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Economic Security of Older Adults during the COVID-19 Crisis: Early Data to Inform Research and Policy

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Abstract

This study documents the credit outcomes of older adults immediately before and after the onset of the COVID-19 pandemic in the US. Using credit data to track indicators of financial distress, this study shows that on average, older adults experienced larger reductions in total household debt in the period after the start of the COVID-19 pandemic, relative to adults age 18 to 49. However, there is significant heterogeneity within the population of older adults, where those with higher incomes, with mortgage debt, and with higher credit scores experienced the largest declines. Lower-income older adults experienced an increase in total debt during this period. We also find that older adults are significantly less likely to be approved for new credit in 2020, with the oldest adults (72 and older) experiencing the largest decline in approval rates among those seeking credit. Our results indicate that a large share of older adults benefited from loan payment accommodations during the COVID-19 pandemic. These borrowers tend to be more vulnerable based on debt and credit characteristics, and suggest caution about how well they will manage debt payments when accommodations expire. Finally, we find small but persistent evidence that people in states harder hit by COVID-19 are also among those most likely to rely on accommodations. Overall, these data suggest significant heterogeneity in the credit experiences of older adults during the COVID-19 pandemic that may affect future household financial security.

Keywords: Consumer Debt, Personal Finances, Retirement, COVID-19

JEL Classification: D12, D14, D15

1 Introduction

Over the past two decades, the proportion of older adults carrying debt into retirement and the levels of debt held by older adults increased substantially (Brown et al., 2020; Collins et al., 2020; Lusardi et al., 2020a; Moulton et al., 2019). This is not necessarily cause for concern, as debt in and of itself is not good or bad. However, recent studies indicate significant heterogeneity in the types and amounts of debt held by older adults, with financially vulnerable older adults holding higher-cost forms of debt and being more likely to experience debt-related financial distress than older adults with higher levels of income and wealth (Butrica and Karamcheva, 2020; Brown et al., 2020; Loibl et al., 2020). These disparities in the debt experiences of older adults are likely to be exacerbated by the COVID-19 pandemic.

There are multiple paths through which the COVID-19 pandemic may affect the economic security of older adults. Disruptions to the economy and risk of disease spread led many older adults who were working prior to the pandemic to exit the labor market (Cheng et al., 2020; Goda et al., 2021; Moen et al., 2020; Quinby et al., 2021), thereby reducing income through wage earnings. Emerging research indicates that as of early 2021, this reduction in labor force participation has not been offset by a subsequent increase in Social Security retirement claiming in the short-term (Goda et al., 2021; Quinby et al., 2021), however the longer-term effects are still unknown. Aside from labor market effects, the economic security of older adults is also a function of their interaction with credit markets, including the use of consumer debt to finance consumption. In this paper, we investigate the effects of the COVID-19 pandemic on the debt levels and credit outcomes of older adults.

On one hand, studies document reduced consumption in the general population after the onset of the COVID-19 pandemic and a subsequent decline in consumer debt levels that can be attributed in part to reduced consumption (Baker et al., 2020; Horvath et al., 2021) or paying down of debt balances. Some of the decline in debt levels, however, may be involuntary — as creditors also contracted their supply of credit during this period (Horvath et al., 2021). Thus, a decline in debt alone is not necessarily a positive outcome, but requires further decomposition of its mechanisms. Further, households experiencing direct financial hardship as a result of the COVID-19 pandemic, either through loss of wage income or medical distress, were often unable to pay their bills (Clark et al., 2021; Schneider et al., 2020).

Some of these households were able to qualify for forbearance or payment accommodations preventing delinquency on debt payments, but this subsequently results in an increase in their level of indebtedness. A recent study estimates that \$2 trillion in consumer and mortgage debt entered forbearance between March and October 2020 (Cherry et al., 2021). Debt in forbearance is not forgiven. It will need to be repaid at a later date either through balloon payments or by being re-amortized into the loan balance. There is increasing evidence of disparities in exits from forbearance, where lower-income individual borrowers and people who are Black borrowers are less likely to exit and resume making payments (Gerardi et al., 2021).

While there are a few studies that analyze trends in credit and debt following COVID-19 in the general population (Cherry et al., 2021; Horvath et al., 2021), ours is the first study to focus explicitly on older adults and to examine heterogeneous effects within the population of older adults. To do this, we construct a new national credit panel of older adults measured quarterly from the first quarter of 2019 through the fourth quarter of 2020. The national credit panel data includes a one percent random sample from more than 250 million adults with complete credit records, resulting in a sample of 2.5 million adults age 18 and older, of whom 1.2 million are age 50 and older. Importantly, our credit panel includes information for all members of the household who have credit, not just the randomly selected individual. This allows us to construct household measures of debt balances. In addition to traditional credit, we supplement our credit panel with data on the use of alternative financial services at the individual level — allowing us to measure changes in reliance and use of high cost forms of credit that may be associated with the COVID-19 pandemic.

We begin our analysis by documenting changes in debt levels and debt use from the fourth quarter of 2019 (Q4-2019), immediately prior to the onset of the COVID-19 pandemic, to the fourth quarter of 2020. We report changes overall and for specific heterogeneous subgroups including by individual age, household size, gender, income, credit score, debt-to-income ratio, whether or not the household held a mortgage as of the Q-2019, racial composition of the ZIP code (majority Black, Latino, white, or no majority) and changes in household composition over the year (decrease, increase, or no change in household size). There are notable differences in trends for particular sub-groups, indicative of a K-shaped recovery. Specifically, our findings indicate that household debt levels declined for older adults in three or more person households, for older adults with the highest income levels (75th percentile or higher) and for older adults with the highest credit scores (800 or higher). By contrast, household debt levels increased for older adults with lower incomes, lower credit scores, and for single person households during this period. Yet reliance on high cost debt for those with the lowest credit scores (580 or lower) fell by more than a third, raising the question of whether access met demand.

We further explore mechanisms underlying changes in debt levels, including changes in credit approval rates during this time period, involuntary closure of and cuts to credit card accounts, and evidence of whether or not the older adult received a payment accommodation like forbearance related to the COVID-19 pandemic. These trends show larger declines in credit approval rates and more involuntary cuts or closures of accounts for older adults (age 50+) than for younger adults (under age 50). Moreover, the gap between older and younger households widened, where the oldest consumers experienced the largest contraction in credit. This contraction was not concentrated among the lowest income and credit score older adults, however, but instead was larger in magnitude for older adults with higher incomes and credit scores, who were more active in the credit market prior to the onset of the COVID-19 pandemic. Similarly, with regard to payment accommodations, older adults with higher incomes and debt levels prior to the pandemic were more likely than lower-income older adults and those with less debt to receive COVID-related debt payment relief.

To better isolate indicators of vulnerability, we estimate a series of regression models predicting the change in debt levels and other credit outcomes from Q4-2019 to Q4-2020. After

controlling for a vector of demographic and financial characteristics, we find that older adults experienced significantly larger reductions in total household debt during COVID-19 relative to adults age 18 to 49. However, we observe significant heterogeneity by income and credit score, where older adults in the highest income percentile and highest credit score category had significantly larger reductions in total debt than those with lower incomes and lower credit scores. Older adults with incomes in the bottom three quartiles of the population income distribution actually experienced a large and statistically significant increase in mortgage debt and credit card debt during this period.

We also find that older adults are significantly less likely to be approved for new credit during this period, with the oldest adults (72 and older) experiencing the largest decline in approval rates among those seeking credit. We also observe that older adults with higher incomes were more likely than those with lower incomes to benefit from payment accommodations during the COVID-19 pandemic; however, controlling for income, those with lower credit scores were also more likely to receive payment accommodations. As might be expected, the rate of delinquency on debt payments declined significantly for older adults during 2020, with this decline being the greatest for older adults with lower credit scores compared to those with higher credit scores.¹

Finally, the third aim of our analysis is to estimate the effects of the varying geographic intensity of the COVID-19 pandemic and variation in geographic mobility during the pandemic on debt and credit outcomes. Our data includes geographic identifiers, allowing us to estimate the relative effects of state level COVID-19 case counts in 2020 and changes in state level mobility rates from Q4-2019 to Q4-2020. After controlling for financial and demographic factors pre-pandemic, we find that older adults living in areas with low mobility (measured as the share of people staying at home) experienced larger reductions in total household debt during the pandemic relative to older adults living in areas with greater mobility. The proportion of older adults receiving payment accommodations was significantly higher in areas with low mobility and in areas with high rates of COVID-19 case counts.

Taken together, the results of this study provide important detail about the depth and breadth of the inequity of financial hardship experienced by older adults as a result of the COVID-19 pandemic. Our findings indicate heterogeneous effects for vulnerable segments of the population. Credit data provides an important lens on the financial lives of older adults that may be missed by examining changes in income or Social Security benefits claiming alone. Many older adults rely on debt to finance consumption, and this study suggests that dynamics changed considerably as a result of the pandemic. Future research is needed to analyze the persistent and longer-term implications of these changes for the economic security of older adults.

2 Prior Literature

¹Initially we hoped to study outcomes by occupation but the credit data lack sufficient detail to define workers into fields that could be more or less challenged by the pandemic.

2.1 Consumer Debt and Credit among Older Adults

Debt is rising among older Americans. The evidence of growing debt among older US households emerged in research as early as 2013 (Collins et al., 2013; Trawinski, 2013). Recent research has demonstrated an ongoing rise in debt carried into consumers' retirement years, with particularly striking developments in mortgage debt (Brown et al., 2020; Collins et al., 2020; Haurin et al., 2019; Lusardi et al., 2020a) and for adults age 70 and older (Bhutta et al., 2020). But the increase is not restricted to mortgage debt, as balances held in retirement years have increased for auto debt, student debt, and credit card debt as well, even as mortgage, auto, and credit card borrowing decreased for younger consumers (Brown et al., 2020; Haurin et al., 2019).

Further, Brown et al. (2020) demonstrate that the increase in debt held in retirement arises not merely from a slowdown of debt origination during and after the Great Recession, which would lead outstanding debt contracts to be older, on average, by 2017 than they were in 2003. Equally consequential was a substantial tilting of new mortgage and auto loan originations toward older borrowers, and away from younger borrowers, between 2003 and 2017. Older Americans, then, are carrying more long-held consumer debt and more recently originated consumer debt than their predecessors managed at similar ages, and are doing so even as they confront the age-dependent harms of the COVID-19 pandemic.

Such a steep increase in debt held late in the life cycle would seem to point next to difficulties in repayment. Older borrowers have repaid comparatively reliably since the democratization of credit in the 1980s, and they have continued to repay reliably throughout the recent decades of rising consumer credit in retirement (Brown et al., 2020; Collins et al., 2020). This pattern leads us to ask whether repayment remains successful, in an absolute and a relative sense, for older borrowers who, in 2020-21, carried this unprecedented retirement debt into the COVID-19 pandemic.

A small set of researchers has begun to examine the likely implications of this rising debt for retirement timing and financial security in retirement. Butrica and Karamcheva (2020) find that indebted older Americans are more likely to work, less likely to be retired, and, on average, expect to work longer than those with less debt. Collins et al. (2020) demonstrate that this rising participation in mortgage markets among retirees is tied to a rising rate of homeownership at older ages, with its attendant financial security implications. Loibl et al. (2020) describe the association between levels of debt, particularly non-housing debt, and psychological stress for older adults. Lusardi et al. (2020b) establish and estimate interest rate risk, and other financial risks, affecting retired borrowers as a result of rising old age debt. Brown et al. (2020) use near-retirement debt and other financial circumstances to project economic hardship in old age for the US cohorts nearing retirement in the 1990s and in the 2010s; they predict a substantial increase in hardship among older men from the 1990s to the 2010s cohort.

Building on the research described above, our current analysis provides an initial look at the consequences of the COVID-19 pandemic for the financial stability of older Americans.

2.2 COVID-19 and the Financial Security of Older Adults

There is a burgeoning body of literature on the economic consequences of the COVID-19 pandemic for US households. Most directly, several studies analyze changes in labor force participation and unemployment in response to the COVID-19 pandemic (e.g. Cheng et al. (2020)), with a few studies focusing on labor trends among older adults (Goda et al., 2021; Moen et al., 2020; Quinby et al., 2021). In a study of labor force exits using data from the Consumer Population Survey (CPS), Cheng et al. (2020) find that adults age 61 and older were more likely to exit the labor force in March 2020 than any other age group (age 25 and older) and were less likely to re-enter the labor market in April 2020.

Quinby et al. (2021) use CPS data to compare changes in labor force exits among adults age 55 and older one year prior to the pandemic to one year after the onset of the pandemic. They find an eight percentage point increase in exits from the labor force among older adults following the onset of the COVID-19 pandemic. However, they observe only a small one percentage point increase in the probability of retirement following the onset of the pandemic. In a similar analysis with CPS data, Goda et al. (2021) also document significant increases in labor force exits following the onset of the pandemic for adults age 50–61, with a smaller increase in exits for adults age 62–70. In a separate analysis, they analyze changes in Social Security retirement applications between March 2020 and March 2021 and find no evidence of a significant increase. Thus, older adults who left the labor force during the COVID-19 pandemic do not appear to be offsetting the reduction in income with retirement benefits in the short-term, although the implications for longer term claiming behavior are unclear.

Reductions in income may be offset in part by reductions in consumption. While not focused on older adults, several studies document reductions in consumption and consumer spending associated with the COVID-19 pandemic in the general population (Baker et al., 2020; Casado et al., 2020; Chetty et al., 2020; Farrell et al., 2020; Horvath et al., 2021). For example, Farrell et al. (2020) find an overall 10 percent decline in consumer spending following the onset of the pandemic. However, the effects on consumption are heterogeneous across a number of dimensions. Baker et al. (2020) find that individuals living in areas with active shelter in place orders experienced larger reductions in consumption than individuals living in areas without such orders. Chetty et al. (2020) find that much of the reduction in spending is concentrated among higher-income households; households in the top income quartile spent 13 percent less as of mid-July 2020 relative to January 2020, whereas households in the bottom income quartile reduced consumption by only 4 percent during the same period. For those experiencing a COVID related loss of income, Farrell et al. (2020) find that receipt of pandemic-related unemployment benefits is associated with a 10 percent increase in consumer spending relative to the prior year.

Changes in income and consumption during the COVID-19 pandemic may be associated with changes in consumer debt. Consumer debt can be an important source of liquidity to smooth consumption for individuals experiencing a loss of income (Braxton et al., 2020; Collins et al., 2015), thereby leading to an increase in debt. On the other hand, pandemic-induced reductions in spending may lead to a decrease in the accumulation of new debt and

may actually allow for the pay down of prior debt balances. Using monthly account-level credit card data, Horvath et al. (2021) find a sharp decrease in credit card balances following the onset of the pandemic, with the reduction being larger for individuals with higher credit scores. In addition to reductions in debt levels, there is some evidence for a reduction in the rate of opening new accounts following the pandemic. The Consumer Financial Protection Bureau (CFPB) (2020) found a 40 percent reduction in new credit card originations after the onset of the pandemic — a rate that remained low through July 2020.

