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The Case of U.S. Consumer Credit Records

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DP 25-01

PUBLISHED
September 2025

FRB CFI PHILADELPHIA

DOI: https://doi.org/10.21799/frbp.dp.2025.01

How Well Do Survey Self-Reports Align with Administrative Data?
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September 2025

Abstract

Surveys are an important source of data on how consumers manage their personal finances, including their credit use and debt management. In this paper, we examine how well individuals' self-reported credit activities in surveys correspond to the administrative data in their credit bureau files. We use anonymized survey data linked with individual-level administrative credit records to assess the levels of agreement between the two data sources for key credit-related attributes — such as credit seeking, credit account ownership, and outstanding balances — across several widely used credit products, such as credit cards, mortgages, and auto loans. We find that survey self-reports generally align well with administrative data, with a large majority of respondents (72 percent) reporting the composition and balances of their existing credit accounts as well as new credit applications in a manner consistent with their credit records. Agreement between the two data sources is generally higher for credit seeking and account ownership than for account balances, higher for installment loans than for revolving credit, and higher for credit products used more frequently than those used less often. When there is disagreement, there is a greater tendency to underreport rather than overreport in surveys, especially for account balances. Additionally, more often than not, demographic characteristics do not explain the level of agreement or disagreement between self-reports and credit records.

Keywords: Survey data, self-reports, credit reporting data, consumer credit, personal finance

JEL Codes: C83, C81, D14, D12

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The authors thank Julia Cheney and Bob Hunt for helpful comments and suggestions.

Survey data provide valuable insights into how people manage their personal finances, including spending, borrowing, and managing debt. While individual financial records — such as those maintained by financial institutions or credit reporting agencies — exist, these administrative data are not always readily accessible or suited for research purposes. Often, they lack detailed background information on individuals, limiting the range of research questions that can be explored. Surveys, despite their own limitations, can fill these research gaps, as they can be specifically designed to gather relevant and targeted information with an extensive set of respondent profiles.

There are several national surveys that regularly collect data on the balance sheet or financial conditions of U.S. consumers. A non-exhaustive list includes the Federal Reserve Board's Survey of Consumer Finances (SCF) and Survey of Household Economics and Decisionmaking (SHED), the Philadelphia Fed Consumer Finance Institute's Labor, Income, Finances, and Expectations (LIFE) Survey, the New York Fed's Survey of Consumer Expectations (SCE), and the Consumer Financial Protection Bureau (CFPB)'s Making Ends Meet (MEM) Survey.

Common survey questions on this topic include how people obtain and use credit, including what types of credit accounts (e.g., credit cards, mortgages, auto loans, student loans, and other personal loans) respondents currently have, how much they owe on their loans and lines of credit, and whether they are keeping up with their debt payments. Respondents are also asked whether they have recently applied for new credit.

How well do these survey self-reports of credit activity correspond to actual credit records? This is an important question for evaluating the efficacy of consumer financial surveys in providing accurate and useful insights into personal financial behavior. To examine this, we conduct an anonymous survey of a national sample of U.S. consumers asking about credit-related information and compare their responses to administrative credit report data on the same individuals, obtained from a national credit bureau. Throughout this paper, we refer to administrative credit report data as *credit records*, which we treat as the benchmark for comparison.[1]

Our study compares survey responses with credit records *at the individual level* to assess agreement.[2] Earlier consumer finance research has primarily focused on comparing national aggregate values of credit accounts and balances estimated from survey data with totals derived from administrative data.[3] Among the few individual-level studies, the focus of comparison was on high-cost credit products[4] or on a single item such as credit score.[5,6] Our study contributes by

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[1] While it is the case that administrative records contain errors, credit reports serve as a plausible benchmark against which the accuracy of survey self-reports is assessed. For additional information on errors in credit records, see Smith et. al (2013) and the studies conducted by the Federal Trade Commission (2012) and the Consumer Financial Protection Bureau (2023).

[2] We do not expect *perfect* agreement between survey and administrative data. As mentioned above, credit records will have some frequency of errors. Survey self-reports also contain errors due to inaccurate or distorted responses (e.g., Bound, Brown, and Mathiowetz 2001; Celhay, Meyer and Mittag 2024; Hariri and Lassen 2017; Pascale, Roemer, and Resnick 2009; Pursiainen 2024).

[3] For example, previous studies have compared totals of accounts or balances estimated from household surveys such as the Survey of Consumer Finances with aggregate credit bureau data or statistical reports such as the G.19, published by the Board of Governors (see Brown et al. 2015; Zinman 2009). They find evidence of underreporting of credit card balances in surveys. In other contexts, this type of aggregate-level comparison has also been used to compare survey results against administrative aggregates on income (Johnson and Moore 2005) and government transfers (Larrimore, Mortenson, and Splinter 2022; Meyer, Mok, and Sullivan 2015; Parker 2011).

[4] Studies by Elliehausen and Lawrence (2001) and Karlan and Zinman (2008) found that survey respondents tended to underreport the past borrowing of short-term, high-interest personal loans. However, it is possible that the stigma typically attached to using high-risk loans, combined with the mode of the surveys (telephone), might have inflated the extent of underreporting because of social desirability concerns, which may not necessarily apply in the same way to more common, mainstream types of credit products.

[5] See Perry (2008) for a comparison between survey-based credit ratings and administrative credit scores.

[6] Some have used linked survey and credit bureau data for purposes other than assessing agreement between the two data sources, such as examining trends or differences in credit use and conditions by consumer background characteristics. See Financial Health Network (2024).

providing a more comprehensive individual-level analysis of agreement, focusing on key consumer credit attributes — such as credit account ownership, and outstanding balances, and new credit applications — for several mainstream credit products, including credit cards, mortgages, and auto loans.[7] Further, we also explore whether the personal characteristics of respondents are related to how closely their self-reported data align with their credit records.

Our findings indicate that across the nine credit measures we use, most exhibit reasonably good agreement between survey self-reports and credit records, with the average percent agreement being 72 percent. Looking specifically at each credit attribute, the vast majority of respondents show agreement with their credit records in reporting both the types of debts and credit accounts they hold (average 83.3 percent) and whether they have applied for new credit (70.4 percent). A smaller but still solid majority also report their balances in a way that matches the information shown in their credit records (average 61 percent).

However, the level of agreement varies depending on the specific credit measures, generally being higher for credit account ownership than for account balances, higher for installment loans than for revolving credit products, and higher for credit products used more frequently than for those used less often. Among cases of disagreement between self-reports and credit records, there is a greater tendency to underreport in surveys (average 17.4 percent) than to overreport (average 10.5 percent), especially for account balances. Additionally, we find that

[7] A recent study in Chile has explored a similar question (Madeira et al. 2022). To our knowledge, ours is among the first in the U.S. context to conduct an individual-level analysis of agreement (or disagreement) between survey and consumer credit records. While limited in consumer credit and debt research, such individual-level analysis using survey and administrative data has been more common for other economic variables, such as reported earnings, assets, employment status, and receipt of government transfers (see Bound, Brown, and Mathiowetz 2001 for a review of the related literature; see also Angel et al. 2019; Celhay, Meyer, and Mittag 2024; Kim and Tamborini 2012, Meyer, Mittag, and Goerge, 2022; Pascale, Roemer, and Resnick 2009).

some individual characteristics are significantly associated with agreement, underreporting, or overreporting on certain credit measures, but not consistently across the nine measures we study.

Linked Survey and Credit Bureau Data

For this study, we contracted with Competiscan, a market research firm, to field an online survey on a sample recruited from their research panel of U.S. consumers and to link the survey data to each respondent's credit records obtained from a national credit bureau.[8] The vendor handled obtaining informed consent and matching credit records at the respondent level using processes that ensure confidentiality. The credit records used for comparison with self-reports were pulled during the same month respondents completed the survey. The final datasets provided to us were fully anonymized and did not contain any personally identifiable information. Using anonymized unique identifiers, we were able to merge the survey data with the corresponding credit records while preserving privacy.

