WHY ADDITION IS BETTER THAN SUBTRACTION:

Measuring Impacts from System-wide Deletion and Suppression of Derogatory Data in Credit Reporting

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Abstract

This study examines proposed policies that would temporarily suspend the credit reporting of derogatory information for all consumers in the US as a response to a crisis such as the COVID-19 pandemic. This study analyzes 10 million de-identified credit records from 2010 and 2017 to simulate the impact of such large-scale suppression/deletion policy proposals on credit scores and on consumer access to credit. Consistent with earlier research, this study found average credit scores rise when derogatory information is suppressed over time, but they also become less accurate when accurate predictive information is removed. As economic theory predicts, lenders respond by raising credit score cut-off thresholds for loan approvals to compensate both for the artificial "credit score inflation" and for the degradation to the performance of the credit risk scores. An impact of this policy is reduced credit access for consumers overall (credit rationing). However, what may be counterintuitive to policymakers trying to help the lowest income households and most vulnerable consumers is that these same groups suffer the greatest reduction in credit access. Findings from this study should give pause to policymakers who would support other efforts to restrict the sharing of derogatory but predictive credit information with the intended aim of aiding members of economically vulnerable households. For instance, policies such as removing paid debt or derogatory payment data after four years instead of seven should be well thought through and rigorously tested to understand tradeoffs. On the other hand, this report finds that polices aimed at filling credit data gaps with the increased reporting of non-financial payment data (proven payment data such as from mobile telecom accounts) improves credit reporting and lending, disproportionately benefiting the credit invisible and members of lower-income households. Full-file reporting would be ideal for these accounts. However, the selective reporting of on-time customers (so-called "positive-only" reporting), at a minimum, represents a vast improvement over the status quo. Currently mobile telecom service providers flood the credit reporting system with collection accounts, either directly or indirectly (so-called "negative only" reporting). That is, they selectively report only their very late customers, so adding on-time customers would be much fairer and would greatly benefit younger, lower-income, and other underserved persons. This study represents a follow-on study to an earlier report titled "Addition is Better than Subtraction" (PERC 2020) which posited key hypotheses examined and quantified in this study.

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Executive Summary and Key Findings

Credit risk models perform better when they utilize greater amounts of accurate, predictive data. For example, a third-party credit score based upon a relatively thicker credit file (more accounts) with longer credit histories, a greater variety of account types, and more key fields (balances, credit limits, etc.) yields better predictions than one based upon a very thin-file credit report that lacks important types of accounts and fields. While both credit file scenarios are technically scoreable using some third-party credit risk models, a lender would be taking undue risk extending credit to a prospective borrower based on the more limited information case than if they had access to the fuller information.[1]

Decades of theoretical and empirical economic research bears out this proposition. Lenders are able to make better decisions when given access to more accurate and predictive data, benefiting borrowers, lenders, and the economy. This is a foundational premise of the national credit information sharing (CIS) system in the United States and in most countries around the world. There are instances, however, when predictive data sharing must be limited. For example, the wave of privacy laws passed in state after state during the 2000s redacted a sufficient volume of personally identifiable information (PII) as to increase the challenge of matching public records containing liens and judgements with credit reports.

"Credit risk models perform better when they utilize greater amounts of accurate, predictive data."

Due to this, nationwide consumer reporting agencies (NCRAs) and States' Attorney's Generals offices agreed to the National Consumer Assistance Plan (NCAP) restricting the inclusion of such government-sourced predictive data points to scenarios where sufficient matching PII is available. The consequence was the removal of a considerable quantity of known accurate predictive data from the national CIS system in an effort to improve NCRA data quality as per the maximum possible accuracy obligation under the Fair Credit Reporting Act (FCRA).

Similarly, industry and regulators/policymakers have established practices and guidelines for managing exogenous shocks—natural disasters or other systemic crises—which may cause widespread and enduring duress upon a borrower population through no fault of their own. This is precisely what has happened with the COVID-19 pandemic, where the global healthcare crisis forced a closing of large sections of an economy resulting in an immediate and pronounced spike in unemployment.

At the beginning of the pandemic, lenders were counseled by federal and state lawmakers and regulators to offer accommodations to borrowers who may be experiencing duress. Typical lender accommodations include loan forbearance, deferrals, or modifications among other tools. When accommodations were provided between lenders and borrowers on credit accounts, a borrower was not required to make a payment, and so was not late if they chose not to make it. Further, the CARES Act prohibited the reporting of late payment or other derogatory indicators for all federally guaranteed student loans during the pandemic and for some period thereafter.

Predictably, the results of this policy protected many borrowers from having their credit scores decline due to the pandemic if they could not and did not make their payments as outlined in their pre-pandemic loan agreements. In fact, over the first five quarters of the pandemic, the national average credit score in the US has risen. No doubt some of this may have been due to the accommodations. But, as of today, the majority of those extended a mortgage forbearance have already exited. In addition, there is now a strong job market, personal

[1] Turner, Michael and Amita Agarwal. "Using non-traditional data for underwriting loans to thin-file borrowers: Evidence, tips and precautions." *Journal of Risk Management in Financial Institutions*. Vol. 1, 2. Pgs. 165-180. Downloaded at: https://www.perc.net/wp-content/uploads/2013/09/pp165-80.pdf

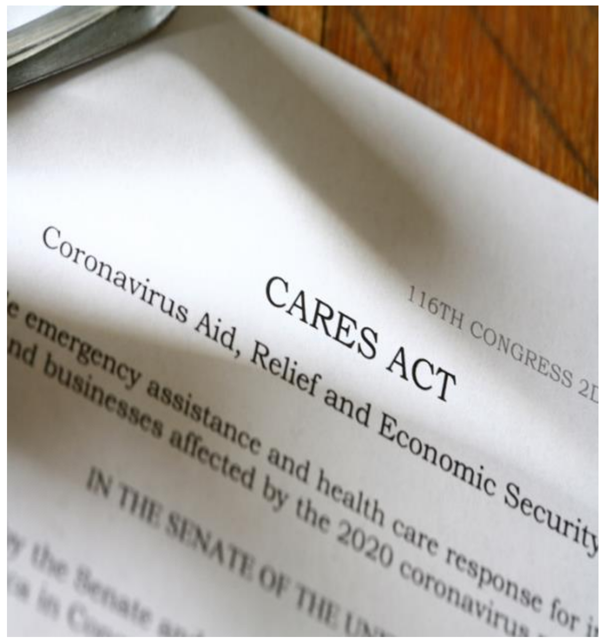
incomes are up, and credit card balances are down. So, many consumers may now also be in better *overall* financial shape. (This could be partially due to the myriad of relief and stimulus in the CARES Acts and other COVID relief measures.) However, financial risks still exist. These include those from COVID variants and risks associated if the transition back to a more normal state is bumpy.

While at this point it looks as though policy makers threaded the needle in terms of policy responses, some policymakers have argued for much broader interventions in credit reporting. These proposals would have prohibited derogatory data reporting in general for all consumers. These may have been based in part on fears that consumers in need would not seek accommodations or lenders would not have provided them as hoped. As the increase in average credit scores suggest, these fears did not appear to have materialized. The proposals may have also been based on an overly simplistic view of such policies that did not take account of credit market reactions to the policies.

"Erecting a substantial barrier to credit would set back efforts to catch up for those in the 40 years of age and younger group relative to Gen-Xers and Baby Boomers."

Take but one example—younger borrowers (aged 18-24): simulations demonstrate a very broad suppression/deletion approach involving both open and closed accounts would mean lenders making poorer lending decisions. In addition, with borrowers no longer having their late payments and other negative behavior credit reported, there would likely be an increase in *moral hazard.* That is, for a given group of borrowers, credit delinquencies likely would rise. Combined, these result in over a 90% reduction in credit access for younger borrowers. This is because lenders would raise credit score cutoffs to compensate for degraded credit information and higher credit delinquency rates.

Millennials, the oldest of whom are turning 40 this year, are just 80% as wealthy as their parents were at this stage in their lives, and the generation younger than Millennials lags further in terms of wealth generation and asset building. As such, erecting a substantial barrier to credit would set back efforts to catch up for those in the 40 years of age and younger group relative to Gen-Xers and Baby Boomers.[2]



This report quantifies the impacts of proposed policies to expand and extend suppression/deletion on lending in the US. The report pays specific attention to impacts experienced by different borrower groups. The simulations use 10 million de-identified credit files from two time frames; 2010-2012 and 2017-2019. The first period reflects the initial recovery from a crisis (Great Recession following the 2008 Financial Crisis) and the second a recovered economy. The results should be considered by policymakers exploring changes to current credit reporting practices in the US and elsewhere.

Key findings include the following:

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[2] Rockeman, Olivia and Saraiva, Catarina. "Millennials Are Running Out of Time to Build Wealth." *Bloomberg*, 3 Jun. 2021, available at: www.bloomberg.com/features/2021-millennials-are-running-out-of-time/

Key Findings

Suppression Degrades Credit Report Data and Harms Consumers: The longer the accurate predictive data is suppressed, the greater the degree of degradation. Suppressing negative payment information from *active* accounts in credit files for 12 months in the 2010 sample results in a 14% reduction in credit access. Extending the suppression to 24 months worsens this reduction in credit access to 17%. When closed accounts are also included this grows to a whopping 29% of persons who would have been accepted are now rejected owing to suppression/deletion. This occurs because the examined suppression policy causes credit score approval cutoffs to rise relatively faster than credit scores. For example, controlling for a target default rate of 3%, the needed cutoff credit score increases from 681 to 721 in the 2017 sample. However, after 48 months of *active* account suppression the average credit score rises from 687 to just 702. So, while the suppression policy does raise credit scores, it is an illusion as many consumers are actually worse off and have reduced access to credit. If the moratorium on reporting derogatory also results a fifty percent rise in delinquencies (moral hazard), the 29% reduction in credit access balloons to 51%—comprising a massive credit crunch. The general, qualitative results are consistent with decades of theoretical and empirical research showing that increased information asymmetries in credit markets (lenders having less information about borrowers) results in lenders rationing credit and raising the cost of credit to account for the increased risk.

Younger, Lower Income Persons, and Minority Communities Are Hit Hardest by Suppression: While fewer people in the aggregate will be able to access affordable mainstream credit the longer a suppression/deletion policy exists or the more broadly it applies, results show these impacts will be uneven in important ways. Younger borrowers, lower-income borrowers and those living in minority-majority areas will experience the greatest negative impacts. In one example, while credit acceptance for the entire population decreases 18%, it drops 46% for the youngest borrowers (18-24). By income, it dropped 19% for the lowest income group but "just" 15% for the highest—a 27% difference. For members of households in white, non-Hispanic majority areas it dropped 17% but in black majority areas it dropped 23% and in Hispanic majority areas it dropped 25%. This pattern of the youngest, lowest income consumers and members of households in minority majority areas being hardest hit by the suppression induced credit crunch persists across the 2010 and 2017 samples and for different lengths and degrees of data suppression.

Instead of Suppression, Policy Should Focus on Filling Data Gaps to Aid Lower Income Persons: Over the past 20 years, much research has been produced (including by the authors of this report) demonstrating the predictive value of non-financial payment data in credit risk assessment. Such non-financial payment data includes regular payments for rent, telecoms, and energy utilities. Including full-file payment data (timely and late payment data) from these accounts in consumer credit reports increases access to credit dramatically for credit invisibles. Credit invisibles have no credit report or lack sufficient data to generate a credit score. They are primarily comprised of lower income persons, younger and elderly Americans, members of minority communities and immigrants. The CFPB estimated about 1 in 5 adults overall are credit invisible. This figure rises to 45% of adults in the lowest income census tracts.

Telecom Companies Unfairly Use the Credit Reporting System: They flood credit bureaus with collections and late payment data, but overwhelmingly do not report timely payment data. This structural problem is particularly unfair to their lowest income customers, many of whom have thin credit reports meaning the late payment data is more likely to be damaging. Full-file credit reporting of account information for all account holders is most beneficial to consumers. But, at a minimum, if large mobile telecom companies use the credit reporting system and/or submit collections to it directly or indirectly, then they should also credit report their on-time customers. Reporting collections plus on-time customers is much better and fairer than just reporting collections. Moreover, large mobile network operators extend hundreds of billions in credit annually for smartphones and other devices to tens of millions of Americans They are creditors and should fully participate in the national CIS.

1. Introduction

From the beginning of the COVID-19 pandemic, it became necessary for lawmakers in the US and globally to quickly implement measures to protect citizens from the economic collateral damage resulting from the public health crisis.[3] [4] [5] With the US unemployment rate hitting 14.8% in May of 2020—the highest rate since the Great Depression—fears of a COVID recession were palpable.[6] While federal dollars for programs such as the Paycheck Protection Program (PPP) and the Pandemic Unemployment Assistance (PUA) captured most of the headlines from the Coronavirus Aid, Relief, and Economic Security Act (CARES Act), instructions to lenders on granting distressed borrowers accommodations for all types of loans was and remains (as of publication) a significant consumer protection.

While data from the past year suggests that the accommodations had the desired effects (*e.g.* borrowers were not punished with lower credit scores through no fault of their own), the consumer protection benefits may also have unintended credit market consequences.[7] However, with the exception of student loans, the CARES Act required consumers to work with their lenders on accommodations. Some policymakers and some consumer advocates, perhaps fearing many consumers in need or lenders would not do this or carry this out as expected, wanted to go much farther.

Specifically, legislation[8] predating the CARES Act contained outright prohibitions on reporting late payment data to nationwide consumer reporting agencies (NCRAs) for potentially a very long period of time. These bills would apply both to the COVID-19 pandemic and all future declared natural or man-made disasters. Talk of such far-reaching policies is not just idle banter. The Health and Economic Recovery Omnibus Emergency Solutions (HEROES) Act and a plan for economic relief contained or supported these broad data suppression measures.[9]

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[3] In a pair of papers PERC released in March and April 2020 discussing lessons learned from PERC's work on small business recovery from natural disasters in the Gulf Coast, we emphasized that speed matters for those planning COVID-19 economic relief.

[4] See: Turner, Michael and Walker, Patrick. "Ensuring the Small Business Paycheck Protection Program Works: Lessons Learned from Gulf Coast SMEs post-Katrina." *Policy and Economic Research Council (PERC)*, 6 Apr. 2020, available at: www.perc.net/wp-content/uploads/2020/04/PPA.pdf

[5] See: Turner, Michael and Walker, Patrick. "PERC Research Findings for COVID-19 Economic Recovery Efforts." *Policy and Economic Research Council (PERC)*, 25 Mar. 2020, available at: www.perc.net/wp-content/uploads/2020/03/C19-White-Paper_03252020_FINAL-1.pdf

[6] Falk, Gene et al. "Unemployment Rates during the COVID-19 Pandemic: A brief." Congressional Research Service, 12 Jan. 2021, available at: fas.org/sgp/crs/misc/R46554.pdf

[7] Buchwald, Elisabeth. "A pandemic paradox: Americans' credit scores continue to rise as economy struggles—here's why." *MarketWatch*, 20 Feb. 2021, available at: www.marketwatch.com/story/a-pandemic-paradox-american-credit-scores-continue-to-rise-as-economy-struggles-heres-why-11613487767

[8] This includes legislation proposed by Senators Brown and Schatz (S. 3508) and Representatives Waters and Sherman (H.R. 6321), United States, Congress, House. *H.R. 6321 – Financial Protections and Assistance for America's Consumers, States, Businesses, and Vulnerable Populations Act*, 2020, available at: www.congress.gov/bill/116th-congress/house-bill/6321?q=%7B%22search%22%3A%5B%22hr+6321%22%5D%7D&s=1&r=1

[9] Warren, Elizabeth and Brown, Sherrod. "Congress must provide immediate relief for consumers. Here's how." *Medium*, 21 Apr. 2020, available at: medium.com/@SenWarren/congress-must-provide-immediate-relief-for-consumers-heres-how-2aeb99672ef9

The problems associated with proposed suppression measures are well-documented.[10] [11] In short, credit bureaus and others (including PERC) argue that suppression measures, if implemented, must at most be a very short-term stopgap measure to address a sudden shock, until a broader credit relief plan is developed and implemented. Using suppression measures at all, but especially if used for all people and for long periods of time, would most likely end up causing much more harm than benefit.

