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Abstract: We study the drivers behind the increasing households' credit scores since the onset of the pandemic. We argue that the main driver is falling credit card utilization. This effect is most visible for households with the lowest credit scores; these households saw the highest increases in credit scores and the largest decreases in credit card utilization. We also show that the forbearance programs shielded individual households' credit scores from significant credit score penalties. However, given the relatively low share of the population enrolled in these programs, these programs were not a significant driver of the increasing credit scores. Our findings provide important guidance to policy makers and lenders about the causes of the recent credit score increase and on expectations of how credit scores may change once the extraordinary policy initiatives from the pandemic recede.

Keywords: COVID-19, pandemic, consumer credit, credit score, credit cards, mortgages, auto loans, forbearance.

JEL codes: E21, G21, G51, I18

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1. Introduction

We analyze the changes in households' credit scores during the early months of the COVID-19 pandemic from March to September 2020. We observe that the credit scores of households have increased since the onset of the pandemic in mid-March, with especially large increases in the lower half of the credit score distribution . Given the unprecedented economic strain in the same period, with the unemployment rate hitting a record 14.8% in April 2020, we investigate reasons for this seemingly counterintuitive increase in the credit scores.

We consider the numerous credit file variables that are collected on consumer borrowing and show that this increase in credit scores is mostly due to credit card deleveraging by households across the whole credit score distribution. This deleveraging may be explained by the cushioning nature of government-provided income support, including direct stimulus payments and expanded unemployment benefits, combined with decreased avenues for spending as communities entered various states of lockdowns.

Another unique feature of the COVID-19 pandemic is the broad availability of standardized forbearance programs that the government enacted through the CARES Act, especially for government-backed mortgages and student loans. These programs were intended to mitigate financial distress of households by allowing them to pause loan payments without incurring any negative consequences, including to their credit scores. Thus, we also analyze the extent to which mortgage forbearance programs contributed to the increase in credit scores. We find that while there were significant benefits for individual households who required payment relief, the number of households taking advantage of forbearance programs was still small. Thus, we conclude that the shielding effect of forbearance programs was not a main driver of credit score changes in the aggregate population.

To our best knowledge, this is the first paper to formally investigate the by-now widely observed increases in the households' credit scores since the onset of the pandemic (Goodman et al. (2021) and numerous media reports[2]). Most of these accounts suggest that the increasing credit scores have been a consequence of generous government income support, forbearance programs included in the CARES Act, and muted consumption activity. However, these accounts do not offer systematic empirical evidence for these claims.

Our paper attempts to fill this gap by investigating mechanisms through which these factors could influence the credit scores during the pandemic. Although we cannot pin down the exact causal impact of each of these factors, we point to two direct mechanisms through which they could affect credit scores, and we subsequently quantify their contribution to the observed increase in credit scores. First, we show credit card utilization fell during the early months of the pandemic, especially in Q2 of 2020, and furthermore, households in the lower part of the credit score distribution actually had the largest decreases in credit card utilization. The falling credit

[2] E.g. Andriotis (2020), Bajoria and Reiss (2021), Leonhardt (2020).

card utilization is a consequence of two factors during the pandemic -- falling consumption as discussed in Horvath et al. (2021) and income support as highlighted in Cox et al. (2020). Using regression analysis, we show that the decrease in credit card utilization is a key credit variable to explain changes in credit scores since the onset of the pandemic, able to explain 30-45% of credit score increases, depending on the credit score quartile to which the household belongs.

Second, we document that compared to pre-pandemic times, there is a significant increase in the share of households reported as current despite missing payments, but interestingly, their credit scores evolved in a very similar way as those of households who continued making payments. Then using event studies framework with data from before and during the pandemic, we quantify that forbearance programs in the CARES Act indeed shielded individual non-paying households from penalties to their credit scores. However, the share of households in forbearance programs was too low to contribute to the increasing credit scores in the whole population, leading us to conclude that decreased credit card utilization was a main driver of the observed increase in credit scores.

Our findings have important implications for policy makers and lenders because they document important borrower behavior during an unprecedented crisis paired with aggressive and robust government policy response and quantify the impacts of different sources of credit score increase. Our research shows that the primary driver behind the increasing credit scores was a widespread fall in credit card utilization. This points towards the fiscal support, as well as pandemic-induced drop in consumption that affected all households regardless whether they enrolled in forbearance programs or not. The impact of forbearance programs, according to our findings, is muted because a relatively small share of the population took advantage of such programs. In turn, policy makers and lenders should expect that once the U.S. economy exits the pandemic environment and the impact of the extraordinary fiscal support measures wears off, the upward trends in credit scores across the whole population may reverse. Although the forbearance programs do not seem to be the main driver of the overall increases, we note that these households' credit scores might not reflect their creditworthiness and they should be monitored more carefully by lenders and policy makers.

2. Data

Our data source is the New York Fed Equifax Consumer Credit Panel (CCP), which is an anonymous, representative sample of 5% of all borrowers in the U.S. and their household members.[3] It contains a large set of credit variables such as credit score, balances, payments and delinquency behavior for a comprehensive set of consumer loan categories. From this dataset, we construct a panel of households by matching household members to primary borrowers and aggregating the borrower-level credit variables to household level, using

[3] The 5% sample of primary borrowers are randomly sampled using the last two digits of their SSN. Household members in the CCP are individuals with Equifax credit files living at the same address as the primary borrower.

the detailed methodology in Lee and van der Klaauw (2010). To lower the computational burden, depending on the analysis, we will use either a shorter but wider household panel using a random sample of 30% of the primary borrowers from December 2019 to September 2020 or a longer but thinner 10% random sample from Q3 2018 to September 2020. The CCP data is provided quarterly in the third month of each quarter through the end of 2019 and then monthly from January 2020 onwards.

To aggregate credit variables measured in dollars and delinquency instances to the household level, we sum them up across all household members, taking into account jointly held loans. To get a representative credit score for each household, we use the average of the Equifax risk scores® for the two household members with the highest credit scores.[4] Henceforth, credit scores discussed in this paper will be household-level credit scores.

3. Increasing credit scores during the pandemic

Figure 1 shows the mean credit score across all households between September 2018 and September 2020 and presents our main observation. The mean credit score had been essentially flat around 712 until March 2020, when it started to increase until it reached seven points higher in September 2020.[5]

This increase in the mean credit score since March 2020 is mainly due to rising credit scores in the lower half of the credit score distribution. As we can see in Table 1, the credit score for the 95th percentile barely changed, and the credit scores for the 75th and 50th percentiles increased by only 3 and 5.5 points, respectively, compared with 16 points for the 5th percentile and 9 points for the 25th. Figure 2 presents this point more granularly. It shows a mean credit score change in the second and third quarter of 2020 for twenty equally sized bins of the credit score distribution, defined as of March 2020. Clearly, households with lower credit scores experienced larger credit score increases. Figure 2 also shows that most of the increase in credit scores occurred in the second quarter. The credit scores still grew in the third quarter but roughly at half the pace compared to the second quarter.

To highlight the unprecedented evolution of the credit scores in Q2 and Q3 of 2020, we compare it with the immediate period before the pandemic and the period surrounding the Global Financial Crisis (GFC). Figures 3, 4 and 5 show the evolution of several key percentiles of the credit score distribution in these three periods, with each percentile's levels normalized to 100 at a fixed date for each figure. First, the increasing credit scores after March 2020 in Figure 3 contrast with the lack of any change in credit scores in the immediate period before the pandemic in Figure 4. Second, as we show in Figure 5, after the fall of Lehman Brothers in September

[4] We experimented with different ways of summarizing households' credit scores. All methods yield similar distributions of household-level scores. We decided to use the average of the two highest scores because we assume that these two scores belong to two most senior household members, whose creditworthiness is most likely to determine the household's financial situation.
[5] We focus on the second and third quarter of 2020, because in this period the credit scores increased the most. They have continued to increase in the subsequent quarters of 2020 and 2021 but to a much lower extent.

2008, the credit scores needed three years to achieve the same relative change that occurred within six months since March 2020.

The contrast between Figure 3 and Figures 4 and 5 is striking but suggests a unique interplay between countervailing economic forces affecting households' creditworthiness since the onset of the pandemic. On one hand, the unemployment rate, arguably the most important macro-economic factor influencing households' creditworthiness, reached the highest level since the Great Depression in Q2 2020, and was much higher than its peak during the GFC. On the other hand, the period since March 2020 distinguishes itself from the other two periods by the U.S. government's intervention both in terms of large-scale direct income support for households and novel forbearance policies aiding distressed borrowers and shielding their credit reports from negative consequences of non-payment. In addition, unprecedented wide-spread lockdowns also limited both credit demand and supply contributing to slower expansion of credit and households' leverage. The above observation leads us to ask which factors contributed to this fast and strong credit score increase, especially in the lower part of the distribution.

