

A Tale of Two Bailouts: Effects of TARP and PPP on Subprime Consumer Debt

Allen N. Berger

University of South Carolina, Wharton Financial Institutions Center, European Banking Center

Onesime Epouhe

Federal Reserve Bank of Philadelphia Supervision, Regulation, and Credit Department

Raluca A. Roman

Federal Reserve Bank of Philadelphia Supervision, Regulation, and Credit Department



ISSN: 1962-5361

Disclaimer: This Philadelphia Fed working paper represents preliminary research that is being circulated for discussion purposes. The views expressed in these papers are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. Any errors or omissions are the responsibility of the authors. Philadelphia Fed working papers are free to download at: <https://philadelphiafed.org/research-and-data/publications/working-papers>.

A Tale of Two Bailouts: Effects of TARP and PPP on Subprime Consumer Debt*

Allen N. Berger
University of South Carolina
Wharton Financial
Institutions Center
European Banking Center
aberger@moore.sc.edu

Onesime Epouhe
Federal Reserve Bank of
Philadelphia
onesime.epouhe@phil.frb.org

Raluca A. Roman
Federal Reserve Bank of
Philadelphia
raluca.roman@phil.frb.org

September 2021

Abstract

High levels of subprime consumer debt can create social problems. We test the effects of the Troubled Asset Relief Program (TARP) and Paycheck Protection Program (PPP) bailouts during the Global Financial Crisis and COVID-19 crisis, respectively, on this debt. We use over 11 million credit bureau observations of individual consumer debt combined with banking, bailout, and local market data. We find that subprime consumers with more TARP institutions in their markets had significantly *increased* debt burdens following these bailouts. In contrast, PPP bailouts were associated with *reduced* subprime consumer debt. Findings are robust to addressing identification concerns, and yield policy implications regarding bailout structures and strings attached to bailout funds.

JEL Classification Codes: G01, G28, D10, D12, E58

Keywords: Household Debt, Subprime Consumer Debt, Banking, Bailouts, TARP, PPP, Financial Crises, COVID-19 Crisis

* The authors thank Jason Brown, Joelle Scally, and Mike Wintoski for their kind help on data questions about the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), and Pat Akey, Paul Freed, Mallick Hossain, Xiaonan (Flora) Ma, Leili Pour Rostami, and Calvin Zhang for valuable comments. Xiaonan (Flora) Ma provided excellent research assistance. We also thank Mateo Echeverri from Haver Analytics for help with some raw macroeconomic variables used in the paper. Editorial assistance from Barbara Brynko is also gratefully acknowledged.

Disclaimer: This Philadelphia Fed working paper represents preliminary research that is being circulated for discussion purposes. The views expressed in these papers are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. Any errors or omissions are the responsibility of the authors. No statements here should be treated as legal advice. Philadelphia Fed working papers are free to download at <https://philadelphiafed.org/research-and-data/publications/working-papers>.

“... he that goes a borrowing, goes a sorrowing.”
Benjamin Franklin, *The Way to Wealth*, a preface to *Poor Richard's Almanac* of 1758.

1. Introduction

Policymakers generally agree that identifying emerging risks in consumer credit markets is vital in promoting a safe and sound financial system and a healthy economy (e.g., Mester, 2015). Consumer debt increased significantly in many countries over the past decades, reaching \$14.56 trillion as of 2020:Q4 in the U.S. alone.¹ This debt raises concerns about its sustainability and implications for the financial system and the macroeconomy (e.g., Debelle, 2004; Eggertsson and Krugman, 2012; Guerreri and Lorenzoni, 2017; Mian, Rao, and Sufi, 2013).

We focus in this paper on subprime consumer debt – obligations of consumers with low credit scores – and study the roles that bailouts play in promoting or deterring such debt. We find strong and opposing effects from two prominent bailout programs during recent crises, the Troubled Asset Relief Program (TARP) and the Paycheck Protection Program (PPP), raising important policy implications.

Subprime consumer debt, particularly mortgages, played significant roles in creating and exacerbating the Global Financial Crisis (GFC). Between 2001 and 2007, subprime mortgages increased from about 2.5% to 8.4% of overall mortgage balances outstanding. (e.g., Foote, Loewenstein, and Willen, 2020). During this time, the quality of underwriting standards deteriorated, leading to subprime mortgages that accounted for disproportionately high shares of defaults and foreclosures (e.g., Demyanyk and Van Hemert, 2011; Purnanandam, 2011; Demyanyk and Loutskina, 2016; Bhutta, Dokko, and Shan, 2017). Mortgage-backed securities (MBS) and other structured finance products based on this debt circulated around the globe leading up to the crisis. Panic about these securities' value during the crisis contributed to the Lehman Brothers failure and spread other financial calamities around the financial world. Debt overhang also slowed the economic recovery in the U.S. after the crisis (e.g., Mian and Sufi, 2011, 2015; Mian, Rao, and Sufi, 2013; Bernanke, 2018).²

The COVID-19 crisis in 2020 featured a severe recession and unemployment spike in the

¹ New York Federal Reserve Household Debt and Credit Report, 2021:Q1.

² Consumer debt is also associated with other major financial crises such as the Great Depression and the Japan's Lost Decade (e.g., Schularick and Taylor, 2012).

U.S. Tens of thousands of businesses disappeared and the unemployment rate reached 14.7% in April 2020 (Bureau of Labor Statistics, 2020). These events were expected to greatly increase subprime consumer debt both because of exacerbated problems in debt repayment and because more consumers would fall into the low-credit-score subprime categories. However, as we will see, this expected ballooning of subprime consumer debt did not occur – this debt actually declined.

We investigate subprime consumer debt using an extraordinary dataset and employing TARP and PPP as quasi-natural experiments that help with identification. We combine over 11 million credit bureau observations of the debt, credit scores, and other characteristics of individual consumers with data on bank conditions, size, and bailout participation, as well as local market information. The TARP and PPP bailouts provide relatively exogenous financial shocks because they were assembled quickly and were largely unanticipated.³

Despite the differences in the nature of and intended targets of these two bailout programs, we are also able to address key policy issues regarding bailout structures and the strings that are attached to the use of government bailout funds. As discussed in more detail next, the TARP bailout restricted the extent to which the bankers and shareholders could benefit but gave no explicit instructions regarding whether and how any of the bailout funds should be lent out. In contrast, the PPP came with specific rules about how the money must be distributed to certain small businesses and their employees. As we will see, these differences likely altered the outcomes for subprime consumers, with significant policy implications.

We also contribute to the bailout and consumer debt literatures more generally. We are unaware of research on the effects of TARP, PPP, or any other bailout on consumer debt generally or subprime consumer debt specifically. The literature on consumer debt often lacks quasi-natural experiments with relatively exogenous shocks like bailouts to help identify causal relations.⁴

³ The Emergency Economic Stabilization Act (EESA) that created TARP failed its first vote in Congress (<https://www.wsj.com/articles/SB122273311165788291>; <https://www.wsj.com/articles/SB122270285663785991>), and when it did pass, the exact nature of the program was not known. The public thought the funds would be used to buy toxic securities in the market, rather than injecting preferred equity into individual banks. Thus, the TARP shocks to individual banks may be considered reasonably exogenous. The Coronavirus Aid, Relief, and Economic Security (CARES) Act that created the PPP was enacted on March 27, 2020, very shortly after the virus was discovered in the U.S., and went into effect quickly in April. Again, this may be considered to be reasonably exogenous and not anticipated by decision makers.

⁴ Studies of consumer debt include Agarwal and Qian (2014); Jappelli and Pistaferri (2014); Brown, Grigsby, van der Klaauw, Wen, and Zafar (2016); and Brown (2021). Other studies focus on consumer credit rather than debt such as

We investigate whether TARP and PPP bailouts are associated with decreased or increased subprime consumer debt, i.e., whether they helped dig subprime consumers out of their debt holes versus dig them in deeper. Neither the TARP bailout of banks nor the PPP bailout of small businesses directly increases or decreases subprime consumer debt. However, the indirect effects may be very powerful and could theoretically go in either direction.

TARP may affect subprime consumer debt through both income shocks and credit shocks to subprime consumers. The income shocks are primarily from changes in commercial credit supply by the banks that received TARP funds.⁵ To the extent that TARP banks increased their credit supplies to businesses, subprime consumers may have positive income shocks from increased employment or higher salaries or wages at these firms. Negative income shocks to these consumers may alternatively occur if TARP banks reduced commercial credit supplies. Subprime consumers may also experience positive or negative credit shocks to the extent that TARP banks increase or decrease credit supplies to these consumers. Thus, the income shocks to subprime consumers from TARP may affect the demand for subprime consumer debt, while the credit shocks may affect the supply of this debt.

The PPP differs in that it provided positive income shocks for subprime consumers, and it had no direct credit shocks to these consumers. The PPP directly provided billions of dollars of increased credit supply to many small businesses with its forgivable loans. As part of the conditions for forgiveness, the PPP mandated that much of the funds be spent on payroll and that employee counts and wages be maintained, which would benefit the employees.⁶ Small businesses likely account for a disproportionately large share of low-paid workers that may be members of subprime households, so the income shocks to this group may be substantial. The PPP income shocks may also be amplified or diminished to the extent that they are accompanied by increased or decreased

Keys, Mukherjee, Seru, and Vig (2010); Bhutta (2011); Rajan, Seru, and Vig (2015); Agarwal, Chomsisengphet, Mahoney, and Stroebel (2018); and Akey, Heimer, and Lewellen (2021).

⁵ For simplicity, we couch the discussion here only in terms of the behavior of the banks that received the bailouts, but acknowledge that general equilibrium effects include the reactions of their competitors as well.

⁶ We acknowledge the possibility that some subprime consumers may experience negative income shocks from the PPP to the extent that PPP funds were distributed to the competitors of their employers, and not to the firms at which they work. A number of studies provide evidence of problems with distribution of the PPP funds – some regions that were more adversely affected and minority-owned businesses received less help (e.g., Granja, Makridis, Yanellis, and Zwick, 2020; Atkins, Cook, and Seamans, 2021), only some types of firms experienced increased survival probabilities (Bartlett and Morse, 2020), and larger firms received earlier preferential PPP access before small firms (e.g., Humphries, Neilson, and Ulyseas, 2020; Balyuk, Prabhala, and Puri, 2021).

conventional (i.e., non-PPP) small business credit. The PPP does not directly affect credit supplies to consumers, as the funds could not be lent to them, although some small effects on bank consumer credit supplies from credit complementarities discussed next cannot be entirely ruled out. Hence, the income shocks from PPP to subprime consumers may affect subprime consumer debt demand, while there is likely very little in the way of credit shocks that affect the supply of this debt.

The effects on subprime consumer debt from income shocks from both the TARP and PPP bailouts are ambiguous, while those of credit shocks from TARP are not. Positive income shocks for subprime consumers from either bailout may reduce their debt by helping some of these consumers pay down their debt or climb out of the subprime category. Alternatively, positive income shocks may induce more subprime debt by raising these consumers' capacities to spend and borrow. The arguments for negative income shocks from TARP are analogous. However, positive or negative credit shocks to subprime consumers from TARP would be expected to change their debt only in the same direction. For example, an increase in credit supply to a subprime consumer may likely increase their debt, but not reduce it.

