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How Does Buy Now, Pay Later Affect Customers' Credit?

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Abstract

In this paper, we explore the relationship between consumers' use of buy now, pay later (BNPL) and their credit reports. BNPL is a deferred payment tool that allows consumers to split transactions into four payments over six weeks. Unlike many other financial products, it is offered primarily by fintech companies and advertised to consumers as free from fees and credit checks. These providers typically do not report a consumer's use of BNPL and subsequent repayment behavior to credit bureaus, which makes studies of BNPL users' credit more challenging.[1] In this analysis, however, we leverage a unique data set combining anonymized survey data and appended credit bureau data collected by the market research firm Competiscan, on behalf of the Consumer Finance Institute (CFI) of the Federal Reserve Bank of Philadelphia.

Keywords: buy now, pay later; BNPL; point-of-sale payments; consumer survey; credit reporting

JEL Classification Codes: D10, D18

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[1] A number of credit bureaus have released reports on BNPL, but these appear to focus on more traditional monthly installment loans as proxies for four-in-six payment products. This conflates the original BNPL product with more traditional personal or installment loans.

Introduction

In this paper, we explore the relationship between consumers' use of buy now, pay later (BNPL) and their credit reports. BNPL is a deferred payment tool that allows consumers to split transactions into four payments over six weeks. Unlike many other financial products, it is offered primarily by fintech companies and advertised to consumers as free from fees and credit checks. These providers typically do not report a consumer's use of BNPL and subsequent repayment behavior to credit bureaus, which makes studies of BNPL users' credit more challenging.[2] In this analysis, however, we leverage a unique data set combining anonymized survey data and appended credit bureau data collected by the market research firm Competiscan, on behalf of the Consumer Finance Institute (CFI) of the Federal Reserve Bank of Philadelphia.

Over the past three years (and notably during the pandemic), the BNPL sector expanded significantly and attracted more customers, especially those under the age of 35. In part due to its growth, BNPL has become a subject of greater interest for many researchers, regulators, and traditional banks. Nevertheless, many questions remain unexplored, especially when it comes to BNPL and its impact on consumers' credit.

Currently, many researchers hypothesize that BNPL will negatively impact users' credit over time. Because BNPL is unreported to credit bureaus, researchers worry that individuals may take out multiple loans simultaneously and overextend themselves. Moreover, the current practice among most BNPL lenders is not to use hard credit checks (for the true four-in-six product) when underwriting. This leads some commentators to speculate about the possibility of overborrowing using BNPL among individuals with limited access to traditional credit products.

This analysis evaluates if these concerns are substantiated by the data. Using our matched data set, we attempt to answer two questions using a variety of statistical techniques. First, are there distinct differences in the credit bureau files of BNPL users and nonusers to the extent that we can use traditional credit data to predict BNPL use? In other words, is it true that individuals with limited credit make up the majority of the user base? And second, does BNPL appear to be correlated with negative changes in users' credit profiles over time?

[2] A number of credit bureaus have released reports on BNPL, but these appear to focus on more traditional monthly installment loans as proxies for four-in-six payment products. This conflates the original BNPL product with more traditional personal or installment loans.

We find that many credit characteristics of BNPL users are different from those of nonusers. However, most of those differences are not strong predictors of future or prior BNPL use. The results of our linear probability models suggest that only a few credit bureau characteristics significantly predict whether an individual is a BNPL user — consumers with a super-prime credit score are about 20 percentage points less likely to use BNPL compared with the lowest credit score group (400–583 range).

A difference in means tests comparing 2021 values with 2020 shows that BNPL users increased their shopping for new credit and had some success in obtaining new revolving accounts. Yet their total available credit and other variables did not change significantly. For nonusers, the notable change was a decline in bankcard and retail balances that mirrors the overall decline in revolving debt in the U.S. during that period. When we use an interaction model to test for differences in the trajectory of credit bureau variables between BNPL users and nonusers, we find only one significant difference: BNPL users increased their number of credit applications by 0.41 between 2020 and 2021 compared with nonusers. That is not surprising, given that the take-up of BNPL is likely to be associated with a greater appetite for new credit. Overall, we find that — at least among consumers with established credit profiles — BNPL use does not seem to significantly affect a consumers' credit profile in the short term.

There are several important caveats to these conclusions. First, none of the associations described above can be interpreted as cause-and-effect relationships; they are correlations. Second, by construction, we cannot estimate effects for survey recipients who could not be matched to their credit reports or who did not have an established credit file; the latter is believed to be an important population for the BNPL market. Thus, we cannot rule out the possibility that the limited explanatory power of our models is the result of incomplete matching in our data. Third, our analysis is limited to those consumers adopting BNPL at the time of our survey; previous analysis of this data noted that BNPL use over the survey period seemed to be characterized by consumers "experimenting" with the new product (Akana, 2022)[3]. BNPL is a new and rapidly evolving product, and the customers it attracts in the future could be different from the ones we captured in our data. Nevertheless, our research is one of the first to document the relationships between BNPL use and traditional consumer credit characteristics.

Literature Review

In the past three years, BNPL use has increased rapidly. From 2019 to 2021, the number of loans issued by the five main U.S. BNPL providers grew by 970 percent, from 16.8 million to 180 million. At the

[3] Tom Akana, "Buy Now, Pay Later: Survey Evidence of Consumer Adoption and Attitudes," Federal Reserve Bank of Philadelphia, June 17, 2022, https://www.philadelphiafed.org/consumer-finance/consumer-credit/buy-now-pay-later-survey-evidence-of-consumer-adoption-and-attitudes.

same time, the dollar value of those originations increased more than 10-fold, from $2 billion to $24.2 billion.[4] Despite this growth, BNPL's impact on consumers' financial well-being is not yet well understood.