We focused on three types of information from the administrative credit records and designed our survey questions to collect similar information to allow for comparison between the two sources. First, for *recent credit seeking*, we asked respondents whether they had applied for any new loans or credit lines in the past three months and compared their responses with the recent credit inquiry information in their credit records.

Second, for *credit account ownership*, we asked respondents whether they currently had any open accounts for each type of credit product (auto loans, home loans, general-purpose credit cards, and private-label retail credit cards) and compared their answers with the corresponding open account information contained in their credit records.

[8] The vendor handled recruiting respondents, administrating the survey, and compensating them for participation.

The third category is *account balances*.[9] For each type of credit account respondents indicated they had, we asked how much they currently owed on those accounts. To reduce the cognitive burden, we provided balance ranges (i.e., bins) for respondents to choose from, instead of asking them to enter specific numeric amounts each time. We then re-coded the corresponding balance information from the credit records into the same bins for comparison. Table 1 details the specific items used, along with how they were defined and constructed in each data source (see Appendix Table A1 for descriptive statistics).

Our final data include 1,750 individuals who completed the survey between April 10 and May 8, 2023, with their credit records successfully matched. To ensure the availability of both survey and credit report data for comparison, one of the key eligibility criteria for the study was having a valid credit score.[10] Focusing on individuals with a credit score as our target population is based on several practical considerations: First, we are primarily interested in individuals who *have and use credit* sufficiently (and are thus likely to be scored)[11] to provide substantive, non-missing responses to questions about their credit activities; second, having a credit score facilitates the reliable and successful matching of individual respondents to their credit bureau records, which is essential for the purposes of this study. For analysis, we weighted the sample to

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[9] Among credit cards, home loans, and auto loans, account status and balances are typically updated each month in credit reports, so for most cases, the information should be concurrent. That said, there is still a possibility that the timing of a respondent's survey-reported loan balances does not fall into the same period when the corresponding loan accounts were updated in their credit report. Such instances of mismatch in reporting timing will likely *deflate* the extent of agreement between the two data sources; therefore, the observed agreement for the balance variables can be considered as lower-bound estimates.

[10] Our sample excludes individuals without a credit record ("credit invisibles") and those with an unscored credit record. The shares of credit invisibles and unscored consumers were estimated to be 2.7 percent and 9.8 percent, respectively, of the U.S. adult population in December 2020. See Consumer Financial Protection Bureau (2025).

[11] To have a credit score generated, one needs sufficient credit information. What qualifies as sufficient varies across scoring models, but it typically requires at least one credit account reported to credit bureaus in the last six months and at least one tradeline with a payment history of six months or more. See Brevoort, Grimm, and Kambara (2016).

be demographically representative of U.S. consumers aged 18 and older with a credit record (see Appendix Table A2 for sample characteristics).[12]

When we compare our weighted sample with available sources on credit segments of U.S. consumers, our sample tends to slightly overrepresent the super prime tier and underrepresent the prime and near prime tiers (see Appendix Figure A1). However, the overall distribution of prime and nonprime respondents is comparable to that of the U.S. consumer population with available credit scores: Prime (prime and super prime combined) makes up 66.4 percent of the sample compared with 64 percent of U.S. consumers; and nonprime (subprime and near prime combined) makes up 33.6 percent of the sample versus 36 percent of U.S. consumers.

Table 1. Items for Comparison Between Survey Self-Reports and Credit Records

	Survey Data	Credit Bureau Data
Credit Seeking	Have you applied for any new loans or credit in the last three months?	Number of inquiries within three months. Re-coded as Y if ≥1, N if 0.
Credit Account Ownership	Do you currently have… • Any auto loans with balances • Any mortgages or home equity loans with balances • Any open general-purpose credit cards • Any department store or retail store credit cards	Number of… • Open auto finance accounts • Open mortgage accounts (including both first-lien and second-lien loans) • Open bankcard accounts • Open retail accounts (including department store accounts) Each re-coded as Y if ≥1, N if 0

[12] Our weights are derived from the CFPB's Make Ends Meet (MEM) Survey, which used its Consumer Credit Information Panel — a random sample of all credit records maintained by a credit bureau — both as a sampling frame and as the basis for post-stratification weighting. To create weights for our sample, we used the demographic distribution of the 2023 MEM sample as benchmarks, with age (18–34, 35–54, 55+), gender (male, female), race and ethnicity (White, Black, Hispanic, Other), and education (high school graduate or less, some college, bachelor's degree or higher) as raking factors. We do not weight by income because the MEM collects household income, whereas our survey gathered information on respondents' personal income. Weights were trimmed at the 1st and 99th percentiles to reduce the influence of extreme weights. See Appendix Table A2 for sample characteristics for both the unweighted and weighted samples, along with a comparison with the target population.

Account Balances	[For each credit type owned] What is the total amount you currently owe on… • Your auto loans [$1–$10K, $10K–$20K, $20K–$30K, $30K–$40K, $40K+] • All your mortgage or home equity loans [$1–$100K, $100K–$200K, $200K–$300K, $300K–$400K, $400K–$500K, $500K+] • Your general-purpose credit cards [$1–$2.5K, $2.5K–5K, $5K–7.5K, $7.5K-$10K, $10K+] • Your department or retail store cards [$1–$250, $251–500, $501–750, $751–$1000, $1000+]	Total balances most recently reported on… • Open auto finance accounts • Open mortgage accounts (including both first-lien and second-lien loans) • Open bankcard accounts • Open retail accounts (including department store accounts) Each re-coded into the same five or six bins of balances as the corresponding survey item

Assessing Individual-Level Agreement Between Survey and Credit Bureau Data

To assess the level of agreement between individuals' survey self-reports and administrative credit records, we focused on four measures: (1) *percent agreement*, i.e., the percentage of respondents whose survey responses are consistent with their credit records. More specifically, we define agreement for credit seeking and credit account ownership as the respondent providing the same yes-or-no response in the survey as indicated in their credit records. For account balances, agreement is defined as the respondent selecting the same bin in the survey as reflected in the credit records after they were re-coded to the matching bins.

In cases of disagreement, we report (2) *percent overreport* and (3) *percent underreport*, which capture the percentage of respondents whose survey responses fall at higher or lower levels, respectively, than their credit records. We also report (4) the *kappa* statistic, a measure of observed agreement between categorical variables beyond what would be expected to occur by chance. Specifically, we use the *prevalence-adjusted, bias-adjusted kappa* for binary variables (such as credit seeking and credit account ownership).[13] For variables with multiple categories (such as account balances), we report *weighted kappa*, which accounts for the distance between categories by assigning greater penalties to disagreements between those that are farther apart.[14]

Table 2. Agreement Between Survey Self-Reports and Credit Records for Credit Seeking, Credit Account Ownership, and Account Balances

	Percent Agreement	Percent Overreport	Percent Underreport	Kappa	
Recent Credit Seeking	70.4	14.1	15.5	0.41	Moderate
Credit Account Ownership					
Auto loans	88.9	6.5	4.5	0.78	Substantial
Home loans	87.1	10.2	2.7	0.74	Substantial
General-purpose credit cards	85.4	6.0	8.6	0.71	Substantial
Retail credit cards	71.9	8.6	19.4	0.44	Moderate
Average for ownership	83.3	7.8	8.8		
Account Balances*					
Auto loans	63.1	8.6	28.3	0.72	Substantial
Home loans	79.2	4.9	15.8	0.87	Near perfect
General-purpose credit cards	58.7	15.8	25.5	0.69	Substantial
Retail credit cards	43.0	20.2	36.7	0.41	Moderate
Average for balances	61.0	12.4	26.6		
Average Across All Nine Items	72.0	10.5	17.4		

Notes: *Survey respondents were asked to assign their credit card, auto, and home loan balances into one of five or six bins. We use the same bins to categorize the numeric value of balances in the credit bureau data. We define agreement as when the respondent assigns their balance to the same bin as the value of the binned data in their credit records. We define over- and underreporting accordingly.

