0, as previously stated. These were randomized and anonymized and referred to as Credit-Scoring Model A and B (model A may not always be the same model from table to table). These credit scoring models are what are referred to as generic scoring models in that they are designed, optimized, and thoroughly tested to predict severe derogatories (such as 90+ days past due on accounts or a bankruptcy). They use data from the main nationwide CRAs as inputs. Such scores are widely used in the lending marketplace.[6] Importantly, both the FICO® Score 9 and the VantageScore 3.0 have been designed to accept and use rental payment data, so when rental payment data are reported to the main nationwide CRAs, these credit scoring models produce scores impacted by these accounts. These are standard, market-used credit scoring models and not research-grade models or specialty alternative data models. The FICO® Score 9 and the VantageScore 3.0 are market competitors that were built independently and have different weights and algorithms for producing credit scores.

The full-file PHA rental payment data were added to traditional credit files (in a research database) from TransUnion to simulate full-file credit reporting. In addition, unmodified credit file data are used to show the "base" case of consumers without the PHA rental data. The rental tradeline creation, production of the VantageScore 3.0, simulation of credit files with the rental data, and production of the "as is" base file data was carried out by TransUnion. FICO used the TransUnion produced data to then produce the FICO® Score 9.

For each of the credit scores, five credit score snapshots were taken. One was an "as is" snapshot in September 2012 that had no PHA rental data because it occurred prior to the

[6] Scoring models other than generic models are also widely used. Some models are designed to predict not severe derogatories in general but specific derogatories, such as bankruptcies (these are called bankruptcy models). Other models may predict payment performance on particular accounts, such as mortgages, whereas yet other models may be built for particular lenders.

included PHA data. Following this were September 2014 and 2015 snapshots. Each of these snapshots was taken twice, once without the PHA rental data and once with the PHA rental data included with the credit file data and credit scores. As such, a comparison between the two 2014 snapshots, for instance, would enable the identification of the specific impacts of adding the PHA rental data to those credit scores. More of the PHA rental data was populated in the year prior to the 2014 snapshot than between the 2014 and 2015 snapshots. For this reason, the 2014 snapshot would have the more recent PHA rental data (at the time of the score production) and as such is given greater attention in this report.

The tenant payments and balances used to create the PHA rental "tradelines" (accounts) only reflect the amount due and the amount paid by the tenant. It does not include the subsidized portion that may be paid by other parties.

The rental data, like other credit-reported data, were reported in or transformed to 30-day buckets. For example, consumers who paid their rent within 30 days of the due date were considered on time, those who paid between days 30 and 59 were counted as 30 days past due, and so on. This is often referred to as the Manner of Payment (MOP).

Because the three participating PHAs (HACC, SHA, and LMHA) do not report full-file account data to the credit bureaus, they do not have their payment data prepared in the customary formats for creating tradelines (reported accounts) at CRAs. The format of the data provided from the PHAs all differed in important ways. As such, each needed to be individually standardized. Generally, the data were provided in an accounting type format. For this reason, it was not uncommon for tenants to have very small amounts on their balances after rent was paid. Sometimes these small amounts would persist for months. Because it was not possible to determine whether these balances reflected true underpayments for a month's rent, other charges, or an account discrepancy, it was determined that if most of the month's rent was paid on time, that payment would be counted as on time.

For example, a person who paid only 40 percent of their rent for month one would be considered late, while a person who paid 75 percent to 100 percent of their rent in month one would be considered on time for that month. Thus, an unpaid balance that was 2.7 times or 3.3 times a person's rent would be considered as being behind by 3 months. This was meant to approximate and standardize the past due status of payments, given the data limitations of this study, while also accounting for the relatively small unpaid balances that appear in the accounting data. For example, for a $200/month rent, if there was a (cumulative) balance of $50 at the end of January, $50 in February, $50 in March, then $250 in April, $450 in May, and $0 in June, then January, February, and March would be counted as on-time; April would have a 30-days-late mark; May, a 60-days-late mark; but June would be back to on time. For some context, the median rent amount due for January 2014 in the sample (and for which these data were available) was $216. For this amount, unpaid balances under $108 would not count as late. It is also worthwhile to note that so-called small-dollar "nuisance" third-party collection accounts with balances of under $100 are sometimes ignored by newer credit-scoring models.[7] In addition, some utilities do not credit report small, unpaid balances (Turner et al., 2009).

An important aspect of credit reporting that is not accounted for in this analysis is how tenant payment behavior may change if tenants become aware that their payments are reported to the nationwide CRAs and that it could impact their credit scores and credit standing. Examples from utilities that began full-file reporting suggest that this could lead to a meaningful decrease in arrears (Turner et al., 2009). Not only does this affect the data furnisher (utilities or property managers potentially) through improved cash flow but also consumers in terms of their credit standing. Whether this holds for PHA full-file credit reporting is not known with certainty. However, if it does hold to some degree, then the results presented in this analysis may understate credit score increases and overstate credit score decreases that would result from full-file credit reporting.

[7] For example, see https://www.creditkarma.com/advice/i/new-vantagescore-4-0-explained/.

## Results

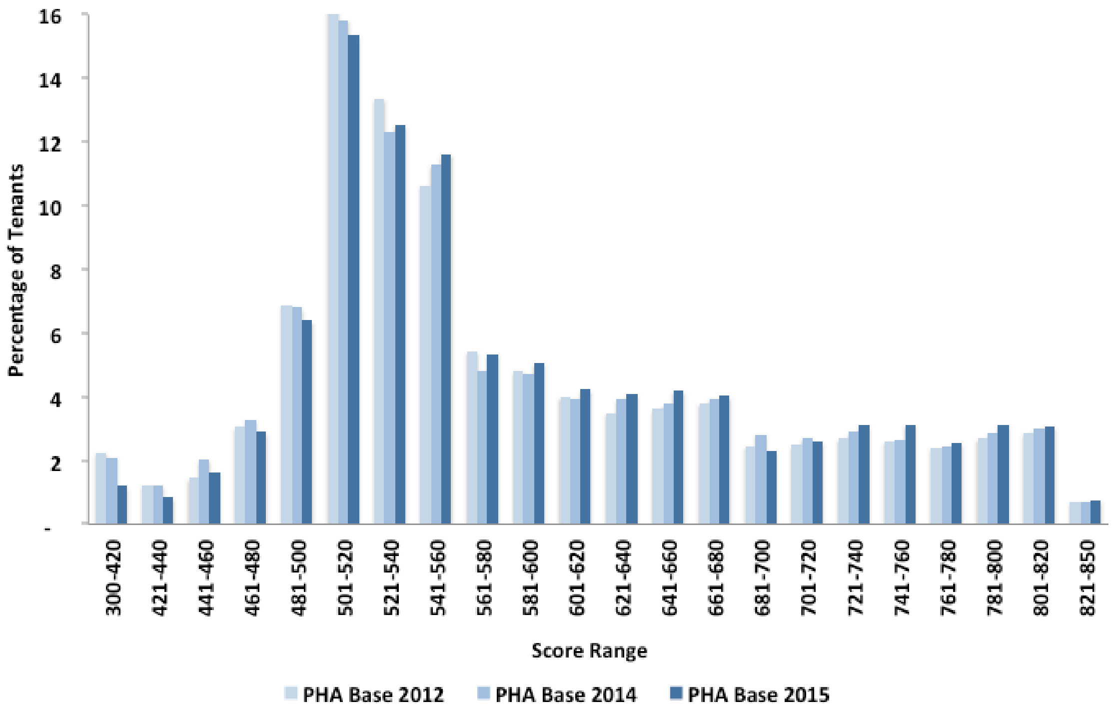
### Record Matching

One of the first issues to be examined in this research was how well PHA tenants could be identified at the nationwide CRAs. For instance, if only a small share of tenants could be matched to records at the CRAs, then either a large share of tenants truly had no CRA records or the data used for matching were somehow insufficient. The match rate of records examined, however, was found to average 92.5 percent across the three PHAs. This is higher than the expectations at the beginning of the project. This finding suggests a high level in confidence in the quality of the PHA data used for matching and that complete credit invisibility, in which the tenant has no data or file at a CRA, likely affects only a small share of PHA tenants. The results that follow are based on tenants with records matched at the CRA. This includes tenants with no accounts reported to the CRA or insufficient information reported to the CRA and as a result are unscorable.

### Credit Profile of PHA Tenants

Figures 1a and 1b present the distribution of credit scores for the two credit-scoring models used over a 3-year period for the two credit-scoring models used in this analysis. The change over time indicates a slight movement to higher credit scores. This may simply reflect the macroeconomic environment in which unemployment was declining during this period (during the recovery from the Great Recession, the headline unemployment rate declined from 8.3 percent at the beginning of 2012 to 5.0 percent by the end of 2015 (U.S. Bureau of Labor Statistics, 2019)). During economic recoveries, it is typical that consumers' financial conditions improve, and rates of common indicators of financial stress decline, such as late payments, arrears, and bankruptcies. As such, overall, credit scores tend to rise.

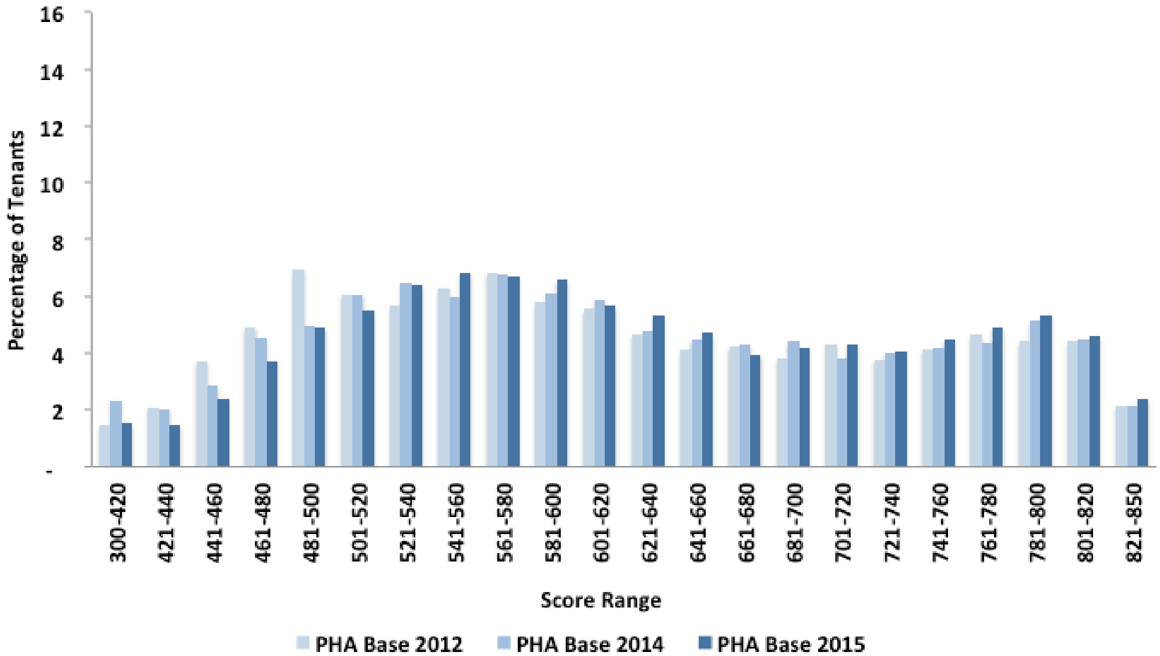
**Figure 1a. Credit-Scoring Model A Distribution of PHA Tenant Sample in 2012, 2014, and 2015 (Scorable Tenant Population, TransUnion Data)**




PHA = public housing agency.