The general media, for example, has frequently speculated about BNPL's effects on consumers. As early as 2020, articles such as CNN's "Buy now, pay later options are growing online. But there are risks" (2020),[5] *Forbes*' "The Dangerous Rise of 'Buy Now, Pay Later' Offers" (2021),[6] and the *New York Times*' "The Downsides of Using Buy Now, Pay Later" (2022)[7] have debated the benefits of BNPL use. These articles recognize BNPL's convenience, accessibility (especially to those without traditional credit), and ability to help individuals fit purchases into their cashflow cycles. Yet the articles also warn of potential consequences. As most BNPL lenders do not report their loans to the national credit reporting agencies, it is possible for consumers to borrow from multiple BNPL providers either simultaneously or sequentially. This poses two potential risks. First, it may facilitate overextension. Second, it may limit lenders' understanding of consumers' indebtedness while making underwriting and account management decisions. Depending on the magnitude of aggregate borrowing using BNPL, this lack of visibility into a consumers' total indebtedness could potentially increase the overall credit risk of unsecured lending.

Regulators such as the Consumer Financial Protection Bureau (CFPB) share these concerns. In December 2021, the CFPB issued market monitoring orders to five of the largest BNPL providers (Affirm, Afterpay, Klarna, PayPal, and Zip).[8] The inquiry aimed to investigate the potential for debt accumulation, regulatory arbitrage, data harvesting, and market conditions more generally. To analyze these issues, the CFPB collected quantitative and qualitative data from the five lenders, including loan volumes, revenue and expense figures, policies on underwriting and repayment, and consumer complaint reviews. In September 2022, it released its findings to the public.

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[4] Consumer Financial Protection Bureau, "Buy Now, Pay Later: Market Trends and Consumer Impacts," September 15, 2022, https://www.consumerfinance.gov/about-us/newsroom/cfpb-study-details-the-rapid-growth-of-buy-now-pay-later-lending/.

[5] Nathaniel Meyersohn, "Buy now, pay later options are growing online. But there are risks," October 10, 2020, https://edition.cnn.com/2020/10/10/business/buy-now-pay-later/index.html.

[6] Robert Farrington, "The Dangerous Rise of 'Buy Now, Pay Later' Offers," August 17, 2021, https://www.forbes.com/sites/robertfarrington/2021/08/17/the-dangerous-rise-of-buy-now-pay-later-offers/.

[7] Peter Coy, "Buy Now, Regret Later?" December 19, 2022, https://www.nytimes.com/2022/12/19/opinion/buy-now-pay-later.html.

[8] Consumer Financial Protection Bureau, "Buy Now, Pay Later: Market Trends and Consumer Impacts," September 15, 2022, https://www.consumerfinance.gov/about-us/newsroom/cfpb-study-details-the-rapid-growth-of-buy-now-pay-later-lending/.

The CFPB investigation articulated a number of potential risks associated with BNPL products. First, it noted that a lack of standardized disclosures concealed important information about loan terms, late fees, and repayment terms. Second, it found that lenders multiplied the number of late and overdraft fees paid by consumers by imposing multiple late fees on the same payment, making multiple attempts to reauthorize failed payments, and mandating autopay. Finally, the CFPB found that BNPL structures and strategies could encourage *loan stacking*, a practice of borrowing from multiple lenders simultaneously, and overextension. Following these findings, the CFPB stated that it would develop guidance for BNPL lenders and begin a series of examinations, similar to those in the credit card industry.

In addition to regulatory agencies, academics have explored the effects of BNPL on consumers. Recent work by Di Maggio, Williams, and Katz (2022)[9] and deHaan et al. (2022)[10] analyzed the effect of BNPL on important indicators of users' financial health (i.e., overdraft fees and deposit account balances) using transaction-level bank account data. Using instrumental variable regression and differences-in-differences analyses, they found that BNPL users were more likely than nonusers to incur overdraft fees, have lower checking balances, and have negative changes in savings balances.

Recent studies used a blend of survey and credit bureau data to explore the profiles of BNPL users and changes in their credit usage and performance over time. For example, Shupe, Li, and Fulford (2023) found that BNPL users had marginally worse credit reports (with lower credit scores and higher delinquency rates), though not significantly worse than nonusers.[11] They also found that users' credit did not seem to suffer greatly over time and that many differences between BNPL borrowers/nonborrowers predated BNPL use.

This paper complements the most recent wave of research. Similar to the Shupe, Li, and Fulford (2023) study, we leverage a data set composed of consumer survey responses and credit bureau data to analyze the relationship between BNPL use and credit over time. Using linear probability models, difference in means tests, and regressions with interacted terms to measure changes in users' credit profiles, we find

[9] Marco Di Maggio, Emily Williams, and Justin Katz, "Buy Now, Pay Later Credit: User Characteristics and Effects on Spending Patterns," NBER, September 2022, https://www.nber.org/papers/w30508.

[10] deHaan et al., "Buy Now Pay (Pain?) Later," SSRN, September 30, 2022, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4230633.

[11] Cortnie Shupe, Greta Li, and Scott Fulford, "Consumer Use of Buy Now, Pay Later: Insights from the CFPB Making Ends Meet Survey," Consumer Financial Protection Bureau, March 2, 2023, https://www.consumerfinance.gov/data-research/research-reports/consumer-use-of-buy-now-pay-later-insights-from-the-cfpb-making-ends-meet-survey.

that BNPL use does not seem to greatly affect consumer's credit in the short run — a finding that mirrors the 2023 study.

This paper also adds to existing BNPL research conducted by CFI in 2021, which created the unique data set used in this paper. The 2021 study measured user demographics and general attitudes toward BNPL.[12] It identified younger, non-White, and lower-earning individuals as primary users of BNPL. It also found that, despite its growing popularity, BNPL remained the least-used payment tool in the study. Not only was it the tool with the lowest rates of satisfaction, but it was the tool users were least likely to reuse. Most important, the study found that most users were drawn to BNPL for its convenience and cost, rather than a lack of credit access.