Reductions in credit use could be the result of supply or demand. There is some evidence in line with supply effects. Horvath et al. (2021) document a 4 percentage point increase in the interest rate spread on new credit cards to borrowers with low credit scores following the onset of COVID-19, with no change in the interest rate spread for higher credit score borrowers. Also in line with supply effects, industry data indicate a 40 percent decrease in the aggregate credit limits on bankcards as of the fourth quarter of 2020 relative to the fourth quarter of 2019 (Equifax, 2021). These studies highlight the importance of considering not only changes in debt levels following the onset of COVID-19, but also the mechanisms underlying changes in levels. In this paper, we construct a proxy measure for the credit approval rate, in addition to indicators of credit line cuts and involuntary account closures. While consumer debt can be a source of liquidity to smooth consumption, required monthly payments can also be a source of financial strain—particularly following an income shock.

Typically, the onset of an economic crisis such as the COVID-19 pandemic would trigger widespread consumer default on debt payments (Dettling and Lambie-Hanson, 2021). Indeed, many consumers reported difficulty paying bills following the onset of the COVID-19 pandemic (Clark et al., 2021; Schneider et al., 2020). However, rather than being reported as being in default on their debt payments, a large proportion of consumers were able to obtain temporary suspension of their debt payments through forbearance.

Using credit panel data, Cherry et al. (2021) estimate that 60 million individuals had a collective \$2 trillion in debt that was in forbearance as of October 2020 including 4.6 percent of credit card trades, 8.8 percent of auto loans, 8.8 percent of mortgages, and 92 percent of student loans. They find that areas with higher unemployment rates, higher COVID-19 case counts, and a higher share of workers employed in an “at-risk” industry had higher shares of the population with loans in forbearance. This higher rate of forbearance for at-risk groups (and slower exits from forbearance) may lead to debt overhang that affects future consumption and labor decisions in the long term.

While the studies described above shed some light on the trends in debt and credit for the general population during the COVID-19 pandemic, they do not focus on trends among older adults explicitly. It is quite possible that the experiences of older adults — many of whom were out of the labor force prior to the onset of the pandemic — may differ from the experiences of younger adults. Further, there is likely substantial heterogeneity between groups of older adults, with some emerging from the pandemic in a significantly better financial position than before, while others emerge with higher levels of debt and increased financial burden, placing economic security at risk.

3 Data and Methods

3.1 Data and Sample Construction

The primary data for this analysis is consumer-level credit attribute data from Experian, one of the three national credit bureaus. Experian credit data includes approximately 300 million unique consumer records at any given point in time, representing more than 90 percent of the US population age 18 and older (Brown et al., 2015).² We obtain a panel level dataset consisting of a one percent random sample of consumers who were in Experian credit data as of a given quarter, beginning with the first quarter of 2019 (Q1-2019) through the fourth quarter of 2020 (Q4-2020). The random sample is generated by including all consumers in the sample with the same last two-digits of a unique eight-digit time-invariant consumer sequence number.³ This allows us to follow the same randomly selected consumers over time, and also allows new consumers to enter the sample over time who have the same last two digits of their consumer sequence number. This process is similar to that used to generate other established credit panels, such as the Federal Reserve Bank of New York Equifax-sourced Consumer Credit Panel (CCP), see Lee and Van der Klaauw (2010).

As of Q4-2019 and Q4-2020, the random sample includes 3.017 and 3.033 million unique individuals, respectively. We exclude individuals with missing data for age or who do not have any trade data, as these are more likely to be individuals under the age of 18 who should not be reported in the data, or individuals with a duplicate thin file.⁴ We also exclude individuals who are deceased as of a given quarter. These restrictions result in a sample of 2.574 and 2.610 million unique individuals in Q4-2019 and Q4-2020. Our analysis sample is further limited to the 2.517 million individuals age 18 and older with credit data in both periods, thus allowing us to calculate changes in debt and credit outcomes before and after the onset of the COVID-19 pandemic. This sample includes 1.242 million individuals age 50 and older—the primary focus of this analysis.

The credit panel data used for this analysis include more than 400 individual credit attributes each quarter, with measures of debt levels by type of debt, new trade activity such as inquiries and account opening, changes to existing trades such as account closures and credit line increases and decreases, payment and delinquency status, and indicators of payment accommodations during the COVID-19 pandemic. The credit panel data also include the age and ZIP code of the consumer each quarter. Further, Experian Marketing Services appends imputed demographic and financial characteristics, such as gender, household income, and

²The number of 300 million unique consumer records is from the raw data and is an over-count of the number of unique adult consumers represented by the data, prior to cleaning the data to remove consumers who are deceased, missing age, or who have thin files that may indicate duplicate records.

³Similar to a Social Security number, Experian assigns a unique, random consumer sequence number to each consumer when they first enter the credit data.

⁴This process for cleaning potential problematic observations from the credit panel data is similar to that used to construct other established credit panels, including the CCP (Lee and Van der Klaauw, 2010)

the estimated monthly debt payment to income ratio for the consumer's household. The credit panel demographic data do not include indicators for race and ethnicity. We merge in U.S Census data on the proportion of residents at the ZIP code level who are Black, the proportion who are White, and the proportion who are Hispanic.

Some of the outcomes for this analysis, such as debt levels, are best constructed at the household level. A unique feature of our credit panel is that it includes data for all other individuals with a credit file living at the same address at the same point in time as the randomly selected individual. In our analysis sample, we have credit data for 6.73 million unique individuals distributed across the 2.517 million people in the random sample age 18 and older. Data on other household members is primarily used to construct household debt levels. Household level data also allows us to construct an indicator for the number of people with a credit file in the household in a given quarter, and track changes in the number of people with a credit file in a household over time.

To better understand the full picture of the debt use of older adults, we supplement the credit panel data with individual level data on the use of alternative financial services from Experian Clarity Services data.⁵ Clarity data includes information on credit sources that do not appear in traditional credit data, such as payday loans, online and storefront small dollar short-term loans, and rent-to-own trades. For this analysis, we merge individual level data on inquiries and new trades in the Clarity data from January 1, 2019 through September 30, 2020, before and after the onset of the COVID-19 pandemic.

Aside from data on credit and debt, we construct indicators of the severity and spread of the COVID-19 pandemic. Our first source of data is from Safegraph on the mobility of individuals, measured in 2019 and 2020 as the monthly average of days spent at home at the ZIP code level. For this analysis, we aggregate the mobility data to the state and construct the average mobility in May 2020 relative to average mobility in May 2019. We categorize states into three groups based on the change in mobility during COVID-19: those with reduced mobility (ratio <0.93), those with moderately reduced mobility (ratio 0.93-0.99), and those with no change in mobility (ratio >0.99).

Our second source of data on COVID-19 spread is the publicly available *New York Times* Case Count Data, which provides information on the number of COVID-19 infections per 100,000 people in a population by state. We construct an indicator for the cumulative rate per 100,000 of COVID-19 infections in a state as of December 31, 2020. We categorize states into three groups based on the number of COVID-19 infections: low (<8,000 cases per 100,000), moderate (8,000 to 11,000 cases per 100,000), and high (>11,000 cases per 100,000).⁶

⁵ For more information about this data source, see <https://www.clarityservices.com/>

⁶We use the distribution of case rates in the US population to determine the cut-points for the categories.

3.2 Credit Variable Construction and Summary Statistics

Table 1 reports summary statistics for key covariates in our analysis sample as of Q4-2019, which is the baseline quarter prior to the onset of the COVID-19 pandemic in 2020. Table 2 reports summary statistics for our outcome variables, typically measured as the change in the variable from Q4-2019 to Q4-2020 unless otherwise indicated. The changes describe the cumulative response to the pandemic as of the end of 2020. Balances are reported in thousands of 2020 dollars. We compare means and standard deviations by the age group of the randomly selected individual (under 50, 50-61, 62-66, 67-71, and 72 and older). Below, we define how these variables are constructed and highlight key differences by age group. For a subset of credit outcomes, we graph trends for the eight quarters from Q1-2019 through Q4-2020. In Table 2, we report the change in various credit outcomes between the second quarter of 2019 and the second quarter of 2020, dividing the sample into these same age subgroups.

3.2.1 Demographic Characteristics

Our first set of demographic indicators measures the number of adults age 18 or older with a credit file in the household of the randomly selected individual as of Q4-2019, in categories (1, 2, or 3 or more consumers). This is a proxy for household size, but excludes children and people in the household who do not have a credit file. In our sample, approximately 19 to 20 percent of the randomly selected individuals age 62 and older live in households with only one consumer. According to 2019 US Census data, 28 percent of adults age 65 and older lived alone. The relatively low share of older adults living in single consumer households in the credit sample may reflect the selectivity of people in credit data being those who are more connected to the financial system and less likely to live alone. It may also reflect the difference between the Census housing unit criteria used to establish single living and the shared mailing address criterion we apply to our Experian data.⁷ Further, there can be a delay between death and when a consumer no longer is reported in credit data which may bias the household size to be larger in credit data particularly at older ages. In addition to the measure of household size, we also construct indicators for adding or losing a household member between Q4-2019 and Q4-2020. We also include indicators measuring the gender of the randomly selected consumer in the household as reported by Experian.

Our second set of demographic indicators measure household income and monthly debt burden using Experian imputed household annual income and monthly debt-to-income (DTI) variables as of Q4-2019. Experian imputes household income for each consumer using a proprietary model that predicts income based entirely on attributes in the consumer's credit file. Experian estimates DTI based on actual and imputed monthly debt payments in the credit file, as a percent of imputed monthly income.⁸ Given this is imputed data, we do not

⁷Housing unit criteria are described by the 2020 Census as follows: A housing unit is a house, an apartment, a group of rooms, or a single room occupied or intended for occupancy as separate living quarters.

⁸Experian reports validating their predictive models using a sample of consumers with verified income

include the level of imputed income or DTI in our models. Rather, we segment consumers by income quartile of the full credit population. As summarized in Table 1, adults are progressively less likely to fall in the lowest population income quartile as they age— with 38 percent of adults age 18-49 falling in the bottom quartile relative to just under 5 percent of adults age 72 and older. For DTI, we rely on a common industry standard of 30 percent or higher indicating a consumer with high debt burden. We also include an indicator for a consumer with no monthly debt payments (DTI of \$0). The share of adults with an estimated DTI of 30 percent or more declines with age in our sample, from 12 percent of adults age 50–61, to only 2.3 percent of adults age 72 and older.

3.2.2 Credit Score

We include indicators for credit score as of Q4-2019.⁹ We group credit scores following industry thresholds as follows: < 580, 581-669, 670-739, 740-799, 800 or higher. Scores below 580 indicate a very poor credit history, whereas scores of 740 or higher are generally considered “prime” scores (Consumer Financial Protection Bureau (CFPB), 2020). Credit scores tend to increase with age (Brown et al., 2020). It is thus not surprising that the proportion of older adults with credit scores below 580 declines monotonically by age category in our sample, with 13 percent of adults age 50–61 having credit scores below 580 and only 3.4 percent of adults age 72 and older having credit scores below 580.

3.2.3 Race and Ethnicity of ZIP Code

To construct the race and ethnicity of the ZIP codes, we use the 2019 American Community Survey (ACS) five-year estimates. We categorize the majority race or ethnicity of the ZIP code as follows: (1) majority Black if more than 50 percent of people in the ZIP code report their race as Black; (2) majority Hispanic if more than 50 percent of the people in the ZIP code report Hispanic ethnicity and not more than 50 percent report Black race; (3) White non-Hispanic if more than 50 percent of the people in the ZIP code identify as White and not more than 50 percent report Hispanic ethnicity; and (4) no majority race or ethnicity if there is no majority race or ethnicity in the ZIP code. In our sample, about 5 percent of randomly selected individuals live in majority Black ZIP codes, and 7 to 10 percent of adults age 50 and older live in majority Hispanic ZIP codes (decreasing by age group).

data

⁹The credit score in our data is the VantageScore 4.0, which is similar to the FICO score, in that both predict the consumer’s likelihood of being 90 or more days past due on any credit obligation over the next 24 months, and both scores range from 300 to 850. More information on the Vantage score is available on Experian’s website at: <https://www.experian.com/assets/consumer-information/product-sheets/overview-vs4-113017.pdf>

3.2.4 Total Household Debt

Total household debt is constructed as the sum of all debt held by all consumers age 18 and older with a credit file living at the same address as the randomly selected individual.¹⁰ Debt is defined to include all trade types reported to the credit bureau, including mortgages, student loans, auto loans, other installment loans, credit cards, other revolving trades, and collections (including medical collections). The total includes debt that is current as well as debt that is delinquent or severely derogatory, debt on accounts that are open or closed, as well as debt that is deferred (e.g. deferred student loans or trades in forbearance). To avoid double counting, we identify any trades that are jointly held and divide by two before aggregating to the household level (most common for mortgages, auto loans and other revolving trades). We also exclude from the total the balance on trades where the individual is only an authorized user (most common for credit card trades). To address outliers, we top code individual debt levels at the 99.5 percentile before aggregating. As reported in Table 2, the average change in total household debt from Q4-2019 to Q4-2020 ranged from an increase of \$7,150 for individuals age 18 to 49, to a decrease of \$3,620 for individuals age 62 to 66. Figure 1 plots changes in total household debt from Q1-2019 through Q4-2020 by age.

In addition to constructing an aggregate measure of total debt, we construct measures of total household credit card debt and total household mortgage debt. Figure 4 and Figure 3 plot the changes in household credit card and mortgage debt among older adults (age 62 and older) from Q1-2019 through Q4-2020. For mortgage debt, we also construct an indicator for a household holding any mortgage debt as of Q4-2019. As summarized in Table 1, the share of individuals living in households with mortgage debt declines with age, from 53 percent of individuals age 50–61 to 33 percent of individuals age 72 and older.

3.2.5 Credit Approval Rate

Debt levels can decrease due to demand, but they can also decrease due to supply constraints. For this study, we develop a proxy measure of the credit approval rate, calculated using the Experian credit panel data as the ratio of the number of new trades opened in the prior six months divided by the number of new inquiries in the prior six months. This follows the approach used by Bhutta and Keys (2016) to develop a measure of supply constraints at the ZIP code level. Here, we construct the measure at the individual consumer level. Importantly, if an individual does not seek credit in the prior six months they will be missing data for this variable. Thus, in addition to measuring changes in the share of consumers who are approved for credit in the prior six month period from Q4-2019 to Q4-2020 (limited to those in the random sample who sought credit in both periods), we also run tabulations using the approval rate among all consumers seeking credit in a given period. As summarized in Section 2, the approval rate among those seeking credit declined substantially during COVID-19, particularly for older adults.

¹⁰In rare cases, there may be multiple randomly-sampled individuals in one household. In these cases, each randomly selected individual's household level debt will be equivalent.

3.2.6 Credit Lines Closed or Cut by Creditor

Creditors can restrict debt use by closing revolving lines of credit (home equity lines of credit and credit cards) or by reducing the credit limit on revolving lines of credit. Such credit line closures and cuts are commonly made by creditors when there is uncertainty in the macro-economic environment (Dempsey and Ionescu, 2021) or when an individual consumer's repayment behavior or credit record suggest financial duress (Federal Trade Commission, 2016). For this study, we construct a combined indicator (0,1) of the randomly selected individual experiencing a creditor initiated closure of a revolving credit line in a six-month period or experiencing a decrease in the credit limit on revolving trades in a six month period. We then calculate the change in a consumer experiencing a credit line cut or closure as of Q4-2020, relative to experiencing a credit line cut or closure as of Q4-2019. The share experiencing cuts or closures increased by more than 5 percentage points for adults age 50–71 between Q4-2019 and Q4-2020.

