United States Government Accountability Office

Report to Congressional Committees

September 2023

CREDIT CARDS

Pandemic Assistance Likely Helped Reduce Balances, and Credit Terms Varied among Demographic Groups

GAO-23-105269

GAO Highlights

Highlights of GAO-23-105269, a report to congressional committees

Why GAO Did This Study

Credit cards are the most common consumer lending product by number of users, with 82 percent of U.S. adults holding a credit card in 2022. However, credit card adoption rates vary by race, ethnicity, and income. Consumers can use credit cards as a convenient means of payment and source of credit. Some consumers do not always pay off their monthly credit card balances and can accumulate interest and fees over time, which can lead to debt burden and affect their financial health. In addition, the COVID-19 pandemic caused significant economic disruptions and has affected consumers' credit card usage.

GAO was asked to review consumer credit card usage. This report examines (1) consumer credit card usage from 2013 through 2019, (2) how the COVID-19 pandemic and related assistance affected credit card usage from March 2020 through December 2021, and (3) how credit card costs and usage vary among racial/ethnic groups.

GAO analyzed a nongeneralizable sample of credit card data from the Federal Reserve for June 2013–December 2021 and used the Census Bureau's American Community Surveys to estimate the median household income and racial and ethnic composition in cardholders' zip codes. GAO also reviewed research from the Consumer Financial Protection Bureau, Federal Reserve, and academics. Further, GAO interviewed representatives of federal agencies, six large credit card issuers, three credit reporting agencies, a banking association, and a consumer advocacy organization.

View GAO-23-105269. For more information, contact Alicia Puente Cackley at (202) 512-8678 or cackleya@gao.gov.

September 2023

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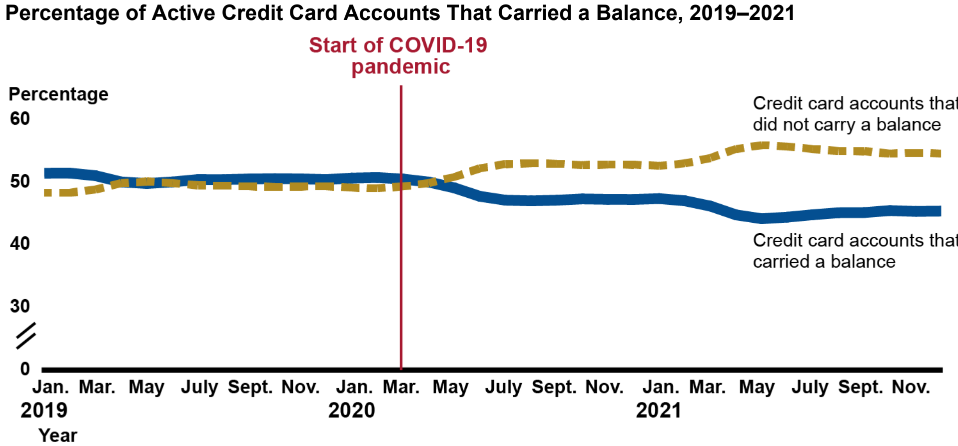
Pandemic Assistance Likely Helped Reduce Balances, and Credit Terms Varied among Demographic Groups

What GAO Found

Approximately half of active credit card accounts carried a balance during the period from June 2013 through 2019, according to GAO's analysis of a nongeneralizable sample of more than 650,000 credit card accounts from the Board of Governors of the Federal Reserve System. This included almost 35 percent of all active accounts in the highest credit score category (720 and above) and more than 30 percent of all active accounts in zip codes with median household incomes of $150,000 or more.

After the onset of the COVID-19 pandemic in March 2020, cardholders in the GAO sample generally paid down credit card balances and carried balances for shorter periods, according to GAO's analysis. Specifically, the share of all active accounts that carried a balance declined from 50 to 45 percent from April 2020 to December 2021 (see figure). Federal pandemic assistance likely contributed to these improvements. GAO analysis suggests that after March 2020, cardholders who carried balances increased their average credit card payments during the months when pandemic assistance payments were disbursed.

Percentage of Active Credit Card Accounts That Carried a Balance, 2019–2021



Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

Note: GAO's analysis was based on a nongeneralizable sample of active general purpose credit card accounts. This figure excludes the percentage of active credit card accounts that were seriously delinquent (90 or more days), which was less than 1 percent during this period.

Cardholder accounts in the sample that were in billing zip codes with a majority of Black or African American or Hispanic or Latino residents likely had higher interest rates and lower credit limits and carried balances longer compared with accounts in predominantly White zip codes, as indicated by GAO analysis. For example, the difference in interest rates was on average about 1.3 percentage points. Cardholders in the sample that were in majority-Black or -Hispanic zip codes continued to face higher interest rates and lower credit limits as compared with cardholders in predominantly White zip codes who had the same credit scores, zip-code income distribution, and revolving status. While accounts in the sample that were in majority-Black or -Hispanic zip codes carried smaller balances than accounts in predominantly White zip codes, higher interest rates combined with carrying balances longer can result in higher credit costs.

Contents

Tables

Figures

Abbreviations

ACS	American Community Survey
CFPB	Consumer Financial Protection Bureau

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U.S. GOVERNMENT ACCOUNTABILITY OFFICE
441 G St. N.W.
Washington, DC 20548

September 29, 2023

The Honorable Sheldon Whitehouse
Chairman
Committee on the Budget
United States Senate

The Honorable Bernard Sanders
Chair
Committee on Health, Education, Labor, and Pensions
United States Senate

Credit cards are the largest consumer lending product by number of users, with 82 percent of U.S. adults holding a credit card in 2022.[1] However, credit card adoption rates vary by income, race, and ethnicity. Credit cards can provide consumers with a convenient means of paying for goods and services and accessing credit. Some consumers carry credit card balances from month to month. These consumers can accumulate interest and fees over time, which could lead to debt burden and affect their financial health. For example, the Consumer Financial Protection Bureau (CFPB) estimated that Americans paid about $120 billion per year in credit card interest and fees from 2018 to 2020, which is about $1,000 per year for each American household.

Since 2020, public policies, federal and private-sector assistance, and restrictions prompted by the COVID-19 pandemic have affected individuals' financial behavior, including credit card usage. Early in the pandemic, consumer reactions to the pandemic, public health policies and restrictions such as stay-at-home orders, and temporary business closures caused significant economic disruptions nationwide. In response, the federal government and credit card issuers took actions to provide financial assistance and debt relief (such as payment deferrals) to consumers.

You asked us to examine credit card usage in the U.S. This report examines (1) credit card usage from 2013 through 2019 and the characteristics of cardholders who carried balances during this period, (2) how the COVID-19 pandemic and related assistance affected credit card

[1]See Consumer Financial Protection Bureau, *The Consumer Credit Card Market* (September 2021) and Board of Governors of the Federal Reserve System, *Economic Well-Being of U.S. Households in 2022* (May 2023).

usage from March 2020 through December 2021, and (3) how credit card costs and usage vary among racial and ethnic groups.

To address all three objectives, we analyzed a 0.1 percent nongeneralizable sample of consumer credit card account data, containing information on more than 650,000 individual credit card accounts, from the Board of Governors of the Federal Reserve System's Capital Assessments and Stress Testing Report (FR Y-14M) for the period from June 2013 through December 2021.[2] Our analysis included only general purpose credit cards, which are credit cards issued on networks, such as Visa, Mastercard, American Express, and Discover, which are accepted by a wide variety of merchants.[3] The Federal Reserve data allowed us to examine credit card usage by account, but the data did not have information that would allow us to link multiple accounts held by an individual cardholder. See appendixes I and II for additional detail on the Federal Reserve data used in our analysis.

Additionally, because Federal Reserve data did not include updated incomes or the race or ethnicity of the cardholders, we supplemented the Federal Reserve data with data from the Census Bureau's 5-Year American Community Surveys for 2013–2020. We used census data on household income and the shares of residents in each zip code who were Asian, Black or African American (referred to as "Black" in this report), Hispanic or Latino (referred to as "Hispanic" in this report), White, and Other.[4] We developed five scenarios representative of different, commonly occurring racial and ethnic compositions of zip codes: predominantly White (86 percent White), majority Black or African American (58 percent Black), majority Hispanic or Latino (62 percent Hispanic), mixed race and ethnicity with majority White (59 percent

[2]The Federal Reserve first started collecting the Y-14M data in June 2012. However, our analysis used data beginning in June 2013 because the Federal Reserve did not collect some data elements until that time. The data are collected from bank holding companies, savings and loan holding companies, and intermediate holding companies with $100 billion or more assets (which generally include all of the largest credit card issuers, according to Federal Reserve staff). As such, we cannot generalize our analysis results to credit card accounts in all banks in the U.S.

[3]Another type of credit card, referred to as a private label card, can only be used at one merchant or a small group of related merchants. American Express and Discover are both payment networks and credit card issuers.

[4]For this report, we derived the race and ethnicity categories from those used in the Census Bureau's 5-Year American Community Surveys for 2013–2020. The Black, White, and Asian race categories are all non-Hispanic. Census Bureau, *American Community Survey and Puerto Rico Community Survey Design and Methodology* (November 2022).

White), and mixed race and ethnicity with no majority. See appendix III for additional detail on the zip-code-level race and ethnicity data and our analysis.

Additionally, we used the Federal Reserve and census data to construct econometric models to estimate the length of time accounts would have carried a balance and how credit terms and revolving balances varied with the racial and ethnic composition of the cardholders' billing zip codes, among other things.[5] In our analysis of credit terms, we controlled for cardholders' credit scores and revolving status and for incomes in cardholders' zip codes.[6] Similarly, in our analysis of revolving balances, we controlled for cardholders' credit scores and the incomes in cardholders' zip codes. Our review was not designed to examine whether any differences in credit card terms and revolving patterns among racial and ethnic groups resulted from fair lending disparities, which cannot be measured as independent factors in our analysis. See appendixes IV through VI for additional information on the methodology and results of our econometric models.

We also reviewed research related to consumer credit card usage conducted by CFPB, the Federal Reserve, and academics, including information on consumers' use of credit products in general and by race and ethnicity. We interviewed staff from CFPB and the Federal Reserve and representatives from six large credit card issuers, three credit reporting agencies, the American Bankers Association, and the National Consumer Law Center.[7] To obtain information on how federal and private-sector pandemic assistance contributed to changes in credit card usage during the COVID-19 pandemic from March 2020 through

[5]To assess the reliability of the Federal Reserve and census data, we reviewed technical documentation and interviewed agency staff knowledgeable about the data. We also conducted electronic testing of the data to assess its reliability and limitations. We determined that the data were sufficiently reliable for examining credit card usage, describing household income and the racial and ethnic composition of cardholders' zip codes, and describing changes in cardholder payment behavior during the disbursements of federal pandemic assistance.

[6]Because the Federal Reserve data did not include updated incomes of cardholders, we controlled for the household incomes in cardholders' zip codes by measuring the percentage of households whose income fell into each of 16 income groups used in our analysis.

[7]The six issuers were American Express, Bank of America, Capital One, Citibank, Discover, and JPMorgan Chase. We selected issuers that had the largest purchase volumes and outstanding balances in their credit card portfolios in 2020. The three credit reporting agencies were Equifax, Experian, and TransUnion.

December 2021, we reviewed reports from CFPB and the Federal Reserve. We also examined data from the Census Household Pulse Survey conducted from April 23, 2020, to October 11, 2021, and the 2020 annual filings from the six issuers we interviewed.[8] See appendix I for additional detail on our objectives, scope, and methodology.

We conducted this performance audit from May 2021 to September 2023 in accordance with generally accepted government auditing standards. Those standards require that we plan and perform the audit to obtain sufficient, appropriate evidence to provide a reasonable basis for our findings and conclusions based on our audit objectives. We believe that the evidence obtained provides a reasonable basis for our findings and conclusions based on our audit objectives.

Background

Overview of the Credit Card Market

In October 2021, credit cards, debit cards, and cash on hand were the three most common ways for consumers to make payments for bills and purchases, according to the Survey and Diary of Consumer Payment Choice.[9] In October 2021, 28 percent of payments were made with credit cards and 29 percent with debit cards.

From 2013 through 2021, the number of consumer credit card accounts steadily increased from about 383 million to about 532 million, and total outstanding credit card balances were $856 billion at year-end 2021, according to the Federal Reserve Bank of New York’s Consumer Credit

[8]The Household Pulse Survey, an experimental data product, is an interagency federal statistical rapid response survey to measure household experiences during the COVID-19 pandemic. The Census Bureau conducts this survey in partnership with five other agencies from the Federal Statistical System. Response rates over our period of analysis ranged from 2.3 percent to 7.5 percent. Census applied weighting adjustments to mitigate nonresponse bias, according to Census. All reported estimates have a relative margin of error of 19 percent or less of the estimate, and all reported comparisons are statistically significant at the 95 percent confidence level.

[9]Federal Reserve Bank of Atlanta, *The 2021 Survey and Diary of Consumer Payment Choice: Summary Results* (Atlanta, GA: Sept. 17, 2022). The Survey and Diary of Consumer Payment Choice is an annual survey, and the 2021 survey was the most recently published survey at the time of our report.

Panel.[10] The top 10 credit card issuers held 82 percent of the outstanding credit card balances in 2021, according to a Federal Reserve report.[11]

Total outstanding credit card balances were relatively small compared to other types of consumer loans. Outstanding credit card balances accounted for 5 percent of the dollar value of consumer loans at year-end 2021, while mortgages and auto loans accounted for 70 percent and 9 percent, respectively, according to the Consumer Credit Panel. However, the interest rates of credit cards tend to be much higher than those of other types of consumer loans. For example, the Federal Reserve reported that in December 2021, the average interest rate for credit cards was about 16 percent, compared with about 5 percent for new auto loans.[12]

In addition, an estimated 84 percent of U.S. adults had a credit card account in 2021, according to a Federal Reserve report.[13] Half of consumers had one or two credit cards, and 20 percent had five or more in 2021, as estimated by the Survey and Diary of Consumer Payment Choice.[14] People with higher and middle-range incomes were more likely to have a credit card, and people with lower incomes were less likely, according to a 2021 Federal Reserve Survey.[15]

The survey also estimated that credit card ownership varied by race and ethnicity: 93 percent for Asian adults, 88 percent for White adults, 77 percent for Hispanic adults, and 72 percent for Black adults. Lower rates

[10]The Federal Reserve Bank of New York's Consumer Credit Panel is a nationally representative 5 percent random sample of all individuals whose credit file includes a Social Security number (usually age 18 and over). According to the bank, the Consumer Credit Panel does not contain lender names, and the data are anonymized.

[11]Board of Governors of the Federal Reserve System, *Report to Congress: Profitability of Credit Card Operations of Depository Institutions* (July 2022).

[12]Board of Governors of the Federal Reserve System, G.19 Statistical Release, "Consumer Credit: March 2022" (May 6, 2022).

[13]Board of Governors of the Federal Reserve System, *Economic Well-Being of U.S. Households in 2021* (May 2022).

[14]Federal Reserve Bank of Atlanta, *2021 Survey and Diary*.

[15]Board of Governors of the Federal Reserve System, *Economic Well-Being of U.S. Households in 2021*. The CARD Act of 2009 requires credit card issuers to consider the consumer's ability to make required payments before opening a credit card account for the consumer. Credit Card Accountability Responsibility and Disclosure Act of 2009, Pub. L. No. 111-24, § 109, 123 Stat. 1734, 1743 (codified at 15 U.S.C § 1665e).

of credit card adoption among Black and Hispanic adults are consistent with lower rates of bank account adoption among Black and Hispanic households.[16] In addition, unbanked households are much less likely to have a credit card, according to the Federal Deposit Insurance Corporation's 2021 National Survey of Unbanked and Underbanked Households.[17]

Key Definitions of Credit Card Use

In this report, we use the term "balance" to refer to the credit card balance at the end of a billing cycle. We classify credit card accounts into six groups based on how cardholders use the cards and whether interest is charged during each month. See appendix II for additional information.

- **Transacting accounts.** If the cardholder pays all of the account balance due for the billing cycle by the due date, we refer to the cardholder as a "transactor" and to the account as a "transacting account."[18] Balances for transacting accounts consist of purchases made during the billing cycle. Repeat transactors are not charged interest on the end-of-cycle balance or on new purchases during the grace period (between the end of a billing cycle and the date payment is due).
- **Revolving accounts.** If the cardholder pays less than the entire account balance due for the billing cycle, or if the cardholder account has been delinquent for less than 90 days, we refer to the cardholder as a "revolver" and to the account as a "revolving account."[19] In contrast with transactors, revolvers are charged interest on the remaining unpaid balances from prior cycles (also called the revolving

[16]See GAO, *Banking Services: Regulators Have Taken Actions to Increase Access, but Measurement of Actions' Effectiveness Could Be Improved,* GAO-22-104468 (Washington, D.C.: Feb. 14, 2022).

[17]Federal Deposit Insurance Corporation, *2021 FDIC National Survey of Unbanked and Underbanked Households* (October 2022).

[18]We assign this status primarily by identifying accounts with a positive starting balance but no finance charges due. As a consequence of our assignment approach, any accounts that are carrying a balance that has a zero percent promotional annual percentage rate are also classified as transacting accounts.

[19]We assign this status primarily by identifying accounts with finance charges incurred in the billing cycle that are not delinquent for more than 90 days. As a consequence of our assignment approach, accounts that were previously carrying a balance and have started to pay off their balance in full are not classified as transacting accounts until they are eligible for their issuer's grace period.

balances), and immediately on any new purchases they make in the current cycle.[20]

- **Seriously delinquent accounts.** If the cardholder does not make at least the minimum payment by the due date, the cardholder is in delinquency. For the purposes of this report, we classify accounts as "revolving accounts" if they are less than 90 days delinquent, and as "seriously delinquent" if they are 90 or more days delinquent.
- **Inactive accounts.** If the cardholder does not have a balance from the previous billing cycle (i.e., did not make purchases prior to the closing of the billing cycle) and has not made any payments in the current month, we classify the account as "inactive."
- **Closed accounts.** If an account can no longer be used because the cardholder has closed it or because the cardholder has died, we classify the account as "closed."
- **Charged-off accounts.** If the account balance has been charged off by the issuer because it is deemed unlikely to be collected, we classify the account as "charged off."

Credit cardholders can transition from month to month among any of the first four groups.

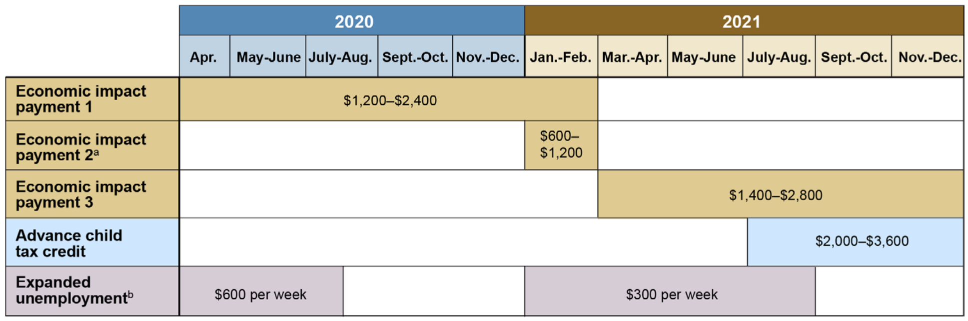
Federal and Private-Sector Assistance Related to the COVID-19 Pandemic

In response to the COVID-19 pandemic, from April 2020 to December 2021 the federal government provided eligible consumers with direct payments, including one-time economic impact payments, multiple advance child tax credit payments, and expanded unemployment insurance in varying amounts (see fig. 1).[21] The amounts of the economic impact payments and advance child tax credit payments were generally based on an individual's or household's income or family status.

[20]Revolving balances can also include fees if cardholders fail to make payments by the due date.

[21]Some states terminated their participation in expanded unemployment insurance programs starting in June 2021, while others participated through September 6, 2021, when the expanded unemployment insurance programs ended.

Figure 1: Disbursement Timeline and Amounts of Federal Pandemic Assistance



Source: GAO. | GAO-23-105269

Note: The amounts of the economic impact payments and the advance child tax credit payments were based generally on an individual's or household's income. Individuals or households with dependents could receive higher amounts of assistance if eligible.

[a]The second economic impact payments began disbursements on Dec. 29, 2020.

[b]In response to the COVID-19 pandemic, the federal government created three temporary unemployment insurance programs that expanded benefit eligibility and enhanced benefits. Specifically, under the Federal Pandemic Unemployment Compensation program, weekly benefits of $600 were available for weeks of unemployment from Mar. 29, 2020, through July 25, 2020, and weekly benefits of $300 were available from Dec. 26, 2020, through Sept. 6, 2021. Some states terminated their participation in the expanded unemployment insurance programs starting in June 2021, while others participated through Sept. 6, 2021.

The federal government also granted a temporary suspension of loan payments for borrowers of certain mortgages and student loans and enacted a moratorium on certain evictions during the pandemic. Additionally, the Small Business Administration's Paycheck Protection Program supported employment by providing forgivable loans to small businesses.[22]

Although not mandated to provide assistance, credit card issuers generally offered voluntary debt assistance programs to cardholders who requested them from March to December 2020, according to a CFPB report and six credit card issuers.[23] These programs included payment deferrals and fee waivers. CFPB reported that about 25 million consumer credit card accounts (with a total of $68 billion in balances) enrolled in payment relief programs in 2020.

[22]For more information, see GAO, *Paycheck Protection Program: Program Changes Increased Lending to the Smallest Businesses and in Underserved Locations,* GAO-21-601 (Washington, D.C.: Sept. 21, 2021). For more information on federal pandemic assistance, see GAO's CARES Act work at https://www.gao.gov/coronavirus.

[23]Consumer Financial Protection Bureau, *The Consumer Credit Card Market*.

A Large Share of Active Cards in Our Sample Carried a Balance before the Pandemic, and Many Continued to Do So for Long Periods

About Half of Cards Carried a Balance from Month to Month, Including Many Held by Cardholders with High Credit Scores and Incomes

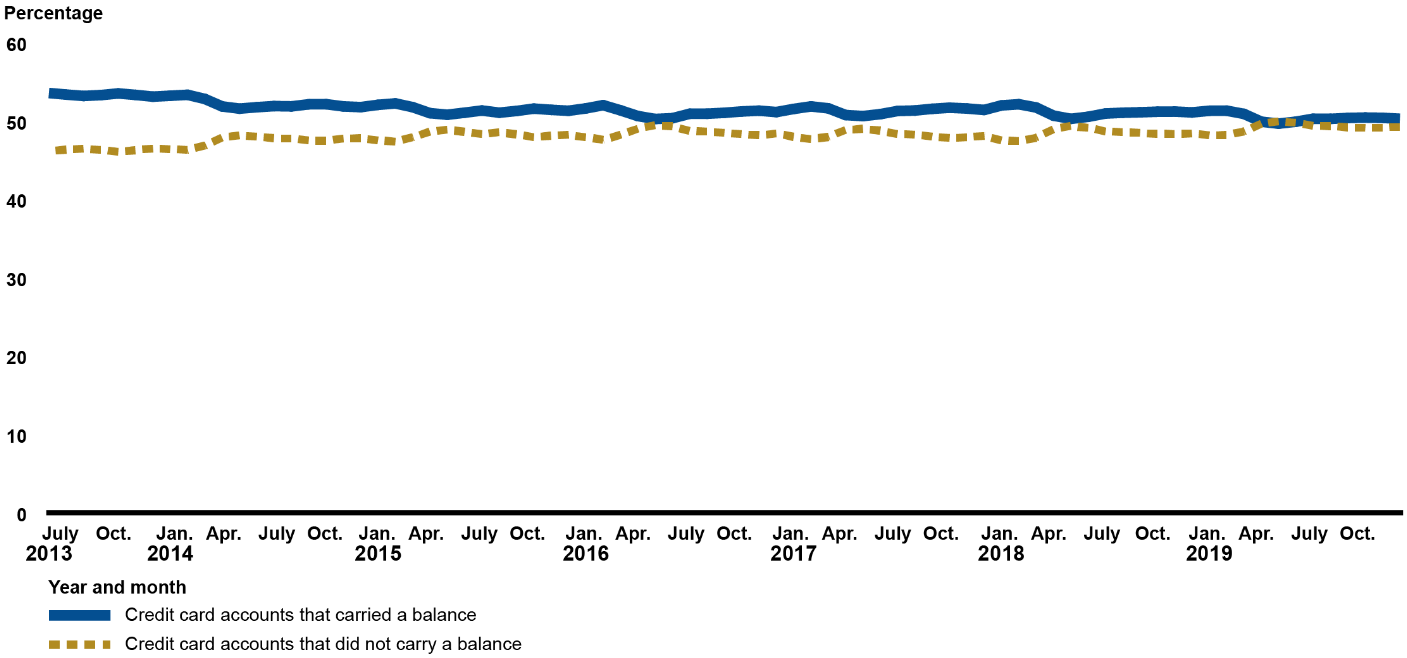
From June 2013 through December 2019, in any given month, approximately half of the active credit card accounts were revolving (carrying a balance), according to our analysis of a sample of more than 650,000 individual credit card accounts from Federal Reserve data.[24] These included many held by cardholders with high credit scores and likely with relatively high incomes.[25] The percentage of both revolving and transacting accounts stayed stable year over year in this period (see fig. 2).[26]

[24]As previously discussed, our analysis was based on a nongeneralizable sample of active general purpose credit card accounts. We discuss credit card usage during the COVID-19 pandemic (2020–2021) later in this report.