This paper, however, focuses on BNPL and its relation to credit. The following sections outline our approach to two central questions: 1) Are there distinct differences in the credit bureau files of BNPL users and nonusers, and 2) is BNPL use associated with changes in users' credit profiles over time? We begin this exploration by providing a description of the data used in this study. Then, we present descriptive statistics, followed by an analysis of the credit and survey data in relation to our two central questions (see the tables/charts in the Appendix). Finally, we discuss implications and next steps.

Data Description

For this study, we relied on two data sets. First, we used survey data collected by CFI and Competiscan, a marketing research company. The data were collected in November 2021 with the aim of gaining insight into BNPL use over the previous 12-month period. It is composed of 2,514 responses and has 163 variables related to BNPL use, such as frequency of BNPL use and reasons for adoption. Second, we used credit bureau data supplied by Competiscan, which compiles monthly snapshots of its panelists' credit histories using data from a national credit reporting agency. This data set was associated with specific panelists in the survey using an anonymized panelist ID that linked each individual to the survey records. The bureau data set contains data for two time periods: November 2020 and November 2021, allowing us to observe respondents' credit characteristics at the time of the survey and 12 months prior to the survey. It contains 547 variables, including credit score, bankruptcy and delinquency flags, and other key credit history data.

[12] Tom Akana, "Buy Now, Pay Later: Survey Evidence of Consumer Adoption and Attitudes," Federal Reserve Bank of Philadelphia, June 17, 2022, https://www.philadelphiafed.org/consumer-finance/consumer-credit/buy-now-pay-later-survey-evidence-of-consumer-adoption-and-attitudes.

Data Preparation

General Overview

To analyze the credit profiles of BNPL users over time, we merged the survey and bureau data using respondents' unique panelist IDs. After merging them, we identified that a portion of respondents were missing credit bureau data at one or both of the observation points; we elected to restrict our analysis to panelists who had a valid credit score, thus meeting the minimum file requirements for scoring, at both observation points (a more detailed explanation of this process is found in the next section). We also removed duplicative and empty variables, leaving 112 variables for analysis.[13] To address the remaining missing data, we imputed variables using a nearest neighbors algorithm.[14] The final data set thus consisted of 1,278 individuals, at two points in time (November 2020 and November 2021), and a total of 114 variables related to individuals' BNPL use and credit history.

Missing Data Analysis

Because the goal of our analysis is to examine the potential impact of BNPL use on an individual's credit report, we required that all respondents in the analysis have a scored report in both observation periods (November 2020 and November 2021). Therefore, any respondents who were missing data in either observation period were removed from the file. Respondents were classified as missing data if they met one of two conditions for either month: They did not appear in the credit bureau data file ("missing file") or they appeared the bureau data file but did not have enough data to generate a credit score ("empty file"). After removing these two populations, 40.5 percent of BNPL users and 56.1 percent of the nonusers remained in the file for analysis (**Table A1**).

When we removed the empty credit records, a higher percentage of BNPL users were dropped from the analysis. This would be expected based on the product's reputation as a solution for those who are not accessing more traditional forms of credit. We know that — historically at least — most BNPL lenders do not perform hard credit checks when underwriting their short-term loans. As a result, applicants with

[13] We define empty variables as variables where, for 30 percent or more of consumers, the values are missing.

[14] *Missing data* refers to cases were respondents have mostly populated fields but have some missing data (NAs). To manage the missing data in our data set, we imputed the variables using a k-nearest neighbor algorithm. This algorithm identifies the k nearest neighbors to a new data point in a data set and classifies or predicts the new data point based on the majority class or average value of the neighboring data points. We implemented the nearest neighbors algorithm using the *step_knnimpute* from the recipes package in R studio. Approximately 3 percent of our final data set was imputed.

limited or no credit history would be less likely to be disadvantaged when applying for a BNPL loan as they might be when applying for more traditional credit products.[15]

There is an important caveat to this interpretation and for our results more generally. The fact that respondents were not successfully matched to a credit bureau file does not necessarily mean they do not have a credit bureau file. We do not have specific insight into the reason a respondent's data were missing in our records; it may be because of matching failures at the vendor or genuine lack of credit. While we observe that the BNPL user population is more likely to have respondents dropped because of missing or incomplete bureau data, we are not comfortable drawing hard conclusions from that fact.

A comparison of the retained and dropped populations for both users and nonusers appears in **Table A2**. For BNPL users, the *dropped* records are relatively concentrated among younger, male, and employed respondents, compared with BNPL users retained in the analysis that follows. For nonusers, the dropped records are relatively concentrated among younger, employed, and minority respondents, compared with the nonusers retained in the analysis. The remainder of this paper will refer only to the retained population.

Descriptive Statistics

Table A3 compares credit report variables for BNPL users and nonusers with credit files at two points in time in our data.[16] Interpreting the following differences is subject to the discussion described previously. We find that BNPL users with credit reports tend to have newer accounts, more open accounts, more accounts with positive balances, higher average balances, and more applications for credit (inquiries) than nonusers with credit reports. These patterns suggest that BNPL users not only have more demand for credit (via inquiries), but that to some extent, they are successful in obtaining it (via new accounts).

On the other hand, these BNPL users have smaller aggregate credit lines on open bankcards than nonusers. Thus, while they appear to want and use credit more, they have less unsecured credit capacity available to them. By construction, then, the average credit lines on their bankcard accounts must also be smaller than for nonusers.