This is because such measures would degrade the integrity of credit file data rendering it more difficult for lenders to differentiate between high-risk and low-risk borrowers. The degradation in the ability of lenders to differentiate high-risk borrowers from low-risk borrowers stems from the suppression and/or deletion of accurate predictive negative data for a non-trivial borrower population (possibly everyone). The longer accurate predictive data is suppressed and the greater the degree of suppression, the greater the degradation in the data's overall predictive value. Degradation in data predictiveness, in turn, results in credit rationing and an increase in the prevailing price of credit—the outcomes associated with adverse selection and moral hazard. Lenders make more mistakes owing to less predictive data (adverse selection), and borrower repayment behavior changes in response to a moratorium on negative payment data reporting (moral hazard). Here too, the longer the period of suppression and the more that is suppressed, the greater the extent of credit rationing and the higher the price of credit, all other things being equal.

For policymakers, the question becomes one of tradeoffs. Some economists are projecting the economy to take off and fully recover to pre-pandemic levels in the very near-term (GDP already has fully recovered), while others express more skepticism and doubt. Given this uncertainty about the direction of the US economy in the coming quarters and several years, compounded with uncertainty about the pandemic and how banks will handle accommodations once the health crisis abates, lawmakers must balance concerns about continuing or implementing new consumer credit reporting protections against the potential damage such measures may cause consumers, the financial sector, and the broader economy.

Reality on the ground demands difficult decisions. This report examines the tradeoffs and attempts to quantify impacts to the consumer credit market given a variety of different potential scenarios. To accomplish this, a large sample of data was acquired from a national consumer reporting agency and used in simulations to estimate impacts on consumers and lenders. The methodology for this analysis follows.

[10] Turner, Michael and Walker, Patrick. "COVID-19 and Credit Reporting: Suppression is Not the Solution." *Policy and Economic Research Council (PERC),* 21 Apr. 2020, available at: www.perc.net/covid19-credit-reporting-no-suppression/

[11] See also: Bykowicz, Julie and Mann, Ted. "No Coronavirus Break for Consumer Credit Scores." *The Wall Street Journal*, 31 Mar. 2020, available at: www.wsj.com/articles/no-coronavirus-break-for-consumer-credit-scores-11585668691?mod=searchresults

2. Methodology

The analysis presented in this paper utilizes several de-identified samples and files. First, two time periods were chosen to add robustness to the results. The first is based on de-identified credit files from October 2010. This was near the peak of unemployment following the credit crisis. In October 2010, the unemployment rate was 9.4%.[12] The credit files would include recent historic data from the financial crisis and peak unemployment. 2010 was also the first full calendar year of the economic recovery from the financial crisis. This would reflect credit markets emerging from a crisis. The second time period represents a more recent period prior to the COVID-19 pandemic. This is based on de-identified credit files from October 2017. Since a two-year observation period was needed after the base credit files, October 2017 was chosen as the base snapshot and October 2019 as the observation snapshot. This is a quarter prior to the first quarter of 2020 when COVID-19 was beginning to have health, social, and financial impacts in the US. The 2017 to 2019 period also represents a fully recovered America around the peak of its business cycle.

As a practical matter, it would not have been possible to use files during the pandemic in this analysis. If we used March 2020 files, since credit files are backward looking, these would not (generally) have credit data reflecting COVID-19. And if we used March 2021 files, simulations for 6 months or 12 months would be possible, but the observation file would need to be a year or two after this. Further, the outcomes (delinquencies or not) during the current crisis could be impacted by the CARES Act provisions and accommodations. Hence, retrospective analysis (commonly used in the credit data industry) was used. Further, this is how lenders would make decisions. They too would not have "current" data with outcomes two years out and so would utilize such retrospective analysis. In addition, if there was a system-wide suppression/deletion in place, it might be challenging to measure outcomes, particularly for generic credit scores such as FICO and VantageScore credit scores. Lenders, as such, might rely more on history, fuller data, for analysis where credit market outcomes were important.

Table 2.1 *Samples for the 2010 Vintage Analysis*

Sample / File	Score / File Snapshot	Period of Data Suppression	Sample Size
No Suppression/Base	October-2010	None	5,000,000
6 Months Suppression	October-2010	Apr 2010 to Oct 2010	4,951,490
12 Months Suppression	October-2010	Oct 2009 to Oct 2010	4,879,954
24 Months Suppression	October-2010	Oct 2008 to Oct 2010	4,764,921
36 Months Suppression	October-2010	Oct 2007 to Oct 2010	4,661,561
48 Months Suppression	October-2010	Oct 2006 to Oct 2010	4,581,733
Observation/Outcome	October-2012	None	4,446,207

For both the base 2010 and 2017 files, PERC requested credit file data and a credit score (VantageScore 3.0) for 5,000,000 randomly chosen consumers/files. Then, for each of the files, a snapshot two years later (2012 and 2019) was produced. This included data on the outcomes for each consumer, namely whether they had any major derogatories between October of 2010 and October of 2012 (or between October 2017 and October 2019). This was used to gauge credit score performance and determine how particular scores in, say, 2010, were associated with delinquency outcomes over the two years following the score. In

[12] U.S. Bureau of Labor Statistics. "Unemployment Rate [UNRATE]." *FRED, Federal Reserve Bank of St. Louis*, available at: fred.stlouisfed.org/series/UNRATE

addition, several files were produced using the base files but with suppression of negative data along the lines of the HEROES Act. In this way we could determine how well the base files were associated with future delinquency outcomes compared to the files with various lengths of data suppression; in other words, how well the credit score worked when it was generated using the base files versus the suppression files.

As is seen in **Tables 2.1** and **2.2**, the sample sizes decrease when data suppression is applied and decrease as the suppression grows longer. This is due to the removal of negative data that which for some files represents all of the data (for instance, only collections accounts). Some consumers will gain a credit file with the reporting of a collection account and will lose it if it is removed.

Also note that the observation files (2012 and 2019) also have a reduced sample size. This is due to the inability to match 100% of the files between the base and observation periods. This commonly occurs when using credit file data over time.

Table 2.2 *Samples for the 2017 Vintage Analysis*

Sample/File	Score/File Snapshot	Period of Data Suppression	Sample Size
No Suppression/Base	October-2017	None	5,000,000
6 Months Suppression	October-2017	Apr 2017 to Oct 2017	4,963,319
12 Months Suppression	October-2017	Oct 2016 to Oct 2017	4,925,563
24 Months Suppression	October-2017	Oct 2015 to Oct 2017	4,876,584
36 Months Suppression	October-2017	Oct 2014 to Oct 2017	4,828,054
48 Months Suppression	October-2017	Oct 2013 to Oct 2017	4,783,881
Observation/Outcome	October-2019	None	4,574,744

Some portion of the files that do not match between the base and observation period may be fragmented files, typically one-off accounts that are considered their own file since they did not match similarly enough to other accounts a consumer may have with a CRA. Since this can get resolved over time, those files that match across a number of years likely have a lower rate of fragmentation.

Unless otherwise noted, the effective samples for much of the calculations in this report are those of the respective observation/outcome files (100% of these matched back to the base file). This is the case since the acceptance rates, delinquency rates, and needed score cutoffs all depend on matching between the base and observation files. And as noted, these would be expected to have a reduced incidence of fragmentation.

Simulation of Suppression on Open/Active Accounts

The following details the suppression of the derogatory data. Given the technical and CRA specific nature of this exercise, PERC worked with analysts from Experian on these details.

- Modify accounts that were Open and Active (reported in the past 6 months/balance date in the last 6 months) as of October 2010 (or 2017).
- Do not modify any of the Closed accounts as of October 2010 (or 2017). Considered them out of scope of the accommodation program. Hence, there is no modification on any closed derogatory accounts.

- For all accounts that are modifiable, suppress the payment history (25 months and 84 months) by replacing any negative status (30dpd, 60dpd, 90dpd, 120-180dpd or Derogatory with a “not reported” status). Do not replace a “current” (C or 0) status with a “not reported” status (“-”) when “current” is present.

- Modify the Enhanced Status to Current (=11) or Current was Delinquent (=31 thru 41) if there is a previous delinquency outside of the window considered.

- Remove all external collections with open date during suppression period.

- Remove all public records with filing date during suppression period.

- Remove Maximum delinquency code if the Maximum delinquency date is within the suppression period.

- Reset Amount Past Due to 0.

- Adjust delinquency counters by the corresponding number of delinquencies removed.

Simulation of Suppression on All Accounts

- Same as above, but applies to all accounts

As we were developing the methodology for this study, there was uncertainty around details of how the proposed legislation of widescale suppression/deletion, such as found in the HEROES Act, would be implemented in practice. One issue was whether the suppression/deletion would also apply to accounts that had already been closed and for which a data furnisher was no longer furnishing information to a CRA. In addition, if the legislation was retroactive in some way, whether past closed accounts would be treated differently than accounts that close in the future. So, consider legislation was passed in March 2021 that was retroactive to March 2020 and then was in effect until March 2022. It was unclear whether closed accounts would be included over the whole period, not at all or just for the March 2021 to March 2022 period. As such we decided to base the initial simulations on the least impactful scenario of only modifying active/open accounts. We then carried out an additional simulation that modified all accounts with derogatory information (open or closed) during a 24-month period. That is, we layered on the more extreme case to gauge what differences that would make. That period, 24 months, seemed a reasonable period since as the writing of this report, accommodations for student loans are already planned to continue until at least the end of September 2021, slightly over a year and a half in all.[13] This also makes clear that the current COVID-19 case or future disasters for which a systemwide data suppression/deletion may apply could easily have such provisions in place for years. This underscores why understanding the impacts of such provisions over extended periods of time is crucial.

Definition of “Bad”

For the definition of delinquency from the observation/outcome files, we created three so-called “bad” variables (Bad0, Bad1, and Bad2). If a file had a delinquency covered by the “bad” definition, then it would be classified as nonperforming. These definitions are defined in the following table.

[13] See https://studentaid.gov/announcements-events/coronavirus

Bad0	90+ Days Past Due (DPD) on accounts within 24-month observation period
Bad1	90+ DPD, defaults, repossessions, public records (including Bankruptcies) filed within 24-month observation period
Bad2	90+ DPD, defaults, repossessions, public records filed (including Bankruptcies), collection accounts within 24-month observation period

Bad0 is the narrowest definition of a *bad* while Bad2 is the broadest. For the purposes of this report, we used the middle definition of Bad1, though we show some of the key results with Bad0 and Bad2 in the appendix. The particular definitions of Bad used did not impact the general qualitative findings. Broader definitions of "bads" had simply produced a higher delinquency rate. That said, some may prefer a narrow definition such a Bad0 that does not include collections or other derogatory data that may relate to an event that did not occur exactly within the observation period. For instance, a collection in the 24-month observation period may come from a non- or under-payment that occurred prior to the observation period. However, a 90-day late payment on an account would be an event occurring in the observation period.

Sociodemographic Variable

In addition to the use of the VantageScore 3.0 credit score and standard credit file credit attributes, this analysis also used appended sociodemographic variables to segment the results. These fields, though from Experian, are not part of credit reports/files and so were appended separately to the traditional credit file data.

For a measure of household income, Experian's *ConsumerView Estimated Household Income V6* was used. The Income V6 model assigns an income amount in thousands to each living unit (household). Several factors are used in the model, including estimated household and individual demographics, housing attributes, transactional purchase data, self-reported and geographic level data such as census and IRS salary bands. Since this is an estimate with an error, it is likely that results segmented by income would underestimate true group differences from the mean. There would likely be an *attenuation bias* on such differences. This is because the group of households with incomes under $30,000, for instance, would also include some higher income households and those with incomes over $150,000 would include some lower income households. That is, the results will be diluted to some extent.

The race/ethnicity data is not estimated at the household level but, instead, has a unit of observation of the Census Block Group level. This is a level between a Census Tract and a Census Block. The US Census notes that the Block Group contains "between 600 and 3,000 people." [14] As such, this is at a large neighborhood or small town level of population. Although the data is US Census data, it was supplied and appended by Experian from Experian's Census Area Projections & Estimates (CAPE) databases.[15] The variables used were ETH6725, the percentage of population that is black alone. This includes both Hispanic and non-Hispanic persons. ETH7102, percentage of population that is Hispanic, and ETH7113, percentage of population that is white alone and non-Hispanic. These were used to segment out consumers who live in black majority Census Block Groups (where ETH6725 $\geq$ 50%), consumers who live in Hispanic majority Census Block Groups (where ETH7102 $\geq$ 50%), minority majority (where ETH7113 < 50%), and white non-Hispanic majority Census Block Groups (where ETH7113 $\geq$ 50%).

[14] See https://www.census.gov/programs-surveys/geography/about/glossary.html#par_textimage_4
[15] For more information on this database see: https://assets.cengage.com/gale/help/dnow/DataMethodology/Experian_CAPE_Tech_Overview-Alteryx.pdf

3. Suppression/Deletion Results

Raw Credit Score Impacts

Previous Findings of Derogatory Data Suppression

As one would expect, removal of derogatory information in credit files has an overall impact of raising credit scores produced on those files. Examples of this were shown in a previous PERC study using data from an NCRA, simulating different restrictions on the inclusion of predictive negative data.[16] Similarly, a study conducted by Federal Reserve Bank economists Avery, Calem, and Canner (2003)[17] found that 15.5% of their sample had medical collection accounts. Removing these accounts raised credit scores for 81.2% of these consumers, had no score impact for 11.8%, but actually lowered the credit score for the remaining 6.9%. This last point should be noted, as even seemingly negative data, like collections, may actually raise a credit score by shifting a consumer to a different score card (a technical scoring issue) or by indicating a longer credit history, thicker credit file, or other such characteristics. In the same way, a seemingly positive account may lower a credit score (for instance by showing a larger credit balance). Overall, in their entire sample, less than 5% of files has a credit score rise of greater than 10 points when the medical collections were removed.