A priori, we cannot know which way the income and credit shocks from TARP would go because the TARP bailouts may either increase or decrease bank credit supplies to firms and consumers.⁷ Many research studies suggest that TARP resulted in increases in commercial credit supplies, especially to small businesses (e.g., Black and Hazelwood, 2013; Li, 2013; Jang, 2017; Berger, Makaew, and Roman, 2019; Chu, Zhang, and Zhao, 2019), consistent with positive income shocks for their subprime consumer employees.⁸ Also consistent with positive income shocks, one study finds more employment opportunities in markets with more TARP bailouts (Berger and Roman, 2017). Research evidence on the effects of TARP on consumer credit supply is more limited, but studies on mortgages also find increases in credit supply, particularly to risky consumers, suggesting positive credit shocks to subprime borrowers (e.g., Duchin and Sosyura, 2014; Agarwal and Zhang, 2018; Chavaz and Rose, 2019). The US Department of the Treasury

⁷ There are a number of channels through which TARP may either increase or decrease credit supplies (see Berger and Roman, 2020 for a complete list). For example, under the "Increased Moral Hazard Channel," bailouts may increase incentives to take on lend and take on greater risks because of perceived enhanced probabilities of future bailouts (e.g., Acharya and Yorulmazer, 2007; Kashyap, Rajan, and Stein, 2008). In contrast, under the "Quiet Life Channel," the additional safety from bailouts may allow for a "quiet life," decreasing bailed-out banks' incentives to lend (e.g., Hicks, 1935; Keeley, 1990; Cordella and Yeyati, 2003; Gropp, Hakenes, and Schnabel, 2011).

⁸ We acknowledge that some studies find no significant changes in commercial credit supply (e.g., Duchin and Sosyura, 2014) or reductions in such supply (e.g., Montgomery and Takahashi, 2014).

Annual Use of Capital Survey confirms these research results, with over 85% of TARP banks responding to a survey question that they increased lending more or reduced it less than otherwise would have occurred. However, the survey also indicated many non-lending uses of the bailout funds.⁹

For PPP, the channels are quite different. PPP provided positive income shocks, but these shocks may be amplified or diminished to the extent that there are also increases or decreases in conventional bank credit. These may occur if PPP funds act as complements or substitutes to conventional funding for small businesses. Under complementarity, PPP funds may have made the recipient firms more creditworthy and allowed them to borrow more conventional credit, resulting in a “multiplier effect” (Karakaplan, forthcoming). Additionally, to the extent that the PPP helps increase banks’ incomes, they may have more funds to lend to other borrowers. Alternatively, under substitution, conventional small business credits may decline as PPP funds essentially replace conventional bank loans that might have otherwise been supplied.

The evidence on complementarity and substitutability is relatively limited. Karakaplan (forthcoming) finds strong complementarities – additional conventional small business loans of under \$1 million, primarily for small banks.¹⁰ Chodorow-Reich, Darmouni, Luck, and Plosser (forthcoming) find substitution – reduced loans of over \$1 million made by very large banks.

Other research supports favorable effects of PPP, although not explicitly for subprime households or their debt. Extant findings suggest that businesses receiving PPP reported better financial health, fewer layoffs, and higher employment (e.g., Autor, Cho, Crane, Goldar, Lutz, Montes, Peterman, Ratner, Villar, and Yildirmaz, 2020; Bartik, Cullen, Glaeser, Luca, Stanton, and Sunderam, 2020; Chetty, Friedman, Hendren, and Stepner, 2020; Hubbard and Strain, 2020; Humphries, Neilson, and Ulyssea, 2020; Li and Strahan, forthcoming).

For both bailouts, subprime consumers may have received positive income and credit shocks through externalities to the extent that the bailouts rescued the real economy and financial system. Research evidence suggests that TARP was successful in both boosting the real economy (e.g., Berger and Roman, 2017) and mitigating financial system risks (e.g., Berger, Roman, and

⁹ <http://www.treasury.gov/initiatives/financial-stability/TARP-Programs/bank-investment-programs/cap/use-of-capital>

¹⁰ Consistent with this, James, Lu, and Sun (2021) find that small banks lent PPP funds more intensively to small businesses than large banks.

Sedunov, 2020). The causal links between PPP and the real economy and financial system are not yet established, but both the real economy and banking industry recovered very quickly after the implementation of the PPP (e.g., Berger and Demirgüç-Kunt, 2021).

Turning to our empirical analysis, we use regression models of individual consumer debt as functions of the proportions of banks receiving TARP funds or the proportion of banks with high PPP lending (PPP loans to total loans \geq 50th percentile of the distribution) in the 10-mile radius of the consumer zip code (results are robust to 5-, 25-, and 50-mile radii, as well as the consumer's county). We focus more attention on the effects of TARP than on PPP because of the availability of data and extant research. We are able to follow the short- and long-term effects of TARP up to eight years following the program, whereas we are only able to measure short-term effects of PPP due to its recency. The deep research on TARP also provides substantial guidance on the channels through which it operates, the variables and functional forms to estimate, the methods of dealing with identification concerns, and the robustness checks to run. The PPP research agenda is much less developed at this stage, and the best methods are not firmly established.

We match a large and detailed dataset on consumers with regulatory datasets on banks, U.S. Treasury information on TARP recipients, and other data sources, as well as data on local market conditions and controls for other government programs that may affect consumer debt. Specifically, we employ the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a 5% nationally representative random sample of U.S. consumers with a credit file. The anonymized CCP data allows us to observe individual levels of total consumer debt outstanding, as well as several subcategories – mortgages, home equity loans and lines of credit, credit card, auto, student, and other consumer debt. We use the Equifax Risk Score to distinguish subprime consumers.

We draw a random sample of the anonymized quarterly CCP observations from 2001:Q1 to 2016:Q4 for our TARP regressions, a total of over 5.6 million observations. We cover eight years before and two four-year periods after TARP to measure short- and long-term effects. For the PPP, the anonymized CCP becomes monthly in January 2020, so we employ six months of post-PPP observations from April to September 2020, and use six time periods prior to the PPP, a total of over 5.5 million observations. We are the first, to our knowledge, to match the anonymized

CCP data with banking and other economic data at the local market level.¹¹

In our main TARP regressions, the dependent variables are $\ln(1 + \text{Consumer Debt})$ and various components of this debt. The key exogenous variables include *TARP* (proportion of bank branches in the consumer's market receiving TARP funds), *Subprime* (dummy if the consumer Equifax Risk Score is below 580), and double and triple interactions among *TARP*, *Subprime*, and two post-TARP time dummies, *Post-TARP1* and *Post-TARP2* for 2009:Q1-2012:Q4 and 2013:Q1-2016:Q4, respectively. We specify controls for other consumer, bank, and county characteristics, plus fixed effects for counties and year-quarter, and in some cases county \times year-quarter. Our coefficients of most interest are on the triple interaction terms $TARP \times Subprime \times Post-TARP1$ and $TARP \times Subprime \times Post-TARP2$, capturing the short- and long-term effects of TARP on subprime consumer debt.

The main PPP regressions are analogous, employing *PPPI* (proportion of banks with high PPP loans in the consumer's market) replacing *TARP*, *Post-PPP* (2020:M4-2020:M10) replacing *Post-TARP1* for short-term effects. Data limitations prevent estimating long-term PPP effects.

We find positive and statistically and economically significant coefficients on the triple interaction terms in the TARP regressions, suggesting strong positive associations between TARP bank bailouts and subprime consumer debt in both the short and long terms. A one-standard-deviation increase in *TARP* is associated with higher subprime debt by 17 percentage points in the short term and another 14 percentage points increase in the long term. Such increases in debt are primarily driven by mortgages and to a lesser extent by credit cards and other loans.

The largest increases in subprime consumer debt are in markets with TARP banks that are larger, better capitalized, and more liquid, which may have a better ability to lend. We also find greater increases in subprime debt in markets with lower consumer education and financial literacy.

We acknowledge identification concerns, including the potential biases from omitted variables, reverse causality, and sample selection, and make best efforts to deal with these. We control for many credit demand and supply factors and fixed effects to mitigate omitted variables bias. We conduct many robustness checks as well, including instrumental variables, a Heckman

¹¹ Tai (2017) previously matches TransUnion credit bureau data with banking and other data.

(1979) self-selection model, and a placebo experiment. We also use alternative definitions of the consumer's local market and subprime consumers and different econometric models, and a supplementary analysis using the full anonymized CCP population aggregated at the county level. Our results are consistent in all of these different tests.

Our PPP results suggest very different consequences – statistically significant reduced subprime consumer debt. Effects of a one-standard-deviation increase are modestly economically significant, about a 3 percentage point decline in the post-PPP period. Such decreases in debt are primarily driven by credit cards. Results are robust to different econometric specifications, different definitions of subprime and PPP, instrumental variables, PSM, and a placebo experiment. Results also hold when we use the fully aggregated anonymized CCP population at county level instead of individual level.¹²

The remainder of the paper is organized as follows. Section 2 provides background information on subprime consumer debt, the two crises, and two bailout programs. Section 3 discusses our datasets. Section 4 present the econometric model and main empirical results for our TARP analysis, while Section 5 focuses on robustness tests for TARP. Section 6 discusses data, methodology, and main effects of the PPP program during the COVID-19 crisis. Section 7 provides robustness tests for PPP. Section 8 draws conclusions and gives policy implications.

2. Background information on subprime consumer debt, the two crises, and the two bailouts

We begin the background discussion by defining subprime consumer debt, who the borrowers are, and why they are important from economic, financial, and policy viewpoints. We next briefly discuss the topic of economic and financial crises and the roles of government bailouts in addressing these crises. We then describe the GFC and COVID-19 crises that brought about the TARP and PPP bailouts, respectively. We finally give some institutional details about TARP and PPP and why these bailouts may have important effects on subprime consumer debt.

¹² A limitation of our study is that the CCP dataset does not contain bank identifiers, so we are unable to match the consumers with the banks that supplied their debt. Rather, we match consumers with the branches of bailed out banks in their local markets. The use of market shares of different branches of different types of banks has precedents in the literature (e.g., Berger, Cerquero, and Penas, 2015; Berger, Bouwman, and Kim, 2017; Berger and Roman, 2017; Beck, Degryse, de Haas, and Van Horen, 2018).

2.1 Subprime consumer debt

There is no set credit score threshold to define subprime borrowers, and there are different brands of credit scores used in the consumer lending industry such as the Equifax Risk Score. Scores vary between 250 and 900, with higher score indicating lower risk. We define subprime as a consumer with an Equifax Risk Score less than or equal to 580. Using this threshold, we identify 18% of the population as subprime (as shown in Table 1). We also employ other cutoffs to ensure robustness.

Subprime credit is generally characterized by higher interest rates, poor quality collateral, and less favorable lending terms to compensate for higher credit risk taken by the lending institution. From a social standpoint, subprime credit may be viewed as a democratization of credit. It provides opportunities for a substantial proportion of the population to participate in the financial system and achieve the American Dream of homeownership and wealth accumulation through house equity, on one hand. On the other hand, the high interest rates and low underwriting standards increase the probability of default and foreclosure for these borrowers, who might find themselves worse off in the long term.

2.2 Economic and financial crises and the roles of government bailouts

Economic and financial crises are recurring and often unavoidable phenomenon (e.g., Demirgüç-Kunt and Detragiache, 1997; Reinhart and Rogoff, 2009; Berger and Bouwman, 2013; Laeven and Valencia, 2018). Arguments persist over the appropriateness of government bailouts during these crises. Bailouts may mitigate the damages from and shorten the durations of these crises. However, bailouts may also create moral hazard problems for the recipients to raise risks that increase the likelihood and severity of future crises. It is clear, however, that government bailouts are relatively permanent features of financial and economic crises, despite trends toward bail-ins and other alternative policies for resolving financially distressed firms (e.g., Berger and Roman, 2020). The TARP bailout of banks and PPP bailout of small businesses that we focus on in this paper are but two of the largest of many government bailouts each during the GFC and COVID-19 crises, respectively.¹³

Conditional on governments engaging in bailouts during a crisis, we argue that it makes most economic sense to focus these bailouts primarily on the economic agents and/or markets that

¹³ See Berger and Roman (2020) for discussions of the many bailouts during the GFC, and Berger and Demirgüç-Kunt (2021) for summaries of COVID-19 crisis bailouts.

are originating and may perpetuating the crisis. Bailouts may have widespread economic and financial consequences, including on parties that are not the direct recipients of the bailouts. As discussed next, the TARP and PPP bailouts of banks and small businesses, respectively, may have significant effects on subprime consumers and their debt both because of the relations of these consumers with banks and small businesses and because these bailouts had significant effects on the real economy and financial system.