4. Drivers of the credit score changes

The Equifax Risk Score® upon which our household credit score is computed is a risk model designed to predict the likelihood of a borrower becoming 90 or more days past due within the next twenty-four month period. While the model behind Equifax Risk Score® is proprietary, commercially available credit scores are generally known to be a function of various credit market variables such as payment behavior, length of credit history, number and type of loans, outstanding and original loan balances, and delinquency history (Federal Trade Commission, 2021). Therefore, we begin our analysis of underlying reasons for the increases in credit scores by looking at the changes in these credit variables during the pandemic. We focus on the second quarter of 2020 because the largest changes in credit scores occurred in this quarter. We also stratify our household sample into four quartiles by the credit score as of March 2020 to study differences in credit score evolution across the whole credit score distribution.

Table 2 presents the summary statistics of the quarterly changes in the main credit variables for auto loans, credit cards, consumer finance loans, mortgages, home equity loans and lines of credit.[6] For each loan category we calculate the average change in outstanding balance, balance at origination, delinquency and default rates and in number of outstanding loans. We contrast these changes in the second quarter of 2020 with the same quarter of 2019 to better understand the evolution of these variables during the initial stages of the pandemic.

[6] We do not look at the student loans because the CARES Act suspended payments and interest on all government student loans.

Table 2 reveals two major differences between these quarters. Q2 2020 saw slower growth in credit balances and declining delinquency rates, both of which are likely explanations for the increases in credit scores. First, the outstanding balances and balances at originations for all types of credit, as well as utilization of revolving credit grew more slowly, or even decreased in the case of credit cards, in Q2 2020 compared to Q2 2019. This is to be expected because in Q2 2020 the economy came to a standstill and uncertainty about the economic outlook shot up, resulting in a lower credit demand and possibly lower credit supply as well. Slower credit growth and reduced credit levels, especially lower credit card utilization, tend to positively impact households' credit scores.

Second, despite a huge increase in unemployment, the share of delinquent and defaulted households did not increase. In fact, for auto loans and credit cards, the share of such households in the lowest quartiles of the distribution decreased in Q2 2020 compared to no change in Q2 2019. Lower incidence of delinquencies should also contribute to the increase in average CSs.

Lower share of delinquencies during the pandemic can be attributed not only to the generous fiscal support for households but also to the CARES Act provisions mentioned before. These provisions allowed households that could not make payments to enter forbearance programs and keep their delinquency status as current. Although we cannot observe which households continued to make payments because of the fiscal support they received, we can identify and calculate the share of households who entered forbearance programs and stopped making payments. This will allow us to assess whether reporting these not-paying households as current also contributed to the increases in the credit scores during the pandemic.

Armed with these two stylized facts of slower credit growth and lower delinquency rates during the pandemic, we estimate the contribution of each of these factors to the increase in credit scores we documented. Specifically, we first dig deeper into which of the consumer loan types and how they contributed to the increasing credit scores. Second, we will analyze how access to forbearance, through the CARES Act provisions, contributed to increasing credit scores.

4.1. Impact of falling credit card utilization

We start with the question which category of consumer loans, i.e., credit cards, mortgages, etc., and changes in which credit variable had the largest impact on the credit scores during Q2 2020. We answer this question by regressing the Q2 2020 change in the households' credit score on the Q2 2020 changes in the credit variables reported in Table 2. We run separate regressions for each of the six credit categories for all households and households stratified by credit score quartiles resulting in 30 equations. Within each regression, we interact some variables to capture possible non-linearities in the relationships. We measure importance of a loan category for changes in credit score with the regression's R-squared, because it indicates the share of variation in the credit score change that can be explained by changes in these variables.[7]

In our regressions, the changes in credit card variables have the largest explanatory power with the R-squared varying between 20 and 25% depending on the credit score quartile. In contrast, the changes in the first lien mortgages, auto and consumer finance loans each explain between 2 and 5% of the variation in the credit score changes, and the changes in the home equity category explain less than 1% of the variation. We conclude that the changes in the credit card debt are the main driver of the credit score changes.[8]

Among all variables in our regressions for credit card debt, the change in the credit card utilization has the largest economic impact on the credit score change. The change in the utilization enters our regressions for credit score change with a statistically significant and negative coefficient. The size of this coefficient varies somewhat depending on the credit score quartile and the magnitude of the change in the utilization. A binned scatter plot in Figure 6 summarizes results from our regressions by showing the relationship between the change in utilization and the change in credit score for all households in our sample during the pandemic, after controlling for household's credit score, changes in delinquency history, and changes in number of consumer loans from March to June 2020. It suggests that a 10-percentage point decrease in credit card utilization is associated with a 9-point increase in credit score.

This strong negative correlation between changes in credit card utilization and changes in credit score helps explain why households in the lower half of the credit score distribution saw higher credit score increases in absolute terms. The reason is that these households experienced larger decreases in credit card utilization. This connection between changing credit card utilization rates and credit score during the pandemic across the credit score distribution becomes very clear when we compare Figures 2 and 7. In both figures we bin households into 20-equally-sized bins by credit score and plot their average changes in credit score (Figure 2) and utilization rates (Figure 7) in Q2 2020 and Q3 2020. As we move towards the lower end of the credit score distribution, households experience higher increases in their credit scores (Figure 2) and higher decreases in utilization rates (Figure 7). In relative terms, back-of-the-envelope calculations using the estimated coefficients from our regressions described in the previous paragraph imply that the changes in utilization rates in Q2 2020 can explain around 30% of the change in the credit score for the lowest credit score decile and 40-45% for the rest.[9]

[7] For brevity, these standard regressions are omitted, and summary of the R-squared values are reported below.
[8] We obtain very similar results in terms of the R-squared and coefficient estimates if we replicate these regressions using data from 2019Q2 instead of 2020Q2, i.e., results are robust.
[9] Investigating the relatively lower explanatory power of the credit card utilization for the lowest decile is beyond the scope of this paper. We suspect that our back-of-the-envelope calculation relying on the impact estimated for broader groups of households underestimates the effect of credit card utilization for these households. The reason is that in a more granular analysis for separate deciles the impact of credit card utilization seems to increase as we move towards the lower CS.

Importance of falling credit card utilization to explain credit score increases is also consistent with the slower increase in the credit scores in the third quarter of 2020 in Figure 2. Figure 7 shows that the overall rate of decreases in the credit card utilization slowed in the third quarter across the whole credit score distribution or even reversed for the households with the highest CSs.

Our conclusion that credit card utilization drives the observed increase in credit scores is intuitive. First, at the aggregate level, credit cards are more likely to have an effect on credit score changes because of their ubiquity among borrowers compared to other loan categories. Second, at the borrower-level, changes in credit card usage are the main driver of the *short-term* changes in the credit score. In contrast to the other categories of retail credit, borrowers typically use credit cards for numerous smaller expenses, many of which are discretionary and thus can be more easily adjusted. Third, credit cards also have large variation in the amount of payment that can be accepted without incurring a late status. Thus, over a short period of time such as a quarter, changes in their credit card utilization are good indicator of changes in borrowers' leverage and propensity to pay their debt, driving the short-term changes in the borrowers' credit score. Finally, our finding is consistent with credit bureaus' claim that the credit card utilization is the main driver of the credit score in addition to delinquency history.[10]

Our finding that falling credit card utilization is a main driver of increasing credit scores naturally gives rise to the question: what led to the falling utilization, especially for the households with low credit scores? Although the CCP does not provide granular data on consumers' credit card behavior, circumstantial evidence allows us to draw some conclusions about the aggregate changes in components of credit card utilization. Utilization in a given month is a ratio of outstanding balance to credit card limit, where outstanding balance is a sum of the unpaid balance from previous month and this month's spending net of payments. Our own summary statistics in Table 2 and aggregate trends reported in Equifax (2021) suggest that falling utilization was due to falling outstanding balances for all credit score quartiles, because limits either stayed roughly constant for lower credit scores or fell slightly for the higher. Then, the remaining question is what contributed to the falling outstanding balances? Was it increased payments, potentially linked to fiscal support, or decreased spending, which could have been caused by lock downs and belt-tightening due to increased unemployment?