[13] Kappa values are sensitive to the baseline prevalence of categories. If most data fall into one category over the other (for example, 80 percent of our respondents answered "no" when asked about recent credit seeking), such imbalanced distribution of the categories can deflate kappa values. To address this issue, the use of *prevalence-adjusted, bias-adjusted kappa* is recommended for binary variables (Byrt, Bishop, and Carlin 1993). See Appendix Table A3 for a comparison of prevalence-adjusted and unadjusted kappa values, along with the prevalence index.

[14] Unlike weighted kappa, the standard unweighted kappa treats all disagreements equally, regardless of severity.

As shown in Table 2, across the nine credit measures examined, the observed percent agreement between survey self-reports and credit records ranges from 43.0 percent to 88.9 percent, with an average agreement of 72.0 percent, an average overreporting of 10.5 percent, and an average underreporting of 17.4 percent. Kappa values for most measures (8 out of 9) fall within the moderate (0.40–0.60) to substantial (0.60–0.80) agreement ranges, with the remaining one indicating near-perfect (0.80–1.00) agreement.[15]

Importantly, there is substantial variation by the type of credit product as well as the type of credit attribute. First, across all credit product types, agreement is generally higher for account ownership than for account balances.[16] Credit seeking also shows higher agreement than account balances. One possible explanation is that balances tend to change from month to month, which requires greater cognitive effort to keep track of in the moment (Srivastava and Raghubir 2002), whereas having an account or having recently applied for new credit involves rather simpler and more stable information, making reporting errors less likely.

Looking specifically by credit product type, agreement is generally higher for installment loans (such as mortgages and auto loans) than for revolving credit (such as credit cards). This is especially true for account balances. Installment loans are often used to finance major purchases and typically come with structured repayment schedules with fixed monthly payments. This helps make balances more predictable and easier for borrowers to track relative to credit cards, where monthly balances and payments tend to fluctuate more. These differences in repayment

[15] For reference, these results are comparable to other studies using kappa statistics to assess agreement between survey and administrative data, where kappa values mostly fall within the fair, moderate, and substantial ranges (e.g., Raina et al. 2002; Thompson et al. 2001).

[16] As mentioned in footnote 9, instances of misalignment between the survey timing and billing/reporting cycles might have contributed to lower agreement for balance measures, although the extent of its impact is uncertain.

structure, predictability, and use cases may influence the varying levels of agreement across these products.

Another pattern of variation by credit product type involves revolving credit products that differ in prevalence and usage frequency. Levels of agreement between self-reports and credit records are higher for general-purpose credit cards than for private-label, retail credit cards, across both account ownership and balance measures. General-purpose credit cards are by far more frequently and more widely used than retail credit cards in the United States.[17] Being more integrated into everyday life, general-purpose credit cards may be more salient to individuals, which could contribute to the higher agreement observed.

When we examine cases where survey self-reports disagree with credit records, respondents are more likely to underreport their credit information than to overreport it, with underreporting especially pronounced for account balances. That we find credit card balances to be underreported in surveys relative to administrative data is consistent with previous studies based on aggregate-level comparisons (see Zinman 2009; Brown et al. 2015).

Given the findings so far, the vast majority of respondents appear to have rather accurate knowledge of the debts and credit accounts they hold (83.3 percent on average), as well as their recent credit applications (70.4 percent), and report them in a way that corresponds to their credit records. While smaller in share, a sizable majority also seem to have a reasonably accurate sense of the balances they carry on their loans and lines of credit, reporting them consistently with their credit records (61.0 percent). Among the remaining cases of disagreement or misreporting, there is a greater tendency to underreport than to overreport in surveys.

[17] See the Federal Reserve Payments Study (2024).

Are Demographic Characteristics Associated with Agreement, Underreporting, and Overreporting?

Next, we examine whether respondents with certain characteristics show higher or lower levels of agreement between their survey self-reports and credit records. We estimate a series of multinomial logistic regressions for the nine credit measures listed in Table 2, using each of those items as a dependent variable with three outcome categories of *agreement*, *overreport*, and *underreport*. This model allows us to see whether any demographic characteristics are positively associated with agreement, and when not, whether they are associated with a particular direction of disagreement, either overreporting or underreporting. Note that this analysis is not causal but rather explores *associations* between individual characteristics and the reporting agreement or disagreement for our credit measures. As possible predictors, we include several key sociodemographic factors, such as gender, age, race and ethnicity, education, and personal income, as well as a variable indicating respondents' overall credit quality, constructed based on credit scores from the credit bureau.[18]

To facilitate interpretation of the regression results, we compute average marginal effects, which represent the average change in the predicted probability of each outcome (agreement, overreport, and underreport) when the predictor changes from 0 to 1, holding all others constant. Since all our predictors are coded as binary or dummy variables, the marginal effects correspond to the change in predicted probabilities when a respondent has a given characteristic, as opposed to belonging to the baseline or reference category. In Table 3, we report only the predictors whose average marginal effects are statistically significant.

[18] This variable was coded as a binary indicator for prime status (prime and super prime) versus nonprime (near prime and subprime). Results are substantively similar when credit scores are assigned to one of four ranges (bins). VantageScore credit scores were used.

Table 3. Respondent Characteristics Significantly Associated with Agreement, Overreporting, and Underreporting

		Gender Male (vs. Female)	Age 18–34 (ref), 35–54, 55+	Race White (ref), Black, Hispanic, Other	Education BA or Higher (vs. No Degree)	Income Lower (ref), Middle, Upper	Credit Score Prime (vs. Nonprime)
Account Ownership							
Auto Loan	Agreement						Prime more likely
	Overreport						Nonprime more likely
	Underreport	Female more likely				Upper more likely than Lower	
Home Loan	Agreement						Prime more likely
	Overreport						Nonprime more likely
	Underreport				BA+ more likely		
General Credit Card	Agreement			White more likely than Other		Upper more likely than Lower	Prime more likely
	Overreport						Nonprime more likely
	Underreport		55+ more likely than 18–34	Other more likely than White		Lower more likely than Upper	
Retail Credit Card	Agreement	Female more likely					
	Overreport						
	Underreport				No degree more likely		Prime more likely

		Gender Male (vs. Female)	Age 18–34 (ref), 35–54, 55+	Race White (ref), Black, Hispanic, Other	Education BA or Higher (vs. No Degree)	Income Lower (ref), Middle, Upper	Credit Score Prime (vs. Nonprime)
Account Balances							
Auto Loan	Agreement						
	Overreport			White more likely than Black and Hispanic			Prime more likely
	Underreport						
Home Loan	Agreement						
	Overreport			White more likely than Black		Upper more likely than Lower	
	Underreport						
General Credit Card	Agreement		18–34 more likely than 55+	White more likely than Other		Lower more likely than Middle and Upper	
	Overreport				BA+ more likely		
	Underreport	Male more likely	55+ more likely than 18–34			Middle and Upper more likely than Lower	
Retail Credit Card	Agreement						
	Overreport				BA+ more likely		
	Underreport						

	Gender Male (vs. Female)	Age 18–34 (ref), 35–54, 55+	Race White (ref), Black, Hispanic, Other	Education BA or Higher (vs. No Degree)	Income Lower (ref), Middle, Upper	Credit Score Prime (vs. Nonprime)
Recent Credit Seeking						
Agreement	Male more likely		Other more likely than White			
Overreport			White more likely than Other			
Underreport	Female more likely					

Notes: Table reports predictors whose average marginal effects are statistically significant (at the 0.05 level or below) for agreement, overreporting, or underreporting for each of the nine credit measures. Based on the results from multinomial logistic regressions. For full plots of average marginal effects, see Appendix Figures A2–A4. For dummy variables, the reference category is labeled “ref.” Region and marital status are included as control variables but are not shown in the results.