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[15] It is possible that because of this, BNPL is targeted at, and attractive to, people with no or limited credit as an alternative to traditional credit products. For these reasons, we expected that we may be able to identify users who transitioned from missing files at the beginning of our observation period to have a nonempty file at later points in time (view **Appendix B** for more detail). Unfortunately, we were unable to identify consistent characteristics that allowed us to include any missing data records with confidence.

[16] Unless otherwise indicated, all descriptive statistics are calculated using weights derived from the American Community Survey to facilitate comparisons to the general population.

In terms of credit performance, BNPL users have a higher bankcard utilization rate, more accounts with a past due balance, and larger balances past due. Consequently, a typical BNPL user has a credit score considerably lower than a typical nonuser — more than 50 points lower (although the average user's credit score in the retained sample is still considered prime).[17]

If we compare the means for users and nonusers separately in 2020 and 2021, we see a few material changes. Not all of those turn out to be statistically significant — we reserve formal statistical tests of those changes for discussion later in the paper.

Analysis

Predicting BNPL Use

Next, we ask whether the observed differences between BNPL users and nonusers with credit reports can explain their decision to adopt BNPL. To investigate this question, we measure how an individual's credit bureau characteristics can predict BNPL use. We explore a number of models to identify such predictive characteristics, including linear probability models and logistic LASSO regressions. As the results of these tests were similar to each other, we will only provide a description of linear probability models using binned credits scores.[18]

We first present a linear probability model with binned credit scores using November 2020 credit bureau data to predict future BNPL use. We measure future use to determine if individuals with certain bureau characteristics (namely, limited credit) are more likely to use BNPL, as is often hypothesized by researchers. Then, we use the November 2021 data to retroactively predict use over the prior 12 months. We evaluate past use to determine if BNPL users exhibit consistent and identifiable bureau characteristics over time.

In both the forward- and backward-looking models, we regress a "user" flag on the 112 credit bureau variables. The user flag was created using the answers to a survey question designed to measure an individual's BNPL use over the course of the past year:

> *How frequently have you used Buy Now, Pay Later (services that allow people to receive a good or service and pay for it in installments, generally over a short time period, with no interest or late fees if paid on time. For example, Affirm, Klarna, Afterpay, Sezzle,*

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[17] Based on CFPB definitions, a prime credit score is between 660 and 719; a super-prime score is 720+. For more information on credit scores, view, https://www.consumerfinance.gov/data-research/consumer-credit-trends/credit-cards/borrower-risk-profiles/.

[18] Results of all other models are available upon request. For each modeling approach, we estimated versions using the raw credit score and the square of squared credit score or credit scores falling into specific ranges (e.g., deciles).

Uplift or any other payment option that allows people to divide a purchase into payments) during the past year?[19]

- *Have not used in the past year*
- *1–3 times in the past year*
- *4–10 times in the past year*
- *11–20 times in the past year*
- *More than 20 times in the past year*

An individual was marked as a *user* if they used BNPL at least once in the past year, based on the survey question.[20] Our final data set contained 345 BNPL users and 933 nonusers using this definition.

As seen on **Tables A4** and **A5**, the two models show that, conditional on having a populated credit report, few variables are statistically significant predictors of BNPL use.[21] The first model, which focuses on predicting future BNPL use, identifies 14 influential variables (Table A4). Among these is credit score, which is especially significant at the super-prime range. As seen in the table, the likelihood of being a BNPL user decreases as a consumer's credit score nears the highest deciles. Indeed, compared with individuals in the first decile bin of credit scores (400–583 range), those in the 10th decile (829–850 range) are 20 percentage points less likely to be a BNPL user, compared with the omitted group (400–583 range). This is an economically significant finding. Below these deciles, however, the effect of relatively high credit scores is about 10 percentage points and too imprecisely measured to be statistically significant.

Following credit score, the most influential variables include the ratio of accounts opened within six months to all accounts (about –7 percentage points), the number of 90 days past due occurrences within 24 months for installment accounts (about –5 percentage points), and the utilization rate on open retail

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[19] As discussed in Akana (2022), there is evidence that respondents included traditional point-of-sale monthly installment loans in reporting their use of BNPL in this survey because of confusion in the market about the definition of *buy now, pay later*. While identification of four-in-six payments as the target population has improved in more recent analyses, the results described here are consistent with other data on BNPL usage reported at the time.

[20] We extended our regression analysis to control for BNPL use intensity, but we found no significant results, possibly because of the small population of heavy and medium users in our sample (N=140).

[21] The timing is relative to the questionnaire. Previous BNPL use is predicted using bureau data from November 2021, which is when the survey was conducted. Future BNPL use is predicted using bureau data that were collected in November 2020, a year prior to the survey.

accounts (about + 3 percentage points). These are modest effects. In total, the regression explains less than 20 percent of the classification into BNPL users and nonusers.

The second version of the model, which predicts previous BNPL use, provides very similar results. Once again, credit score is one of the few predictive variables. Super-prime credit scores predict a lower likelihood (about –17 percentage points) of being a user, but the effect is measured less precisely than in Table A4. The only other economically significant effect is for the number of severe past due (90 DPD+) occurrences on installment accounts (about –.05 percentage points).

Overall, the regression analyses suggest that credit bureau information alone is of limited use in predicting BNPL use among consumers with established credit at this stage in the product's evolution.

Measuring Changes in Credit Characteristics over Time

As noted earlier, we document the changes over time in the credit characteristics of BNPL users and nonusers separately. To measure these changes, we conduct a difference in a means test on 19 credit bureau variables for each group over the sample period.[22]

Looking at basic changes across the two groups, we see similarities and differences. Most of the changes over time were small and statistically insignificant. In general, BNPL users show an increase in shopping for credit (inquiries) and a resulting increase in open bankcard and revolving accounts (**Table A6**). While balances and balances past due fell, the declines were not statistically significant. Total bankcard credit lines increased, but not in the sense of statistical significance.