Evidence from Opportunity Insights data (Chetty et al. (2020)) shows that spending trends differed between low- and high-income households during the pandemic. Because income and credit scores have a strong positive correlation, this can help us make inferences about aggregate spending and payment behavior of households with different credit scores. At the beginning of the pandemic, spending dropped precipitously for all income groups and was lower by 29% and 36% with respect to the January 2020 spending for low- and high-income groups, respectively. However, spending for the low-income group fully recovered to January 2020

[10] See here: https://www.myfico.com/credit-education/whats-in-your-credit-score.

levels by the end of Q2, and remained at that stable level through Q3. For the high-income group, spending was still 12.5% below January 2020 levels at the end of Q2 and 7% below at the end of Q3. Because spending by the low-income households rebounded fairly quickly to its pre-pandemic level and their credit card utilization still fell, it suggests that fiscal support might have enabled this group to increase their payments during the pandemic above their payments from before the pandemic. For the high-income people, the findings from Opportunity Insights data are intuitive, as the lockdown played a more important role in limiting their avenues for spending as they had a higher share of discretionary spending, for example, entertainment and shopping for non-essentials. Hence, for this group it is less clear whether their payment behavior changed significantly during the pandemic.

4.2. Changes in credit score for households in forbearance programs

In this section, we investigate how the CARES Act protections for forborne and non-paying households impacted credit scores. We check the extent to which provisions contributed to the rise in credit scores in the aggregate population, and also how individual households benefited. First, we determine the share of households in mortgage and auto loan forbearance programs who stopped repaying and compare the trends in their credit scores to those of paying households using event study methodology. Finally, we shed more light on these relative trends in credit scores by estimating the benefits from the CARES Act provisions using, as a counterfactual, households who stopped repaying in the same period of 2019.

To isolate the relevant groups of households, we impose the following filters on our data. First, we focus only on two main categories of credit for which enrollment in forbearance programs was meaningful: mortgages and auto loans. Second, we focus on households who are reported as current and have exactly one mortgage (or a constant number of auto loans) throughout December 2019 to September 2020. Third, from that group of households, we identify two subgroups – one is comprised of households whose outstanding loan balances in mortgages (or auto loans) have not decreased in the last three months. We label this group "enrolled in forbearance and not paying" since their delinquency status remains current despite lack of repayment activity. The second subgroup consists of all other current households.[11]

[11] Several observations are in order. First, using this method, we do not make any distinction between partial or full payments. Second, we choose the period of three months for the following reasons. Using only one month would be the least conservative option and would lead to a volatile group of non-paying households because we would capture those who might have forgotten to pay on time. Choosing two months does not significantly affect our results because the share of the current but not paying households is very similar to the one when we use three months. Moreover, choosing three months allows us to compare numbers of non-paying households with those from 2019 more accurately, because the frequency of our data before January 2020 is quarterly. Third, we rely on our own definition of forborne households, because while the CCP does have some direct reporting of enrollment in forbearance programs through its narrative code variables, the reporting is incomplete as narrative codes are optional and limited to two codes per loan.

Figure 8 presents the evolution of the share of the not paying but current households among all households with one mortgage or auto loans since May 2020.[12] First, the share of such households is higher for mortgages, and much smaller for auto loans. In September, the share of non-paying but current households with a mortgage stood at around 5.2% of all households with one mortgage, compared with 1.1% of such households for auto loans. Second, although these shares peaked in July for both loan categories, for auto loans they gradually fell, whereas for mortgages they did not. Third, the shares of these households are higher in the lower credit score quartiles. For example, for mortgages, the share of such households in the lowest credit score quartile reached approximately 10%. Fourth, there is significant entry into and exit from the "enrolled in forbearance and not paying" status month-over-month, as shown by the different colored stacked bars.[13]

To get the clearest picture of whether we can observe credit score protection thanks to the CARES Act, in our following analysis, we zoom in on the groups of households for which we can obtain the strongest and most precise estimate of the impact of the CARES Act provisions. First, we focus only on the households with mortgages because the share of forborne and not-paying households for auto loans has been considerably lower. Second, within the group of households with mortgages, we focus on forbearance-enrolled households who stopped repaying in March and were still not paying by September – these are the households who are represented in the blue bar in September in Figure 8.

In Figure 9 we compare the evolution of average credit scores of the group of "in forbearance and not paying" households before and during the pandemic to the evolution of average credit scores of the current households who have continued to pay their mortgages throughout the duration of our sample. Comparing these two groups allows for a sharp estimate of divergence in relative credit score trends because we compare groups with the same credit report status but on two extremes of payment behavior during the pandemic. Moreover, to further increase the comparability between these two groups, in both groups we included only the households who were current and paying their mortgages until March 2020 and excluded those who were flagged as delinquent after March 2020. For all four credit score quartiles, after a parallel evolution before the pandemic, the average credit scores of the two groups showed a minor degree of divergence. The key observation is that the divergence seems quite small, especially considering that the not-paying cohort suspended payments for seven consecutive months from March through September.

[12] These shares are zero prior to May 2020 because we focus on households who made payments pre-pandemic, and we use 3-month difference in balances to define the non-paying households. Please note that households labelled as such in May stopped repaying at least in March 2020.

[13] For more detail on the forbearance programs and their evolution through the pandemic see Haughwout et al (2020) and (2021).

Figure 10 provides a clearer picture of the size of this divergence by replotting Figure 9 in a difference-in-differences fashion. More specifically, this figure plots the estimated coefficients $\widehat{\beta_t}$ and confidence intervals around them from the following regression

$$CS_{ht} = FE_h + FE_t + \sum_{t=-3,t\neq 0}^{6} \beta_t D_{ht} + \epsilon_{ht}.$$

In this regression, CS_{ht} denotes the household *h*'s credit score in month *t*, FE_h is a household fixed effect, FE_t is a month fixed effect, D_{ht} are time dummies capturing relative differences in the credit score trends over time for the group of households who are current but not paying during the pandemic with respect to the group that is paying throughout the whole duration of the sample. Time *t* denotes calendar months from December 2019 (*t* = *-3*) to September 2020 (*t* = *6*) with March 2020 as a reference month (*t* = *0*).

Figure 10 shows that the largest divergence between the groups is for the lowest credit score quartile and is still relatively small. On average the cumulative change in credit score for the not-paying group was only 4.8 points lower than for the paying group in September. For the highest credit score quartile, the cumulative credit score change for the not-paying group was only 1.5 points lower. The lack of sizeable divergence in the scores of these two groups suggests that the CARES Act provisions could be an important factor shielding the "not repaying" households from significant credit score penalties.

To estimate the shielding effect of the CARES Act provisions, we compare the impact of missing mortgage payments on a household's credit score before the COVID-19 pandemic to the impact of missing mortgage payments under forbearance during the pandemic. To do so, we regress the households' credit score on indicators for missing initial and following quarters of mortgage payments, controlling for household and time fixed effects as well as for changes in credit card utilization, which we found to be an important short-term predictor of credit scores. This leads to the following regression equation:

$$CS_{ht} = FE_h + FE_t + \beta_1 1\{misspay\ 1st\ qtr\ since\ Q1\}_{h,t} + \beta_2 1\{misspay\ 2nd\ qtr\ since\ Q2\}_{h,t} + \gamma \Delta util_{ht} + \epsilon_{ht}$$

We run these regressions separately on quarterly data from Q1-Q3 of 2019 and Q1-Q3 2020. For each year, we focus on households who were current and making mortgage payments in Q1 but did not pay at least for one quarter in Q2 and Q3. We define a missing payment during a quarter the same as before, i.e., the mortgage balance did not decrease from the previous quarter. Moreover, in the 2020 sample, we focus on households whose delinquency status remains "current" through Q3 as we wish to study the credit score penalty for non-paying borrowers enrolled in forbearance. Finally, we run these regressions separately for two samples of households. The larger sample, displayed in columns 1 and 3 in Table 3, includes households who were current on mortgage loans as of Q1, but may have had delinquencies on other non-mortgage loans in Q1. The smaller sample, which is displayed in columns 2 and 4 in Table 3 includes households who were current on all loans in Q1, including non-mortgage loans. We separate these two types of households to control for a potential lower credit score impact of the additional missed payments on mortgages once the households are already delinquent on other loans.