Overall, the relationship between demographic characteristics and our credit measures — including by specific credit attributes and credit products — varies considerably in direction and magnitude.

To present the results in a more accessible way, we organize the discussion by credit attribute category (credit account ownership, account balances, and credit seeking), and within each, we first highlight predictors that are statistically significant for more than one credit product and then also note some of the product-specific patterns.

Credit Account Ownership. First, respondents with prime credit scores are significantly more likely to report information in surveys that aligns with their credit records for holding auto loans, home loans, and general credit cards, while those with nonprime scores are more likely to overreport ownership of these accounts. This, however, does not extend to retail credit cards, where those with prime scores are instead more likely to underreport having such accounts.

We see a few instances of significant differences based on income, education, and gender, but the signs of these effects vary across different credit products.[20] For example, college-educated respondents are more likely than those without a degree to underreport having home loans, but for retail credit cards, those without a degree are the ones more likely to underreport. Female respondents are more likely to underreport having auto loans but are more likely to show reporting agreement for retail credit card ownership, compared with male respondents. Moreover, respondents with upper incomes ($100,000 or more) are more likely than those with lower incomes (under $40,000) to underreport auto loan ownership but to show agreement for general credit card ownership, whereas it is lower-income respondents who are more likely to underreport general credit card ownership.

[20] This variation is illustrated more precisely in the Appendix Figures A2–A4.

Although limited to a single credit product, a few additional characteristics are associated with a higher probability of underreporting account ownership: Older respondents (ages 55+) and those who identify as Other Race are more likely to underreport having general credit cards than younger respondents (ages 18–34) and White respondents, respectively.

Account Balances. Looking at the agreement between self-reported balance and credit records, college-educated respondents are more likely than those without a degree to overreport their credit card balances, both for general and retail credit cards. White respondents are more likely than non-White respondents to overreport balances on their auto loans and home loans, but they are more likely to show agreement for general credit card balances.

There are several significant predictors specific to the reporting of general credit card balances. For example, younger respondents (under 34) and those with lower incomes (under $40,000) are more likely to report general credit card balances consistent with their credit records, whereas older respondents (ages 55+) and those with middle ($40,000–$99,999) and upper ($100,000+) incomes are more likely to underreport them. Underreporting of general credit card debt is also more likely to occur among male respondents than female respondents.

When it comes to other loans, respondents with prime credit scores are more likely than those with nonprime scores to overreport their auto loan balances, and upper-income respondents are more likely than lower-income respondents to overreport their home loan balances.

Credit Seeking. Male respondents are more likely to show agreement in the reporting of their recent credit applications, whereas female respondents are more likely to underreport them. Respondents of Other Race are more likely to show agreement than White respondents, who are more likely to overreport having recently applied for new credit.

All in all, certain individual characteristics are found to be statistically significant in predicting agreement, overreporting, or underreporting, but the patterns vary considerably by credit attribute as well as credit product. No single characteristic is consistently associated with higher or lower agreement, as the direction and statistical significance of the associations differ depending on the specific measure. Specifically, characteristics one would expect to be related to more experience with credit[21] or higher financial literacy[22] do not appear to be consistently predictive of how well self-reported credit information aligns with administrative records.

Conclusion

Managing existing credit accounts and seeking new credit when needed are important for many Americans to achieve their financial goals. The credit attributes examined in this paper — credit seeking, account ownership, and outstanding balances — are highly relevant to personal finances and are regularly asked and measured in several national surveys of U.S. consumers and households. By examining how closely individuals' responses to credit-related questions correspond to their administrative credit report data, this study provides insights into the validity of self-reported survey data in measuring credit behavior and conditions.

Our findings indicate that, overall, individuals' self-reported credit information aligns reasonably well with their credit records, with the vast majority (72 percent) showing agreement

[21] For example, older individuals and those with higher credit scores generally have more experience managing credit accounts than younger individuals and those with lower credit scores. Some studies suggest that the longer and more regularly people have experience with financial programs (e.g., government transfers), the less likely they are to misreport them in surveys (Celhay, Meyer, and Mittag 2024; Meyer, Mittag, and Goerge, 2022; Pascale, Roemer, and Resnick 2009).

[22] Financial literacy has been found to correlate with greater accuracy in self-reports of financial information (Madeira and Margaretic 2022; Perry 2008).

between the two data sources on average. However, there is substantial variation depending on the specific credit measure, with agreement generally higher for items that are easier for respondents to track and recall. For example, agreement is higher for credit account ownership and credit seeking than for account balances, which may result from the fact that balances tend to fluctuate every month and require more frequent attention to monitor accurately. The type of credit product also matters, with higher agreement observed for products with fixed monthly payments, such as installment loans, which are easier to track and recall in terms of loan status and balance, compared with revolving credit, which involves greater month-to-month variability in balances and payments. Finally, agreement tends to be higher for more prevalent and more commonly used credit products, such as general credit cards, compared with those used less frequently, such as retail credit cards, for which lower usage frequency may increase the likelihood of reporting errors in surveys.[23]

Understanding these patterns of variation in the agreement between self-reports and administrative records helps not only in the interpretation of consumer finance survey data but also in informing the design of survey questions. For example, commonly used survey measures of credit account ownership and credit seeking appear to capture relatively accurate information. However, when asking about account balances, especially for credit products with lower levels

[23] It is possible that some of the disagreement between survey self-reports and credit records stems from administrative errors or timing issues in the credit bureau data. For instance, even if respondents report their credit information accurately in the survey, if the credit bureau data has not yet been updated to reflect the most current status of their accounts, this could appear as disagreement between the two data sources. In fact, the observed disagreement is higher for credit measures that may be more sensitive to misaligned timing between the survey and the monthly update of credit report data, such as balances, compared with more stable measures such as account ownership. This timing issue may be more prevalent for revolving credit, where balances fluctuate frequently from month to month, than for installments, whose balances decline incrementally, making it more likely that self-reported and administrative balances may fall into the same bin even if they are mismatched by a month. However, the current data are not equipped to identify the exact sources of reporting discrepancies and their relative impact, so we leave this as a question for future research.

of reporting agreement, researchers may consider strategies to improve response accuracy. One approach could be to include special instructions that prompt respondents to recall their balances more carefully or to check their recent statements before responding (see Egglestone and Reeder 2018). The findings of this study help identify which types of credit-related survey measures are more reliable and which are more prone to reporting errors that may require additional consideration during questionnaire design.

References

Angel, Stefan, Franziska Disslbacher, Stefan Humer, and Matthias Schnetzer. 2019. "What Did You Really Earn Last Year?: Explaining Measurement Error in Survey Income Data." *Journal of the Royal Statistical Society Series A: Statistics in Society* 182 (4): 1411-1437.

Bound, John, Charles Brown, and Nancy Mathiowetz. 2001. *Measurement Error in Survey Data.* Vol. 5, in *Handbook of Econometrics*, edited by James J. Heckman and Edward Leamer, 3705-3843. Elsevier.

Brevoort, Kenneth P., Philipp Grimm, and Michelle Kambara. 2016. "Credit Invisibles and the Unscored." *Cityscape* 18 (2): 9-34.

Brown, Meta, Andrew Haughwout, Donghoon Lee, and Wilbert van der Klaauw. 2015. "Do We Know What We Owe? Consumer Debt As Reported by Borrowers and Lenders." *Federal Reserve Bank of New York Economic Policy Review* 21 (1): 19-44.

Byrt, Ted, Janet Bishop, and John B. Carlin. 1993. "Bias, Prevalence and Kappa." *Journal of Clinical Epidemiology* 46 (5): 423-429.

Celhay, Pablo, Bruce D. Meyer, and Nikolas Mittag. 2024. "What Leads to Measurement Errors? Evidence from Reports of Program Participation in Three Surveys." *Journal of Econometrics* 238 (2): 105581.