2.3 The GFC and COVID-19 crises

The GFC was a banking crisis as defined by Berger and Bouwman (2013), a financial crisis that originated in the banking sector. As discussed in the Introduction, the expansion of subprime credit prior to the crisis and losses on and difficulties in valuing the financial securities based on this credit played significant roles in creating and amplifying this crisis. As the housing price bubble burst, and housing prices started to tumble in 2006, losses on mortgage-backed securities (MBS) and related securities started to mount, as well as questions about how to value these securities.

These problems spread to other financial markets in 2007:Q3. Loss of confidence and freezes impaired the operations of the interbank lending and syndicated loan markets, creating liquidity issues for some banks that could no longer easily borrow or sell portions of the loans they originated. These problems worsened considerably after a number of failures and near failures of thrifts, banks, and investment banks that were tied to subprime mortgages and the securities based on them, especially the Lehman Brothers bankruptcy in September 2008 that shook public confidence. The banks also suffered capital losses on their mortgage portfolios, as well as their MBS and other securities, so they had both liquidity and capital problems.

The GFC also spawned an economic crisis, often referred to as the Great Recession in the U.S., the most significant recession since the Great Depression of the 1930s. The recession was in large part caused by reductions in bank credit supply that harmed borrowers and the real economy. The credit supply reductions were mostly due to substantial losses in bank capital as well as the liquidity issues from the financial market problems (e.g., Thakor, 2015a, b, 2016). Given that these bank capital and liquidity problems were causing the economic damages, the most logical form of bailout was a bank bailout, and TARP was the largest of numerous bank bailouts during the crisis.

COVID-19 began as a public health crisis in Wuhan, China, in December 2019, but later

became a worldwide pandemic and economic crisis. The disease was first detected in the U.S. in January 2020, and by February, it was a pandemic and economic crisis in the U.S. The U.S. unemployment rate increased from 3.5% in February 2020 to 4.4% in March and to 14.7% in April, a record high since the Great Depression.¹⁴

The economic crisis came about both because of private-sector reactions to the disease by consumers, workers, and businesses, and because of government restrictions on economic activities to reduce virus spread. Consumers reduced their purchases involving personal contact, reducing economic demand, and workers avoided places of employment involving personal contact, reducing economic supply. Government restrictions and shutdowns of businesses, schools, travel, etc. further crippled economic supply, and those that lost jobs or business income as a result also reduced demand for goods and services.

Small businesses were generally harder hit by the crisis than large businesses, with over 70,000 permanently closing and many more temporarily being shut down by July 2020.¹⁵ In particular, small firms in hospitality and personal services industries were often financially devastated by the crisis. Thus, a bailout of small businesses such as the PPP was the most logical place for bailouts. The banking industry, by contrast, performed quite well during the crisis, and required no bailouts (e.g., Berger and Demirgüç-Kunt, 2021).

2.4 The TARP and PPP bailouts

TARP was proposed in September 2008 as the financial crisis and recession were deepening and was called the Troubled Asset Relief Program because the original plan was to purchase “troubled assets.”. Although the GFC originated in the third quarter of 2007, it had considerably deepened by September 2008. Several large financial institutions had failed or required rescues, including Bear Stearns, Indy Mac, Washington Mutual, and Lehman Brothers, others were in precarious condition, and some credit markets had stopped functioning.

The U.S. Congress failed to pass the TARP on the first attempt, resulting in a stock market crash. On the second try in October 2008, TARP was authorized by Congress in accordance with the Emergency Economic Stabilization Act of 2008 (EESA) and was one of the largest government

¹⁴ See <https://www.wsj.com/articles/april-jobs-report-coronavirus-2020-11588888089>.

¹⁵ See <https://www.forbes.com/sites/andrewbender/2020/07/29/covid-19-claims-nearly-73000-us-businesses-with-no-end-in-sight/?sh=24d8bdd85d73>.

interventions to address the GFC. Its main goals were to ensure that the financial system and economy would not collapse by improving the condition of financial institutions via purchasing up to \$700 billion of their “troubled assets” to allow markets to stabilize and avoid further losses, encourage financial institutions to restart lending, and stimulate the real economy.

However, the \$700 billion was later judged insufficient for these purposes. Instead, the Capital Purchase Program (CPP, the main component of TARP) authorized the U.S. Treasury to invest up to \$250 billion of the \$700 billion in preferred equity of selected financial institutions to enhance their capital ratios. The CPP distributed \$204.9 billion into 709 banking organizations over 2008:Q4-2009:Q4, including an initial \$125 billion on October 28, 2008, to nine large “involuntary” participants that were essentially required to take the funds. In return, the Treasury received preferred equity paying dividends at a rate of 5% for the first five years and 9% thereafter, as well as stock warrants. Most of the banks paid back the funds in 2009 or 2010, and the Treasury eventually recovered 112.7% of the funds invested via dividends, warrants, and repayments.^{16,17}

As indicated in the Introduction, the TARP bailout came with strings attached to avoid enriching bank executives and shareholders, but with no explicit rules on whether and to whom the bailout funds should be lent out. Some of these restrictions were applied at program implementation in October 2008, while others were imposed later in February 2009. For executives, banks were restricted from making golden parachute payments. Senior executives were also limited to \$500,000 total annual compensation and tax deductibility and could not benefit from incentive compensation schemes that encourage “unnecessary and excessive risks.” There were also claw-back requirements on any incentive compensation based on earnings that were subsequently restated. Additionally, for banks that missed six quarterly dividend payments, the government could appoint up to two voting directors on the bank’s board of directors, exercising direct corporate governance (Mücke, Pelizzon, Pezone, and Thakor, 2021). For shareholders, TARP banks could not increase dividends on their common shares or repurchase common stock or preferred shares junior to the Treasury’s investment during the first three years of the Treasury’s ownership of preferred stock.

¹⁶ See <http://www.treasury.gov/initiatives/financial-stability/reports/Pages/Monthly-Report-to-Congress.aspx>.

¹⁷ However, research suggests that this was a relatively low rate of return to U.S. taxpayers, given the risks (e.g., Flanagan and Purnanandam, 2021).

The PPP bailout of small businesses was part of the 2020 CARES Act passed into law on March 27, 2020. The PPP was much bigger than TARP with many more participants, and in most cases, it did not require any payments in return. The PPP distributed \$525 billion in forgivable loans between April and August 2020 to over 5.2 million small businesses to support employee jobs, their compensation and health-care benefits, and related overhead expenses such as mortgage interest, rents, and utilities.¹⁸ With few exceptions, the PPP limited participation to firms with 500 or fewer full-time equivalent employees, and included other net worth and net income limits.

The PPP loans came with an interest rate of 1% and a two-year maturity before June 5, and a five-year maturity thereafter. The amounts of these loans were approximately equal to 2.5 times the applicant's average monthly payroll costs. The loans were initially fully forgiven and tax free if firms kept all workers at full pay for eight weeks after the loans were issued and use at least 75% of the loan proceeds to cover employee payroll costs. At the end of May 2020, the threshold for payroll costs was lowered to 60% and firms could use the funds up to 24 weeks rather than 8 weeks after receiving them.¹⁹

While the PPP was designed to aid small businesses, many banks also benefited. Firms had to submit their applications directly to the PPP lenders, about 94% of which were banks, which reviewed the materials and funded the loans. The lenders earned fees between 1% and 5%. The banks were encouraged to extend the funds to their existing relationship customers. The PPP loans imposed no credit risk to banks and carried a zero-risk weight under regulatory capital rules.²⁰ The banks may also be indirectly supported because some of their relationship borrowers are made safer and more likely to repay other loans.²¹

The structures of these two bailout programs and the strings attached to the uses of their funds likely have strong implications for subprime consumer debt that we study in this paper. The PPP likely provided more positive income shocks for subprime consumers per dollar of the bailouts

¹⁸ The PPP was reopened with additional funds on January 11, 2021, but our focus is on the bailout in 2020.

¹⁹ See <https://home.treasury.gov/policy-issues/coronavirus/assistance-for-small-businesses/paycheck-protection-program>, <https://www.wsj.com/articles/community-lenders-to-get-10-billion-of-ppp-small-business-loans-11590678108>

²⁰ See <https://www.federalregister.gov/documents/2020/04/13/2020-07712/regulatory-capital-rule-paycheck-protection-program-lending-facility-and-paycheck-protection-program>

²¹ The PPP also appears to have benefited fintech firms that provide financial services to small businesses (e.g., Erel and Liebersohn, 2020).

as well as many more dollars. This is because virtually all of the PPP funds went to small businesses, and most of these funds were directed to payroll. As noted previously, small businesses likely employ disproportionately more low-income members of subprime consumer households as employees than large businesses. In contrast, the research and government reports summarized above suggest that TARP funds were not lent out in full, were more than fully repaid to the Treasury, and some of the loan dollars went to large businesses. The other key difference is that TARP provided significant positive credit shocks to subprime consumers, whereas such shocks are minimal at most from PPP. Thus, as shown next, the two programs yield very different outcomes.

3. Data and sample construction for TARP and PPP

Our credit bureau consumer microdata from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP) includes U.S. consumers with valid Social Security numbers and credit histories.²² All individuals residing in the same household are added to the file. The data track individuals over time and are refreshed quarterly from 1999 to the present.

The dataset contains individual-level data on virtually every outstanding debt owed by each individual, payments, and adverse events associated with credit accounts. The dataset also contains a number of individual characteristics such as year of birth, credit bureau score, whether an account is jointly shared with another household member, and billing zip code. The panel selection is based on a unique sampling design to extract information from consumer credit reports and track individuals' access to and use of credit across time and their geographic location at the zip code level (see Lee and van der Klaauw, 2010 for more details).

Because the dataset is very large (about 40 million individuals each quarter), we use random samples for our main analyses, we use an aggregated sample at the county level in a robustness check. For the TARP analysis, we obtain a 1% random sample with quarterly anonymized CCP data for the period 2001:Q1 to 2016:Q4, covering eight years before and eight years after TARP implementation. We define two post-TARP periods, 2009:Q1-2012:Q4 and 2013:Q1-2016:Q4 to assess short- and long-term effects.

For the PPP, we use a 5% random sample over a much shorter time interval. The

²² The sample remains representative of the target U.S. population over time as some consumers are deceased or others become of age to be included.

anonymized CCP becomes monthly in January 2020, and we are able to employ six months of post-PPP observations from April to September 2020, i.e., 2020:M4-2020:M9. To have a matching six time periods prior to PPP, we use three quarterly time periods from 2019, i.e., 2019:Q2-2019:Q4, and three monthly time periods from January to March 2020, i.e., 2020:M1-2020:M3.

We apply the following filters to the raw anonymized CCP data to provide clear answers to our questions and eliminate data errors. We keep only observations in which: 1) consumer is in the primary sample; 2) the consumer record has no duplicates; 2) the consumer zip code is in one of the 50 U.S. states and the District of Columbia; 3) birth year is not missing, and consumer age is 18 years or older; 4) the credit score is not missing and between 300 and 900.

We construct dependent variables in the form of total consumer debt and different categories of mortgage, home equity loan (HELOAN), home equity line of credit (HELOC), credit card, student loans, auto loans, and other consumer loans. Because debts in anonymized CCP are recorded both for each individual and per joint/co-maker/shared account if the consumer has joint accounts, we joint adjust all debts to be on a per-individual level.

Consumer-level explanatory variables are constructed using birth year, Equifax Risk Score, joint account indicators, and number of credit inquiries by the consumers to control for credit demand. To merge the consumer data to the bank data, we calculate the distance from each consumer zip code to closest bank branch zip code, based on the FDIC Summary of Deposits. For each consumer, we select the 10-mile radius around their zip code, as their market. The TARP bailout variable is constructed as the proportion of bank branches in the market belonging to banks that received TARP bailouts.