As Table 3 shows, the penalties for missing payments in 2019 are substantially higher than for the households enrolled in forbearance in 2020. In 2019, for households with no delinquencies in non-mortgage loans, the credit score penalty for missing an initial quarter of mortgage payments is 13.7 points. For households with other delinquencies, the credit score penalty is estimated to be a little lower at 11.4 points consistent with our expectations. Interestingly, we find that there is essentially no additional penalty for missing a second quarter of mortgage payments, as the point estimates of credit score change for both groups in 2019 are around +3 points, though insignificant for the group with no other delinquencies.[14] These credit score penalties starkly contrast with those in 2020, when the penalties for missing the first quarter of mortgage payments is only 1.2 points for households with other delinquencies and 0.9 points for households without other delinquencies. In both 2019 and 2020, we found that a 10-percentage point increase in credit card utilization is associated with a credit score decrease between 3.3 to 3.4 points on average. Although this estimate is lower than the one presented in Figure 7, these estimates cannot be readily compared to each other because they come from regressions run on a different sample of households.

Although the 2019 results are an imperfect counterfactual, our results in Table 3 provide additional evidence for a significant beneficial reprieve granted by the CARES Act to the forborne and not paying households. Its provisions prevented an approximately 10-13-point drop in credit scores for forbearance enrollees who stopped paying their mortgage.

Although the CARES Act benefits are substantial for individual households, we conclude that they could not be a significant contributor to the increasing credit score trend in our full household sample as identified in Figure 1 and Table 1. The reason is that households that are in mortgage forbearance and not paying make up less than 2% of all households in our sample. Had these non-paying households' credit scores not been shielded so that they had incurred the 13-point penalty identified above, the increase in the mean credit score between March and June 2020 would still be 4.14 points (4.14=4.4-13*0.02), instead of the observed 4.4 points.

5. Conclusion

[14] Slightly lower credit score penalty for missing payments for two quarters reflects the fact that such households have been delinquent for close to 180 days and they might have started to repair their finances.

Households' average credit score increased substantially in the first two quarters since the onset of the pandemic. This increase was due to significant improvements in the credit scores of the households in the lower half of the credit score distribution. We provide evidence that the substantial decreases in credit card utilization were a significant driver of the increasing credit scores.

We also showed that the CARES Act provisions requiring the lenders to report as current households missing payments under the forbearance programs provided a significant shield to the households' credit scores. Nevertheless, given the low share of such households in the overall sample, these provisions were not an important driver of the overall credit score increase. At the same time, it has to be noted that, from a risk management perspective, the lack of penalty for missed payments lowers the informativeness of credit scores as a measure of creditworthiness for individual households. This requires closer monitoring of such households in the near term for burgeoning risks.

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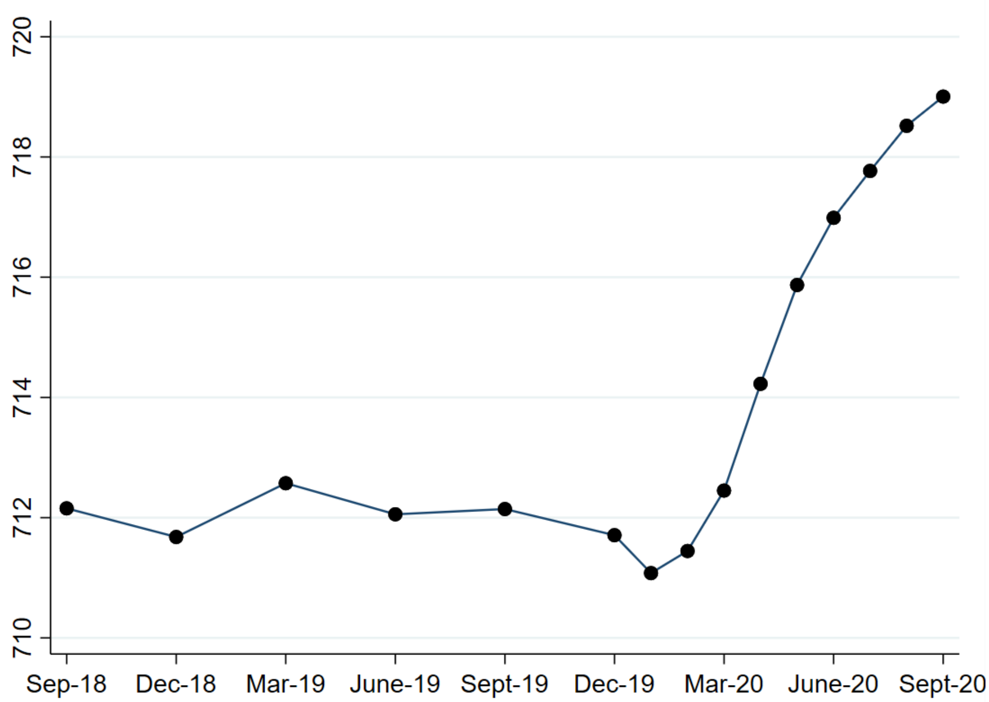
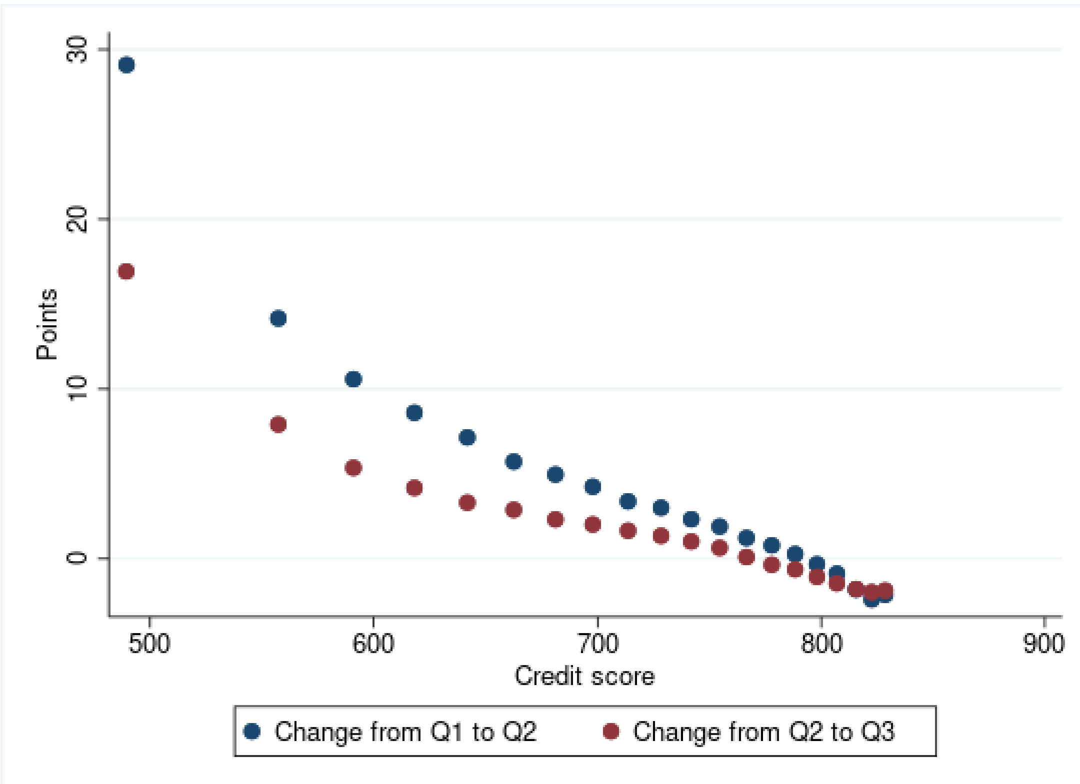
Figures