[25]We approximated cardholders' incomes by using the median household income in the cardholder's billing zip code.

[26]During this period, a substantial number of accounts were inactive each month. While the share of total accounts that were inactive generally declined over time, it ranged from 27 percent to 36 percent of the total accounts each month. Additionally, accounts that were seriously delinquent (90 or more days) ranged from 0.3 percent to 0.6 percent over this period.

Figure 2: Percentage of Active Credit Card Accounts That Did and Did Not Carry a Balance, June 2013–December 2019



Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

Note: Our analysis was based on a nongeneralizable sample of active general purpose credit card accounts. This figure excludes the percentage of active credit card accounts that were seriously delinquent (90 or more days), which was less than 1 percent during this period.

Credit Score Categories

Credit scores are used by lenders to determine consumers' eligibility for credit, including credit cards. Credit scores can be classified into categories based on the consumer's creditworthiness. A consumer with a higher credit score is considered more likely to repay a debt. For this report, we applied the credit score categories used by the Consumer Financial Protection Bureau in their credit card reporting:

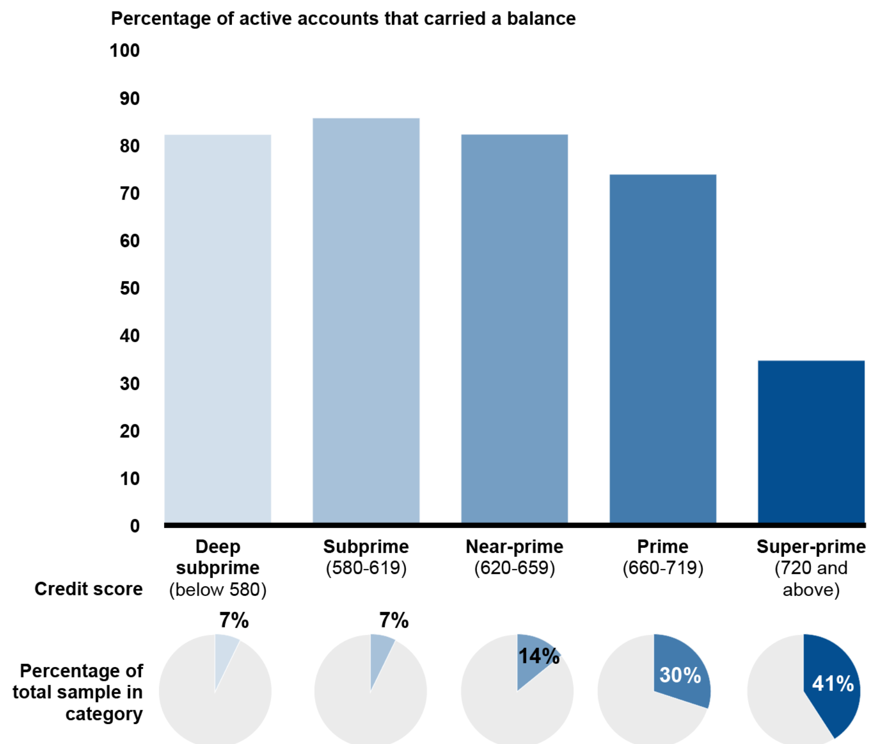
- Deep subprime (below 580)
- Subprime (580–619)
- Near-prime (620–659)
- Prime (660–719)
- Super-prime (720 and above)

Source: GAO and Consumer Financial Protection Bureau. | GAO-23-105269

Active accounts held by cardholders with super-prime credit scores (720 and above) were less likely to carry a balance than those held by cardholders with credit scores below 720, according to our analysis of

Federal Reserve data for June 2013–December 2019 (see fig. 3).[27] About 35 percent of active accounts held by super-prime cardholders carried a balance, compared with 74–86 percent of active accounts held by cardholders in the lower credit score categories.

Figure 3: Average Percentage of Active Credit Card Accounts That Carried a Balance, by Credit Score of Account Holder, June 2013–December 2019



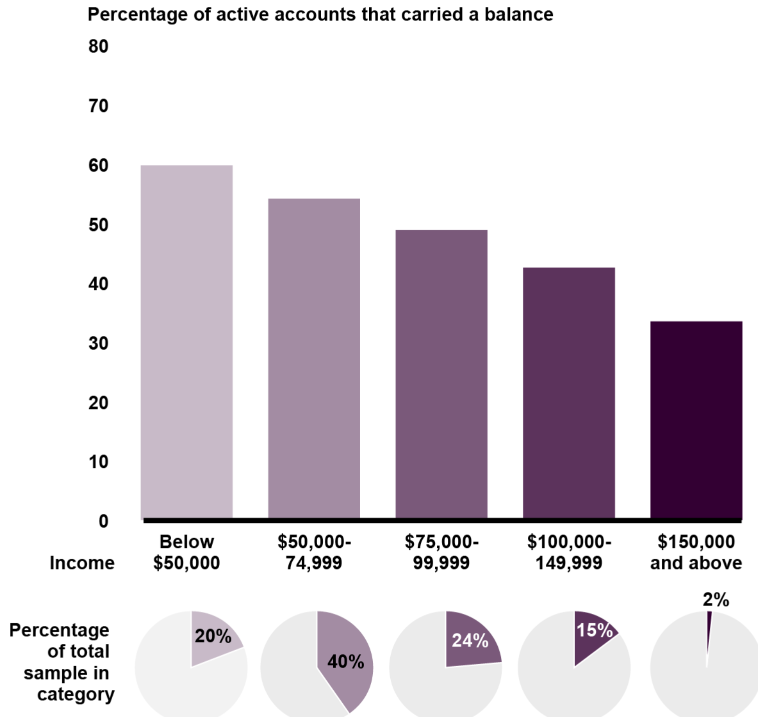
Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

Note: Our analysis was based on a nongeneralizable sample of active general purpose credit card accounts. For each credit score category, we first calculated the percentage of credit card accounts that carried a balance out of the total number of active credit card accounts in that credit score category for each month from June 2013 through Dec. 2019, and then took the average over all months. Our credit score data included multiple types of credit scores, such as FICO and Vantage, which were used and reported by credit reporting agencies and credit card issuers.

[27]The amount of unpaid debt, including credit card balances, is typically one of the factors considered in determining a consumer's credit score. There are no industry standard credit score categories used by credit reporting agencies and credit card issuers. For this report, we applied the credit score categories used by CFPB in its 2021 consumer credit card market report.

Furthermore, large percentages of active accounts, regardless of income level, carried a balance from June 2013 through December 2019 (see fig. 4). Accounts held by cardholders who lived in zip codes with a lower median household income were more likely to carry a balance, according to our analysis. However, many accounts in higher-income zip codes also carried balances. For instance, about 33 percent of accounts in zip codes with median household incomes of $150,000 or more carried a balance, as did about 43 percent of accounts in zip codes with incomes between $100,000 and $150,000.

Figure 4: Average Percentage of Active Credit Card Accounts That Carried a Balance, by Median Household Income of Cardholder's Zip Code, June 2013–December 2019



Source: GAO analysis of data from the Board of Governors of the Federal Reserve System and the Census Bureau's American Community Survey. | GAO-23-105269

Note: Our analysis was based on a nongeneralizable sample of active general purpose credit card accounts. For each median household income category, we first calculated the percentage of credit card accounts that carried a balance out of the total number of active credit card accounts in that credit score category for each month from June 2013 through Dec. 2019, and then took the average over all months.

Many Cardholders Carried a Balance for at Least a Year

Revolving Episode

A revolving episode is the period during which an account continuously carries a balance. For example, an account that carries a balance from March to June has had a revolving episode of 4 months. For the purpose of our report, a revolving episode ends when a cardholder pays off the full balance on the account, or the account transitions to seriously delinquent, inactive, or closed status. Each time an account starts revolving again, the account begins a new revolving episode.

Source: GAO. | GAO-23-105269

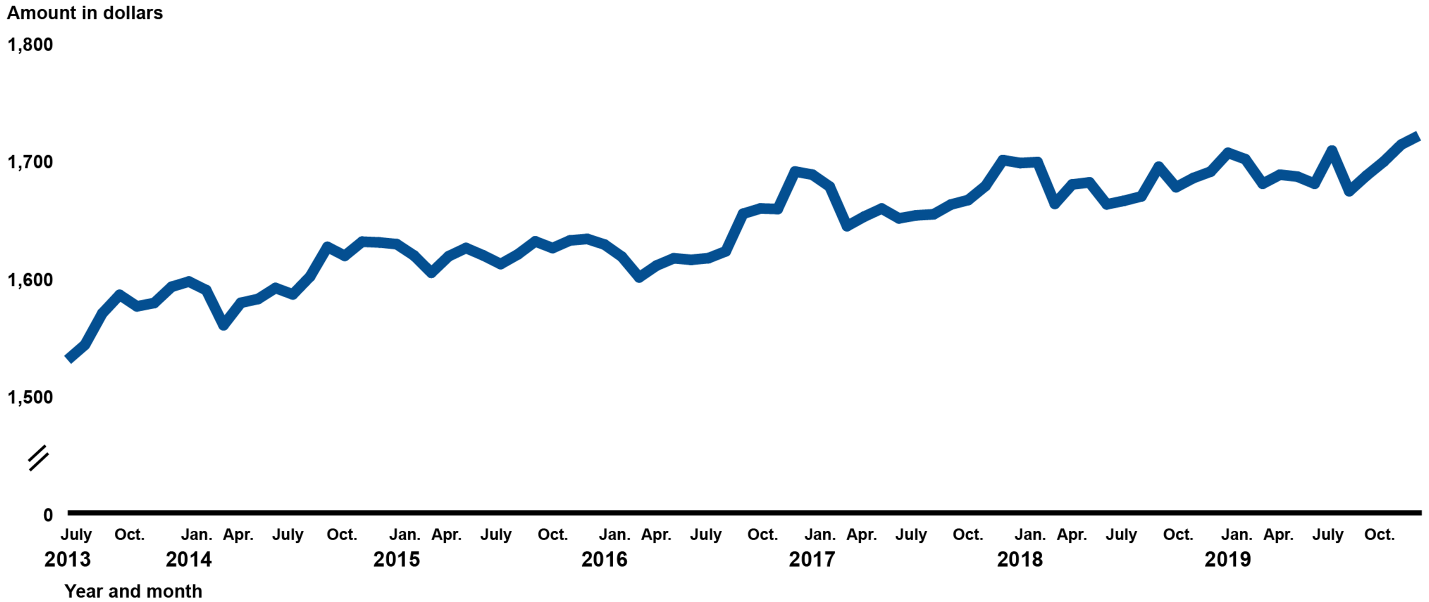
Our analysis also found that most accounts that revolved carried a revolving balance for at least a year. From June 2014 through December 2019, of accounts that were revolving in any given month, approximately 80 percent were in a long-term revolving episode (1 year or more).[28] Further, the median nominal revolving balance grew from $1,530 in June 2013 to $1,720 in December 2019, or 12 percent (see fig. 5).[29] After adjusting for inflation, the median revolving balance remained relatively stable, growing by 2 percent during this period.[30]

[28]Because we defined long-term revolving episodes as 1 year or more, June 2014 was the earliest month for which our data would allow us to make an accurate count of long-term status. Similar to our definition of long-term status, a Federal Reserve study defines credit card accounts that carried a balance for more than 6 of the past 12 months as "heavy revolver accounts." See Robert Adams and Vitaly Bord, "The Effects of the COVID-19 Shutdown on the Consumer Credit Card Market: Revolvers versus Transactors" (Board of Governors of the Federal Reserve System, Oct. 21, 2020), accessed Jan. 24, 2022, https://www.federalreserve.gov/econres/notes/feds-notes/the-effects-of-the-covid-19-shutdown-on-the-consumer-credit-card-market-revolvers-versus-transactors-20201021.htm.

[29]Cardholders are obligated to repay the nominal amount of their credit card balances. Changes in nominal balances reflect changes in the price level and changes in the real value of the balances.

[30]In December 2021 dollars, the median revolving balances were $1,827 in June 2013 and $1,867 in December 2019.

Figure 5: Credit Card Median Nominal Revolving Balance, June 2013–December 2019



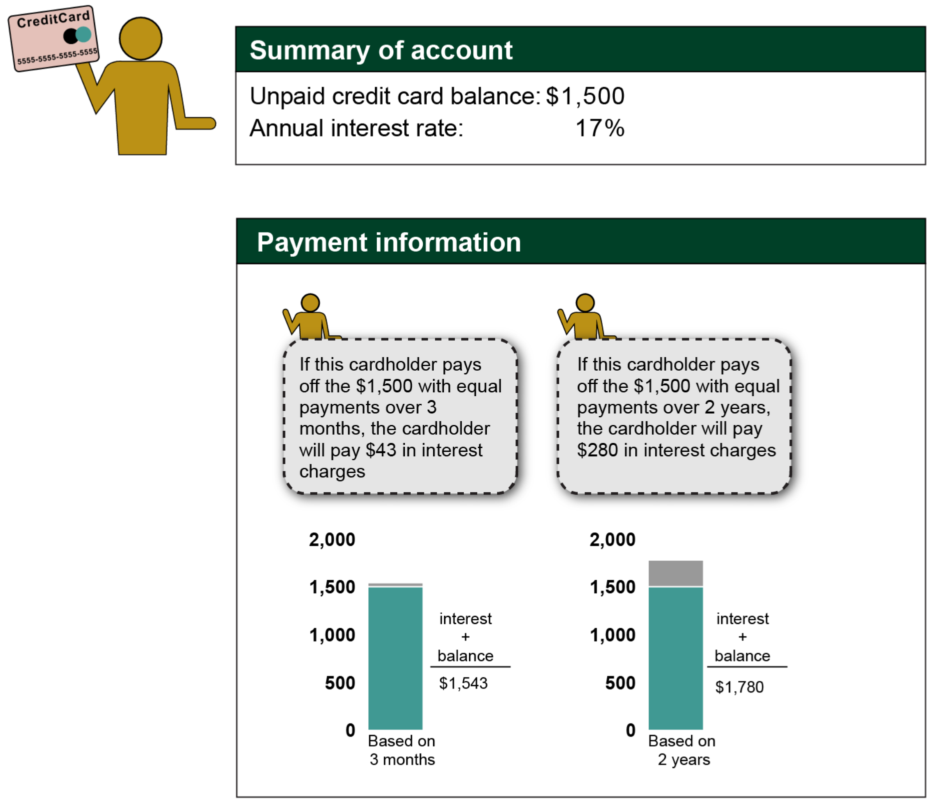
Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

Note: Our analysis was based on a nongeneralizable sample of active general purpose credit card accounts.

Cardholders with accounts that carried a balance from month to month had different spending patterns than cardholders with accounts that did not carry a balance. Our analysis of Federal Reserve data found that from June 2013 through December 2019, fewer revolvers made purchases with their credit cards and those who did generally spent less than transactors. Specifically, on average, 55–64 percent of revolvers made purchases in any given month during this period, compared with 79–84 percent of transactors. In addition, among cardholders who made a purchase, the monthly median purchase ranged from approximately $164–$224 for revolvers and $436–$622 for transactors.

Cardholders can incur a relatively high cost of credit if they carry credit card balances for a considerable amount of time (see fig. 6).

Figure 6: Simulated Costs for a Cardholder Who Carries a Balance for Different Lengths of Time



Source: GAO analysis. | GAO-23-105269

Note: The average interest rate for credit cards that were assessed interest was 16.9 percent in Dec. 2019, according to the Board of Governors of the Federal Reserve System. We rounded the interest rate to 17 percent and interest charges to whole dollar amounts. We assumed the cardholder did not make new purchases on the given credit card while carrying the balance and paid off the balance in equal monthly payments. For illustration purposes and ease of calculation, we developed these examples by calculating the interest charges based on a monthly rate by dividing the annual interest rate by 12. In practice, credit card interest charges are typically compounded on a daily basis.

According to our analysis of Federal Reserve data from June 2013 through December 2019, 5–11 percent of revolving accounts reached or exceeded their credit limits in a given month. Credit cards offer cardholders immediate access to credit, so cardholders with accounts that have exhausted their available credit may need to cut back or delay spending, dip into their savings, or borrow from other sources. For example, a 2021 CFPB survey estimated that half of consumers who had difficulty paying bills or expenses borrowed either from a bank; from an alternative financial service provider using an auto-title loan, a payday loan, or through a pawn shop; or from friends and family.[31] Of those who borrowed, 21 percent used at least one form of alternative financial services.

Some of these consumers likely faced higher borrowing costs. For example, the average annual credit card interest rate was about 17 percent in December 2019.[32] In contrast, the annual interest rate on a 2-week payday loan of $100 with a typical $15 fee can be almost 400 percent.[33] Furthermore, consumers who miss or delay paying a bill may face delinquency on their credit records, which can increase the costs of borrowing in the future, according to CFPB's survey.

Cardholders in Our Sample Generally Paid Down Balances during the Pandemic

After March 2020, More Cardholders Paid Off Their Balances, and Revolvers Carried Balances for Shorter Periods

An increasing share of cardholders paid off their balances after the onset of the pandemic in March 2020. Our analysis of a sample of more than 650,000 individual credit card accounts from Federal Reserve data showed that the share of active credit card accounts that were revolving declined from 50 percent in April 2020 to 45 percent in December 2021 (see fig. 7).[34] During the same period, the share of transacting accounts increased from 50 percent to 54 percent. By comparison, our analysis of data from June 2013 through March 2020 found that the shares of

[31]Consumer Financial Protection Bureau, *Consumer Use of Payday, Auto Title, and Pawn Loans: Insights from the Making Ends Meet Survey*, Research Brief No. 2021-1 (May 2021). The report was based on information from the first two waves of CFPB's Making Ends Meet survey, conducted in June 2019 and June 2020.

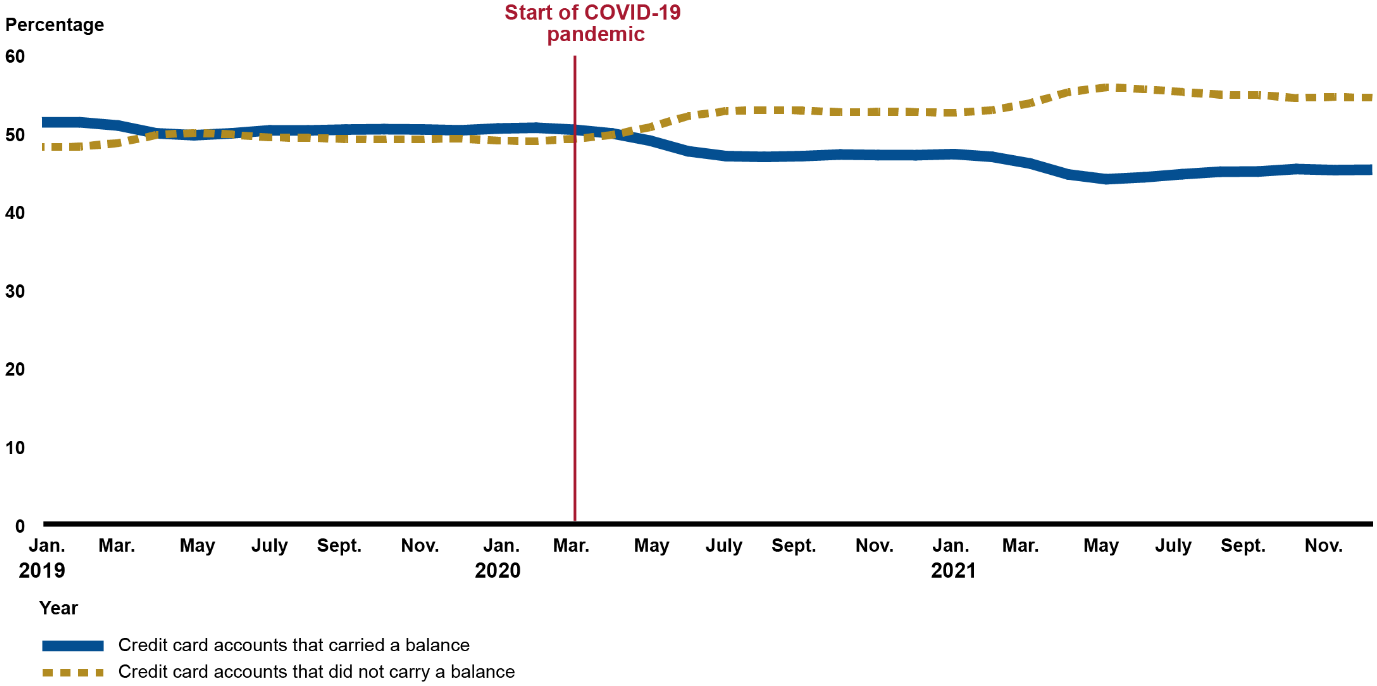
[32]Board of Governors of the Federal Reserve System, *Report to the Congress on the Profitability of Credit Card Operations of Depository Institutions* (Washington, D.C.: November 2020).

[33]Payday loans are a form of small-dollar, short-term consumer credit. Payday loans can be rolled over to effectively last for longer than 2 weeks. See Consumer Financial Protection Bureau, *Market Snapshot: Consumer Use of State Payday Loan Extended Payment Plans* (April 2022).

[34]During this period, less than 1 percent of active accounts were seriously delinquent.

revolving and transacting accounts stayed relatively stable year over year, as previously discussed.

Figure 7: Percentage of Active Credit Card Accounts That Carried a Balance, 2019–2021



Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

Note: Our analysis was based on a nongeneralizable sample of active general purpose credit card accounts. This figure excludes the percentage of active credit card accounts that were seriously delinquent (90 or more days), which was less than 1 percent during this period.

To examine how the pandemic affected credit card usage, we analyzed data from June 2013 through December 2021. We used multivariate regression models to compare revolving episodes during the period April 2020–December 2021 (the first part of the pandemic) with those during the period June 2013–March 2020. We made this comparison because various conditions (related to public health, the economy, and public policy) prevailed during the pandemic that might have affected credit card usage.[35]

[35]Some of the conditions of the pandemic that could have affected credit card usage included public health conditions (e.g., social distancing), economic conditions (e.g., employment levels), and policy responses (e.g., pandemic-related government assistance).

We focused on two key characteristics of a cohort of new revolving episodes: (1) durations of revolving episodes and (2) account statuses after the end of revolving episodes. We simulated the distributions of revolving episode durations under pandemic and prepandemic conditions. These distributions provide insight into the proportion of revolving episodes that lasted for specific numbers of months. We also simulated the distributions of account statuses after the revolving episodes ended under pandemic and prepandemic conditions. These distributions provide insight into the proportion of revolving episodes that transitioned to transacting, seriously delinquent and charged-off, inactive, or closed status. Our analysis does not explain the reasons for differences in credit card usage under prepandemic and pandemic conditions, and thus does not establish a causal relationship between such conditions and credit card usage. See appendix IV for additional information on the methodology and results of our analysis.

Our analysis suggests that the conditions that prevailed during the pandemic were associated with the following changes in revolvers' credit card usage:

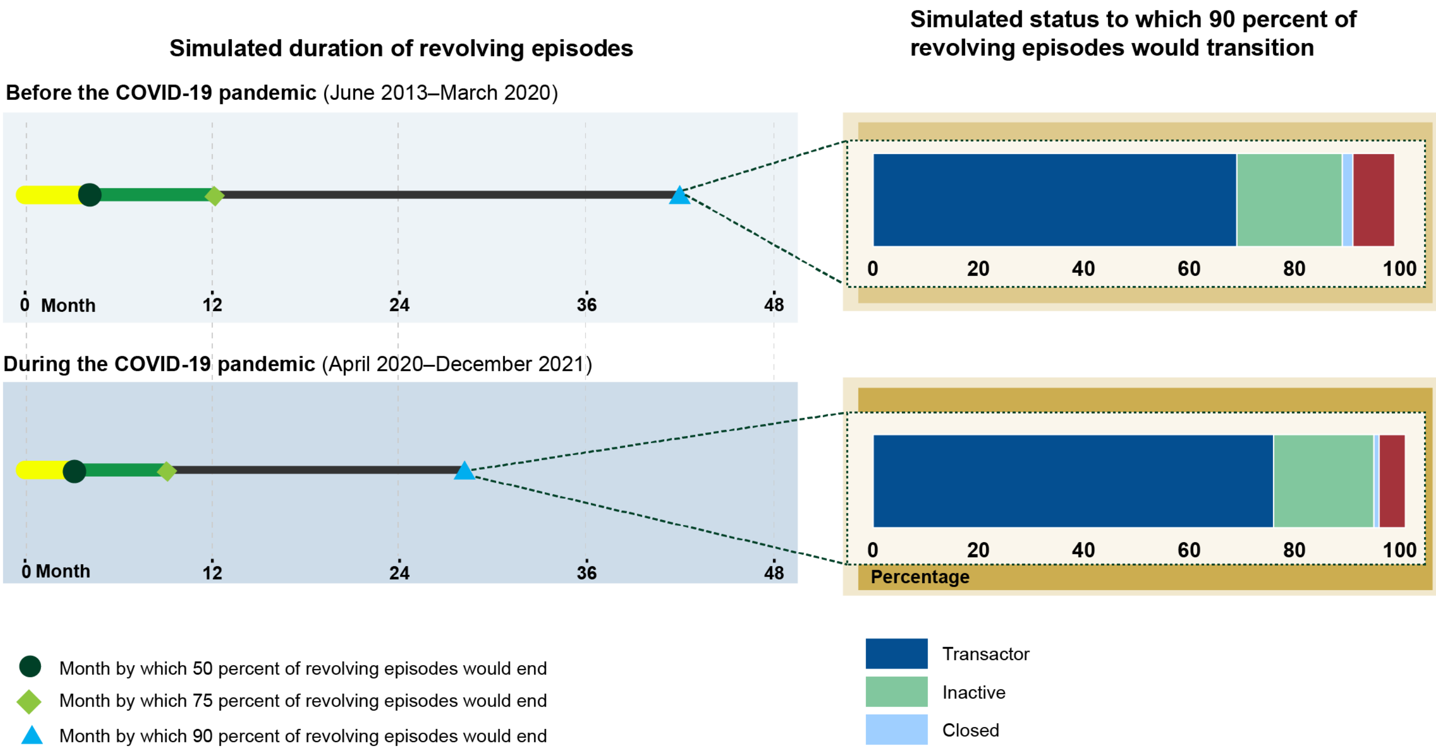
- **Shorter revolving episodes.** Our analysis indicates that pandemic conditions were associated with shorter revolving episodes. For example, it indicates that under pandemic conditions, about 90 percent of revolving episodes would end sometime between 1 and 28 months, with 50 percent of the revolving episodes ending within 3 months (see fig. 8).[36] In comparison, under prepandemic conditions, about 90 percent of revolving episodes would end sometime between 1 and 42 months—1.5 times longer than it would take under pandemic conditions—with 50 percent of the revolving episodes ending within 4 months.
- **More transitions to transacting status.** For the 90 percent of revolving episodes that would end sometime between 1 and 28 months under pandemic conditions, our analysis indicates that about

[36]An account can have multiple revolving episodes of varying durations. We report on the 90th percentile of the distribution of durations for a cohort of new revolving episodes because it generally illustrates the experience of a typical revolving account in a given month. For example, over the period of July 2016–July 2017—a year selected in the middle of the time period covered by our data—the typical (median) revolving account in our data was in a revolving episode of somewhere between 39 and 50 months. However, in this time period, more than 90 percent of new revolving episodes in our data ended within this time. The duration of a typical (median) new revolving episode was generally between 4 and 5 months. For more information on our analysis methodology and results, see app. IV.