We obtain commercial bank balance sheet and income data from quarterly Call Reports.²³ We aggregate the Call Report data of all the banks in multibank BHCs (Bank Holding Companies) or use the individual bank data otherwise. For convenience, we will use the term *bank* to mean either type of entity. We merge this bank data with TARP transactions data for the period October 2008 to December 2010 and TARP recipients list from the U.S. Treasury's website.²⁴ We manually

²³ We exclude firm-quarter observations that do not refer to commercial banks (RSSD9331 different from 1), the bank failed before 2009:Q1 (i.e., before observation of TARP effects) or have missing or incomplete financial data for assets or equity, or have missing data for our key variables.

²⁴ See <http://www.treasury.gov/initiatives/financial-stability/Pages/default.aspx>.

match by name and location the institutions in the list with their corresponding RSSD9001 (Call Reports ID) where available based on information in the National Information Center.²⁵

The PPP bailout data come from the Call Reports that show PPP loans made by banks during the COVID-19 crisis. As noted previously, we convert all bank-level data, including TARP and PPP, to the consumer market level (10-mile radius) based on their branch distributions. TARP=1 or PPP=1 if there is a TARP recipient bank branch or a branch of a bank with PPP Loans/Total Loans \geq 50th percentile of the distribution) within a 10 miles radius of the consumer zip code.

We collect county-level characteristics such as unemployment rate and house price index (HPI) from Haver Analytics / U.S. Census Bureau and the CoreLogic Solutions, respectively. We also use additional local market variables for other analyses from the FFIEC (Federal Financial Institutions Examination Council) Census data. COVID-19 forbearance rates for various consumer products come from the anonymized CCP dataset.²⁶

Figure 1 Panels A and B show the geographical distribution of the TARP and PPP bailouts across U.S. counties, respectively. We show the weighted proportion of TARP and PPP banks based on their proportions of branches in the counties in which they operate over 2008:Q4-2009:Q4 for TARP and over 2020:Q2-2020:Q3 for PPP. Darker colors represent more bailout participation.

Panel A shows that the highest concentrations of TARP banks are in counties on near the West and East Coasts, generally consistent with the higher density regions in terms of bank consumers, median income, and GDP growth. The PPP bank distribution is more varied, with the highest concentrations in the central part of the U.S. as well as the East Coast. Interestingly, the smallest proportions of PPP banks were in the West.

Table 1 Panel A provides definitions of our variables, and Panels B and C show summary statistics for the TARP and PPP samples, respectively. The data show that 52.3% of bank branches in consumer markets received TARP, and 43.7% have high PPP participation. Our key dependent variables are consumer debt measures. We take the natural log after adding one to the raw values

²⁵ We exclude thrifts and S&Ls that do not have Call Report information.

²⁶ All financial variables are adjusted using the Federal Reserve Bank of St. Louis FRED seasonally adjusted GDP implied deflator to be in real 2016:Q4 dollars for the TARP dataset and in 2020:Q3 dollars for the PPP dataset.

to avoid taking the log of zero. The average consumer has a total debt burden $\ln(1+Total\ Consumer\ Debt)$ of 8.099 (\$49,281) in the TARP sample, and 8.422 (\$60,712) in the PPP sample. The average credit scores are 690 and 710, and 18% and 14% of consumers in the TARP and PPP samples are subprime, respectively, based on the 580 cutoff.

In the interest of brevity, we only briefly mention the sets of control variables – details are in the table. *Consumer Characteristics* control for credit demand and include *Consumer Age* (calculated based on birth year), *Joint Account* indicator (indicator for accounts with joint ownership), and number of credit inquiries the consumer made in the past 12 months, $\ln(1+No.\ Credit\ Inquiries\ last\ 12mos)$. *Local Bank Characteristics* control for credit supply and include proxies for bank CAMELS (supervisory variables measuring capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to market risk), *Bank Size*. For the TARP sample, we also include controls for bank participation on other regulatory programs during the GFC such as the Discount Window and Term Auction Facility (e.g., Berger, Black, Bouwman, and Dlugosz, 2017), the FDIC Federal Deposit Transaction Account Guarantee Program (TAGP) and the Temporary Debt Guarantee Program (TDGP), the Small Business Lending Fund (SBLF), and membership into the Federal Home Loan Bank (FHLB) system. For the PPP sample, we also include forbearance rates for several credit products including mortgages, home equity, credit cards, and auto loans. *Local Market Characteristics* of county unemployment rate (*UR*) and the house price index (*HPI*), as well as *County* and *Year-Quarter* fixed effects are also included to control for other local demand factors in the consumer county or unobserved temporal patterns.²⁷

Simple summary statistics show that the average subprime consumer increased their debt burden after the TARP program relative to the pre-TARP period by \$13,755 (60%) from \$24,048 to \$37,803. In contrast, the average subprime consumer decreased their debt burden after the PPP program relative to the pre-PPP period by almost \$1,000 (3%) from \$33,956 to \$32,988. While these statistics provide some suggestive potential trends for the subprime consumers around the two bailout programs, we will investigate these more rigorously using regression analysis which allows us to control for other covariates affecting consumer debt.

²⁷ In unreported results, all our main findings for both TARP and PPP bailouts effects on subprime consumer debt and subcomponents hold and have similar economic magnitudes also when using alternative more stringent fixed effects, such as *Zip Code* and *Year-Quarter* fixed effects or *Census Tract* and *Year-Quarter* fixed effects.

4. Regression analysis of the effects of TARP bailouts on consumer debt

4.1 Methodology

To test the impact of bailouts on consumer debt, we estimate difference-in-difference-in-difference (DIDID) models with interactions for bailouts, whether the time period is after the bailouts, and whether the borrower is subprime. For the TARP bailouts, the model is specified as follows:

$$\begin{aligned}
 Y_{i,t} = & \beta_0 + \beta_1 TARP_{i,t} + \beta_2 \cdot Subprime_{i,t} + \beta_3 \cdot TARP_{i,t} \times Subprime_{i,t} + \\
 & \beta_4 \cdot TARP_{i,t} \times Post \circ TARP1 ('09-'12)_t + \beta_5 \cdot TARP_{i,t} \times Post \circ TARP2 ('13-'16)_t + \\
 & \beta_6 \cdot Subprime_{i,t} \times Post \circ TARP1_t + \beta_7 \cdot Subprime_{i,t} \times Post \circ TARP2_t + \\
 & \boxed{\beta_8 \cdot TARP_{i,t} \times Subprime_{i,t} \times Post \circ TARP1_t} + \boxed{\beta_9 \cdot TARP_{i,t} \times Subprime_{i,t} \times Post \circ TARP2_t} + \\
 & \beta_{10} \cdot Consumer\ Characteristics_{i,t} + \beta_{11} \cdot Local\ Bank\ Characteristics_{i,t-4} + \\
 & \beta_{12} \cdot Local\ Market\ Characteristics_{i,t-4} + \beta_{13} \cdot County\ FE_i + \beta_{14} \cdot YearQuarter_t + \varepsilon_{i,t}.
 \end{aligned} \tag{1}$$

where i indexes consumers and t indexes year-quarter. The key dependent variable $Y_{i,t}$ is debt for consumer i at time t . Our main measure is $\ln(1 + Total\ Consumer\ Debt)$, and we also use components for mortgages and the other debt types. The key explanatory variables are $TARP_{i,t}$, the proportion of bank branches belonging to TARP banks in consumer i 's market, $Post-TARP1_t$ and $Post-TARP2_t$, dummies for 2009:Q1-2012:Q4 and 2013:Q1-2016:Q4, respectively, and $Subprime_{i,t}$, a dummy for a consumer Equifax Risk Score of 580 or less. Our main focus is on the triple difference-in-difference-in-difference (DIDID) interaction terms, $TARP_{i,t} \times Subprime_{i,t} \times Post-TARP1_t$ and $TARP_{i,t} \times Subprime_{i,t} \times Post-TARP2_t$, which show how TARP bailouts affect subprime consumer debt after implementation of the bailouts in the short and long terms. The control variables are described previously, and the standard errors are clustered by consumer.

4.2 Results for the effects of TARP bank bailouts on total consumer debt

Table 2 Panel A shows main TARP results. The coefficients corresponding on the triple interactions, $TARP \times Subprime \times Post-TARP1$ and $TARP \times Subprime \times Post-TARP2$, are consistently positive and significant at 1% level across all specifications for total consumer debt, consistently suggesting that TARP bank bailouts are associated with increases in subprime consumer debt. Results are also economically meaningful. A one-standard-deviation increase in TARP is associated with about 17 percentage points greater short-term subprime consumer debt

and another 14 percentage points in the long run.²⁸

The findings are robust to different measures of the dependent variable, specifications of the econometric model, and local market definitions for the consumer. Dropping some or all banks' characteristics or county controls, adding more fixed effects such as multidimensional County×Year-Quarter, or changing the clustering, leaving our conclusions unchanged. We also change how we calculate total debt by altering the inclusion of different types of student debt and changing the geographic size of the market and find consistent results.

Other explanatory variables also have significant effects. Among the consumers' characteristics, the number of inquiries in last 12 months and the joint account indicator are associated with higher total debt, while consumer age is associated with lower total debt. Bank size and management quality tend to be associated with a significantly higher total consumer debt, while bank earnings is associated with lower level of consumer debt. As expected, county unemployment rate is associated with decreased consumer debt, while a high home price index is associated with higher debt.

4.3 Results for the effects of TARP bank bailouts on components of consumer debt

We decompose the total debt into the different products and run a separate regression for each (e.g., mortgage, HELOAN, HELOC, credit card, auto loan, student loan, and other consumer loans). There are two types of student loans: The vast majority of student loans are public loans issued by the federal government with no credit check. Private student loans are issued by banks after credit checks of the student and co-borrowers.²⁹

Table 2 Panel B presents disaggregated debt results for each type of loan for the full specification. Results suggest that TARP is primarily associated with increased mortgage and home equity debt to riskier subprime borrowers. We also observe some increases in debt to a lower extent from other consumer products, but results are not always present in both post-TARP

²⁸ To calculate the percent change in the dependent variable, we use the following formula: $\Delta y = 100 * (\exp^{\beta * (\text{stdv } TARP)} - 1)$. Focusing on Table 2, Panel A, column (1), a coefficient of 0.644 on the interaction term $TARP \times Subprime \times Post\ TARP1$ (<580), suggests that, during *Post-TARP1* ('09-'12), total debt for subprime consumers increased by about 17% ($=100 * (\exp^{0.644 * (0.243)} - 1)$), while the interaction term $TARP \times Subprime \times Post\ TARP2$ (<580) suggests that during *Post-TARP2* ('13-'16), total debt for subprime consumers increased by about 14% ($=100 * (\exp^{0.527 * (0.243)} - 1)$).

²⁹ Other consumer loans include personal revolving or installment, health care, veterinary, and furniture loans.

periods. We also find a decline in consumer debt from other consumer loans.³⁰

5. Robustness tests for the TARP results

This section provides a variety of robustness checks to confirm that our results are not driven by endogeneity, sample selection concerns, or other econometrics issues.

5.1 Addressing endogeneity concerns using an instrumental variable analysis

We first address the potential endogeneity of our TARP variables. For example, TARP capital might be more often provided to the strongest banks, which may be more likely to gain a competitive advantage, yielding a spurious relationship. We employ an instrumental variable (IV) analysis to isolate the causal impact of TARP on subprime consumer debt.