Figure 1. Average credit score of households, September 2018 - September 2020



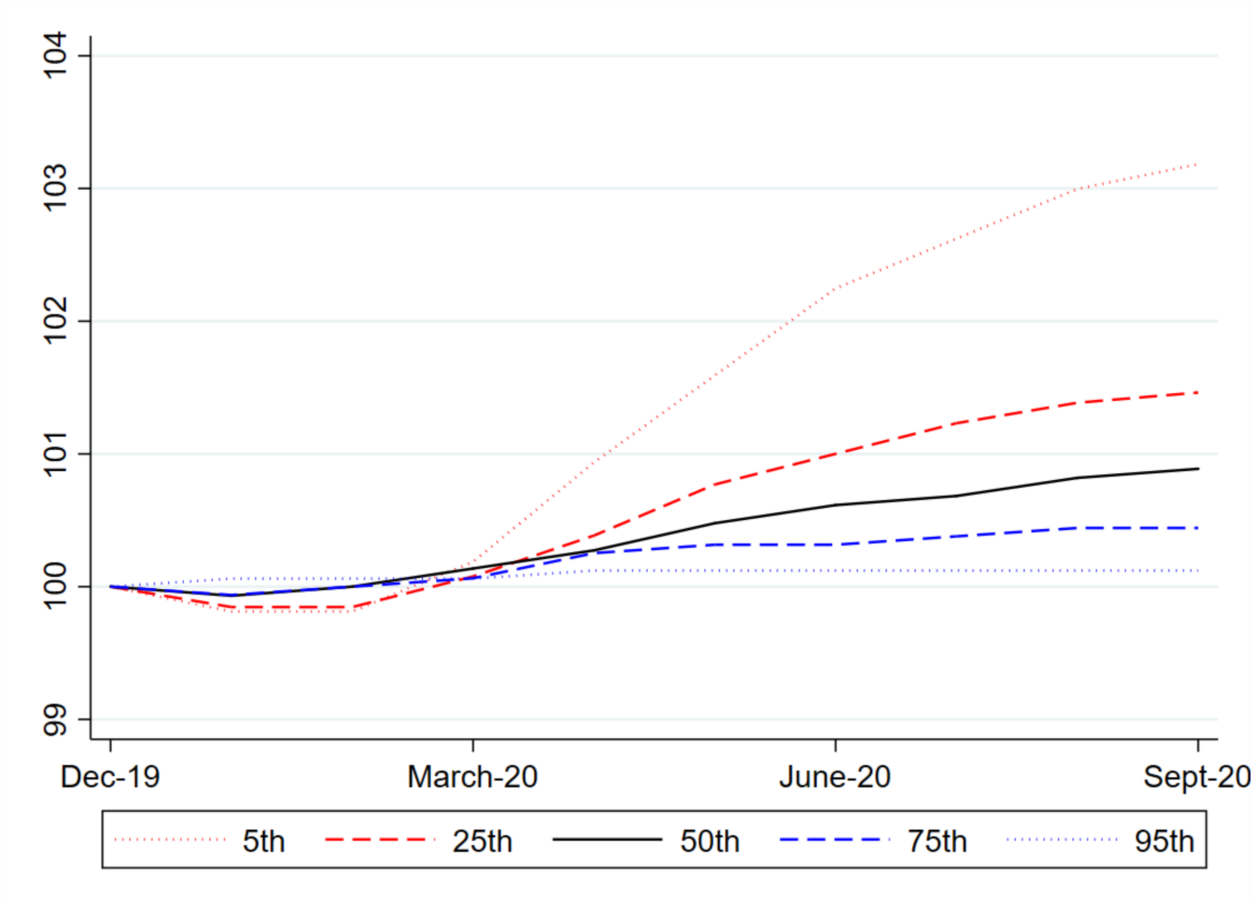
Note: This figure shows the average credit score of households from September 2018 to September 2020. The sample consists of households belonging to a random 10% of Consumer Credit Panel primary borrowers.

Figure 2. Quarter-over-quarter change in credit scores in 2020, by credit score percentiles.



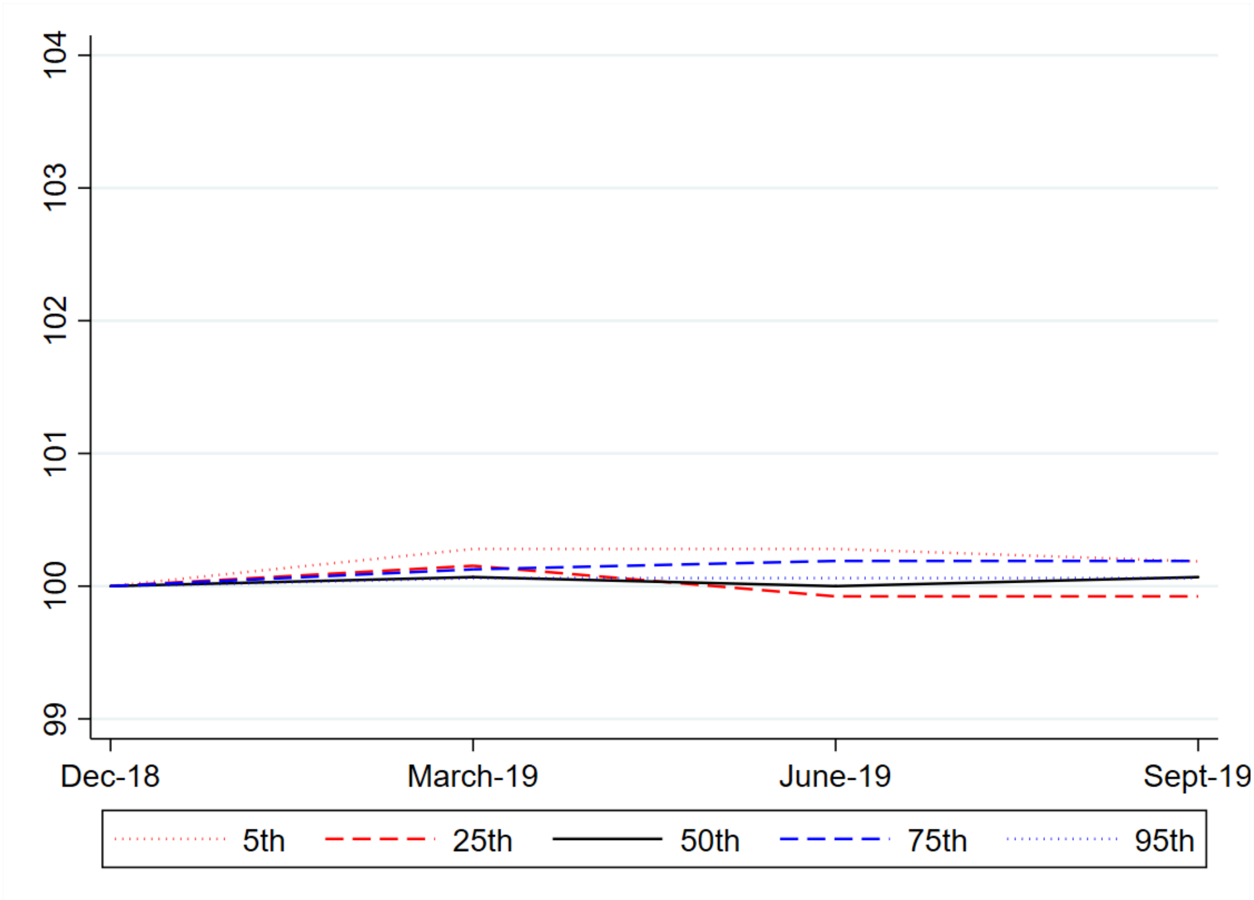
Notes: This figure plots the quarterly change in household credit scores, by credit score quintiles defined as of March 2020. The blue dots represent change in credit score that occurred from end of Q1:2020 to end of Q2:2020, and the red dots represent the change in credit score from end of Q2:2020 to end of Q3:2020. The sample consists of households belonging to a random 30% of Consumer Credit Panel primary borrowers.