FICO carried out analyses to determine how the removal of judgments and tax liens by the National Consumer Assistance Plan (NCAP)[18] would impact FICO scores and their performance.[19] They found that 6% to 7% of the FICO scoreable population would be impacted from the removal of the judgments and tax liens. While the majority of these consumers would see a credit score rise, three-quarters of the rises were in the 1 to 19-point range. As with the Federal Reserve work, a small portion of consumers would have a credit score fall as a result of the removal of the public records. In the affected population, the typical score increase is about 10 points and the share with scores over 640 only rises by less than 5 percentage points. This translates to much less than 1% for the entire FICO scoreable population. FICO also finds no material score performance impact from the data removal, where consumers move between risk tiers that affect the price of their credit.

Why such small impacts? First, the median pre-NCAP FICO Score 9 for the affected population is 565. So, a small credit score rise would likely have little real, material impacts in the lending marketplace. Second, many of the affected population with judgments and liens also had other types of negative/derogatory data (such as late payments, collections, bankruptcies) in their credit reports. So, the removal of one or even two types of negative data had little impact.

Larger Scale Derogatory Data Suppression

Unlike these examples, the proposed data suppression contemplated in the HEROES Act is extensive and over an indeterminate period of time. **Table 3.1** shows the raw credit score impacts from the suppression derogatory data on active accounts for 36 months using the 2010 sample. These impacts are much larger

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[16] Turner, Michael, Walker, Patrick, & Moore, Kazumi. “Addition is Better than Subtraction: The Risks from Data Suppression & Benefits of Adding More Positive Data in Credit Reporting.” *Chapel Hill: Policy & Economic Research Council (PERC)*, Jun. 2020, available at: www.perc.net/wp-content/uploads/2020/06/credit-data-suppression-deletion-addition.pdf

[17] Avery, Robert, Calem, Paul, & Canner, Glenn. “Credit Report Accuracy and Access to Credit.” *Federal Reserve Bulletin*, 2004, pp. 297-322, available at: www.federalreserve.gov/pubs/bulletin/2004/summer04_credit.pdf

[18] Lee, Tommy. “NCAP Public Record Removals Have Little Impact to FICO Scores.” *FICO Blog*, 17 May 2017, available at www.fico.com/blogs/ncap-public-record-removals-have-little-impact-fico-scores

[19] *Id.*

than was seen in the Federal Reserve or FICO NCAP analyses.[20] Specifically, around 30% of the entire sample in **Table 3.1** either see credit score increases of 10 points or more or become unscoreable with the data suppression.

Table 3.1 *Credit Score Change from Suppressing 36 Months of Derogatory Credit Information from Active Accounts (2010 Sample)*

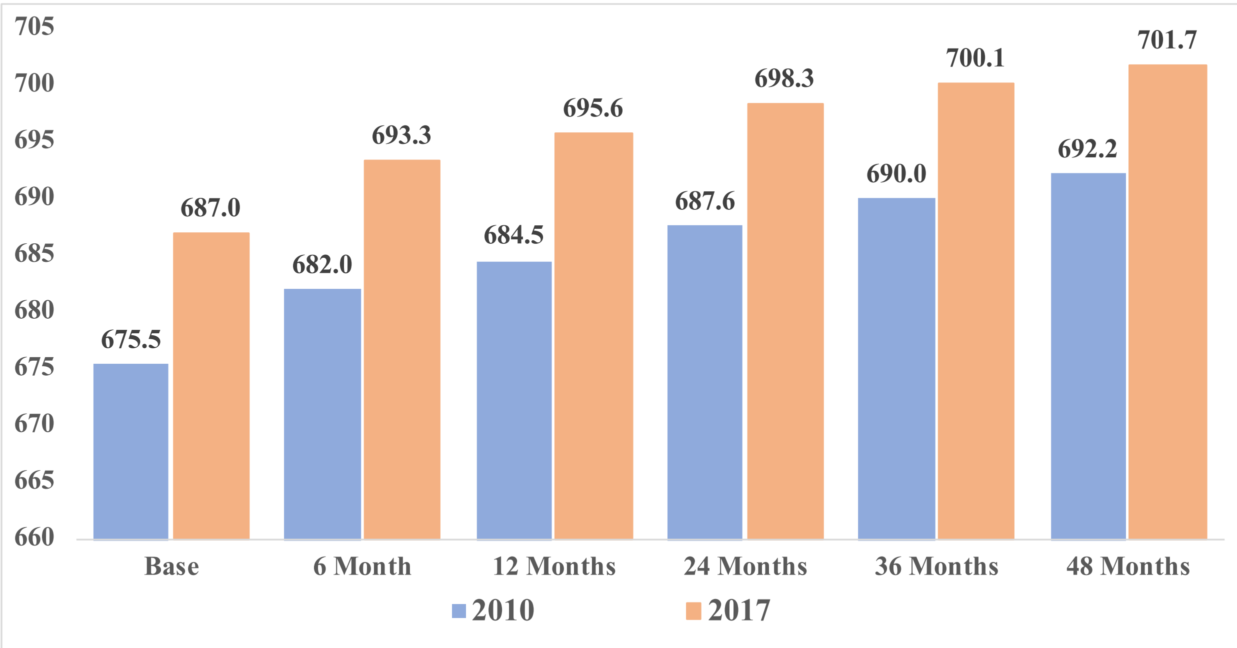
Credit Score Change	Frequency	Percent (%)
100+ Point Decrease	132	0.0%
50-99 Point Decrease	2,388	0.0%
20-49 Point Decrease	10,363	0.2%
10-19 Point Decrease	7,941	0.2%
1-9 Point Decrease	11,717	0.2%
No Change	3,095,467	61.9%
1-9 Point Increase	184,703	3.7%
10-19 Point Increase	214,622	4.3%
20-49 Point Increase	374,819	7.5%
50-99 Point Increase	314,386	6.3%
100+ Point Increase	181,731	3.6%
Initially Unscorable	215,054	4.3%
Became Unscorable	386,677	7.7%
Total	**5,000,000**	**100.0%**
Mean Score Change (Scorable Population Only)	**14.38 Points Increase**	

A large share of the sample shown in **Table 3.1**, 17.4%, sees credit score rises of 20+ points, while 10 percent see 50+ point score rises. However, since most consumers do not have recent derogatories (derogatory credit information), close to two-thirds see little to no credit score change. Overall, the average credit score change for the sample is a rise of 14.38 points.

Figure 3.1 shows the average credit scores for different lengths of negative data suppression on active accounts, ranging from 6 to 48 months. This is shown for both the 2010 samples and the 2017 samples. These results are based on only those consumers that were scorable across all lengths of negative data suppression. This enables an apples-to-apples comparison, in which the average score is not impacted by consumers dropping out of the sample because they may have become unscorable.

[20] As anticipated in Turner, Walker, and Moore (**see:** note 13 on pp. 11-16), the impacts from such a wide-scale data suppression are more in line with those seen in a 2003 report by the Information Policy Institute (the predecessor organization of PERC) titled "The Fair Credit Reporting Act: Access, Efficiency & Opportunity." (**See:** Michael Turner et al., *The Fair Credit Reporting Act: Access, Efficiency and Opportunity*. Washington, DC: The National Chamber Foundation, June 2003, available at http://www.perc.net/wp-content/uploads/2013/09/fcra_report.pdf).

Figure 3.1 *Average Credit Score with Different Lengths of Derogatory Credit Information Suppression on Active Accounts*



As one would expect, the longer the period of negative data suppression, the more the average credit score rises. This is true for both time periods.

Some may believe that the average credit score for the US remains relatively stable over time. In fact, average credit scores are dynamic, and heavily influenced by swings in the business cycle. For example, owing to the mortgage meltdown and the ensuring financial crisis, the unemployment rate in October 2010 was 9.4% but had fallen to 4.1% by October 2017.[21] So also as one would expect, the average credit scores in the 2017 samples are higher than those from the 2010 samples. By including analysis from a business cycle's rough trough and peak lend additional robustness to the analysis.

The results in **Figure 3.1** show that the longer the period of negative data suppression, the smaller is the incremental impact, at least in terms of average credit scores. For instance, 12 months of active account suppression raises scores by 8.6 points in 2017. But add on another year and scores rise by "only" a further 2.6 points. So, although the impacts do grow over time, the first months or year are the most impactful. This is not surprising given that more recent data is typically weighted more heavily in credit scores than older data. Therefore, suppression of derogatory data in the last 12 months should have a bigger impact than suppression of older derogatory data. However, there are a number of factors that may also come into play in this.

The results clearly show that suppressing derogatory data raises raw credit scores. And the longer the suppression, the more the credit scores rise.

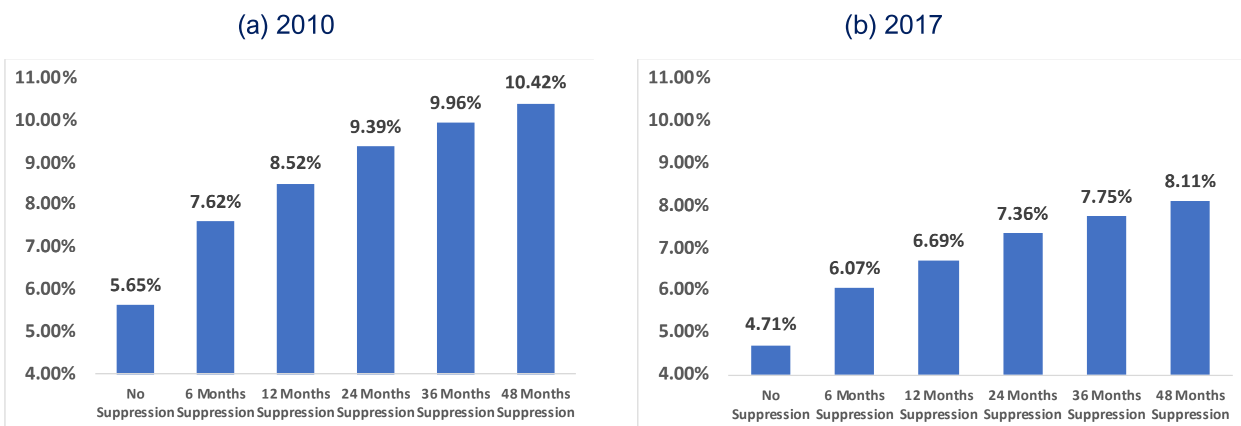
[21] *Supra* at note 12.

Credit Score Performance and Delinquency Rates

The degradation of the performance of credit scores with the removal of the derogatory data results in more higher risk individuals being given higher credit scores in 2010 and 2017. A relatively greater share of these consumers then had severe delinquencies in the two-year observation period that followed these credit snapshots. This meant that for a group of consumers with, for instance, credit scores in the 640 and above range, a greater share would have a severe derogatory if the scores were based on credit files with suppressed derogatory data.

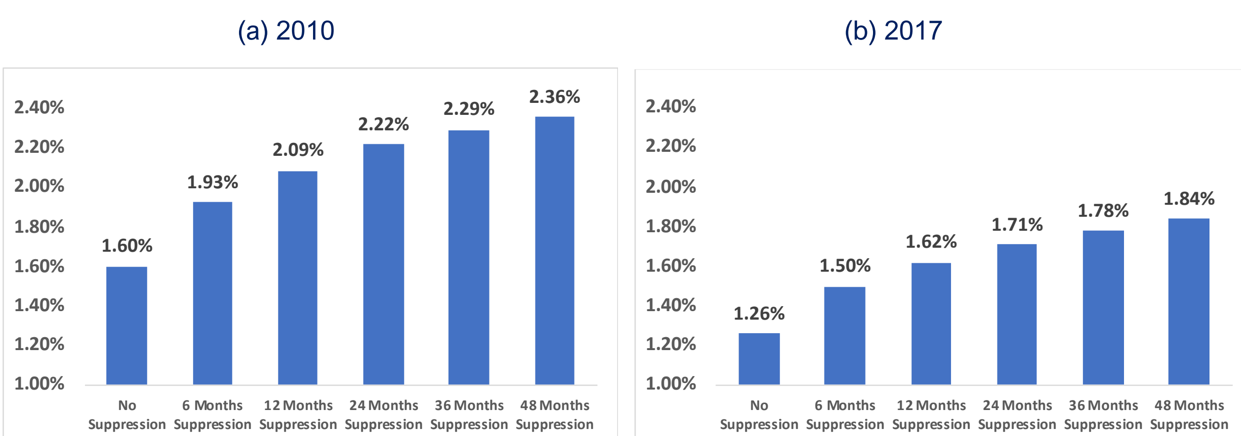
Figures 3.2 (a) and **(b)** show the total severe delinquency rate for a credit score cutoff of 640 in 2010 and 2017. As discussed in the Methodology section, severe delinquency is defined as a 90+ DPD on an account, in addition to defaults, repossessions, bankruptcies and the like. A score cutoff of 640 may be a good proxy for a cutoff for mainstream credit that is more affordable than subprime interest rates.

Figure 3.2 *Delinquency Rate with 640 Credit Score Cutoff*



Figures 3.3 (a) and **(b)** show the total severe delinquency rate for a credit score cutoff of 760 in 2010 and 2017. A score cutoff of 760 may be a good proxy for a cutoff for the lowest-priced, "best" credit available with risk-based pricing.

Figure 3.3 *Delinquency Rate with 760 Credit Score Cut Off*

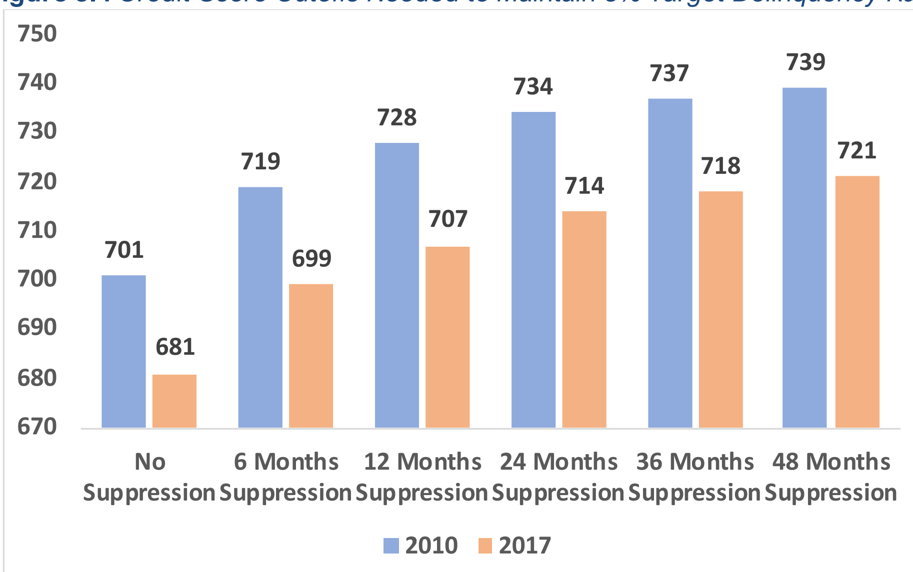


Credit Score Cutoffs

As seen in the previous sections, as derogatory data is suppressed, lenders would expect to see delinquency and default rates rise for particular cutoff points. The logical response by lenders wishing to maintain their target default rates (or at least not have them explode) would be to raise their credit score cutoffs.