Notes: n= 9,219 for PHA Base 2015, Scorable; n=9,219 for PHA Base 2014, Scorable; n=9,074 for PHA Base 2012, Scorable. Columns may not sum up to 100 percent due to rounding.

**Figure 1b. Credit-Scoring Model B Distribution of PHA Tenant Sample in 2012, 2014, and 2015 (Scorable Tenant Population, TransUnion Data)**




PHA = public housing agency.
Notes: n= 5,321 for PHA Base 2015, Scorable; n=5,251 for PHA Base 2014, Scorable; n=5,110 for PHA Base 2012, Scorable. Columns may not sum up to 100 percent due to rounding.

Another way to view the distributions is using a credit score tier distribution because access to credit and the pricing of credit are not functions of a particular score as much as they are functions of broad credit bands or tiers into which a consumer would fall. For instance, a consumer would likely face the same loan terms and application decision whether having a credit score of 350 or 450. In both cases the consumer would be viewed as very high risk, and despite the 100-point difference between the scores, the consumer would remain in the same tier. On the other hand, if a credit score of 620 represents an important cutoff in terms of a credit decision or pricing, then whether the consumer had a credit score of 618 or 622 could make a large difference.

The Policy and Economic Research Council (PERC) and the Federal Trade Commission (FTC) have recognized this and have used credit score tiers to better estimate the material impacts of credit score changes in their data quality analyses. Because different lenders may use different scores, have different underwriting criteria, have different cutoffs, serve different populations, and so on, there is no *one* credit score tier. Nonetheless, the use of a general set of tiers has been found useful. The following example (table 1) of credit score tiers is based on one used by the CFPB in their "Analysis of Differences between Consumer and Creditor Purchased Credit Scores" (CFPB, 2012).

**Table 1. Example of Credit Score Tiers**

| | |
|---|---|
| **Over 740** | Super Prime |
| **681–740** | Prime |
| **621–680** | Near Prime |
| **620 and under** | Subprime |

Source: CFPB, 2012

The set of credit score tiers in table 1 is also instructive in terms of mortgage lending because a score of 620 is often considered a minimum for obtaining a conventional mortgage.[8] However, those in the near prime category, while meeting the minimum score needed for a conventional mortgage, would typically be offered the loan at a higher price (higher interest rates and generally worse terms) compared with prime and super prime consumers, the latter category typically representing the category associated with the best pricing and terms, everything else constant.

It should also be noted that the FICO® Score 9 and the VantageScore 3.0 are not identical scoring models, and a 620 score in one is not to be treated identically as a 620 score in the other. That said, the scores track fairly closely for our purposes. These tiers are only used for illustrative purposes, and comparisons between FICO® Score 9 and VantageScore 3.0 in terms of particular scores should not be made.

Using these tiers, tables 2a and 2b show the credit score tier distribution for the PHA tenant sample population between 2012 and 2015. As seen in figure 1, there is a shift between 2012 and 2015 toward improved credit profiles for the PHA tenant sample.

**Table 2a. Credit-Scoring Model A Tiers Distribution (Scorable Population, TransUnion Data)**

| | PHA 2012 Base (%) | PHA 2014 Base (%) | PHA 2015 Base (%) |
|---|---|---|---|
| **Super Prime** | 11 | 12 | 13 |
| **Prime** | 8 | 8 | 8 |
| **Near Prime** | 11 | 12 | 12 |
| **Subprime** | 70 | 68 | 67 |

Notes: n= 9,219 for PHA Base 2015, Scorable; n=9,219 for PHA Base 2014, Scorable; n=9,074 for PHA Base 2012, Scorable. Columns may not sum up to 100 percent due to rounding.

Table 2a shows that the subprime population shrank from 70 percent to 67 percent between 2012 and 2015. Other than the potential impact of the economy, this shift could also be caused by a change in the precise makeup of the sample for each of the years, as sometimes, a consumer matched in 2015 may not be able to be matched with the 2012 archive data. As

[8] For an example of the 620 minimum in mortgage lending see Fannie Mae lending criteria: https://www.fanniemae.com/content/guide/selling/b3/5.1/01.html.

such, the samples would not necessarily be identical over the three periods. Table 2b shows similar credit standing improvements over time with the second credit-scoring model.

**Table 2b. Credit-Scoring Model B Tiers Distribution (Scorable Population, TransUnion Data)**

| | PHA 2012 Base (%) | PHA 2014 Base (%) | PHA 2015 Base (%) |
|---|---|---|---|
| **Super Prime** | 20 | 20 | 22 |
| **Prime** | 12 | 12 | 13 |
| **Near Prime** | 13 | 14 | 14 |
| **Subprime** | 55 | 54 | 52 |

Notes: n= 5,321 for PHA Base 2015, Scorable; n=5,251 for PHA Base 2014, Scorable; n=5,110 for PHA Base 2012, Scorable. Columns may not sum up to 100 percent due to rounding.

**Table 3. Unscorable Rates by Credit-Scoring Model (TransUnion Data)**

| | Model A (%) | Model B (%) |
|---|---|---|
| **2012** | 49.1 | 9.6 |
| **2014** | 49.4 | 11.1 |
| **2015** | 49.5 | 12.6 |

Notes: n=10,042 for 2012; n=10,372 for 2014; n=10,545 for 2015. Columns may not sum up to 100 percent due to rounding.

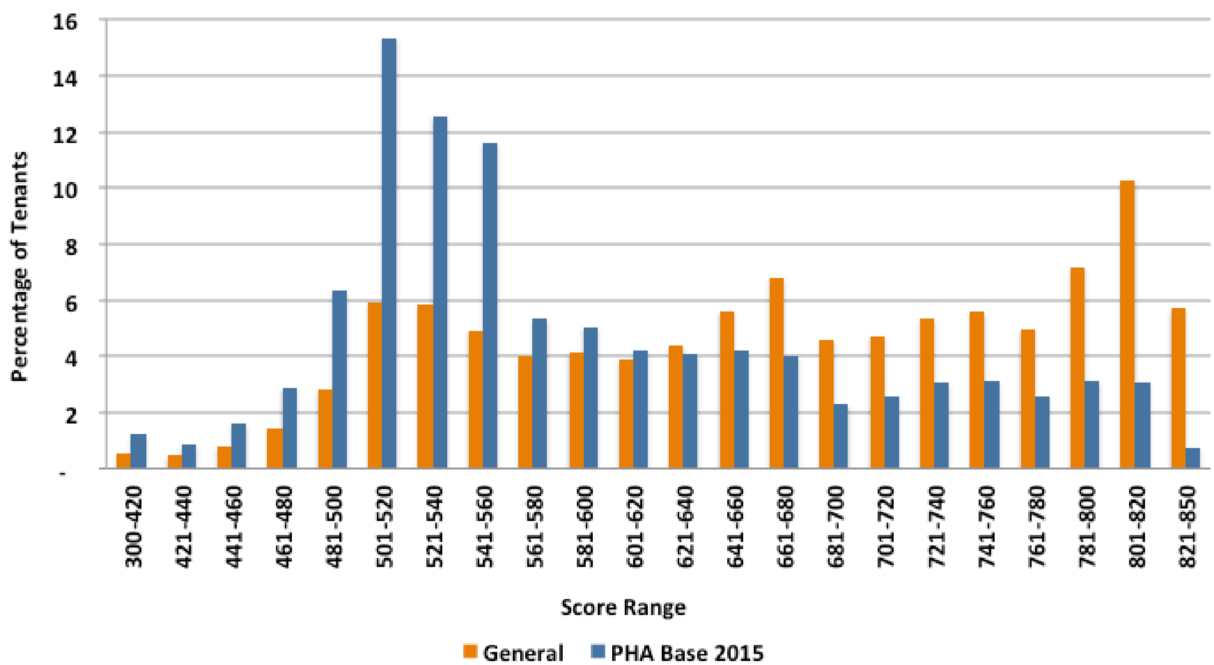
Table 3 shows the unscorable rate for the tenant sample for each scoring model among consumers who were matched at the CRA. Thus, for instance, among the consumers with a credit file in the 2015 sample, 12.6 percent were unscorable with Model B due to insufficient data. The difference in unscorability rates between the two credit-scoring models results from different minimum scoring criteria. One should not conclude that one score is better than another from just looking at scorability differences. Lenders choose scores in terms of how useful they are for the segments which the lenders serve and how accurate they are, both overall and in different segments. As such, score developers take into account these considerations and other factors in score model development. Thus, greater scorable rates in and of themselves should not be viewed positively. Much depends on the algorithm and how the scorability rates were produced. The addition of useful payment data in credit files has the potential to both increase the scorability rates and the accuracy of credit scores.

The large difference between the results for the models may show that a large share of the PHA tenant are scorable with some models but not others. The PHA tenant sample is not made up of mostly thick-file, very credit-active consumers that would be scorable with all models. It is safe to say that many are on the margins of scorability. It should also be noted that the PHA tenant population is sufficiently different from the national population; as such, the reader should not assume the identities of Model A and B based on score distributions or scorability rates from other samples, such as national samples.

In a national sample, the CFPB found that about 19 percent of the overall population was unscorable, either due to lack of data or credit file or otherwise insufficient data when using a traditional credit score and credit data (CFPB, 2015). However, in the lowest income census tracts, this rate was 45 percent (CFPB, 2015)[9].