Consumer Financial Protection Bureau. January 2023. "Annual Report of Credit and Consumer Reporting Complaints." https://files.consumerfinance.gov/f/documents/cfpb_fcra-611-e_report_2023-01.pdf.

—. June 2025. "Technical Correction and Update to the CFPB's Credit Invisibles Estimate." https://files.consumerfinance.gov/f/documents/cfpb_update-credit-invisibles-estimate_2025-06.pdf.

Egglestone, Jonathan, and Lori Reeder. 2018. "Does Encouraging Record Use for Financial Assets Improve Data Accuracy? Evidence from Administrative Data." *Public Opinion Quarterly* 82 (4): 686-706.

Elliehausen, Gregory, and Edward C. Lawrence. 2001. "Payday Advance Credit in America: An Analysis of Customer Demand." *Monograph* (Georgetown University Credit Research Center) 35. https://profiles.umsl.edu/ws/portalfiles/portal/39918702/GeorgetownStudy.pdf.

Federal Trade Commission. December 2012. *Report to Congress Under Section 319 of the Fair and Accurate Credit Transactions Act of 2003.* https://www.ftc.gov/sites/default/files/documents/reports/section-319-fair-and-accurate-credit-transactions-act-2003-fifth-interim-federal-trade-commission/130211factareport.pdf.

Financial Health Network. December 2024. "Pulse Points: Disparities in Credit Scores and Length of Credit History." https://finhealthnetwork.org/wp-content/uploads/2024/12/Pulse-Points_-Disparities-in-Credit-Scores-and-Length-of-Credit-History.pdf.

Hariri, Jacob Gerner, and David Dreyer Lassen. 2017. "Income and Outcomes: Social Desirability Bias Distorts Measurements of the Relationship Between Income and Political Behavior." *Public Opinion Quarterly* 81 (2): 564-576.

Johnson, Barry, and Kevin Moore. 2005. "Consider the Source: Differences in Estimates of Income and Wealth from Survey and Tax Data." Working Paper. Board of Governors of the Federal Reserve System. January. https://www.federalreserve.gov/econresdata/scf/files/johnsmoore.pdf.

Karlan, Dean, and Jonathan Zinman. 2008. "Lying About Borrowing." *Journal of the European Economic Association* 6: 510-521.

Kim, Chang Hwan, and Christopher R. Tamborini. 2012. "Response Error in Earnings: An Analysis of the Survey of Income and Program Participation Matched with Administrative Data." *Sociological Methods & Research* 43 (1): 39-72.

Larrimore, Jeff, Jacob Mortenson, and David Splinter. 2022. "Unemployment Insurance in Survey and Administrative Data." *FEDS Notes.* Board of Governors of the Federal Reserve System. July 5. https://doi.org/10.17016/2380-7172.3135.

Madeira, Carlos, and Paula Margaretic. 2022. "The Impact of Financial Literacy on the Quality of Self-Reported Financial Information." *Journal of Behavioral and Experimental Finance* 34. doi:https://doi.org/10.1016/j.jbef.2022.100660.

Madeira, Carlos, Paula Margaretic, Felipe Martinez, and Pedro Roje. 2022. "Assessing the Quality of Self-Reported Financial Information." *Journal of Survey Statistics and Methodology* 10 (5): 1183-1210.

Meyer, Bruce D., Nikolas Mittag, and Robert M. Goerge. 2022. "Errors in Survey Reporting and Imputation and Their Effects on Estimates of Food Stamp Program Participation." *Journal of Human Resources* 57 (5): 1605-1644.

Meyer, Bruce D., Wallace K. C. Mok, and James X. Sullivan. 2015. "The Under-Reporting of Transfers in Household Surveys." *Working Paper.* University of Chicago Harris School of Public Policy Studies. June.

Parker, Julie. 2011. "SNAP Misreporting on the CPS: Does It Affect Poverty Estimates?" *Working Paper.* Social, Economic, and Housing Statistics Division, U.S. Census Bureau.

September. https://www.census.gov/content/dam/Census/library/working-papers/2011/demo/SEHSD-WP2012-01.pdf.

Pascale, Joanne, Marc I. Roemer, and Dean Michael Resnick. 2009. "Medicaid Underreporting in the CPS: Results from a Record Check Study." *Public Opinion Quarterly* 73 (3): 497-520.

Perry, Vanessa Gail. 2008. "Is Ignorance Bliss? Consumer Accuracy in Judgments About Credit Ratings." *Journal of Consumer Affairs* 42 (2): 189-205.

Pursiainen, Vesa. 2024. "Inaccurate Borrower Information and Credit Risk: Evidence from Marketplace Loans." *Review of Corporate Finance Studies.* doi:https://doi.org/10.1093/rcfs/cfae025.

Raina, Parminder, Vicki Torrance-Rynard, Micheline Wong, and Christel Woodward. 2002. "Agreement Between Self-Reported and Routinely Collected Health-Care Utilization Data Among Seniors." *Health Services Research* 37 (3): 751-774.

Smith, L. Douglas, Michael Staten, Thomas Eyssell, Maureen Karig, Beth A. Freeborn, and Andrea Golden. 2013. "Accuracy of Information Maintained by US Credit Bureaus: Frequency of Errors and Effects on Consumers' Credit Scores." *Journal of Consumer Affairs* 47 (3): 588-601.

Srivastava, Joydeep, and Priya Raghubir. 2002. "Debiasing Using Decomposition: The Case of Memory-Based Credit Card Expense Estimates." *Journal of Consumer Psychology* 12 (3): 253-264.

Thompson, Betsy L., O'Connor, Patrick, Raymond Boyle, Michael Hindmarsh, Nagi Salem, Katrina Wynkoop Simmons, Edward Wagner, John Oswald, and Suzanne M. Smith. 2001. "Measuring Clinical Performance: Comparison and Validity of Telephone Survey and Administrative Data." *Health Services Research* (36) 4: 813-825.

Zinman, Jonathan. 2009. "Where Is the Missing Credit Card Debt? Clues and Implications." *Review of Income and Wealth* 55 (2): 249-265.