Among nonusers, if anything, shopping for credit and the resulting new credit appears to have declined slightly, but the changes were not statistically significant (**Table A7**). One exception was the number of retail accounts that decreased. Balances on bankcards and retail accounts fell more than 16 percent, which is both economically and statistically significant. Risk scores rose in the statistical sense, but the increase was only about 5 score points.

Did Outcomes for BNPL Users and Nonusers Diverge?

Having documented the changes in characteristics over time within each group, we explore whether the trajectories of these groups was different. To do that, we estimate a regression model in which we interact the *BNPL user* variable with a time dummy variable (in which 0 is equal to 2020, and 1 is equal to

[22] The 19 selected variables were identified as the most influential when running an initial exploratory LASSO regression.

2021).[23] This model allows us to compare how changes in the 19 credit bureau variables vary across users and nonusers over the two time periods (2020 and 2021). Our estimating equation takes the following form:

$$y = \beta 0 + \beta 1(\,BNPL\ User) + \beta 2\ (Time) + \beta 3\ (BNPL\ User * Time).$$

As seen in **Table A8**, the interaction terms for almost all credit bureau variables are small and statistically insignificant. The only variable with a statistically significant change in trajectories between the two groups is the number of inquiries over the past 12 months. Indeed, BNPL users see a 0.41 increase in the number of inquiries between 2020 and 2021 compared with nonusers. Given the average number of applications in our data is 1.45, this is an economically significant divergence in the credit shopping behavior of BNPL users and nonusers.

We caution that this difference does not imply that the use of BNPL increases the number of credit applications in the sense of a cause-and-effect relationship. The better interpretation is that the demand characteristics associated with BNPL use (and conversely nonuse) documented earlier are persistent. In addition, the results in Tables A6, A7, and **A8** suggest that, even though BNPL users apply for more credit than nonusers, the resulting effect does not materially change the preexisting differences in open accounts and balances between these two groups.

Additional Analyses with 2022 Data

We extended our analysis using newly released credit bureau data from August 2022 to see if changes to users' and nonusers' credit files manifested differently over a longer observation period. Similar to our analyses in the previous sections, we used linear probability models, difference in means tests, and regressions with interacted effects to predict BNPL use and measure changes in the credit profiles of users and nonusers.

The addition of an extra year of data did not change our findings. Once again, the linear probability models identified few variables that could predict BNPL use. Similarly, the difference in means tests and regression with interacted terms revealed few differences in the credit profile changes of BNPL users and

[23] Economists sometimes estimate a test for a "difference in differences." Our approach here is in the spirit of a difference-in-differences test but not precisely so, because we have not established that all the required assumptions for such a test have been satisfied.

nonusers over time. As the outcomes of these tests resembled those of our original analysis, they were not included in this report.

Conclusion

In this paper, we analyze the relationship between BNPL use and an individual's credit profile. We conduct this analysis to determine if traditional credit bureau variables can reliably predict BNPL use and to evaluate concerns that BNPL use could negatively affect consumers' credit. We do this using two approaches. First, we use linear probability models to identify credit characteristics that either predict BNPL use or explain such use after the fact. Both approaches show that only a few credit bureau variables help to predict BNPL use or nonuse. Consumers with super-prime credit scores are about 20 percentage points less likely to use BNPL, relative to the lowest credit score group (400–583 range). Next, we examine how the credit bureau characteristics of BNPL users and nonusers change over time. A difference in means test shows that BNPL users shop more for new credit and obtain more new credit. In contrast, among nonusers, there appears to be little or no change in shopping intensity or resulting new credit. Unlike BNPL users, nonusers experience a statistically significant decline in revolving balances in a period where aggregate revolving balances in the U.S. were recovering from large declines that occurred early in the COVID-19 pandemic.[24]

Finally, we compare the trajectories of credit bureau variables of BNPL users and nonusers and find the only statistically and economically significant differences were in credit applications; the difference in shopping intensity of BNPL users and nonusers increased. This does not mean that BNPL use increases shopping behavior, but rather, it suggests there is persistence in the demand characteristics that explain the adoption of BNPL in the first place. Even with an increase in the relative shopping intensity, however, BNPL users did not obtain more credit than nonusers in the sense of statistical significance. Overall, it appears that among users with established credit, BNPL use does not significantly affect consumers' credit profile in the short term.

It is important to note that this analysis has a number of limitations. First, our data cover only a short time span. It is possible that there is a more complex relationship between credit and BNPL use in the long term. Moreover, we worked with the survey responses and credit bureau data of only 1,278 individuals. A larger sample size could reveal different results. Finally, without greater insight into the reasons for empty

[24] According to the Federal Reserve Board's G.19 statistical release, between November 2020 and November 2021, nominal revolving balances increased 6.4 percent.

credit bureau files, or in the inability to match survey respondents to their credit files, our analysis cannot suggest conclusions about the use of BNPL by consumers without established credit.[25]

[25] Additional insights about this segment of consumers can be found in Akana (2022).