To see how the PHA tenant sample population compares with the general CRA population, we compare the 2015 distribution to a general population distribution for December 2014. This is shown in figure 2.

**Figure 2. Credit-Scoring Model A Distribution of PHA Tenant Sample in 2015 and a General Population Sample in December 2014 (TransUnion Data)**




PHA = public housing agency.
Notes: n= 9,219 for PHA Base 2015, scorable without the rental data.

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[9] In the CFPB analysis, low-income census tracts are defined as those tracts where the median household income is below 50 percent of the median household income of the area surrounding it (either the MSA or the county). In this way, the measure of low income is relative to an area and not based on particular national income levels.

Figure 2 shows that the PHA tenant sample population skews more to the lower end of the credit score distribution relative to the general population, indicating a population with a higher expected credit risk.

This difference is also clearly seen in the credit score tier distributions seen in table 4, in which 67 percent of the PHA tenant sample is subprime, compared with 35 percent in the general population.

**Table 4. Credit Score Tiers Distribution (Scorable PHA Sample and General Population, TransUnion Data)**

| | PHA 2015 Base (%) | General Population (%) |
|---|---|---|
| **Super Prime** | 13 | 34 |
| **Prime** | 8 | 15 |
| **Near Prime** | 12 | 17 |
| **Subprime** | 67 | 35 |

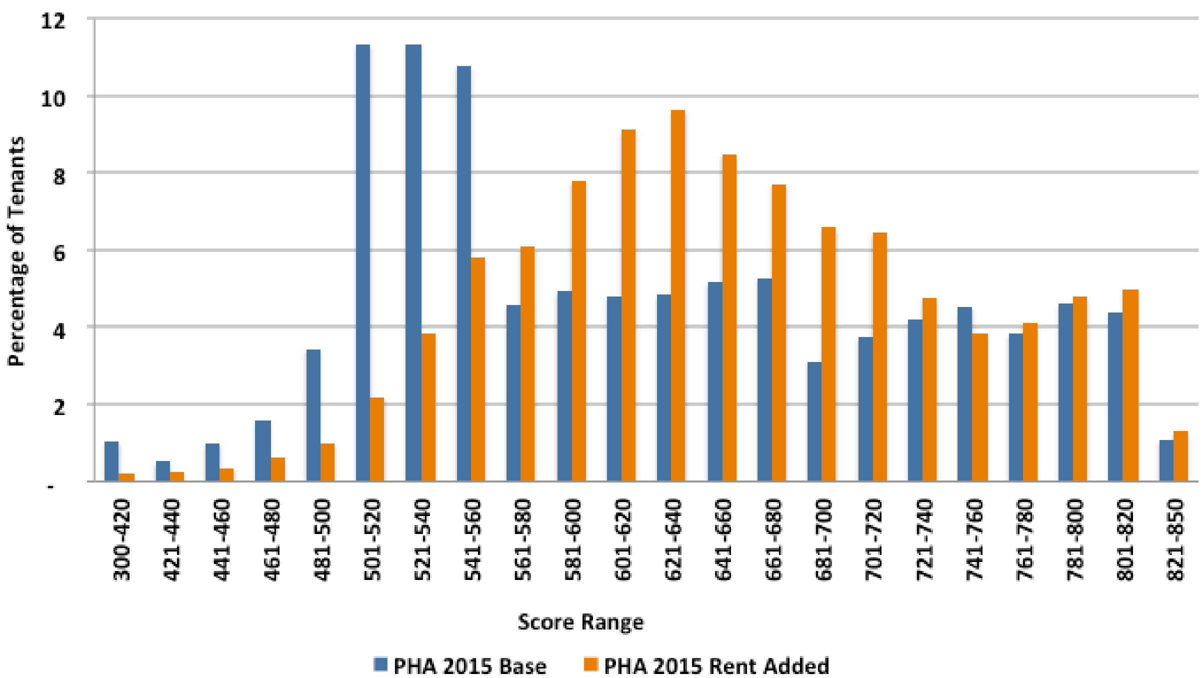
Notes: n= 9,219 for PHA Base 2015, Scorable. Columns may not sum up to 100 percent due to rounding.

## Effects of the Inclusion of Rental Data

*Including Simulated On-Time-Only Rental Data*

The first simulation was produced using a subsample of the base 2015 PHA tenant sample taken from two PHAs (HACC and SHA). The actual rental payments are added as a new tradeline (account), imposing the condition that all payments are assumed on time (assuming no delinquencies).[10] This tells us how the samples' credit scores would change if the rental payment data were reported to the CRAs and all payments were paid on time. The simulation demonstrates the most beneficial outcome possible of reporting, in which, say, PHA tenants were told that their rental payment would be reported, so they made all payments on time. Although this does not reflect the real world, it does act as one bookend. It is also worthwhile to note that the status quo with nonfinancial payment data, such as rent or utility payments, is another extreme, in which collections and very late payments are reported but on-time payments are not.

**Figure 3. Effect of Adding Simulated On-Time PHA Rent Accounts to Credit Score Distribution of PHA Tenant Sample in 2015 (Credit Scoring Model A, TransUnion Data)**




PHA = public housing agency. The PHA 2015 Base in this figure is a subsample based on only two PHAs. Note: n=6,853.

[10] We performed this experiment early in the project prior to receiving data from the LMHA as a first step in producing full-file tradelines. We thought the results were sufficiently interesting that we decided to present them in the paper.

Adding the on-time rental accounts has a dramatic effect on the credit score distribution, shifting the distribution to much higher scores. This can be seen in the credit tiers distribution seen in table 5.

**Table 5. Credit Score Tiers Distribution**
**(PHA Sample and General Population, Credit Scoring Model A, TransUnion Data)**

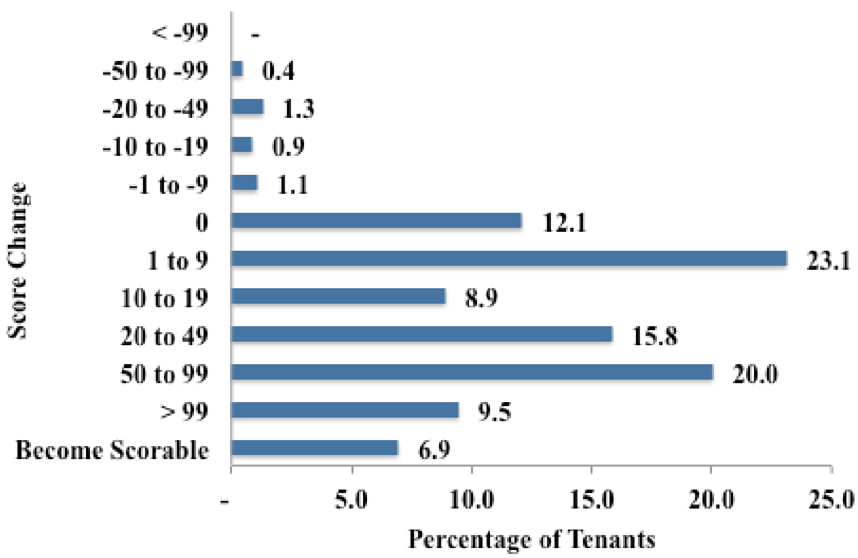
| | PHA 2015 Base (%) | Simulated On-Time-Only Rental Data Added (%) |
|---|---|---|
| **Super Prime** | 18 | 19 |
| **Prime** | 11 | 18 |
| **Near Prime** | 15 | 26 |
| **Subprime** | 55 | 37 |

PHA = public housing agency.
Notes: n=6,853. Columns may not sum up to 100 percent due to rounding.

Table 5 shows that the subprime share of the 2015 PHA tenant sample drops from 55 percent to 37 percent with the inclusion of on-time rental accounts.

Because distributional change can obscure how individual scores may change, figure 4a shows how individual credit scores change with the addition of on-time rental accounts.

**Figure 4a. Effect of Adding Simulated On-Time-Only PHA Rent Data to Credit Scores of PHA Tenant Sample in 2015 (Credit-Scoring Model A, TransUnion Data)**




PHA = public housing agency.
Note: n=6,853.

Figure 4a indicates that 9.5 percent of tenants would see a credit score rise of more than 99 points with an on-time rental account added to their credit report. We can also see that nearly 30 percent would have a 50-plus-point score increase, and 45 percent would have a 20-plus-point score increase. Interestingly, a small share of consumers would witness a credit score decrease. Such counterintuitive impacts can result from the added account changing the average age of accounts, representing a recently opened account, changing balances, or changing the "score card" of the model.

Table 6 shows the credit score tier distribution for those that became scorable with the on-time rental data.

**Table 6. Credit Score Tier Distribution of the Tenants who Become Scorable with Simulated On-time Rental Payments (TransUnion Data)**

| | HUD PHA Newly Scorable Tenants (%) | PHA 2015 Base + On Time Rent (%) | PHA 2015 Base (%) |
|---|---|---|---|
| **Super Prime** | 0 | 19 | 18 |
| **Prime** | 48 | 18 | 11 |
| **Near Prime** | 39 | 26 | 15 |
| **Subprime** | 14 | 37 | 55 |

PHA = public housing agency.
Note: n=6,853, subsample of PHA 2015 Base, Credit-Scoring Model A.

It is interesting to see from table 6 that it is the previously unscorable population (those scorable because of the addition of rental data) that has the smaller share of tenants with subprime credit scores compared with other distributions, such as the PHA 2015 base or even the general population. This no doubt results from the fact that this population had, essentially, mostly blank slates when an on-time account was added. This group, as seen in table 6, also has no consumers with a super prime score, which likely results from the fact that these blank slates are thin-file accounts with insufficient depth of credit history to produce a super prime score. Nonetheless, it is important to see that tenants who gain scorability from a positive account and are otherwise credit report "blank slates" should not unduly fear that they will have a subprime score.