3.2.7 Use of Alternative Financial Services

In addition to traditional forms of credit, our data includes information about the use of alternative financial services (AFS) from Experian's Clarity Services data. We construct an indicator (0,1) if the randomly selected individual made a new inquiry for AFS credit that was reported in the Clarity data (by one of the Clarity creditors) in a quarter. This identifies a consumer who is seeking higher cost, often short-term forms of credit—a proxy for potential financial distress. Figure 2 plots the proportion of subprime older adults with AFS inquiries by quarter, from Q1-2019 through Q3-2020. We define subprime as having a credit score below 580 as of Q4-2019. There was a sharp decrease in AFS inquiries during the second quarter of 2020 that slightly increased as of Q3-2020. For this study, we calculate the change in having any Clarity inquiry at the consumer level before and after the onset of the COVID pandemic (any inquiry during the 6 month period of Q2 and Q3 of 2020, less any inquiry during the 6 month period of Q2 and Q3 2019).

3.2.8 Payment Delinquencies

For this study, we construct an overall indicator (0,1) of payment delinquencies that takes the value of 1 if the randomly selected individual was presently 60 to 180 days late on any debt payment in a given quarter. This is aggregated across all debt types. It does not code as delinquent payments that are more than 180 days late or derogatory (often in collections or charged-off), but instead is intended to capture debt that is recently delinquent. As reported in Table 2 there was a decrease in the share of consumers who were delinquent on debt from Q4-2019 to Q4-2020, with the decrease being larger for younger individuals ages 18-49 relative to older age groups. Part of this is because the overall rate of delinquency for older individuals was already low prior to the onset of the COVID-19 pandemic, as visualized in Figure 5.

3.2.9 Payment Accommodations on Installment Loans

Following the onset of the COVID-19 pandemic, numerous consumers received accommodations on their debt payments, including temporary suspension of required payments. For student loans, forbearance was automatic. For mortgages federally insured by Fannie Mae, Freddie Mac, or the Federal Housing Administration (FHA), forbearance was required as an option if a homeowner sought leniency due to a COVID-19 related financial hardship. Many lenders of non-federally insured mortgages also offered temporary forbearance during this period (Cherry et al., 2021). There were no requirements for automobile and other installment lenders to offer forbearance; however, many offered temporary payment suspension without delinquency for distressed consumers.

For this study, we construct an indicator (0,1) that takes the value of 1 if an individual received any payment forbearance in any quarter of 2020 on mortgages, automobile loans, personal loans, or student loans. We identify forbearance in the credit data as trades with a non-zero balance but with no required monthly payment, or as trades coded by the creditor as in forbearance or as being affected by a natural disaster.¹¹ This is a commonly used approach to identify trades in forbearance using credit data (e.g. Cherry et al. (2021)). As reported in Table 2, a substantial share of older adults received accommodations on installment loans during COVID-19. Including student loans, 16 percent of adults ages 50–61 and 6 to 9 percent of adults ages 62–71 received an accommodation on a mortgage, auto, or personal loan in 2020.

3.3 Methods

The first aim of our analysis is descriptive, exploring changes in credit and debt during the COVID-19 pandemic for older adults. To measure change, we take the difference between the level of each credit and debt outcome as of the end of Q4-2020 and the level of the outcome as of the end of Q4-2019. We then run a series of cross-tabulations of means, comparing the levels of change in outcomes across categories of key covariates. This allows us to identify particular groups of older adults who may be more or less affected by the COVID-19 pandemic. Estimating change as of the end of the fourth quarter in each period holds constant seasonal variation in credit use and provides a reduced-form indication of total change as of the end of 2020.

The second aim of our analysis is to better isolate particular characteristics at baseline (Q4-2019) associated with subsequent financial hardship during the COVID-19 pandemic. To do this, we estimate a series of regression models predicting change in debt levels and other credit outcomes from Q4-2019 to Q4-2020. The empirical specification for these Ordinary Least Squares (OLS) models is as follows:

¹¹For this study, we rely on a series of Spotlight Premier Attributes created by Experian to measure payment accommodations during the COVID-19 pandemic, including CARES Act trades that have a non-zero balance with no required monthly payment (indicative of payment deferral or forbearance), as well as trades with creditor codes for forbearance or natural disaster.

$$\Delta(Y)_{i,z} = \alpha + \beta(D)_i + \theta(Z)_i + \epsilon_{i,z} \quad (1)$$

where ΔY is the level change in the outcome calculated as the change in levels in Q4-2020 from the level in Q4-2019 for individual i in ZIP code z . \mathbf{D} is a vector of individual characteristics as of Q4-2019 including number of adults in the household with a credit file, imputed income quartile, imputed DTI (in categories), credit score (in categories), gender of the individual, and an indicator for holding a mortgage. We also control for losing or gaining a consumer with a credit file in the household from Q4-2019 to Q4-2020. \mathbf{Z} is a vector of indicators for the race and ethnicity of the ZIP code; and, ϵ is an individual-level error term clustered at the household level.¹²

For payment accommodations, the outcome is an indicator (0,1) for any payment accommodations in 2020 (these are not reported for prior periods, making a Δ estimate impossible). We estimate linear probability models for this outcome including the same covariates identified in equation (1).

The third aim of our analysis is to estimate the association of the varying geographic intensity of the COVID-19 pandemic and geographic mobility reduction during the pandemic with debt and credit outcomes. To do this, we re-estimate the models in Equation 1, but include a vector of indicators, \mathbf{X} , at the state level s for person i .

$$\Delta(Y)_{i,z} = \alpha + \beta(D)_i + \theta(Z)_i + \omega(X)_{i,s} + \epsilon_{i,z} \quad (2)$$

The values of \mathbf{X} take two forms in separate OLS estimates: (1) measuring the change in people's mobility from Q4-2019 to Q4-2020 based on cellular telephone records, and (2) the per capita rate of COVID-19 infection in the population at the state level during 2020. We show in the tables only the coefficients, ω , for each measure of \mathbf{X} using three categorical indicators of each measure. Mobility categories include states that had the highest rates of people staying home more in 2020 than 2019, relative to states where mobility did not change as much. Per capita case rates are indicators of states with higher case rates relative to those with lower rates.

4 Findings

4.1 Debt Levels

Table 3 reports debt levels as of the fourth quarter of 2019, before the pandemic, and changes from Q4-2019 to Q4-2020. Total household debt for adults age 50 and older decreased, on average, over the year. At the same time, debt levels increased for households under the age

¹²We allow ϵ to covary within the household in the rare cases in which multiple household members belong to the random sample.

of 50. However, we observe substantial heterogeneity among both older and younger adults. The magnitude of the mean change in balances over the period is dwarfed by the sample variation in the individual-level household change in balances, and this holds both overall and for each age group from under age 50 to those age 72+. Meaningful subsets of older borrowers did in fact borrow more, and meaningful subsets of younger consumers paid down debt. At various points below we investigate the opposing trends of relevant subgroups.

While debt increases are generally greater, and decreases smaller, for the under 50 age group than for the older age groups, some other demographic patterns remain true regardless of age: Single-adult households on average experienced pronounced debt increases over the pandemic, and two-adult households experienced more modest debt increases, while debt balances decreased on average for households containing three or more adults with credit reports. This relationship between debt growth and household size appears at every age. By income quartile, debt balances decline over the pandemic on average only for the fourth income quartile, and increase for lower-income quartiles. This is true at all ages. (The decline in debt for younger people in the higher-income quartile is, however, quite modest, while the decline for older people in the higher-income quartile is on the order of \$10,000.)

Debt changes are negative for mortgage holders and positive for non-mortgage holders across all age groups, and the divergence here is large. Households that gain a member see an increase in debt of almost \$60,000 or more, and those that lose a member see a drop in debt of \$55,000 or more, for all age groups. This is in part mechanical, as we track debt at the household level at each wave, and departing members take their debt with them. Finally, women and men show similar debt changes over the year for all age groups, with men reducing debt by a small amount more in three of the older age groups.

There are, however, several differences that emerge across age groups. All age groups show some increase in debt for the lowest credit score group, those with VantageScore credit scores under 580. But people with middling credit scores among the under 50 age group increase their debt substantially over the pandemic year, while older people with middling credit scores in many cases show decreasing or relatively flat balances. High scorers of all age groups decreased their debt, on average, with the 50-61 year-old group decreasing average debt by \$10,090.

The pattern of debt change by neighborhood race and ethnicity characteristics is similar for the old and the young, in that debt changes were the smallest (or most negative) in Zip codes in which a majority of residents identify as Black, largest (or least negative) in Zip codes in which a majority of residents identify as Hispanic, and in between these two poles for Zip codes in which a majority of residents identify as White. However, mean debt levels rise in all three of these neighborhood race/ethnicity categories for residents under 50, while debt levels decline for residents of majority Black and majority White neighborhoods for each of the older age groups.

Finally, debt balances decline for those who had debt-to-income ratios (DTI) of 30 percent or more in Q4-2019, regardless of age group. It is the moderate debt young and old who differ meaningfully, as young people with moderate debt loads (1 to 29 percent) increased their debt and older people with moderate debt loads decreased their debt over 2020. Given

the marked declines in debt for the older, higher credit score, higher income, and mortgage holding subgroups, the picture that emerges from Table 3 is one of declining pandemic-era debt among the older and economically advantaged, and rising debt for most others. At the same time, residents of majority Black neighborhoods and people with substantial pre-pandemic debt relative to income also show steep balance declines.

4.1.1 OLS Sub Group Analysis: Debt Levels

While the means in these summary tables are informative, we also seek to understand differences in credit outcomes controlling for other factors that are also associated with aging households. For example, we expect older households to be taking on less debt, and that incomes may also decline with age. Using a regression framework, we can estimate conditional means for changes in credit outcomes.

Table 7 Column (1) shows OLS regressions with controls for each age group, relative to consumers under age 50. All of the coefficient estimates are negative, but not very large—about \$8,000 to \$17,000. The estimates for mortgage balances in Column (2) comprise the majority of this balance. Mortgage balances decreased on average, controlling for other factors, by \$7,000 for 50–61 year olds, and over \$14,000 for 72+ year old creditors. Credit card debt declines from the end of 2019 to the end of 2020 by around \$172 for 50–61 year olds, and \$400 more more for older consumers. The general pattern is declining balances, especially for mortgage loans.

Table 8 provides estimates conditional on age group, highlighting any heterogeneity within each group in terms of changes from Q4-2019 to Q4-2020, before and during the pandemic. These estimates highlight which subgroups are showing larger changes in credit down each column, as well as differences by each age group. Many of the estimates are both statistically significant and substantial in magnitude. There are a few notable trends in Table 8, however. Predictably, balances decline more for people who have had a decrease in the number of consumers with credit records at the same address, and increase when the number increases. Also, across age groups, people with mortgages show larger declines in overall debt balances.

Table 9 shows mortgage balances as a subset of Table 8. In this table the magnitudes are larger in size, and show more differences within age groups. Again, the changes in the number of consumers per household are related to large changes in mortgage balances. The estimates by income show large increases in mortgage balances among the middle income groups relative to people in the highest quartile of income.¹³ Mortgage balances also increased among lower credit score older adults relative to those with with credit scores of 800 or above (the omitted reference category). People who had the highest debt-to-income ratios in 2019 shows larger declines in mortgage balances by the end of 2020. There are not large differences in estimates within these groups by age in general, however.

Table 10 follows the same style of OLS regression estimates from Tables 8 and 9, for credit card balance changes only. Credit card balances increased for older adults in the bottom

¹³These estimate exclude the mortgage indicator used in other tables.

half of the income distribution. Credit card balances appear to have decreased more for people with lower credit scores, which could be related to a lack of access or restrictions on credit limits. People with mortgages saw larger declines in credit card debt, as did people in majority-Black race zip codes. Again, there are not large differences across age groups controlling for other factors.

4.2 Credit Availability

One might be tempted to infer from the evidence on balance changes that older, well-off, and relatively indebted fileholders chose to rein in borrowing in 2020, whether out of financial caution or fear of contagion in retail spaces. The evidence in Table 4, however, indicates that the supply side of the credit market behaved differently in 2020 as well. For each of our age groups, Table 4 first reports the share of people who had a revolving credit line that was closed by the associated lender, or had a line whose credit limit was lowered by the lender, in the six months prior to Q4-2019.

Next, Table 4 reports the change in the share that experienced a cut or closed line in the six months prior to Q4-2019 relative to the six months prior to Q4-2020. We interpret this second entry as the change in the rate at which revolving credit was curtailed by lenders during the pandemic. We find a clear age pattern in the pandemic-era change in the rate at which people experience lender-side credit cuts. While the share of fileholders experiencing cuts increased by 2.1 percentage points during the pandemic for those under 50, cuts increased by between 3.7 and 3.8 percentage points for those ages 50–71.¹⁴

Increases in credit cuts were substantially greater for the highest income quartile consumers. At the same time, they were also greater not for the highest credit score group, which overlaps heavily with the highest-income quartile group, but instead for those with more middling credit scores. Increases in credit cuts were also more common among mortgage holders, residents of majority Latinx and White neighborhoods, and those with higher debt-to-income ratios. To take one example, the share of 67-71 year-olds with debt-to-income ratios above 30 who experienced credit cuts increased by 7.8 percentage points, on a 2019 base of 27.9 percent. By and large, older consumers with higher incomes, older consumers with moderate credit scores, and older consumers with more debt (relative to income) faced substantially higher rates of involuntary credit reductions during the pandemic. These consumers may have represented increased risk to creditors at a time when older borrowers were seen to be particularly susceptible to the more severe manifestations of COVID-19. At the same time, it seems noteworthy that the targets of lenders' increased credit cuts do not appear to have been younger borrowers, who were most exposed to the risk of job loss posed by the pandemic recession.

Having considered the termination of existing credit, we turn in Table 5 to the extension of new credit during the pandemic. Table 5 reports our approximation of the approval rate for

¹⁴Only consumers in the credit data age 72 and above saw a smaller increase in cuts, at 1.8 percentage points.

new credit applications, described above in subsection 3.2.5.

For each age group, Table 5 contains first the inferred approval rate based on credit inquiries and credit line openings during the last six months of 2019. Then, in a second column, Table 5 reports this same approval measure for the last six months of 2020.¹⁵ The counts of fileholders with inquiries in the latter half of 2019 and the latter half of 2020 can be read across the bottom of Table 5, and they reveal a slowdown in applications for formal credit during the pandemic. For example, the total number of fileholders with inquiries decreases by 5.5 percent, from 813,591 in the second half of 2019 to 771,073 in the second half of 2020.

Despite fewer inquiries, the inferred approval rate declines for most sample subgroups. The approval rate falls for every one of our age groups, and falls most for the oldest borrowers. It falls by 5.0 percentage points for the under 50, 9.8 percentage points for those age 50–61, 11.5 percentage points for those age 62–66, 13.5 percentage points for those age 67–71, and 12.9 percentage points for those 72 and older. The selection of consumers into applying for credit may have differed in 2019 and 2020, with the 2020 selection creating a smaller but not necessarily more creditworthy group. Nevertheless, the near-monotonic relationship between approval rate drops and age does not seem to suggest lenders reliably came to the aid of older borrowers seeking credit during the pandemic.