76 percent of these revolving episodes would transition to transacting status (see fig. 8).[37] In comparison, for the 90 percent of revolving episodes that would end sometime between 1 and 42 months under prepandemic conditions, a smaller share of revolving episodes (about 69 percent) would transition to transacting status.

- **Fewer transitions to seriously delinquent and charged-off, inactive, or closed status.** Our analysis also indicates that under pandemic conditions, revolving episodes would be less likely to become seriously delinquent and charged off or to transition to inactive or closed status, as shown in figure 8.

Figure 8: Simulated Length of Credit Card Revolving Episodes and Status after End of Revolving Episodes under Prepandemic and Pandemic Conditions



Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

Note: Our analysis was based on a nongeneralizable sample of general purpose credit card accounts. We used statistical models and simulations to compare revolving episodes under pandemic

[37]We do not project the distribution of the statuses that follow all revolving episodes, given that the time period for our data is not long enough to estimate with confidence the distribution of transition destinations of the longest revolvers.

and prepandemic conditions. However, our analysis does not explain the reasons for differences in credit card usage under these conditions, and thus does not establish a causal relationship between such conditions and credit card usage. See app. IV for more information on our methodology.

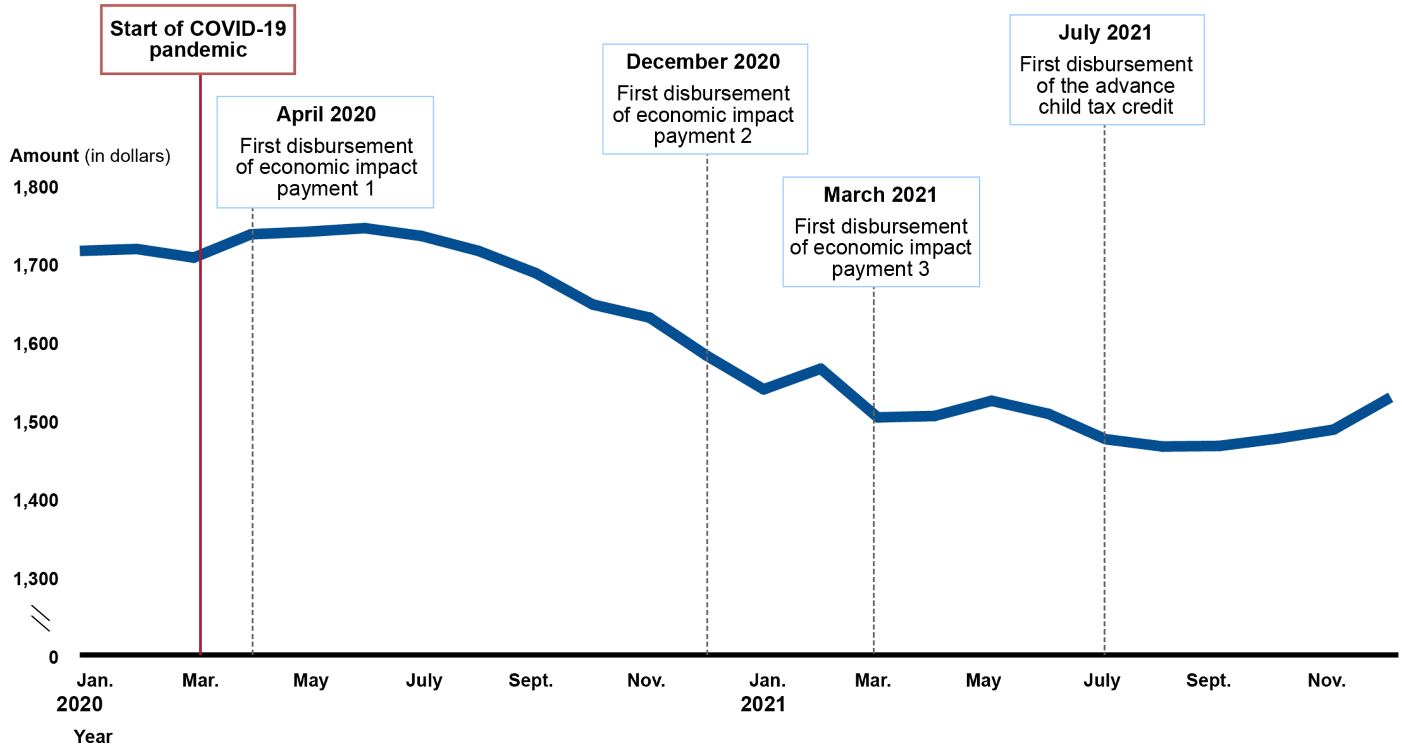
Pandemic Assistance Was Associated with Lower Balances, Improved Credit Scores, and Fewer Delinquencies

Reduced Balances

Pandemic-related assistance provided by the federal government and credit card issuers likely contributed to cardholders paying down their credit card balances, according to our analysis. Specifically, we estimated that median nominal revolving balances declined from approximately $1,737 in April 2020 to $1,529 in December 2021, or about 12 percent (see fig. 9).[38] By comparison, we estimated that median nominal revolving balances generally increased from June 2013 through March 2020, as previously discussed.

[38]In December 2021 dollars, the median revolving balance was $1,889 in April 2020, which was 19 percent higher than that in December 2021. Changes in nominal balances reflect changes in the price level and changes in the real value of the balances, as previously discussed. A study found that credit card spending decreased from January to April 2020, which contributed to the initial decline in credit card balances in April 2020. The study also found that credit card revolving balances continued to decrease from April 2020 to early 2021, even though credit card spending slowly started to recover after April 2020. During this period, cardholders increased their credit card payments, which drove the decline in revolving balances. See Robert M. Adams, Vitaly M. Bord, and Bradley Katcher, “Why Did Credit Card Balances Decline So Much during the COVID-19 Pandemic” (Board of Governors of the Federal Reserve System, Dec. 3, 2021), accessed Jan. 24, 2022, https://www.federalreserve.gov/econres/notes/feds-notes/why-did-credit-card-balances-decline-so-much-during-the-covid-19-pandemic-20211203.html.

Figure 9: Median Nominal Credit Card Revolving Balances, 2020–2021



Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

Note: Our analysis was based on a nongeneralizable sample of active general purpose credit card accounts.

Some cardholders who received pandemic-related assistance reported using it to pay down their credit card balances, according to the Census Bureau's Household Pulse Survey. Of the respondents who reported receiving or expecting to receive the first economic impact payments, an estimated 14–16 percent used or planned to use the funds to pay down debts, including credit card debt.[39] The estimated percentage increased

[39]Census conducted the Household Pulse Survey each week from April 23 to July 21, 2020, and every 2 weeks starting in August 2020. We reviewed the surveys conducted from April 23, 2020, to October 11, 2021. In the surveys conducted from June 11 to July 21, 2020, from January 6 to March 29, 2021, and from April 14 to July 5, 2021, respondents were asked if they received or expected to receive an economic impact payment and on what they spent the payment, including paying down credit card balances, student loans, or other debts. The 95 percent confidence intervals for the estimates ranged from about 13 to 17 percent.

to 50–54 percent in the surveys conducted after the distributions of the second and third economic impact payments.[40]

The survey results are in line with our analysis of Federal Reserve data, which estimated that cardholders increased their next credit card payments by an average of $20 and $61 when the second and third economic impact payments were disbursed, respectively.[41] The average payment amount also increased by $37 in each month when the advance child tax credit payments were disbursed.[42] These increases are in addition to an overall average increased payment of $40 per month toward credit card balances for revolving accounts from March 13, 2020, through the end of December 2021. Given that the median monthly payment by revolvers was $131 from June 2013 through December 2021, the increases in the average credit card payment amounts during the pandemic were substantial in general, and especially in the months following each of the three federal economic impact payments and the advance child tax credit payments. See appendix V for additional information on our analysis.

While not all cardholders were eligible to receive federal pandemic cash assistance, other factors may have provided additional cash flows to help cardholders pay down their balances. For example, during the pandemic, some cardholders may have benefited from appreciation of financial

[40]The 95 percent confidence intervals for the estimates ranged from 49 to 54 percent based on surveys conducted after the distribution of the second economic impact payments, and from 48 to 59 percent based on surveys conducted after the third economic impact payments.

[41]Our analysis also estimated that cardholders reduced their credit card payments by an average of $49 in March 2020 when the COVID-19 pandemic was declared. When the first economic impact payments were disbursed in April 2020, cardholders on average increased their payments, largely reversing the March 2020 decrease. Another study found that the distribution of the first economic impact payments was associated with a substantial increase in payments on rents, mortgages, and credit cards. See Scott R. Baker et al., "Income, Liquidity, and the Consumption Response to the 2020 Economic Stimulus Payments" (NBER Working Paper No. 27097, Sept. 15, 2020) https://www.nber.org/papers/w27097.pdf. A study also reported that cardholders eligible for the economic impact payments increased their credit card payments substantially at the start of 2021, which was likely supported by the second and third economic impact payments. See Adams, Bord, and Katcher, "Why Did Credit Card Balances Decline."

[42]Not all households were eligible to receive the economic impact payments or the advance child tax credit since these types of assistance were generally based on an individual's or household's income or family status. We did not have data that would have allowed us to determine which cardholders were eligible for these pandemic assistance payments. As a result, our estimates on the effect of pandemic assistance funds used payment data for cardholders who both did and did not receive such funds.

assets or a refinancing of their mortgage. Other cardholders may have been eligible for a pause on their student loan payments. As a result, these cardholders may have had more cash to pay down balances, according to the Federal Reserve's research, CFPB staff, and some industry participants with whom we spoke.[43]

Improved Credit Scores

Many cardholders' credit scores improved during the pandemic. Our analysis of Federal Reserve data found that revolvers on average had an increase of 20 points in their credit scores from March 2020 through December 2021. In comparison, revolvers on average had an increase of 7 points over a similar period from March 2018 through December 2019. Additionally, 71 percent of revolvers saw an increase in their credit scores from March 2020 through December 2021, compared with 65 percent of revolvers from March 2018 through December 2019.

Consistent with our analysis, three credit card issuers and two credit reporting agencies told us that credit scores increased for cardholders across credit score categories during the pandemic. They attributed this trend to cardholders paying down their credit card balances. Two of these companies added that cardholders with subprime credit scores saw larger increases in their credit scores compared with cardholders in other credit score categories.[44]

Fewer Delinquencies

Federal pandemic assistance and credit card issuers' voluntary payment assistance programs likely provided support to some cardholders and decreased delinquencies, according to CFPB and several industry participants.[45] As previously discussed, issuers' payment assistance programs generally included payment deferrals and fee waivers. Our

[43]Adams, Bord, and Katcher, "Why Did Credit Card Balances Decline." The industry participants were two credit card issuers and two credit reporting agencies.

[44]A study also found that credit scores for all borrowers generally increased after March 2020, especially for borrowers with lower credit scores. Also, credit card utilization of borrowers with lower credit scores decreased early in the pandemic, which likely contributed to increased credit scores. The decrease in credit card utilization could reflect consumers reducing spending and using pandemic assistance to pay down debt. See Sarena Goodman et al., "Developments in the Credit Score Distribution over 2020" (Board of Governors of the Federal System, Apr. 30, 2021), accessed May 24, 2023, https://www.federalreserve.gov/econres/notes/feds-notes/developments-in-the-credit-score-distribution-over-2020-20210430.html.

[45]The industry participants were six credit card issuers, the American Bankers Association, and two credit reporting agencies. All issuers surveyed by CFPB reported offering pandemic-related relief programs. See Consumer Financial Protection Bureau, *The Consumer Credit Card Market*.

analysis of Federal Reserve data found that the percentage of seriously delinquent credit card accounts generally declined from April 2020 to December 2021.[46]

A relatively small share of cardholders enrolled in the voluntary payment assistance programs, according to four large issuers.[47] For instance, two of the issuers told us about 3–4 percent of their credit card customers enrolled in a payment assistance program. CFPB found that cardholders with lower incomes or credit scores or who were non-White were more likely to enroll in payment assistance programs. Three credit card issuers and a credit reporting agency also noted that many cardholders who were enrolled in payment assistance programs continued to make payments or only used the programs for a short period.

In an October 2020 comment letter to CFPB, the National Consumer Law Center stated that unlike the mandatory mortgage assistance programs, the voluntary credit card payment assistance programs may have reached only consumers financially sophisticated enough to request them.[48] The center also noted that enrollment was subject to the discretion of the issuer. It said that, as a result, these voluntary assistance programs may not have reached some consumers in need of assistance.

[46]Our analysis also found that the share of seriously delinquent accounts started to increase in the second half of 2021, although it largely remained below prepandemic levels. Two credit card issuers and three credit reporting agencies reported a similar increase in delinquencies after the end of the pandemic assistance in 2021. Additionally, the Federal Reserve Bank of New York reported that the percentage of credit cardholders who became 90 or more days delinquent during the fourth quarter of 2022 surpassed that percentage from before the pandemic among younger cardholders. The percentage was rising for older cardholders but had not yet reached prepandemic levels. The bank stated that rising interest rates, inflation, and the end of various forms of pandemic assistance may have been possible contributing factors to rising delinquency rates.

[47]The six credit card issuers we spoke with had terminated their pandemic-related payment assistance programs or had only a small percentage of credit card accounts remaining in these programs by the end of 2020, according to their 2020 annual filings. See Consumer Financial Protection Bureau, *The Consumer Credit Card Market*.

[48]National Consumer Law Center, “Re: CARD Act Rules Review Pursuant to the Regulatory Flexibility Act; Request for Information Regarding Consumer Credit Card Market, Docket No. CFPB–2020–0027” (Oct. 27, 2020).

Cardholders in Our Sample in Areas with Majority-Black or -Hispanic Residents Likely Had Less Favorable Credit Terms and Carried Balances Longer

Credit Terms in Majority-Black or -Hispanic Zip Codes Were Generally Worse Than Those in Predominantly White Zip Codes

Our analysis of a sample of more than 650,000 individual credit card accounts from Federal Reserve data suggests that, in comparison with cardholder accounts in billing zip codes with predominantly White residents, accounts in billing zip codes with more Black or Hispanic residents on average had higher interest rates and lower credit limits.[49] We found these differences both before and after controlling for differences in other cardholder characteristics that can influence credit card terms (credit scores, incomes in their zip codes, and revolving status).[50] Our analysis could not determine whether the racial and ethnic

[49]In this report, we use the term “Black” to refer to “Black or African American” and “Hispanic” to refer to “Hispanic or Latino.” Our analysis did not identify a cluster of zip codes with a majority of Asian residents, and therefore we do not present results on majority-Asian zip codes. We do not report on the “Other” race and ethnicity category because of the small number of observations of credit card accounts in the Federal Reserve data that were located in zip codes with residents in this category. As previously discussed, the Federal Reserve collects data on credit card accounts from credit card issuers. However, credit card issuers are not permitted to collect information on the race or ethnicity of the cardholders. See apps. III and VI for additional information on our econometric analysis of the association between credit terms and race and ethnicity in cardholders’ zip codes.

[50]Because the Federal Reserve data did not include updated incomes of cardholders, we controlled for the income distribution in cardholders’ zip codes, based on the household incomes from Census’s American Community Surveys for 2013–2020. We measured the distribution of income in cardholders’ zip codes as the percentage of households with income in each of 16 income groups. See app. VI for additional information on our methodology.

disparities in credit terms resulted from fair lending disparities, which cannot be measured as independent factors in our analysis.[51]

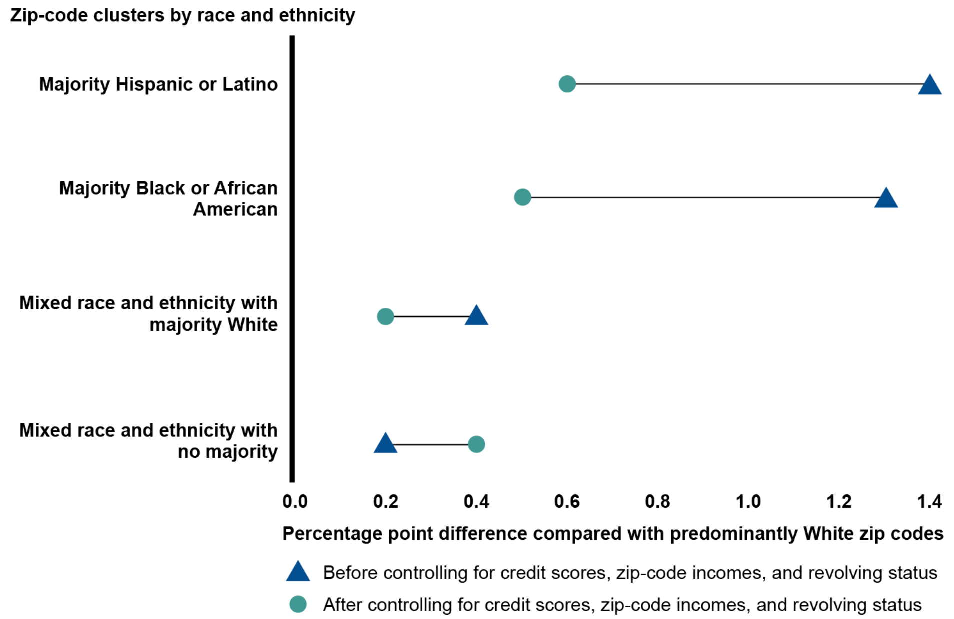
Interest Rates

Using data from June 2013 through December 2021, our analysis suggests that accounts in billing zip codes with a greater share of Black or Hispanic residents had higher interest rates on average than accounts in billing zip codes with predominantly White residents (see fig. 10).[52] Specifically, we estimated that interest rates were about 1.3 percentage points higher on average for accounts in billing zip codes with a majority of Black residents, and 1.4 percentage points higher for zip codes with a majority of Hispanic residents. Among credit card accounts with the same credit score, zip-code income distribution, and revolving status, these differences persisted, although they were smaller (see fig. 10). For instance, interest rates were 0.5 percentage points higher on average for accounts in billing zip codes with a majority of Black residents, and 0.6 percentage points higher for accounts in billing zip codes with a majority of Hispanic residents, relative to accounts in predominantly White zip codes. See appendixes III and VI for additional information on our methodology and the results of our analysis.

[51]Credit card issuers are prohibited from making lending decisions based on borrowers' race or ethnicity. 12 U.S.C. § 1691(a).

[52]For context, the median interest rate for accounts in predominantly White billing zip codes was 17.5 percent in December 2019.

Figure 10: Estimated Average Interest Rate Differences for Cardholder Accounts by Race and Ethnicity of Billing Zip Codes, June 2013–December 2021



Source: GAO analysis of data from the Board of Governors of the Federal Reserve System and the Census Bureau's American Community Survey. | GAO-23-105269

Note: Our analysis was based on a nongeneralizable sample of general purpose credit card accounts. Because data from the Board of Governors of the Federal Reserve System do not provide the race or ethnicity of cardholders, we supplemented with race and ethnicity data of the accounts' billing zip codes, as reported by the Census Bureau's 5-year American Community Surveys for 2013–2020. We used econometric analysis to estimate the associations between credit card interest rates and the zip-code clusters of varying racial and ethnic composition; zip-code clusters of predominantly White residents served as the reference group. We do not account for all possible factors related to differences in interest rates for cardholders in different racial and ethnic groups, which may result from various unobservable factors. Also, the existence of differences in interest rates does not establish whether fair lending disparities have occurred. We rounded the results of the interest rate differences to the nearest hundredth. See apps. III and VI for additional information on our methodology and the results of our analysis.

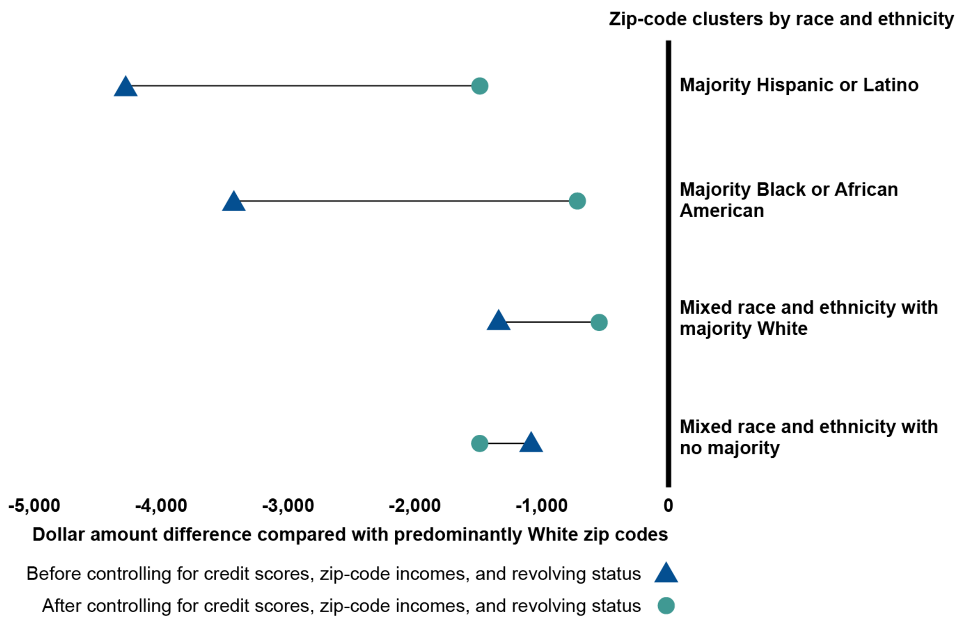
Credit Limits

Using data from June 2013 through December 2021, our analysis suggests that accounts in billing zip codes with a greater share of Black or Hispanic residents had lower credit limits on average than accounts in billing zip codes with predominantly White residents (see fig. 11).[53] Specifically, credit limits for accounts in billing zip codes with a majority of Black or Hispanic residents were on average about $3,412 and $4,285 lower, respectively. Further, as shown in figure 11, among credit card

[53]The median credit limit for accounts in predominantly White billing zip codes was $8,100 in December 2019.

accounts with the same credit score, zip-code income distribution, and revolving status, these differences persisted, although they were smaller. For instance, credit limits were on average $710 lower for accounts in billing zip codes with a majority of Black residents, and $1,477 lower for accounts in billing zip codes with a majority of Hispanic residents. See appendixes III and VI for additional information on our methodology and the results of our analysis.

Figure 11: Estimated Average Credit Limit Differences for Cardholder Accounts by Race and Ethnicity in Billing Zip Codes, June 2013–December 2021



Source: GAO analysis of data from the Board of Governors of the Federal Reserve System and the Census Bureau's American Community Survey. | GAO-23-105269

Note: Our analysis was based on a nongeneralizable sample of general purpose credit card accounts. Because data from the Board of Governors of the Federal Reserve System do not provide the race or ethnicity of cardholders, we supplemented with race and ethnicity data of the accounts' billing zip codes, as reported by the Census Bureau's 5-year American Community Surveys for 2013–2020. We used econometric analysis to estimate the associations between credit card credit limits and the zip-code clusters of varying racial and ethnic composition; zip-code clusters of predominantly White residents served as the reference group. We do not account for all possible factors related to differences in credit limits for cardholders in different racial and ethnic groups, which may result from various unobservable factors. Also, the existence of differences in credit limits does not establish whether fair lending disparities have occurred. We rounded the results for the credit limit differences to the nearest whole dollar amount. See apps. III and VI for additional information on our methodology and the results of our analysis.