As an example of this, consider a target delinquency rate of 3%. **Figure 3.4** shows how the credit score cutoff would need to be raised to maintain that target delinquency rate as derogatory data is suppressed longer and longer.

Figure 3.4 *Credit Score Cutoffs Needed to Maintain 3% Target Delinquency Rate*



Supporters of suppression/deletion may argue while cut-off points are rising, so too are credit scores. The net effect, then, should be minimal as the rise in cutoff scores is washed out by the increase in credit scores across the borrower population.

While this may seem intuitive at first blush, what matters is the relative change in credit scores versus the change in cutoff scores. As long as credit scores increase by roughly the same amount as the increase in cutoff scores, then credit access will remain unaffected. However, should either the cutoff score or average credit score increase by more than the other, then credit access will be expanded or contracted. Figure 3.5 below compares changes in average credit score with changes in cutoff scores.

Figure 3.5 *Credit Score Cutoffs Needed to Maintain 3% Target Delinquency Rate and Average Credit Scores for 2017 for Various Durations of Negative Data Suppression*

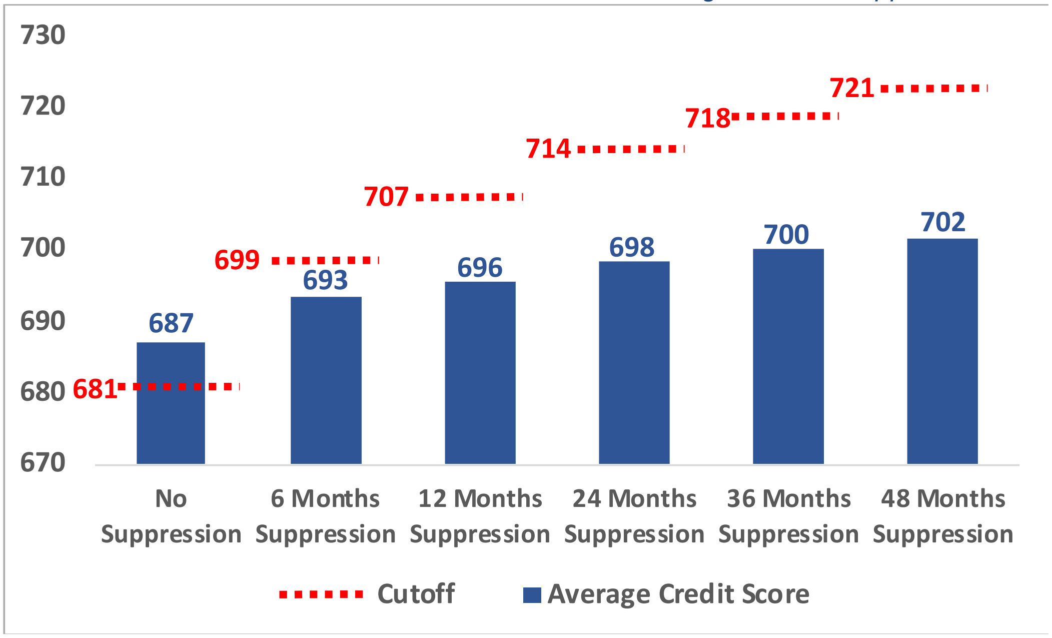


Figure 3.5 combines the cutoff credit score and the average credit scores for different lengths of data suppression. This makes clear a key dynamic of consumer lending that would occur with a wide-scale derogatory data suppression. Credit scores rise with the suppression, but importantly the needed credit score cutoffs rise relatively faster. Six months of suppression has average scores rising 6 points, but the cutoff rising 19 points. A further 6 months raises average scores by 3 more points, but the needed score cutoff rises by 7 more points. Rising raw average credit scores are clearly an illusion in the context of access to consumer credit. As the average credit score rises, the scores needed for particular types or prices of credit rise even faster resulting in marginally increased rates of financial exclusion. This creates an illusion that borrowers are better off while in reality, they would be worse off.

Acceptance Rates

While the subsection above discussed how suppression/deletion policies impact cutoff credit scores, this subsection translates what that means in terms of credit access. In other words, given the increases in cutoff credit scores and raw credit scores, how does the policy of suppression/deletion impact access to affordable mainstream credit?

Given the finding above that cutoff scores increase more over time than average credit scores, we would expect access to credit to be reduced. Further, given that a policy of suppression/deletion involves the exclusion of accurate predictive data from models built in part using that very same data, we would expect that model performance would decline. Owing to reduced access to predictive data, lenders will make more mistakes, and will begin rationing credit. As Table 3.2 below shows, this is in fact exactly what the data reveals.

Table 3.2 *Target Acceptance Rates for Different Lengths of Derogatory Credit Suppression (2010 Sample)*

Target Delinquency Rate	No Suppression	6 Months Suppression	12 Months Suppression	24 Months Suppression	36 Months Suppression	48 Months Suppression
1%	13%	9%	7%	6%	5%	3%
2%	32%	28%	26%	25%	25%	24%
3%	41%	38%	35%	34%	34%	34%
4%	49%	44%	42%	41%	40%	40%
5%	57%	48%	46%	45%	45%	44%
Acceptance Relative to the No Suppression Scenario						
1%	100%	69%	57%	45%	38%	26%
2%	100%	86%	81%	78%	76%	74%
3%	100%	92%	86%	83%	82%	82%
4%	100%	89%	86%	83%	82%	81%
5%	100%	84%	82%	79%	78%	77%

For example, a risk-averse lender targeting a 2% default rate (also referred to as a non-performing loan or "NPL" rate) with full-file data in place (and no suppression/deletion policy) would accept 32% of applicants. However, given a policy of suppression/deletion, the same lender would reduce their acceptance by 19% at 12 months, and by 26% at 48 months. The same general pattern holds for any given target default rate—the longer the period of suppression/deletion, the higher the rate of financial exclusion for credit-seeking Americans.

While **Table 3.2** summarized results using a large sample of borrowers from 2010—to simulate the impacts on access to credit during a downturn in the business cycle and recovery (in this case from a financial crisis)—**Table 3.3** below summarizes results using a large population of borrowers from 2017 to simulate the impacts during a period of economic growth and a fully recovered economy. Here too the decision to exclude predictive negative data from credit reports results in credit rationing by lenders as credit risk models become less predictive and measures are taken to mitigate against increased risk.

A somewhat risk-tolerant lender accepting a 5% default or NPL rate who would accept 67% of applicants with full-file data (and no policy of suppression/deletion in place), would reduce their acceptance rate by 8% after just one year, and by nearly 20% by month 48 of a suppression/deletion policy. Put differently, 1 in 5 people who would be accepted for affordable mainstream credit with a full-file regime in place will now be forced to seek credit from higher-cost fringe financial institutions such as payday lenders, pawn shops, title lenders and others given a suppression/deletion policy.

Table 3.3 *Target Acceptance Rates for Different Lengths of Derogatory Credit Suppression (2017 Sample)*

Target Delinquency Rate	No Suppression	6 Months Suppression	12 Months Suppression	24 Months Suppression	36 Months Suppression	48 Months Suppression
1%	22%	16%	13%	10%	6%	3%
2%	42%	38%	37%	35%	34%	33%
3%	51%	47%	46%	45%	44%	43%
4%	62%	56%	52%	51%	50%	50%
5%	67%	63%	62%	59%	55%	54%
Acceptance Relative to the No Suppression Scenario						
1%	100%	70%	58%	44%	25%	15%
2%	100%	91%	87%	83%	81%	80%
3%	100%	94%	91%	89%	87%	86%
4%	100%	91%	84%	82%	81%	80%
5%	100%	94%	92%	89%	82%	81%

While these aggregated findings are eye-opening and present compelling evidence for policymakers, it is also helpful to look at credit market impacts on different groups of borrowers. The following subsections explore how persons with different age, income, and race/ethnicity may be affected should Congress take actions to expand current practices around reporting predictive negative payment data to credit bureaus.

Consumer Access to Credit

Removal of predictive data from consumer credit reports will have the greatest impact on people with relatively thinner credit files—whether the data is positive or negative. This stems from the fact that thin-file borrowers have very little data in their credit report to begin with, so removing any predictive data results in a larger credit score impact than is the case with a thick file borrower on average. Of course, this all depends upon the contents of one's credit report, as a person with both a thick file but extensive and substantial negative data (e.g. bankruptcy, liens, multiple collections and defaults, many delinquencies) could be dramatically affected by a policy of suppression/deletion depending upon the expansiveness of the policy (old negatives and new ones suppressed/deleted) and extensiveness (length of policy).

Given all of this, with respect to how the removal of predictive negative data from credit reports affects borrowers in different age cohorts, evidence from previous studies demonstrates that younger Americans will be the most negatively impacted. Younger borrowers are less credit experienced, and have fewer open and active credit accounts in their credit reports on average than more mature and credit experienced borrowers. The evidence from simulations using data from both 2010 and 2017 bears this out.

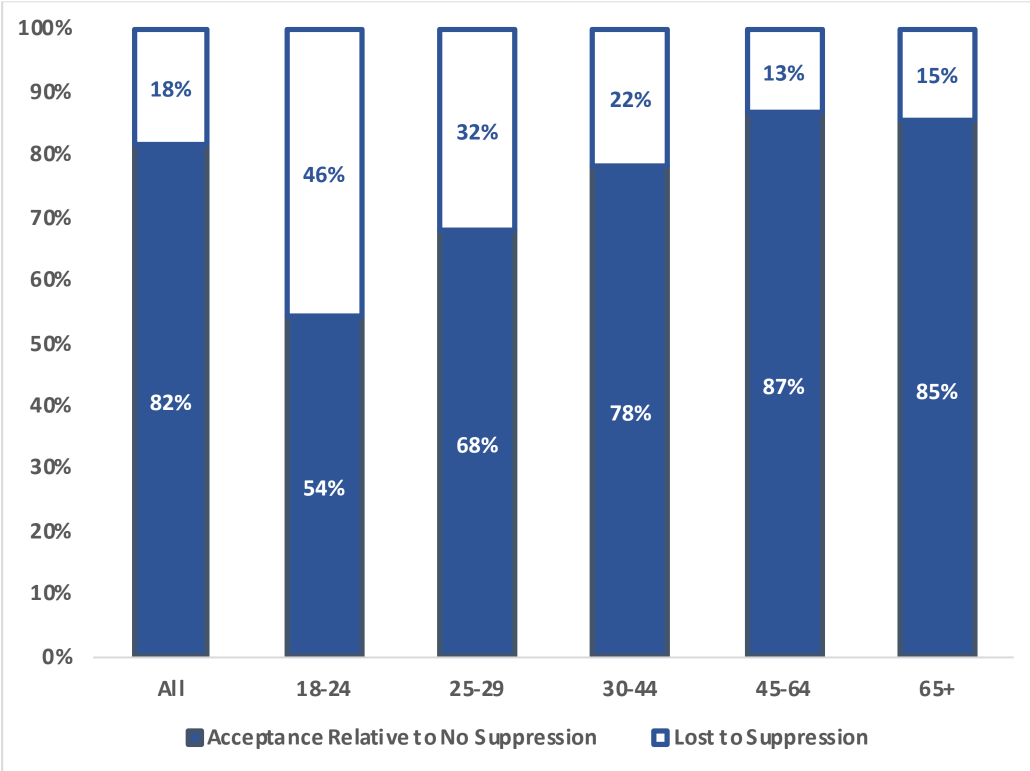
In the 2017 sample, access to credit for the entire population declines by 9% after just one year of suppression/deletion, but by 25% for persons aged 18-24. Extending the suppression/deletion policy to 48 months reduces overall credit access by 14%, but by 38% for the 18-24 year old borrower population. The results using the 2010 sample are even starker for younger borrowers, where access to credit drops 31% after just one year and by a whopping 46% at four years for the 18-24 year old borrower population.

Table 3.4 *Relative Acceptance Rates for 3% Target Delinquency Rate for Different Lengths of Derogatory Credit Suppression, By Age*

Age Group	No Suppression	6 Months Suppression	12 Months Suppression	24 Months Suppression	36 Months Suppression	48 Months Suppression
			2017			
All	**100%**	**94%**	**91%**	**89%**	**87%**	**86%**
18-24	100%	81%	75%	69%	65%	62%
25-29	100%	90%	86%	82%	80%	78%
30-44	100%	92%	89%	86%	84%	83%
45-64	100%	94%	92%	90%	89%	88%
65+	100%	97%	96%	95%	94%	94%
			2010			
All	**100%**	**92%**	**86%**	**83%**	**82%**	**82%**
18-24	100%	80%	69%	61%	57%	54%
25-29	100%	86%	78%	72%	69%	68%
30-44	100%	90%	84%	81%	79%	78%
45-64	100%	94%	90%	88%	87%	87%
65+	100%	94%	89%	87%	86%	85%

Figure 3.6 below shows the varying impacts of a HEROES Act style regime of data suppression/deletion out to four years. The overall credit reduction of 18% somewhat masks the disparate impact upon younger borrowers. For those aged 18-24, nearly half will lose access to affordable sources of mainstream credit, while nearly one-third of those aged 25-29 will similarly be rejected. The long-term consequences of this policy involve delayed development of asset building and wealth creation at a minimum, and could impact decisions about when/whether to start a family, investment decisions and other personal financial decisions that cannot be predicted or quantified at this juncture. Suffice it to say, the impacts on younger Americans from an extended suppression/deletion regime could be profound and enduring.

Figure 3.6 *Change in Acceptance by Age Relative to No Suppression Scenario for 48 Months of Suppression, 3% Target Delinquency Rate (2010)*



While the relationship between income tier and reduced access to credit over time with a policy of suppression/deletion is not as pronounced, it exists nonetheless and most negatively affects lower-income persons relative to those with higher income. As summarized below in Table 3.5, after just one year, acceptance rates decline by 10% for persons earning $30,000 or less (roughly 45% of all working Americans) but by just 7% for those earning $150,000 per year or more. Similarly, by extending the regime of suppression/deletion out to four years, acceptance rates drop by 16% for those earning $30,000 per year or less, and by only 13% for those earning $150,000 per year or more. That's a difference of roughly 20% between these two income tiers and highlights the fact that HEROES Act suppression/deletion regime will most likely result in the unintended consequence of reducing access to affordable sources of mainstream credit for lower-income Americans.

Table 3.5 *Relative Acceptance Rates for 3% Target Delinquency Rate for Different Lengths of Derogatory Credit Suppression, By Household Income*

Household Income (000)	No Suppression	6 Months Suppression	12 Months Suppression	24 Months Suppression	36 Months Suppression	48 Months Suppression
			2017			
All	**100%**	**94%**	**91%**	**89%**	**87%**	**86%**
<30	100%	93%	90%	87%	85%	84%
30-49	100%	93%	90%	87%	86%	84%
50-99	100%	94%	91%	89%	87%	86%
100-149	100%	94%	92%	90%	88%	87%
150+	100%	95%	93%	91%	90%	89%
			2010			
All	**100%**	**92%**	**86%**	**83%**	**82%**	**82%**
<30	100%	92%	84%	82%	81%	81%
30-49	100%	91%	84%	81%	80%	80%
50-99	100%	91%	86%	83%	82%	81%
100-149	100%	93%	88%	85%	84%	84%
150+	100%	94%	89%	87%	86%	85%

Figure 3.7 below makes this point graphically. On average, a four-year suppression/deletion policy would reduce acceptance rates by 18%. The impacts on the lower income groups are greater than average, and less than average on the higher income groups. Put differently, extending suppression/deletion to four years will have the greatest negative effect on low- to moderate-income persons, who comprise the vast majority of working Americans. These are the very same people Congress seeks to protect through the CARES Act.