Appendix A: Tables and Figures

Table A1. Number of Records Dropped by Data Cleaning Stage

	All Individuals		Users		Nonusers	
	N	%	N	%	N	%
Starting Population	2514	100%	852	100%	1662	100%
No Credit Bureau Match	1089	43.3%	463	54.3%	626	38%
Empty Credit Bureau File	134	5.3%	39	4.6%	95	5.7%
Additional Cleaning (i.e., invalid credit scores)	13	0.5%	5	0.6%	8	0.5%
Total Dropped	1236	49.2%	507	59.5%	729	43.9%
Remainder	1278	50.8%	345	40.5%	933	56.1%

Table A2. Descriptive Statistics for Retained and Dropped Populations

Variable	BNPL Users		Nonusers	
	Retained	Dropped	Retained	Dropped
Number of Observations	345	507	933	729
By Income				
<$75, 000	75.36%	77.12%	66.77%	67.17%
$75,000+	24.64%	22.88%	33.23%	24.87%
By Age				
18–35	18.55%	61.93%	12.00%	33.06%
36–55	39.71%	26.23%	39.12%	39.51%
56+	41.74%	11.83%	48.87%	27.43%
By Gender				
Female	75.36%	54.47%	66.67%	65.24%
Male	24.63%	45.53%	33.34%	34.76%
By Race/Ethnicity				
White (Non-Hispanic)	72.17%	73.37%	82.32%	75.86%
Non-White	27.83%	26.63%	17.68%	24.14%
By Employment				
Employed	69.57%	79.49%	59.60%	66.94%
Not Employed	30.43%	20.51%	40.41%	33.06%

Table A3. Descriptive Statistics for BNPL Users and Nonusers with Existing Credit Files[26]

	2020		2021	
Variable	**BNPL Users**	**Nonusers**	**BNPL Users**	**Nonusers**
Unweighted Number of Observations	389	1036	389	1036
Share of Individuals with Nonempty Credit File	89.97%	90.73%	89.97%	91.02%
Credit Score	683.8	739.6	687.4	744.1
Age of Newest Account	20.1	24.6	19.4	24.6
Age of Newest Account – Bankcard	30.8	45.1	32.4	47.9
Age of Newest Account – Installment	43.9	46.8	43.6	45.4
Age of Oldest Account	223.6	256.7	233.1	263.7
Age of Oldest Account – Bankcard	173.4	219.3	177.2	225.0
Age of Oldest Account – Installment	143.7	146.7	145.4	161.0
Number Inquiries (Last 12 Months)	1.8	1.3	2.2	1.2
Number of Accounts Recently Updated	9.4	7.6	9.8	7.4
Number of Accounts Recently Updated – Installment	3.1	2.0	3.0	2.0
Number of Accounts Recently Updated – Revolving	6.8	6.0	7.2	5.9
Number of Accounts w/Balance > $0	7.2	5.0	7.3	4.9
Number of Accounts w/Past Due Balance > $0	0.8	0.4	0.9	0.4
Number of Accounts w/Past Due Balance > $0 – Revolving	0.6	0.3	0.7	0.3
Number of Open Accounts	8.8	7.4	9.2	7.2
Number of Open Accounts – Bankcard	4.1	4.2	4.5	4.2
Number of Open Accounts – Installment	2.9	1.9	2.8	1.9
Total Balance on Open Accounts – Bankcard	6940.5	6445.6	6459.7	5374.6
Total Balance on Open Accounts – Retail	1038.5	530.8	1024.6	412.4
Total Balance Past Due	2271.2	1043.1	1628.0	1179.3
Total High Credit Amount on Open Bankcards	30225.0	39179.0	30907.0	39180.0
Bankcard Utilization – %	22.9	16.5	20.9	13.7

[26] BNPL users and nonusers are assigned as a one point-in-time indicator (this study does not track adopters over the two years). The statistics presented in this table are based on the credit bureau data at two points in time (November 2020 and November 2021). These statistics show the averages for consumers with valid credit, nonempty reports in both time periods.

Regression Analysis

Table A4. Linear Probability Model with Binned Credit Scores (2020)

Variable	Estimate		Std. Error	t value	Pr(>|t|)
(Intercept)	0.283	**	0.099	2.869	0.004
Credit Score (583,644]	0.020		0.056	0.364	0.716
Credit Score (644,684]	-0.112	.	0.062	-1.794	0.073
Credit Score (684,728]	-0.109		0.067	-1.627	0.104
Credit Score (728,769]	-0.090		0.071	-1.270	0.204
Credit Score (769,791]	-0.146	.	0.075	-1.939	0.053
Credit Score (791,802]	-0.126	.	0.077	-1.648	0.100
Credit Score (802,811]	-0.107		0.081	-1.321	0.187
Credit Score (811,829]	-0.200	*	0.081	-2.465	0.014
Credit Score (829,850]	-0.204	*	0.081	-2.513	0.012
% Accts. Opened Within 6 Mo. to Accts.	-0.071	***	0.020	-3.614	0.000
Number 90 Days Past Due Occurrences Within 24 Mo. Installment Accts.	-0.050	**	0.018	-2.831	0.005
% Balance to High Credit Open Retail Accts. w/Update - 3 Mo.	0.027	**	0.009	3.119	0.002
Age Newest Sales Finance Acct.	-0.001	.	0.000	-1.800	0.072
Number 30 Days Past Due Occurrences Within 6 Mo. Revolving Accts.	-0.033	.	0.018	-1.811	0.070
% Balance to Ttl. Loan Amt Open Installment Accts. with Update Within 3 Mo.	0.009	.	0.006	1.649	0.099
Ttl. Collection Amt. Unpaid	0.000	.	0.000	1.661	0.097
Age Newest Bankcard Acct.	0.000	.	0.000	-1.684	0.092
Ttl. Balance Department Store Accts. with Update Within 3 Mo.	0.000	.	0.000	1.713	0.087
Number Accts. Opened Within 12 Mo.	0.024		0.017	1.378	0.168
Number Open Retail Accts.	0.017		0.011	1.585	0.113
Number Retail Accts.	0.007		0.004	1.538	0.124
Number Inquiries Within 12 Mo.	0.005		0.011	0.504	0.614
% Balance to High Credit Open Bankcard Accts. with Update Within 3 Mo.	0.005		0.006	0.951	0.342
Number Installment Accts. Reported Within 3 Mo.	0.003		0.007	0.468	0.640
Number Open Sales Finance Accts.	0.002		0.027	0.087	0.931
Number Accts. with Update Within 3 Mo. with Balance > $0	0.001		0.006	0.221	0.825
Number Accts. Major Derogatory	0.001		0.008	0.101	0.919
Ttl. Credit Limit/High Credit Open Bankcard Accts. with Update Within 3 Mo.	0.000		0.000	-1.430	0.153
Age Oldest Bankcard Acct.	0.000		0.000	-0.098	0.922
Ttl. Balance Open Retail Accts. with Update Within 3 Mo.	0.000		0.000	-1.450	0.147
Age Oldest Installment Acct.	0.000		0.000	-0.077	0.938
Age Newest Department Store Acct.	0.000		0.000	-0.381	0.704
Age Newest Retail Acct.	0.000		0.000	-0.391	0.696
Number Installment Accts.	-0.001		0.002	-0.260	0.795
Number Revolving Accts. Opened Within 12 Mo.	-0.006		0.020	-0.316	0.752
Number Sales Finance Accts. Unpaid Major Derogatory Within 24 Mo.	-0.133		0.129	-1.032	0.302