*On Time (Positive) Only Rental Data Reporting Impacts for an Experian Subsidized Sample and General Population Sample*

**Table 7a. Credit Score Tiers Distribution of Previously Unscorable Population Comparing HUD PHA to Experian's Subsidized Sample**

| | 2015 HUD PHA Previously Unscorable (%) | 2014 Experian Subsidized No-Hit Sample (%) |
|---|---|---|
| **Prime (661–850)** | 73 | 59 |
| **Nonprime (601–660)** | 18 | 38 |
| **Subprime (300–600)** | 9 | 3 |

EXP = Experian. PHA = public housing agency.
Notes: This table uses credit score tiers that were used in the Experian analysis, which are slightly different from the ones used in the rest of this analysis.
Source: Experian RentBureau, 2014

Table 7a compares the HUD PHA previously unscorable results from table 6 with impacts from positive rental data credit reporting of subsidized renters from an Experian Sample of no-hit, unscorable consumers. This Experian sample of subsidized renters likely includes some HUD Section 8 tenants. Note that these results use different definitions of credit score tiers than the rest of this report. Nonetheless, table 7a shows a similar pattern, namely that consumers that had no credit file (no-hits), were more likely to gain a prime credit score with the addition of the positive rental data than the prime credit score rate found in the general population. In addition, only a relatively small share become scorable with a subprime credit score. As noted previously, this is no doubt due to the fact these consumers' credit files are relatively blank slates in which a *positive only* account is added.

**Table 7b. Credit Score Tiers Distribution of Experian's Subsidized Sample**

| | 2014 Experian Subsidized Sample without Rental Data (%) | 2014 Experian Subsidized Sample with Rental Data (%) |
|---|---|---|
| **Prime (661–850)** | 17 | 21 |
| **Nonprime (601-660)** | 12 | 23 |
| **Subprime (300–600)** | 65 | 53 |
| **Score Exclusions** | 6 | 3 |

Notes: This table uses credit score tiers that were used in the Experian analysis, which are slightly different from the ones used in the rest of this analysis. Columns may not sum up to 100 percent due to rounding.
Source: Experian RentBureau, 2014

**Table 7c. Credit Score Tier Changes for a General, Nonsubsidized Experian Sample***

| | Experian Nonsubsidized Sample without Rental Data (%) | Experian Nonsubsidized Sample with Rental Data (%) | General |
|---|---|---|---|
| **Prime (661-850)** | 51 | 52 | 55 |
| **Nonprime (601-660)** | 18 | 21 | 14 |
| **Subprime (300-600)** | 30 | 27 | 31 |
| **Score Exclusions** | 1 | 0 | - |

*This table uses credit score tiers that were used in the Experian analysis, which are slightly different from the ones used in the rest of this analysis. *General* is a national sample general distribution used in figure 2 (this is not from the Experian analysis). Columns may not sum up to 100 percent due to rounding.
Source: Experian RentBureau, 2019

Table 7b shows that, as with the HUD sample, the consumers in the Experian "subsidized renters" sample are relatively high risk, with some 65 percent of consumers who had credit files falling in the subprime category before the rental data are added. This figure falls 53 percent when the positive rental data are added.

To add context to the discussion, table 7c compares credit score tier change results from a random sample of Experian's RentBureau database that were not subsidized. This "general" sample had about 400,000 leases that were positive (were paid-as-agreed leases) and were current, open, or active leases.

The score tier distribution of this sample is much more closely aligned to that of the national general sample. Here we see relatively little change in the score tier distribution when the positive rental data are added. That said, the share of consumers classified as score exclusions or subprime falls from 31 percent to 27 percent with the addition of the positive rental data in their credit files (and scores). A key group benefiting in this general population, though not shown in those figures, is those who gain credit files with the rental data. This represents 11 percent of the general sample. As seen in Table 7a, adding a positive tradeline to a blank slate of a no-hit credit report can have a very positive credit score impact for the consumer.

It is also important to note that of the "nonsubsidized" sample, 76 percent were considered thick file, meaning they already had more than two accounts in their credit files before the rental data were added. This also explains why there was relatively little score tier migration with the addition of rental data. By comparison, only 48 percent of the subsidized Experian sample were thick file before the rental data were added. This fits general findings on this topic (and logic) that those most affected with the addition of new accounts in credit files are first those with no data, then those with little data, while those with a lot of data (thick files) see less impact. Table 10e in this paper shows that only 44 percent of the 2014 PHA sample was "thick file" prior to the addition of the rental data.

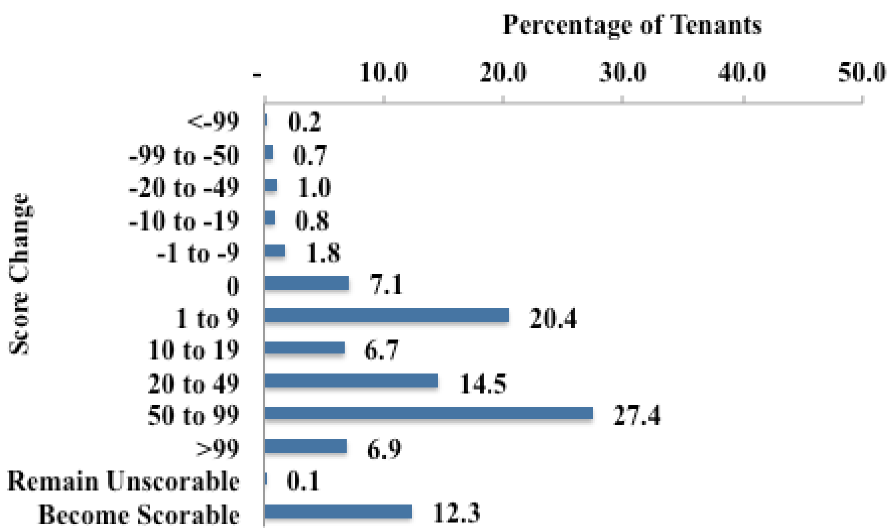
Finally, it is also important to note that credit scores based on more information or thicker files tend to be better able to predict outcomes, and lenders tend to put more weight on them.

So, for instance, a consumer with a 620 thin file score might not be accepted for a product (such as a credit card), whereas one with a 620 thick file score might be. That is, in addition to the score impacts of adding new accounts, there is also a benefit from thickening the credit files.

### *Impacts of Reporting Only Positive (Actual) PHA Rental Accounts*

This section examines the impacts for the case in which only the tenants with *actual* on-time rental payment histories had their rental payments reported to the CRAs to be used in credit scores. As will be seen later in this section in table 9a, some 65 percent of tenants were considered on time (paying within 30 days of the payment due date) up to the entire 24 months prior to the 2014 credit score snapshot. Unlike the PHA results from the previous subsection, these are not simulated, but actual on-time accounts. This type of reporting is not a theoretical exercise but is how the reporting of rental tradelines (accounts) occurs with Experian. While full-file (positive and negative) rental data is reported to Experian's RentBureau, only paid-as-agreed accounts are then reported to the main consumer credit file database that the main generic credit scores like FICO® Score 9 and VantageScore 3.0 utilize.

**Figure 4b: Credit Score Changes from Adding Actual Positive Only PHA Rental Data (2014 Positive Only Sample, Model A, TransUnion Data)**

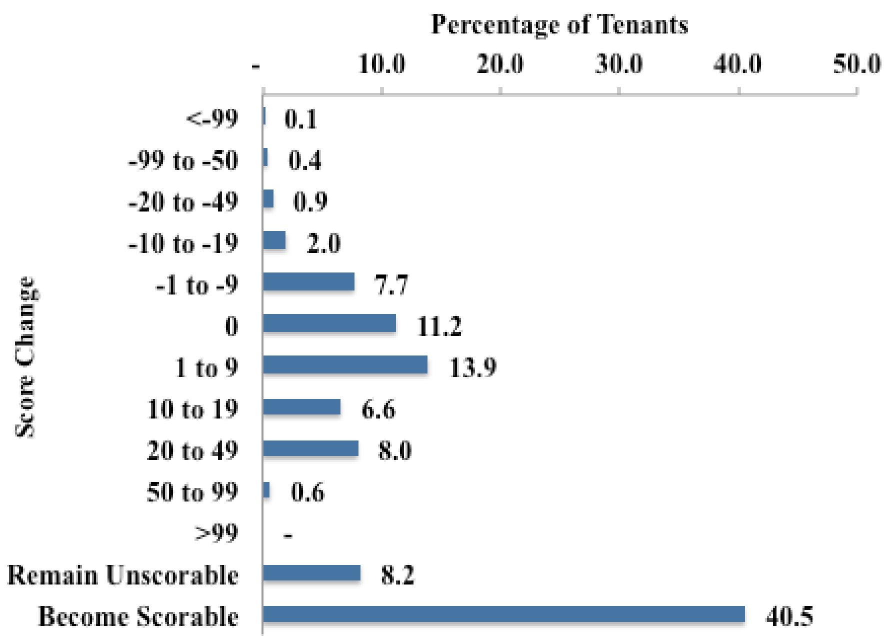



N=6,770.

Figures 4b and 4c show that among the positive-only 2014 subsample, the overwhelming movement in credit scores tends to be increases. For Model A, close to 50 percent see credit score increase of 20 points or greater, while unscorability is virtually eliminated.

For Model B, shown in Table 4c, the score changes appear to be more muted, though there is still the clear skew to positive score changes and unscorability is greatly reduced.

**Figure 4c: Credit Score Changes from Adding Actual Positive Only PHA Rental Data (2014 Positive Only Sample, Model B, TransUnion Data)**




N=6,770.

Figures 4a, 4b, and 4c do nonetheless show a small share of tenants with credit score declines with the addition of on-time rental histories. This may be due to two aspects of credit-scoring models that were discussed previously. First, although an account may be *on time,* there are other aspects of the account, such as balances and date opened, that can impact the credit score. So, while a tradeline may be "positive" it could still lower a credit score due to attributes other than the so-called manner of payment (that is, the timeliness of payments). For instance, by opening up a new credit card account a person may lower their credit score even if they make payments on time if the "newness" of the account or the balance acts to lower their score. Second, by adding another account to a credit file the particular "card" or model used to actually score the file may shift from a thin-file model to a thicker-file model (for instance). It is possible that the particular attributes of the individual's file might produce a score of 633, with the thin file model for instance, and a score of 631 with the thicker file model. However, as noted earlier, lenders tend to look more favorably on thicker file consumers than thinner file consumers, given the improved accuracy of scores based on more data (and more real payment history of the consumer). So, a thick file consumer with a 631 score might be accepted for credit, while a thin file consumer with a 633 score might not be accepted.