4.2.1 OLS Sub Group Analysis: Credit Access

Table 7 Columns (4) and (5) show changes in credit approval rates and involuntary credit line reduction rates, and Column (6) shows changes in consumers seeking alternative financial services (AFS) credit as reported as inquiries in Clarity data. All estimates for age categories include controls. It appears that approval rates declined for all consumers, and even more among older consumers. Compared to younger people in the constant, people ages 50–61 have about 2.4 percentage points lower approval rates; those age 72 and older show a reduction by 8.6 percentage points. Credit access appears to be becoming more constrained after the COVID-19 pandemic among older people. The cuts to credit in Column (5) are generally small, with those ages 50–61 slightly more likely to experience cuts than younger consumers ages 18–49 (the omitted group) and those age 72 and older slightly less likely to experience credit line cuts. In Column (6) the change in seeking AFS credit is negative and small in magnitude across all older age groups relative to younger age consumers. These estimates are statistically different from zero, but not from each other.

Table 11 shows changes in approval rates conditional on age group. The largest reductions in approval rates are for people with high debt-to-income ratios, although the estimates are similar across age groups. Table 12 shows the changes in rates of involuntary credit limit decreases. Several groups show higher rates of limit cuts, including women, lower-income

¹⁵Note that these calculations are based only on those consumers whose files show any inquiry in the period covered by the approval measure. For this reason, we do not provide the means of individual-level changes in approval rates, as repeat applicants will be a smaller and selected group, and perhaps of limited interest as we seek to understand the supply of new credit during the pandemic.

people, and people with high debt-to-income ratios. People with lower credit scores show larger decreases in credit line cuts from 2019 to 2020, with similar estimates across age groups. The estimates in Table 13 are all quite small in magnitude. The change in the rate of seeking AFS credit is generally negative—people are seeking less AFS credit over the COVID-19 pandemic. Inquiries declined more for lower-income borrowers, and more for older low-income borrowers. AFS inquiries are also down more among lower-credit score borrowers, as well as those with higher debt-to-income ratios. There is little evidence of older households finding credit harder to access and turning to AFS at higher rates.

4.3 Delinquency and Payment Accommodations

Together, the evidence on credit line cuts and closures and on credit application approval rates suggests some degree of new credit disadvantage facing older borrowers. If this is true, it represents a turn against a long recent history of relative repayment success, and of expanding credit availability, for older borrowers (Collins et al., 2020; Moulton et al., 2019; Brown et al., 2020). It is in this context that we next examine younger and older borrowers' reliance on borrower accommodations during the pandemic. Table 6 reports the share of each of our sample subgroups that benefited from accommodations on mortgages, auto loans, personal installment loans, or student loans during 2020. For each age range, the first column reports the proportion who benefited from any installment loan accommodation, while the second column reports the proportion who benefited from mortgage, auto, or personal loan accommodations, setting aside student loans given their attachment to an early stage of the life cycle and the fact that student loan accommodations were extended to all student loan borrowers.

The rate of accommodations declines with age whether or not we include student loan accommodations, but it declines considerably more steeply with age when student loans are included. Including student loans, 29.8 percent of those under 50, 16.0 percent of 50-61, 9.3 percent of 62 to 66, 6.3 percent of 67-71 years old, and 2.8 percent of those over age 71 benefited from accommodations in 2020. Accommodations increase steeply from the first to the fourth income quartile for all age groups when student loans are excluded. They are, however, relatively flat in income for younger borrowers when we include student loans. In contrast to this increasing income pattern, accommodation rates decrease approximately monotonically with credit score for each of the age groups. Recall that these rates of accommodation by credit score are unconditional on income, and vice versa. Despite the extensive overlap between those with high income and those with high credit scores, accommodations are most prevalent both in the highest income quintile and in the lowest credit score range. Accommodations also favor mortgage holders, residents of majority Black zip codes, and people with high debt balances relative to income.

Throughout these demographic and financial circumstance comparisons, older borrowers remain substantially less likely to receive installment loan accommodations from their lenders in 2020. Figure 5 provides a helpful summary of the relationship among delinquency, accommodation, and age. Through all four quarters of 2019, the share of young people in the credit

data with at least one account whose repayment is 60 or more days past due ranges between five and six percent. Older borrowers' 60 days past due delinquency rates, on the other hand, are low and level. The share of those 72 and older with an account 60 or more days past due remains stable at just above one percent, and the share of the 67 to 71 year-old people in the credit data with an account 60 or more days past due remains stable at two percent. As a result, we observe substantial declines in delinquency from the first quarter of 2020 forward for younger borrowers, whose repayment delinquency leaves much room for improvement via pandemic accommodations, while older borrowers' delinquency rates respond minimally to payment accommodations.

Together, this history implies a partial convergence of delinquency rates for young and older consumers over the course of 2020. Payment holidays, forbearance, and deferment produced meaningful credit healing for young borrowers struggling with repayment, and yet were of little consequence for older borrowers. No similar intervention addressed the particular pandemic-era credit struggles of older borrowers, which appear to have included lenders' declining rates of approval of new credit applications from older borrowers, trimming of existing revolving credit lines, and closing of existing revolving accounts.

4.3.1 OLS Sub Group Analysis: Credit Distress

Table 7, Column (7) displays changes in 60-day or more late payments. Column (8) shows the overall rates of loan accommodations (excluding credit cards). Column (9) shows the rate excluding credit cards and student loans (which may be less relevant for older households). After controlling for covariates, it appears older people have larger declines in late payment rates from 2019 to 2020 relative to younger people. They are also less likely to have a loan accommodation. Column (8) excludes student loans, and still shows lower rates of accommodations at older ages.

Table 14 shows changes in 60-day late payments for each age group. Lower-income consumers show larger changes in late-payment rates, with larger estimates for older people. Lower credit score borrowers show larger reductions in late payment rates, consistently across age groups. This could be driven in part by this group using more loan accommodations, shifting late payments to deferred status. Indeed, Table 15 shows higher rates of accommodations for lower credit score and higher debt-to-income ratio borrowers. Accommodation rates are lower among lower-income borrowers. These patterns generally are smaller for older age groups, however. Looking at non-student loans in Table 16, the patterns are similar. Lower credit score and high debt-to-income ratio borrowers show more accommodations, lower-income fewer payment accommodations. Notably, borrowers in both majority Black and Latino Zip codes show higher rates of non-student loan accommodations, although these patterns are less pronounced among older age groups.

4.4 State Level COVID-19 Responses and Credit Outcomes

Li et al. (2020) show that lockdowns limited consumption in local areas with more severe restrictions. Tables 17–23 show OLS regression estimates using the same changes in outcomes and controls as prior tables, focusing on indicators at the state level for people in a given state reducing mobility by staying at home more relative to pre-pandemic periods (Panel A), as well as overall state COVID-19 cases per capita (Panel B). The constant comparison group in Panel A estimates are states where mobility was close to unchanged from pre-pandemic levels.¹⁶ In Panel B the comparison are states with low case rates per capita.¹⁷

Tables 17 shows estimates for mobility and case rates for changes in debt levels overall from the end of 2019 to 2020. The estimates for states where people stayed home at higher rates show about \$6,000 in lower debt among 18–50 year-olds, and among 50–61 year-olds. The estimate for declines in debt are smaller at older ages, but still significantly different from zero. The magnitudes are consistent with differential effects of the COVID-19 pandemic across the US. Panel B shows that places with the highest COVID-19 cases per capita had no changes in levels of debt. More moderate case rates are associated with modest decreases in total household debt levels.

Table 11 Panel A shows no association between mobility rates and changes in approval rates from 2019 to 2020. Panel B shows a larger decline in approval rates for people 72 and older in states with higher case rates. The magnitudes are small but suggest that older people in high COVID-19 case states were less likely to gain access to credit during the pandemic relative to people in low case rate states. Turning to credit line cuts, Table 19 shows rate cuts were less likely in states where mobility was reduced during the pandemic in Panel A. The patterns are similar by age group. In Panel B, rate cuts are more common in states with higher case rates, although again small in magnitude.

For late payments in Table 21, Panel A shows lower late payment rates in states with less mobility during the pandemic. These estimates are mainly among younger households and quite small in size. Panel B shows higher late payments among younger people (under age 50) in states with higher rates of COVID-19. There are few statistically significant estimates for older consumers, however. There is no clear pattern by age.

Tables 22 and 23 show the rate of loan payment accommodations. Table 22 shows mixed patterns. Panel A shows more accommodations in states with lower rates of mobility. Panel B shows higher accommodation rates in states with high COVID-19 cases. All of these estimates are small in size, but are consistent with economic stresses from the pandemic leading to more need for accommodations. Table 23 is clearer, and given the low incidence of student loans for older people is perhaps more informative. Places with less mobility show lower rates of loan payment accommodations, with slightly lower rates at older ages. Panel B shows higher rates of accommodations in states with higher COVID-19 case rates. This is consistent with people in states harder hit by the pandemic needing payment plans for their mortgages, automobile and personal loans.

¹⁶AL, DE, IN, LA, MS, NC, NM, OK, OR, SC, VA, and WI.

¹⁷DC, HI, MD, ME, NH, OR, VA, VT, and WA

5 Conclusion

This report investigates the effects of the COVID-19 pandemic on the debt levels and credit outcomes of older adults in the US. In general, older adults appear to have reduced debt over the pandemic from 2019 to 2020. However, the decline in debt is not uniform. Older people with higher incomes and better credit tended to reduce their debt more, especially older people with a mortgage, many of whom reduced the mortgage balances substantially, over the year.

Lower income people, people with lower credit quality and people without mortgages tended to increase their debt balances over 2020. The evidence suggests improving debt circumstances for advantaged older households over the course of the pandemic, and worsening credit circumstances for relatively disadvantaged older households.

Our data reveal declining credit access during the pandemic for all consumer age groups, with particularly pronounced losses of credit access among older households. Based on unconditional summary means, we find that the increase in credit account closings and line cuts was nearly twice as great for consumers ages 50–71 as for consumers under the age of 50, and that credit approval rates declined more than three times as much during 2020 for applicants aged 67 and above as for applicants who were under 50. These patterns persist even controlling for other factors with the regression estimates. Installment loan payment accommodations (including mortgage forbearance) were considerably more common among consumers who were under the age of 50 than they were for older consumers. This may, of course, arise from younger borrowers' greater pre-pandemic payment delinquency rates, and our evidence indicates that younger borrowers' repayment standing improved greatly through the pandemic-era lender leniency, while the oldest borrowers' repayment standing was approximately unchanged.

There are differential effects of the pandemic across states. Places with higher case rates and more mobility used more credit and were more likely to receive loan accommodations. These places may also show more stress as loan payment plans expire in 2022.

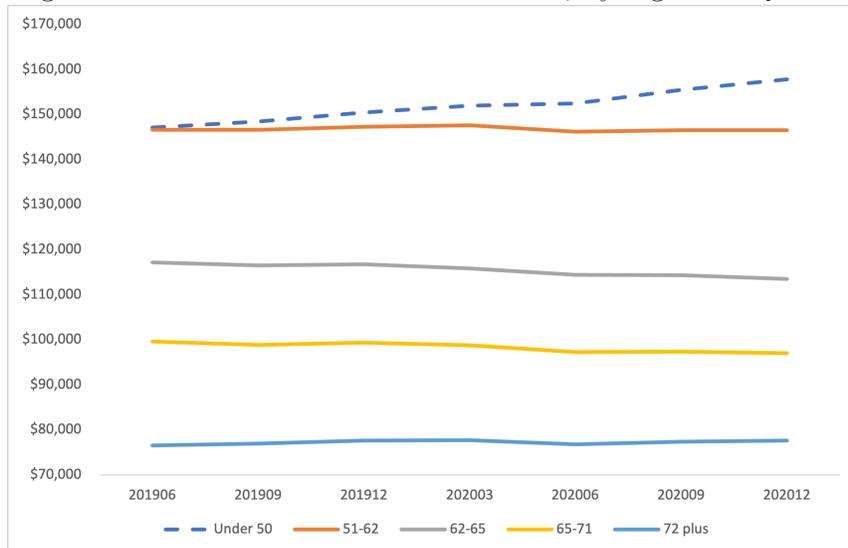
One year into the COVID-19 pandemic, these data do not indicate widespread economic hardship among current Social Security beneficiaries or those nearer to claiming ages. On average people in their 50s on the cusp of retirement have thus far weathered the pandemic without taking on excessive debt loads. Lower-income and more economically vulnerable populations have had more challenges, and may also struggle when loan payment accommodations expire. It is too soon to predict how people currently in the labor market will change their assumptions about work and savings, or decisions about claiming OASI or SSDI benefits.

The most recent Social Security actuarial estimates (Office of the Chief Actuary, 2021) assume lower labor productivity and output (as well as slowing population growth and rising mortality rate). Rising debt loads for households are not likely to be a drag that exacerbates any economic slowdowns, but reduced access to credit could be a potential challenge for people who need to borrow for housing or other activities. Ongoing monitoring of trends in

the credit data may prove useful to understand beneficiaries' economic well-being.

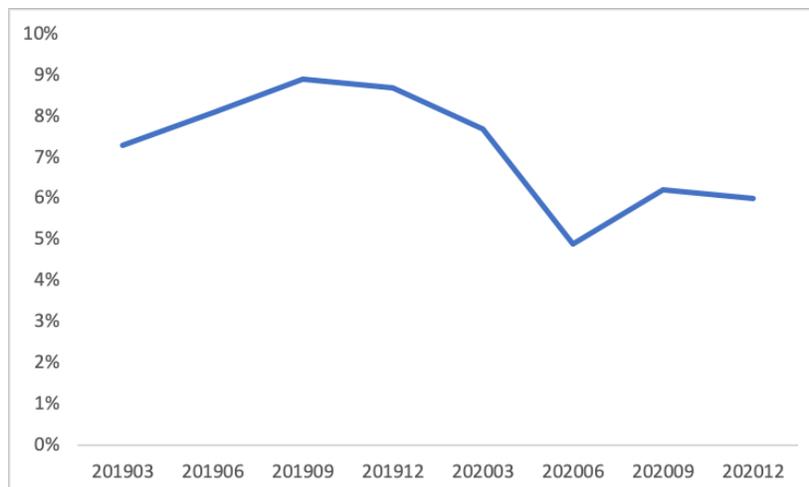
6 Figures

Figure 1: Total Household Debt Balance, by Age and Quarter



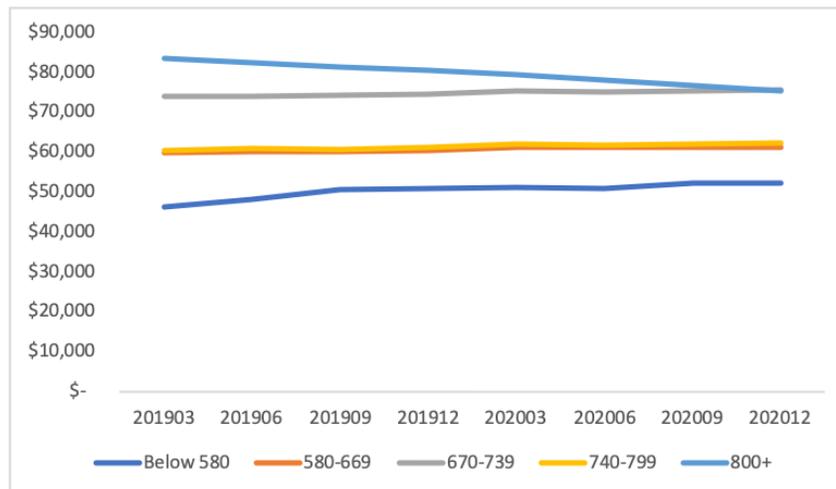
Source: Experian National Data Sample 2019-20. N=2.5M. Figure shows relatively flat total debt balances for people age 51 and older, with the lowest balances among people age 72 and older. Debt levels rise modestly for people age 18 to 50.