Appendix Figures and Tables

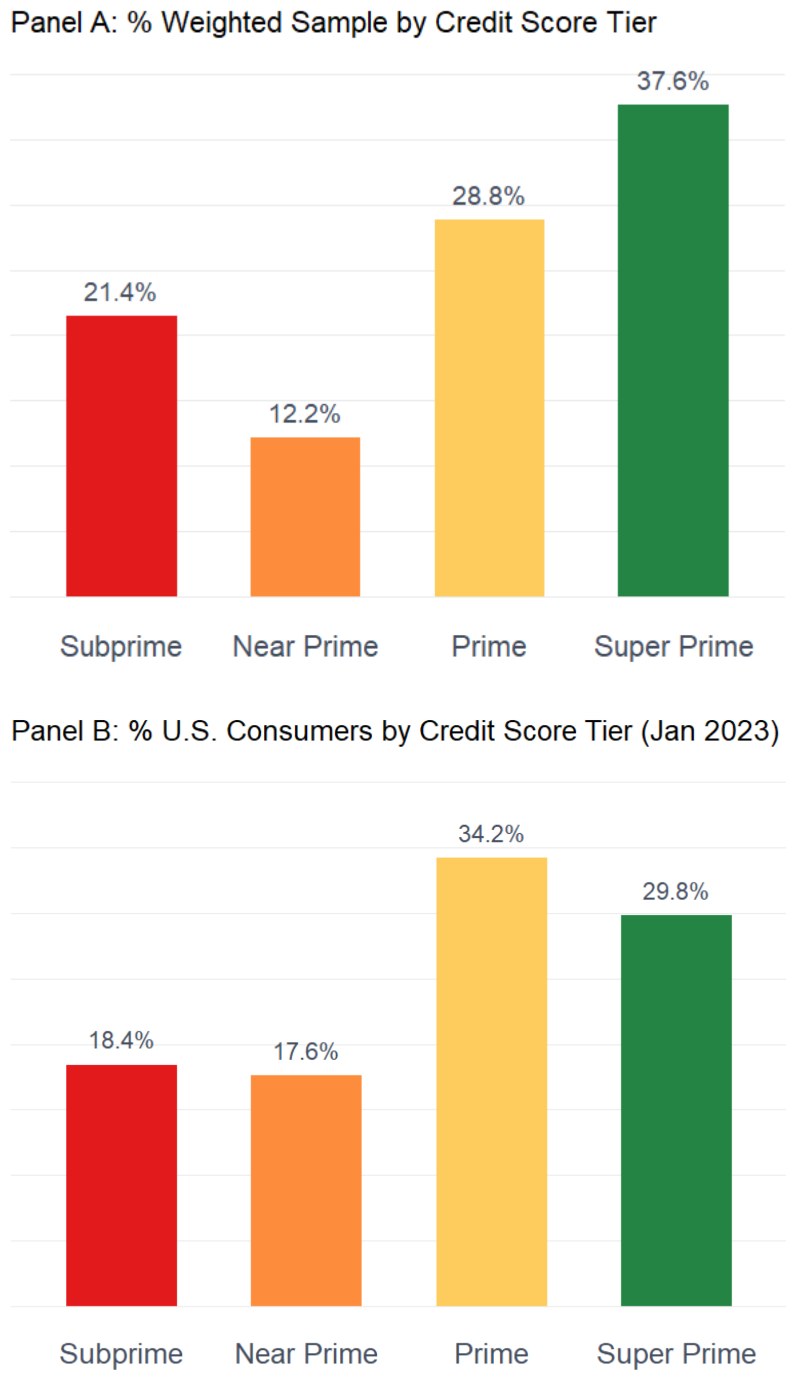

Figure A1. Comparison of Credit Score Tier Distributions Between the Weighted Study Sample (Panel A) and U.S. Consumers (Panel B)

Note: The data on consumers are based on the U.S. population with available credit scores in January 2023, as published in the CreditGauge report by VantageScore.

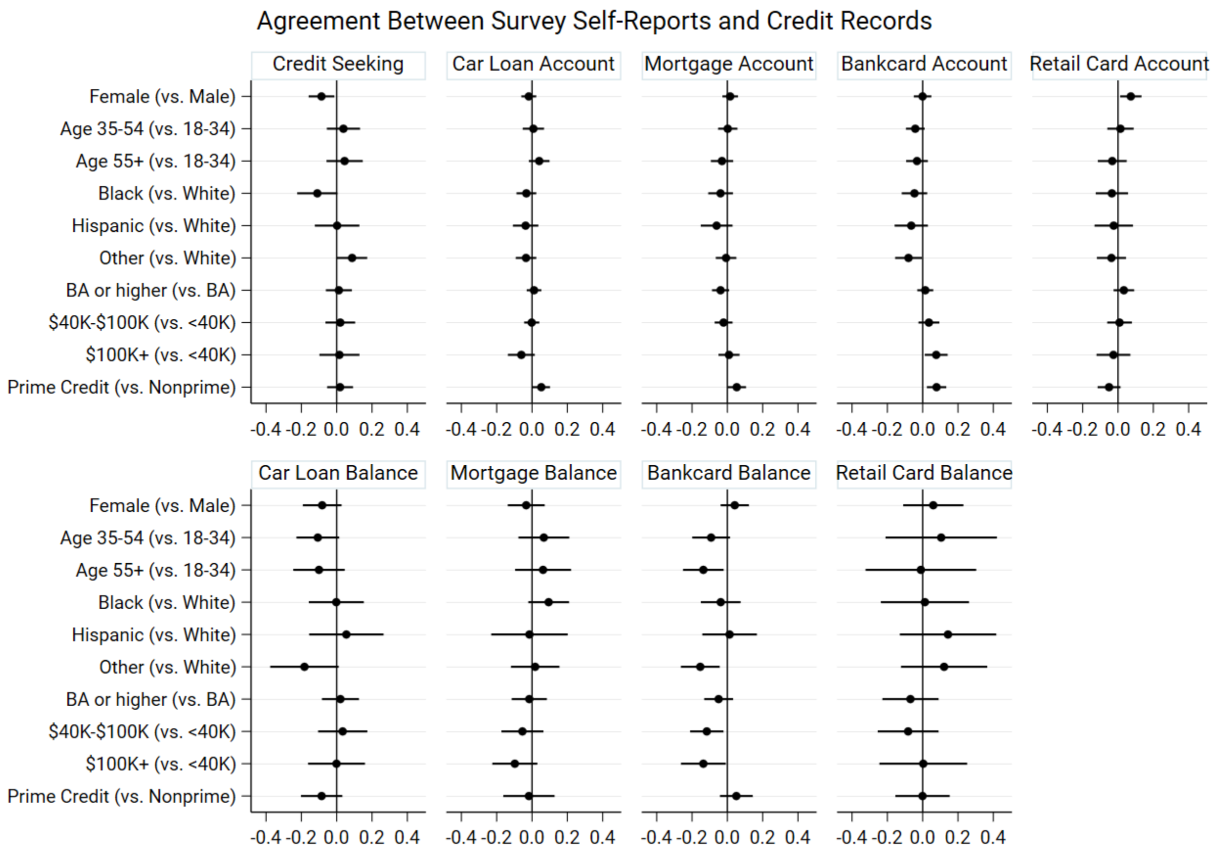

Figure A2. Average Marginal Effects of Respondent Characteristics on Providing Survey Responses Consistent with Credit Records (i.e., Agreement).

Note: Derived from multinomial logistic regressions. Estimates represent the average change (in percentage points) in the probability of accurate reporting as each predictor changes from 0 (baseline category) to 1 (relevant category).

For factors with statistically significant marginal effects on agreement:

Credit Seeking. Female respondents are 8.6 percentage points less likely than male respondents to show agreement for recent credit applications. Respondents of Other Race are 8.7 percentage points more likely than White respondents.

Credit Account Ownership. Respondents with prime credit scores are 5.2 percentage points more likely than those with nonprime scores to show agreement for owning auto loans, 5.3 percentage more likely for home loans, and 7.9 percentage points more likely for general credit cards. Those identifying as Other Race are 8.0 percentage points less likely than White respondents to show agreement for general credit card ownership. Respondents with upper incomes ($100K+) are 7.7 percentage points more likely than those with lower incomes (under $40K) to show agreement for general credit card ownership. Female respondents are 7.3 percentage points more likely than male respondents to show agreement for retail credit card ownership.

Account Balances. In reporting general credit card balances, respondents aged 55 and older are 13.6 percentage points less likely than those aged 18–34 to show agreement. Respondents of Other Race are 15.3 percentage points less likely than White respondents. Respondents with upper ($100K+) and middle ($40K–$100K) incomes are 13.6 and 11.6 percentage points less likely, respectively, than those with lower incomes (under $40K) to show agreement for reported general credit card balances.