Prior research finds that banks' political connections affected the bank's probability of receiving TARP capital injections (e.g., Bayazitova and Shivdasani, 2012; Li, 2013; Duchin and Sosyura, 2014; Berger and Roman, 2015, 2017). Following this research, we use as an instrument for TARP the *Subcommittees on Financial Institutions & Capital Markets*, a binary dummy equal to 1 if a bank is headquartered in the election district of a House member who served on the Financial Institutions Subcommittee or Capital Markets Subcommittee of the House Financial Services Committee in 2008 or 2009.³¹

Given that the basis of the TARP variable is also binary, we use a dummy endogenous variable model and follow a three-step approach as in Wooldridge (2002) procedure 18.4.1. In the first stage, we use a bank-level probit model in which we regress the TARP recipient binary on the political instrument and all bank controls from our main regression model to predict the probability of a bank to receive TARP. We then aggregate the TARP binary fitted value from the first stage weighted by the banks' branches proportions in the 10-mile consumer zip code radius and use this variable as instrument for the final stage.³²

³⁰ Our findings for TARP bailouts effects on subprime consumer debt and subcomponents hold and have similar economic magnitudes also when using alternative more stringent fixed effects, such as *Zip Code* and *Year-Quarter* fixed effects or *Census Tract* and *Year-Quarter* fixed effects.

³¹ We use the MABLE/Geocorr2k software on the Missouri Census Data Center website to associate banks with congressional districts by using the zip codes of their headquarters.

³² Wooldridge (2002) procedure 18.4.1, also mentioned in Angrist and Pischke (2009), is useful when the endogenous variable X is binary, since estimation is typically inefficient when 2SLS is used directly for this case. Improved efficiency is obtained by first regressing X on the included and excluded instruments via probit or logit, predicting the

We report the first stage results in Table A.1 of Appendix A, and the final-stage results for the IV specification in Table 3 Panel A. The first-stage results indicate that the instrumental variable is positively related to TARP injections as hypothesized, and the first-stage F -test statistics suggest that the instrument is valid. The final-stage IV coefficients corresponding to the triple DIDID variables of interest are positive and statistically significant at 1% level for total debt as well as mortgages, HELOC, HELOAN, and credit cards as well as both private and public student loans during both TARP periods. The IV estimates are somewhat larger in absolute value than the OLS estimates, consistent with average treatment effects (e.g., Jiang, 2017). That is, banks with political connections may make more subprime loans.

5.2 Addressing sample selection concerns using the Heckman’s (1979) selection model

To mitigate potential selection bias, we use Heckman’s (1979) two-step procedure. This approach controls for selection bias introduced by bank and government choices about TARP by incorporating TARP decisions into the econometric estimation. The first step is the same probit model as the IV estimation. In the second stage, the consumer debt variables are the dependent variables, and we include the self-selection parameter (*Inverse Mills Ratio*) estimated from the first stage weighted by the banks’ branches’ proportions in the 10-mile radius of the consumer zip code.

The second-stage results are reported in Table 3 Panel B. The coefficients on the *Inverse Mills Ratio* are generally not statistically significant with exception of HELOAN and HELOC products, where it is weakly significant. This suggests that sample selection bias may not be a severe issue. The results continue to suggest that TARP bailouts are associated with statistically and economically significant increases in subprime consumer debt.

5.3 Alternative *Subprime* measure

In Table 4, we redefine *Subprime* as an indicator for consumers with Equifax Risk Score below 620 instead of 580. The DIDID terms on total consumer debt remains positive and statistically significant and consistent with our main results. The effects on individual products also mimic our main results.

probability \hat{X} , and using \hat{X} as the single instrument (this method involves three steps and not just two). We follow this and use a probit for predicting the probability of the TARP Recipient binary and instrument our *TARP Recipient* variable by the weighted TARP Recipient binary fitted value and $TARP \times Subprime \times Post\ TARP1$ and $TARP \times Subprime \times Post\ TARP2$ by the product of the weighted TARP Recipient binary fitted value with the two post-TARP periods and the *Subprime* indicator. As indicated in Wooldridge (2002, pp. 236-237) and other sources, this method is not the same as the forbidden regression, as we use obtained variables as instruments, and not as regressors.

5.4 Addressing selection concerns using a falsification test and matched sample

To rule out other selection concerns, we randomly assign individuals to subprime group, maintaining the original statistical distribution and then rerun our regressions with all other variables unchanged. The results of this placebo experiment are reported in Table 5 Panel A. We find that the triple DID coefficients are all statistically insignificant.

We also do a matched sample analysis based on propensity score probabilities, using a logistic regression. The propensity score is the probability of a consumer being in the subprime segment given a number of similar consumers, bank, and local market conditions from our main model. Subprime consumers are matched to corresponding non-subprime counterparts based on the absolute difference in the propensity score. Pairs with the smallest difference are regarded as a matched pair and are selected to be part of our matched pair analysis sample. Using only the matched pair sample, we repeat the individual debt level regression analysis in Table 5 Panel B. The positive and significant coefficients on our triple difference-in-difference variable across most regression equations (with the exception of the last column corresponding to other consumer loans) are consistent and reinforce our main results.

5.5 TARP mechanisms investigation

In Table 6 Panels A and B, we conduct an additional analysis to help understand the mechanisms through which TARP may have increased consumer debt. We consider: 1) changes in credit supply; 2) changes in consumer credit consumption or utilization; and 3) changes in consumer repayments of debt. To test these, we report results for several indicators of credit, utilization, and payments based on the anonymized CCP data as dependent variables.³³ In Panel A, we use $\ln(1+Total\ Consumer\ Credit)$ in column (1), $\ln(1+HELOC\ Limit)$ and $\ln(1+Card\ Limit)$ in columns (2)-(3), and $HELOC\ Utilization\ Rate$ and $Card\ Utilization\ Rate$ in columns (4)-(5), the latter being calculated as the ratio of the outstanding balance on each product to their corresponding limit. Panel B columns (1)-(9) reports results for total payment rate and decomposition by products.

The results suggest that TARP increased consumer debt through increases in credit and higher utilization for subprime consumers, while not observing much significant effects on

³³ We caution that data on these indicators are imperfect in that, for example, payments reported may more often reflect scheduled payments, which mix demand and supply forces. Nevertheless, these tests can provide a crude indication of which suggested mechanisms may be at work.

payments. Results are economically significant. In Panel A column (1), we find that the average subprime consumer received higher total credit due to bank bailouts by about 16 percentage points in the short-term first period after TARP (2009:Q1-2012:Q4) and another 11 percentage points increase in credit in the long term. In addition, for the credit card utilization rates, consumers increase credit card utilization by about 11 percentage points in both periods after TARP. These results are consistent with the research discussed in the Introduction suggesting that TARP yielded positive income and debt shocks to subprime consumers through increased credit supply.

5.6 Cross-section tests by bank size, capital, and liquidity

We next conduct analyze for which types of banks the documented effects are the strongest and weakest, focusing on three bank characteristics: size, capital, and liquidity.

Prior TARP literature (e.g., Black and Hazelwood, 2013; Li, 2013; Duchin and Sosyura, 2014) finds that different bank size and different financial strength may have different lending behavior after TARP bailouts, which may have different consequences on consumer debt.

First, we examine separately the proportions of large TARP banks ($GTA > \$10$ billion) and small TARP banks ($GTA \leq \$10$ billion) in the markets using *TARP Large* and *TARP Small* variables and interactions. Table 7 Panel A shows that all effects are concentrated in the large banks. The strong findings for large banks compared to small banks may be related to large banks having higher moral hazard incentives to lend to subprime consumers due to their greater access to implicit government guarantees.

Second, we consider separately the proportions of TARP banks with low- versus high-equity to GTA ratio (*Capital Adequacy* relative to the median) and low- versus high-liquid assets to GTA ratio (*Liquidity* relative to the median) before the TARP program in 2008:Q3. Results in Table 7 Panels B and C suggest that the higher subprime consumer debt effects from TARP effects are primarily from banks with more capital and liquidity, that may have greater lending capacities.

5.7 Cross-section tests for consumer education and literacy

We next check how the results may be influenced by consumer education and exposure to financial literacy mandates. The consumer behavior literature (e.g., Campbell, 2006; Brown, Grigsby, van der Klaauw, Wen, and Zafar, 2016) finds that exposure to education reduces consumer reliance on debt and improves their repayment behavior. We differentiate between consumers in counties with

low- versus high-consumer education (percent of population with a Bachelor’s or higher degree relative to the median) and those in local markets with low- versus high-financial literacy mandates (based on literacy mandates and economics education reforms in the state, following Brown, Grigsby, van der Klaauw, Wen, and Zafar (2016)).

Regression estimates are shown in Table 8 Panels A and B. We find that higher debt burden effects of TARP are primarily driven by subprime consumers in low education areas, while literacy and economics education mandates also seem to have some effect on the margin for total debt, mortgages and HELOAN, but not for other products.

5.8 Cross-section tests by other consumer and county characteristics

In additional unreported cross-section tests, we differentiate between subprime consumers who are young versus old (using 65 years old age as cutoff), those in minority and non-minority counties (using the median of the percent of minorities in the county as cutoff based on the FFIEC Census data),³⁴ those living in low- and high-income counties (using the FFIEC Census low-median-income (LMI) indicators, where low and median income are denoted as “low income”), urban and rural areas (using the FFIEC Census urban/rural indicator), and high and low unemployment rate (UR) (using the median of the variable as cutoff) and high and low house price index (HPI) (using the median of the CoreLogic Solutions HPI variable as cutoff). The data suggest that TARP subprime consumer debt effects generally hold for all groups studied, except the magnitudes tend to be higher for older consumers, high income counties, urban areas, high unemployment rate areas, and high HPI expensive areas.

5.9 Additional evidence from full anonymized CCP sample aggregated at county level

We conduct additional tests in which we use the full anonymized CCP consumer sample aggregated at the county level. Thus, we sum up all financial variables such as debt holdings across all consumers over each quarter and we calculate the percent of consumers that are *Subprime* instead of the dummy. All bank characteristics including *TARP* are now calculated at the county level. This analysis serves two purposes: 1) it constitutes a robustness check of our previous results, and 2) it allows us to investigate subprime debt normalized by income, addressing a broader question.

³⁴ FFIEC Census data are from: <https://www.ffiec.gov/censusapp.htm>.

Results are presented in Table 9. They show effects on total consumer leverage ratios measured several ways in columns (1)-(3) and effects on components in columns (4)-(11). These ratios are calculated as consumer debt aggregated at county level scaled by county income from the Bureau of Economic Analysis. We find consistent increases in subprime consumer leverage in both periods, albeit effects appear to be somewhat stronger in the second post-TARP period. Thus, bailouts did not only increase subprime consumer on an absolute basis, but it also increased subprime consumer leverage, which may suggest additional difficulties in repayment.

6. Analysis of the effects of PPP bailouts on consumer debt during COVID-19 crisis

Next, we analyze effects of the PPP bailouts during the COVID-19 crisis on debt of subprime consumers.

6.1 Methodology

We use a DIDID methodology, very similar to that employed for the TARP bailouts, but we replace the TARP indicator with the PPP indicator for above-median participation in the program. The PPP bailouts are interacted with a *Subprime* indicator and *Post-PPP* dummy covering the period of 2020:M4 to 2020:M9 as follows:

$$\begin{aligned}
 Y_{i,t} = & \delta_0 + \delta_1 PPP_{i,t} + \delta_2 \cdot Subprime_{i,t} + \delta_3 \cdot PPP_{i,t} \times Subprime_{i,t} + \\
 & \delta_4 \cdot PPP_{i,t} \times Post \circ PPP (2020' M4 - ' M9)_t + \delta_5 \cdot Subprime_{i,t} \times Post \circ PPP_t + \\
 & \boxed{\delta_6 \cdot PPP_{i,t} \times Subprime_{i,t} \times Post \circ PPP_t} + \\
 & \delta_7 \cdot Consumer\ Characteristics_{i,t} + \delta_8 \cdot Local\ Bank\ Characteristics_{i,t-4} + \\
 & \delta_9 \cdot Local\ Market\ Characteristics_{i,t-4} + \delta_{10} \cdot County\ FE_i + \delta_{11} \cdot YearQuarter_t + \varepsilon_{i,t}.
 \end{aligned} \tag{2}$$

where all of the other variables are as described above in the TARP model.