Our results are consistent with other studies that found meaningful racial and ethnic differences in credit costs and the amount of credit approved or the likelihood of receiving approval for other types of credit products, including auto, mortgage, and small business loans.[54] However, our analysis does not on its own offer an explanation of what might be driving our results. Our analysis was not designed to determine all the potential reasons for racial and ethnic disparities in the interest rates cardholders were charged or credit limits, which may be due to factors that either are not captured in the data we analyzed or cannot be measured. Such factors could include the extent to which cardholders compare credit terms when choosing a card, competition among lenders, and lender-specific risk evaluation or loan approval processes.[55] Differences in these factors may be incidentally associated with race and ethnicity, or these factors can themselves be influenced by race and ethnicity, and therefore

[54]For information on auto loans, see Alexander W. Butler, Erik J. Mayer, and James P. Weston, “Racial Disparities in the Auto Loan Market,” *Review of Financial Studies*, vol. 36, no. 1 (2023): 1–41. For information on mortgage loans, see Robert Bartlett et al., “Consumer-Lending Discrimination in the FinTech Era,” *Journal of Financial Economics*, vol. 143, no. 1 (2022): 30–56; Ping Cheng, Zhenguo Lin, and Yingchun Liu, “Racial Discrepancy in Mortgage Interest Rates,” *Journal of Real Estate Finance and Economics*, vol. 51, no. 1 (2015): 101–120; and Neil Bhutta, Aurel Hizmo, and Daniel Ringo, “How Much Does Racial Bias Affect Mortgage Lending? Evidence from Human and Algorithmic Credit Decisions” (working paper, Finance and Economics Discussion Series, Board of Governors of the Federal Reserve System, Aug. 2, 2022), https://www.federalreserve.gov/econres/feds/how-much-does-racial-bias-affect-mortgage-lending.htm. However, another study suggests that associations between borrowers’ race and ethnicity and their mortgage rates are offset by associations between borrowers’ race and ethnicity and their discount points, weakening associations between borrowers’ race and ethnicity and the total price for their mortgage. See Neil Bhutta and Aurel Hizmo, “Do Minorities Pay More for Mortgages?” *Review of Financial Studies*, vol. 34, no. 2 (2021): 763–789. For information on small business loans, see Mels de Zeeuw and Brett Barkley, “Mind the Gap: Minority-Owned Small Businesses’ Financing Experiences in 2018,” *Consumer & Community Context,* vol. 1, no. 2 (2019), https://www.federalreserve.gov/publications/files/consumer-community-context-201911.pdf.

[55]For information on borrowers comparing credit terms, see Victor Stango and Jonathan Zinman, “Borrowing High versus Borrowing Higher: Price Dispersion and Shopping Behavior in the U.S. Credit Card Market,” *The Review of Financial Studies*, vol. 29, no. 4 (2016): 979–1006, and Cheng, Lin, and Liu, “Racial Discrepancy in Mortgage Interest Rates.” For information on lender competition, see Butler, Mayer, and Weston, “Racial Disparities in the Auto Loan Market,” and Bhutta, Hizmo, and Ringo, “How Much Does Racial Bias Affect Mortgage Lending?” The latter study also discusses how differences in mortgage approval may be associated with lender-specific loan approval processes, including stricter credit standards for all borrowers. Another study also stated that issuers’ internal risk-based pricing models may place different emphasis on risk factors such as credit scores and late payments, and hence cardholders may receive different interest rates from different issuers. See Stango and Zinman, “Borrowing High versus Borrowing Higher.” As previously discussed, credit card issuers are prohibited from making lending decisions, including decisions about credit terms offered, based on borrowers’ race and ethnicity. 12 U.S.C. § 1691(a). Our analysis could not determine whether the racial and ethnic disparities in credit terms faced by cardholders resulted from fair lending disparities, which cannot be measured as independent factors in our analysis.

act as channels through which race and ethnicity influence interest rates or credit limits.

Cardholders in Majority-Black or -Hispanic Zip Codes Likely Carried Balances for Longer Than Those in Predominantly White Zip Codes

We examined how the duration of revolving episodes (periods when an account continuously carries a balance) varied among cardholders on the basis of their billing zip code's racial and ethnic mix. To do so, we used multivariate regression models and simulations to compare the distributions of revolving episode durations for cardholder accounts in five clusters of billing zip codes with different racial and ethnic composition. We made this comparison separately for revolving episodes during the period before the pandemic (June 2013–March 2020) and during the period of the pandemic (April 2020–December 2021). We compared revolving episodes by racial composition of zip codes separately for the prepandemic and pandemic periods because various conditions (e.g., those related to public health, the economy, and public policy) prevailed during the pandemic that might have affected credit card usage and may have done so differently for different groups.

Our analysis suggests that under prepandemic conditions, revolving episodes of accounts in majority-Black or -Hispanic billing zip codes were associated with the following differences when compared with revolving episodes of accounts in predominantly White billing zip codes.

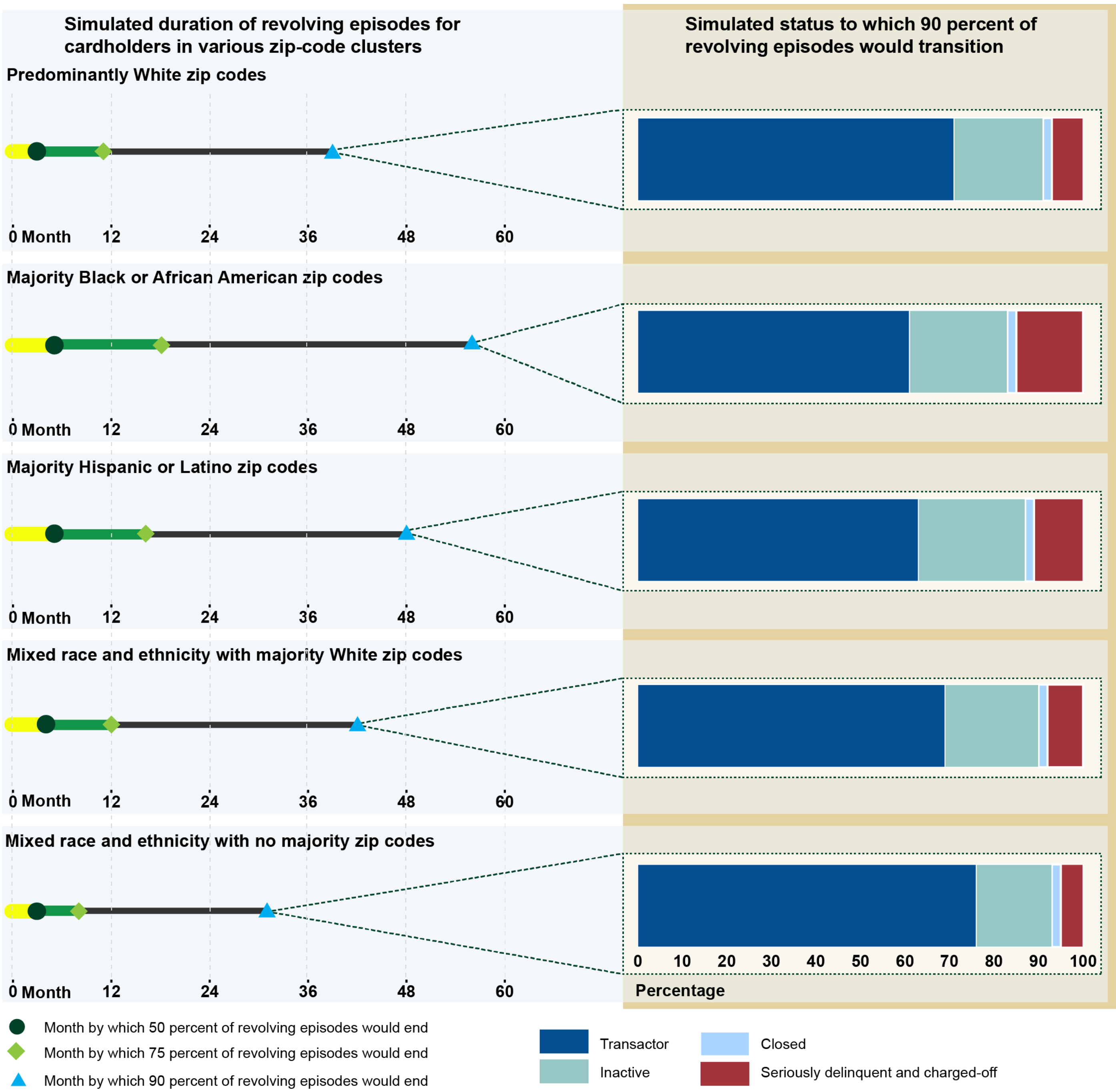
- **Longer revolving episodes.** Our analysis indicates that accounts in majority-Black billing zip codes likely had longer revolving episodes than those in predominantly White billing zip codes. For example, it indicates that about 90 percent of revolving episodes in predominantly White zip codes likely ended sometime between 1 and 39 months, with 50 percent of the revolving episodes ending within 3 months (see fig. 12).[56] In comparison, about 90 percent of revolving episodes in majority-Black zip codes likely ended sometime between 1 and 56 months, with 50 percent of the revolving episodes ending within 5 months. Cardholders in majority-Hispanic zip codes similarly had longer revolving episodes (see fig. 12).
- **Fewer transitions to transacting status.** For the 90 percent of revolving episodes of accounts in predominantly White billing zip codes that ended sometime between 1 and 39 months, our analysis indicates that about 71 percent of them likely transitioned to transacting status. In comparison, a smaller share of revolving

[56]As previously noted, we report on the 90th percentile of the results because this percentile is more representative of accounts that were in a revolving episode in any given month than is the median. See app. IV for additional information on our analysis.

episodes of accounts in majority-Black or -Hispanic billing zip codes likely transitioned to transacting status. For example, of the 90 percent of revolving episodes in majority-Black zip codes that ended within 56 months, 61 percent likely transitioned to transacting status. Results for majority-Hispanic zip codes were similar (see fig. 12).

- **More transitions to seriously delinquent and charged-off or inactive status.** Our analysis also indicates that revolving episodes of accounts in majority-Black or -Hispanic billing zip codes were more likely to transition to seriously delinquent and charged-off or inactive status than those in predominantly White billing zip codes, as shown in figure 12.

Figure 12: Simulated Length of Credit Card Revolving Episodes and Status after End of Revolving Episodes, by Race and Ethnicity in Billing Zip Codes, June 2013–December 2019



Source: GAO analysis of data from the Board of Governors of the Federal Reserve System and the Census Bureau. | GAO-23-105269

Note: Our analysis was based on a nongeneralizable sample of general purpose credit card accounts. Because data from the Board of Governors of the Federal Reserve System do not provide the race or ethnicity of cardholders, we supplemented with race and ethnicity of the accounts' billing zip codes, as reported by the Census Bureau's 5-year American Community Surveys for 2013–2020. We used statistical models and simulations to compare revolving episodes for each of the five zip-code clusters of varying racial and ethnic composition; zip-code clusters of predominantly White residents served as the reference group. However, our analysis does not explain the reasons for differences in revolving episode durations among different racial and ethnic clusters of zip codes, and thus does not establish a causal relationship between revolving episode duration and the racial and ethnic composition in cardholders' zip codes. See apps. III and IV for additional information on our analysis.

Furthermore, consistent with our findings on credit card usage during the pandemic, discussed earlier, our analysis indicates that under pandemic conditions, revolving episodes for all accounts would likely shorten. In particular, our analysis indicates that for accounts in majority-Black or -Hispanic billing zip codes, about 90 percent of revolving episodes would end within 39 months and 32 months, respectively. However, accounts in billing zip codes with more Black or Hispanic residents would still have longer revolving durations than accounts in predominantly White billing zip codes under pandemic conditions. See appendixes III and IV for additional information on our analysis.

Our results are consistent with another study that found meaningful differences in credit card revolving patterns on the basis of race and ethnicity.[57] However, similar to our findings on interest rates and credit limits, our analysis does not on its own offer an explanation of what might be driving our results. Our analysis was not designed to determine all the potential reasons for racial and ethnic disparities in credit card revolving patterns, which may be due to factors that either are not captured in the data we analyzed or cannot be measured. Such factors could include cardholders' liquidity needs or their assessments of the characteristics of credit cards compared with those of other payment methods.[58] Differences in these factors may be incidentally associated with race and ethnicity, or these factors can themselves be influenced by race and

[57]See Jae Min Lee and Yoon G. Lee, "Multidimensional Credit Attitude and Credit Card Debt Behavior in the United States," *Review of Behavioral Finance*, vol. 14, no. 2 (2022): 183–196.

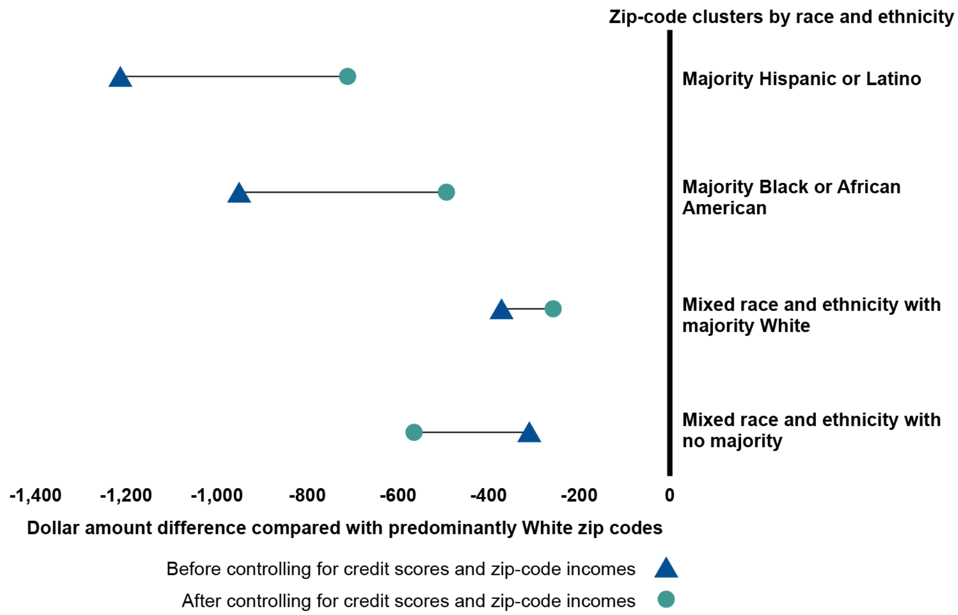
[58]For example, see Irina A. Telyukova, "Household Need for Liquidity and the Credit Card Debt Puzzle," *Review of Economic Studies*, vol. 80 (2013): 1148–1177, and Claire Greene and Joanna Stavins, "Credit Card Debt Puzzle: Liquid Assets to Pay Bills" (Federal Reserve Bank of Boston Working Papers, no. 22-8, June 2022), accessed Feb. 23, 2023, https://www.bostonfed.org/publications/research-department-working-paper/2022/credit-card-debt-puzzle-liquid-assets-to-pay-bills.

ethnicity, and therefore act as channels through which race and ethnicity influence revolving patterns.

Our analysis also suggests that, despite their likelihood of carrying balances for longer, accounts in majority-Black or -Hispanic billing zip codes carried lower revolving balances than accounts in billing zip codes with predominantly White residents (see fig. 13).[59] Specifically, revolving balances carried by accounts in billing zip codes with a majority of Black or Hispanic residents were $953 and $1,212 lower, respectively, compared with accounts in billing zip codes with predominantly White residents. Among credit card accounts with the same credit score and zip-code income distribution, these differences persisted, although they were smaller. For instance, revolving balances were $492 lower on average for accounts in billing zip codes with a majority of Black residents, and $711 lower for accounts in billing zip codes with a majority of Hispanic residents. A lower revolving balance may reduce the absolute credit costs for accounts in majority-Black or -Hispanic billing zip codes. However, these accounts likely still paid more for each dollar of credit card use because they generally faced higher interest rates and carried their balances for longer.

[59]For context, the nominal median revolving balance for all accounts was $1,720 in December 2019. See app. VI for additional information on our analysis.

Figure 13: Estimated Revolving Balance Differences for Cardholder Accounts by Race and Ethnicity of Billing Zip Codes, June 2013–December 2021



Source: GAO analysis of data from the Board of Governors of the Federal Reserve System and the Census Bureau's American Community Survey. | GAO-23-105269

Note: Our analysis was based on a nongeneralizable sample of general purpose credit card accounts. Because data from the Board of Governors of the Federal Reserve System do not provide the race or ethnicity of cardholders, we supplemented with race and ethnicity data of the accounts' billing zip codes, as reported by the Census Bureau's 5-year American Community Surveys for 2013–2020. We used econometric analysis to estimate the associations between credit balances carried by cardholders and the zip-code clusters of varying racial and ethnic composition; zip-code clusters of predominantly White residents served as the reference group. We do not account for all possible factors related to differences in revolving balances for cardholders in different racial and ethnic groups, which may result from various unobservable factors. Also, the existence of differences in revolving balances does not establish whether fair lending disparities have occurred. We rounded the results for the revolving balance differences to the nearest whole dollar amount. See apps. III and VI for additional information on our methodology and the results of our analysis.

Agency Comments

We provided a draft of this report to CFPB and the Federal Reserve for review and comment. The agencies provided technical comments, which we incorporated, as appropriate.

As agreed with your offices, unless you publicly announce the contents of this report earlier, we plan no further distribution until 30 days from the report date. At that time, we will send copies of this report to the appropriate congressional committees, the Director of CFPB, the Chair of the Federal Reserve, and other interested parties. In addition, the report will be available at no charge on the GAO website at https://www.gao.gov.

If you or your staff have any questions about this report, please contact me at (202) 512-8678 or cackleya@gao.gov. Contact points for our Offices of Congressional Relations and Public Affairs may be found on the last page of this report. Key contributors to this report are listed in appendix VII.

Alicia Puente Cackley
Director, Financial Markets and Community Investment

Appendix I: Objectives, Scope, and Methodology

This report examines (1) credit card usage from 2013 through 2019 and the characteristics of cardholders who carried balances during this period, (2) how the COVID-19 pandemic and related assistance affected credit card usage from March 2020 through December 2021, and (3) how credit card costs and usage vary among racial and ethnic groups.

Federal Reserve and Census Bureau Data

To address all three objectives, we obtained a 0.1 percent nongeneralizable sample of consumer credit card account data from the Board of Governors of the Federal Reserve System's Capital Assessments and Stress Testing Report (FR Y-14M) from June 2013 through December 2021.[1] After cleaning and preparing the data, we had 30.5 million account-month observations of monthly billing cycle data on more than 650,000 individual credit card accounts. The Federal Reserve credit card data are collected from bank holding companies, savings and loan holding companies, and intermediate holding companies with $100 billion or more in assets. As a result, we cannot generalize the results of our analysis to credit card accounts in all banks in the U.S. The Federal Reserve data allowed us to examine credit card usage by account, but the data did not have information that would allow us to link multiple accounts held by a given individual cardholder. We also cannot link accounts to a specific issuer.

Our analysis included only general purpose credit cards issued on networks, such as Visa, Mastercard, American Express, and Discover, which are accepted by a wide variety of merchants.[2] We removed account-month observations with an address outside of the 50 U.S. states and the District of Columbia—that is, excluding addresses in the U.S. territories and outside of the U.S. See appendix II for more information on the Federal Reserve data.

We supplemented the Federal Reserve data with data from the Census Bureau's 5-Year American Community Surveys for 2013–2020. We used census data on household income and the shares of residents in each zip code who were Asian, Black or African American (referred to as "Black" in this report), Hispanic or Latino (referred to as "Hispanic" in this report),

[1]The Federal Reserve first started collecting the Y-14M data in June 2012. However, our analysis used data beginning in June 2013 because the Federal Reserve did not collect some data elements until that time.

[2]Another type of credit card, referred to as a private label card, can only be used at one merchant or a small group of related merchants. American Express and Discover are both payment networks and credit card issuers.

White, and Other. See appendixes II and III for more information on the census data.

Analysis of Credit Card Account Status

We analyzed the Federal Reserve data to describe different aspects of credit card usage from June 2013 through December 2021, including by cardholder characteristics such as credit score, estimated median household income, and racial and ethnic composition of cardholders' billing zip codes. We generally classify credit card accounts into six groups on the basis of how cardholders use the cards and how the accounts accrue interest charges during each month: transacting, revolving, seriously delinquent, inactive, closed, and charged off (see app. II for additional information on the definitions of the six account statuses).

We examined the share of active accounts by status, including the share of revolving accounts, transacting accounts, and seriously delinquent accounts, and how the share of those accounts changed over time from June 2013 through December 2021. We also calculated the percentage of active accounts that were revolving from June 2013 through December 2019 by credit score category and zip-code-level median household income, averaged over this period.

Additionally, we analyzed the amount of median nominal revolving balance carried by revolving accounts and the percentage of revolving accounts that reached or exceeded their credit limits from June 2013 through December 2021. We analyzed nominal balance amounts because they represent the account balance that cardholders are obligated to repay. While this approach focuses on the cardholder experience, changes over time in nominal balances reflect changes in the price level as well as changes in the real value of the balances.

We also used econometric analysis to estimate the revolving balances carried by cardholders in zip codes with different racial and ethnic composition during the same period.[3] Furthermore, we compared the percentages of transacting accounts and revolving accounts that made purchases and the purchase amounts. All dollar amounts are in nominal terms unless otherwise noted.

[3]See app. VI for additional information on the analysis and results.

Analysis of Revolving and Transacting Episode Durations

We calculated the duration of revolving episodes—that is, the number of consecutive months revolving accounts carried a balance—using Federal Reserve data from June 2013 through December 2021. We assigned the accounts to five categories based on the total duration of their revolving episodes: short-term revolving accounts, which revolved for 3 months or less; medium-term revolving accounts, which revolved for 4–11 months; long-term revolving accounts, which revolved for 12 months or more; and accounts we observed to be revolving for short or medium terms but for which we did not observe the full episode because the observation occurred at the start or end of the account's appearance in our data. We report on the fraction of long-term episodes from June 2014 through December 2020 because too many of the observations in the first and last years of our data are not complete episodes.

For accounts that were revolving in a given month, we also identified the status of each revolving account in the following month in order to construct econometric models that estimated the probability that revolvers would either pay off their bill or become seriously delinquent. This analysis allowed us to estimate the distribution of the number of months revolving episodes would have been expected to last under conditions that prevailed during the COVID-19 pandemic (April 2020–December 2021) and before the pandemic (June 2013–March 2020).[4] We conducted similar analysis for transacting episodes.

Our econometric models also allowed us to examine the distribution of revolving and transacting episode durations under prepandemic conditions (June 2013–March 2020) and pandemic conditions (April 2020–December 2021) by the racial and ethnic composition of cardholders' billing zip codes. Our analysis does not account for all possible factors or establish causal relationships related to differences in the revolving or transacting episode durations and account status under prepandemic and pandemic conditions. Our analysis also does not account for all possible factors or establish causal relationships related to differences in the revolving or transacting episode durations and account status for cardholders in zip-code clusters with different racial or ethnic composition. See appendixes III and IV for additional information on the methodology and results of our analysis.

[4]Some of the conditions could include public health conditions, economic conditions such as employment levels, and effects of policy responses, such as restrictions and government assistance in response to the pandemic.

Analysis of Credit Cost Differences

To estimate differences in credit costs for revolvers who carry balances for different amounts of time, we used the 2019 average credit card interest rate as published by the Federal Reserve and calculated interest charges for two hypothetical cardholders carrying a balance over different numbers of months.[5] We also reviewed Consumer Financial Protection Bureau (CFPB) reports for information on what consumers would be likely to do when they had difficulty paying for a bill or expense, and how that might affect their credit costs.[6]

Additionally, we constructed econometric models to examine the relationships between cardholders' credit card terms (interest rates and credit limits) and the racial and ethnic composition of their zip codes. Our results should be interpreted with caution. Our analysis was not designed to determine all the potential reasons for racial and ethnic disparities in credit terms, which may be due to factors that are either not captured in the data we analyzed or cannot be measured. Differences in these factors may be incidentally associated with race and ethnicity, or these factors can themselves be influenced by race and ethnicity, and therefore act as channels through which race and ethnicity influence credit terms. See appendixes III and VI for additional information on the methodology and results of our analysis.

Analysis of Credit Card Usage in Association with Pandemic-Related Responses

To identify federal and private-sector COVID-19 pandemic assistance and understand how the assistance may have contributed to changes in credit card usage during the pandemic, we reviewed reports from GAO, the

[5]Board of Governors of the Federal Reserve System, *Report to Congress: Profitability of Credit Card Operations of Depository Institutions* (Washington, D.C.: November 2020).

[6]Consumer Financial Protection Bureau, *Consumer Use of Payday, Auto Title, and Pawn Loans: Insights from the Making Ends Meet Survey*, Research Brief No. 2021-1 (May 2021) and *Insights from the Making Ends Meet Survey*, Research Brief No. 2020-1 (July 2020). The first CFPB report was based on information from the first two waves of the agency's Making Ends Meet survey, conducted in June 2019 and June 2020.