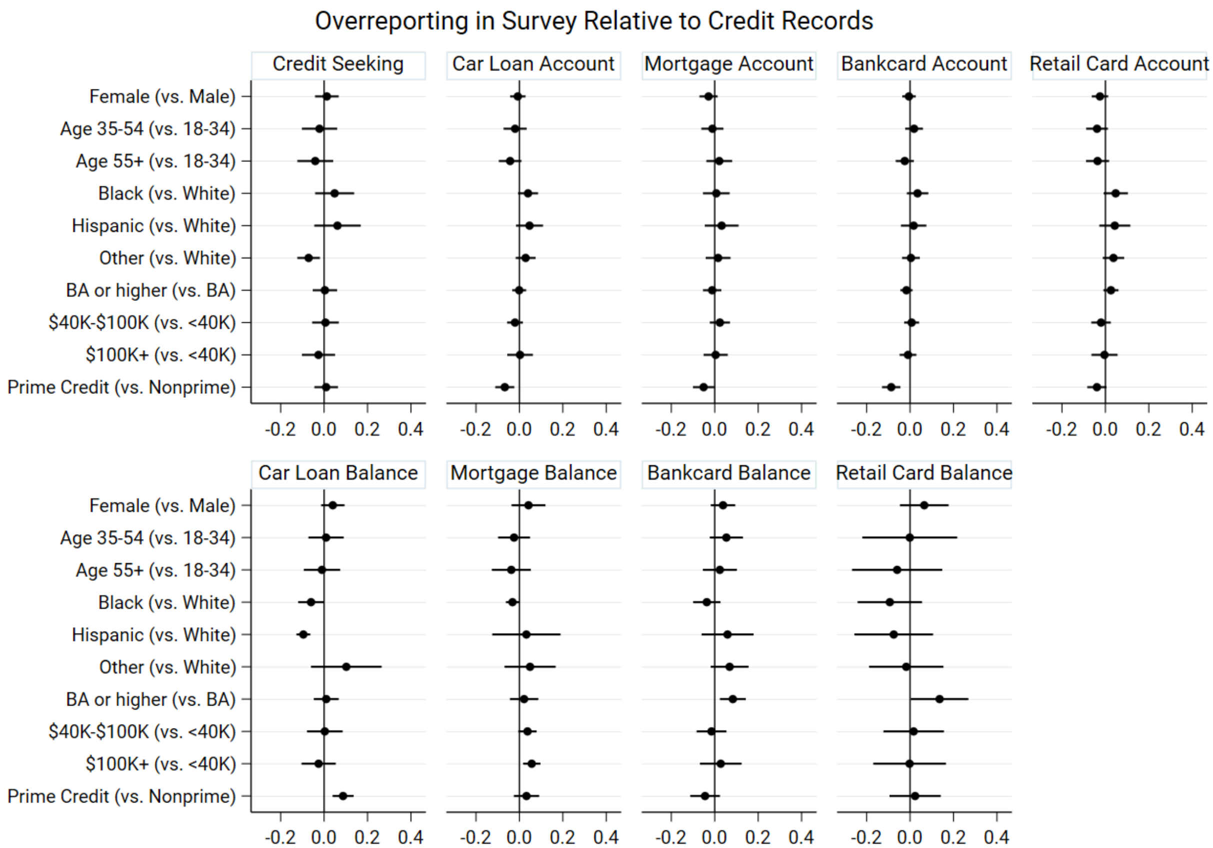

Figure A3. Average Marginal Effects of Respondent Characteristics on Overreporting in Survey Self-Reports Relative to Credit Records

Note: Derived from multinomial logistic regressions. Estimates represent the average change (in percentage points) in the probability of accurate reporting as each predictor changes from 0 (baseline category) to 1 (relevant category).

For factors with statistically significant marginal effects on overreporting:

Credit Seeking. Respondents of Other Race are 7.1 percentage points less likely than White respondents to overreport recent credit applications.

Credit Account Ownership. Respondents with prime credit scores are 6.7 percentage points less likely than those with nonprime scores to overreport auto loan ownership, 5.1 percentage points less likely to overreport home loan ownership, and 8.7 percentage points less likely to overreport general credit card ownership.

Account Balances. Black respondents are 6.0 and 3.2 percentage points less likely than White respondents to overreport auto loan and home loan balances, respectively. Hispanic respondents are 9.5 percentage less likely than White respondents to overreport auto loan balances. Respondents with prime credit scores are 8.8 percentage points more likely than those with nonprime credit scores to overreport auto loan balances. Upper-income respondents ($100K+) are 5.7 percentage points more likely than lower-income respondents (under $40K) to overreport home loan balances. College-educated respondents are 8.4 and 13.6 percentage points more likely than those without a college degree to overreport general credit card balances and retail credit card balances, respectively.

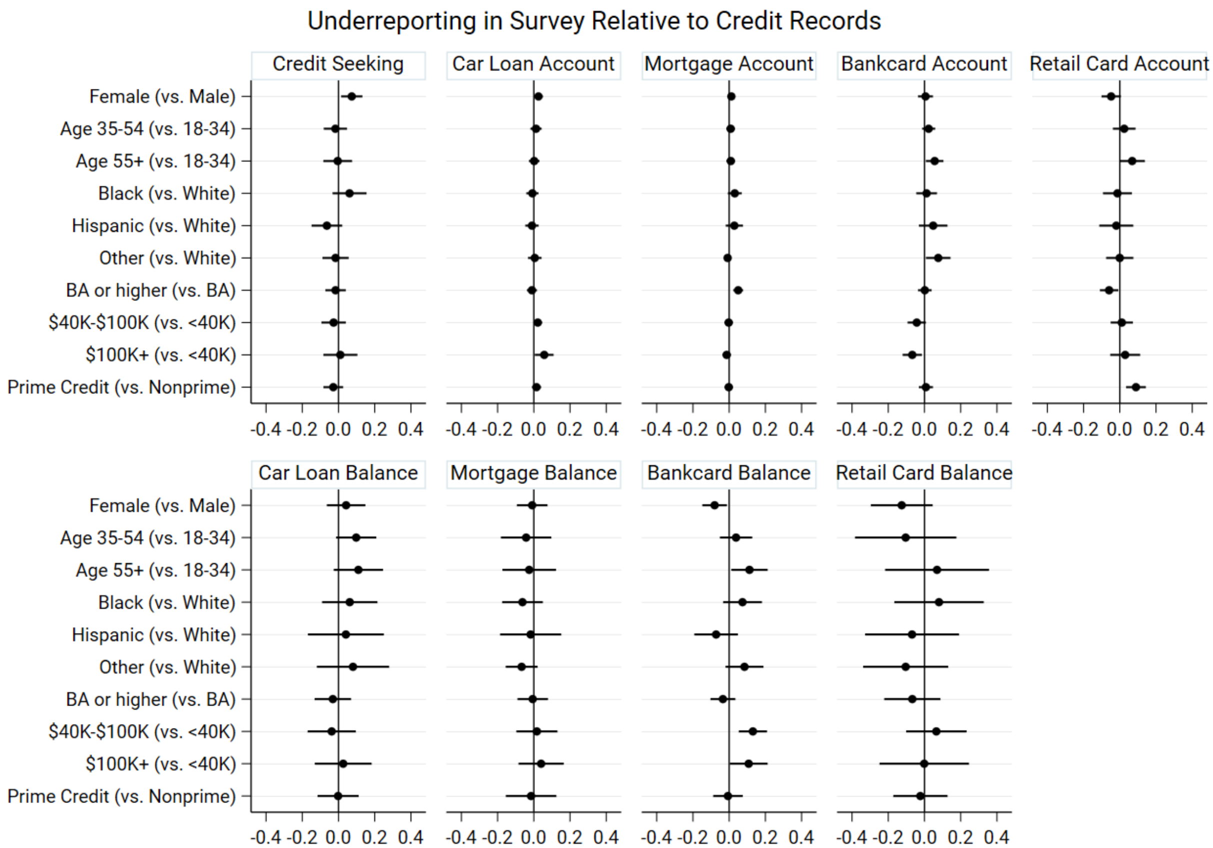

Figure A4. Average Marginal Effects of Respondent Characteristics on Underreporting in Survey Self-Reports Relative to Credit Records

Note: Derived from multinomial logistic regressions. Estimates represent the average change (in percentage points) in the probability of accurate reporting as each predictor changes from 0 (baseline category) to 1 (relevant category).

For factors with statistically significant marginal effects on underreporting:

Credit Seeking. Female respondents are 7.3 percentage points more likely than male respondents to underreport recent credit applications.