**Table 8a: Credit Scoring Model A Tier Distribution Changes from Adding Positive Only PHA Rental Data (2014, TransUnion Data)**

| | Positive-Only Subsample | | Entire Sample | |
|---|---|---|---|---|
| | PHA 2014 Base (%) | Positive Only Rental Accounts Added (%) | PHA 2014 Base (%) | Positive Only Rental Accounts Added (%) |
| **Super Prime** | 13 | 14 | 10 | 11 |
| **Prime** | 9 | 18 | 7 | 13 |
| **Near Prime** | 12 | 24 | 10 | 19 |
| **Subprime** | 54 | 43 | 61 | 54 |
| **Unscorable** | 12 | 0 | 11 | 3 |
| ***621+ Credit Score*** | *33* | *57* | *28* | *43* |

N=6,770 for the positive only sample, N=10,372 for the entire sample. Columns may not sum up to 100 percent due to rounding.

**Table 8b: Credit Score Credit Scoring Model A Tiers with Added Positive Only PHA Rental Data for Those Who Were Previously Unscorable (2014, TransUnion Data)**

| | Previously Unscorable (%) |
|---|---|
| **Super Prime** | 0 |
| **Prime** | 48 |
| **Near Prime** | 41 |
| **Subprime** | 10 |
| **Unscorable** | 1 |

N=842. Columns may not sum up to 100 percent due to rounding.

The first two columns of Table 8a show results from positive-only reporting on the subsample of tenants with positive-only rental histories. This is about 65 percent of the 2014 sample. Here we see that the results are similar to what was shown with the subsidized tenants from the Experian analysis shown in Table 7b. In the Experian subsidized sample, the share of tenants with nonprime or better credit scores rose from 29 percent of the sample to 44 percent. In the 2014 PHA sample (Table 8a) the near prime or better share rises from 33 percent to 57 percent of the sample (note that these two tables use different score tier definitions).

The last two columns of Table 8a examine the entire 2014 PHA sample. For these calculations, the base case, as always, does not contain the PHA rental data. For the last column that includes the positive only data, for those with positive rental accounts the credit score with the rental data was used and for the remainder of tenants the base credit score with no rental data was used. This then shows, for the entire tenant sample, how the credit score tier distribution would change if rental data were reported only for tenants with positive rental accounts. So, for all tenants, the 621+ credit score share rise from 28 percent to 43 percent with positive-only reporting.

**Table 8c: Credit Scoring Model B Tier Distribution Changes from Adding Positive Only Rental Data (2014, TransUnion Data)**

| | Positive-Only Sample | | Entire Sample | |
|---|---|---|---|---|
| | PHA 2014 Base (%) | Positive Only Rental Accounts Added (%) | PHA 2014 Base (%) | Positive Only Rental Accounts Added (%) |
| **Super Prime** | 13 | 14 | 10 | 11 |
| **Prime** | 7 | 20 | 6 | 14 |
| **Near Prime** | 7 | 16 | 7 | 12 |
| **Subprime** | 24 | 43 | 27 | 40 |
| **Unscorable** | 49 | 8 | 49 | 23 |
| ***621+ Credit Score*** | *28* | *49* | *23* | *37* |

N=6,770 for the positive only sample, N=10,372 for the entire sample. Columns may not sum up to 100 percent due to rounding.

**Table 8d: Credit Score Credit Scoring Model A Tiers with Added Full-File Rental Data for Those Who Were Previously Unscorable (2014, TransUnion Data)**

| | Previously Unscorable (%) |
|---|---|
| **Super Prime** | 1 |
| **Prime** | 25 |
| **Near Prime** | 16 |
| **Subprime** | 41 |
| **Unscorable** | 17 |

N=3,301. Columns may not sum up to 100 percent due to rounding.

Table 8c shows that with Credit Scoring Model B, among those with the positive rental accounts, the 621+ credit score share of the sample rises from 28 percent to 49 percent. For the entire 2014 PHA tenant sample this rate rises from 23 percent to 37 percent.

Tables 8b and 8d show that the majority of tenants that become scorable with the positive-only reporting achieve a near prime or better credit score. Though, with one credit score this is close to 90 percent achieving a 621+ score but for the other it is slightly over 50 percent.

### *Including Full-File Rental Data*

Including full-file PHA rental data requires adding a Manner of Payment (MOP) indicator for whether a particular month's rental payment is delinquent and, if so, how delinquent. Standard credit reporting classifies delinquencies in terms of 30-day buckets. In this classification, sufficient payments made before 30 days after the due date are considered on time. Those made 30 to 59 days after the due date are considered 30 Days Past Due (DPD), and so on. Whereas this system is aligned to credit card, auto loan, mortgage, utility, and many other obligations, it is very forgiving of late payments for rent. For many tenants, being 2 or 3 weeks late is not considered on time, and landlords may even begin eviction procedures. So, although PHAs or other landlords may report that X percent of their tenants have been late, this would likely greatly overstate the rate of delinquency that would be reported by a CRA. Table 9a shows the maximum delinquency rate for the PHA in the PHA sample.

The first row of table 9a indicates that 65 percent of all tenants have payment histories in which all their payments (for 24 months prior to October 2014) would have been reported as on time—that is, none of the payments are reported as late (30+ days past due). The second row indicates that a further 20 percent of tenants were, at most, 30 to 59 days past due, or 30 DPD, and so on.

**Table 9a. PHA Rental Max/Worst Delinquency Rates by 30-Day CRA Classifications**

| | Over 24-Month Period (%) | Over 12-Month Period (%) |
|---|---|---|
| **On Time** | 65 | 75 |
| **30 DPD** | 20 | 14 |
| **60 DPD** | 7 | 5 |
| **90 DPD** | 3 | 2 |
| **120 DPD** | 2 | 1 |
| **150 DPD** | 1 | 1 |
| **180+ DPD** | 1 | 1 |

CRA = credit reporting agency. DPD = days past due. PHA = public housing agency.
Notes: Based on PHA 2015 sample, n=10,545. October 2012–September 2014 is the 24-month period, and October 2013–September 2014 is the 12-month period. Columns may not sum up to 100 percent due to rounding.

An important note regarding the above data is that small balances were excluded. This means that if a tenant, for instance, underpaid his or her rent by $8 one month, and that was a running balance month after month, but otherwise rent was paid on time, the payments would still be considered on time. Excluding the reporting of a small balance is a consumer-friendly approach practiced by other nonfinancial payment reporters, such as utilities. Such small positive balances can result from a tenant continuing to pay a previous amount due after a rent increase or a small charge added on a month's rent that goes unnoticed. The second note is that balances owed by tenants prior to the initial payments reported were also excluded. So, if a tenant owed 3 months' rent in January 2014 but payment reporting to the CRAs began in February 2014, then the February payment would be considered on time if a sufficient payment was received in February 2014. That is, tenants are held accountable for payment going forward from the date of the first CRA reporting.

Table 9b puts the data from table 9a into significant credit-reporting categories. The on-time category is the same as table 9a. The 30 DPD and the 60 DPD categories are also the same, but 30 DPD is labeled Minor Delinquencies, as this is the least severe of the delinquencies.

This has the least negative impact on credit scores, and some data furnishers do not ever report 30 DPDs but report those as on time until 60 DPD is reached (this is one reporting option tested in this report).

Previous analysis by the Policy and Economic Research Council (PERC) has shown that adding an account with a past 30 DPD can even raise a consumer's credit score in some cases if the consumer was thin file or had other minor delinquencies (Turner et al., 2012). In these cases, the impact of adding one more accounts or adding an account with an older account date benefits the consumer's score more than the negative aspect of having a minor delinquency. For consumers with otherwise sufficiently thick, clean, and long-lasting credit histories, adding an account with a minor delinquency might be expected to lower their credit score. This is why it is wise to test how added data will impact credit scores and not assume that "positive" data will only raise scores and "negative" data will only lower scores.

The 60 DPD category indicates a moderate delinquency. 90 DPD is typically considered a "severe" delinquency and can have a larger impact on credit scores if a consumer has no other severe delinquencies. For instance, if a consumer has a pristine credit report, then adding a 90+ DPD can have large negative impact, but if a consumer has other 90+ DPDs and collection accounts, then adding one more account with a 90+ DPD may have little impact. The 90+ DPD category includes 90 DPD, 120 DPD, 150 DPD, and 180+ DPD. Finally, when accounts reach 180+ DPD, they are typically considered charge-offs or defaults.

**Table 9b. PHA Rental Max/Worst Delinquency Rates by Significant Categories**

| | Over 24-Month Period (%) | Over 12-Month Period (%) |
|---|---|---|
| **On Time** | 65 | 75 |
| **Minor Delinquency (30 DPD)** | 20 | 14 |
| **Moderate Delinquency (60 DPD)** | 7 | 5 |
| **Severe Delinquency (90+ DPD)** | 8 | 5 |
| **Charge Off (180+)** | 1 | 1 |

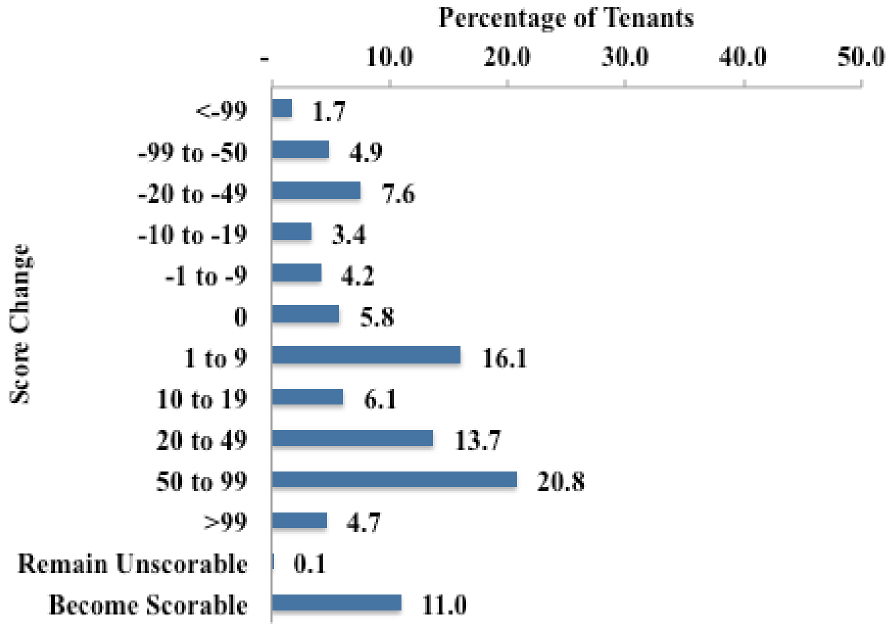
Notes: Based on PHA 2015 sample, n=10,545. October 2012–September 2014 is the 24-month period, October 2013–September 2014 is the 12-month period. Columns may not sum up to 100 percent due to rounding.