Figure 3. Credit scores by percentile during pandemic, index December 2019 = 100



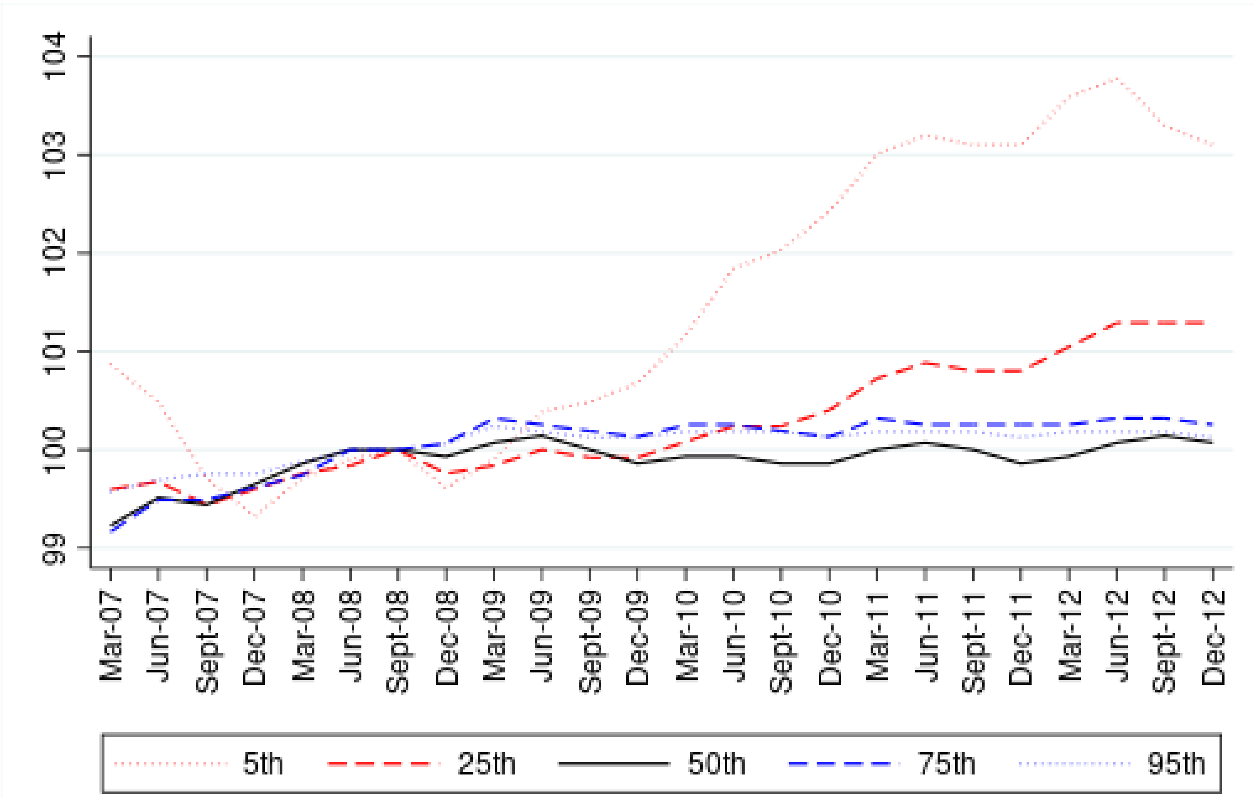
Note: This figure displays the trends in household credit scores for the 5th, 25th, 50th, 75th, and 95th percentiles of household credit scores from December 2019 to September 2020. Each percentile of credit scores is normalized, with index = 100 for December 2019. In December 2019, the credit scores for the percentiles were as follows: 5th – 534, 25th – 650, 50th – 732, 75th – 792, 9th – 824. The sample consists of households belonging to a random 10% of Consumer Credit Panel primary borrowers.

Figure 4. Credit scores by percentile pre-pandemic, index December 2018 = 100



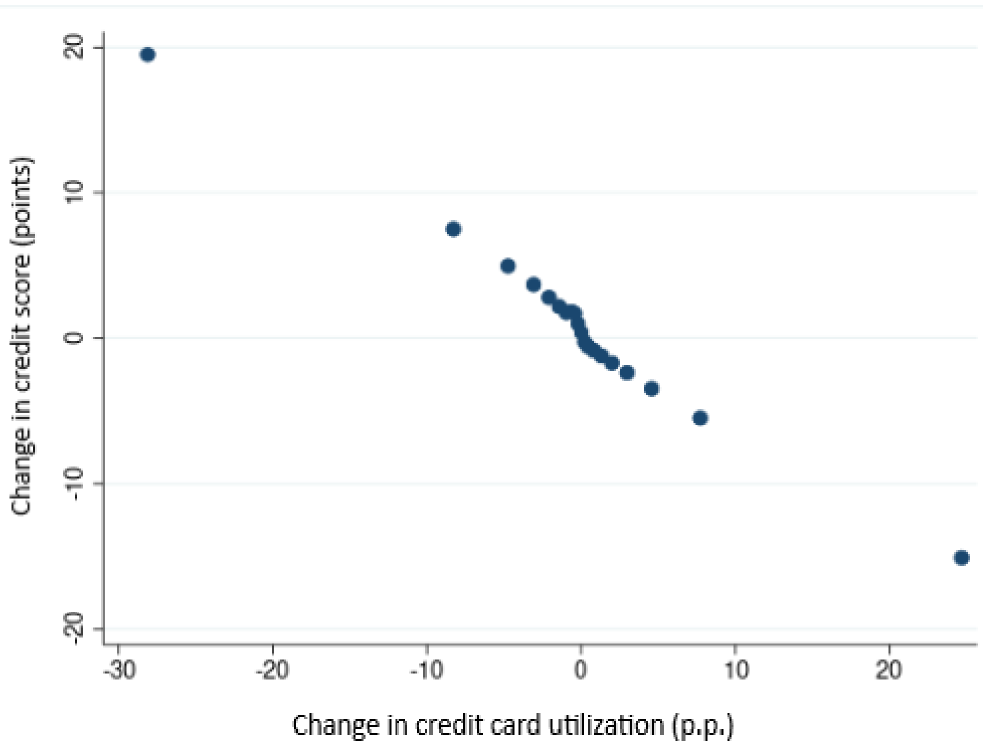
Note: This figure displays the trends in household credit scores for the 5th, 25th, 50th, 75th, and 95th percentiles of household credit scores from December 2018 to September 2019. Each percentile of credit scores is normalized, with index = 100 for December 2018. In December 2018, the credit scores for the percentiles were as follows: 5th – 535, 25th – 650, 50th – 732, 75th – 790, 95th – 824. The sample consists of households belonging to a random 10% of Consumer Credit Panel primary borrowers.

Figure 5. Credit Scores by percentile during GFC, index September 2008 = 100



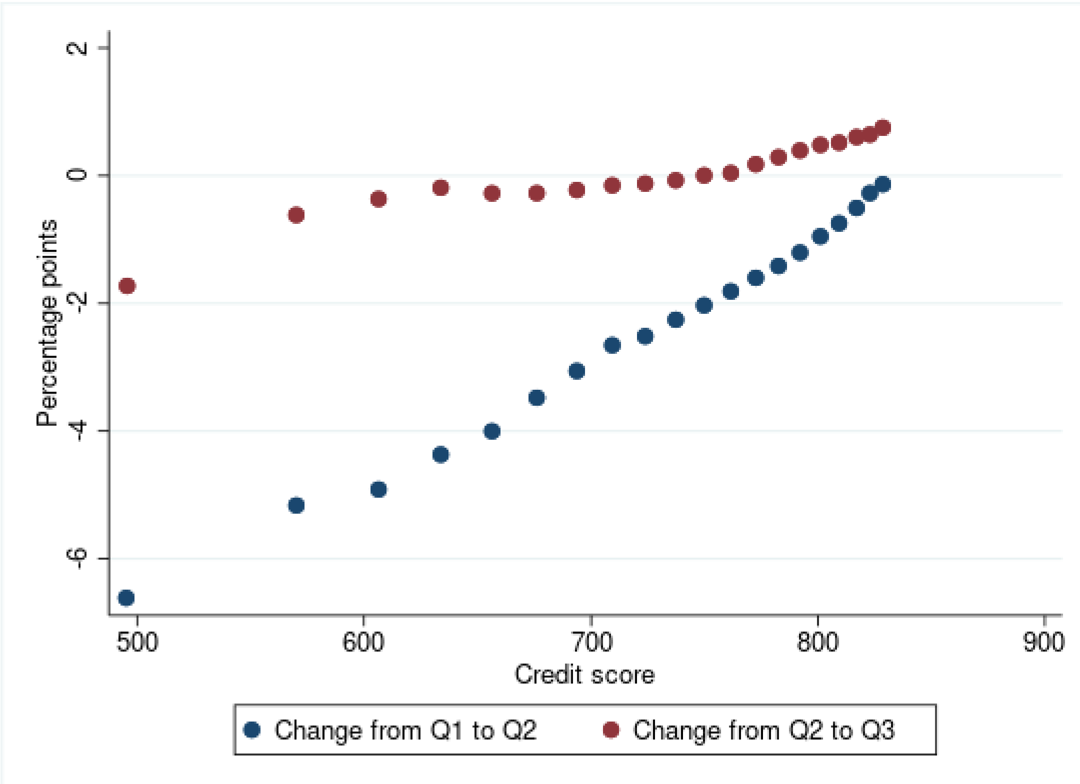
Note: This figure displays the trends in household credit scores for the 5th, 25th, 50th, 75th, and 95th percentiles of household credit scores. Each percentile of credit scores is normalized, with index = 100 for October 2008. In September 2008, the credit scores for the percentiles were as follows: 5th – 516, 25th – 621, 50th – 713, 75th – 780, 95th – 819. The sample consists of households belonging to a random 10% of Consumer Credit Panel primary borrowers.

Figure 6. Binscatter plot of change in credit score vs change in the credit card utilization, March – June 2020.



Note: This figure is a binned scatter plot (with twenty bins) of the change in credit score from March to June 2020 versus the change in credit card utilization over the same period, after controlling for household's credit score, changes in delinquency history, and change in number of consumer loans. The sample consists of households belonging to a random 30% of Consumer Credit Panel primary borrowers.