Federal Reserve, and CFPB.[7] We also reviewed the 2020 annual filings from six large credit issuers: American Express, Bank of America, Capital One, Citibank, Discover, and JPMorgan Chase. We selected these issuers because they had the largest purchase volume and outstanding balances in their credit card portfolios in 2020.

Additionally, using Federal Reserve data, we compared revolving accounts' credit scores on average during the pandemic (March 2020–December 2021) and before the pandemic (March 2018–December 2019). Specifically, we estimated the average credit score point increase and the share of revolvers that saw an increase in their credit score during each of these two periods.

Further, we conducted a regression analysis to estimate the average amount by which cardholders increased their payments when the three waves of economic impact payments and advance child tax credit payments were disbursed during the pandemic.[8] In addition, we examined data from the Census Bureau's Household Pulse Survey conducted from April 23, 2020, to October 11, 2021, related to how

[7]See for example, GAO, *Stimulus Checks: Direct Payments to Individuals during the COVID-19 Pandemic*, GAO-22-106044 (Washington, D.C.: June 29, 2022) and *COVID-19: Opportunities to Improve Federal Response and Recovery Efforts*, GAO-20-625 (Washington, D.C.: June 25, 2020); Robert M. Adams, Vitaly M. Bord, and Bradley Katcher, "Why Did Credit Card Balances Decline So Much during the COVID-19 Pandemic" (Board of Governors of the Federal Reserve System, Dec. 3, 2021), accessed Jan. 24, 2022, https://www.federalreserve.gov/econres/notes/feds-notes/why-did-credit-card-balances-decline-so-much-during-the-covid-19-pandemic-20211203.html; Robert Adams and Vitaly Bord, "The Effects of the COVID-19 Shutdown on the Consumer Credit Card Market: Revolvers versus Transactors" (Board of Governors of the Federal Reserve System, Oct. 21, 2020), accessed Jan. 24, 2022, https://www.federalreserve.gov/econres/notes/feds-notes/the-effects-of-the-covid-19-shutdown-on-the-consumer-credit-card-market-revolvers-versus-transactors-20201021.html; and Consumer Financial Protection Bureau, *The Consumer Credit Card Market* (September 2021) and *Consumer Finances During the Pandemic: Insights from the Making Ends Meet Survey* (December 2021).

[8]See app. V for additional information on the regression analysis.

survey respondents used or planned to use the federal economic impact payments, including to pay down credit card and other debts.[9]

Data Reliability Assessments

To assess the reliability of the Federal Reserve's credit card data, we conducted electronic testing for missing data and obvious errors, reviewed the Federal Reserve's technical documentation, and interviewed staff from the Federal Reserve and CFPB who were knowledgeable about the data. We determined that the Federal Reserve data were sufficiently reliable for the purpose of examining the distribution of credit card accounts by account status, cardholder characteristics, and revolving patterns for June 2013–December 2021.

Additionally, we reviewed technical documentation related to Census's 5-year American Community Surveys for 2013–2020, and determined that the data were sufficiently reliable for describing the household income and racial and ethnic composition in cardholders' zip codes. Further, we assessed the reliability of data from Census's Household Pulse Survey conducted from April 23, 2020, to October 11, 2021, related to how survey respondents used or planned to use the federal economic impact payments. We conducted data testing and reviewed Census's technical documentation, and we found these data to be sufficiently reliable for describing how pandemic cash assistance contributed to changes in credit card balances.

To assess the data reliability of the crosswalk of zip codes and zip-code tabulation areas, we reviewed information from Census and UDS Mapper (owner of the crosswalk data), including descriptions of the data and how the data can be used. We determined the crosswalk data to be sufficiently reliable for our purpose of matching zip codes in the Federal Reserve's Y-14M data to zip-code tabulation areas in Census's 5-year American Community Surveys.

For all of our objectives, we also interviewed knowledgeable staff from CFPB and the Federal Reserve and representatives from the six large credit card issuers we selected, three credit reporting agencies (Equifax,

[9]The Household Pulse Survey, an experimental data product, is an interagency federal statistical rapid response survey to measure household experiences during the COVID-19 pandemic. The Census Bureau conducts this survey in partnership with five other agencies from the Federal Statistical System. Response rates over our period of analysis ranged from 2.3 percent to 7.5 percent. Census applied weighting adjustments to mitigate nonresponse bias, according to Census. All reported estimates have a relative margin of error of 19 percent or less of the estimate, and all reported comparisons are statistically significant at the 95 percent confidence level.

Experian, and TransUnion), the American Bankers Association, and the National Consumer Law Center.

We conducted this performance audit from May 2021 to September 2023 in accordance with generally accepted government auditing standards. Those standards require that we plan and perform the audit to obtain sufficient, appropriate evidence to provide a reasonable basis for our findings and conclusions based on our audit objectives. We believe that the evidence obtained provides a reasonable basis for our findings and conclusions based on our audit objectives.

Appendix II: Data and Descriptive Statistics

We used data from the Board of Governors of the Federal Reserve System for all three of our objectives and from the Census Bureau for two of them. This appendix describes the steps we took to clean the data and create our analysis variables. It also describes the analysis dataset and the descriptive statistics we analyzed.

Federal Reserve Credit Card Data

To examine consumer credit card usage, we obtained a 0.1 percent nongeneralizable sample of consumer credit card account data from the Federal Reserve's Capital Assessments and Stress Testing Report (FR Y-14M). For each account and month, the credit card account data included monthly observations on purchase amounts, fees, interest charges, cycle ending balances, payment amounts, whether an account was closed, and the number of days a payment was past due. For each account and month, the data also included observations on the cardholder's billing zip code and credit score, and the interest rate and credit limit on the account, among other things. The data we analyzed are an unbalanced panel with observations on each account for months during the period from June 2013 through December 2021; the specific months for which we have information vary from account to account.[1]

The Federal Reserve credit card data are collected from bank holding companies, savings and loan holding companies, and intermediate holding companies with $100 billion or more in assets.[2] Therefore, we cannot generalize the results of our analysis to credit card accounts in all banks in the U.S. Additionally, the data sample excluded observations with an address in a zip code that had only one credit card issuer in that month. The percentage of accounts excluded ranged from 0.3 percent of accounts with billing zip codes in New Jersey to 12 percent of those in Vermont. Our analysis included only general purpose credit cards issued on networks, such as Visa, Mastercard, American Express, and Discover, which are accepted by a wide variety of merchants. The Federal Reserve data allowed us to examine credit card usage by account, but the data did not have information that would allow us to link multiple accounts held by

[1]The Federal Reserve first started collecting the Y-14M data in June 2012. However, our analysis used data beginning in June 2013 because the Federal Reserve did not collect some data elements until that time.

[2]The top 10 credit card issuers held 82 percent of the outstanding credit card balances as of December 31, 2021, as reported by the Federal Reserve. See Board of Governors of the Federal Reserve System, *Report to Congress: Profitability of Credit Card Operations of Depository Institutions* (July 2022).

a given individual cardholder. We also cannot link accounts to a specific issuer.

To prepare the Federal Reserve data for our analysis, we performed the following steps:

- We identified 358,626 fully duplicate observations, which we dropped.
- The reference numbers assigned to accounts were assigned by the issuers, so while account reference numbers are unique within an issuer, they may not be unique across issuers.[3] We identified accounts with the same reference numbers that were active in the same month, which likely occurred because of this issue. To address this issue, we separated accounts by first assigning unique identification numbers to those duplicate accounts that had different account origination dates. For the smaller number of duplicate account reference numbers in a month that had the same origination date, we separated them by billing zip code.
- We removed account-month observations with a billing address outside of the 50 U.S. states and the District of Columbia—that is, we excluded addresses in the U.S. territories and outside of the U.S.

To further prepare the Federal Reserve data for analysis, we imputed values for variables with missing values where possible. Some accounts in the data did not have information for one or more of the following variables in some months: cycle ending balance, payment amount, and fees and interest charges. To address this data limitation, we used values of other relevant variables and imputed the missing values for these variables to the extent possible. For example, for accounts missing cycle ending balances, we replaced missing observations with the sum of promotional balances, cash advance volume, penalty balances, and other balances if those values were available. Table 1 describes the relationships we used to impute these variable observations with missing values.

[3]The account reference number is a unique identifier for each credit card account that is different from the credit card's account number and stays the same from month to month.

Table 1: Relationships Used to Impute Credit Card Data Variable Observations with Missing Values

Variable	Description of imputation
Cycle ending balance	Equals the sum of the promotional balances, cash advance balances, penalty balances, and other balances at the end of the billing cycle.
Payment amount	Equals zero if account was newly opened. Equals the sum of cycle beginning balance, new purchases, balance transfers, cash advances, convenience checks, interest, and fees, and less cycle ending balance and other credits.
Fees and interest charges	Equals the sum of cycle ending balance and new purchases, and less cycle beginning balance, payments, and credits.

Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

For all account-month observations with the previous month's cycle ending balance available, we constructed a cycle beginning balance equal to the previous month's cycle ending balance. If the previous month's cycle ending balance was not available, we set the cycle beginning balance to zero if the account was new (defined as an account that was opened within 3 months of the observation). If the previous month's cycle ending balance was not available and the account was not newly issued, we set the cycle beginning balance to be equal to the sum of the cycle ending balance, payments, and credits, less new purchases, balance transfers, cash advances, convenience checks, interest, and fees if those values were available.

For each account-month observation, we created a new variable describing the status of the account. To track the status of an account, we created six categories for the account status for each month to classify credit card accounts based on how cardholders use the cards and whether interest is charged during each month.[4]

- **Transacting accounts.** If the cardholder pays all of the account balance due for the billing cycle by the due date, we refer to the cardholder as a "transactor" and to the account as a "transacting account." We primarily assign this status by identifying accounts with a positive starting balance but no finance charges due.[5] Repeat

[4]We assigned status according to the payment actions in the month, not the spending decisions in that month.

[5]As a consequence of our assignment approach, any accounts that are carrying a balance that has a zero percent promotional annual percentage rate are also classified as transacting accounts.

transactors are not charged interest on the end-of-cycle balance or on new purchases during the grace period (between the end of a billing cycle and the date payment is due). Accounts with 1 inactive month (defined below) that is both preceded and followed by transacting months are classified as transacting, even though they have no balance to pay off in 1 month.

- **Revolving accounts.** If the cardholder pays less than the entire account balance due for the billing cycle, or if the cardholder's account has been delinquent for less than 90 days, we refer to the cardholder as a "revolver" and to the account as a "revolving account." We primarily assign this status by identifying accounts with interest charges incurred in the billing cycle that are not delinquent for more than 90 days.[6] In contrast with transactors, revolvers are charged interest on the remaining unpaid balances from prior cycles (also called revolving balances), and immediately on any new purchases they make in the current cycle.[7]
- **Seriously delinquent accounts.** If the cardholder does not pay at least the minimum payment due for 90 days or more, we classify the account as seriously delinquent. We use the issuer's identification of delinquency for this classification, and it overrides other designations based on our account status definitions.
- **Inactive accounts.** If the cardholder has no starting balance or payment activity in the billing cycle, we classify the account as inactive. In this case, the cardholder would have chosen not to use the card to make purchases in the prior month and therefore would have no balance to pay, even though the account is still active in the sense that the cardholder *could* continue to use it. As we have designated statuses, technically, it is impossible for accounts to pass directly from revolving status to inactive status. This is because before an account could meet our criteria for inactive status, the cardholder would have to pay off the revolving balance in the month before and switch to transacting status for 1 month. However, it is not uncommon for an account to go inactive after the revolving balance is paid off. To capture this movement in our transition model, for any single month of transacting status that followed a revolving month and preceded an inactive month, we reassigned the account to revolving status for that

[6]As a consequence of our assignment approach, accounts that were carrying a balance previously and have started to pay off their balance in full are not classified as transacting accounts until they are eligible for their issuer's grace period.

[7]Revolving balances can also include fees if cardholders fail to make payments by the due date.

month. This approach allowed us to catalogue these transitions as movements from revolving status to inactive status.

- **Closed accounts.** We classify accounts as closed if the customer has requested their closure or if the customer has died. Closed accounts are flagged as such by the issuer and these flags override other designations, including delinquency.
- **Charged-off accounts.** Charged-off accounts are flagged as such by the issuing institution. These accounts have generally been seriously delinquent and the institution has reason to believe the balance will not be paid.

After we conducted the data cleaning steps described above, the final dataset included 30.5 million account-month observations on 655,033 general purpose credit card accounts (see table 2).

Table 2: Information on General Purpose Credit Card Account Data Analyzed by GAO

Total number of credit card accounts	Total number of account-month observations	Average number of observations per account	Minimum number of observations per account	Maximum number of observations per account
655,033	30,469,820	47	1	103

Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

Note: General purpose credit cards are credit cards issued on networks, such as Visa, Mastercard, American Express, and Discover, which are accepted by a wide variety of merchants.

In the models of status transitions (see app. IV), we used the next month's status, so we created a variable that captured the next month's status associated with the account. This variable was left missing when the current month was the last observation included in the dataset. We collapsed our six status categories into five because not all accounts passed through the seriously delinquent status prior to being charged off. We combined these two statuses here to account for the rare instances when an account would be revolving or delinquent for less than 90 days and transition directly to charged-off status. Further, it did not make logical sense for a transacting account to transition directly to seriously delinquent status, so in the few cases where that occurred, we dropped the account-month observation as containing an error. Once we captured the next status, we had no further need for closed or charged-off accounts, so we dropped these from our data.

Census Bureau Income and Race/Ethnicity Data

To derive the median household income and the racial and ethnic composition of cardholders' zip codes, we used data from the Census Bureau's 5-Year American Community Surveys (ACS) for 2013–2020. We matched ACS data at the zip-code tabulation area level to cardholders' zip codes in the credit card data.[8] We matched the last year of each 5-year ACS average with the year of the credit card billing cycle for credit card data from June 2013 through December 2020. For instance, credit card accounts with a billing cycle month in 2013 were matched to the 2009–2013 5-year ACS. The only exception was for credit card accounts with a billing cycle month in 2021, which we matched with the 2016–2020 5-year ACS because the 2017–2021 ACS data were not available at the time we created the dataset.[9]

We adjusted median household incomes for inflation and measured them in constant 2021 dollars using the Consumer Price Index for All Urban Consumers. Using the zip-code median household incomes, we created six income groups: under $25,000, $25,000–$49,999, $50,000–$74,999, $75,000–$99,999, $100,000–$149,999, and $150,000 and above. We then assigned credit card accounts to one of these groups based on the estimated median household income in the cardholders' zip codes. Additionally, we merged the Federal Reserve credit card data with ACS's income distribution data, which include the number of households in each zip-code tabulation area that fall into 16 more granular nominal income groups, for our regression analyses related to credit terms and revolving balances (as discussed in app. VI).

To describe the racial and ethnic composition of cardholders' billing zip codes, we used the shares of residents in each zip code that were non-Hispanic White, Asian, Black or African American (referred to as "Black" in this report), Hispanic or Latino of any race (referred to as "Hispanic" in this report), and Other.

Descriptive Statistics

Table 3 presents descriptive statistics for the variables in our analysis.

[8]Zip-code tabulation areas are generalized areal representations of U.S. Postal Service zip code service areas, which are not areal features but a collection of mail delivery routes.

[9]Census reported that it had to make special adjustments to the results of the 2020 1-year ACS due to a higher-than-usual nonresponse rate during the COVID-19 pandemic.

Table 3: Characteristics of Consumer Credit Card Accounts, June 2013–December 2021

Variable	Mean	Standard deviation	Median	Minimum	Maximum
Data from the Board of Governors of the Federal Reserve System on credit card accounts					
Outstanding balance due at the end of a billing cycle	$1,749	$3,539	$312	-$335,497	$198,776
Payment made by cardholders per month	$540	$1,829	$70	-$341,867	$480,771
Annualized interest rate of the account	17.3%	6.2%	17.0%	0%	32.7%
Credit limit	$9,070	$8,457	$7,000	$0	$500,000
Credit score	751	80	768	1	991
Interest charges incurred	$51	$67	$29	-$21,162	$8,266
Data from the Census Bureau on distribution of household income in cardholders' zip codes					
Median household income	$77,962	$30,989	$71,561	$3,948	$290,796
Percentage of households in a zip code with household income that was under $10,000	5.6%	3.9%	4.6%	0.0%	100.0%
Percentage of households in a zip code with household income of $10,000–$14,999	4.1%	2.7%	3.5%	0.0%	100.0%
Percentage of households in a zip code with household income of $15,000–$19,999	4.1%	2.4%	3.7%	0.0%	100.0%
Percentage of households in a zip code with household income of $20,000–$24,999	4.3%	2.3%	4.1%	0.0%	100.0%
Percentage of households in a zip code with household income of $25,000–$29,999	4.2%	2.1%	4.0%	0.0%	100.0%
Percentage of households in a zip code with household income of $30,000–$34,999	4.3%	2.0%	4.2%	0.0%	100.0%
Percentage of households in a zip code with household income of $35,000–$39,999	4.1%	1.8%	4.0%	0.0%	100.0%

Variable	Mean	Standard deviation	Median	Minimum	Maximum
Percentage of households in a zip code with household income of $40,000–44,999	4.1%	1.8%	4.1%	0.0%	100.0%
Percentage of households in a zip code with household income of $45,000–$49,999	3.7%	1.6%	3.7%	0.0%	100.0%
Percentage of households in a zip code with household income of $50,000–$59,999	7.4%	2.4%	7.4%	0.0%	100.0%
Percentage of households in a zip code with household income of $60,000–$74,999	9.7%	2.7%	9.7%	0.0%	100.0%
Percentage of households in a zip code with household income of $75,000–$99,999	12.8%	3.3%	12.8%	0.0%	100.0%
Percentage of households in a zip code with household income of $100,000–$124,999	9.4%	3.3%	9.5%	0.0%	100.0%
Percentage of households in a zip code with household income of $125,000–$149,999	6.3%	3.0%	6.2%	0.0%	100.0%
Percentage of households in a zip code with household income of $150,000–$199,999	7.3%	4.5%	6.6%	0.0%	100.0%
Percentage of households in a zip code with household income that was $200,000 and above	8.5%	8.7%	5.4%	0.0%	100.0%
Data from the Census Bureau on racial and ethnic composition of cardholders’ zip codes					
Percentage of Asian residents	6.8%	10.1%	3.1%	0%	100%
Percentage of Black or African American residents	10.0%	15.0%	4.3%	0.0%	100.0%
Percentage of Hispanic or Latino residents	16.6%	19.1%	9.2%	0.0%	100.0%
Percentage of White residents	63.2%	26.1%	69.8%	0.0%	100.0%

Variable	Mean	Standard deviation	Median	Minimum	Maximum
Percentage of residents who were Other race	3.3%	3.5%	2.7%	0.0%	100.0%

Source: GAO analysis of data from the Board of Governors of the Federal Reserve System and Census Bureau. | GAO-23-105269

Note: Negative values in outstanding balances and payment amounts could be due to data entry errors or to cardholders being owed a credit at the end of the billing cycle. Additionally, the minimum and maximum values of credit scores could be due to data errors since credit scores generally range from 300 to 850.We used the Census Bureau's 5-Year American Community Surveys for 2013–2020.

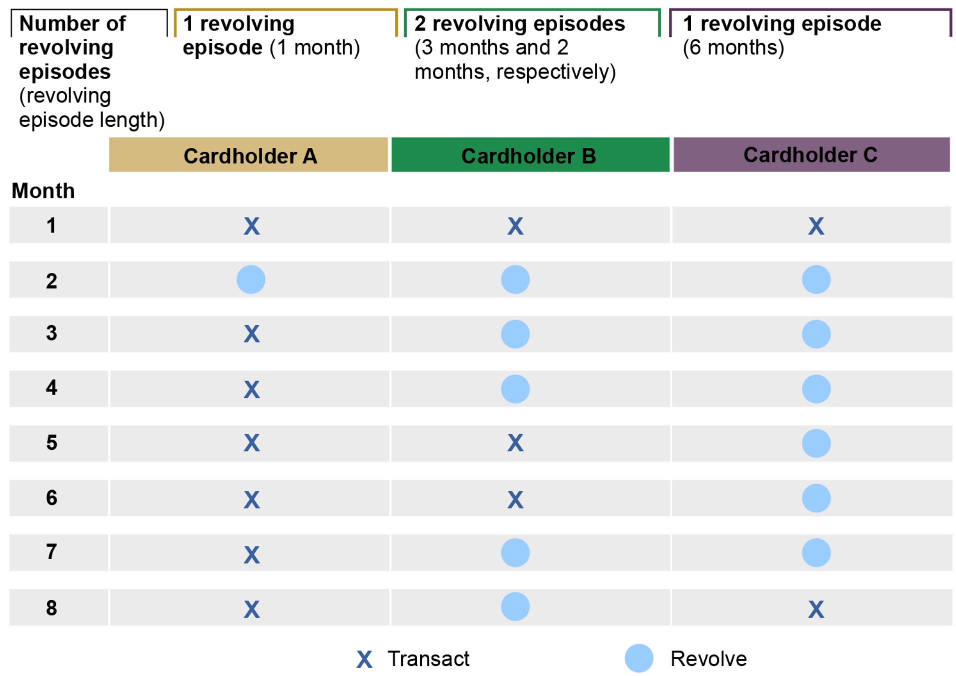
Analysis of Credit Card Usage

Account status. We calculated the share of active accounts (i.e., transacting, revolving, or seriously delinquent) by status for each month for the period from June 2013 through December 2021. Additionally, we calculated the average share of active accounts that were revolving, by credit score category and zip-code-level median household income, for the period from June 2013 through December 2019.

Revolving balances. For revolving accounts, we calculated the median revolving balance amount for the period from June 2013 through December 2021. Additionally, we calculated the percentage of accounts that reached or exceeded their credit limit for each month for the period from June 2013 through December 2019. Furthermore, we calculated the shares of transacting accounts and revolving accounts that made purchases, and purchase amounts for those that did. All dollar amounts are in nominal terms unless otherwise noted.

Durations of revolving and transacting episodes. We calculated the duration of revolving episodes using Federal Reserve data from June 2013 through December 2021. We defined a revolving episode as a period of 1 or more consecutive months in which a credit card account is in revolving status (see fig. 14). A revolving episode ends when the status of the account changes from revolving to transacting, seriously delinquent, inactive, closed, or charged off. Each account can have multiple revolving episodes. Similarly, we defined a transacting episode as a period of 1 or more consecutive months in which the credit card account is in transacting status.

Figure 14: Examples of Revolving Episodes of Differing Lengths



Source: GAO. | GAO-23-105269

We assigned the account-months that were in an episode for 12 months or more the designation “long term” for the purposes of our descriptive statistics, regardless of where they were in that episode.[10]

[10]Because we defined long-term revolving episodes as lasting 1 year or more, December 2020 was the last date for which we had data to make an accurate count of long-term status.

Appendix III: Cluster Analysis of Race/Ethnicity in Cardholders' Zip Codes

We conducted a statistical analysis to identify racial and ethnic distributions that were typical for the zip codes of credit cardholders in our analysis. This appendix presents the development, estimation, results, and limitations of this analysis.

Data

We used a 0.1 percent nongeneralizable sample of credit card accounts from the Board of Governors of the Federal Reserve System's Y-14M credit card data from June 2013 through December 2021, which included zip-code information. Additionally, we used zip-code-level racial and ethnic composition data from the Census Bureau's 5-year American Community Surveys from 2013 through 2020. See appendix II for additional information on the data.

Methodology

Our report examined how credit terms, revolving episode durations, and revolving balances of cardholders varied by race and ethnicity. We estimated these differences using econometric models that accounted for the racial and ethnic characteristics of cardholders' zip codes. To illustrate the implications of the models' estimates, we used cluster analysis methods to identify racial and ethnic distributions that were typical for the zip codes in our population. We used the models to estimate how outcomes varied across these typical zip codes.

To implement the cluster analysis, we identified a set of zip codes of "typical" racial and ethnic composition in September 2016—the middle month of our prepandemic period (June 2013–December 2019). This approach helped address two aspects of our data. First, the mix of zip codes represented in our data shifted moderately from June 2013 through December 2021 because individual credit card accounts entered and exited our data, and some changed their billing address to new zip codes during our period of analysis. Second, the racial and ethnic composition of the zip codes also changed over this period.

To determine whether zip-code clusters using alternative time periods would produce substantially different results, we also identified a set of "typical" zip codes in September 2017 (the middle month of the entire data period), as well as at the beginning and ending points of the period in June 2013 and December 2021. While we found small shifts in the racial and ethnic composition of the zip codes between June 2013 and December 2021, the zip code clusters in September 2016 and September 2017 were similar. As a result, we used the clusters from September 2016 in all of our models on revolving episode durations, credit terms, and revolving balances by race and ethnicity in cardholders' zip codes (discussed in subsequent appendixes). This approach helped ensure that the variations in our model results are associated with variables included in the models and not changes in the zip-code clusters.

We used a k-means cluster algorithm to identify clusters of zip codes with similar racial and ethnic composition in our data. The algorithm grouped zip codes such that those within a cluster were as similar as possible and zip codes in different clusters were as different as possible. We selected the k-means algorithm because it was computationally inexpensive and produced a centroid vector of racial and ethnic percentages for each cluster. We used Stata to identify the clusters, using Euclidean distance as our measure of (dis)similarity. Our implementation of the algorithm used a random selection of the race and ethnicity composition of five zip codes as the starting centers for the five clusters and allowed for up to 10,000 iterations of the algorithm.