Figure 3.7 *Acceptance by Household Income Relative to No Suppression Scenario for 48 Months of Suppression, 3% Target Delinquency Rate (2010)*

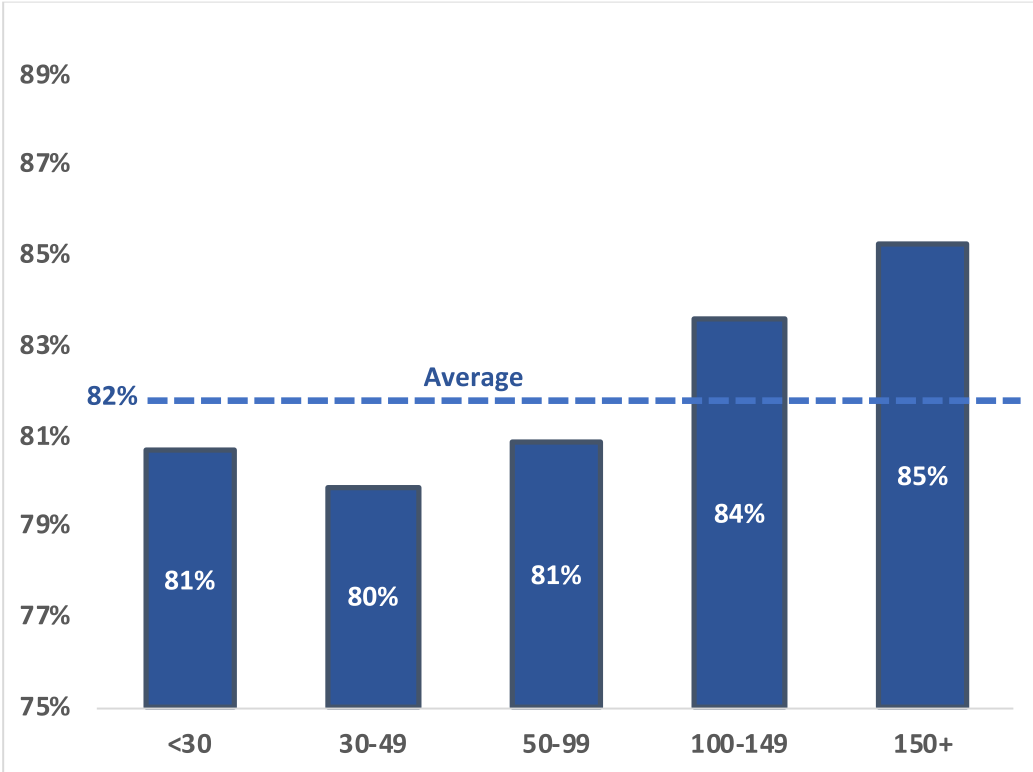


Figure 3.8 *Acceptance by Racial/Ethnic Composition of Area Relative to No Suppression Scenario for 48 Months of Suppression, 3% Target Delinquency Rate (2010)*

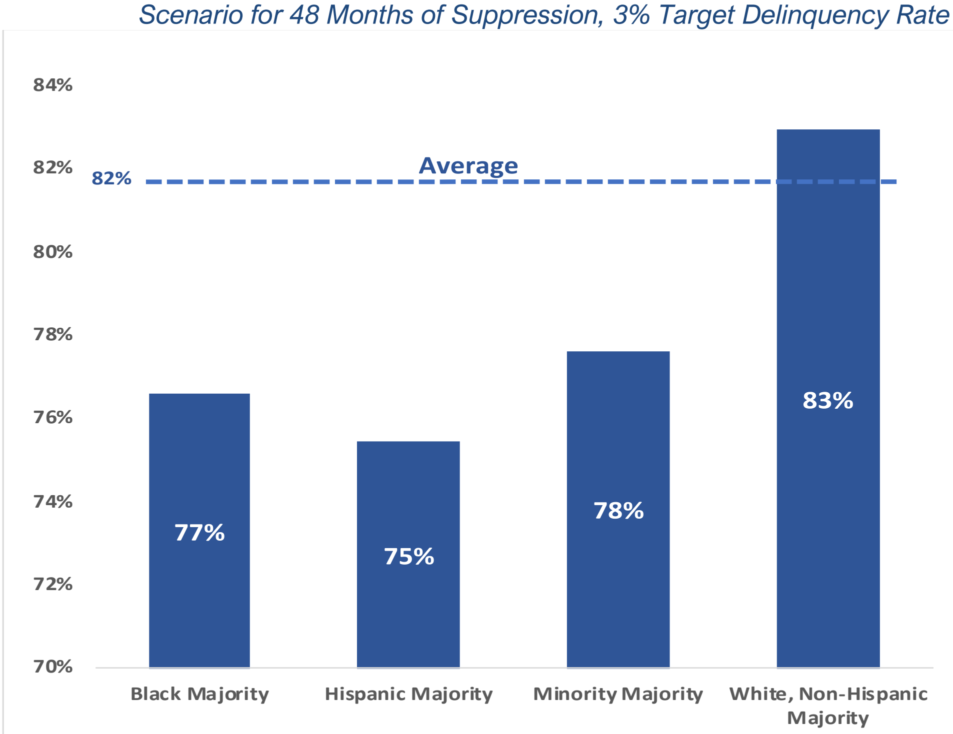


Figure 3.8 shows that the reduced credit access from the data suppression/deletion is worse for members of households in majority minority areas (Census Block Groups). While credit access declines by 19% overall, it declines by 23% in black-majority areas and 25% in Hispanic-majority areas. In minority-majority areas overall, it declines 22%.

Lawmakers in the US and globally must weigh these facts heavily when considering future policy measures to aid borrowers in the wake of the COVID-19 pandemic. Should the healthcare crisis go sideways, there will be enormous political pressure (again) to do something. Extending and expanding existing accommodations to something like the HEROES Act provisions might be low-hanging politically popular fruit. While the optics and intentions are no doubt good, the actual impacts on groups of borrowers lawmakers seek to protect may not be positive. The reductions in acceptance rates, and ratcheting up of the price of credit associated with the sustained removal of predictive data from the national credit information sharing system will only increase over time as the suppression/deletion regime is extended. Similarly, expanding accommodations to include closed files, past negatives, or all negatives will only magnify the degree and extent of harms in terms of reduced credit access and increased credit prices. These outcomes, in turn, will reduce overall economic growth and will dampen any recovery efforts.

The credit market impacts quantified above are all associated with adverse selection impacts (Type 1 and Type 2 errors) and with a degradation in the national credit reporting system's data quality. This is, however, only part of the picture, one that only deals with selecting applicants to approve or reject. As borrowers come to understand that late payment data is not being reflected in consumer credit reports, a growing number of borrowers may be tempted to become increasingly delinquent or outright default on existing debt in the absence of any reputational damage. This is the moral hazard effect, which is well established in theoretical economic literature. The following section seeks to quantify this effect from an extended/expanded suppression/deletion regime.

Accounting for Moral Hazard

Thus far, we have examined how the suppression of derogatory information would degrade the ability of lenders to identify and rank order applicants in terms of credit risk. This touches on the *Adverse Selection* problem in lending that results from *Asymmetric Information*. Credit bureaus and credit information sharing are institutional responses to help address this problem. In short, credit bureaus help lenders assess applicant risk. As seen previously, degrading important data reduces the ability of credit bureaus to aid lenders. In turn, this results in degraded lending, and ultimately, consumer harm in terms of reduced access to credit and/or higher priced credit.

Moral Hazard is the other major *Adverse Selection* problem that credit bureaus and information sharing aid lenders with. This problem centers on the likelihood or incentives a borrower has to repay the loan as agreed *after* the loan has been granted. So, while *Adverse Selection* occurs before loans have been granted, *Moral Hazard* occurs after they have been granted. That is, once a borrower has been approved, what incentives exist for the borrower to repay the loan? The incentive the credit bureaus and credit information sharing provide the borrower is that repaying as agreed will, generally speaking, improve the borrower's *credit reputation* and improve their ability to obtain future credit and or on better terms. Not repaying as agreed has the opposite impact, again speaking generally. In this way, a borrower has their "credit reputation" on the line as collateral, perhaps instead of traditional collateral. The ability to substitute credit reputation for traditional collateral is particularly useful for lower income and lower asset individuals.

The incentive for borrowers associated with credit reporting has been demonstrated theoretically and empirically.[22] [23] [24] Among this evidence was somewhat of a natural experiment PERC wrote about in a 2009 report.[25] A utility in the Detroit area began reporting payments to a credit bureau. There was little change in payment behavior since the customers of the utility were (apparently) largely unaware of this change. But after the media in the Detroit area highlighted the change in a heavily publicized "media storm," late payments and accounts in arrears for the utility plummeted. Consumers were used to financial accounts being reported to the credit bureaus, but not non-financial accounts, such as utilities. Once consumers became aware of this utility reporting, many rapidly changed their payment behavior.

The fact that individuals respond to incentives is understood. As such, following a moratorium on reporting derogatory information to credit bureaus, it is logical that there would be an increase in late payments and defaults because of the moratorium. This would be particularly true for loans with no traditional collateral to repossess/evict and loans of insufficient size to warrant legal action (all of which could also be curtailed in a national emergency). Individuals would not need to connect these dots – there would no doubt be unscrupulous websites advising consumers that they may want to reconsider paying their obligations, even if they could pay them, since the repercussions of nonpayment have been greatly diminished. In such a case, among consumers that could pay their obligations, some share would likely continue to do so, some might find it an easy decision to stop paying, and some might be torn.

The true consumer and economic damage from this would not really come from consumers being late or less likely to payoff *existing* obligations; that would just be a one-off transfer from lenders and investors to borrowers. The harm would be from lender expectations about the changing performance of loans granted moving forward. Lenders would raise lending standards, expecting an increase in delinquencies and defaults. So if lenders expected that delinquencies would rise 50% for portfolios, then a portfolio with a 3% delinquency rate would rise to 4.5%. To maintain the 3% delinquency rate under the increase in moral hazard, lenders would choose standards and cutoffs associated with a 2% delinquency rate before the increase in moral hazard, expecting that it would be 3% with the increase in moral hazard. Such a change in the delinquency rate does not seem that implausibly large, given how such rates move due to a variety of factors such as the business cycle. For instance, among credit card loans, the charge-off rate was 10.54% in Q4 2009 and fell to 3.76% by Q4 2019.[26]

With large-scale derogatory data suppression, lenders would be hit with a double whammy. It would be more difficult to assess borrower risk (the adverse selection problem) and borrowers would become riskier, in that they would be less likely to repay loans as agreed (the moral hazard problem). Lenders would raise standards and credit score cutoffs to account for both factors (they may also adjust standards to account for macroeconomic conditions that may be occurring if policies to suppress derogatory data were a response to a major event).

Although it is difficult to estimate exactly how borrowers would respond to a systemwide suppression of derogatory data, it is straightforward to model some simple hypothetical scenarios.

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[22] See Padilla, Jorge and Pagano, Marco. "Sharing Default Information as a Borrower Discipline Device." *European Economic Review,* vol. 44, 2000, pp. 1951-1980. *SSRN*, available at: ssrn.com/abstract=183972

[23] See Vercammen, James A. "Credit Bureau Policy and Sustainable Reputation Effects in Credit Markets." *Economica, vol. 62, no. 248*, Nov. 1995, pp. 461-478. *JSTOR*, available at: www.jstor.org/stable/2554671

[24] See Brown, Martin and Zehnder, Christian. "Credit Reporting, Relationship Banking, and Loan Repayment." *Journal of Money, Credit and Banking*, vol. 39, no. 8, December 2007, pp. 1883-1918. *SSRN*, available at: papers.ssrn.com/sol3/papers.cfm?abstract_id=968387

[25] Michael Turner et al. "Credit Reporting Customer Payment Data: Impact on Customer Payment Behavior and Furnisher Costs and Benefits." *Chapel Hill: Political & Economic Research Council (PERC)*, Mar. 2009, available at: www.perc.net/wp-content/uploads/2013/09/bizcase_0.pdf

[26] U.S. Bureau of Labor Statistics. "Charge-Off Rate on Credit Card Loans, All Commercial Banks." *FRED, Federal Reserve Bank of St. Louis*, available at: fred.stlouisfed.org/series/CORCCACBS

In what follows, we factor into the acceptance rates a 25%, 50%, 75% and 100% increase in delinquency associated with the data suppression. So, a 2% delinquency rate (without the increase in moral hazard) would become either 2.5%, 3%, 3.5%, or 4% with the increase in moral hazard problem. This increase in delinquency is assumed to occur uniformly. So with the 50% increase scenario, we assume a credit score associated with a 2% delinquency rate, it would rise to 3%. A score associated with a 4% delinquency rate, it would rise to 6%, and so on. Overall, this results in a 50% rise in delinquency. This simple exercise can shed light on how such an increase in moral hazard might impact lending.

Table 3.6 *Acceptance Rate for Increases in Delinquency Combined with Different Lengths of Derogatory Credit Suppression, 4% Delinquency Rate 2010 Sample)*

Increase in Delinquency	No Suppression	6 Months Suppression	12 Months Suppression	24 Months Suppression	36 Months Suppression	48 Months Suppression
0%	49%	44%	42%	41%	40%	40%
25%	43%	39%	37%	36%	35%	35%
50%	39%	34%	33%	32%	31%	31%
75%	35%	32%	30%	28%	27%	27%
100%	32%	28%	26%	25%	25%	24%
	Acceptance relative to No Suppression Scenario / No Increase in Delinquency					
0%	100%	89%	86%	83%	82%	81%
25%	87%	80%	75%	73%	72%	71%
50%	80%	70%	68%	66%	64%	63%
75%	71%	64%	60%	57%	56%	55%
100%	66%	57%	54%	51%	50%	49%

Table 3.6 shows that where acceptance would be 49% of applicants with no data suppression (upper left corner of the table), it falls to 40% with 48 months of suppression but no increase in delinquency due moral hazard (right side of top row). However, it falls further to 24% if there is a 100% increase in delinquencies due to a reduced ability to control moral hazard (fifth row down). In this case, acceptance for credit is cut in half.

Even a “small” increase in delinquency, such a 25% rise from 2% to 2.5% has big impacts. For 6 months of suppression, acceptance falls from 49% to 44% with the reduced ability to overcome the adverse selection problem and then to 39% with a 25% increase in delinquency.

Table 3.7 shows the results using the 2017 sample.