Overall, only 8 percent of tenants have rental payment histories with one or more 90+ DPD delinquencies over the 24-month period (October 2012 to September 2014). Some of these tenants may have other accounts with severe delinquencies, collections, or other major derogatories, and so they may not see that large of a credit score impact from the PHA account.

### *Credit Score Changes from Adding Full-File Rental Data*

Figure 5a contains results for Model A credit score changes when full-file PHA rental data are added to credit files in the 2014 sample.

**Figure 5a. Impact of Adding Full-File PHA Rent Accounts to Credit Scores of PHA Tenant Sample in 2014 (Credit-Scoring Model A, TransUnion Data)**

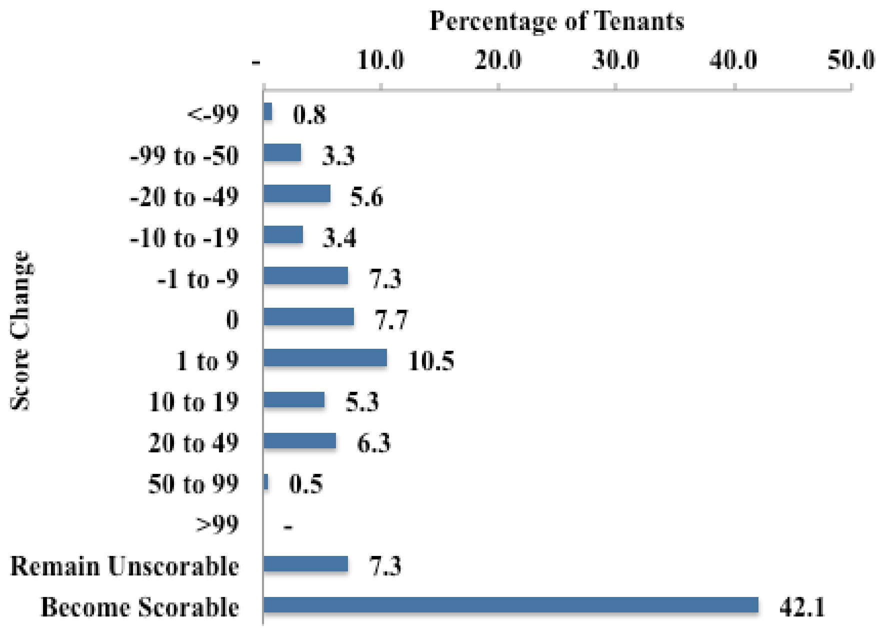



PHA = public housing agency.
Notes: n=10,372. Columns may not sum up to 100 percent due to rounding.

This shows, overall, about three times as many credit score increases as decreases. Whereas more than 25 percent of PHA tenants witness a 50-point or greater increase in their credit score, around 6.4 percent witness a similar credit score decrease.

Figure 5b contains the results for the second credit-scoring model. The credit score impacts are much more symmetric in the second credit scoring model. In this model, while 23 percent see a credit score increase with the added account, 20 percent see a credit score decline.

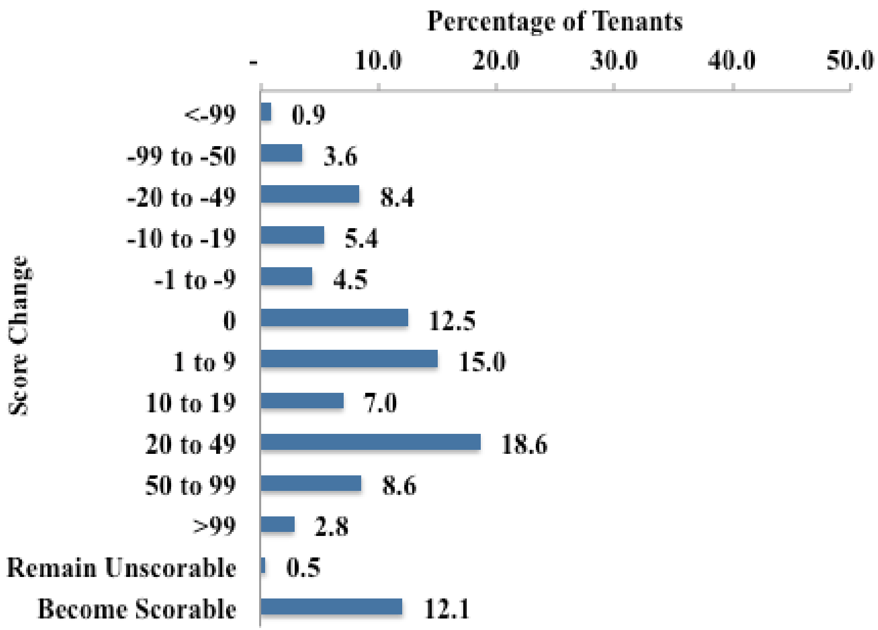
**Figure 5b. Impact of Adding Full-File PHA Rent Accounts to Credit Scores of PHA Tenant Sample in 2014 (Credit-Scoring Model B, TransUnion Data)**




PHA = public housing agency.
Notes: n=10,372. Columns may not sum up to 100 percent due to rounding.

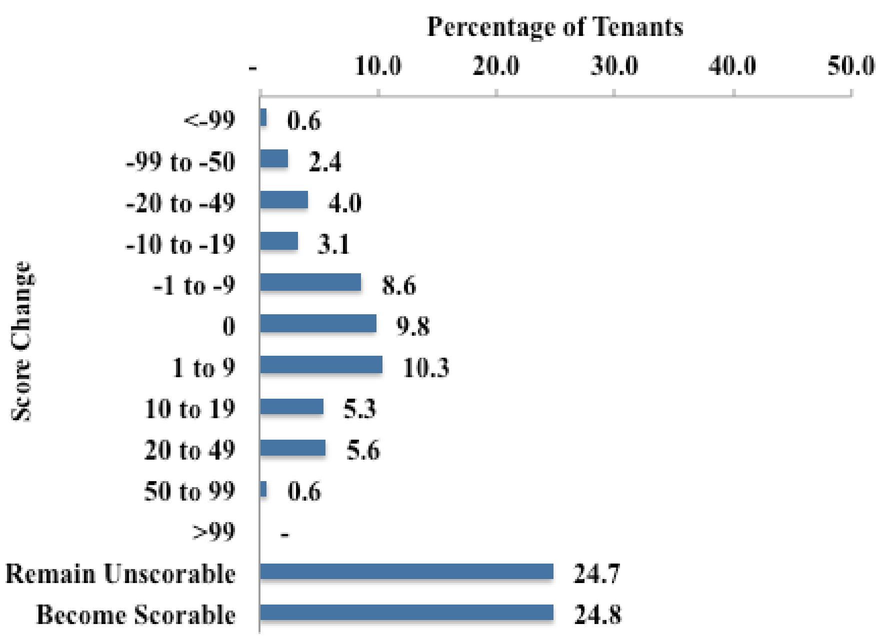
A similar pattern is seen with the 2015 sample, as shown in figures 6a and 6b, though the overall share of score rises is closer to twice the share of the overall score decreases in this sample. On the other hand, the Model B credit score changes tend to be more symmetric, as with the 2014 results. Generally, the impacts from the added rental data appear to be smaller in the 2015 snapshot than in the 2014 snapshot. This is no doubt due to the fact that the rental data was on average more "recent" in the 2014 snapshot than in the 2015 snapshot.

**Figure 6a. Impact of Adding Full-File PHA Rent Accounts to Credit Scores of PHA Tenant Sample in 2015 (Credit-Scoring Model A, TransUnion Data)**




PHA = public housing agency.
Notes: n=10,545. Columns may not sum up to 100 percent due to rounding.

**Figure 6b. Impact of Adding Full-File PHA Rent Accounts to Credit Scores of PHA Tenant Sample in 2015 (Credit-Scoring Model B, TransUnion Data)**




PHA = public housing agency.
Notes: n=10,545. Columns may not sum up to 100 percent due to rounding.

On the other hand, the other credit-scoring model's score changes tended to be more symmetric.

As noted previously, looking beyond raw credit score changes and examining how these changes impact the credit risk tier distribution for the sample can provide additional important insights. The change in the tenants' credit tier distribution is shown in table 10a.

**Table 10a. Credit-Scoring Model A Tier Changes from Adding Full-File Rental Data (2014, TransUnion Data)**

| | PHA 2014 Base (%) | Full-File Rental Accounts Added (2014) (%) |
|---|---|---|
| **Super Prime** | 10 | 10 |
| **Prime** | 7 | 13 |
| **Near Prime** | 10 | 19 |
| **Subprime** | 61 | 57 |
| **Unscorable** | 11 | 0 |
| | | |
| ***621+ Credit Score*** | *28* | *43* |

Notes: n=10,372. Columns may not sum up to 100 percent due to rounding.

Tier change results from adding the full-file PHA rental payment data shown in table 10a indicate a dramatic improvement in the identified credit quality of the PHA tenants. Specifically, without the full-file data, 28 percent are super prime, prime, or near prime; that is, they are more able to access lower-cost, mainstream credit, including having the minimum credit score criteria for mortgages. After the full-file data are added, this percentage rises to 43 percent. The total subprime share decreases modestly as tenants both move up from subprime and move to subprime from other tiers and from the unscorable category.

As seen in table 10a, there is an 11-percent shift overall from unscorable to scorable with the added data. These tenants that shift from being unscorable end up in relatively high tiers. Table 10b shows that some 70 percent of unscorable tenants move to either prime or near prime.

**Table 10b. Credit Score Credit-Scoring Model A Tiers with Added Full-File Rental Data for Those Who Were Previously Unscorable (2014, TransUnion Data)**

| | Previously Unscorable (%) |
|---|---|
| **Super Prime** | 0 |
| **Prime** | 35 |
| **Near Prime** | 35 |
| **Subprime** | 29 |
| **Unscorable** | 1 |

Notes: n=1,153. Columns may not sum up to 100 percent due to rounding.