The pool of zip codes we used to generate clusters were those included in the September 2016 month of our data, and each zip code was repeated as often as the number of accounts appearing in that zip code. This weighted our cluster centers toward the racial and ethnic composition of zip codes that appeared more frequently in our data, allowing our clusters to be a more typical representation of the racial and ethnic characteristics of the accounts in our data, rather than of the zip codes in our data.

A potential limitation of the k-means algorithm was that it required us to specify the number of clusters for the algorithm to identify. We therefore did not use the data to identify the best-fitting number of clusters, such as with hierarchical clustering methods. To address this limitation and identify an appropriate number of clusters, we ran the algorithm multiple times while varying the number of clusters from five to eight. Our estimates using the five-cluster approach produced five clusters similar to five of the clusters identified when identifying more than five clusters, so we decided to use the more concise approach to develop our illustrative racial and ethnic compositions.

Results

We identified the following five clusters:

- Zip codes of predominantly White residents
- Zip codes with a majority of Hispanic or Latino residents
- Zip codes with a majority of Black or African American residents

- Zip codes with a mix of all racial and ethnic groups with a majority of White residents
- Zip codes with a mix of all racial and ethnic groups with no majority (where the share of Asian residents is the highest among all clusters)

Our cluster analysis did not identify a cluster of zip codes with a majority of Asian residents.

Table 4 outlines the racial and ethnic composition of the representative zip codes that have the average characteristics of each of the clusters.

Table 4: Racial and Ethnic Composition of Zip Code Clusters, September 2016

Cluster name	White	Black or African American	Hispanic or Latino	Asian	Other
Cluster 1: Predominantly White	86%	4%	5%	3%	3%
Cluster 2: Majority Hispanic or Latino	21	9	62	6	2
Cluster 3: Majority Black or African American	25	58	12	3	3
Cluster 4: Mixed race and ethnicity with majority White	59	11	18	8	4
Cluster 5: Mixed race and ethnicity with no majority	30	7	20	37	6

Source: GAO analysis of data from the Board of Governors of the Federal Reserve System and Census Bureau. | GAO-23-105269

Note: Percentages do not sum to 100 percent due to rounding.

Appendix IV: Econometric Analysis of Revolving and Transacting Episode Durations

We conducted econometric analysis of the durations of revolving and transacting episodes and transitions under pandemic and prepandemic conditions, as well as revolving and transacting episodes for cardholders in zip codes with different racial and ethnic composition. This appendix presents the development, estimation, results, and limitations of these analyses.

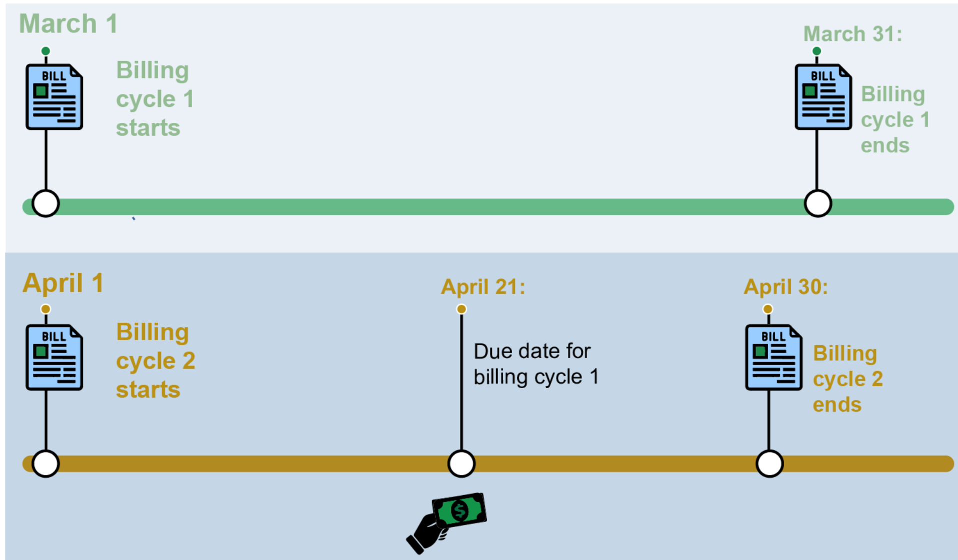
Data and Definitions

We used a 0.1 percent nongeneralizable sample of credit card accounts from the Board of Governors of the Federal Reserve System's Y-14M credit card data from June 2013 through December 2021. We supplemented these data with zip-code-level racial and ethnic composition data from the Census Bureau's 5-year American Community Surveys from 2013 through 2020. See appendix III for full details on the use of zip-code racial and ethnic composition. For our analysis of revolving episodes, we limited our sample to all accounts revolving in the month of the observation. Similarly, for our analysis of transacting episodes, we limited the sample to all accounts transacting in the month of the observation.

Our outcome variable in all of the analyses was the status of the credit card account in the following month, for which we used five categories.

Transacting accounts. Accounts for which the cardholder paid all of the balance due for the billing cycle by the due date, thereby not accruing any interest charges on purchases (see fig. 15). Accounts with 1 inactive month (defined below) that is both preceded and followed by transacting months are classified as transacting, even though they have no balance to pay off in 1 month. An implication of how we define transacting accounts is that if a cardholder is taking advantage of a promotion that provides zero percent interest on a revolving balance for a fixed period of time, the card account will remain classified as transacting until any remaining balances are charged a positive interest rate at the end of the promotional period.

Figure 15: Illustrative Example of Credit Card Billing Cycle



Source: GAO analysis. | GAO-23-105269

Revolving accounts. Accounts for which the cardholder paid less than the entire balance due for the billing cycle, therefore incurring interest on the outstanding balance and any new purchases. We included in this category any accounts that were delinquent (i.e., the cardholder paid less than the minimum balance due by the due date) for less than 90 days.

Seriously delinquent and charged-off accounts. Accounts for which the cardholder did not pay at least the minimum balance due for 90 days or more or for which the card issuer has charged off the account balance due. Not all accounts passed through the seriously delinquent status prior to being charged off, so we combined these two statuses to account for the rare instances when an account would be revolving or delinquent for less than 90 days and transition directly to charged-off status.

Inactive accounts. Accounts with no starting balance or payment activity in the billing cycle. In these cases, the cardholders chose not to use the card to make purchases in the prior month and therefore had no balance to pay, even though the accounts were still active in the sense that the cardholder could continue to use the card. Technically, it is impossible for credit card accounts to pass directly from revolving status to inactive status. This is because before an account could meet our criteria for inactive status, the cardholder would have to pay off the revolving balance in the month before and switch to transacting status for 1 month. However, it is not uncommon for an account to go inactive after a revolving balance is paid off. To capture this movement in our econometric models, for any single month of transacting status that followed a revolving month and preceded an inactive month, we reassigned the account to revolving status for that month. This approach allowed us to catalogue these transitions as movements from revolving status to inactive status.

Closed accounts. Accounts closed by the cardholder or the issuer. In addition to customer requests, issuers close accounts for a variety of reasons, including fraud or death of the cardholder.

The primary independent variable used in our models is the account's "time-in-status"—in other words, the number of months the account has been in the same status as it is in the current observation. For example, if an account was in transacting status in the previous month and is revolving this month, its time-in-status is 1. If an account first started revolving in January and has done so in every month since, the time-in-status in June is 6 and the time-in-status in July is 7. The total length of the revolving episode is equal to the time-in-status of the last month before the account transitions into another status type.

Episode Durations

We analyzed two relevant populations of revolving accounts with differing distributions of revolving episode durations:

- **Revolving episodes of a cohort of revolving accounts.** This population provides insight into the overall probability that a new revolver may revolve for different durations.
- **Total revolving episode duration of the population of revolvers at a given point in time.** This population provides insight into the probability of encountering a revolving account in the middle of a revolving episode of a particular duration, out of the population of revolving accounts in a given time period.

As demonstrated in table 5, these populations had very different distributions. Overall, the median observed duration of all revolving episodes pooled as one cohort was 4 months. However, the median account in revolving status across our entire sample was in a revolving episode that we observed lasting 32 months. In other words, while the median episode was short—4 months—the typical account currently revolving was in a long term revolving episode, one that had more in common with the 90th percentile of revolving episodes—32 months—than with the median episode.

Table 5: Observed Revolving Episode Durations for June 2013–December 2021

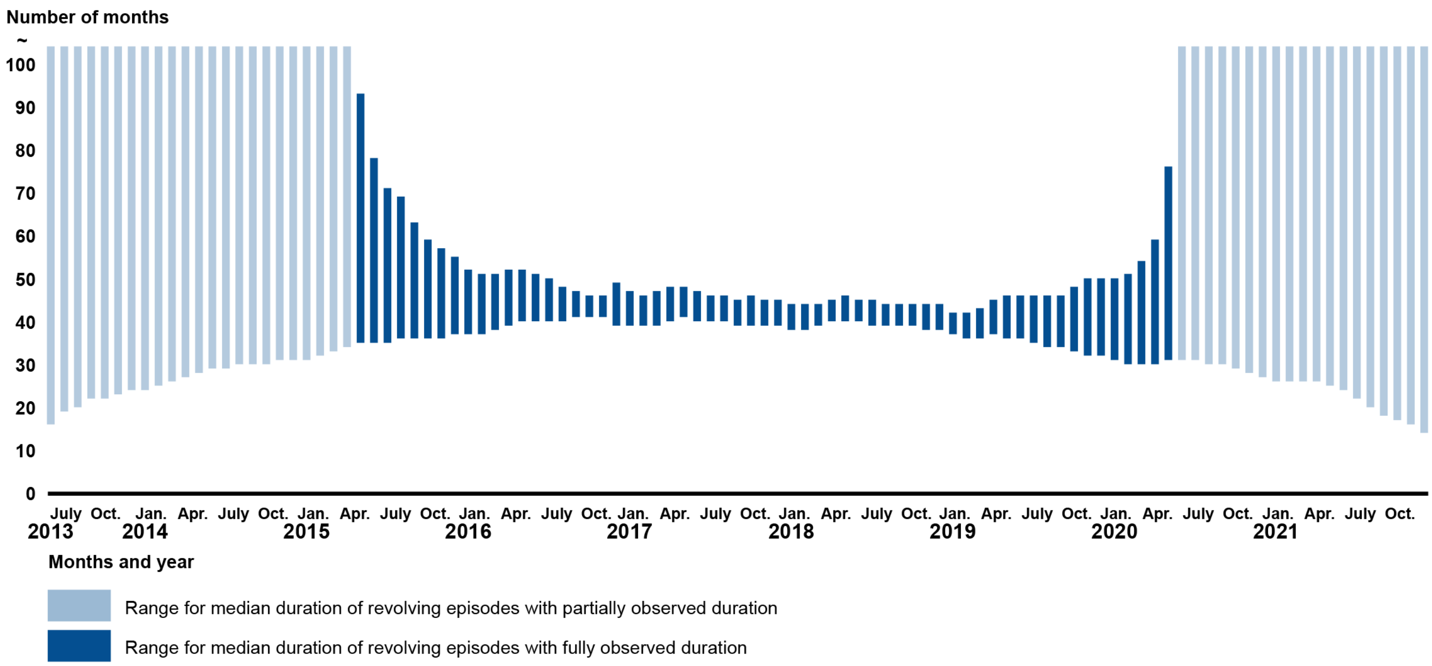
	10th percentile	Median	90th percentile
Observed duration of revolving episodes, as a pooled cohort	1 month	4 months	32 months
Observed duration of revolving episodes for all accounts in revolving status	4 months	32 months	93 months

Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

Furthermore, many of our revolving episodes were right-censored (we could not observe when the episode ended because it ended after the period of our dataset), left-censored (we could not observe when the episode started because it started before the period of our dataset), or both (we were unable to observe the entire span of the episode). Of the observations of accounts in revolving status available to be used in our analyses of revolving episodes, 3.2 million were left-censored and 3.3 million were right-censored. In contrast, 5.2 million account observations were in revolving episodes whose start and finish we were able to observe. Because we were more likely to observe the full length of a shorter episode than a longer one, the total observed length of the episodes of which those observations were a part was very different between observations in uncensored episodes (average of 24 months) and in censored episodes (average of 62 and 60 observed months for left- and right-censored episodes, respectively).

We were able to capture the impact of censoring on our ability to directly measure the durations of revolving episodes. For each revolving episode, we looked at the observable length and, if the episode was censored, we considered the possibility that its true length was longer than the longest possible observable length. We could then calculate the median of the revolving episode length in our data in two ways: (1) we could assume all of these episodes in our data were fully observed, and (2) we could assume that none of the censored revolving episodes in our data were shorter than the longest observable episode (i.e., that they were at least 104 months long). These two approaches gave lower and upper bounds to the possible median statistic of revolving episode length. The range of uncertainty about the median value due to censoring varied over our dataset, such that we were able to measure the median episode in a revolving cohort more precisely—because the median episodes were shorter—than the median of the revolving account observations.[1] Furthermore, we could measure the median of revolving account observations with substantially more precision in the middle months of our data than we could nearer the beginning and end (see fig. 16).

Figure 16: Length of Median Revolving Episode for Accounts in Revolving Status by Month



Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

To address challenges posed by censoring for measuring episode duration directly, we took an indirect approach to modeling details about revolving episode lengths, as described in detail later in this appendix. This indirect approach allowed us to maximize the use of observations in our sample, including censored episodes, to build simulated distributions of the durations of a revolving episode cohort for revolving accounts under prepandemic or pandemic conditions, as well as for revolving accounts from billing zip codes of different racial and ethnic composition.

[1]Generally, we could measure the median revolving episode in a new cohort either precisely or with only 1 month difference between maximum and minimum possible median durations.

Because our descriptive results on revolving episode durations highlighted the importance of longer-duration revolving accounts, we report on the 90th percentile of the distribution of durations for a cohort of new revolving episodes to provide an illustration of the experience of a typical revolving account in a given month.

Methodology of Analysis of Revolving Episodes under Prepandemic and Pandemic Conditions

We used a multinomial logit model to estimate relationships between the number of months an account has been in revolving status and the likelihood it would either continue revolving in the next month or transition to a different account status, under pandemic and prepandemic conditions. We used the coefficients to derive probabilities that an account in revolving status would continue to revolve or transition conditional on the number of months in revolving status, under pandemic and prepandemic conditions. We then used these conditional probabilities to construct two Markov transition matrices, one for the pandemic period and one for the prepandemic period. Finally, we used the Markov transition matrices to simulate the path a hypothetical cohort of revolving episodes (i.e., all revolving episodes that start in the same month) would take over time under pandemic and prepandemic conditions and to estimate the share of the cohort that would exit revolving status in each month and into which status.

Multinomial logit analysis. We used multinomial logit models to estimate the probability that an account in revolving status would either continue to revolve or transition to each of the other four account statuses (transacting, inactive, seriously delinquent, or closed) as a function of the account's time-in-status under pandemic and prepandemic conditions.[2]

We assume that after a certain period of revolving, the time-in-status matters less than it did originally, and we assume that the continuation and exit probabilities are constant once an account has been revolving long term (at least 18 months). We assume this constant transition risk

[2]Multinomial logit analysis has been used in a variety of contexts to measure transitions from a baseline state to several outcome states. For example, it has been used to measure teacher career paths, credit union decline, and labor market life cycles. See GAO, *National Credit Union Administration: Additional Actions Needed to Strengthen Oversight,* GAO-21-434 (Washington, D.C.: Sept. 23, 2021); Christian Duel, "Expanding the Markov Chain Toolbox: Distributions of Occupation Times and Waiting Times," *Sociological Methods & Research*, vol. 50, no. I (2021): 401–428; and Cassandra M. Guarino, Abigail B. Brown, and Adam E. Wyse, "Can Districts Keep Good Teachers in the Schools That Need Them Most?," *Economics of Education Review*, vol. 30 (2011): 962–979.

after 18 months of revolving.[3] This allows us to balance the loss of long-term revolving accounts from our dataset due to left censoring with the restricted assumptions imposed by assuming a constant transition risk.

We specified our baseline model as follows:

$$P(Next\ status_i) = f(\alpha + \tau_i + \pi_{COVID}(\alpha_{COVID} + \tau_i))$$

where *P(Next status$_i$)* is the status of the revolving episode in the next month. The other variables are as follows: α is the constant and served to capture the long-term likelihood of transition, along with any fixed factors that affect the probability of transition; τ_i is a vector of indicator variables to capture the individual account's current time in revolving status in the first 18 months of the status; and π_{COVID} is an indicator for whether the account-month observation was in April 2020–December 2021. We limited our sample to all account-months where we classified the account as revolving in the current month and were able to identify the status of the account in the next month.

We included 18 indicator variables to control for the number of months an account had been in revolving status, one for each of the first 18 months of the revolving episode. We reserved the long-term revolving status as the reference category, and therefore the constant of the model effectively estimated the coefficient for those accounts in long-term revolving status of 19 months or longer. This approach assumed that the probabilities of continuing to revolve or transitioning to another status were constant once a revolving episode lasted longer than 18 months ("long-term revolving episode").

We used this approach to address left censoring, as previously discussed.[4] We dropped all account-month observations that were in the first measured 18 months of a left-censored revolving episode, but retained the rest of the censored revolving episodes after the first 18 months since we no longer needed a precise measure of the time-in-status.

[3]We conducted sensitivity analyses on our definition of long-term revolving accounts and determined that a 24-month threshold gives qualitatively similar results.

[4]Our approach to address the left censoring issue is similar to methodology in other research. See Steven J. Haider and Jacob Alex Klerman, "Dynamic Properties of Welfare Caseload," *Labour Economics*, vol. 12 (2005): 629–648.

We used the multinomial logit model to address the right censoring issue. The model allowed each revolving episode to contribute the information that was captured in our data: the revolving episodes either continued to revolve for an additional month or transitioned to one of the other four account statuses in a particular month.

Additionally, we interacted all indicators (including the constant term) with a COVID-19 pandemic indicator to allow for separate estimates of transition probabilities during the pandemic period. We included all months in the period April 2020–December 2021 in our COVID-19 indicator, since April was the first month when all payment decisions were made after the pandemic was declared on March 13, 2020.

We did not control for calendar time, except for interacting an indicator for months that occurred after the declaration of the pandemic in March 2020. We determined this approach was reasonable because our descriptive findings suggested that the number of revolving accounts as a percentage of active accounts had little or no change over time except modest seasonal fluctuations and during the months when the pandemic was declared or when government pandemic assistance payments were disbursed.

We used a similar approach to model relationships between the number of months an account had been in transacting status and the likelihood it either continued to transact or transitioned to one of the other account statuses during the pandemic and prepandemic periods. When analyzing transacting episodes, we had only four possible states to transition to: continuing to transact, revolving, inactive, and closed. Transacting accounts cannot transition in 1 month to seriously delinquent status.

Markov chain analysis. To simulate the distributions of revolving episode durations and transitions under pandemic and prepandemic conditions, we used a Markov chain analysis. We first used the estimated multinomial logit models described above to derive probabilities that an account in revolving status would either continue to revolve or transition to another status conditional on the number of months in revolving status, before and during the pandemic. We then used the conditional probabilities to construct pandemic and prepandemic Markov chain transition matrices. Finally, we passed a state vector representing a hypothetical cohort of revolving accounts through each of the transition matrices repeatedly to simulate the share of the original cohort still revolving each month over the course of a decade (i.e., 120 months) along with the initial status of accounts that transitioned out of revolving status.

Using the coefficients of the multinomial logit model, we calculated the conditional probabilities using the following pair of formulas, for a particular set of values for the vector τ:

$$P(Next\_status5 = 1|\tau) = \frac{1}{1 + \exp\left(f_0(\tau)\right) + \sum_{s=2}^{4} \exp\left(f_s(\tau)\right)}$$

and

$$P(Next\_status5 = s|\tau) = \frac{\exp\left(f_s(\tau)\right)}{1 + \exp\left(f_0(\tau)\right) + \sum_{s=2}^{4} \exp\left(f_s(\tau)\right)}$$

where s = (0, 2, 3, 4) for the statuses other than revolver status (which is s = 1). For our transactor models, s = 0 is our baseline outcome instead. The vector τ is a vector of indicator variables for the time-in-status of the conditional probabilities being calculated, where all are equal to zero except for the element that is equal to the indicator for the time-in-status being calculated, which is set to one. For example, if the time-in-status is a vector of indicators, a card that has been revolving for 6 months will be coded as a zero for all elements of the vector except for the sixth element, which is coded as a one. If that account is in its 6th month after March 2020, then the time-in-status interacted with the COVID indicator will also have a one in the sixth element.

Generically, a Markov chain model describes how individuals move between various states. Such a model can be represented as follows:

$$S(t)_{(K\ x\ 1)} = M(t)_{(K\ x\ K)} S(t-1)_{(K\ x\ 1)}$$

where t is the time period, S(t) is a vector that contains the share of individuals in each of K states, and M(t) is the transition matrix between the states, which translates the state vector $S(t-1)$ to its state in the next period: $S(t)$. The K possible states include all of the possible states: revolving for each of the 18 months and long term, as well as the other statuses a revolver can transition to. Because we were looking at one cohort of revolving episodes, we treated each of the other four statuses as absorbing states and did not model the transition back into revolving status here. We kept the prepandemic and pandemic periods separate and estimated two different Markov chains for the two conditions, even though in practice, many revolving episodes bridged the two periods. As a result, for our revolving episode models, our M(t) is a 23 by 23 transition matrix.

We allowed the probability of transitioning from revolving status to another status to vary by time-in-status in S(t-1) for the first 18 months, and then those probabilities would remain constant as the account entered long-term time-in-status. Once a revolving episode transitioned to a different status, we treated that status as an absorbing state for the purpose of the revolving episode cohort's distribution (though in real life, those episodes may reenter revolving status at a future time).[5] Therefore, our state vector S(t) would be a 23 by 1 vector:

$$S(t) = \begin{bmatrix} revolve_1 \\ revolve_2 \\ \vdots \\ revolve_{18} \\ revolve_{long\ term} \\ transact \\ inactive \\ delinquent \\ closed \end{bmatrix}$$

Our transition matrix M(t) would be a 23 by 23 matrix:

$$M(t) \\ = \left[\begin{array}{ccccccc|cccc}
0 & p_{revolve_2} & 0 & \cdots & 0 & 0 & 0 & p_{transact_1} & p_{inactive_1} & p_{delinquent_1} & p_{closed_1} \\
0 & 0 & p_{revolve_3} & \cdots & 0 & 0 & 0 & p_{transact_2} & p_{inactive_2} & p_{delinquent_2} & p_{closed_2} \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & \cdots & 0 & p_{revolve_18} & 0 & p_{transact_17} & p_{inactive_17} & p_{delinquent_17} & p_{closed_17} \\
0 & 0 & 0 & \cdots & 0 & 0 & p_{revolve_lt} & p_{transact_18} & p_{inactive_18} & p_{delinquent_18} & p_{closed_18} \\
0 & 0 & 0 & \cdots & 0 & 0 & p_{revolve_lt} & p_{transact_lt} & p_{inactive_lt} & p_{delinquent_lt} & p_{closed_lt} \\
0 & 0 & 0 & \cdots & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{array}\right]$$

The transition probability matrix, M(t), remained constant over calendar time, with the exception of a "permanent" change (within the scope of our data) that occurred at the start of the pandemic.[6] We therefore

[5]We focused our analysis on the distribution of an episode cohort, so even though an account can reenter revolving status in the future, it cannot reenter the same cohort of revolving status.

[6]Another study also used a similar approach. See Haider and Klerman, "Dynamic Properties of Welfare Caseload."

constructed two separate transition probability M(t) matrices, one for transitions under prepandemic conditions and one for transitions under pandemic conditions. For revolving episodes that overlapped both the prepandemic and pandemic periods, they contributed the information about their transition risk in each month to the period that each month occurs in: for example, for a revolving episode that lasted from January 2020–June 2020, its continuation as a revolver in January–March would contribute to the estimation of the baseline transition risks for revolvers in months 1–3, and it would contribute to both the baseline and the pandemic interaction risk estimates for revolvers in months 4–6. When we used those estimates for the Markov chain analyses, we were simulating hypothetical scenarios where either the average prepandemic or the average pandemic conditions persisted indefinitely. This facilitated an understanding of the magnitude of the shift in cardholder behavior but does not attempt to model the evolving distribution of revolver episodes that begin prior to the pandemic and resolve at various points after the pandemic began.

To simulate the predicted outcomes of a revolving episode cohort, our S(1) is a vector with a 1 in the first row, followed by all zeros. Each time we multiplied M(t) by S(t-1), we captured the resulting S(t) as the distribution of the revolving episode cohort by months since the start of the revolving episode.

We used a similar approach to simulate the distribution of transacting episode durations and transitions.

Assumptions and Limitations

Our analysis of revolving episodes has limitations, and our results should be interpreted with caution. The sample of credit card accounts we analyzed may not represent the population of all credit card accounts, and thus the sample of revolving episodes we analyzed may not represent the population of all revolving episodes. It follows that our results reflect the sample of revolving episodes we analyzed and may not generalize to other revolving episodes.

In our multinomial logit model specification, we assumed that the relationships between the number of months an account has spent in revolving status and the likelihood it either continues to revolve or transitions to another status were constant during the prepandemic period. We also assumed that the relationships were constant, but possibly different, during the pandemic period. As a result, the derived Markov transition matrices for the pandemic and prepandemic periods were also constant (but different). We assumed constant relationships during the prepandemic period because the share of accounts in revolving status varied little over time prior to the pandemic. We assumed constant relationships during the pandemic period because that period is short relative to the typical duration of revolving episodes in our data, which limited our ability to reliably estimate more complex relationships.