Figure 2: AFS Inquiries by Quarter, Share of Subprime Consumers (credit score < 580) Age 62+ with Inquiries



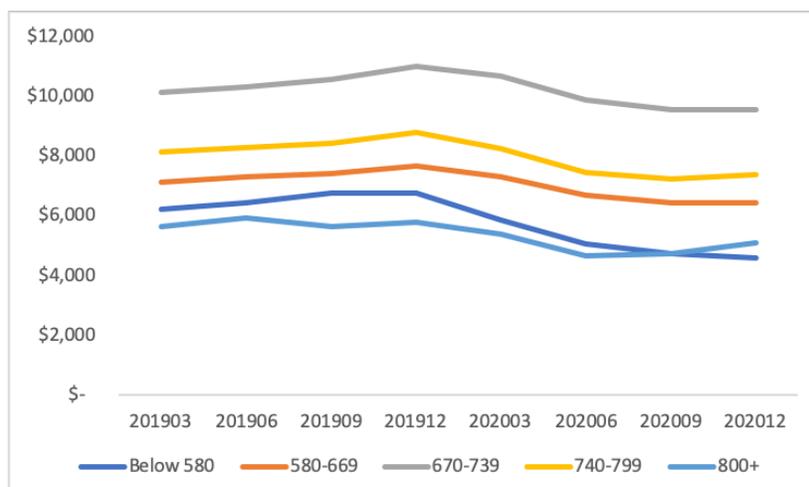
Source: Experian Clarity Matched Sample conditional on credit score category in 2019 below 580. N=310,693. Figure shows a decline from around 8% to 5% in Q2-2020 after the pandemic in the rate of people seeking AFS credit. By Q4-2020 level rise to 6%.

Figure 3: Household Mortgage Balance, by Credit Score and Quarter Among Older Borrowers



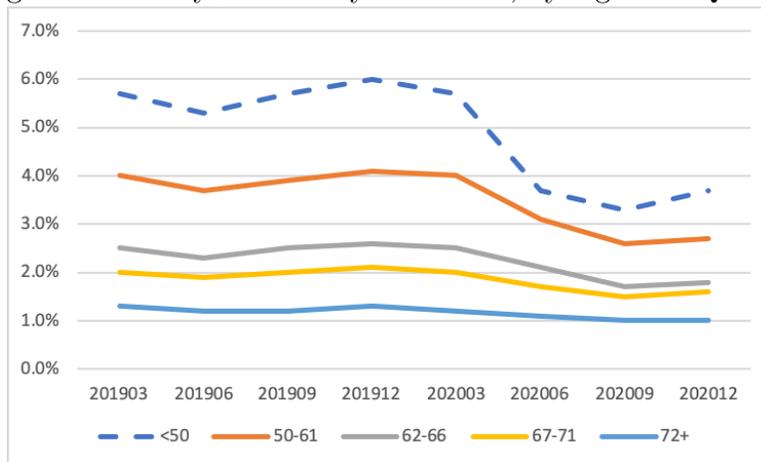
Source: Experian National Data Sample 2019-20 conditional on age. Figure shows relatively flat or declining mortgage debt balances for people age 51 and older, with the lowest balances among people with the lowest credit scores (below 580). Debt levels rise modestly for people with lower scores and decline among those with the highest scores (800+).

Figure 4: Household Credit Card Balance, by Credit Score and Quarter, Among Older Borrowers



Source: Experian National Data Sample 2019-20. Figure shows relatively declining credit card debt balances after Q1-2020 for people age 51 and older, with the lowest balances among people with the lowest credit scores (below 580) and the highest (800+). Debt levels rise modestly for people with the highest scores (800+) since Q2-2020.

Figure 5: 60-Day+ Late Payment Rate, by Age and Quarter



Source: Experian National Data Sample 2019-20. Figure shows lower default rates for all age group, with people 50 and under declining from 6% down to 3% after Q2-2020. The oldest age cohorts have the lowest default rates.

7 Tables

Table 1: Summary Distributional Statistics for Demographic and Financial Covariate Factors by Age: Q4-2019

	Under 50	50-61	62-66	67-71	72+
HH Size 1	16.5	16.9	18.8	20.2	20.6
HH Size 2	36.1	34.4	39.6	42.9	39.4
HH Size 3+	47.4	48.7	41.6	36.9	40.0
HH Decrease	19.8	17.2	14.9	12.9	12.2
HH Increase	20.2	17.4	13.8	12.2	12.6
HH No Chg	60.1	65.4	71.2	74.9	75.2
Men	52.3	49.7	48.5	48.3	46.4
Women	47.7	50.3	51.5	51.7	53.6
Inc P25	38.4	16.9	11.9	9.3	4.8
Inc P25-50	24.0	21.8	20.0	19.8	28.3
Inc P50-75	20.2	26.4	30.6	33.9	41.4
Inc P75+	17.4	34.9	37.5	36.9	25.4
<580	23.3	13.0	7.9	5.8	3.4
580-669	24.6	21.1	18.2	17.2	29.7
670-739	22.1	18.8	16.9	15.6	15.9
740-799	18.4	19.8	22.2	23.5	21.7
800+	11.4	26.9	34.7	37.8	29.1
No credit score	0.3	0.3	0.2	0.1	0.1
No DTI	6.8	7.8	12.4	15.4	22.4
DTI 1-29	67.9	70.1	70.3	67.8	43.6
DTI 30+	10.9	10.5	6.3	4.5	1.6
Missing	14.4	11.6	11.0	12.3	32.4
No Mortgage	52.6	47.1	53.2	58.2	67.5
Has Mortgage	47.4	52.9	46.8	41.8	32.5
Maj Black Zip	5.6	5.0	4.4	4.8	4.6
Maj Latinx Zip	11.1	9.3	7.9	6.9	6.5
Maj White Zip	75.5	79.0	81.6	82.9	83.9
No Maj Zip	7.9	6.7	6.1	5.4	5.0

Source: Experian National Data Sample 2019-20. Each factor is share of total. Each section may not sum to 100 due to rounding. HH Size and change based on number of consumers per address in credit record and does not represent standard definitions for households in other data. Income based on Experian 'Insight' imputed from tax form 1040-based models. Zip code race based on Census ACS shares of total population in zip code.

Table 2: Summary Statistics for Credit Outcomes by Age: Q4-2019–Q4-2020

	Under 50	50-61	62-66	67-71	72-
Δ Total Balance	7,152 (201,167)	-1,226 (205,625)	-3,618 (200,154)	-2,612 (175,380)	-291 (140,366)
Δ Mortgage Balance	5,226 (158,979)	-1,154 (157,387)	-2,463 (149,824)	-1,416 (133,031)	89 (110,104)
Δ Cr Card Balance	-1,359 (15,622)	-1,647 (16,834)	-1,577 (17,539)	-1,304 (14,572)	-942 (11,552)
Approval Rate 2019Q4	0.623 (0.713)	0.724 (0.750)	0.737 (0.726)	0.752 (0.719)	0.715 (0.684)
Approval Rate 2020Q4	0.573 (0.708)	0.626 (0.726)	0.622 (0.705)	0.617 (0.684)	0.579 (0.650)
Δ Apprv Rate	-0.027 (0.945)	-0.077 (0.996)	-0.090 (0.967)	-0.107 (0.960)	-0.130 (0.913)
Δ Limit Decrease	0.040 (0.532)	0.052 (0.569)	0.053 (0.574)	0.055 (0.571)	0.028 (0.522)
Δ AFS Inquiry Q2Q320	-0.013 (0.312)	-0.011 (0.243)	-0.006 (0.187)	-0.005 (0.157)	-0.002 (0.104)
Δ 60+ Late	-0.023 (0.274)	-0.014 (0.228)	-0.007 (0.185)	-0.005 (0.171)	-0.003 (0.135)
Accommodations-CC	0.298 (0.457)	0.160 (0.366)	0.093 (0.291)	0.063 (0.243)	0.028 (0.164)
Accommodations-CC-Stu	0.082 (0.275)	0.089 (0.284)	0.061 (0.239)	0.046 (0.210)	0.022 (0.146)
Obs	1,256,634	504,509	212,881	148,973	394,181

Source: Experian National Data Sample 2019-20. Δ is difference between Q4-2020 and Q4-2019 levels in whole 2020 \$s, except AFS which is Q2+Q3 differences. Approval rate is ratio of approved credit lines to applications, conditional on at least one application. 60+ late is rate of 60 day or more late payments. Accommodation is a payment reduction or deferral in place in 2020, excluding credit cards (-CC), and then excluding credit cards and student loans (-Stu). Mean values. Standard deviation in parentheses (SD).

Table 3: Total Household Debt by Age: Q4-2019 Balances and Balance Changes for Q4-2019-Q4-2020

	Under 50		50-61		62-66		67-71		72+	
	2019	Δ	2019	Δ	2019	Δ	2019	Δ	2019	Δ
All	153,927	7,152	151,773	-1,226	120,812	-3,618	101,745	-2,612	77,710	-291
HH Size 1	50,887	37,332	57,564	18,420	44,473	14,117	38,396	13,653	18,368	12,583
HH Size 2	157,719	15,776	132,180	3,492	97,207	1,199	80,667	562	49,377	3,396
HH Size 3+	186,768	-9,874	198,319	-11,378	177,700	-16,201	160,844	-15,185	136,229	-10,561
HH Decrease	182,833	-55,548	207,509	-60,825	196,457	-68,933	176,287	-66,147	142,340	-55,007
HH Increase	119,445	72,929	147,935	58,927	120,592	67,263	108,617	70,352	81,831	66,102
HH No Chg	155,999	5,686	138,162	-1,624	105,021	-3,711	87,804	-3,607	66,495	-2,483
Men	155,910	7,213	157,112	-1,691	125,302	-3,016	106,148	-2,822	81,415	-1,100
Women	157,360	7,305	147,384	-676	115,254	-3,987	96,469	-2,373	73,139	532
Inc P25	87,842	6,569	65,677	4,413	63,232	3,880	58,087	6,585	57,045	872
Inc P25-50	121,052	9,383	92,813	5,717	86,198	1,787	78,668	1,248	73,536	2,382
Inc P50-75	169,807	14,027	126,200	2,269	93,189	-281	78,308	-148	63,548	1,612
Inc P75+	326,272	-2,588	249,764	-10,948	180,185	-11,617	146,681	-9,270	109,390	-6,594
No DTI	114,216	10,057	64,740	6,689	49,990	3,715	42,706	3,322	40,821	3,369
DTI 1-29	155,735	9,068	153,329	-1,536	125,577	-4,417	109,729	-4,931	89,793	-3,455
DTI 30+	277,869	-2,924	308,668	-9,858	302,608	-17,034	279,520	-6,738	295,922	-19,659
No Mortgage	32,733	36,365	28,005	22,709	22,073	15,937	18,546	12,732	12,320	11,619
Has Mortgage	288,536	-25,295	261,970	-22,536	232,863	-25,810	217,528	-23,966	213,493	-25,020
<580	88,140	4,279	85,081	2,973	87,545	797	83,282	2,177	80,443	1,782
580-669	125,568	7,503	122,123	1,932	106,225	-1,083	94,555	1,092	82,369	1,412
670-739	166,430	10,223	164,755	2,837	132,278	-10	118,808	-1,142	92,376	865
740-799	190,818	12,356	165,142	710	119,324	-1,821	94,484	-1,144	64,635	1,033
800+	268,269	-2,008	189,573	-10,090	131,753	-8,872	105,473	-6,597	74,377	-3,917
No credit score	49,017	4,483	47,578	6,522	44,902	-22	47,314	15,460	79,999	8,946
Maj Black Zip	119,551	1,046	133,585	-9,748	118,430	-10,300	104,646	-6,121	75,800	-3,582
Maj Latinx Zip	117,750	8,444	122,932	4,964	113,414	-209	98,685	369	77,443	1,837
Maj White Zip	160,680	7,285	154,544	-1,535	118,852	-3,608	99,696	-2,657	75,889	-197
Obs	1,256,634	1,256,634	504,509	504,509	212,881	212,881	148,973	148,973	394,181	394,181

Source: Experian National Data Sample 2019-20. Note: Δ is change in balance Q4-2019-Q4-2020. Mean values.

Table 4: Involuntary Credit Line Cut Rates by Age: Q4-2019 Levels and Changes Q4-2019–Q4-2020

	Under 50		50-61		62-66		67-71		72+	
	2019	Δ	2019	Δ	2019	Δ	2019	Δ	2019	Δ
All	0.238	0.040	0.327	0.052	0.340	0.053	0.341	0.055	0.274	0.028
HH Size 1	0.222	0.033	0.283	0.045	0.307	0.049	0.318	0.053	0.281	0.034
HH Size 2	0.268	0.044	0.333	0.053	0.351	0.063	0.356	0.063	0.311	0.042
HH Size 3+	0.222	0.040	0.339	0.053	0.345	0.047	0.335	0.046	0.235	0.011
HH Decrease	0.227	0.041	0.330	0.053	0.348	0.049	0.343	0.051	0.259	0.022
HH Increase	0.234	0.042	0.331	0.053	0.342	0.050	0.335	0.054	0.262	0.023
HH No Chg	0.244	0.040	0.326	0.051	0.338	0.055	0.341	0.056	0.279	0.030
Men	0.221	0.033	0.292	0.037	0.297	0.042	0.299	0.043	0.245	0.020
Women	0.264	0.049	0.367	0.068	0.385	0.066	0.383	0.068	0.304	0.036
Inc P25	0.173	0.014	0.216	0.012	0.226	0.016	0.230	0.009	0.219	-0.001
Inc P25-50	0.222	0.049	0.248	0.039	0.243	0.035	0.239	0.026	0.146	-0.019
Inc P50-75	0.297	0.070	0.366	0.070	0.367	0.068	0.369	0.070	0.299	0.040
Inc P75+	0.338	0.053	0.402	0.065	0.407	0.064	0.397	0.068	0.387	0.066
No DTI	0.146	0.067	0.241	0.054	0.269	0.049	0.271	0.057	0.285	0.076
DTI 1-29	0.256	0.053	0.361	0.064	0.383	0.070	0.396	0.073	0.413	0.069
DTI 30+	0.378	0.092	0.434	0.102	0.449	0.094	0.455	0.103	0.480	0.095
No Mortgage	0.205	0.030	0.274	0.039	0.299	0.044	0.310	0.047	0.261	0.027
Has Mortgage	0.276	0.052	0.375	0.063	0.386	0.064	0.384	0.066	0.302	0.029
<580	0.259	-0.055	0.301	-0.068	0.310	-0.084	0.333	-0.093	0.329	-0.121
580-669	0.205	0.061	0.247	0.050	0.225	0.032	0.203	0.016	0.094	-0.018
670-739	0.191	0.084	0.279	0.085	0.285	0.069	0.288	0.052	0.256	-0.027
740-799	0.254	0.070	0.357	0.075	0.360	0.073	0.356	0.070	0.330	0.076
800+	0.343	0.058	0.420	0.071	0.423	0.076	0.418	0.087	0.421	0.085
No credit score	0.005	0.012	0.004	0.003	0.003	0.009	0.007	0.020	0.017	0.013
Maj Black Zip	0.213	0.026	0.285	0.037	0.304	0.047	0.315	0.046	0.254	0.023
Maj Latinx Zip	0.233	0.046	0.302	0.052	0.306	0.056	0.317	0.047	0.255	0.022
Maj White Zip	0.241	0.041	0.333	0.054	0.345	0.055	0.344	0.057	0.277	0.029
Obs	1,256,634	1,256,634	504,509	504,509	212,881	212,881	148,973	148,973	394,181	394,181

Source: Experian National Data Sample 2019-20. Q42019 value is an indicator of a consumer with a line cut. Note: Δ is change in rate of line cuts from Q4-2019 to Q4-2020. Mean values.