Credit Account Ownership. Female respondents are 2.6 percentage points more likely than male respondents to underreport auto loan ownership. Upper-income respondents ($100K+) are 5.7 percentage points more likely than lower-income respondents (under $40K) to underreport auto loan ownership. College-educated respondents are 5.0 percentage points more likely than those without a degree to underreport home loan ownership. For general credit card ownership, respondents aged 55 and older are 5.6 percentage points more likely than those aged 18–34 to underreport, and respondents of Other Race are 7.6 percentage points more likely than White respondents. Upper-income respondents are 6.7 percentage points less likely than lower-income respondents to underreport general credit card ownership. College-educated respondents are 5.9 percentage points less likely than those without a degree to underreport retail credit card ownership. Respondents with prime credit scores are 8.9 percentage points more likely than those with nonprime scores to underreport retail credit card ownership.

Account Balances. Female respondents are 8.0 percentage points less likely than male respondents to underreport general credit card balances. Respondents aged 55+ are 11.2 percentage points more likely than those aged 18–34 to underreport general credit card balances. Respondents of upper ($100K+) and middle ($40K–$100K) incomes are 10.8 and 13.1 percentage points more likely, respectively, to underreport general credit card balances compared with those with lower incomes (under $40K).

Table A1. Descriptive Statistics

	Unweighted N	Weighted Mean	Weighted SD
Survey Data			
Proportion (prop.) of respondents with new credit application	1692	0.21	0.41
Prop. respondents with open auto loans	1694	0.33	0.47
Prop. respondents with auto loan balance <$10,000	580	0.39	0.49
Prop. respondents with auto loan balance $10,001–$20,000	580	0.32	0.47
Prop. respondents with auto loan balance $20,001–$30,000	580	0.16	0.37
Prop. respondents with auto loan balance $30,001–$40,000	580	0.08	0.27
Prop. respondents with auto loan balance >$40,000	580	0.05	0.22
Prop. respondents with open mortgages	1705	0.38	0.49
Prop. respondents with mortgage balance <$100,000	719	0.39	0.49
Prop. respondents with mortgage balance $100,001–$200,000	719	0.30	0.46
Prop. respondents with mortgage balance $200,001–$300,000	719	0.14	0.35
Prop. respondents with mortgage balance $300,001–$400,000	719	0.08	0.28
Prop. respondents with mortgage balance $400,001–$500,000	719	0.03	0.16
Prop. respondents with mortgage balance >$500,000	719	0.06	0.23
Prop. respondents with open general-purpose credit cards	1698	0.82	0.38
Prop. respondents with credit card balance <$2,500	1046	0.44	0.50
Prop. respondents with credit card balance $2,501–$5,000	1046	0.17	0.38
Prop. respondents with credit card balance $5,001–$7,500	1046	0.11	0.31
Prop. respondents with credit card balance $7,501–$10,000	1046	0.11	0.31
Prop. respondents with credit card balance >$10,000	1046	0.17	0.38
Prop. respondents with open retail credit cards	1693	0.42	0.49
Prop. respondents with retail card balance <$250	308	0.36	0.48
Prop. respondents with retail card balance $251–$500	308	0.22	0.41
Prop. respondents with retail card balance $501–$7500	308	0.13	0.33
Prop. respondents with retail card balance $751–$1000	308	0.13	0.34
Prop. respondents with retail card balance >$1,000	308	0.16	0.37
Credit Bureau Data			
Proportion (prop.) of respondents with new credit application	1102	0.29	0.46
Prop. respondents with open auto loans	1750	0.31	0.46
Prop. respondents with auto loan balance <$10,000	585	0.36	0.48
Prop. respondents with auto loan balance $10,001–$20,000	585	0.27	0.44
Prop. respondents with auto loan balance $20,001–$30,000	585	0.17	0.38
Prop. respondents with auto loan balance $30,001–$40,000	585	0.10	0.30
Prop. respondents with auto loan balance >$40,000	585	0.10	0.30
Prop. respondents with open mortgages	1750	0.31	0.46

Prop. respondents with mortgage balance <$100,000	640	0.30	0.46
Prop. respondents with mortgage balance $100,001–$200,000	640	0.28	0.45
Prop. respondents with mortgage balance $200,001–$300,000	640	0.21	0.41
Prop. respondents with mortgage balance $300,001–$400,000	640	0.10	0.29
Prop. respondents with mortgage balance $400,001–$500,000	640	0.05	0.21
Prop. respondents with mortgage balance >$500,000	640	0.07	0.26
Prop. respondents with open general-purpose credit cards	1750	0.84	0.36
Prop. respondents with credit card balance <$2,500	1496	0.49	0.50
Prop. respondents with credit card balance $2,501–$5,000	1496	0.14	0.35
Prop. respondents with credit card balance $5,001–$7,500	1496	0.09	0.28
Prop. respondents with credit card balance $7,501–$10,000	1496	0.06	0.23
Prop. respondents with credit card balance >$10,000	1496	0.22	0.41
Prop. respondents with open retail credit cards	1750	0.53	0.50
Prop. respondents with retail card balance <$250	876	0.69	0.46
Prop. respondents with retail card balance $251–$500	876	0.07	0.26
Prop. respondents with retail card balance $501–$7500	876	0.04	0.19
Prop. respondents with retail card balance $751–$1000	876	0.03	0.17
Prop. respondents with retail card balance >$1,000	876	0.17	0.38

Table A2. Comparing the Demographic Characteristics of the Study Sample to the Credit Visible Population and General Adult Population Distributions

	Sample		Credit Visible Population (2023 CFPB MEM Survey)	U.S. Adult Population (2023 CPS)
	Unweighted	Weighted		
Gender				
Female	58.8%	51.9%	51.0%	51.0%
Male	41.2	48.1	49.0	49.0
Age Group				
18–34	17.9	21.4	22.1	29.2
35–54	52.9	34.6	33.7	32.3
55 and older	29.2	44.0	44.1	38.5
Race and Ethnicity				
White	72.8	62.5	61.2	61.3
Black	10.2	12.1	11.9	12.1
Hispanic	4.7	15.2	16.8	17.5
Other	12.3	10.3	10.1	9.1
Education Level				
High school or less	13.0	25.2	26.4	38.2
Some college	32.0	34.3	34.0	26.4
Bachelor's degree or higher	55.0	40.5	39.6	35.4
Personal Income				
$39,999 or less	31.5	36.9	-	53.6
$40,000 to $79,999	34.8	34.6	-	26.2
$80,000 or more	33.7	28.5	-	20.2
Household Income				
$50,000 or less	-	-	42.0	26.8
$50,001 to $80,000	-	-	18.2	18.1
$80,001 to $125,000	-	-	19.3	20.9
More than $125,000	-	-	20.6	34.1

Note: The sample is weighted to be demographically representative of individuals aged 18 and older who have credit records at one of the credit bureaus — the so-called credit visible population. This population tends to skew older and better educated than the general adult population. Because of the trimming of extreme weights, the weighted sample's demographic distributions differ slightly from the target population benchmarks. All analyses reported in the text are conducted on the weighted sample.

Table A3. Comparison Between Standard Kappa and Prevalence-Adjusted Bias-Adjusted Kappa

	Standard Kappa	Prevalence-Adjusted Bias-Adjusted Kappa	Prevalence Index	Bias Index
Recent Credit Seeking	0.28	0.41	0.42	-0.01
Credit Account Ownership				
Auto loans	0.75	0.78	0.36	0.02
Home loans	0.72	0.74	0.31	0.07
General-purpose credit cards	0.47	0.71	-0.67	-0.03
Retail credit cards	0.44	0.44	0.05	-0.11

Note: Based on the prevalence index, there is evidence of a prevalence effect, especially for new credit applications and general-purpose credit card ownership. When such an effect is present, standard kappa values tend to be deflated, and using the prevalence-adjusted kappa is recommended for more accurate estimates (Byrt, Bishop, and Carlin 1993). In the absence of a prevalence effect, the standard and prevalence-adjusted kappa values are identical. Cf. The bias index refers to systematic differences between two sources (e.g., two raters) in how they classify the data into categories, which is less relevant for this study.

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