6.2 Results for the effects of PPP bank bailouts on total consumer debt

Table 10 Panel A shows results of our DIDID regressions looking at the impact of the PPP bailouts on subprime consumer debt. Unlike TARP bailouts, here the results consistently indicate that local markets with a higher proportion of PPP lenders are associated with a decline in debt in the subprime segment. The regression coefficients corresponding to the triple interactions, $PPP \times Subprime \times Post-PPP$, are consistently negative and significant at 1% level across all regression specifications for total consumer debt. Results are also moderately economically meaningful. We find a one-standard-deviation increase in PPP presences is associated with about a 3 percentage

points decline in subprime consumer debt after the PPP implementation.³⁵

These results are robust to different specifications of the model as well as definitions of the dependent variable. Our initial definition of PPP variable uses a radius of 10 miles around the consumer zip code. Changing the radius to 10, 25, 50 miles, or the county does not change our main finding. Dropping some or all banks' characteristics control variables from the regression also has very limited impact on the results. We also change how we calculate total debt by first including both private and public student debt in the calculation. Then we only include private student debt or remove all student debt on the third specification. We also include specifications with different fixed effects such as multidimensional County×Year-Quarter or control for county-level household income to account for stimulus checks to consumers during the crisis that may have boosted local income levels; however, this is less of a concern given that over 80% of adult American consumers received these. All of these do not materially impact our findings. The findings for the control variables are similar to those for the TARP analysis.

6.3 Results for the effects of bank bailouts on individual consumers debt portfolios

We also decompose the total debt into the different products and run a separate regression for each in Table 10 Panel B. The results suggest that a higher percentage of PPP banks in the consumer's market is primarily associated with decreased credit card debt to riskier subprime borrowers, but we also observe slightly higher private student debt.³⁶

7. Robustness tests for the PPP results

The identification concerns for TARP also apply to PPP bailouts, and thus, we conduct several tests to mitigate concerns of endogeneity, sample selection, and other econometrics issues.

7.1 Addressing endogeneity concerns using an instrumental variable analysis

We first address the potential endogeneity of our PPP variables. For example, banks with concentrations of small business borrowers with more subprime consumer employees may make

³⁵ To calculate the percent change in the dependent variable, we use the following formula: $\Delta y = 100 * (\exp^{\beta * (\text{stdv } PPP)} - 1)$. Focusing on Table 10, Panel A, column (1), a coefficient of -0.123 on the interaction term $PPP \times Post\ PPP \times Subprime (<580)$ suggests that, during *Post-PPP* (2020:M3-M9), total debt for subprime consumers decreased by about 3% ($= 100 * (\exp^{(-0.123) * (0.224)} - 1)$).

³⁶ Our findings for the PPP bailout effects on subprime consumer debt and subcomponents hold and have similar economic magnitudes also when using alternative more stringent fixed effects, such as *Zip Code* and *Year-Quarter* fixed effects or *Census Tract* and *Year-Quarter* fixed effects.

more PPP loans to these businesses, yielding a spurious relationship. We employ an instrumental variable (IV) analysis to isolate the causal impact of PPP on subprime consumer debt.

Prior research finds that banks' involvement and interactions with the Small Business Administration (SBA) via the 7(a) main SBA lending platform for small businesses in 2019 increased these banks' likelihood to participate and lend more via PPP in 2020 (e.g., Barraza, Rossi, and Yeager, 2020; Lopez and Speigel, 2021). Lenders that were already certified as SBA 7(a) banks prior to the launch of the PPP program were automatically eligible for the PPP and familiar with SBA processes, requiring no additional efforts for them to participate, whereas other lenders had to submit the SBA Lender Agreement (Form 3506) and also become familiar with the SBA processes. Thus, we use as an instrument a proxy for the intensity of a bank's lending interaction with the SBA prior to the COVID-19 crisis. This is $SBA_7(a)_2019$, the natural logarithm of one plus the total dollar amount of SBA loans a bank made via the SBA 7(a) lending program in 2019. It is reasonable to conceive that a bank's pre-pandemic interaction with SBA would not affect subprime consumer debt other than through the PPP program.

Given that the basis of the PPP variable is a dummy, we use a dummy endogenous variable model and follow a three-step approach as in Wooldridge (2002) procedure 18.4.1 that we also used for TARP. In the first stage, we use a bank-level probit model in which we regress the PPP indicator for above-median participation in the program on the SBA prior interaction instrument, and all bank controls from our main regression model to predict the probability of a bank being a PPP lender. We then aggregate the PPP binary fitted value from the first stage weighted by the banks' branches proportions in the 10-mile consumer zip code radius and use this variable as instrument for the final stage.³⁷

We report the first-stage results in Table A.2 of Appendix A, and the final-stage results for the IV specification in Table 11 Panel A. The first-stage results indicate that the instrument is positively related to TARP injections as hypothesized, and the first-stage F -test statistics suggest that the instrument is valid. The final stage IV coefficients corresponding to the triple DIDID

³⁷ We use the same Wooldridge (2002) procedure 18.4.1 for endogenous binary variables discussed for TARP. We employ a probit for predicting the probability of being a PPP lender and instrument our PPP variable by the weighted PPP binary fitted value and $PPP \times Subprime \times Post\ PPP$ by the product of the weighted PPP binary fitted value with the post-PPP period and the *Subprime* indicator. As indicated previously, this method is not the same as the forbidden regression, as we use obtained variables as instruments, and not as regressors.

variables of interest are negative and statistically significant at 1% level for total debt as well as credit cards, auto loans, student, and other consumer debt in the post-PPP period. The IV estimates are much larger in absolute value than the OLS estimates, consistent with strong average treatment effects in which 7(a) banks supplied much more PPP credit than others (e.g., Jiang, 2017).

7.2 Addressing sample selection concerns using the Heckman’s (1979) selection model

To mitigate potential selection bias, we employ Heckman’s (1979) two-step procedure. This approach controls for selection bias introduced by bank and firm choices about PPP by incorporating PPP decisions into the econometric estimation. The first step is the same probit model as the IV estimation. In the second stage, we include the self-selection parameter (*Inverse Mills Ratio*) estimated from the first stage weighted by the banks’ branches’ proportions in the 10-mile radius of the consumer zip code.

The second-stage results are reported in Table 11 Panel B. The coefficients on the *Inverse Mills Ratio* are generally not statistically significant with a few exceptions, so selection bias may not be a severe issue. The results continue to suggest that PPP bailouts are associated with statistically and economically significant decreases in subprime consumer debt.

7.3 Alternative *Subprime* measures

We test robustness of our main results for PPP when using two alternative proxies for *Subprime* and report the results in Table 12. We first redefine *Subprime* as an indicator equal to one for consumers with Equifax Risk Score below 620 in Panel A. We then address an additional concern. Credit scores may have been affected by the CARES Act restrictions for delinquency reporting to credit bureau during the COVID-19 crisis (e.g., Berger, Bouwman, Norden, Roman, Udell, and Wang, 2021). To address this, we redefine *Subprime* as an indicator equal to one if consumers had an average Equifax Risk Score below 580 in the pre-PPP / pre-CARES Act period and report this in Panel B. In both cases, we find that the DIDID term on total consumer debt remains negative and statistically significant and consistent with our main results. Effects on individual products also generally mimic our main results, except that sometimes student debt or mortgage debt also show a decline.

7.4 Addressing selection concerns using a falsification test and matched sample

In Table 13 Panels A and B, we also address concerns that alternative confounding forces that affect PPP banks could be related to our credit score cutoff for subprime and drive our results. As for TARP, we conducted two tests. First, we randomly assign individuals to subprime group,

maintaining the original statistical distribution and then rerun our regressions with all other variables unchanged. We find that the triple DID coefficients are all statistically insignificant, confirming that our results are not driven by alternative data or econometrics issues. Second, to reduce the selection bias caused by the potential non-random *Subprime* assignment, we also did a matched sample analysis based on propensity score probabilities, using a logistic regression. The propensity score is the probability of a consumer being in the subprime segment. Subprime consumers are matched to corresponding non-subprime counterparts based on the absolute difference in the propensity score and pairs with smallest difference are regarded as a matched pair and selected to be in the matched pair analysis sample. Using only the matched pair sample, we repeated the individual debt-level regression analysis. Our main results continue to hold.

7.5 Alternative PPP measures

Table 14 Panels A and B provide robustness checks using alternative PPP measures. Panel A defines a *PPP lender* as a dummy for whether a bank provided PPP loans in the local market (regardless of the percentile of PPP intensity, that is $PPP\ Loans/Total\ Loans > 0$). Panel B uses $PPP\ Loans/Total\ Loans$. Our results continue to hold, are even larger in magnitude, and statistically significant.

7.6 Dynamic effects of PPP bailouts

Table 15 examines the month-by-month dynamics of the relation between PPP bailouts and subprime consumer debt. In this table, we replace the DID term $PPP \times Post-PPP \times Subprime$ from equation (2) with interactions of the *PPP* with *Subprime* and with month dummies for each month after PPP commenced and until the end of our sample (April to September, denoted as ‘M4-‘M9) to examine the timing of the PPP effects on consumer debt. We find steady declines in total consumer debt in each of the months after PPP started, but these appear to be most pronounced in June and August 2020. Results are consistently driven by declines in credit card debt in all months and only in the first month also by a decline in HELOC debt.

7.7 PPP mechanisms investigation

In Table 16 Panels A and B, we conduct an additional analysis to help understand the mechanisms through which PPP bailouts may have decreased consumer debt and driven our main results. We again consider the same three potential mechanisms: 1) changes in credit supply; 2) changes in consumer credit consumption or utilization; and 3) changes in consumer repayments of debt. To

test these, we report results for several indicators of credit, utilization, and payments based on the anonymized CCP data as dependent variables. In Panel A, we provide results for consumer credit and utilization, while in Panel B, we report results for consumer payment rates.

The results suggest that, unlike TARP, PPP did not affect consumer debt through changes in credit, but rather we observe a somewhat lower utilization rate for credit cards. We also see potentially higher repayment rates overall for subprime consumers, primarily driven by repayments in credit cards and auto loans, likely the most important loans for subprime consumers in a crisis.

Results are economically significant. Looking at Panel A column (5) for credit cards, we find that the average subprime consumer reduced credit card utilization rate due to PPP bailouts by about 0.4 percentage points after PPP bailouts started.³⁸ Looking at Panel B, there is an average increase in total debt repayment rate by 0.4 percentage points in column (1), and this is about 0.2 percentage points increase in repayment for credit cards and 0.6 percentage points increase in auto loans in columns (5) and (6), respectively. However, these results may be understated as the payment information is imperfect in the anonymized CCP dataset.

7.8 Additional evidence from full anonymized CCP sample aggregated at county level

Finally, we conduct additional tests in which we use the full anonymized CCP population aggregated at the county level, analogous to the TARP analysis. Results are presented in Table 17. They show effects on total consumer leverage ratios and components in columns (1)-(11). We find consistent decreases in subprime consumer leverage after the PPP bailouts implementation. Thus, PPP bailouts did not only decrease subprime consumer on an absolute basis, but also decreased subprime consumer leverage, suggesting potentially positive macroeconomic consequences. The results by products find decreases in leverage across several credit products, including mortgages, home equity, credit cards, and other consumer loans as contributing to the overall effects.

8. Conclusions and policy implications

High levels of subprime consumer debt are associated with problems for low-income households who have difficulties climbing out their financial holes, as well as with broad financial and

³⁸ These economic magnitudes are calculated in the same manner as those for consumer debt in Section 4.2.

economic difficulties. We investigate the roles of two very large U.S. government bailouts – TARP and PPP – on this debt. We employ anonymized credit-bureau microdata from the FRBNY Consumer Credit Panel/Equifax Data (CCP), which has rich information on individual consumer debt, credit scores, and other attributes. We employ over 11 million observations – more than 5.5 million observations each for analyses of the two crises. We match these data with regulatory datasets on banks in each of the consumers’ individual 10-mile radius local markets, as well as other bailout and local market information. We use TARP and PPP bailouts as quasi-natural experiments to help with causal interpretations. Both bailouts provide relatively exogenous financial shocks, but we include additional analyses to address remaining identification concerns.