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.4098 on 1241 degrees of freedom
Multiple R-squared: 0.1726, Adjusted R-squared: 0.1486
F-statistic: 7.191 on 36 and 1241 DF, p-value: < 2.2e-16

Table A5. Linear Probability Model with Binned Credit Scores (2021)

Variable	Estimate		Std. Error	t value	Pr(>|t|)
(Intercept)	0.247	*	0.099	2.509	0.012
Credit Score (583,644]	-0.031		0.060	-0.509	0.611
Credit Score (644,684]	-0.150	*	0.066	-2.275	0.023
Credit Score (684,728]	-0.147	*	0.065	-2.273	0.023
Credit Score (728,769]	-0.135	.	0.071	-1.894	0.058
Credit Score (769,791]	-0.096		0.075	-1.288	0.198
Credit Score (791,802]	-0.092		0.075	-1.229	0.219
Credit Score (802,811]	-0.154	.	0.079	-1.951	0.051
Credit Score (811,829]	-0.186	*	0.077	-2.431	0.015
Credit Score (829,850]	-0.168	*	0.080	-2.101	0.036
Ttl. Collection Amt. Unpaid	0.000	***	0.000	5.694	0.000
Ttl. Balance Open Retail Accts. with Update Within 3 Mo.	0.000	**	0.000	2.959	0.003
% Balance to High Credit Open Bankcard Accts. with Update Within 3 Mo.	0.012	*	0.006	2.002	0.045
% Balance to Ttl. Loan Amt. Open Installment Accts. with Update Within 3 Mo.	0.011	*	0.005	2.064	0.039
Number 90 Days Past Due Occurrences Within 24 Mo. Installment Accts.	-0.050	*	0.022	-2.305	0.021
Ttl. Credit Limit/High Credit Open Bankcard Accts. with Update Within 3 Mo.	0.000	*	0.000	-2.392	0.017
Number Revolving Accts. Opened Within 12 Mo.	0.020	.	0.010	1.946	0.052
Number Sales Finance Accts. Unpaid Major Derogatory Within 24 Mo.	0.024		0.152	0.156	0.876
Number Open Sales Finance Accts.	0.023		0.028	0.817	0.414
Number Revolving Accounts Opened Within 12 Months	0.020		0.019	1.024	0.306
Number Retail Accts.	0.007		0.004	1.569	0.117
Number Accts. Opened Within 12 Mo.	0.004		0.016	0.219	0.826
Number Installment Accounts Reported Within 3 Months	0.003		0.007	0.370	0.711
Number Open Retail Accts.	0.002		0.011	0.165	0.869
Number Accts. with Update Within 3 Mo. with Balance > $0	0.001		0.005	0.274	0.784
Number Installment Accts.	0.000		0.002	0.151	0.880
Age Oldest Bankcard Acct.	0.000		0.000	0.015	0.988
Ttl. Balance Department Store Accounts with Update Within 3 Months	0.000		0.000	-1.246	0.213
Age Newest Retail Acct.	0.000		0.000	-0.409	0.683
Age Oldest Installment Acct.	0.000		0.000	-0.656	0.512
Age Newest Department Store Acct.	0.000		0.000	-0.824	0.410
Age Newest Bankcard Acct.	0.000		0.000	-1.179	0.239
Age Newest Sales Finance Acct.	0.000		0.000	-1.078	0.281
Number 30 Days Past Due Occurrences Within 6 Mo. Revolving Accts.	-0.002		0.013	-0.188	0.851
% Balance to High Credit Open Retail Accts. w/Update – 3 Mo.	-0.004		0.008	-0.530	0.596
Number Accts. Major Derogatory	-0.009		0.008	-1.082	0.279
% Accts. Opened Within 6 Mo. to Accts.	-0.027		0.018	-1.498	0.134

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.4098 on 1241 degrees of freedom
Multiple R-squared: 0.1726, Adjusted R-squared: 0.1486
F-statistic: 7.191 on 36 and 1241 DF, p-value: < 2.2e-16