**Table 10c. Credit-Scoring Model B Tier Changes from Adding Full-File Rental Data (2014, TransUnion Data)**

| | PHA 2014 Base (%) | Full-File Rental Accounts Added (2014) (%) |
|---|---|---|
| **Super Prime** | 10 | 10 |
| **Prime** | 6 | 14 |
| **Near Prime** | 7 | 14 |
| **Subprime** | 27 | 54 |
| **Unscorable** | 49 | 7 |
| | | |
| ***621+ Credit Score*** | *23* | *38* |

Notes: n=10,372. Columns may not sum up to 100 percent due to rounding.

Table 10c shows that with the second credit-scoring model, the share of consumers who are scorable and have credit scores over 620 rises from 23 percent to 38 percent with the addition of the full-file PHA rental data. However, the percentage of previously unscorable tenants that end up in the prime and near prime tiers is much lower than in Model A.

It is important to note that unscorability does not drop to 0 percent when the rental data are added because the added data include some "sparse" accounts for which only a few months of rent is reported. These sparse accounts included tenants who may have moved a few months after the start point for the data collection. This reflects the real world: sometimes reported accounts have a long history, sometimes they do not. Relatively shorter histories might be expected when a data furnisher (an entity that reports data to a CRA) begins reporting. Table 10d shows that for Model B 54 percent of the unscorable achieve subprime credit score, 15 percent remain unscorable, and the remainder (about 32 percent) become near prime or better.

**Table 10d. Credit-Scoring Model B Tiers with Added Full-File Rental Data for Those Who Were Previously Unscorable (2014, TransUnion Data)**

| | Previously Unscorable (%) |
|---|---|
| **Super Prime** | 1 |
| **Prime** | 17 |
| **Near Prime** | 15 |
| **Subprime** | 54 |
| **Unscorable** | 15 |

Notes: n=10,372. Columns may not sum up to 100 percent due to rounding.

Table 10e shows that the majority of the 2014 base sample tenant population is "thin file," that is having fewer than three tradelines or accounts in their credit file. After the full file rental data is added the share with no accounts in their file goes from a little over a third to 0 percent and a slight majority become "thick file."

**Table 10e: Credit Scoring Model B Tiers with Added Full-File Rental Data for Those Who Were Previously Unscorable (2014, TransUnion Data)**

| | Number of Accounts | Base (%) | Full File Rent Data Added (%) |
|---|---|---|---|
| **Thin File** | 0 | 34 | 0 |
| | 1 | 14 | 33 |
| | 2 | 9 | 15 |
| **Thick File** | 3+ | 44 | 53 |

N=10,372.

This table confirms that the 2014 sample is composed of a large share of individuals with credit files that are on the margins of scorability.

Tables 11a, 11b, 11c, and 11d show the full-file results for the 2015 sample, with patterns similar to the 2014 data. In table 11c the super prime, prime, and near prime groups rise from 29 percent of the PHA tenants to 40 percent of the tenants when the full-file rental data are added to the second credit-scoring model (Credit-Scoring Model B). In the first credit-scoring model shown in table 11a (Credit-Scoring Model A), this share rises from 24 percent to 37 percent.

**Table 11a. Credit-Scoring Model A Tier Changes from Adding Full-File Rental Data (2015, TransUnion Data)**

| | PHA 2015 Base (%) | Full-File Rental Accounts Added (2015) (%) |
|---|---|---|
| **Super Prime** | 11 | 11 |
| **Prime** | 6 | 14 |
| **Near Prime** | 7 | 13 |
| **Subprime** | 26 | 38 |
| **Unscorable** | 50 | 25 |
| | | |
| ***621+ Credit Score*** | *24* | *37* |

Notes: n=10,545. Columns may not sum up to 100 percent due to rounding.

**Table 11b. Credit-Scoring Model A Tiers Distribution with Added Full-File Rental Data for Those Who Were Previously Unscorable (2015, TransUnion Data)**

| | Previously Unscorable (%) |
|---|---|
| **Super Prime** | 1 |
| **Prime** | 14 |
| **Near Prime** | 13 |
| **Subprime** | 23 |
| **Unscorable** | 50 |

Notes: n=5,224. Columns may not sum up to 100 percent due to rounding.

**Table 11c. Credit-Scoring Model B Tier Changes from Adding Full-File Rental Data (2015, TransUnion Data)**

| | PHA 2015 Base (%) | Full-File Rental Accounts Added (2015) (%) |
|---|---|---|
| **Super Prime** | 11 | 10 |
| **Prime** | 7 | 14 |
| **Near Prime** | 11 | 15 |
| **Subprime** | 59 | 59 |
| **Unscorable** | 13 | 0 |
| | | |
| ***621+ Credit Score*** | *29* | *40* |

Notes: n=10,545. Columns may not sum up to 100 percent due to rounding.

**Table 11d. Credit-Scoring Model B Tiers Distribution with Added Full-File Rental Data for Those Who Were Previously Unscorable (2015, TransUnion Data)**

| | Previously Unscorable (%) |
|---|---|
| **Super Prime** | 0 |
| **Prime** | 43 |
| **Near Prime** | 21 |
| **Subprime** | 32 |
| **Unscorable** | 4 |

Notes: n=1,326. Columns may not sum up to 100 percent due to rounding.

As can be seen in the eight data tables above (tables 10 and 11, a–d), the inclusion of a fully reported PHA rental payment tradeline dramatically reduces the incidence of unscorability. Many of those who become scorable are moved into some variant of a prime score (super prime, prime, or near prime) and not a subprime score. The share of tenants with 621-plus credit score also rises noticeably with the full-file reporting.

### *Example of Tenant Credit Price Impacts from Adding Rental Data*

Given varied underwriting procedures for the same type of credit, different credit scores in use, different score cutoffs used, different data used (application data, supplemental data), and different types of credit (mortgage, auto, credit card, etc.), it becomes clear that attempting to estimate *precise* credit price impacts from credit score changes is a complex task beyond the scope (and the data) of this analysis. However, a useful approach to getting some measure of the credit price impacts from credit score changes is to use an example of credit score ranges (tiers) and corresponding average interest rates. What follows in table 12 is a set of credit score tiers with average APRs for new auto loans taken from an article published in NerdWallet. The author of the article sourced the APR data from Experian.

**Table 12: Example of Price of Credit (Average APR) by Credit Score for New Auto Loans**

| Tier Name | Score Range | Average APR (%) |
|---|---|---|
| Super Prime | 781-850 | 3.7 |
| Prime | 661-780 | 4.6 |
| Nonprime | 601-660 | 7.5 |
| Subprime | 501-600 | 11.9 |
| Deep Subprime | 300-500 | 14.4 |

This example comes from Bev O'Shea. “What Credit Score Do You Need to Buy a Car?” NerdWallet. Feb. 4, 2019. It was originally sourced from Experian Information Solutions.
https://www.nerdwallet.com/blog/finance/credit-score-needed-to-buy-car/

Table 13 then uses the tiers and average APRs from table 12 to produce weighted average interest rates with and without the rental data for the 2014 PHA sample.

**Table 13: Example of Price of Credit Impacts from Credit Reporting PHA Rental Data**

| | Model A (%) | Model B (%) |
|---|---|---|
| **Scorable Samples Only** | | |
| **Base** | **8.9** | **10.0** |
| Positive Only | 8.8 | 9.1 |
| Full File | 9.0 | 9.3 |
| | | |
| **Entire Sample** | | |
| **Base** | **10.4** | **10.2** |
| Positive Only | 9.3 | 8.9 |
| Full File | 9.4 | 9.1 |

N=10,372 for Entire 2014 Sample, N= 9,219 for Model B Scorable Sample,
N=5,251 for Model B Scorable Sample. Based on 2014 PHA Sample.

The *Scorable Sample Only* results are based on tenants who are scorable with and without the tenant rental data. The *Base* results are the weighted average without the rental payment data, the *Positive Only* are the weighted average results if only credit scores with rental data are used for the tenants with on-time rental payment histories with the remaining having their credit score without the rental data, and the *Full File* results use the credit scores with rental data for all of the tenants.

For the *Scorable Sample Only* results it is interesting to see that with Scoring Model A there is very little change in the weighted APR with either positive-only reporting or full-file reporting relative to the base case of no rental data reporting. However, this may not be surprising since one of the credit scores examined had a fairly symmetric credit score change distribution with the addition of rental data. However, with Scoring Model B both positive-only and full-file reporting lower the weighted average APRs for the 2014 PHA scorable sample.

For the *Entire Sample* results, those who were unscorable needed to be assigned an APR. Since unscorable consumers are considered higher risk, it seemed reasonable to assign the subprime or deep subprime APR to this group. From the first three rows of Table 12 it is clear that the average APR for the scorable tenants was higher than the nonprime rate. So, choosing the nonprime rate of 7.5 percent did not seem reasonable. To err on the conservative side, we chose to assign the subprime rate of 11.9 percent to the unscorables and not the higher deep subprime rate. The results for *Entire Sample* are unambiguous. In all cases, when the unscorable are also accounted for, the average APR drops by at least a full percentage point with rental data reporting, regardless of type of credit reporting (positive-only or full-file).

While these results should be viewed as an illustrative example, this example shows that for the overall tenant sample, the status quo of no credit reporting is the least beneficial case.

In this example, it is assumed that all tenants would be approved for the credit offered. In reality, a low score or no score could result not in just a higher interest rate but in a loan not being approved. Those without a sufficient credit score could have few decent options other than resorting to high cost lenders and the like (pawn shops, check cashers, and payday lenders).

## Summary of Results

**Table 14: Summary of Credit Tier Changes from Credit Reporting PHA Rental Data, 2014 PHA Sample (TransUnion Data)**

| | | Score A | | | Score B | | |
|---|---|---|---|---|---|---|---|
| Score Range | Tier Name | Base (%) | Positive Only (%) | Full File (%) | Base (%) | Positive Only (%) | Full File (%) |
| Over 740 | Super Prime | 10 | 11 | 10 | 10 | 11 | 10 |
| 681-740 | Prime | 7 | 13 | 13 | 6 | 14 | 14 |
| 621-680 | Near Prime | 10 | 19 | 19 | 7 | 12 | 14 |
| Under 621 | Subprime | 61 | 54 | 57 | 27 | 40 | 54 |
| No Score | No Score | 11 | 3 | 0 | 49 | 23 | 7 |
| | *621+* | 28 | 43 | 43 | 23 | 37 | 38 |

N=10,372 for Entire 2014 Sample, N= 9,219 for Model B Scorable Sample, N=5,251 for Model B Scorable Sample. Based on 2014 PHA Sample.