We find strong evidence that subprime consumers with higher proportions of TARP banks in their local markets *increased* debt burdens following these bailouts, and that these increases were large and long lasting. We find that a one-standard-deviation increase in the presence of TARP bailouts is associated with 17 percentage points higher subprime debt in the short-term period after TARP from 2009:Q1-2012:Q4, and another 14 percentage points increase in the long-term period 2013:Q1-2016:Q4. The increases in debt were primarily driven by mortgages, and to a lesser extent also by credit card and student loans. These results are robust to a number of identification checks. Additional analyses suggest that subprime consumers not only increased their debt on the absolute basis but also on a relative to income basis.

Our PPP results suggest very different consequences. Specifically, we find that PPP bailouts are associated with moderately *reduced* subprime consumer debt by about 3 percentage points. Given the data limitations, we measure short-term effects only. Again, the findings are robust to a good number of identification checks, including an instrumental variable analysis and sample selection estimations. Both the TARP and PPP results are robust to using fully aggregated anonymized CCP population at county level instead of individual level.

While we cannot directly compare the bailouts, which are very different and occurred under disparate circumstances, the structures of the programs and the strings attached to them provide some possible explanations of the stark differences in results. The PPP likely resulted in much bigger positive income shocks for subprime consumers that helped them repay their debt. The PPP dollars were much greater and virtually all of the funds went to small businesses, mostly to payroll. These likely benefited low-income employees in subprime consumer households and resulted in

reduced demand for subprime consumer debt. In contrast, TARP funds were not lent out in full, were more than fully repaid to the U.S. Treasury, and some of the loan dollars went to large businesses that may less often employ low-wage subprime consumers. Additionally, the extant research suggests that TARP resulted in significant credit shocks to subprime borrowers, with increased credit supply to these borrowers. In contrast, any credit shocks to consumers from the PPP are likely quite small. Thus, it may be that the positive credit shocks to the subprime consumers from TARP may have allowed these consumers to borrow more, whereas the larger positive income shocks for subprime consumer households from the PPP may have helped these households reduce their debt. In effect, it appears that the effects of increased subprime consumer debt supply from TARP may have dominated the outcomes during the earlier period, whereas the effects of reduced subprime consumer debt demand from the income shocks from PPP may have dominated during the later period.

Our findings suggest some potentially narrow as well as broad policy implications. At the narrow end, our findings suggest a possible previously unknown social cost of TARP bailouts to add to the long list of costs and benefits of these bailouts. The results also suggest a possible benefit of PPP bailouts, which has received less study.

In terms of broad policy implications, it seems that the differences in program structures and the nature of strings attached may have played outsized roles in the social consequences. The mandate that PPP funds be allocated to small businesses with most of funds to payroll, as opposed to only restricting benefits to executives and shareholder payouts under TARP may provide policy guidance for future bailouts.

Finally, our findings have implications for the more general research literatures on both bailouts and consumer debt. To our knowledge, there are no TARP, PPP, or other bailout studies on the effects of bailouts on consumer debt. There is also very little in the way of consumer debt literature using quasi-natural experiments with relatively exogenous shocks for identification. We encourage additional research using consumer debt generally and subprime consumer debt specifically using rich data sources and exogenous shocks such as those employed here.

References

- Acharya, V.V. and Yorulmazer, T., 2007. Too many to fail—An analysis of time-inconsistency in bank closure policies. *Journal of Financial Intermediation*, 16(1), pp.1-31.
- Agarwal, S., Chomsisengphet, S., Mahoney, N. and Stroebel, J., 2018. Do banks pass through credit expansions to consumers who want to borrow?. *Quarterly Journal of Economics*, 133(1), pp.129-190.
- Agarwal, S. and Qian, W., 2014. Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in Singapore. *American Economic Review*, 104(12), pp. 4205-30.
- Agarwal, S. and Zhang, Y., 2018. Effects of government bailouts on mortgage modification. *Journal of Banking and Finance*, 93, pp.54-70.
- Akey, P., Heimer, R.Z. and Lewellen, S., 2021. Politicizing consumer credit. *Journal of Financial Economics*, 139(2), pp.627-655.
- Angrist, J. D., Pischke, J-S., 2009. Mostly harmless econometrics. Princeton University Press, Princeton, N.J.
- Atkins, R., Cook, L.D. and Seamans, R., 2021. Discrimination in lending? Evidence from the Paycheck Protection Program. New York University Working Paper.
- Autor, D., Cho, D., Crane, L., Goldar, M., Lutz, B., Montes, J., Peterman, W., Ratner, D., Villar, D., and Yildirmaz, A. and 2020, November. An evaluation of the Paycheck Protection Program using administrative payroll microdata. MIT Working Paper.
- Balyuk, T., Prabhala, N.R. and Puri, M., 2021. Small bank financing and funding hesitancy in a crisis: Evidence from the Paycheck Protection Program. Duke University Working Paper.
- Barraza, S., Rossi, M. and Yeager, T.J., 2020. The short-term effect of the Paycheck Protection Program on unemployment. Universidad de San Andrés Working Paper.
- Bartik, A.W., Cullen, Z.B., Glaeser, E.L., Luca, M., Stanton, C.T. and Sunderam, A., 2020. The targeting and impact of Paycheck Protection Program loans to small businesses. University of Illinois at Urbana-Champaign Working Paper.
- Bartlett, R.P. and Morse, A., 2020. Small business survival capabilities and policy effectiveness: Evidence from Oakland. University of California at Berkeley Working Paper.
- Bayazitova, D. and Shivdasani, A., 2012. Assessing TARP. *Review of Financial Studies*, 25(2), pp. 377-407.
- Beck, T., Degryse, H., De Haas, R. and Van Horen, N., 2018. When arm's length is too far: Relationship banking over the credit cycle. *Journal of Financial Economics*, 127(1), pp.174-196.
- Berger, A.N., Black, L., Bouwman, C., and Dlugosz, J., 2017. Bank loan supply responses to Federal Reserve emergency liquidity facilities. *Journal of Financial Intermediation*, 32, pp.1-15.
- Berger, A.N. and Bouwman, C.H., 2013. How does capital affect bank performance during financial crises?. *Journal of Financial Economics*, 109(1), pp.146-176.
- Berger, A.N., Bouwman, C.H. and Kim, D., 2017. Small bank comparative advantages in alleviating financial constraints and providing liquidity insurance over time. *Review of Financial Studies*, 30(10), pp.3416-3454.

- Berger, A.N., Bouwman, C.H., Norden, L., Roman, R.A., Udell, G.F. and Wang, T., 2021. Piercing through opacity: Relationships and credit card lending to consumers and small businesses during normal times and the COVID-19 Crisis. Federal Reserve Bank of Philadelphia Working Paper.
- Berger, A.N., Cerqueiro, G. and Penas, M.F., 2015. Market size structure and small business lending: Are crisis times different from normal times?. *Review of Finance*, 19(5), pp.1965-1995.
- Berger, A.N., and Demirgüç-Kunt, A., 2021. Banking research in the time of COVID-19. University of South Carolina Working paper.
- Berger, A.N., Makaew, T. and Roman, R.A., 2019. Do business borrowers benefit from bank bailouts?: The effects of TARP on loan contract terms. *Financial Management*, 48(2), pp.575-639.
- Berger, A.N. and Roman, R.A., 2015. Did TARP banks get competitive advantages?. *Journal of Financial and Quantitative Analysis*, 50(6), pp.1199-1236.
- Berger, A.N. and Roman, R.A., 2017. Did saving Wall Street really save Main Street? The real effects of TARP on local economic conditions. *Journal of Financial and Quantitative Analysis*, 52(5), pp.1827-1867.
- Berger, A.N. and Roman, R.A., 2020. TARP and other bank bailouts and bail-ins around the world: Connecting Wall Street, Main Street, and the financial system. Academic Press.
- Berger, A.N., Roman, R.A. and Sedunov, J., 2020. Did TARP reduce or increase systemic risk? The effects of government aid on financial system stability. *Journal of Financial Intermediation*, 43, p.100810.
- Bernanke, B., 2018. Financial Panic and Credit Disruptions in the 2007-2009 Crisis. The Brookings Institution Working Paper.
- Bhutta, N., 2011. The community reinvestment act and mortgage lending to lower income borrowers and neighborhoods. *Journal of Law and Economics*, 54(4), pp.953-983.
- Bhutta, N., Dokko, J. and Shan, H., 2017. Consumer ruthlessness and mortgage default during the 2007 to 2009 housing bust. *Journal of Finance*, 72(6), pp.2433-2466.
- Black, L.K. and Hazelwood, L.N., 2013. The effect of TARP on bank risk-taking. *Journal of Financial Stability*, 9(4), pp.790-803.
- Brown, J., 2021. Response of consumer debt to income shocks: The case of energy booms and busts. *Journal of Money, Credit, and Banking*.
- Brown, M., Grigsby, J., van der Klaauw, W., Wen, J. and Zafar, B., 2016. Financial education and the debt behavior of the young. *Review of Financial Studies*, 29(9), pp.2490-2522.
- Bureau of Labor Statistics, 2020, Unemployment rate rises to record high 14.7 percent in April 2020, The Economics Daily, at <https://www.bls.gov/opub/ted/2020/unemployment-rate-rises-to-record-high-14-point-7-percent-in-april-2020.htm>.
- Campbell, J. Y., 2006, Household Finance, *Journal of Finance*, 61, 1553-1604.
- Chavaz, M. and Rose, A.K., 2019. Political borders and bank lending in post-crisis America. *Review of Finance*, 23(5), pp.935-959.
- Chetty, R., Friedman, J., Hendren, N. and Stepner, M., 2020. The economic impacts of COVID-19: Evidence from a new public database built from private sector data. Opportunity Insights Working Paper.

- Chodorow-Reich, G., Darmouni, O., Luck, S., and Plosser, M.C., Forthcoming. Bank liquidity provision across the firm size distribution. *Journal of Financial Economics*.
- Chu, Y., Zhang, D. and Zhao, Y.E., 2019. Bank capital and lending: Evidence from syndicated loans. *Journal of Financial and Quantitative Analysis*, 54(2), pp. 667-694.
- Cordella, T. and Yeyati, E.L., 2003. Bank bailouts: moral hazard vs. value effect. *Journal of Financial Intermediation*, 12(4), pp.300-330.
- Debelle, G., 2004. Household debt and the macroeconomy. *BIS Quarterly Review*, March .
- Demirgüç-Kunt, A. and Detragiache, E., 1997. The determinants of banking crises-evidence from developing and developed countries. IMF Working Paper.
- Demyanyk, Y. and Loutskina, E., 2016. Mortgage companies and regulatory arbitrage. *Journal of Financial Economics*, 122(2), pp.328-351.
- Demyanyk, Y. and Van Hemert, O., 2011. Understanding the subprime mortgage crisis. *Review of Financial Studies*, 24(6), pp.1848-1880.
- Duchin, R. and Sosyura, D., 2014. Safer ratios, riskier portfolios: Banks' response to government aid. *Journal of Financial Economics*, 113(1), pp.1-28.
- Eggertsson, G.B. and Krugman, P., 2012. Debt, deleveraging, and the liquidity trap: A Fisher-Minsky-Koo approach. *Quarterly Journal of Economics*, 127(3), pp.1469-1513.
- Erel, I. and Liebersohn, J., 2020. Does FinTech substitute for banks? Evidence from the Paycheck Protection Program. Ohio State University Working Paper.
- Flanagan, T. and Purnanandam, A., 2021. Did banks pay fair returns to taxpayers on TARP?. University of Michigan Working Paper.
- Foote, C.L., Loewenstein, L. and Willen, P.S., 2020. Cross-sectional patterns of mortgage debt during the housing boom: evidence and implications. Federal Reserve Bank of Boston Working paper.
- Granja, J., Makridis, C., Yannelis, C. and Zwick, E., 2020. Did the Paycheck Protection Program hit the target?. University of Chicago Working Paper.
- Gropp, R., Hakenes, H. and Schnabel, I., 2011. Competition, risk-shifting, and public bail-out policies. *Review of Financial Studies*, 24(6), pp.2084-2120.
- Guerrieri, V. and Lorenzoni, G., 2017. Credit crises, precautionary savings, and the liquidity trap. *Quarterly Journal of Economics*, 132(3), pp.1427-1467.
- Heckman, J.J., 1979. Sample selection bias as a specification error. *Econometrica: Journal of the Econometric Society*, pp.153-161.
- Hicks, J.R., 1935. Annual survey of economic theory: the theory of monopoly. *Econometrica: Journal of the Econometric Society*, pp.1-20.
- Hubbard, R.G. and Strain, M.R., 2020. Has the Paycheck Protection Program succeeded? Columbia University Working Paper.
- Humphries, J.E., Neilson, C.A. and Ulyssea, G., 2020. Information frictions and access to the Paycheck Protection Program. *Journal of Public Economics*, 190, p.104244.
- James, C.M., Lu, J., and Sun, Y., 2021. Time is money: Real effects of relationship lending: Evidence from community bank lending in the Paycheck Protection Program. University of Florida Working Paper.
- Jang, K.Y., 2017. The effect of TARP on the propagation of real estate shocks: Evidence from