It follows from these assumptions that our simulated distributions of revolving episode durations and transitions for the prepandemic and pandemic periods are averages for each period. In both periods, we did not attempt to parse factors other than time-in-status that might affect risks of transitions, such as income, age, or other factors that might affect credit card usage. For the pandemic period in particular, our results are suggestive of revolving episode durations and transitions assuming the state of the pandemic from April 2020 through December 2021 were to continue for an extended period of time for the average credit cardholder. However, the actual distribution of revolving episode durations and transitions during some or all of the pandemic period might differ from our simulated distributions because the conditions might not persist sufficiently past our estimation period to have the simulated effect on all revolving episodes, particularly those with longer durations. For example, direct government pandemic assistance to individuals largely ended at the end of 2021, and therefore we would expect that the conditions under which revolvers are paying down their balances in 2022 might not be the same as those we measured in 2020 and 2021. Further, neither our results for the pandemic period nor our results for the prepandemic period are necessarily generalizable to other periods.

In addition, while we allowed relationships between the number of months an account spent in revolving status and the likelihood it either continued to revolve or transitioned to another status to vary between the pandemic and prepandemic periods, we cannot explain the reasons why those relationships vary. The pandemic period differed from the prepandemic period in a variety of ways that could have affected credit card usage, including public health conditions (e.g., social distancing), economic conditions (e.g., employment levels), and public policies (e.g., pandemic-related government assistance). Our approach does not identify the effects of specific pandemic conditions on credit card usage, and thus we do not establish causal effects of any particular pandemic condition.

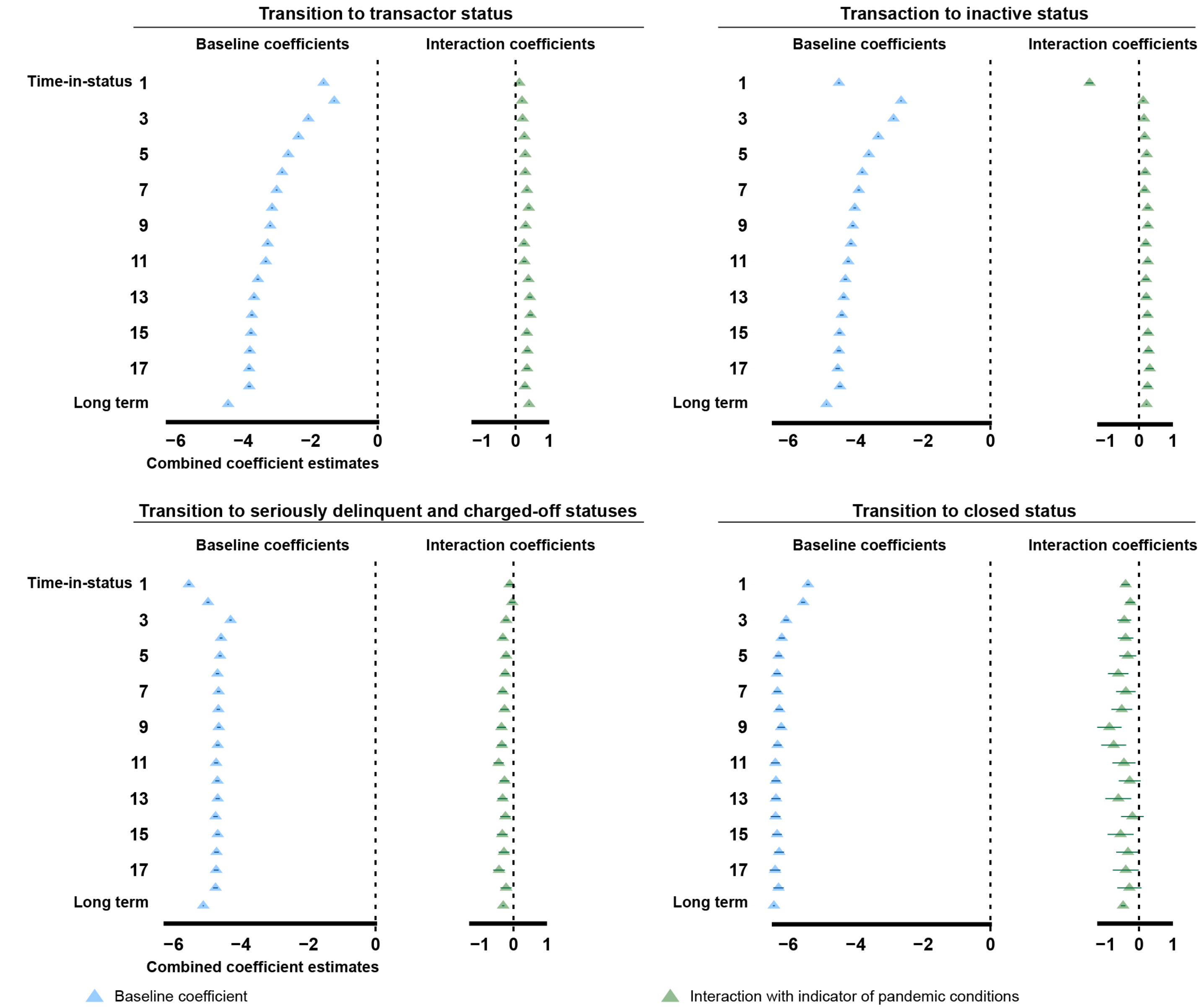
Similar limitations apply to our analysis of transacting episodes.

Results

Our analysis suggests that pandemic conditions were associated with shorter revolving episodes. Also, under pandemic conditions, once the revolving episodes ended, a larger share of accounts would have transitioned to transacting status, and fewer would have transitioned to seriously delinquent and charged-off, inactive, or closed status.

Figure 17 presents the estimated coefficients from the multinomial logit model of credit card accounts in revolving status as a function of the time spent in the current revolving episode, under prepandemic and pandemic conditions, for each of the four transition outcomes modeled. In all cases, a negative value of a baseline coefficient indicates that the outcome is less likely than that of the reference category—remaining in revolver status. A positive value of an interaction coefficient indicates that the outcome is more likely than the baseline coefficient suggests, but not necessarily more likely than the reference category outcome.

Figure 17: Multinomial Logit Combined Coefficients for Transitions from Revolving Episode to Next Status, under Prepandemic and Pandemic Conditions



Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

Note: Baseline combined coefficient estimates are the sum of the constant term and each time-in-status coefficient for each of the 1–18 time-in-status rows. The long-term row is the constant of the regression. Interaction combined coefficient estimates are the sum of the overall coefficient of the interacted variable and each time-in-status interacted coefficient for each of the 1–18 time-in-status rows. The long-term row is the overall coefficient of the interacted variable. The error bars show the 95 percent confidence intervals for time-in-status. In all cases, the confidence intervals in the time-in-status rows correspond with the confidence intervals of the time-in-status baseline coefficient or interaction term. The long-term rows illustrate the confidence intervals for the constant or overall coefficient of the interacted variable. As a consequence, each row in the figure contains all the necessary coefficient information for estimating the probability of transition for an account in a revolving episode in the given time-in-status, given values of the interaction term(s).

The Markov chain analysis produced a discrete probability distribution of a hypothetical cohort of revolving episodes that started to revolve at the same time. For reporting purposes, we focused on the distribution of revolving episode durations as a statistic that illustrated the length of time we would expect accounts to spend in a revolving episode. To summarize the distribution, we selected the first month in which the percentage of the revolving episode cohort that remained in revolving status was strictly less than 0.5, 0.75, and 0.9. This allowed us to identify the month in which the 50th, 75th and 90th percentiles of the cohort had left revolving status. We also calculated the cumulative distribution of status destinations by the time 90 percent of the cohort had exited revolving status.

Methodology of Analysis of Revolving Episodes by Race/Ethnicity in Cardholders' Zip Codes

Methodology. To analyze revolving episode durations and transitions for cardholders in zip codes with different racial and ethnic composition, we used the same multinomial logit and Markov chain analysis approaches. We expanded on our baseline multinomial logit models and interacted them with the racial and ethnic composition of the cardholder's zip code. To more efficiently implement the expanded model's computations, we separately estimated the model parameters, first using all revolving episodes for the period from June 2013 through March 2020 and then using all revolving episodes for the period from April 2020 through December 2021. Specifically, we estimated the parameters of the following equation using observations of accounts in revolving status in each period:

$$\begin{aligned} P(Next\ status_i) &= f(\alpha + \tau_i + \pi_{\%\ Black}(\alpha_{Black} + \tau_i) \\ &+ \pi_{\%\ Hispanic}(\alpha_{Hispanic} + \tau_i) + \pi_{\%\ Asian}(\alpha_{Asian} + \tau_i) \\ &+ \pi_{\%\ Other}(\alpha_{Other} + \tau_i)) \end{aligned}$$

In this specification, $\pi_{\%\ Black}, \pi_{\%\ Hispanic}, \pi_{\%\ Asian}, \pi_{\%\ Other}$ represent the percentages of Black or African American residents, Hispanic or Latino residents, Asian residents, and residents of Other race or ethnicity in the cardholder's zip code. The percentage of White residents in the zip code serves as the reference category. We treated the time-in-status variables as we did in the baseline models.

To make our results concrete and to effectively interpret our estimated coefficients, we used our five zip-code clusters by racial and ethnic composition as scenarios. We plugged in the cluster amounts for $(\pi_{\%\ Black}, \pi_{\%\ Hispanic}, \pi_{\%\ Asian}, \pi_{\%\ Other})$ and calculated the conditional probabilities for each of the five clusters. See appendix III for a discussion of how we derived the five illustrative zip code clusters.

We then used the same process with a Markov transition matrix to transform the conditional probabilities to distributions of revolving episode durations and transitions, where each cluster scenario had a separate set of values for M(t).

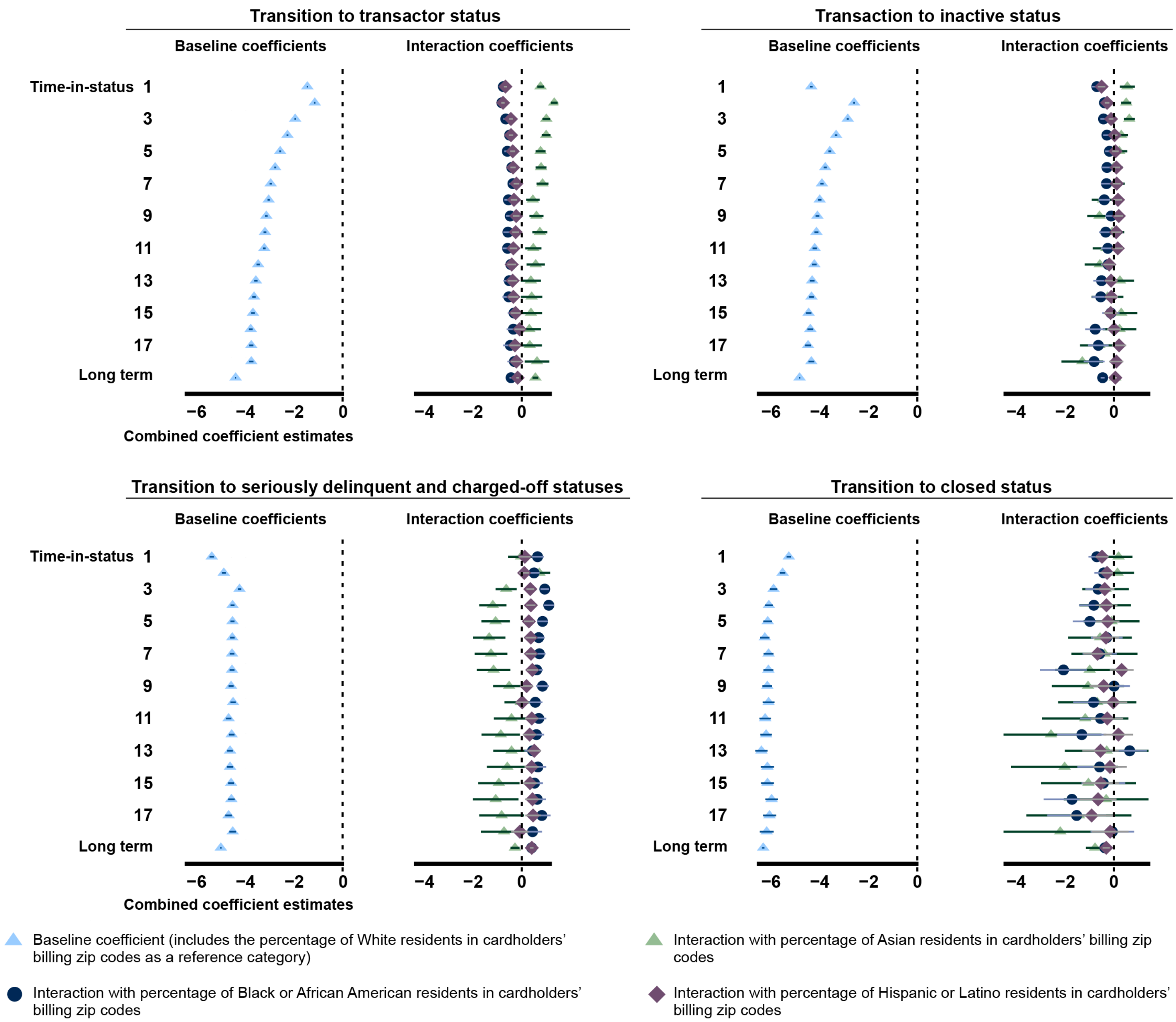
Assumptions and limitations. In addition to the limitations of our baseline models discussed earlier, our expanded models have the following additional limitation and should be interpreted with caution. Our analysis does not on its own offer an explanation of what might be driving our results, and we could not determine all the potential reasons for racial and ethnic differences in credit card revolving patterns, which may be due to factors that are either not captured in the data we analyzed or cannot be measured. Such factors can include cardholders' liquidity needs or personal assessments of the characteristics of credit cards compared to those of other payment methods.[7] Differences in these factors may be incidentally associated with race and ethnicity, or these factors themselves may be influenced by race and ethnicity, and therefore act as channels through which race and ethnicity influence revolving patterns.

Results. Figure 18 presents the estimated coefficients from the multinomial logit model of credit card accounts in revolving status as a function of the time spent in the current revolving episode and the racial and ethnic composition of the cardholder's billing zip code, for each of the four transition outcomes modeled. In all cases, a negative value of a baseline coefficient indicates that the outcome is less likely than that of the reference category—remaining in revolver status. A positive value of an interaction coefficient indicates that the outcome is more likely than the

[7]For example, see Irina A. Telyukova, "Household Need for Liquidity and the Credit Card Debt Puzzle," *Review of Economic Studies*, vol. 80 (2013): 1148–1177, and Claire Greene and Joanna Stavins, "Credit Card Debt Puzzle: Liquid Assets to Pay Bills" (Federal Reserve Bank of Boston Working Papers, no. 22-8, June 2022), accessed Feb. 23, 2023, https://www.bostonfed.org/publications/research-department-working-paper/2022/credit-card-debt-puzzle-liquid-assets-to-pay-bills.

baseline coefficient suggests, but not necessarily more likely than the reference category outcome.

Figure 18: Multinomial Logit Combined Coefficients for Transitions from Revolving Episode to Next Status, by Race and Ethnicity in Cardholders' Billing Zip Codes



Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

Note: Baseline combined coefficient estimates are the sum of the constant term and each time-in-status coefficient for each of the 1–18 time-in-status rows. The long-term row is the constant of the regression. Interaction combined coefficient estimates are the sum of the overall coefficient of the interacted variable and each time-in-status interacted coefficient for each of the 1–18 time-in-status rows. The long-term row is the overall coefficient of the interacted variable. The error bars show the 95 percent confidence intervals for time-in-status. In all cases, the confidence intervals in the time-in-status rows correspond with the confidence intervals of the time-in-status baseline coefficient or interaction term. The long-term rows illustrate the confidence intervals for the constant or overall coefficient of the interacted variable. As a consequence, each row in the graphic contains all the necessary coefficient information for estimating the probability of transition for an account in a revolving episode in the given time-in-status, given values of the interaction term(s). We omit reporting the results for the Other racial group category because the group is small and not necessarily cohesive.

Appendix V: Econometric Analysis of Credit Card Payments

This appendix presents the development, estimation, results, and limitations of our econometric analysis of credit cardholders' payment amounts toward revolving balances before and during the COVID-19 pandemic.

Generally, cardholders can decide to pay any amount between zero and their total balance, though if they pay less than their minimum payment amount, they will enter delinquency and be subject to additional fees. Each cardholder's decisions are driven by a multitude of idiosyncratic factors, such as their earnings that month, the timing of their pay, other irregular expenses, and the relative interest rates of different debt obligations.

However, we might expect that certain factors observable in our data, such as the payment amount in the previous months, would influence the amount a cardholder chooses to pay. For example, we found that 23 percent of cardholders with revolving balances paid the same amount toward their balance as they did in the previous month, compared with only 9 percent of transacting cardholders. We might also expect that cardholders would reconsider the amounts they pay toward their balance if their balance is increasing. Also, according to research by JPMorgan Chase Institute, their sample of checking account holders who also had a Chase credit card and who received tax refunds made, on average, substantially larger payments toward their credit card balances when their tax refund arrived and then slowly added to their credit card debt over the year as the extra funds ran out.[1]

Furthermore, payment decisions might have changed during the COVID-19 pandemic—for example, in response to substantial increases in uncertainty from the pandemic or to pandemic-related government assistance that started to flow to individuals and their employers beginning in April 2020.

Methodology

Using the Board of Governors of the Federal Reserve's Y-14M credit card data from June 2013 through December 2021, we modeled the decisions revolvers made about credit card payment amounts, including the potential association between various pandemic-related events and

[1]Diana Farrell, Fiona Greig, and Amar Hamoudi, *Tax Time: How Families Manage Tax Refunds and Payments* (JPMorgan Chase Institute, 2019).

cardholders' payment amounts.[2] To examine these dynamics, we developed a baseline model and an extended model to estimate the amount paid each month by cardholders who had revolved in the prior month.

Our baseline model is as follows:

$$\begin{aligned} \textit{Payment amount} \\ &= \alpha + \beta_1 * \textit{cycle beginning balance} + \beta_2 * \textit{usual payment} \\ &+ \beta_3 * \textit{change in revolving balance} + \beta_4 * \textit{COVID} + \tau + \varepsilon \end{aligned}$$

where Payment amount is the amount paid by the cardholder in a given month.

The other variables are as follows:

- *Cycle beginning balance* is the total balance at the start of the month.
- *Usual payment* is the average of the amount paid over the previous 3 months.
- *Change in revolving balance* is the difference between the revolving balance of the prior month and that from 3 months prior. We defined revolving balance as the difference between the cycle beginning balance and the amount paid in that cycle. A positive amount in the difference indicates that the revolving balance has grown, and a negative amount indicates it has decreased.
- *COVID* is an indicator for whether or not the estimated payment due date occurred after March 13, 2020 (when the COVID-19 pandemic was declared). Our data did not have payment due dates, so we estimated the payment due dates by adding 21 days to the date of the previous cycle ending date, which is the minimum allowed timing for payment due dates.
- τ is a vector of indicators for the months of the year (with September as the reference month).

We used a fixed-effects ordinary least squares modeling approach, with the fixed effects at the account ID level. We further used robust standard errors to allow for heteroscedasticity between accounts and serial correlation within each account.

[2]For more information on the Federal Reserve data and the definition of a "revolver," see app. II.

Because we used lagged information about cardholders in our model, we dropped the first 3 months that each account appears in the data. We further dropped any observations with negative cycle beginning balances, negative payments, or negative average payment estimates.

We then extended the baseline model to estimate the association between payment choices and the COVID-19 pandemic initial shutdown in March 2020, as well as the four federal-level disbursements of cash assistance directly to individuals. Our extended model is as follows:

$$\begin{aligned} Payment\ amount &= \alpha + \beta_1 * cycle\ beginning\ balance + \beta_2 * usual\ payment \\ &+ \beta_3 * change\ in\ revolving\ balance + \beta_4 * COVID + \beta_5 \\ &* shutdown + \gamma_1 * eip\ 1 + \gamma_2 * eip\ 2 + \gamma_3 * eip\ 3 + \delta * CTC_t \\ &+ \tau + \varepsilon_{it} \end{aligned}$$

In addition to our indicator for the entire pandemic period (*COVIDit*), we constructed five indicator variables to capture potential differences in credit card payments made in the month immediately following the shutdown and in the months when disbursements of each of the pandemic assistance payments were made.[3] The advance child tax credit payments were disbursed six times in 2021, so we flagged each of those payment cycles as potentially influenced by the credit. We defined indicators for each of these five different pandemic-related events as follows:

- Indicator for initial shutdown month for observations with an estimated payment due date that occurred after March 13, 2020, and on or before April 13, 2020 (*shutdown*)
- Indicator for the first economic impact payment if the observation's estimated payment was after April 10, 2020, and on or before May 10, 2020 (*eip 1*)
- Indicator for the second economic impact payment if the observation's estimated payment was after December 29, 2020, and on or before January 30, 2021 (*eip 2*)

[3]The federal government declared the COVID-19 pandemic on March 13, 2020. The first disbursements of the three economic impact payments occurred on April 10, 2020, December 29, 2020, and March 17, 2021. The first disbursement of the advance child tax credit payments occurred on July 15, 2021.

- Indicator for the third economic impact payment if the observation's estimated payment was after March 17, 2021, and on or before April 17, 2021 (*eip 3*)
- An indicator for the advance child tax credit payments is assigned to all observations where the observation's estimated payment was after July 15, 2021, ending with the last month of our data in December 2021 (*CTC*)

We again used fixed effects and robust standard errors to allow for heteroscedasticity between accounts and serial correlation within each account.

Limitations

Our analysis has limitations and our results should be interpreted with caution. In all cases, our estimates of effect sizes were average effect sizes of the entire population of revolving accounts in our sample of the Y-14M data. We were not able to determine which cardholders associated with the accounts in our sample received pandemic assistance. As a result, our estimates of the effect of pandemic assistance funds used payment data for cardholders who both did and did not receive such funds.

Additionally, the effect sizes of the economic impact payments and the advance child tax credit were not directly comparable because a much smaller population would have been eligible to receive the advance child tax credits than was eligible to receive the economic impact payments. In both cases, we did not know what fraction of cardholders in our sample received either type of payment. Further, we were not able to determine that these increased credit card payment amounts were due to the federal payments or to other events that occurred with similar timing that would have facilitated some cardholders' average increase in payments.

Results

Table 6 lists the results of our model estimates for both the baseline and extended models.

Table 6: Estimated Coefficients of Credit Card Payment Amounts Made by Revolving Accounts

Variable	Baseline model coefficients (t-statistic)	Extended model coefficients (t-statistic)
Average recent payments	0.22***	0.22***
	(25.34)	(25.30)
Account balance	0.09***	0.09***
	(79.12)	(79.11)

Variable	Baseline model coefficients (t-statistic)	Extended model coefficients (t-statistic)
Change in revolving balance	0.05***	0.05***
	(25.36)	(25.37)
COVID-19-era	42.89***	39.53***
	(25.19)	(21.38)
Shutdown	—	-88.42***
		(-22.33)
Economic impact payment I	—	-44.23***
		(-11.22)
Economic impact payment II	—	20.07***
		(4.51)
Economic impact payment III	—	60.79***
		(13.36)
Advance child tax credit	—	36.51***
		(14.55)
Month indicator		
January	5.46***	6.65***
	(2.73)	(3.23)
February	15.37***	19.00***
	(7.42)	(9.15)
March	42.25***	48.80***
	(20.74)	(23.91)
April	28.20***	37.37***
	(13.94)	(17.62)
May	18.92***	25.48***
	(9.77)	(13.02)
June	10.70***	15.04***
	(5.42)	(7.55)
July	12.39***	14.82***
	(6.33)	(7.53)
August	13.80***	13.72***
	(6.96)	(6.92)
October	-4.16**	-3.86**
	(-2.2)	(-2.04)
November	-5.74***	-5.47***
	(-3.04)	(-2.89)
December	-1.93	-0.81
	(-0.99)	(-0.41)

Variable	Baseline model coefficients (t-statistic)	Extended model coefficients (t-statistic)
Constant	-39.24***	-42.63***
	(-6.02)	(-6.54)
Fixed effects at the account level:	Yes	Yes
N	8.2 million	8.2 million
R^2: Within	0.04	0.04
Between	0.44	0.44
Overall	0.18	0.18

Legend: ** = significantly different from zero at the 95 percent confidence level; *** = significantly different from zero at the 99 percent confidence level; — = not applicable

Source: GAO analysis of data from the Board of Governors of the Federal Reserve System. | GAO-23-105269

In general, payments made by revolvers suggest that only a small portion of their payment decision was associated with the total balance in the current month (9 cents for every dollar of balance) and a much larger weight (22 cents for every dollar) was placed on the average payment over the previous 3 months. The positive coefficient on the change in revolving balance suggests that cardholders would, on average, increase their payments slightly in response to a rising revolving balance, though they only increased it by 5 cents for every dollar the balance increased. We also found a strong seasonal effect, in line with prior research, suggesting that, on average, revolvers would pay the most toward their balances in March or April, consistent with a tax refund effect.