Figure 7. QoQ change in credit card utilization in 2020, by credit score quintile

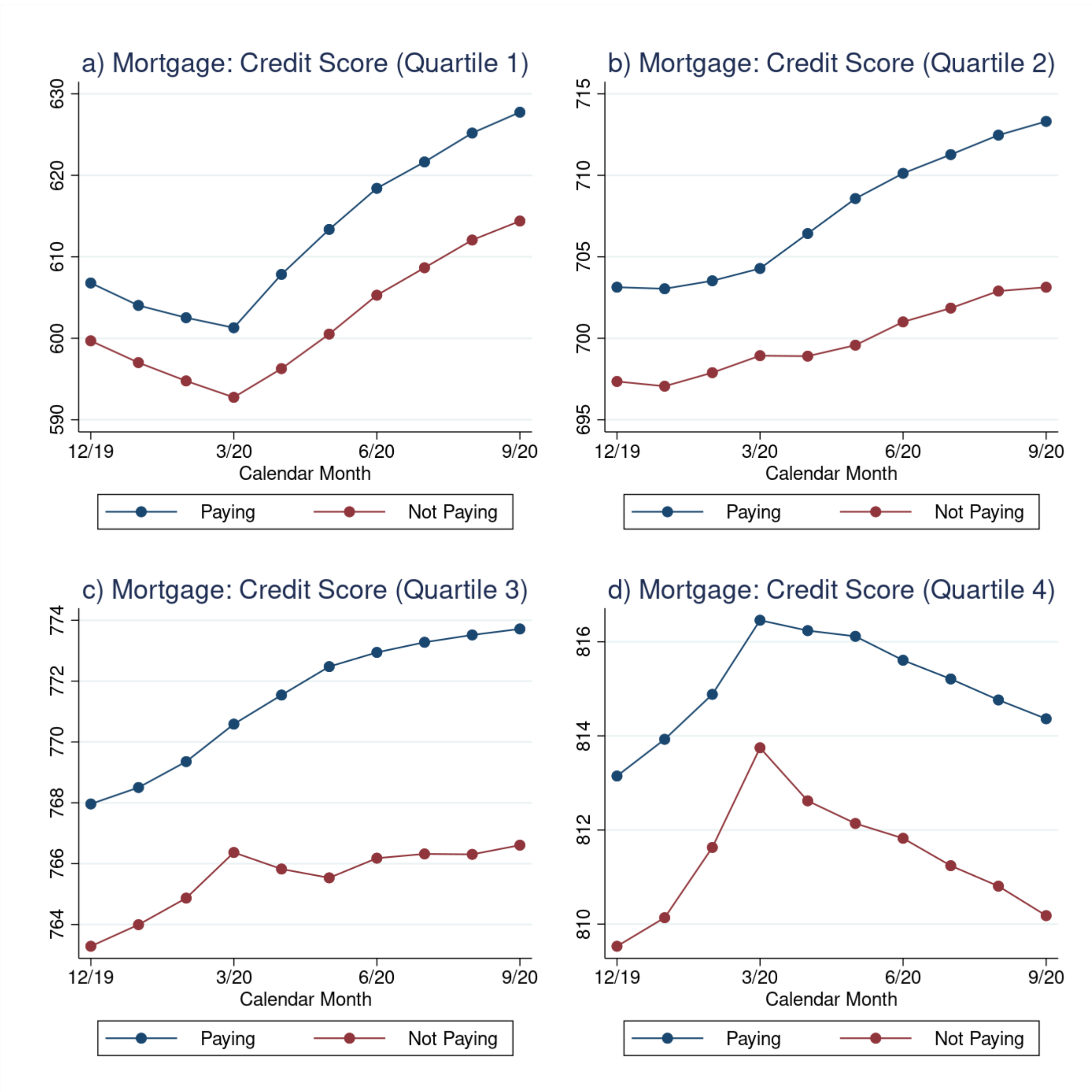


Note: This figure displays the change in household credit card utilization from March 2020 to June 2020 (blue dots), and from June 2020 to September 2020 (red dots) for quintiles of our sample, where the quintiles are defined using the credit score in March of 2020. The sample consists of households belonging to a random 30% of Consumer Credit Panel primary borrowers.

Figure 8. Share of non-paying but current households by loan type

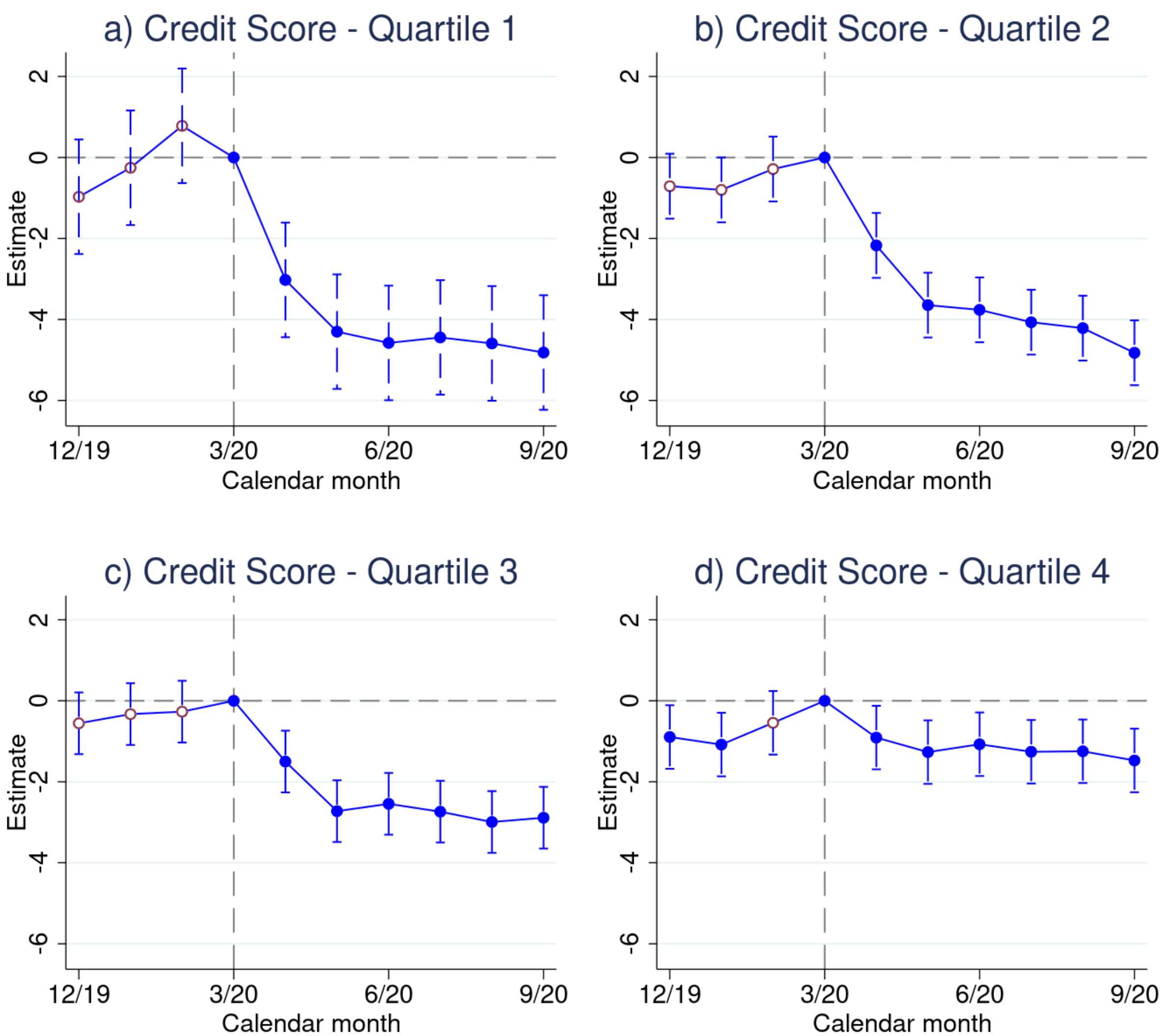
Note: The top panel of this figure shows the share of households with auto loans (restricted to households with a constant number of auto loans over the sample period) who are not paying their auto loans but still in "current" status, by credit score quartile, for each month between May-September 2020. Each monthly bar is further split to show the first month in which households entered the "not-paying and current" status. The bottom panel of the figure shows the share of households with one mortgage who are not paying their mortgages but still in "current" status, also by credit score quartile. To compute these shares, we restrict the sample to households who have an auto loan (or mortgage loan) between December 2019 and September 2020, then a household is determined to be "not paying" if their outstanding loan balance has not decreased in the last three months. The credit score quartiles are determined using the credit score distribution as of March 2020.