Table 3.7 *Acceptance Rate for Increases in Delinquency Combined with Different Lengths of Derogatory Credit Suppression, 4% Delinquency Rate 2017 Sample)*

Increase in Delinquency	No Suppression	6 Months Suppression	12 Months Suppression	24 Months Suppression	36 Months Suppression	48 Months Suppression
0%	62%	56%	52%	51%	50%	50%
25%	52%	49%	47%	46%	45%	45%
50%	48%	45%	43%	42%	41%	40%
75%	45%	41%	39%	38%	38%	37%
100%	42%	38%	37%	35%	34%	33%
	Acceptance relative to No Suppression Scenario / No Increase in Delinquency					
0%	100%	91%	84%	82%	81%	80%
25%	83%	79%	77%	75%	74%	73%
50%	78%	73%	70%	67%	66%	65%
75%	73%	66%	64%	62%	61%	60%
100%	68%	62%	59%	56%	55%	54%

The results from the 2017 sample are broadly similar to what was seen with the 2010 sample. With the 2017 data, credit acceptance falls by just under 50% in the most extreme case of 48 months suppression and 100% increase in delinquency.

Using the 2010 sample and 48 months of suppression with a 100% increase in delinquency due to moral hazard, we break down the credit access impacts by age and household income. This is the 49% figure from the lower right of Table 3.6.

Figure 3.9 shows a shocking decrease in credit acceptance for younger consumers. Access is essentially wiped out with a 92% reduction.

Figure 3.9 *Acceptance Rate Relative to No Suppression Scenario with 100% Increases in Delinquency Combined with 48 Months of Derogatory Credit Suppression, 4% Delinquency Rate, by HH Income (2010 Sample)*

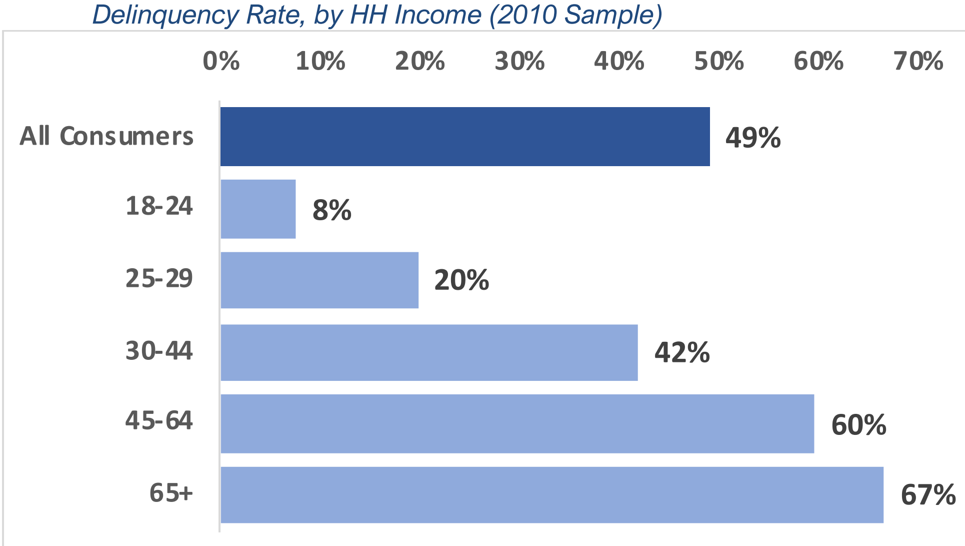


Figure 3.10 *Acceptance Rate Relative to No Suppression Scenario with 100% Increases in Delinquency Combined with 48 Months of Derogatory Credit Suppression, 4% Delinquency Rate, by Age (2010 Sample)*

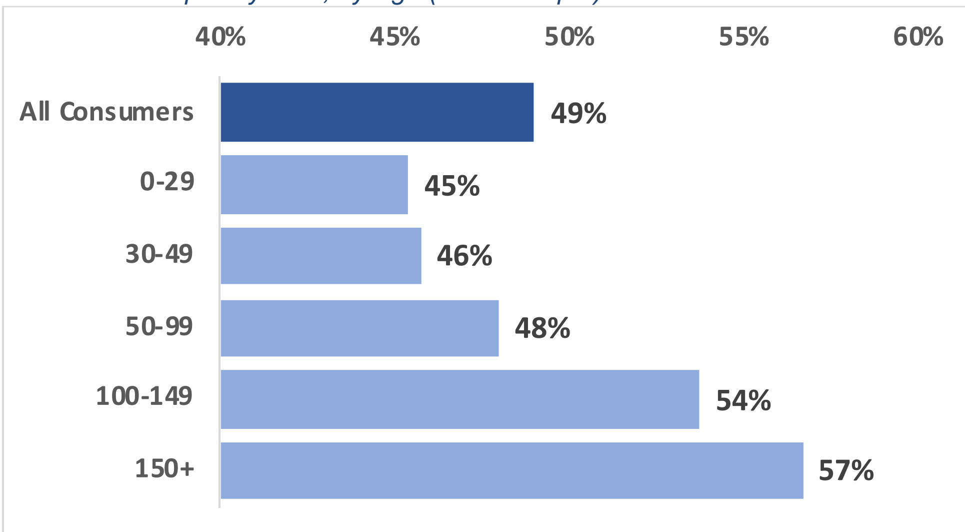
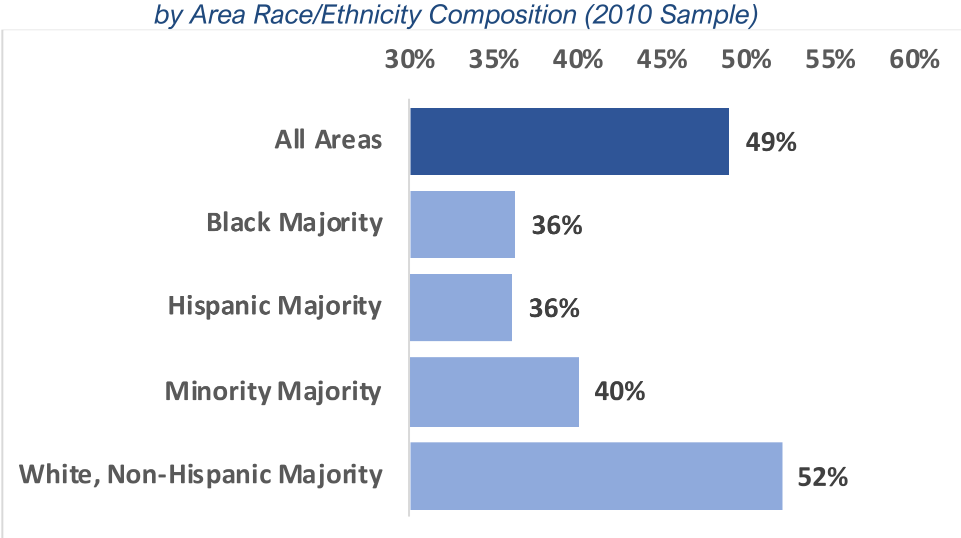


Figure 3.10 shows a less shocking decrease in credit acceptance for lower-income consumers than for younger consumers, but there is still a large disparity by income. Members of the lowest income households see a 55% decrease in acceptance while members of the highest see “only” a 43% decrease.

Figure 3.11 *Acceptance Rate Relative to No Suppression Scenario with 100% Increases in Delinquency Combined with 48 Months of Derogatory Credit Suppression, 4% Target Delinquency Rate, by Area Race/Ethnicity Composition (2010 Sample)*



As seen previously, **Figure 3.11** shows that the reduced credit access from the data suppression/deletion is worse for members of households in majority minority areas. Combined with the impact of the simulated increase in delinquencies, the figures grow starker. While credit access declines by 51% overall, it declines by 64% in black-majority areas and Hispanic-majority areas. In minority-majority areas overall, it declines 60%.

Suppression on Open and Closed Derogatory Accounts

Table 3.8 *Acceptance Rate with Suppression on Open and Closed Accounts (2010 Sample)*

Target Delinquency Rate	No Suppression	24 Months Suppression on Open Derog Accounts	24 Months Suppression on All Derog Accounts	24 Months Suppression on All Derog Accounts + MH (25%)	24 Months Suppression on All Derog Accounts + MH (50%)	24 Months Suppression on All Derog Accounts + MH (100%)
1%	13%	6%	0%	0%	0%	0%
2%	32%	25%	20%	14%	9%	0%
3%	41%	34%	29%	24%	20%	12%
4%	49%	41%	36%	31%	27%	20%
5%	57%	45%	41%	36%	32%	25%
Acceptance relative to the No Suppression Scenario						
1%	100%	45%	1%	0%	0%	0%
2%	100%	78%	63%	43%	27%	0%
3%	100%	83%	71%	59%	49%	29%
4%	100%	83%	73%	64%	55%	41%
5%	100%	79%	73%	63%	56%	44%

Table 3.8 shows the impact of suppressing all derogatory information, including on closed accounts for a 24-month period. The first column shows that, with no suppression, about half of the sample (49%) could be accepted with a target delinquency rate of 4%. Add on suppression of derogatory information on open accounts and this falls to 41%. Add on to this the suppression of derogatory information on all accounts (including closed accounts) and it falls to 36%. Adding to that an increase in delinquencies due to a worsening moral hazard problem, it then falls further. It would fall to 20% if there was a 100% rise in delinquencies. In this extreme case, credit access would fall from 1 in 2 people to 1 in 5.

More comprehensive suppression clearly results in a more pronounced credit crunch.

Figure 3.12 *Acceptance Rate Relative to No Suppression Scenario with 100% Increases in Delinquency Combined with 24 Months of Derogatory Credit Suppression on All Accounts, 4% Delinquency Rate, by Age (2010 Sample)*

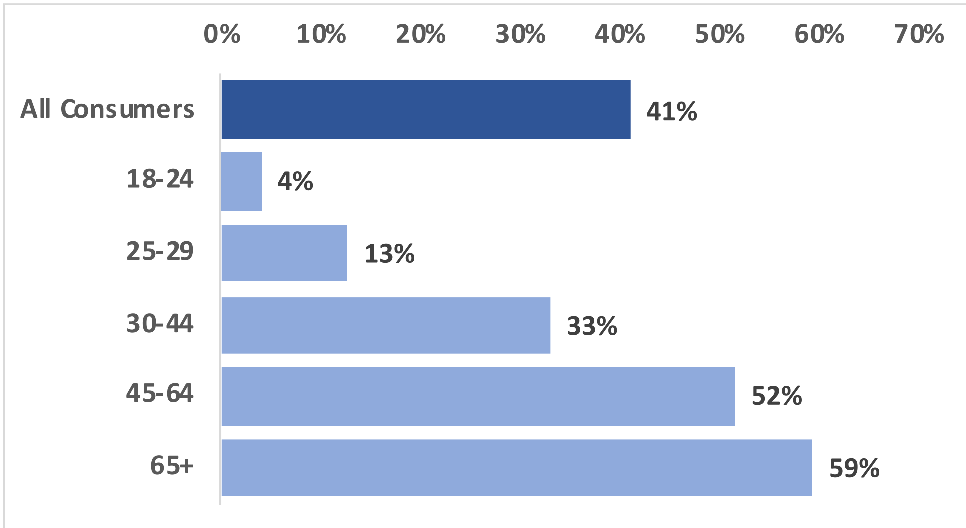


Figure 3.13 *Acceptance Rate Relative to No Suppression Scenario with 100% Increases in Delinquency Combined with 24 Months of Derogatory Credit Suppression on All Accounts, 4% Delinquency Rate, by HH Income (2010 Sample)*

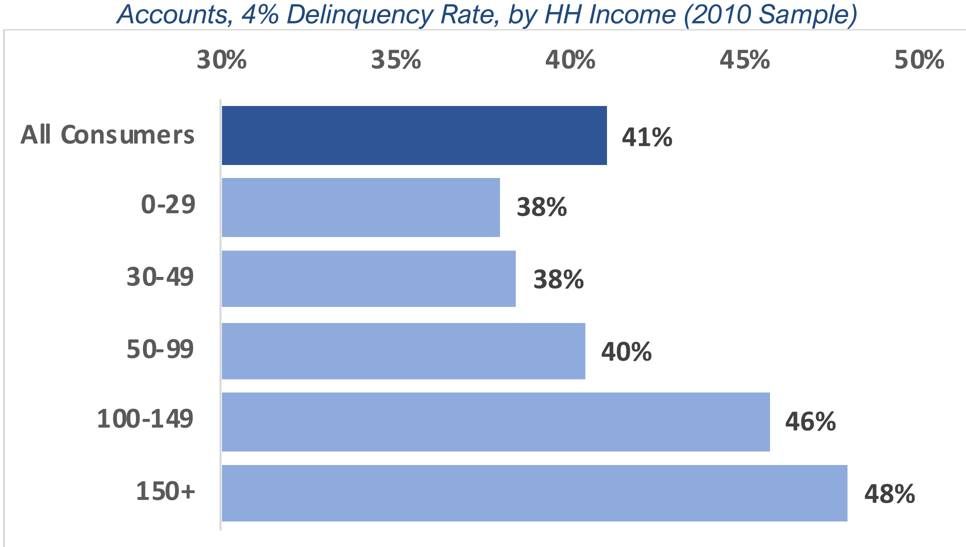
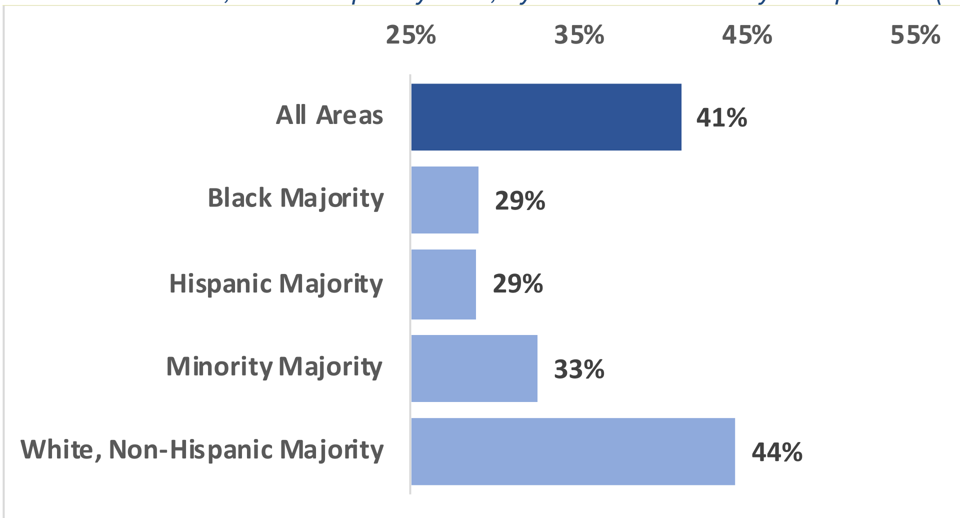


Figure 3.14 *Acceptance Rate Relative to No Suppression Scenario with 100% Increases in Delinquency Combined with 24 Months of Derogatory Credit Suppression on All Accounts, 4% Delinquency Rate, by Area Race/Ethnicity Composition (2010 Sample)*



Figures 3.12 and **3.13** show, as before, that it is the youngest borrowers and members of the lowest income households that would suffer most from a suppression-induced credit crunch. The impacts are even more pronounced when derogatory data suppression is applied to all accounts, even closed ones.