In our baseline model, we estimated that during the pandemic, revolvers paid on average $43 more per month than prior to the pandemic. This is consistent with our other findings that revolvers were able to pay off their balances more quickly during the pandemic.

Our extended model suggests that variations in payment patterns during the pandemic were associated with the timing of the disbursements of federal pandemic cash assistance, though other events concurrent with the timing of the assistance payments may have been driving some of our estimates. In the extended model, we found that overall during the period after March 13, 2020, through the end of December 2021, cardholders paid an additional $40 each month on average. However, in the initial shutdown, prior to assistance payments, revolvers paid on average $49 less than prior to March 2020.[4] This suggests either that revolvers might have been keeping cash in reserve due to the extreme uncertainty or that they had lost income in the days immediately following the shutdown.

When the first economic impact payments were disbursed in April 2020, cardholders on average increased their payments from the March 2020 decrease by $44, for a net reduction of $5 prior to prepandemic baselines. The second and third economic impact payments were associated with increases of $20 and $61 in credit card payments, respectively, beyond the average increase during the pandemic. This is consistent with increased proportions of people reporting using the economic impact payments to pay down debt, as estimated by the Census Bureau's Household Pulse Survey, as previously discussed in the report.[5]

Finally, in every month in which the advance child tax credit payments were sent out, revolvers increased their credit card payments by an average of $37 beyond the average increase during the pandemic. Because the advance child tax credit payments were recurring generally for 6 months, these payments were associated with the largest overall contribution of additional credit card payments ($219).

[4]The $49 dollar amount is the net of an increase in $40 for all months after the start of the pandemic and a decrease during the initial shutdown of $88 (difference was due to rounding).

[5]Census conducted the Household Pulse Survey each week from April 23 to July 21, 2020, and every 2 weeks starting in August 2020. We reviewed the surveys conducted from April 23, 2020, to October 11, 2021. In the surveys conducted from June 11 to July 21, 2020, from January 6 to March 29, 2021, and from April 14 to July 5, 2021, respondents were asked if they received or expected to receive an economic impact payment and on what they spent the payment, including paying down credit card balances, student loans, or other debts. The 95 percent confidence intervals for the estimates ranged from about 13 to 17 percent based on surveys conducted after the distribution of the first economic impact payments, from 49 to 54 percent based on surveys conducted after the distribution of the second economic impact payments, and from 48 to 59 percent based on surveys conducted after the third economic impact payments.

Appendix VI: Econometric Analysis of Credit Card Terms and Revolving Balances by Race/Ethnicity in Cardholders' Zip Codes

This appendix presents the development, estimation, results, and limitations of our econometric analyses of disparities in credit card interest rates, credit limits, and revolving balances associated with differences in racial and ethnic composition in cardholders' billing zip codes.

Data and Variable Definitions

We used a 0.1 percent nongeneralizable sample of credit card accounts from the Board of Governors of the Federal Reserve System's Y-14M credit card data from June 2013 through December 2021. We supplemented our analysis with zip-code-level data on race and ethnicity and median household income from the Census Bureau's 5-year American Community Surveys from 2013 through 2020. See appendix II for details on the datasets and their construction and appendix III for full details on the use of zip-code-level racial and ethnic composition data.

In these models, we examined three credit card outcomes: interest rates, credit limits, and revolving balances. Interest rates and credit limits are credit card terms that are offered by the card issuer and accepted by the cardholder. Revolving balances are the result of cardholders' purchase and payment decisions, which are likely informed by their interest rate and credit limit, along with other factors. The definitions of these outcomes are as follows:

- **Credit card interest rate.** The current interest rate for general purchases on the account, in percentage points. Note that actual interest rate assessed may differ if the account has purchases that qualify for a promotional rate or that are being charged a penalty rate or different rate for balance transfers or cash advances. Likewise, if the account is transacting and eligible for the grace period, the account holder will not pay the listed rate but will instead pay 0 percent.
- **Credit limit.** The maximum amount of credit available for a credit card account.
- **Revolving balance (for revolving accounts only).** The calculated balance of the difference between the account's beginning balance and payment amount. Revolving balances are treated as positive when the beginning balance exceeds the payment amount.

Methodology

Credit Card Term Regressions

We used econometric models to estimate relationships between credit card terms (interest rates and credit limits) and the racial and ethnic composition of cardholders' billing zip codes. For each of the two credit card terms, we estimated the parameters of the following specification:

$$y = \alpha + \beta_1 * \%Asian + \beta_2 * \%Black + \beta_3 * \%Hispanic + \beta_4 * \%Other\ Race/Ethnicity + X'\Gamma + \varepsilon$$

In these models, y is either the interest rate on the card or the credit limit; %Asian, %Black, %Hispanic, and %Other Race/Ethnicity are the percentages of Asian, Black or African American, Hispanic or Latino, and other people who are not White, respectively, in the cardholder's billing zip code; X is a vector of other variables; and ε is the error term. The percentage of White residents is the omitted racial category.

In our baseline specification, *X* included indicators for the month and the cardholder's state of residence. In other specifications, *X* also included variables measuring the cardholder's credit score, the status of the account, and the income distribution in the cardholder's billing zip code. We estimated the parameters of these models using all account-month observations for accounts in transacting, revolving, and inactive status.

We measured account status using indicator variables for whether the account was revolving or inactive; transacting was the omitted status. We controlled for account status in our regressions because it may reflect various factors that affect credit terms, though the sign of the association and the direction of any underlying causal effects are ambiguous. For example, inactive accounts may be associated with higher interest rates not because the issuer assigned a higher interest rate as a result of account inactivity, but because the cardholder decided to use the high interest rate card as little as possible to avoid the high interest charges. Similarly, revolving accounts may have lower credit limits because they have had a history of high credit utilization. Alternatively, issuers might increase their limits seeing an opportunity for a high-return customer who is signaling, through their use of credit, that they may use more of it if given the opportunity.

We also controlled for the cardholders' credit scores because they incorporate information about an individual's credit history and credit usage, and card issuers use credit scores to help make credit underwriting decisions. Some research suggests that credit scores are also correlated with individuals' race and ethnicity.[1]

We controlled for the income distribution in cardholders' zip codes. We measured the distribution of income in cardholders' zip codes as the percentage of households with income in each of 16 income groups; $60,000–$74,999 was the omitted income group.[2]

In all cases, we assume that our standard errors will have independent errors between zip codes but we allow for possible correlation across error terms within zip codes, so we cluster our error terms on zip code, providing more conservative standard errors and confidence intervals.

Revolving Balance Regressions

We used similar econometric models to estimate relationships between revolving balance amounts and the racial and ethnic composition of the cardholders' billing zip codes. We estimated the parameters of these models using only account-month observations of accounts in revolving status and omitted variables measuring account status from our regression models, but otherwise used the same approach.

Scenario Development

To provide a more concrete scale of effect sizes measured in our credit term and revolving balance regressions, we created illustrative scenarios using the representative racial and ethnic clusters of zip codes as described in appendix III. The cluster centroids allowed us to use realistic combinations of racial and ethnic groups to estimate the overall marginal effect of moving from one zip code cluster to another.

To calculate the marginal effects, we

- multiplied the percentage of each group from a zip code cluster centroid with its respective estimated model coefficient,

[1]See Board of Governors of the Federal Reserve System, *Report to the Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit* (August 2007), and Robert B. Avery, Kenneth P. Brevoort, and Glenn B. Canner, "Credit Scoring and Its Effects on the Availability and Affordability of Credit," *The Journal of Consumer Affairs*, vol. 43, no. 3 (2009).

[2]We used more granular income categories in our regression analysis as compared with our descriptive analysis. The income groups used for the regression analysis are as follows: below $10,000, $10,000–$14,999, $15,000–$19,999, $20,000–$24,999, $25,000–$29,999, $30,000–$34,999, $35,000–$39,999, $40,000–$44,999, $45,000–$49,999, $50,000–$59,999, $75,000–$99,999, $100,000–$124,999, $125,000–$149,999, $150,000–$199,000, and $200,000 and above.

- summed the individual products for each centroid, and
- calculated the difference between each centroid and the one representing predominantly White zip codes.

This allowed us to estimate the overall effect of moving from a predominantly White zip code to one of our other groupings, while holding constant all other factors controlled for in the model.

Assumptions and Limitations

Our analysis has limitations and our results should be interpreted with caution. The sample of credit card accounts we analyzed may not represent the population of all credit card accounts, so our results reflect the sample of accounts we analyzed and may not generalize to other credit card accounts. Similarly, our results may not generalize to other time periods.

Omitted variable bias poses a validity threat to our models, just as it does to any ordinary least squares regression. Our analysis was not designed to determine all the potential reasons for differences in credit card terms associated with the racial and ethnic composition of cardholders' zip codes, which may be due to factors that are either not captured in the data we analyzed or cannot be measured. Such factors could include the extent to which cardholders compare credit terms when choosing a card, competition among lenders, and lender-specific risk evaluation or loan approval processes.[3] Differences in these factors may be incidentally associated with race and ethnicity, or these factors may themselves be

[3]For a discussion of borrowers comparing credit terms, see Victor Stango and Jonathan Zinman, "Borrowing High versus Borrowing Higher: Price Dispersion and Shopping Behavior in the U.S. Credit Card Market," *The Review of Financial Studies*, vol. 29, no. 4 (2016): 979–1006, and Ping Cheng, Zhenguo Lin, and Yingchun Liu, "Racial Discrepancy in Mortgage Interest Rates," *Journal of Real Estate Finance and Economics*, vol. 51, no. 1 (2015): 101–120. For a discussion of lender competition, see Alexander W. Butler, Erik J. Mayer, and James P. Weston, "Racial Disparities in the Auto Loan Market," *Review of Financial Studies*, vol. 36, no. 1 (2023): 1–41; Robert Bartlett et al., "Consumer-Lending Discrimination in the FinTech Era," *Journal of Financial Economics*, vol. 143, no. 1 (2022): 30–56; and Neil Bhutta, Aurel Hizmo, and Daniel Ringo, "How Much Does Racial Bias Affect Mortgage Lending?" Evidence from Human and Algorithmic Credit Decisions" (working paper, Finance and Economics Discussion Series, Board of Governors of the Federal Reserve System, Aug. 2, 2022), https://www.federalreserve.gov/econres/feds/how-much-does-racial-bias-affect-mortgage-lending.htm. The latter study also discusses how differences in mortgage approval may be associated with lender-specific loan approval processes, including stricter credit standards for all borrowers or varying quality of services provided. For a discussion of differences in how issuers evaluate risk factors, see Stango and Zinman, "Borrowing High versus Borrowing Higher." The authors argue that issuers' internal risk-based pricing models may place different emphasis on risk factors such as credit scores and late payments, and hence cardholders may receive different interest rates from different issuers.

influenced by race and ethnicity, and therefore act as channels through which race and ethnicity influence credit terms.

Results

In all of our models, we found statistically and practically significant differences in interest rates, credit limits, and revolving balances associated with different racial and ethnic zip code clusters before and after controlling for other factors that would be expected to influence these parameters—that is, cardholders' credit scores, household incomes in their zip codes, and revolving status.

Interest rates. Table 7 presents estimated coefficients from different specifications of our econometric model of credit card interest rates.

Table 7: Estimated Differences in Credit Card Interest Rates by Race and Ethnicity in Cardholders' Billing Zip Codes, June 2013–December 2021

Variables	Model 1 coefficient (t-statistic)	Model 2 coefficient (t-statistic)	Model 3 coefficient (t-statistic)	Model 4 coefficient (t-statistic)
Percentage of residents in billing zip code who are:				
Black or African American	2.17*** (38.91)	1.42*** (26.91)	0.83*** (16.29)	0.72*** (13.02)
Asian	-0.81*** (-8.88)	0.26*** (3.19)	0.35*** (4.34)	0.52*** (5.96)
Hispanic or Latino	2.22*** (41.59)	1.56*** (31.85)	1.06*** (22.63)	0.94*** (18.84)
Other	2.68*** (10.84)	1.84*** (7.9)	1.06*** (4.7)	0.96*** (4.25)
Account status:				
Revolving	—	3.72*** (241.31)	2.60*** (154.79)	2.60*** (154.29)
No activity	—	2.38*** (167.26)	2.45*** (170.72)	2.45*** (170.27)
Credit score	—	—	-0.01*** (-156.98)	-0.01*** (-155.71)
Percentage of households in billing zip code with household incomes:				
Under $10,000	—	—	—	0.08 (0.26)
$10,000–$14,999	—	—	—	0.42 (1.05)
$15,000–$19,999	—	—	—	0.58 (1.39)

Variables	Model 1 coefficient (t-statistic)	Model 2 coefficient (t-statistic)	Model 3 coefficient (t-statistic)	Model 4 coefficient (t-statistic)
$20,000–$24,999	—	—	—	-0.77* (-1.82)
$25,000–$25,999	—	—	—	-0.30 (-0.69)
$30,000–$34,999	—	—	—	-0.38 (-0.89)
$35,000–$39,999	—	—	—	0.09 (0.2)
$40,000–$44,999	—	—	—	0.55 (1.22)
$45,000–$49,999	—	—	—	-0.06 (-0.13)
$50,000–$59,999	—	—	—	0.27 (0.71)
$75,000–$99,999	—	—	—	0.39 (1.19)
$100,000–$124,999	—	—	—	-0.11 (-0.3)
$125,000–$149,999	—	—	—	-0.15 (-0.37)
$150,000–$199,999	—	—	—	-0.50 (-1.42)
$200,000 and above	—	—	—	-0.42* (-1.67)
Constant	13.83*** (84.74)	11.80*** (84.19)	22.69*** (150.53)	22.67*** (82.96)
F-test of all income variables	—	—	—	F(15, 30175) = 5.01***
State fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
N	30.3 million	30.3 million	30.0 million	30.0 million
R^2	0.04	0.11	0.13	0.13

Legend: * = significantly different from zero at 90 percent confidence level; *** = significantly different from zero at the 99 percent confidence level; — = not applicable

Source: GAO analysis of data from the Board of Governors of the Federal Reserve System and Census Bureau. | GAO-23-105269

As shown in table 7, in all of our models, our racial composition variables were statistically significant, as were all control variables, with the exception of the income groups. However, the income groups were jointly statistically significant.

Increases in the percentage of residents who were Black, Hispanic, and Other race in a cardholder's zip code were associated with a significantly higher credit card interest rate. While the estimated effects are reduced somewhat when control variables are added to the model, the differences remain substantial.

In the model without controls, an increase in the percentage of Asian residents in the cardholder's zip code was associated with a modest reduction in interest rates. However, when we controlled for additional factors that might affect interest rates, the sign of the association flipped, and the percentage of Asian residents in a cardholder's billing zip code became associated with an increase in interest rates. This happens when a variable is added to the model that is both correlated with the Asian percent coefficient and with lower interest rates. Cardholders living in zip codes with more Asian residents were more likely to be transactors and have higher incomes and credit scores than other minority groups. Once we controlled for those correlations, our model revealed a disparity in interest rates for zip codes higher in Asian residents relative to similarly situated zip codes with lower concentrations of Asian residents and higher concentrations of White residents.

Both revolvers and inactive cardholders faced higher interest rates than transactors—over 2 percentage points after controlling for zip-code incomes and credit scores. As expected, cardholders with higher credit scores generally had lower interest rates—every 10-point increase in credit score was associated with a reduction of 0.1 percentage point in interest rate. While controlling for zip-code-level income composition overall was statistically significant, the coefficients on individual income groups were generally not statistically significant and their sign followed no particular pattern. This suggests that any association between zip-code incomes and interest rates was sufficiently weak and was not captured by the zip-code-level income measures.

Credit limits. Table 8 presents estimated coefficients from alternative specifications of our econometric model of credit limits on credit cards.

Table 8: Estimated Differences in Credit Limits by Race and Ethnicity in Cardholders' Billing Zip Codes, June 2013–December 2021

Variable	Model 1 coefficient (t-statistic)	Model 2 coefficient (t-statistic)	Model 3 coefficient (t-statistic)	Model 4 coefficient (t-statistic)
Percentage of residents in billing zip code who are:				
Black or African American	-5,440***	-4,822***	-2,638***	-1,036***
	(-48.71)	(-45.75)	(-29.78)	(-13.15)
Asian	1,221***	310	125	-3,112***
	(3.51)	(0.97)	(0.47)	(-19.46)
Hispanic or Latino	-7,100***	-6,511***	-4,582***	-2,347***
	(-57.26)	(-56.17)	(-46.06)	(-30.72)
Other	-6,498***	-5,842***	-3,020***	-1,576***
	(-13.64)	(-13.16)	(-7.92)	(-4.78)
Account status:				
Revolving	—	-3,507***	160***	269***
		(-135.76)	(7.02)	(12.18)
No activity	—	-3,678***	-3,655***	-3,563***
		(-139.7)	(-147.34)	(-148.13)
Credit score	—	—	47***	46***
			(341.99)	(344)
Percentage of households in billing zip code with household incomes:				
Under $10,000	—	—	—	2,374***
				(4.73)
$10,000–$14,999	—	—	—	-864
				(-1.41)
$15,000–$19,999	—	—	—	-2,594***
				(-4.03)
$20,000–$24,999	—	—	—	-296
				(-0.47)
$25,000–$25,999	—	—	—	-666
				(-1.03)
$30,000–$34,999	—	—	—	-782
				(-1.24)
$35,000–$39,999	—	—	—	-1,660**
				(-2.52)
$40,000–$44,999	—	—	—	-906
				(-1.37)
$45,000–$49,999	—	—	—	-156
				(-0.21)

Variable	Model 1 coefficient (t-statistic)	Model 2 coefficient (t-statistic)	Model 3 coefficient (t-statistic)	Model 4 coefficient (t-statistic)
$50,000–$59,999	—	—	—	556 (0.99)
$75,000–$99,999	—	—	—	-568 (-1.12)
$100,000–$124,999	—	—	—	617 (1.13)
$125,000–$149,999	—	—	—	-483 (-0.76)
$150,000–$199,999	—	—	—	557 (0.91)
$200,000 and above	—	—	—	13,544*** (30.3)
Constant	11,866*** (25.92)	14,239*** (34.18)	-22,757*** (-61.39)	-23,066*** (-50.89)
F-test of all income variables	—	—	—	F(15, 30185) = 315.24***
State fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
N	30.4 million	30.4 million	30.0 million	30.0 million
R^2	0.03	0.07	0.21	0.23

Legend: ** = significantly different from zero at the 95 percent confidence level; *** = significantly different from zero at the 99 percent confidence level; — = not applicable

Source: GAO analysis of data from the Board of Governors of the Federal Reserve System and Census Bureau. | GAO-23-105269

Our results for our credit limit analysis paralleled those of the interest rate analysis. Higher concentrations of Black, Hispanic, and Other residents in a zip code were associated with substantially lower credit limits, though the scale of the penalty was reduced as controls were added to the model. In the baseline model without other controls, higher concentrations of Asian residents in a zip code were associated with higher credit limits, but this association switched sign once additional controls were added. Once all of our controls were added to the model, Asian concentrations were associated with the largest credit limit penalties.

In addition, both revolving and inactive accounts were associated with credit limits of more than $3,000 less than transacting accounts in the model without controlling for characteristics that may influence credit limits. After we controlled for credit scores, revolving accounts had somewhat higher credit limits than transacting accounts with similar credit scores. Our analysis estimated that higher credit scores were associated with higher credit limits—an increase of 10 points in credit score was associated with an almost $500 increase in credit limits. Once again, our analysis found a more ambiguous association between zip-code incomes and credit limits.

Revolving balances. Table 9 presents estimated coefficients from alternative specifications of our econometric model of balances on credit cards in revolving status.

Table 9: Estimated Differences in Revolving Balances by Race and Ethnicity in Cardholders' Billing Zip Codes, June 2013–December 2021

Variables	Model 1 coefficient (t-statistic)	Model 2 coefficient (t-statistic)	Model 3 coefficient (t-statistic)
Percentage of residents in billing zip code who are:			
Black or African American	-1,517***	-1,426***	-775***
	(-27.03)	(-25.38)	(-13.17)
Asian	314*	312*	-1,009***
	(1.95)	(1.95)	(-7.08)
Hispanic or Latino	-2,008***	-1,939***	-1,129***
	(-35.02)	(-33.84)	(-20.41)
Other	-1,663***	-1,518***	-811***
	(-6.74)	(-6.23)	(-3.47)
Credit score	—	2***	2***
		(23.86)	(20.13)
Percentage of households in billing zip code with household incomes:			
Under $10,000	—	—	260
			(0.67)
$10,000–$14,999	—	—	-718
			(-1.42)
$15,000–$19,999	—	—	495
			(0.71)
$20,000–$24,999	—	—	-391
			(-0.78)
$25,000–$25,999	—	—	45
			(0.08)
$30,000–$34,999	—	—	-282
			(-0.52)
$35,000–$39,999	—	—	-1,567***
			(-2.84)
$40,000–$44,999	—	—	-589
			(-1.04)

Variables	Model 1 coefficient (t-statistic)	Model 2 coefficient (t-statistic)	Model 3 coefficient (t-statistic)
$45,000–$49,999	—	—	-97 (-0.16)
$50,000–$59,999	—	—	809 (1.58)
$75,000–$99,999	—	—	165 (0.39)
$100,000–$124,999	—	—	824* (1.76)
$125,000–$149,999	—	—	1139** (2.14)
$150,000–$199,999	—	—	1,816*** (3.35)
$200,000 and above	—	—	4,204*** (11.45)
Constant	4,693*** (17.62)	3,347*** (12.31)	2,888*** (7.32)
F-test of all income variables	—	—	F(15, 27644) = 72.05***
State fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
N	10.6 million	10.6 million	10.6 million
R^2	0.01	0.01	0.02

Legend: * = significantly different from zero at 90 percent confidence level; ** = significantly different from zero at the 95 percent confidence level; *** = significantly different from zero at the 99 percent confidence level; — = not applicable

Source: GAO analysis of data from the Board of Governors of the Federal Reserve System and Census Bureau. | GAO-23-105269

As shown in table 9, our analysis suggests cardholders in zip codes with more residents of Black, Hispanic, and Other race and ethnicity carried statistically significant and substantially lower balances than cardholders in predominantly White zip codes. After we controlled for credit scores and zip-code incomes, the size of the association reduced by about half but remained substantively and statistically significant.

Our analysis also suggests cardholders in zip codes with high shares of Asian residents had slightly higher revolving balances (ones that were only statistically different from zero at the less strict $p < 0.1$ confidence level). Once we controlled for credit scores and zip-code incomes, cardholders in zip codes with high shares of Asian residents had substantially lower revolving balances relative to otherwise similar cardholders in zip codes with higher concentrations of White residents.

Cardholders who carried a balance and lived in zip codes with greater concentrations of higher-income households and households with higher credit scores had higher revolving balances.

Results of scenarios. Table 10 shows the estimated differences in interest rates, credit limits, and revolving balances of credit card accounts for cardholders in four hypothetical zip codes compared with those of accounts for cardholders in a zip code that is predominantly White. We derived these estimates using estimated coefficients from specifications with both the baseline model without controls and the full set of control variables.

Table 10: Estimated Differences in Credit Terms and Revolving Balances by Race and Ethnicity in Cardholders' Billing Zip Codes, June 2013–December 2021

	Difference compared with cardholders in predominantly White zip codes					
	Percentage point difference in interest rates		Dollar amount difference in credit limits		Dollar amount difference in revolving balances	
Racial and ethnic zip code clusters	Without controls for revolving status, credit scores, and zip-code incomes	With controls for revolving status, credit scores, and zip-code incomes	Without controls for revolving status, credit scores, and zip-code incomes	With controls for revolving status, credit scores, and zip-code incomes	Without controls for credit scores and zip-code incomes	With controls for credit scores and zip-code incomes
Majority Hispanic or Latino residents	1.4	0.6	-$4,285	-$1,477	-$1,212	-$711
Majority Black or African American residents	1.3	0.5	-3,412	-710	-953	-492
Mixed race and ethnicity with majority White residents	0.4	0.2	-1,330	-540	-374	-258
Mixed race and ethnicity with no majority residents	0.2	0.4	-1,079	-1,489	-308	-564

Source: GAO analysis of data from the Board of Governors of the Federal Reserve System and Census Bureau. | GAO-23-105269

As shown in table 10, our analysis suggests that cardholders in zip codes with higher shares of Black, Hispanic, or Asian residents had higher interest rates, lower credit limits, and lower revolving balances compared with zip codes with higher shares of White residents. For example, cardholders in majority-Black zip codes had 1.3 percentage points higher interest rates than cardholders in predominantly White zip codes, and cardholders in majority-Hispanic zip codes had interest rates 1.4 points higher. Consistent with lower credit limits, cardholders in majority-Black and majority-Hispanic zip codes carried lower revolving balances. Also, zip codes with mixed race and ethnicity but no majority had the highest share of Asian residents among the five zip code clusters. Cardholders in these zip codes had interest rates that were 0.2 percentage points higher, credit limits that were $1,079 lower, and revolving balances that were $308 lower. The differences in credit terms and revolving balances for cardholders in zip codes of different racial and ethnic mixes continued to exist after we controlled for factors that can contribute to differences in credit terms or revolving balances.

Appendix VII: GAO Contact and Staff Acknowledgments

GAO Contact

Alicia Puente Cackley, 202-512-8678 or cackleya@gao.gov

Staff Acknowledgments

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