Table 5: Credit Approval Rate for Consumers by Age: Q4-2019 and Q4-2020

	Under 50		50-61		62-66		67-71		72+	
	2019	2020	2019	2020	2019	2020	2019	2020	2019	2020
All	0.623	0.573	0.724	0.626	0.737	0.622	0.752	0.617	0.715	0.579
HH Size 1	0.577	0.541	0.679	0.593	0.711	0.612	0.740	0.626	0.717	0.573
HH Size 2	0.658	0.597	0.739	0.642	0.764	0.641	0.762	0.619	0.736	0.599
HH Size 3+	0.612	0.565	0.727	0.625	0.723	0.610	0.749	0.612	0.687	0.558
HH Decrease	0.570	0.562	0.689	0.618	0.692	0.606	0.715	0.611	0.664	0.562
HH Increase	0.598	0.574	0.699	0.636	0.696	0.607	0.705	0.614	0.652	0.557
Men	0.615	0.564	0.691	0.597	0.692	0.587	0.709	0.588	0.679	0.553
Women	0.642	0.593	0.757	0.660	0.780	0.662	0.794	0.647	0.750	0.608
Inc P25	0.506	0.500	0.603	0.559	0.657	0.582	0.679	0.584	0.662	0.523
Inc P25-50	0.652	0.602	0.686	0.622	0.699	0.620	0.708	0.617	0.655	0.556
Inc P50-75	0.741	0.643	0.808	0.694	0.808	0.692	0.819	0.675	0.765	0.625
Inc P75+	0.730	0.619	0.756	0.617	0.734	0.589	0.741	0.583	0.706	0.561
No DTI	0.374	0.485	0.419	0.512	0.496	0.531	0.499	0.574	0.523	0.545
DTI 1-29	0.646	0.591	0.740	0.639	0.763	0.636	0.784	0.628	0.761	0.604
DTI 30+	0.901	0.701	0.917	0.713	0.890	0.697	0.888	0.682	0.819	0.552
No Mortgage	0.538	0.527	0.647	0.597	0.699	0.628	0.726	0.630	0.714	0.605
Has Mortgage	0.721	0.622	0.784	0.646	0.772	0.618	0.779	0.607	0.716	0.553
<580	0.349	0.395	0.397	0.426	0.411	0.418	0.428	0.424	0.373	0.355
580-669	0.732	0.638	0.776	0.663	0.745	0.640	0.745	0.609	0.669	0.518
670-739	0.755	0.662	0.819	0.685	0.795	0.658	0.803	0.662	0.720	0.576
740-799	0.713	0.627	0.809	0.676	0.813	0.677	0.818	0.657	0.797	0.626
800+	0.656	0.604	0.737	0.628	0.751	0.616	0.760	0.613	0.731	0.606
No credit score	0.011	0.190	0.000	0.183	0.000	0.425	0.000	0.292	0.000	0.200
Maj Black Zip	0.504	0.496	0.658	0.596	0.672	0.619	0.726	0.628	0.696	0.539
Maj Latinx Zip	0.603	0.551	0.687	0.596	0.683	0.592	0.685	0.588	0.655	0.534
Maj White Zip	0.639	0.587	0.738	0.636	0.751	0.632	0.765	0.622	0.724	0.589
Obs	497,583	490,789	173,441	161,653	59,319	51,685	35,228	29,783	48,020	37,163

Levels as of Q4-2019 and Q4-2020 (not Δ s), conditional on a credit application. Source: Experian National Data Sample 2019-20. Mean values.

Table 6: Accommodations Rates for Loans (modified or deferred payments) by Age in 2020
 - Excluding Credit Cards (CC), or Credit Cards *and* Student Loans (St)

	Under 50		50-61		62-66		67-71		72+	
	Acc-CC	Acc-CC,-St	Acc-CC	Acc-CC,-St	Acc-CC	Acc-CC,-St	Acc-CC	Acc-CC,-St	Acc-CC	Acc-CC,-St
All	0.298	0.082	0.160	0.089	0.093	0.061	0.063	0.046	0.028	0.022
HH Size 1	0.288	0.079	0.138	0.075	0.088	0.054	0.059	0.040	0.028	0.021
HH Size 2	0.287	0.092	0.143	0.084	0.081	0.055	0.056	0.043	0.027	0.022
HH Size 3+	0.309	0.076	0.179	0.096	0.108	0.070	0.073	0.053	0.029	0.022
HH Decrease	0.321	0.083	0.182	0.098	0.116	0.075	0.079	0.056	0.035	0.027
HH Increase	0.309	0.086	0.181	0.101	0.111	0.072	0.081	0.060	0.033	0.026
HH No Chg	0.286	0.081	0.148	0.083	0.085	0.056	0.057	0.042	0.026	0.020
Men	0.260	0.085	0.150	0.094	0.095	0.065	0.065	0.049	0.030	0.024
Women	0.347	0.083	0.172	0.085	0.093	0.058	0.061	0.044	0.026	0.020
Inc P25	0.311	0.059	0.147	0.077	0.105	0.069	0.087	0.064	0.059	0.048
Inc P25-50	0.291	0.080	0.149	0.077	0.088	0.054	0.061	0.042	0.018	0.014
Inc P50-75	0.314	0.095	0.161	0.084	0.084	0.052	0.052	0.036	0.021	0.016
Inc P75+	0.259	0.123	0.171	0.106	0.100	0.069	0.068	0.052	0.044	0.036
No DTI	0.111	0.007	0.019	0.005	0.009	0.004	0.006	0.004	0.003	0.002
DTI 1-29	0.318	0.080	0.164	0.088	0.102	0.065	0.074	0.053	0.053	0.041
DTI 30+	0.454	0.238	0.380	0.245	0.304	0.225	0.248	0.203	0.229	0.200
No Mortgage	0.277	0.061	0.120	0.054	0.062	0.034	0.041	0.026	0.016	0.011
Has Mortgage	0.321	0.105	0.195	0.119	0.129	0.091	0.093	0.073	0.052	0.043
<580	0.391	0.088	0.237	0.114	0.173	0.100	0.135	0.085	0.085	0.059
580-669	0.323	0.098	0.198	0.111	0.125	0.080	0.081	0.058	0.019	0.015
670-739	0.334	0.080	0.194	0.103	0.128	0.080	0.096	0.067	0.041	0.030
740-799	0.191	0.064	0.122	0.072	0.069	0.048	0.046	0.036	0.023	0.019
800+	0.161	0.071	0.098	0.062	0.058	0.042	0.041	0.033	0.027	0.022
No credit score	0.007	0.003	0.002	0.001	0.000	0.000	0.000	0.000	0.003	0.003
Maj Black Zip	0.377	0.095	0.227	0.117	0.144	0.084	0.109	0.072	0.049	0.036
Maj Latinx Zip	0.264	0.098	0.170	0.115	0.123	0.095	0.093	0.078	0.047	0.041
Maj White Zip	0.299	0.080	0.154	0.083	0.087	0.056	0.057	0.041	0.025	0.019
Obs	1,256,634	1,256,634	504,509	504,509	212,881	212,881	148,973	148,973	394,181	394,181

Source: Experian National Data Sample 2020 only. Acc-CC are accommodations excluding credit card loans. Acc-CC,-St exclude both credit cards and student loans. Note: 2019 rates not available (Δ unavailable).

Table 7: Age-based Differences in Changes in All Balances (000), Mortgages (000), Credit Cards (000), Credit Approval Rates, Credit Limit Cuts, AFS (Clarity) Inquires, Delinquencies and Accommodations, With Controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Δ Tot Bal (000)l	Δ Mort Bal (000)	Δ CC (000)	Δ Apprv Rate	Δ Cuts Rate	Δ AFS Inq Rate	Δ 60+ Late Rate	Acc-CC Rate	Acc-CC-Stu Rate
50-61	-8.241*** (0.362)	-7.118*** (0.280)	-0.172*** (0.029)	-0.024*** (0.004)	0.003** (0.001)	-0.003*** (0.000)	-0.002*** (0.000)	-0.123*** (0.001)	0.005*** (0.000)
62-66	-13.209*** (0.509)	-11.116*** (0.383)	-0.443*** (0.044)	-0.040*** (0.007)	-0.000 (0.001)	-0.003*** (0.001)	-0.005*** (0.000)	-0.158*** (0.001)	-0.007*** (0.001)
67-71	-15.109*** (0.534)	-12.647*** (0.406)	-0.446*** (0.043)	-0.058*** (0.009)	0.001 (0.002)	-0.004*** (0.001)	-0.009*** (0.001)	-0.170*** (0.001)	-0.012*** (0.001)
72+	-16.938*** (0.383)	-14.507*** (0.295)	-0.377*** (0.030)	-0.086*** (0.008)	-0.007*** (0.001)	-0.007*** (0.000)	-0.025*** (0.000)	-0.166*** (0.001)	-0.014*** (0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	2,377,741	2,377,741	2,377,741	373,416	2,377,741	2,377,741	2,377,741	2,377,741	2,377,741
Mean	2.778	2.052	-1.358	-0.048	0.043	-0.010	-0.016	0.196	0.071
StDv	190.680	148.486	15.279	0.960	0.546	0.256	0.235	0.397	0.256

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Balances in \$1,000. Δ is change in rate Q4-2019-Q4-2020. OLS Regressions. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample Q4-2019, Q4-2020.

Table 8: Change in Total Balances (000) by Age: Q4-2019–Q4-2020

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
HH Size 2	11.364*** (0.450)	3.330*** (0.633)	3.604*** (0.876)	2.008* (0.985)	3.422*** (0.450)
HH Size 3+	9.022*** (0.459)	5.816*** (0.657)	4.289*** (1.060)	1.435 (1.147)	3.085*** (0.514)
HH Decrease	-60.700*** (0.615)	-58.218*** (1.105)	-62.556*** (1.884)	-59.879*** (2.163)	-48.714*** (1.128)
HH Increase	62.948*** (0.598)	59.664*** (1.053)	71.567*** (1.984)	75.116*** (2.430)	69.408*** (1.116)
Women	0.182 (0.362)	0.705 (0.573)	-1.855* (0.867)	-0.240 (0.906)	0.727 (0.453)
Inc P25	-9.428*** (0.833)	-6.324*** (1.553)	0.590 (2.654)	4.214 (3.100)	-2.765 (1.942)
Inc P25-50	-5.498*** (0.778)	0.464 (1.136)	2.602 (1.805)	1.757 (1.866)	1.922* (0.951)
Inc P50-75	3.804*** (0.679)	2.636*** (0.790)	3.385*** (0.994)	2.875** (1.035)	2.000*** (0.597)
<580	-16.455*** (1.012)	-0.771 (1.846)	-3.051 (4.355)	-4.255 (5.655)	1.174 (3.679)
580-669	-9.873*** (0.856)	-0.083 (1.384)	-1.422 (2.345)	-1.279 (2.811)	1.830 (1.525)
670-739	-1.402* (0.703)	5.127*** (0.880)	4.643*** (1.249)	1.459 (1.736)	3.567*** (0.894)
740-799	0.870 (0.638)	2.357*** (0.638)	0.323 (0.819)	-0.532 (0.822)	0.450 (0.480)
DTI 1-29	9.650*** (0.653)	9.890*** (0.796)	7.012*** (0.942)	4.139*** (0.836)	3.235*** (0.453)
DTI 30+	18.315*** (1.003)	13.988*** (1.626)	6.909 (3.531)	13.603** (4.670)	-0.061 (5.104)
Mortgage	-67.434*** (0.467)	-47.629*** (0.748)	-40.638*** (1.058)	-35.445*** (1.054)	-34.462*** (0.571)
Maj Black Zip	-8.839*** (1.169)	-10.627*** (2.359)	-8.244* (3.834)	-4.796 (3.359)	-4.574** (1.727)
Maj Latinx Zip	-3.985*** (0.471)	1.276 (0.884)	-0.211 (1.288)	1.279 (1.590)	0.627 (0.713)
Obs	1,153,658	486,122	207,115	145,713	385,133
Mean	7.257	-1.180	-3.516	-2.590	-0.225
StDv	199.177	204.165	199.971	175.770	140.393

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Balances in \$1,000. Δ is change in rate Q4-2019-Q4-2020. OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample Q4-2019, Q4-2020.

Table 9: Change in Mortgage Balances (000) by Age: Q4-2019–Q4-2020

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
HH Size 2	-1.431*** (0.359)	-2.503*** (0.487)	-0.615 (0.665)	-0.841 (0.742)	-0.249 (0.357)
HH Size 3+	-11.386*** (0.364)	-4.337*** (0.520)	-3.722*** (0.807)	-4.941*** (0.896)	-6.455*** (0.421)
HH Decrease	-32.821*** (0.476)	-34.743*** (0.835)	-39.146*** (1.390)	-38.010*** (1.636)	-32.027*** (0.867)
HH Increase	44.439*** (0.474)	38.639*** (0.809)	46.391*** (1.487)	49.201*** (1.813)	47.537*** (0.882)
Women	-1.046*** (0.291)	0.472 (0.443)	-1.366* (0.652)	0.230 (0.691)	0.528 (0.356)
Inc P25	4.978*** (0.670)	7.929*** (1.115)	9.673*** (1.887)	10.028*** (2.257)	3.921** (1.391)
Inc P25-50	7.125*** (0.632)	9.103*** (0.853)	8.302*** (1.319)	5.533*** (1.393)	5.268*** (0.739)
Inc P50-75	12.034*** (0.575)	8.392*** (0.609)	7.931*** (0.756)	6.280*** (0.817)	5.039*** (0.484)
<580	3.281*** (0.775)	7.059*** (1.336)	3.347 (2.989)	1.777 (3.882)	3.167 (2.562)
580-669	5.858*** (0.691)	6.886*** (1.016)	3.450* (1.702)	2.176 (2.055)	2.370* (1.128)
670-739	8.806*** (0.619)	8.200*** (0.720)	6.011*** (0.976)	2.538 (1.317)	2.758*** (0.712)
740-799	12.331*** (0.594)	8.780*** (0.567)	4.996*** (0.706)	3.697*** (0.713)	2.232*** (0.417)
DTI 1-29	0.221 (0.591)	-6.128*** (0.663)	-6.190*** (0.725)	-5.978*** (0.681)	-4.439*** (0.377)
DTI 30+	-14.507*** (0.788)	-16.195*** (1.139)	-17.630*** (2.400)	-8.942** (3.144)	-17.859*** (3.525)
Maj Black Zip	-4.125*** (0.779)	-7.188*** (1.562)	-5.625* (2.485)	-3.222 (2.209)	-2.886* (1.149)
Maj Latinx Zip	1.222** (0.396)	1.794** (0.696)	-0.577 (1.034)	0.043 (1.235)	0.723 (0.598)
Obs	1,153,658	486,122	207,115	145,713	385,133
Mean	5.264	-1.132	-2.384	-1.405	0.141
StDv	157.699	156.247	149.381	132.910	109.844

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Balances in \$1,000. Δ is change in rate Q4-2019-Q4-2020. OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample Q4-2019, Q4-2020.