Figure 9 – Credit scores of paying and not paying households by credit score quartile for mortgage borrowers



Note: In this figure, we plot the average credit scores over time of the group of "in forbearance and not paying" households (red line) and the average credit scores of the current households who have continued to pay their mortgages and stay current throughout our sample period (blue line), by credit score quartile. Households in both groups are required to have a current mortgage as of March 2020, and the group of "in forbearance and not paying" in this figure are households who stopped repaying in March 2020 and were still not paying by September. The credit score quartiles are determined by the credit score distribution as of March 2020.

Figure 10. Differences-in-differences estimates for credit scores of paying (control) and not paying (treatment) households by credit score quartile for mortgage borrowers



Note: This figure plots the estimated coefficients $\hat{\beta}_t$ and confidence intervals from the following regression, $CS_{ht} = FE_h + FE_t + \sum_{t=-3,t\neq 0}^{6} \beta_t D_{ht} + \epsilon_{ht}$, where CS_{ht} denotes the household's h credit score in month t, FE_h is a household fixed effect, FE_t is a month fixed effect, D_{ht} are time dummies capturing differences in the credit score evolution over time for the group of the households who are current but not paying during the pandemic with respect to the group that is paying throughout the whole duration of the sample. Time *t* denotes calendar months from December 2019 (*t* = -3) to September 2020 (*t* = 6) with March 2020 as a reference month (*t* = 0). Solid dots (opposed to open dots) denote that the estimated coefficient is statistically different from zero, with 95% confidence. The credit score quartiles are determined by the credit score distribution as of March 2020.

Tables

Table 1. Household credit scores, by month

Month	Mean	Percentile				
		5th	25th	Median	75th	95th
Sep-18	712.2	536.5	651	731.5	790.5	824
Dec-18	711.7	535	650.5	731.5	790	824
Mar-19	712.6	536.5	651.5	732	791	824.5
Jun-19	712.1	536.5	650	731.5	791.5	824.5
Sep-19	712.1	536	650	732	791.5	824.5
Dec-19	711.7	534	649.5	732	791.5	824
Jan-20	711.1	533	648.5	731.5	791	824.5
Feb-20	711.4	533	648.5	732	791.5	824.5
Mar-20	712.5	535	650	733	792	824.5
Apr-20	714.2	539	652	734	793.5	825
May-20	715.9	542.5	654.5	735.5	794	825
Jun-20	717.0	546	656	736.5	794	825
Jul-20	717.8	548	657.5	737	794.5	825
Aug-20	718.5	550	658.5	738	795	825
Sep-20	719.0	551	659	738.5	795	825

Note: This table displays summary statistics of household credit scores for households constructed from a 10% random sample of CCP primary borrowers.

Table 2. Quarter-over-Quarter changes of credit variables in 2019 versus 2020

		1st quartile		2nd quartile		3rd quartile		4th quartile	
Loan type	Average change in:	2019Q2	2020Q2	2019Q2	2020Q2	2019Q2	2020Q2	2019Q2	2020Q2
	Credit score	7.03	14.59	-1.95	3.64	-2.83	0.88	-3.32	-1.70
All	Total loan balance	3535	1411	4537.36	940.19	1691.38	-1249.31	-2863.92	-6659.48
	Total balance at origination	5216	2430	6846.78	2165.50	2926.14	-1342.97	-4160.78	-9783.75
	Share of delinquent loans	-0.01	-0.03	0.00	-0.01	0.00	0.00	0.00	0.00
	Share of loans in default	-0.01	-0.03	0.00	-0.01	0.00	0.00	0.00	0.00
	Number of loans	0.21	-0.02	0.09	-0.25	-0.13	-0.43	-0.24	-0.48
Auto	Total loan balance	492	-397	221.43	-624.81	-58.64	-586.78	-74.02	-511.63
	Total balance at origination	716	-605	373.04	-919.46	-72.74	-822.74	-180.54	-700.50
	Share of delinquent loans	0.00	-0.02	0.00	-0.01	0.00	0.00	0.00	0.00
	Share of loans in default	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00
	Number of loans	0.03	-0.04	0.01	-0.06	-0.01	-0.05	-0.01	-0.04
Cards	Total loan balance	49	-425	44.33	-1029.02	68.14	-1297.63	643.54	-833.12
	Total credit limit	875	374	1231.09	-52.64	419.71	-1182.89	-804.35	-2388.10
	Share of delinquent loans	-0.01	-0.02	0.00	-0.01	0.00	0.00	0.00	0.00
	Share of loans in default	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00
	Number of loans	0.16	0.00	0.09	-0.14	-0.07	-0.29	-0.16	-0.34
	Utilization	-0.01	-0.05	0.00	-0.03	0.01	-0.02	0.01	0.00
Consumer finance	Total loan balance	36	36	53.20	-36.57	26.76	-32.80	19.97	-14.96
	Total balance at origination	113	136	161.68	46.68	85.56	-49.87	40.56	-66.93
	Share of delinquent loans	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Share of loans in default	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
	Number of loans	0.02	0.02	0.02	0.00	0.01	-0.01	0.01	-0.01
First lien	Total loan balance	2802	2006	4257.17	2816.59	2090.35	1329.19	-3299.79	-4912.16
	Total balance at origination	3218	2218	4951.92	3016.95	2776.85	1094.11	-2801.56	-5897.98
	Share of delinquent loans	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00
	Share of loans in default	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Number of loans	0.02	0.01	0.02	0.01	0.00	0.00	-0.02	-0.02
HE loans	Total loan balance	24	-8	14	-26.74	10.77	-53.91	3.28	-75.23
	Total balance at origination	28	-2	17	-14.56	17.89	-56.54	11.81	-86.02
	Share of delinquent loans	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Share of loans in default	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Number of loans	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
HELOCs	Total loan balance	51	19	44.67	-21.26	-189.15	-293.76	-44.37	-214.10
	Total credit limit	116	61	221.14	118.75	13.20	-71.70	-226.82	-525.24

Share of delinquent loans	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Share of loans in default	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Number of loans	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01
Utilization	0.00	0.07	0.02	0.00	0.00	-0.02	-0.01	-0.01

Note: This table displays summary statistics of the changes of credit variables from Q1 to Q2 of 2019 or 2020 for households constructed from a 10% random sample of CCP primary borrowers. Households are divided into quartiles by their credit score as of March of 2019 for the summary statistics from 2019Q2, and by credit score as of March 2020 for the summary statistics for 2020Q2.

Table 3. Effect of missing mortgage payments on credit score, 2019 vs 2020

	(1)	(2)	(3)	(4)
VARIABLES	2019 Incl. borrowers with other Q1 delinquencies	2019 No other Q1 delinquencies	2020 Incl. borrowers with other Q1 delinquencies	2020 No other Q1 delinquencies
Change in utilization	-31.350***	-33.551***	-35.762***	-32.867***
	(4.440)	(9.710)	(1.013)	(0.873)
First qtr missed payment	-11.375***	-13.668***	-1.238***	-0.938***
	(1.063)	(1.894)	(0.120)	(0.106)
Second qtr missed payment	3.564*	3.015	1.104***	1.184***
	(1.975)	(3.827)	(0.331)	(0.299)
Constant	612.376***	658.295***	740.266***	763.677***
	(0.717)	(1.242)	(0.074)	(0.064)
Observations	4,696	1,108	81,380	59,690
R-squared	0.945	0.941	0.977	0.975

Notes: This regression summary table shows the results from regressing households' credit score on an indicator for missing an initial quarter of mortgage payments and an indicator for missing a second quarter of payments, controlling for household and time fixed effects as well as for changes in credit card utilization, which we found to be an important short-term predictor of credit scores.

$$CS_{ht} = FE_h + FE_t + \beta_1 1\{misspay\ 1st\ qtr\ since\ Q1\}_{h,t} + \beta_2 1\{misspay\ 2nd\ qtr\ since\ Q2\}_{h,t} + \gamma \Delta util_{ht} + \epsilon_{ht}$$

For columns 1 and 2, the regression was run on quarterly data from Q1-Q3 of 2019. For columns 3 and 4, the regression was run on quarterly data from Q1-Q3 of 2020. For all regressions, the samples were constructed by first selecting households who had mortgages and were current on their mortgages in Q1 of the year. In the 2020 regressions, we further restricted the sample to households whose delinquency status remains "current" through Q3 to focus on non-paying borrowers enrolled in forbearance. Finally, columns 2 and 4 summarize regressions in which we further restrict the sample by removing households who had any other non-mortgage delinquencies during the sample period.