Figure 3.14 shows that while credit access declines by 59% overall with 24 months of derogatory data suppression on all accounts and a 100% increase in delinquencies, it declines by 71% in black-majority areas and Hispanic-majority areas. In minority-majority areas overall, it declines 67%.

4. Impact of Adding Telecom (and Other Nonfinancial) Account Payment Information[27]

Typically, a person's mortgage, credit card, auto, and other such financial accounts are fully reported to the major consumer credit bureaus (NCRAs), meaning that both their on-time and late payments are reported. Consumers can benefit from the on-time payments reported and can have their credit reputation dinged with late payments. That said, the overwhelming majority of payments are made on-time or are not late enough to be reported as late. Among fully reported accounts, most data is "positive."

With telecom accounts, although most payments consumers make are also "on-time," consumers do not benefit from this. This is the case since telecom accounts are not fully reported (they are reported in a negative-only manner). The major telecom service providers do not report positive, on-time data, but instead flood the consumer credit reporting system with very negative payment data (such as collections). So if a consumer wants to build or improve their credit profile, they cannot do so with a telecom service account. But if they are very late in paying their account, they may find a collection on their credit report, potentially lowering their credit score. The large telecom companies could report positive data to the NCRAs but choose not to do so. Unfortunately, there are many consumers who are customers of the telecom companies with little financial credit data on their credit reports who would benefit from such a practice.

It may be that telecom companies don't want to send "a list" of their on-time customers to the consumer credit bureaus for fear that competitors could market to them. One solution to this would be for the CRAs to agree not to provide such detailed information on competitors to telecoms companies (which CRAs would likely agree to). What makes the non-reporting of positive payment data even more surprising is that the telecoms companies rely on the NCRAs for determining customer/applicant eligibility. They base this on data provided by banks, credit card issuers and the like. They take from the system but do not give to it (at least not full-file, positive data).

An August 2018 Quarterly Consumer Trends publication from the CFPB titled "Collection of Telecommunication Debt," provides some useful statistics on the magnitude of the telecom negative reporting.[28] That report showed that between mid-2013 and the beginning of 2018, approximately between two and four million new distinct telecom collections per quarter were reported to the NCRAs.

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[27] This section is an update of a similar section from PERC's June 2020 Report "Addition is Better than Subtraction: The Risks from Data Suppression and Benefits of Adding More Positive Data in Credit Reporting."

[28] Bucks, Brian, Singer, Susan, & Tremper, Nicholas. "Quarterly Consumer Credit Trends: Collection of Telecommunication Debt." *Consumer Financial Protection Bureau (CDIA)*, Aug. 2018, available at: files.consumerfinance.gov/f/documents/bcfp_consumer-credit-trends_collection-telecommunications-debt_082018.pdf

Figure 4.1 *Share of Consumers with a Telecom Collection (between Q3 2013 and Q1 2018)*

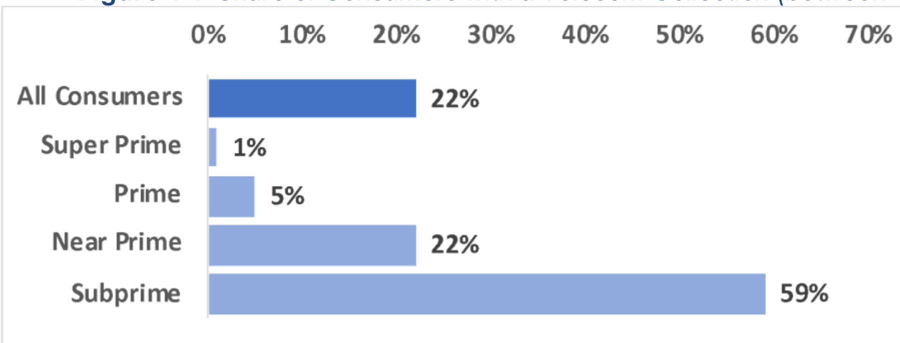
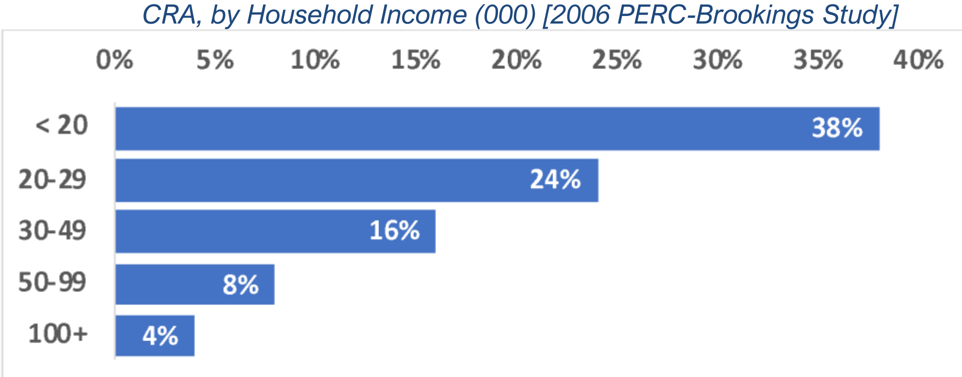


Figure 4.1 shows that between Q3 2013 and Q1 2018, 22% of all consumers had one or more telecoms collection. The majority, 59%, of consumers with a subprime credit score had a telecom collection. Clearly, negative telecom reporting is not a minor issue. Telecoms is a largescale negative-only reporting industry.

On the other hand, PERC's analysis has definitely shown that reporting full-file (positive and negative data) of telecom payment data can assist telecom customers, particularly those with little traditional credit information in their credit files (thin-files and no-files).

Who would benefit from greater full file or on-time reporting by telecoms?
In the 2006 joint PERC-Brookings report "Give Credit where Credit is Due," it was found that 14% of consumers with a telecom account reported to a CRA had no traditional accounts on their credit file.[29] In that same study it was found that lower income individuals with a telecom account reported were much more likely to be "thin-file," meaning having fewer than three traditional accounts reported in their credit file (shown in **Figure 4.2**). Thin-file consumers, particularly those with no active and open accounts, may be unscorable by traditional credit scores and face barriers to lower priced credit.

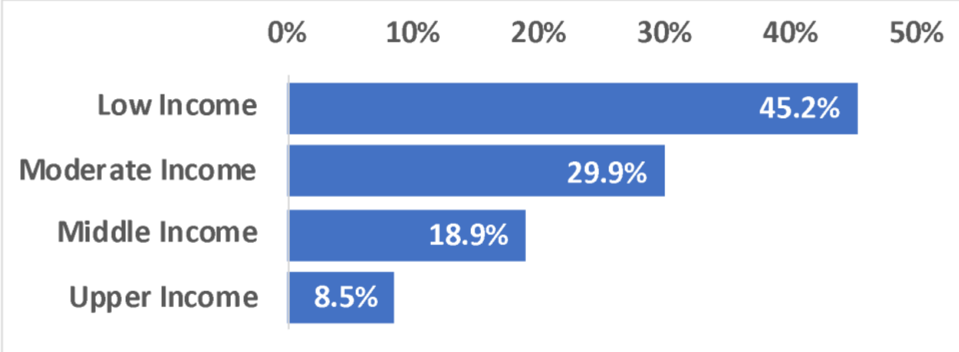
Figure 4.2 *Thin-file Traditional Account Rate for Consumers with a Telecom Account Fully Reported to a CRA, by Household Income (000) [2006 PERC-Brookings Study]*



In 2015, the CFPB published findings from a comprehensive accounting of the unscorable population and found that overall, 19% of consumers were unscorable by traditional credit scores due to insufficient data, stale data, or no data. In the lowest-income census tracts, this figure was found to be an astonishing 45%. (**See Figure 4.3**).[30]

[29] Turner, Michael and Lee, Alyssa. "Give Credit Where Credit is Due: Increasing Access to Affordable Mainstream Credit Using Alternative Data." Washington, DC: The Brookings Institution, Dec. 2006, available at: www.perc.net/wp-content/uploads/2013/09/alt_data.pdf
[30] Brevoort, Kenneth, Grimm, Philipp, & Kambara, Michelle. "Data Point: Credit Invisibles." *Consumer Financial Protection Bureau (CDIA)*, May 2015, available at: files.consumerfinance.gov/f/201505_cfpb_data-point-credit-invisibles.pdf

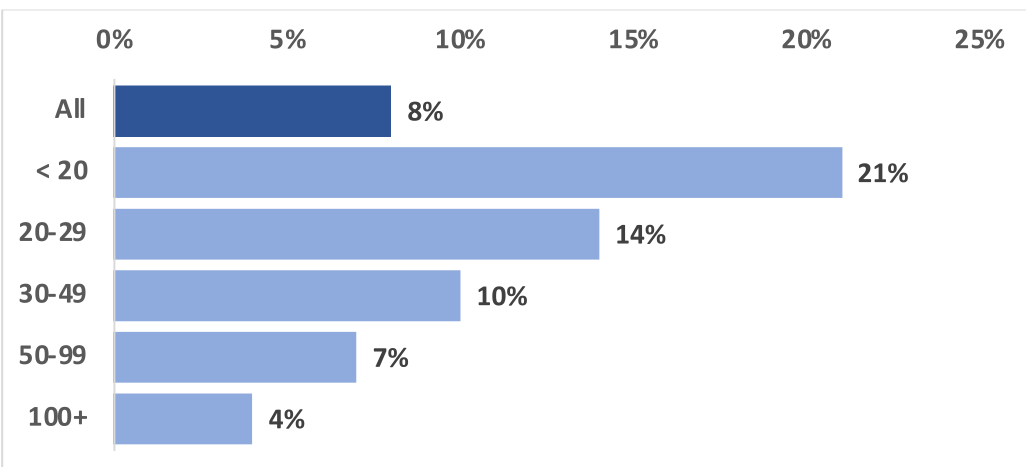
Figure 4.3 *Estimated Unscorable Rate for Adults, by Census Tract Income Level [2015 CFPB Study]*



The PERC-Brookings results and the CFPB findings demonstrate that the problem of credit invisibility and unscorability is much, much greater for members of lower-income households. The PERC-Brookings results underscores that this is also the case for telecom customers.

In a 2012 PERC report, "A New Pathway to Financial Inclusion," it was found that adding a telecom or utility full-file account to credit reports could increase access to credit for consumers.[31] This study utilized credit data from 2009 and 2010, making it somewhat contemporary to the 2010 data used in the previous section. In the 2012 study credit access increased because of two main drivers. First, by adding accounts to those who had no traditional financial accounts and were otherwise unscorable and, second, by improving the scoring model performance for those who were already scorable by adding more data. That is, the added accounts made more consumers credit visible and scorable and improved score performance for the already scorable. Not surprisingly, as seen in the previous section, members of lower-income households benefited the most (**Figure 4.4**).

Figure 4.4 *Increase in Acceptance Rates by Adding Telecom/Utility Data, by Household Income (000), Assuming a 3% Delinquency Rate [2012 PERC Study]*



As **Figure 4.4** shows, while members of the highest income households see relatively little impact from the addition of full-file utility and telecom account data, members of the lowest-income households see large,

[31] Michael Turner et al. "A New Pathway to Financial Inclusion: Alternative Data, Credit Building, and Responsible Lending in the Wake of the Great Recession*." Policy & Economic Research Council (PERC)*, Jun. 2012, available at: www.perc.net/wp-content/uploads/2013/09/WEB-file-ADI5-layout1.pdf

meaningful benefits. In the example shown in **Figure 4.4**, credit acceptance for members of lowest income households would rise 21%.

That study also showed that the majority of consumers who are already scoreable and had many accounts reported in their credit files would see little impact from adding one more account.

Data on score impacts from Experian's Boost also show that the majority (73%) see no credit score impact (using the VantageScore 4.0) when consumer-permissioned accounts that include at least one telecom account are added to consumer credit files.[32] 23% would see a credit score increase with around 4% seeing a score decline. In that sample, 12% of the consumers saw score rises of 10 points or greater. Unlike the illusory score changes with suppression/deletion, the 2006 PERC/Brookings and 2012 PERC studies demonstrated that the *addition* of predictive data increases access to credit (just as the removal of it decreases access to credit).

The addition of data from utility and telecom accounts tends to have the largest impacts for those on the credit data margins, that is the no-file, thin-file and otherwise unscorable consumers. Not surprisingly then, those most in need of reported data are those who benefit most when it is reported. In addition to the segmentation of the credit invisible by income, the CFPB also found much higher rates of unscorability among black, Hispanic and younger (adult) Americans. Correspondingly, the PERC analysis found much higher benefits from the addition of utility and telecom payment data for these same groups of consumers.

Adding new data will cause lenders to test and modify lending criteria, and the updated models will become ever more optimized for the new data. The addition of new types of data cannot degrade models that are built to use it and can only improve their performance. The adjustment is part of how benefits of new data will be realized. For instance, in the PERC utility and telecom analysis, score cut-offs were moved down to account for lower default rates at higher and middle-level scores.[33] This is the opposite of what would occur with the removal of predictive negative data, as was shown in the previous section.

Since negative telecom account data, particularly in the form of collection accounts, is already widely reported to the CRAs, what is most lacking is the positive, on-time data. As Figure 4.4 shows, low-income households could greatly benefit from telecoms reporting this missing on-time payment data. And as Figure 4.2 shows, lower income telecom customers need accounts reported to help build their credit history. This would also help "balance out" the negative collections reporting. As policymakers are looking for solutions in this time of crisis, instead of suppressing true but negative data, consumers could benefit by the promotion of reporting of true, positive telecom data. Telecom companies simply reporting full-file, or only on-time accounts in addition to the very late payment accounts (such as when they would typically go to collections anyway) would be an improvement to the status quo of little to no on-time reporting.

From the perspective of the overall effectiveness of the credit reporting system and ultimately consumer access to credit, PERC believes that full-file reporting would most benefit consumers. For this reason, PERC supports full-file reporting (reporting both positive and negative data). The fact that reporting predictive derogatory data benefits consumers, particularly lower-income consumers, was demonstrated in the previous section. So, there are clear benefits to reporting derogatory telecom account data. But we also believe the perfect should not be the enemy of the better. Reporting (at the very least) on-time telecom payment data to a system already awash in telecom collections can make the current credit reporting system better, fairer, and more inclusive. The telecom industry currently and selectively reports its most

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[32] Figures were provided by Experian for this study. The Boost product would create a positive-only tradeline for accounts such as telecom account permissioned by the consumer.
[33] It should also be easier to demonstrate to lenders how adding positive telecom data would impact scores, since this can be done now with retrospective data analysis. On the other hand, demonstrating how not reporting negative data during the current unprecedented crisis and economic downturn would be a much more challenging exercise until data on actual consumer and loan outcomes are gathered over the next couple of years.

late customers to the credit reporting system via mainly collections. Why shouldn't it then, at a minimum, also selectively report its on-time customers? This would exclude those with a spotty payment history. The large telecom companies should volunteer to do this to aid their customers. At a minimum, large telecoms that utilize credit reporting and/or report negative data to the system (either directly or indirectly) should report on-time accounts to the NCRAs as a matter of fairness.