Table 10: Change in Credit Card Balances (000) by Age: Q4-2019–Q4-2020

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
HH Size 2	-0.089** (0.028)	-0.427*** (0.041)	-0.346*** (0.061)	-0.429*** (0.063)	-0.205*** (0.030)
HH Size 3+	-1.257*** (0.029)	-1.154*** (0.043)	-1.251*** (0.070)	-1.279*** (0.077)	-1.117*** (0.036)
HH Dec	-4.622*** (0.055)	-4.567*** (0.103)	-5.047*** (0.192)	-4.737*** (0.205)	-3.991*** (0.105)
HH Inc	3.277*** (0.036)	3.215*** (0.064)	4.081*** (0.122)	4.270*** (0.149)	3.802*** (0.068)
Women	-0.011 (0.028)	0.021 (0.047)	-0.046 (0.076)	-0.068 (0.074)	0.018 (0.037)
Inc P25	2.650*** (0.066)	3.196*** (0.133)	3.227*** (0.222)	3.193*** (0.266)	1.979*** (0.166)
Inc P25-50	2.084*** (0.061)	2.904*** (0.099)	2.305*** (0.155)	2.099*** (0.166)	1.293*** (0.079)
Inc P50-75	1.241*** (0.052)	1.699*** (0.067)	1.344*** (0.086)	1.116*** (0.089)	0.790*** (0.051)
<580	-3.616*** (0.076)	-3.851*** (0.148)	-4.178*** (0.379)	-4.388*** (0.487)	-3.091*** (0.312)
580-669	-3.241*** (0.063)	-3.302*** (0.121)	-3.100*** (0.195)	-2.760*** (0.236)	-2.003*** (0.121)
670-739	-2.625*** (0.050)	-2.581*** (0.071)	-2.083*** (0.109)	-1.939*** (0.139)	-1.372*** (0.075)
740-799	-1.809*** (0.041)	-2.222*** (0.052)	-1.937*** (0.074)	-1.621*** (0.073)	-0.971*** (0.040)
DTI 1-29	-0.048 (0.043)	-0.279*** (0.057)	-0.303*** (0.066)	-0.502*** (0.061)	-0.470*** (0.035)
DTI 30+	0.056 (0.074)	-0.782*** (0.131)	-1.406*** (0.307)	-0.826* (0.378)	-1.910*** (0.408)
Mortgage	-2.153*** (0.038)	-1.584*** (0.063)	-1.590*** (0.094)	-1.396*** (0.087)	-1.445*** (0.047)
Maj Black Zip	-1.254*** (0.158)	-2.049*** (0.311)	-1.888*** (0.503)	-1.509** (0.460)	-0.697** (0.219)
Maj Latinx Zip	0.185*** (0.031)	0.134* (0.057)	0.089 (0.099)	0.182 (0.126)	0.032 (0.059)
Obs	1,153,658	486,122	207,115	145,713	385,133
Mean	-1.354	-1.639	-1.564	-1.287	-0.935
StDv	15.402	16.743	17.505	14.523	11.486

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Balances in \$1,000. Δ is change in rate Q4-2019–Q4-2020. OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample Q4-2019, Q4-2020.

Table 11: Change in Credit Approval Rates by Age: Q4-2019–Q4-2020

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
HH Size 2	0.005 (0.006)	0.030** (0.011)	0.019 (0.019)	-0.027 (0.024)	0.010 (0.022)
HH Size 3+	-0.006 (0.006)	0.011 (0.011)	0.022 (0.019)	-0.047 (0.026)	0.008 (0.023)
HH Decrease	0.040*** (0.005)	0.035*** (0.010)	0.010 (0.018)	0.027 (0.025)	0.055* (0.023)
HH Increase	0.027*** (0.005)	0.039*** (0.009)	0.030 (0.017)	0.028 (0.024)	0.035 (0.022)
Women	0.002 (0.004)	-0.010 (0.007)	-0.010 (0.013)	-0.022 (0.017)	-0.008 (0.016)
Inc P25	0.034*** (0.008)	0.010 (0.014)	-0.037 (0.026)	-0.014 (0.036)	-0.065* (0.033)
Inc P25-50	0.063*** (0.008)	0.039** (0.012)	0.011 (0.023)	0.039 (0.029)	-0.007 (0.027)
Inc P50-75	0.035*** (0.007)	0.035*** (0.010)	-0.008 (0.017)	0.006 (0.022)	0.012 (0.020)
<580	-0.021* (0.010)	0.044** (0.016)	0.080** (0.029)	0.033 (0.040)	0.083* (0.036)
580-669	-0.077*** (0.010)	-0.027* (0.014)	0.030 (0.024)	-0.054 (0.032)	0.005 (0.029)
670-739	-0.070*** (0.009)	-0.039** (0.013)	-0.010 (0.022)	-0.031 (0.029)	0.041 (0.026)
740-799	-0.061*** (0.009)	-0.046*** (0.012)	-0.020 (0.019)	-0.036 (0.024)	-0.015 (0.021)
DTI 1-29	-0.184*** (0.010)	-0.200*** (0.019)	-0.125*** (0.031)	-0.204*** (0.044)	-0.226*** (0.031)
DTI 30+	-0.322*** (0.011)	-0.304*** (0.021)	-0.196*** (0.036)	-0.288*** (0.052)	-0.346*** (0.041)
Mortgage	-0.021*** (0.005)	-0.032*** (0.009)	-0.033* (0.015)	-0.024 (0.020)	-0.002 (0.018)
Maj Black Zip	0.001 (0.008)	-0.000 (0.016)	0.069* (0.029)	0.047 (0.038)	-0.020 (0.035)
Maj Latinx Zip	-0.020*** (0.006)	-0.003 (0.011)	0.008 (0.021)	0.027 (0.030)	0.009 (0.026)
Obs	243,044	80,302	23,292	12,680	14,098
Mean	-0.027	-0.076	-0.090	-0.107	-0.129
StDv	0.948	0.997	0.968	0.959	0.912

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Δ is change in rate Q4-2019–Q4-2020 for consumers with applications for credit in both periods. OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample Q4-2019, Q4-2020.

Table 12: Change in Rate of Involuntary Credit Limit Decreases by Age: Q4-2019–Q4-2020

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
HH Size 2	-0.001 (0.002)	-0.006* (0.002)	0.000 (0.004)	-0.003 (0.004)	-0.004 (0.002)
HH Size 3+	0.003* (0.002)	-0.004 (0.002)	-0.008* (0.004)	-0.007 (0.004)	-0.003 (0.002)
HH Dec	0.009*** (0.001)	0.010*** (0.002)	0.005 (0.004)	0.010* (0.005)	0.010*** (0.003)
HH Inc	0.009*** (0.001)	0.007** (0.002)	0.003 (0.004)	0.009* (0.005)	0.008*** (0.003)
Women	0.017*** (0.001)	0.029*** (0.002)	0.021*** (0.003)	0.022*** (0.003)	0.015*** (0.002)
Inc P25	0.032*** (0.002)	0.042*** (0.003)	0.057*** (0.005)	0.055*** (0.007)	0.048*** (0.005)
Inc P25-50	0.022*** (0.002)	0.026*** (0.003)	0.041*** (0.005)	0.042*** (0.005)	0.033*** (0.003)
Inc P50-75	0.017*** (0.002)	0.012*** (0.002)	0.020*** (0.004)	0.025*** (0.004)	0.023*** (0.003)
<580	-0.118*** (0.003)	-0.148*** (0.004)	-0.169*** (0.006)	-0.181*** (0.008)	-0.169*** (0.006)
580-669	-0.014*** (0.002)	-0.032*** (0.003)	-0.048*** (0.005)	-0.059*** (0.006)	-0.012** (0.004)
670-739	0.001 (0.002)	-0.007* (0.003)	-0.029*** (0.004)	-0.053*** (0.005)	-0.080*** (0.004)
740-799	-0.004 (0.002)	-0.005* (0.003)	-0.014*** (0.004)	-0.028*** (0.004)	-0.019*** (0.003)
DTI 1-29	0.003 (0.002)	0.024*** (0.003)	0.030*** (0.004)	0.022*** (0.004)	-0.001 (0.003)
DTI 30+	0.050*** (0.003)	0.078*** (0.004)	0.073*** (0.007)	0.077*** (0.009)	0.049*** (0.008)
Mortgage	-0.009*** (0.001)	-0.010*** (0.002)	-0.001 (0.003)	-0.000 (0.003)	-0.003 (0.002)
Maj Black Zip	0.013*** (0.002)	0.008* (0.004)	0.011 (0.006)	0.008 (0.007)	0.006 (0.004)
Maj Latinx Zip	0.012*** (0.002)	0.007* (0.003)	0.013** (0.005)	0.002 (0.006)	0.003 (0.003)
Obs	1,153,658	486,122	207,115	145,713	385,133
Mean	0.040	0.053	0.054	0.056	0.028
StDv	0.534	0.571	0.576	0.572	0.524

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Δ is change in rate Q4-2019–Q4-2020. OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample Q4-2019, Q4-2020.

Table 13: 2019-2020 Change in AFS Inquiry Rate in Clarity Data by Age: Q2+Q3 Combined

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
HH Size 2	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.002 (0.001)	-0.002*** (0.000)
HH Size 3+	-0.002* (0.001)	-0.002 (0.001)	-0.003* (0.001)	-0.003* (0.001)	-0.002*** (0.001)
HH Decrease	0.005*** (0.001)	0.001 (0.001)	0.003* (0.001)	0.002 (0.001)	0.001* (0.001)
HH Increase	0.004*** (0.001)	0.002* (0.001)	0.002 (0.001)	0.001 (0.001)	-0.001* (0.001)
Women	-0.002** (0.001)	-0.002* (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.000)
Inc P25	0.001 (0.001)	-0.013*** (0.002)	-0.013*** (0.003)	-0.016*** (0.003)	-0.010*** (0.002)
Inc P25-50	0.000 (0.001)	-0.004*** (0.001)	-0.002 (0.001)	0.001 (0.002)	-0.001 (0.001)
Inc P50-75	0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)	0.001 (0.001)	-0.000 (0.000)
<580	-0.051*** (0.001)	-0.048*** (0.002)	-0.042*** (0.004)	-0.039*** (0.004)	-0.027*** (0.003)
580-669	-0.014*** (0.001)	-0.017*** (0.001)	-0.013*** (0.002)	-0.019*** (0.002)	-0.006*** (0.001)
670-739	0.004*** (0.001)	0.003*** (0.001)	0.002 (0.001)	-0.001 (0.001)	-0.002* (0.001)
740-799	0.003*** (0.000)	0.002** (0.001)	0.001 (0.001)	-0.000 (0.001)	0.001 (0.000)
DTI 1-29	-0.011*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.001 (0.001)	-0.001 (0.000)
DTI 30+	-0.041*** (0.001)	-0.030*** (0.002)	-0.023*** (0.003)	-0.030*** (0.004)	-0.025*** (0.004)
Mortgage	0.011*** (0.001)	0.004*** (0.001)	0.002** (0.001)	0.002* (0.001)	0.002*** (0.000)
Maj Black Zip	-0.002 (0.002)	-0.003 (0.002)	-0.000 (0.003)	-0.001 (0.003)	-0.001 (0.001)
Maj Latinx Zip	-0.008*** (0.001)	-0.001 (0.001)	-0.004* (0.002)	0.001 (0.002)	0.001 (0.001)
Obs	1,153,658	486,122	207,115	145,713	385,133
Mean	-0.013	-0.011	-0.006	-0.005	-0.002
StDv	0.312	0.243	0.187	0.157	0.104

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Δ is change in rate for the combined Q2+Q3 in 2019 and 2020 (Q420 unavailable). OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample Q2+Q3 for 2019, and Q2+Q3 for 2020. Consumer variables as of Q4-2019

Table 14: Change in 60+ Day Late Payment Rates by Age: Q4-2019–Q4-2020

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
HH Size 2	0.001 (0.001)	0.000 (0.001)	-0.001 (0.001)	-0.004** (0.001)	-0.001 (0.001)
HH Size 3+	-0.002* (0.001)	-0.002* (0.001)	-0.003* (0.001)	-0.005*** (0.001)	-0.002*** (0.001)
HH Decrease	0.007*** (0.001)	0.004*** (0.001)	0.002 (0.001)	0.004* (0.002)	0.003*** (0.001)
HH Increase	0.004*** (0.001)	0.002* (0.001)	0.001 (0.001)	0.003 (0.002)	0.004*** (0.001)
Women	-0.002*** (0.000)	-0.002** (0.001)	0.001 (0.001)	0.002* (0.001)	-0.001 (0.000)
Inc P25	0.031*** (0.001)	0.049*** (0.002)	0.050*** (0.003)	0.059*** (0.003)	0.043*** (0.002)
Inc P25-50	0.002* (0.001)	0.008*** (0.001)	0.010*** (0.002)	0.011*** (0.002)	0.007*** (0.001)
Inc P50-75	-0.002*** (0.001)	-0.001 (0.001)	0.001 (0.001)	-0.000 (0.001)	-0.001 (0.001)
<580	-0.217*** (0.001)	-0.215*** (0.003)	-0.200*** (0.005)	-0.204*** (0.007)	-0.185*** (0.005)
580-669	-0.031*** (0.001)	-0.042*** (0.001)	-0.042*** (0.002)	-0.049*** (0.003)	-0.042*** (0.002)
670-739	-0.006*** (0.001)	-0.002* (0.001)	-0.004*** (0.001)	-0.007*** (0.001)	-0.013*** (0.001)
740-799	-0.003*** (0.000)	-0.000 (0.000)	-0.001 (0.000)	-0.001 (0.001)	0.001** (0.000)
DTI 1-29	-0.009*** (0.001)	0.001 (0.001)	0.001 (0.001)	0.001* (0.001)	0.000 (0.000)
DTI 30+	-0.008*** (0.001)	-0.006*** (0.002)	0.006* (0.003)	-0.003 (0.004)	0.002 (0.004)
Mortgage	-0.008*** (0.001)	-0.006*** (0.001)	-0.003*** (0.001)	-0.002* (0.001)	-0.001* (0.001)
Maj Black Zip	0.003 (0.001)	-0.000 (0.002)	0.004 (0.003)	0.005 (0.003)	0.008*** (0.002)
Maj Latinx Zip	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.002)	-0.001 (0.002)	0.002 (0.001)
Obs	1,153,658	486,122	207,115	145,713	385,133
Mean	-0.024	-0.014	-0.007	-0.005	-0.003
StDv	0.275	0.228	0.185	0.171	0.135

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Δ is change in rate Q4-2019-Q4-2020. OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample Q4-2019, Q4-2020.]