Table 14 summarizes the credit tier changes and the scorability changes with a shift from no rent reporting to positive-only reporting to full-file credit reporting. Scorability increases in the shift from no reporting to positive-only reporting. It then further increases in the shift to full-file reporting. In terms of achieving greater scorability, full-file reporting, not surprisingly, outperforms positive-only reporting.

As for the share of the sample with a credit score greater than 620, reporting (either positive-only or full file) is superior to the base case, the status quo of no credit reporting. In one of the scoring models there is a slightly higher rate of greater than 620 credit scores for the full-file reporting scenario.

**Table 15: Summary of the Example of Price of Credit Impacts from Credit Reporting PHA Rental Data (Average APRs for Auto Loans, 2014 PHA Sample)**

| | Score A | | | Score B | | |
|---|---|---|---|---|---|---|
| | Base (%) | Positive Only (%) | Full File (%) | Base (%) | Positive Only (%) | Full File (%) |
| Only Scorable Tenants | 8.9 | 8.8 | 9.0 | 10.0 | 9.1 | 9.3 |
| All, Assuming 11.9% APR for Unscorables | 10.4 | 9.3 | 9.4 | 10.2 | 8.9 | 9.1 |
| All, Assuming 14.4% APR for Unscorables | 11.6 | 9.9 | 9.6 | 10.5 | 9.0 | 9.1 |

N=10,372 for Entire 2014 Sample, N= 9,219 for Model B Scorable Sample,
N=5,251 for Model B Scorable Sample. Based on 2014 PHA Sample.

Table 15 then translates the score changes with the rental data using an example distribution of average APRs by credit score shown in the previous section. Here, only looking at Model A with the tenants who are already scorable with and without the added rental data, we see no meaningful difference with the addition of the rental data. For Model B of the already scorable case and all the cases for both scoring models where the impact on the unscorable tenants are accounted for, we see a meaningful lowering of the average APR for the sample. The most dramatic decline is with Score A, assuming a 14.4 percent APR for the unscorable tenants, and a shift from the base scenario of no reporting to the full-file reporting scenario, where the average APR drops two percentage points.

These results show the total, average impact over the entire sample, something that should be of interest to policymakers. For subgroups, such as thin-file tenants that have an on-time rental history reported, the impacts would be greater than average.

While full-file credit reporting will not necessarily result in moving a large percentage of PHA subsidized housing tenants into homeownership or small business ownership in the relative near-term (or ever), it does increase the likelihood of an asset-building outcome. More likely, however, is that those who move from unscorable to some variant of prime credit will qualify for affordable mainstream credit options (credit card, auto financing, personal loan) whereas before the only options available were high cost fringe financial institutions such as pawn shops, payday lenders, title lenders, check cashing services and other high cost lenders. The net result should be greater access to larger amounts of more affordable credit. In other words, credit access will be made fairer and more inclusive.

*Areas for Future Research*

There are a number of areas that could be explored with future research, they include:

- How does tenant payment behavior change with credit reporting rental data?
- How does modifying the minimum overdue balances reported or definitions of late payments impact credit scores?
- How might the results change with PHAs that have higher or lower delinquency rates?
- How might the results change with the length of the rental history data reported? For instance, segmenting out tenants with only 6 months of reported data, then those with 1 year, then those with 2 years, and then those with 3 years.

Some of these may be able to be examined with the dataset used in this research, some would require a new research design and additional data.

## Conclusion

The findings from our analysis of the credit score and credit profile impacts from credit-reporting subsidized rental payment data in consumer credit files warrant further attention from policymakers and stakeholders.

The results of this study found that the PHA sample examined is composed of relatively high-risk consumers as measured by credit scores. Of the public housing residents with credit scores, 54 percent to 67 percent (depending on the scoring model) had a credit score of 620 or less (subprime) in the 2014 sample. This compares to a rate of 35 percent in the general population, using one of the credit-scoring models. The unscorability rate ranged between 11 percent and 49 percent of the 2014 sample, depending on the scoring model. This compares to the overall national rate of 19 percent and the low-income census tract rate of 45 percent found by the CFPB (CFPB, 2015).

With the 2014 credit scores, the rate of unscorability falls from 49 percent to 7 percent in one model and falls from 11 percent to 0 percent in the other model with the addition of full-file rental payment data. The addition of PHA rental data among those with only positive payment histories also lowered the unscorability rates, although to a lesser degree, to 23 percent and 3 percent, respectively.

The share of consumers who were scorable and had credit scores above 620 noticeably increased with the addition of the full-file rental payment data. With the 2014 credit scores, using the first credit-scoring model, the share of consumers who had a score over 620 increased 65 percent, increasing from 23 percent of the sample to 38 percent of the sample with the addition of the full-file PHA rental data. The addition of PHA rental data among those with only positive payment histories raised this to a slightly lower 37 percent. For the second model, this rate rose 54 percent, from 28 percent of the sample to 43 percent of the sample. The addition of positive-only data also raised this to 43 percent. Credit scores above 620 are typically considered some type of prime and are accepted for conventional mortgage loans by Fannie Mae and Freddie Mac and generally yield more affordable credit.

To the extent that rental payment information is available, the problem of credit invisibility and unscorability can be dramatically reduced; many who were formerly unscorable could achieve some variant of a prime credit score. Thus, now visible to mainstream lenders and armed with a solid credit score, many who formerly had to have their real credit needs fulfilled by high-cost lenders may be able to qualify for mainstream, affordable sources of credit.

In addition, it is important to note that there may be a business case for credit reporting as it could (and likely would to some extent) encourage greater on-time rent paying behavior. An interesting finding of this paper is that we did not find, overall, large tenant credit profile impact differences between full-file credit reporting and positive-only reporting in terms of share of consumers who move to some variant of prime with the addition of the rental data, although full-file credit reporting raises scorability more than positive-only reporting. How

PHAs choose to report could be impacted by these findings, the business decisions of the PHAs, data quality issues, and how PHAs want to incent their tenants.

All three nationwide CRAs, Experian, TransUnion and Equifax now accept the reporting of rental accounts. TransUnion and Equifax use full-file rental reporting in their main consumer databases and Experian uses positive-only rental reporting in their main consumer database. These are the databases that FICO® Score 9 and VantageScore 3.0 credit scores employ. Both of those credit scores use rental data when available.

For PHAs contemplating reporting we would recommend, as always, that they do so in a tenant-friendly way, such as not reporting small, unpaid balances. We also recommend clear communication with tenants regarding credit reporting and how they could be impacted by it and could benefit from it. The accounts reported should not be explicitly identified as government subsidized. PHAs should also test their data with CRAs to the extent possible to verify how their tenants would be impacted. The full-file results in this paper found that 65 percent of accounts were on time when viewed over a 24-month period and when using 30-day delinquency buckets (that is paid their rent within 30 days of the due date), excluding small unpaid balances. Particular attention should be paid to examining potential credit score impacts if a PHA's delinquency rate is much above the 35 percent rate found in the sample in this study.

Lack of capacity or IT issues among PHAs may present a challenge to reporting. During the recruitment phase of this research, we encountered instances where collecting the data needed for this research was a sufficient challenge to preclude participation in the study. For such PHAs, a third-party intermediary who can help them work with nationwide CRAs to ensure reliable, standardized reporting of high-quality data may be one option (for example Credit Builders Alliance carries out such work). Additional funds from government sources or private sector donors could also aid those PHAs that wish to report but lack the needed capacity and or IT.

The real costs to credit reporting are often less about IT and hard costs (these have declined over the years) and more the soft costs of setting up workflows and processes to collect and report accurate and timely data in the needed formats. Here, HUD could collaborate with the CRAs and put together a resource guide and best practices for PHA credit reporting.

While all manner of nonfinancial business entities are entitled to and do report late payment data to nationwide CRAs, relatively few report on-time and other "positive" data. In other words, energy utilities, media companies, and property managers typically report credit transgressions but not "good" credit behavior. A 2014 CFPB report found that the combination of rental, cable, cellular, utilities, and leasing together accounted for 17.1 percent of all consumer collection accounts, second only to medical collections (CFPB, 2014). On the other hand, only a small share of consumer credit reports at the national CRAs have positive data on nonfinancial accounts reported. This research joins others in showing that the inclusion of more useful information in credit reports and used by credit scores (such as full-file, nonfinancial account data) can help make credit granting more inclusive.[11]

[11] For instance, see Barron and Staten, 2003; Turner et al, 2006; Turner et al., 2003; Jappelli and Pagano, 2002; Djankov, McLiesh, and Schleifer, 2005; and Patrice Ficklin and Paul Watkins, 2019.

## Appendix: Examples of Costs Associated with Credit Reporting

| **Reporting Methodology** | **Price Points** | **Level of Effort Required to Setup to Report** |
|---|---|---|
| Credit Bureau Fees (if direct reporting) | ☐ One-time credit bureau application, credentialing, and setup: $0–$150<br><br>☐ Ongoing credit bureau annual data furnishing fees: $0 | High—Have to set up with each of the three bureaus individually and provide data directly, sometimes in different file formats. |
| Third-Party Service Provider Fees (if not direct reporting) | ☐ One-time set up fee that varies—sometimes waived<br><br>☐ Ongoing monthly fee + additional per unit/per transaction cost (generally around $2–$15) | Medium—There may be some back-end integrations available, or the service may simply be a payment processing one. Not all third parties report to all three bureaus. |
| CBA-Esusu Rent Reporter | ☐ One-time setup fee of $3,500—can raise grant funds to subsidize fully or partially—cost includes first-year CBA membership, which is $315<br><br>☐ Ongoing annual fee based on total number of units (no per unit/per transaction cost)—starts at $1,500/year | Low—The fees may seem high but very little configuration and no data formatting required. With the setup fee comes a significant amount of training for staff, access to our toolkit of resident engagement template materials, and more. Ongoing costs cover access to monthly file formatting for all three bureaus, data quality control, dispute management, and aggregate outcome tracking. See below for more detail for that footnote! |
| Other Potential Cost to Consider… | • Staff time<br>• Legal fees associated with document review and risk assessment<br>• Fees associated with PM software integration and/or development of customized reports<br>• Costs related to getting access to and pulling credit reports and scores for coaching and outcome tracking purposes<br>• Fees associated with developing and printing related marketing and education materials | |

Source: Credit Builders Alliance (CBA)[12]

[12] The CBA assists nonprofits, including some PHAs, with credit reporting to the nationwide CRAs. For more information about CBA, see https://www.creditbuildersalliance.org/.

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