Table A6. Difference in Means Test (2020–2021) – BNPL Users

Name		2020 Average	2021 Average	Diff. in means	P value
Age of Newest Account		20.12	19.38	-0.74	0.47
Age of Newest Account – Bankcard		30.79	32.39	1.60	0.16
Age of Newest Account – Installment		43.87	43.6	-0.27	0.92
Number Inquiries (Last 12 Months)	*	1.81	2.16	0.35	0.05
Number of Accounts Recently Updated	*	9.37	9.84	0.47	0.01
Number of Accounts Recently Updated – Installment		3.11	3.03	-0.08	0.64
Number of Accounts Recently Updated – Revolving	*	6.83	7.15	0.32	0.03
Number of Accounts w/Balance > $0		7.18	7.27	0.09	0.63
Number of Accounts w/Past Due Balance > $0		0.77	0.89	0.12	0.40
Number of Accounts w/Past Due Balance > $0 – Revolving		0.56	0.73	0.17	0.13
Number of Open Accounts	*	8.77	9.2	0.43	0.02
Number of Open Accounts – Bankcard	*	4.14	4.46	0.32	0.00
Number of Open Accounts – Installment		2.85	2.75	-0.10	0.41
Number of Open Accounts – Retail		1.9	1.87	-0.03	0.61
Risk Score		683.78	687.38	3.60	0.26
Ttl. Balance on Open Accounts – Bankcard		6940.5	6459.7	-480.80	0.33
Ttl. Balance on Open Accounts – Retail		1038.5	1024.6	-13.90	0.91
Ttl. Balance Past Due		2271.2	1628	-643.20	0.20
Ttl. High Credit Amount on Open Bankcards		30225	30907	682.00	0.43

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table A7. Difference in Means Test (2020–2021) – Non-BNPL Users

Name		2020 Average	2021 Average	Diff. in means	P value
Age of Newest Account		24.59	24.57	-0.02	0.99
Age of Newest Account – Bankcard	*	45.11	47.86	2.75	0.00
Age of Newest Account – Installment		46.82	45.39	-1.43	0.26
Number Inquiries (Last 12 Months)		1.33	1.23	-0.10	0.27
Number of Accounts Recently Updated		7.55	7.43	-0.12	0.08
Number of Accounts Recently Updated – Installment		2.00	1.97	-0.03	0.45
Number of Accounts Recently Updated – Revolving		6.03	5.93	-0.10	0.45
Number of Accounts w/Balance > $0		4.98	4.94	-0.04	0.65
Number of Accounts w/Past Due Balance > $0		0.39	0.39	000	0.90
Number of Accounts w/Past Due Balance > $0 – Revolving		0.32	0.34	0.02	0.66
Number of Open Accounts		7.35	7.22	-0.13	0.12
Number of Open Accounts – Bankcard		4.23	4.2	-0.03	0.65
Number of Open Accounts – Installment		1.92	1.92	0.00	0.96
Number of Open Accounts – Retail	*	1.36	1.29	-0.07	0.00
Risk Score	*	739.58	744.05	4.47	0.03
Ttl. Balance on Open Accounts – Bankcard	*	6445.6	5374.6	-1071.00	0.00
Ttl. Balance on Open Accounts – Retail	*	530.82	412.4	-118.42	0.02
Ttl. Balance Past Due		1043.1	1179.3	136.20	0.61
Ttl. High Credit Amount on Open Bankcards		39179	39180	1.00	1.00

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table A8. Differences in Credit Variables Between Users and Nonusers (2020–2021)

Variable	Estimate (BNPL User * Time)		Std. Error	T value	Pr(>|t|)
Age Newest Installment Acct.	0.21		4.94	0.04	0.97
Age of Newest Acct.	-1.49		3.38	0.44	0.66
Age of Newest Bankcard	-2.58		4.6	-0.56	0.58
Number Accts. Reported Within 3 Mo.	0.57		0.56	1.01	0.32
Number Accts. w/Update Within 3 Mo. with Balance > $0	0.15		0.44	0.35	0.73
Number Accts. with Past Due Amount > $0	0		0.13	0.01	0.99
Number Inquiries (Last 12 Months)	0.41	*	0.18	2.27	0.02
Number Installment Accts Reported Within 3 Mo.	-0.04		0.32	-0.12	0.90
Number of Open Retail Accts.	0.06		0.19	0.30	0.76
Number Open Accts.	0.55		0.57	0.96	0.34
Number Open Bankcard Accts.	0.28		0.36	0.79	0.43
Number Open Installment Accts.	-0.06		0.31	-0.18	0.86
Number Revolving Accts. Reported Within 3 Mo.	0.41		0.47	0.88	0.38
Number Revolving Accts. w/Past Due Amount > $0	0.04		0.12	0.35	0.73
Risk Score	2.83		8.11	0.35	0.73
Ttl. Balance Open Bankcard Accts. w/Update Within 3 Mo.	134.2		927	0.15	0.88
Ttl. Balance Open Retail Accts. w/Update Within 3 Mo.	162.52		191.67	0.85	0.40
Ttl. Past Due Amount Accts. with Update Within 3 Mo.	-530.73		635.54	-0.84	0.40

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Appendix B. Data Processing Procedures

Empty Files Analysis

As stated in the data preparation section, we removed respondents with empty credit records from our final data set. Prior to removing these respondents, we explored their credit record history over time to determine if they could be included into our analysis.

First, we looked at whether individuals with empty records in November 2020 continued to have empty records between November 2020 and January 2022. **Table B1** shows the percentage of individuals with empty records in November 2020 that continued to have empty files in later months. As seen next, most respondents continued to have empty files throughout the time period. For example, in August 2021, 95 percent of respondents continued to have empty files.

Table B1. Percentage of Empty November 2020 Files That Remained Empty Between November 2020 and January 2022

	2020		2021												2022
	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan
% of empty Nov 2020 files that remained empty	100	100	96	97	96	95	94	79	94	95	91	92	92	88	88

To determine if recurring credit files corresponded to a consistent group of respondents, we measured the number of months that respondents with empty November 2020 files continued to have empty files in subsequent months. As shown in **Table B2**, 33 percent of respondents with empty November 2020 files continued to have empty files for all months between November 2020 and 2022. More than 90 percent of those consumers had nonmissing credit files for two or fewer months.

Table B2. Number of Quarters in which Respondents with Empty November 2020 Files Continued to Have Empty Quarters

Number of quarters that file appears 'empty':	% of empty Nov 2020 files
9	1%
11	1%
12	7%
13	14%
14	44%
15	33%