Table 15: Accommodation Rates for Non-Credit Card Loans in 2020 by Age

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
HH Size 2	-0.010*** (0.001)	-0.009*** (0.001)	-0.012*** (0.002)	-0.005** (0.002)	-0.005*** (0.001)
HH Size 3+	0.017*** (0.001)	0.018*** (0.001)	-0.000 (0.002)	0.001 (0.002)	-0.003*** (0.001)
HH Decrease	0.014*** (0.001)	0.009*** (0.001)	0.012*** (0.002)	0.006** (0.002)	0.004*** (0.001)
HH Increase	0.015*** (0.001)	0.019*** (0.001)	0.010*** (0.002)	0.011*** (0.002)	0.004*** (0.001)
Women	0.075*** (0.001)	0.020*** (0.001)	-0.002 (0.001)	-0.005*** (0.001)	-0.003*** (0.001)
Inc P25	-0.105*** (0.002)	-0.163*** (0.002)	-0.112*** (0.003)	-0.066*** (0.004)	-0.028*** (0.002)
Inc P25-50	-0.080*** (0.002)	-0.109*** (0.002)	-0.074*** (0.002)	-0.045*** (0.003)	-0.023*** (0.001)
Inc P50-75	-0.006*** (0.001)	-0.054*** (0.001)	-0.037*** (0.002)	-0.027*** (0.002)	-0.018*** (0.001)
<580	0.429*** (0.002)	0.334*** (0.003)	0.251*** (0.004)	0.178*** (0.005)	0.099*** (0.003)
580-669	0.294*** (0.002)	0.230*** (0.002)	0.170*** (0.003)	0.119*** (0.003)	0.062*** (0.002)
670-739	0.247*** (0.002)	0.140*** (0.002)	0.099*** (0.002)	0.075*** (0.003)	0.045*** (0.001)
740-799	0.075*** (0.001)	0.053*** (0.001)	0.031*** (0.002)	0.019*** (0.002)	0.009*** (0.001)
DTI 1-29	0.154*** (0.001)	0.096*** (0.001)	0.057*** (0.001)	0.043*** (0.001)	0.037*** (0.001)
DTI 30+	0.234*** (0.002)	0.245*** (0.002)	0.198*** (0.004)	0.167*** (0.006)	0.180*** (0.005)
Mortgage	0.047*** (0.001)	0.033*** (0.001)	0.033*** (0.001)	0.026*** (0.001)	0.017*** (0.001)
Maj Black Zip	0.046*** (0.002)	0.053*** (0.003)	0.034*** (0.004)	0.031*** (0.004)	0.012*** (0.002)
Maj Latinx Zip	-0.051*** (0.001)	0.016*** (0.002)	0.030*** (0.003)	0.028*** (0.003)	0.016*** (0.001)
Obs	1,153,658	486,122	207,115	145,713	385,133
Mean	0.301	0.161	0.094	0.063	0.028
StDv	0.459	0.368	0.292	0.243	0.165

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Rates for 2020 (not Δ ; accommodations unavailable for 2019). OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample.

Table 16: Accommodation Rates for Non-Credit Card and Non-Student Loans in 2020 by Age

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
HH Size 2	-0.004*** (0.001)	-0.005*** (0.001)	-0.006*** (0.001)	-0.000 (0.001)	-0.003*** (0.001)
HH Size 3+	-0.008*** (0.001)	-0.001 (0.001)	-0.002 (0.002)	0.001 (0.002)	-0.003*** (0.001)
HH Decrease	0.008*** (0.001)	0.005*** (0.001)	0.008*** (0.002)	0.003 (0.002)	0.003*** (0.001)
HH Increase	0.007*** (0.001)	0.010*** (0.001)	0.006*** (0.002)	0.010*** (0.002)	0.003*** (0.001)
Women	-0.004*** (0.001)	-0.008*** (0.001)	-0.007*** (0.001)	-0.005*** (0.001)	-0.004*** (0.000)
Inc P25	-0.110*** (0.001)	-0.083*** (0.002)	-0.055*** (0.003)	-0.033*** (0.003)	-0.016*** (0.002)
Inc P25-50	-0.080*** (0.001)	-0.063*** (0.002)	-0.043*** (0.002)	-0.030*** (0.002)	-0.018*** (0.001)
Inc P50-75	-0.051*** (0.001)	-0.040*** (0.001)	-0.026*** (0.001)	-0.021*** (0.001)	-0.015*** (0.001)
<580	0.137*** (0.001)	0.155*** (0.002)	0.132*** (0.004)	0.101*** (0.004)	0.064*** (0.003)
580-669	0.107*** (0.001)	0.117*** (0.002)	0.094*** (0.003)	0.073*** (0.003)	0.045*** (0.001)
670-739	0.058*** (0.001)	0.062*** (0.001)	0.051*** (0.002)	0.044*** (0.002)	0.031*** (0.001)
740-799	0.023*** (0.001)	0.028*** (0.001)	0.018*** (0.001)	0.013*** (0.001)	0.008*** (0.001)
DTI 1-29	0.051*** (0.000)	0.052*** (0.001)	0.035*** (0.001)	0.030*** (0.001)	0.028*** (0.000)
DTI 30+	0.187*** (0.001)	0.171*** (0.002)	0.157*** (0.004)	0.146*** (0.005)	0.161*** (0.005)
Mortgage	0.015*** (0.001)	0.036*** (0.001)	0.034*** (0.001)	0.026*** (0.001)	0.018*** (0.001)
Maj Black Zip	0.021*** (0.001)	0.030*** (0.002)	0.015*** (0.003)	0.016*** (0.003)	0.008*** (0.001)
Maj Latinx Zip	0.027*** (0.001)	0.038*** (0.002)	0.037*** (0.002)	0.032*** (0.003)	0.016*** (0.001)
Obs	1,153,658	486,122	207,115	145,713	385,133
Mean	0.084	0.090	0.062	0.046	0.022
StDv	0.277	0.286	0.240	0.210	0.146

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Rates for 2020 (not changes; accommodations unavailable for 2019). OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample.

Table 17: Δ All Debt Balance (000): Stay at Home Rate at State Level as of May 2020 and Total COVID-19 Case Rate Per Capita, with Controls

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
Panel A: Stay at Home Rate					
Stayed Home More	-5.636***	-6.029***	-3.253*	-4.482**	-2.216**
	(0.657)	(1.000)	(1.491)	(1.616)	(0.746)
Moderate Stay Home	-0.790*	-1.197*	-0.315	-2.206*	0.115
	(0.386)	(0.590)	(0.861)	(0.938)	(0.421)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	1,145,317	481,938	202,792	144,447	383,105
Mean	7.724	-0.417	-3.018	-2.276	0.046
StDv	190.562	190.851	188.163	167.365	132.749
Panel B: Cases Per Capita					
Moderate Per Cap Cases	-2.008***	-1.761	-2.656*	-2.952*	0.220
	(0.575)	(0.914)	(1.279)	(1.432)	(0.634)
High Per Cap Cases	0.831	-0.694	-3.242*	-3.043	0.615
	(0.612)	(0.962)	(1.405)	(1.563)	(0.658)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	1,145,317	481,938	202,792	144,447	383,105
Mean	7.724	-0.417	-3.018	-2.276	0.046
StDv	190.562	190.851	188.163	167.365	132.749

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Balances in \$1,000. Δ is change in rate $Q4-2019-Q4-2020$. OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample.

Table 18: Δ Approval Rate: Stay at Home Rate at State Level as of May 2020 and Total COVID-19 Case Rate Per Capita

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
Panel A: Stay at Home Rate					
Stayed Home More	-0.002 (0.007)	-0.002 (0.012)	0.031 (0.022)	0.024 (0.029)	0.017 (0.027)
Moderate Stay Home	0.003 (0.005)	0.013 (0.010)	0.014 (0.018)	0.008 (0.024)	0.016 (0.022)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	241,664	79,750	22,934	12,590	14,018
Mean	-0.028	-0.076	-0.092	-0.108	-0.130
StDv	0.948	0.997	0.968	0.960	0.913
Panel B: Cases Per Capita					
Moderate Per Cap Cases	0.004 (0.007)	0.001 (0.013)	0.002 (0.023)	-0.005 (0.030)	-0.059* (0.028)
High Per Cap Cases	0.004 (0.008)	-0.019 (0.014)	0.002 (0.025)	-0.014 (0.032)	-0.065* (0.030)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	241,664	79,750	22,934	12,590	14,018
Mean	-0.028	-0.076	-0.092	-0.108	-0.130
StDv	0.948	0.997	0.968	0.960	0.913

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Δ is change in rate Q42019-Q4-2020. OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample.

Table 19: Δ Credit Limit Cut Rate: Stay at Home Rate at State Level as of May 2020 and Total COVID-19 Case Rate Per Capita

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
Panel A: Stay at Home Rate					
Stayed Home More	-0.004*	-0.004	-0.009*	-0.017***	-0.005
	(0.002)	(0.003)	(0.004)	(0.005)	(0.003)
Moderate Stay Home	-0.005***	-0.004*	-0.011**	-0.008*	-0.004*
	(0.001)	(0.002)	(0.003)	(0.004)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	1,145,317	481,938	202,792	144,447	383,105
Mean	0.041	0.053	0.054	0.056	0.028
StDv	0.535	0.571	0.576	0.573	0.524
Panel B: Cases Per Capita					
Moderate Per Cap Cases	0.006***	0.006	0.003	0.010*	0.006*
	(0.002)	(0.003)	(0.004)	(0.005)	(0.003)
High Per Cap Cases	0.008***	0.009**	0.001	0.005	0.004
	(0.002)	(0.003)	(0.005)	(0.006)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	1,145,317	481,938	202,792	144,447	383,105
Mean	0.041	0.053	0.054	0.056	0.028
StDv	0.535	0.571	0.576	0.573	0.524

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Δ is change in rate $Q_4 2019 - Q_4 2020$. OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample.

Table 20: Δ AFS Inquiry: Stay at Home Rate at State Level as of May 2020 and Total COVID-19 Case Rate Per Capita

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
Panel A: Stay at Home Rate					
Stayed Home More	0.005*** (0.001)	0.003** (0.001)	0.001 (0.001)	0.005*** (0.001)	0.001** (0.001)
Moderate Stay Home	0.001 (0.001)	0.002 (0.001)	0.000 (0.001)	0.002 (0.001)	0.001* (0.000)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	1,145,317	481,938	202,792	144,447	383,105
Mean	-0.013	-0.011	-0.006	-0.005	-0.002
StDv	0.312	0.243	0.187	0.157	0.104
Panel B: Cases Per Capita					
Moderate Per Cap Cases	-0.001 (0.001)	0.002 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.001 (0.001)
High Per Cap Cases	0.001 (0.001)	0.004** (0.001)	0.000 (0.001)	0.000 (0.001)	0.002*** (0.001)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	1,145,317	481,938	202,792	144,447	383,105
Mean	-0.013	-0.011	-0.006	-0.005	-0.002
StDv	0.312	0.243	0.187	0.157	0.104

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Δ is change in rate Q2+Q3 of 2019 to Q2+Q3 of 2020. OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample.

Table 21: Δ 60+ Day Late Payment Rate: Stay at Home Rate at State Level as of May 2020 and Total COVID-19 Case Rate Per Capita

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
Panel A: Stay at Home Rate					
Stayed Home More	-0.005*** (0.001)	-0.001 (0.001)	-0.004** (0.001)	0.002 (0.001)	-0.000 (0.001)
Moderate Stay Home	-0.001 (0.001)	-0.000 (0.001)	-0.002* (0.001)	0.000 (0.001)	-0.000 (0.001)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	1,145,317	481,938	202,792	144,447	383,105
Mean	-0.023	-0.014	-0.007	-0.005	-0.003
StDv	0.275	0.228	0.185	0.170	0.135
Panel B: Cases Per Capita					
Moderate Per Cap Cases	0.003** (0.001)	0.000 (0.001)	-0.001 (0.001)	0.002 (0.001)	0.001 (0.001)
High Per Cap Cases	0.003** (0.001)	0.000 (0.001)	0.002 (0.001)	0.003* (0.002)	0.001 (0.001)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	1,145,317	481,938	202,792	144,447	383,105
Mean	-0.023	-0.014	-0.007	-0.005	-0.003
StDv	0.275	0.228	0.185	0.170	0.135

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Δ is change in rate Q4-2019–Q4-2020. OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample.

Table 22: Accommodations - Excluding Credit Cards and Including Student Loans: Stay at Home Rate at State Level as of May 2020 and Total COVID-19 Case Rate Per Capita

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
Panel A: Stay at Home Rate					
Stayed Home More	-0.002 (0.001)	0.004* (0.002)	0.006** (0.002)	-0.000 (0.002)	-0.001 (0.001)
Moderate Stay Home	-0.001 (0.001)	0.004** (0.001)	0.004* (0.002)	0.002 (0.002)	0.000 (0.001)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	1,145,317	481,938	202,792	144,447	383,105
Mean	0.301	0.161	0.095	0.063	0.028
StDv	0.459	0.368	0.293	0.243	0.165
Panel B: Cases Per Capita					
Moderate Per Cap Cases	0.004** (0.001)	0.007*** (0.002)	0.010*** (0.002)	0.007*** (0.002)	0.002** (0.001)
High Per Cap Cases	0.005*** (0.002)	0.008*** (0.002)	0.009*** (0.002)	0.007*** (0.002)	0.004*** (0.001)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	1,145,317	481,938	202,792	144,447	383,105
Mean	0.301	0.161	0.095	0.063	0.028
StDv	0.459	0.368	0.293	0.243	0.165

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample.

Table 23: Accommodations - excluding Student Loans *and* Student Loans: Stay at Home Rate at State Level as of May 2020 and Total COVID-19 Case Rate Per Capita

	(1)	(2)	(3)	(4)	(5)
	18-49	50-61	62-66	67-71	72+
Panel A: Stay at Home Rate					
Stayed Home More	-0.006*** (0.001)	-0.004** (0.001)	-0.004* (0.002)	-0.004* (0.002)	-0.003*** (0.001)
Moderate Stay Home	0.002* (0.001)	0.002 (0.001)	-0.000 (0.001)	0.001 (0.001)	-0.000 (0.001)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	1,145,317	481,938	202,792	144,447	383,105
Mean	0.084	0.090	0.062	0.046	0.022
StDv	0.277	0.286	0.241	0.210	0.146
Panel B: Cases Per Capita					
Moderate Per Cap Cases	0.002** (0.001)	0.005*** (0.001)	0.008*** (0.002)	0.007*** (0.002)	0.003*** (0.001)
High Per Cap Cases	0.008*** (0.001)	0.010*** (0.001)	0.009*** (0.002)	0.008*** (0.002)	0.004*** (0.001)
Controls	Yes	Yes	Yes	Yes	Yes
Obs	1,145,317	481,938	202,792	144,447	383,105
Mean	0.084	0.090	0.062	0.046	0.022
StDv	0.277	0.286	0.241	0.210	0.146

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

OLS Regressions conditional on age group. Standard errors in parentheses (SE), clustered at household level. Controls include number of consumers per credit record address, change in HH size, gender, income, credit score, mortgage, debt-to-income ratios and zip code race. Source: Experian National Data Sample.

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