This approach could also include utility data or rental payment data. PERC recently released a joint report with HUD that found material credit score rises and large reductions in credit invisibility with the reporting of on-time HUD Public Housing Authority rental payment data.[34] Again it is important to emphasize that full-file reporting is generally better for the credit reporting system (and consumers) than such selective reporting. But reporting on-time *plus* collections customers is far better than reporting just collection customers alone (and it's much fairer too).

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[34] Turner, Michael and Walker, Patrick. "Potential Impacts of Credit Reporting Public Housing Rental Payment Data." *U.S. Department of Housing and Urban Development (HUD)*, Feb. 2020, available at: www.perc.net/wp-content/uploads/2020/02/Potential-Impacts-of-Credit-Reporting.pdf

5. Conclusion and Policy Prescriptions

Recapitulation of Key Results from Simulations

Results using simulations on 10 million actual credit records show that the sort of wide-scale suppression of the most recent derogatory data for consumers that was proposed as part of the HEROES Act (and other legislation) would have enormous negative credit score performance and consumer credit access impacts. This should not be surprising given the importance of recent data and derogatory data in risk assessment. While raw credit scores do rise with the suppression of negative data, as expected, credit score cutoffs needed to maintain portfolio performance rise even faster. The longer the suppression lasts or the broader its scope, the worse the impact.

For example, in a sample examined from 2017, the average credit score is 687 without any data suppression and the cutoff needed for a portfolio with a delinquency rate of 3% is 681. Hence, the average credit score is above the cutoff. However, with just 6 months of derogatory data suppression on active accounts, the average score rises 6 points to 693, but the score cutoff needs to rise 18 points to 699 just to maintain portfolio performance. The average score is now insufficient. Extend this to 48 months of suppression and the average credit score rises a further 9-points to 702 but the score cutoff needs to rise a further 22-points to 721. Clearly, credit access for consumers is reduced when score cutoffs rise faster than the increases in the raw credit scores. There is a superficial *illusion* that consumers are better off due to the raw score rises, but in reality, they are harmed.

These and other findings also demonstrate that the greatest (marginal) harm comes from the initial 6 or 12 months of data suppression, though harm continues to grow over time as suppression continues. That is, the first year of suppression is much more damaging than the harm from extending suppression from year 3 to year 4. This should give pause to policymakers considering system wide data suppression for “relatively” short periods of time such as 6 months or a year.

With 48 months of data suppression, credit acceptance falls about 20% in portfolios with a target delinquency rate of 5%. However, for the lowest risk portfolios (those with a 1% target default rate), which can proxy for the best, lowest priced credit, the reduction in acceptance is massive. Acceptance is reduced over 70%. Together these suggest that data degradation results in not just reduced credit but also a shift to more expensive credit.

However, what should be most concerning to policymakers is that younger individuals, members of lower income households, and members of households in minority majority areas are most negatively impacted by the data suppression. For instance, in the 2010 sample (with a 3% target default rate) credit acceptance declines about 20% for members of households with incomes under $50,000 a year but by “only” 15% for members of households with incomes of $150,000 a year or greater. By borrower age, the difference is even more stark. 18 to 24 year-olds would see a 46% acceptance reduction while those 45 and older would see “only” a 14% reduction. Where the average credit access reduction would be 18%, it would be 23% for those living in black majority communities and 25% for those living in Hispanic majority communities. Younger persons, lower-income households, and households in minority majority areas would see a devastating credit crunch, while older, higher income households would be much less impacted. Given that the employment impacts from COVID-19 were much worse for younger and lower income households and members of minority groups, this type of credit crunch induced by data suppression would truly be a perverse policy response to the economic impacts of the pandemic.

These results do not take account of how *consumers* might respond in the event that late payments and derogatory data would not to be reported to the credit bureaus. It would be counter to theory and empirical evidence and simply unfathomable to believe that there would be no consumer/borrower response. Adding an increase in *moral hazard* acts to amplify the consumer harm. The most extreme example simulated was a doubling of the delinquency rate at each credit score cutoff. Here a portfolio with a 2% delinquency would see it rise to 4% with the increased moral hazard associated with the suppression of reporting derogatory events such as late payments. In this case, instead of overall credit acceptance falling close to 20% with 48 months of data suppression, it falls to around 50%. Even assuming 24 months of suppression and "only" a 50% increase in the delinquency rate results in credit acceptance falling by a third.

The socioeconomic disparities in the impacts from the data suppression persist with the addition of the moral hazard effect. In the case where delinquencies double and there is 48 months of data suppression, using the 2010 sample and target delinquency rate of 4%, instead of acceptance *just* halving, it is cut 80% for those aged 25 to 29-year-olds and over 90% for the 18 to 24-year-old group. For members of the lowest-income households, acceptance drops 55% but only 43% for those from the highest income households. In this scenario the average impact is a 51% reduction in credit access but for members of households in black or Hispanic majority areas the reduction is 64%.

Finally, the above findings do not include the suppression of all accounts, just the open/active ones. For the 24-month suppression period, with suppression extended to all accounts, the credit crunch is even worse. In the 2010 sample, assuming a 4% target delinquency rate, credit acceptance drops 59% overall when we add a 100% increase in delinquencies (moral hazard). As before, lower income households and younger borrowers fare worse still.

What makes this even more troubling is that it is precisely the lowest income households and the young with few assets that most rely on information sharing as a tool to access credit. These borrowers can substitute this information and so-called "reputational collateral" for longstanding relationships with lenders and financial and traditional assets (or co-signers with assets) that they may not have. Damaging information sharing damages an important tool of financial inclusion.

Other Consequences from Wide-scale Data Suppression

If such a wide-scale data suppression as simulated were imposed, score builders and lenders would no doubt try to respond by altering underwriting and reoptimizing models for the new environment. But these efforts would be unlikely to solve the credit access problems. First, a number of studies have shown that re-optimizing credit scoring models cannot solve problems that are caused with the widescale removal of important data. The data matters and changing algorithms can only do so much. Some of the problem may be mitigated as models are re-optimized, but typically not all or even most of it. Second, it would take time to update models. In the mortgage market, models from the 1990s and 2000s are still in use. Lenders typically need to test them and update systems that use them. That takes time. Third, if all lenders suddenly did start to change the way they lend and the models they use in a less then fully tested way, this may add an additional layer of uncertainty. Secondary markets could balk at this. Fourth, it is negative data that is used to build and test models and gauge portfolio performance. If the sharing of such data is suppressed, many in the industry could be flying blind. This would result in obvious safety and soundness concerns.

An important caveat to our findings is that with the sort of massive disruption to credit reporting and credit scoring such wide-scale data suppression would cause, it is difficult to estimate the *exact* credit market impacts of such a policy. Afterall, such suppression would not be a small change on the margins. There would be market and consumer responses and counter responses. Some types of credit would be more impacted than others. Some mitigation would be attempted. But it would be wishful thinking to assume that a mitigation approach would arise to completely counter the consumer harm from the damage inflicted on the credit reporting system. It would be folly to enact a policy that would be expected to result in large-scale harm to consumers directly but then simply hope that some untested, indirect market response would occur to completely offset the harm.

The simulations may also be giving a rosier picture than would be the reality in some cases. For instance, consider younger borrowers and those new to credit that may only have a few years of credit history. If most or all their history has been during the suppression period, lenders may view this as a situation in which they have no solid, reliable insight into their true credit profiles. As a result, credit access may decline more for this group than the simulations suggest or, lenders may rely more on collateral, causing more disparate impacts for low-asset/wealth/collateral households. In addition, as mentioned, different types of loans rely *more* on credit scores and credit bureau data in the underwriting process than others (for instance depending on whether there is collateral). So, the impacts would likely vary by loan type.

There would also be additional and important secondary impacts. Information sharing enlivens competition between lenders. Borrowers can shop around because they can easily demonstrate their risk level via third-party credit information sharing. Disrupting this mechanism would likely dampen these competitive pressures.

Lenders in the best position to handle the suppression of negative data sharing would be the largest lenders. These lenders would have large internal databases of actual borrower performance and sizable analytic departments. Small, community lenders that rely most on third party data and third-party analytics solutions using credit bureau data would likely be most negatively impacted.

The suppression of sharing data would mean that lenders, in general, would be blinded in important ways to new customers and so may respond by “raising the drawbridge” to some extent and focusing on their existing customers on which they have fuller information. This would be most harmful to younger borrowers, new to credit borrowers, and those seeking to build or rebuild their credit. This could have longer-term knock-on effects for this cohort at the beginning of their credit life. This could ultimately delay building assets via homes and small businesses.

There were a number of policy responses to COVID-19 and its economic impact. Among these were monetary policy, including the lowering of the effective federal funds rate and the purchasing of mortgage-backed securities to lower mortgage rates. Borrowers responded to lower mortgage rates with a refi boom, which put more money in their pockets. This channel of monetary policy could have been short-circuited if such credit was restricted or made more expensive due to an upending of credit information sharing. In short, a suppression of derogatory data would be massively disruptive and leave few good workarounds. And worse, it appears that it would harm most those most in need.

Policy Implications

The CARES Act with a much narrower and focused credit reporting response appears to have been largely successful. Those responses combined with separate massive fiscal and monetary responses meant that credit scores rose during the COVID-19 economic crisis. This was not because information was suppressed or papered over but because consumers in need received actual aid in terms of financial aid and deferments of loans or other payment holidays. Credit card debt levels actually declined during this period. Consumers are now in better credit shape. Information sharing and a credit system *not* massively disrupted through large-scale data suppression can now help propel the economic recovery.

We hope that this success would mean that the sort of derogatory data suppression contemplated in the HEROES Act will not be given serious consideration in the future. We know what works well, and it is not that.

On the other hand, the simulations carried out here to examine a massive suppression of derogatory data demonstrate a point that may be counter-intuitive to some. The sharing of derogatory data can benefit consumers and, in particular, younger and lower income consumers. Of course it is not the underlying negative events that are beneficial as for many individuals and families, late payments, collections, bankruptcies, and the like may represent periods of extreme financial stress. But papering over those episodes by suppressing information neither solves the real underlying problems involved nor helps the consumer credit market. Instead, it only makes matters worse. For this reason, policies aimed at limiting the reporting of predictive, derogatory data in general should not be taken at face value as being pro-consumer or pro-poor. This includes policies such as removing derogatory payment data after four years instead of seven. There could be worthwhile reasons for such policies, but the policies must be evaluated objectively to determine costs, benefits, and tradeoffs.

Finally, contrary to suppressing information, efforts to fill credit data gaps would both improve the overall credit reporting system and disproportionately benefit members of lower-income households, the young, and members of ethnic and racial minority groups. For policymakers, the lowest hanging fruit are mobile telecom accounts. While mobile telecom service providers selectively report customers that are very late to the Nationwide CRAs, typically via collection accounts, they do not report those customers who pay on time. They "ding" consumers but do not "reward" them even though they use the Nationwide CRAs. This seems very unfair. While we support full-file credit reporting as it is ultimately best for consumers, a better approach to collections-only reporting is as follows. If a mobile telecom service provider selectively reports collections directly or indirectly, or uses the National CRAs, then, at a minimum, it should also selectively report its on-time customers. On-time plus collections reporting would be much fairer to its customers than just collections reporting, particularly benefiting its lower-income customers.

Appendix: Results with Alternative Definitions of "Bads"

As discussed in the Methodology section, the three definitions of Bad we considered in the analysis are described below.

Bad0	90+ Days Past Due (DPD) on accounts within 24-month observation period
Bad1	90+ DPD, defaults, repossessions, public records (including Bankruptcies) filed within 24-month observation period
Bad2	90+ DPD, defaults, repossessions, public records filed (including Bankruptcies), collection accounts within 24-month observation period

Calculations in the body of the paper use the middle definition (Bad1). The following tables reproduce tables 3.2 and 3.3 using the narrower definition of Bad (Bad0) and a broader version (Bad2). Qualitatively, the results do not change. The rates of nonperformance or levels do change with the narrower and broader definitions, as expected.

Table A1 *Target Acceptance Rates for Different Lengths of Derogatory Credit Suppression (2010 Sample), Bad0 Definition*

Target Delinquency Rate	No Suppression	6 Months Suppression	12 Months Suppression	24 Months Suppression	36 Months Suppression	48 Months Suppression
1%	16%	12%	10%	9%	8%	7%
2%	33%	30%	28%	27%	26%	26%
3%	43%	39%	37%	36%	35%	35%
4%	51%	45%	43%	42%	41%	41%
5%	59%	51%	47%	46%	46%	45%
Acceptance relative to the No Suppression Scenario						
1%	100%	76%	65%	56%	51%	44%
2%	100%	89%	83%	80%	78%	77%
3%	100%	92%	86%	84%	83%	82%
4%	100%	87%	84%	82%	81%	80%
5%	100%	87%	81%	79%	78%	77%

Table A2 *Target Acceptance Rates for Different Lengths of Derogatory Credit Suppression (2010 Sample), Bad2 Definition*

Target Delinquency Rate	No Suppression	6 Months Suppression	12 Months Suppression	24 Months Suppression	36 Months Suppression	48 Months Suppression
1%	0%	0%	0%	0%	0%	0%
2%	18%	14%	13%	11%	10%	9%
3%	30%	26%	25%	23%	23%	22%
4%	37%	34%	32%	31%	30%	29%
5%	42%	39%	38%	36%	35%	35%
Acceptance relative to the No Suppression Scenario						
1%	100%	NA	NA	NA	NA	NA
2%	100%	80%	72%	62%	54%	49%
3%	100%	88%	83%	79%	76%	75%
4%	100%	90%	87%	83%	82%	79%
5%	100%	94%	91%	85%	84%	83%

Table A3 *Target Acceptance Rates for Different Lengths of Derogatory Credit Suppression (2017 Sample), Bad0 Definition*

Target Delinquency Rate	No Suppression	6 Months Suppression	12 Months Suppression	24 Months Suppression	36 Months Suppression	48 Months Suppression
1%	26%	20%	18%	16%	15%	14%
2%	44%	40%	39%	37%	37%	36%
3%	55%	49%	48%	47%	46%	46%
4%	64%	59%	56%	52%	52%	52%
5%	68%	65%	64%	62%	61%	59%
Acceptance relative to the No Suppression Scenario						
1%	100%	77%	70%	63%	56%	53%
2%	100%	91%	88%	85%	83%	81%
3%	100%	88%	86%	84%	83%	82%
4%	100%	93%	88%	82%	81%	81%
5%	100%	95%	93%	91%	89%	87%

Table A4 *Target Acceptance Rates for Different Lengths of Derogatory Credit Suppression (2017 Sample), Bad2 Definition*

Target Delinquency Rate	No Suppression	6 Months Suppression	12 Months Suppression	24 Months Suppression	36 Months Suppression	48 Months Suppression
1%	0%	0%	0%	0%	0%	0%
2%	22%	16%	16%	13%	11%	10%
3%	35%	30%	30%	28%	27%	26%
4%	43%	38%	38%	37%	36%	35%
5%	48%	45%	45%	43%	42%	41%
Acceptance relative to the No Suppression Scenario						
1%	NA	NA	NA	NA	NA	NA
2%	100%	70%	70%	60%	51%	47%
3%	100%	84%	84%	80%	77%	74%
4%	100%	89%	89%	87%	84%	81%
5%	100%	93%	93%	90%	87%	85%