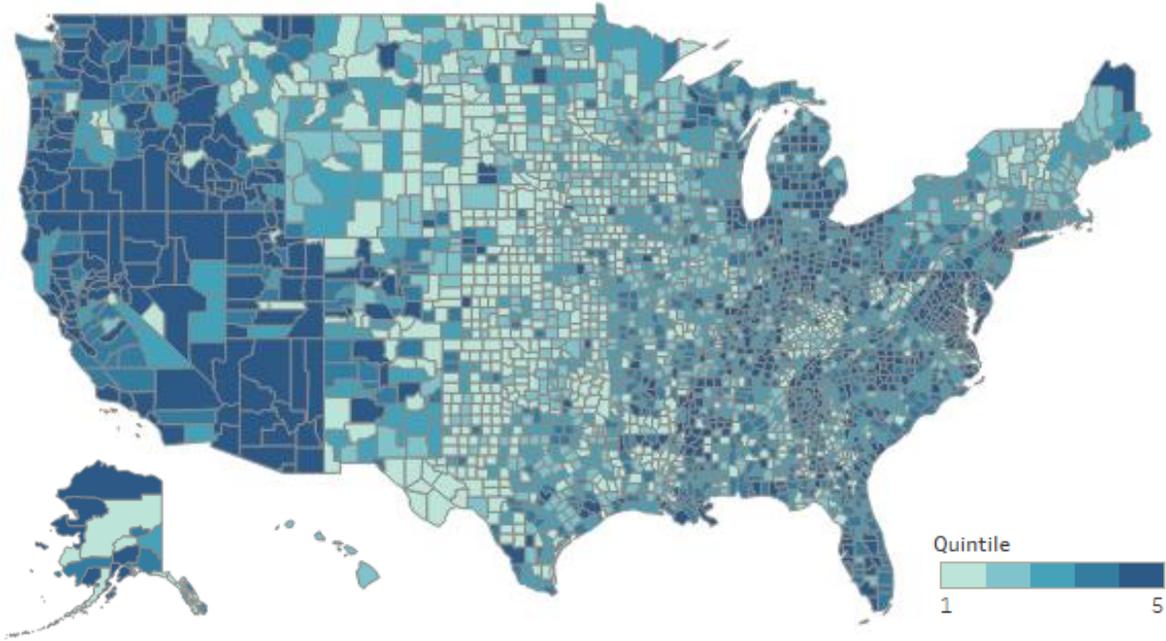
- geographically diversified banks. *Journal of Banking and Finance*, 83, pp.173-192.
- Jappelli, T. and Pistaferri, L., 2014. Fiscal policy and MPC heterogeneity. *American Economic Journal: Macroeconomics*, 6(4), pp.107-36.
- Jiang, W., 2017. Have instrumental variables brought us closer to the truth. *Review of Corporate Finance Studies*, 6, 127-140.
- Karakaplan, M., Forthcoming. This time is really different: The multiplier effect of the Paycheck Protection Program (PPP) on small business bank loans. *Journal of Banking and Finance*.
- Kashyap, A., Rajan, R. and Stein, J., 2008. Rethinking capital regulation. Maintaining stability in a changing financial system. Paper prepared for Federal Reserve Bank of Kansas City symposium on “Maintaining stability in a changing financial system”, Jackson Hole, Wyoming, August 21-23, 2008.
- Keeley, M.C., 1990. Deposit insurance, risk, and market power in banking. *American Economic Review*, pp.1183-1200.
- Keys, B.J., Mukherjee, T., Seru, A. and Vig, V., 2010. Did securitization lead to lax screening? Evidence from subprime loans. *Quarterly journal of economics*, 125(1), pp.307-362.
- Laeven, M.L. and Valencia, M.F., 2018. Systemic banking crises revisited. IMF Working Paper.
- Lee, D. and van der Klaauw, W., 2010. An introduction to the FRBNY Consumer Credit Panel. FRB of New York Staff Report, (479).
- Li, L., 2013. TARP funds distribution and bank loan supply. *Journal of Banking and Finance*, 37(12), pp.4777-4792.
- Li, L. and Strahan, P., Forthcoming. Who supplies PPP loans (and does it matter)? Banks, relationships and the COVID Crisis. *Journal of Financial and Quantitative Analysis*.
- Lopez, J.A. and Spiegel, M.M., 2021. Small business lending under the PPP and PPPLF programs. Federal Reserve Bank of San Francisco Working Paper.
- Mester, L.J., 2015. Consumer credit: Suggested directions for policy-relevant research. Remarks at the Conference on Regulating Consumer Credit, Philadelphia, PA, at <https://www.clevelandfed.org/newsroom%20and%20events/speeches/sp%2020150501%20consumer%20credit%20suggested%20directions>.
- Mian, A. and Sufi, A., 2011. House prices, home equity-based borrowing, and the US household leverage crisis. *American Economic Review*, 101(5), pp.2132-56.
- Mian, A., Rao, K. and Sufi, A., 2013. Household balance sheets, consumption, and the economic slump. *Quarterly Journal of Economics*, 128(4), pp.1687-1726.
- Mian, A. and A. Sufi, 2015. Household debt and defaults from 2000 to 2010: Facts from credit bureau data. University of Chicago Working Paper.
- Montgomery, H. and Takahashi, Y., 2014. The economic consequences of the TARP: The effectiveness of bank recapitalization policies in the US. *Japan and the World Economy*, 32, pp.49-64.
- Mücke, C., Pelizzon, L., Pezone, V. and Thakor, A.V., 2021. The Carrot and the Stick: Bank Bailouts and the Disciplining Role of Board Appointments. University of Washington in St. Louis Working Paper.
- Purnanandam, A., 2011. Originate-to-distribute model and the subprime mortgage crisis. *Review of Financial Studies*, 24(6), pp.1881-1915.

- Rajan, U., Seru, A. and Vig, V., 2015. The failure of models that predict failure: Distance, incentives, and defaults. *Journal of Financial Economics*, 115(2), pp.237-260.
- Reinhart, C.M. and Rogoff, K.S., 2009. This time is different: Eight centuries of financial folly. Princeton University Press.
- Schularick, M. and Taylor, A.M., 2012. Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. *American Economic Review*, 102(2), pp.1029-61.
- Tai, M., 2017. House prices and the allocation of consumer credit. Working Paper.
- Thakor, A.V., 2015a. The financial crisis of 2007–2009: Why did it happen and what did we learn?. *Review of Corporate Finance Studies*, 4(2), pp.155-205.
- Thakor, A., 2015b. Lending booms, smart bankers, and financial crises. *American Economic Review*, 105(5), pp.305-09.
- Thakor, A.V., 2016. The highs and the lows: A theory of credit risk assessment and pricing through the business cycle. *Journal of Financial Intermediation*, 25, pp.1-29.
- Wooldridge, J. M. 2002. Econometric analysis of cross section and panel data. Cambridge, MA: MIT Press.

Figure 1: Weighted Proportion of Bailouts by U.S. Counties (Heat Map)

This figure presents the geographical distribution of the TARP and PPP bailouts across the counties in the U.S. in Panels A and B, respectively. We show the distribution in terms of the average weighted proportion of TARP and PPP banks for each county based on their FDIC proportions of bank branches over 2008:Q4-2009:Q4 for TARP and 2019:Q2-2020:M9 for PPP. The distribution is based on whether banks received TARP bailout funds at any time in 2008 or 2009 or whether banks provided PPP loans any time over 2019:Q2-2020:M9. The figure presents five categories, which were obtained based on an equal quintiles' methodology, with darker colors representing more TARP bank participation.

Panel A: TARP Bailouts (participant banks in the TARP program)



Panel B: PPP Bailouts (PPP participant banks \geq 50th percentile in PPP Loans/Total Loans)

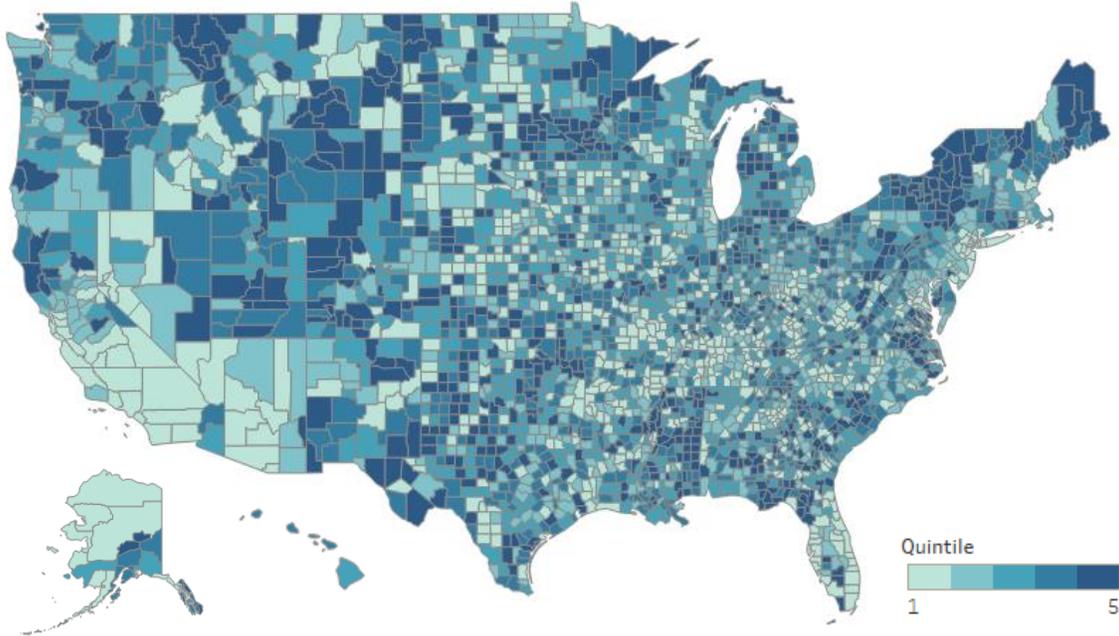


Table 1: Variable Definitions, Sources, and Summary Statistics

This table provides definitions and data sources in Panel A, and summary statistics in Panel B for the variables used in our TARP analysis and Panel C for the variables used in our PPP analysis. The table uses a 1% random sample for the TARP analysis and a 5% random sample for the PPP analysis from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period for the TARP analysis is 2001:Q1–2016:Q4. The sample period for the PPP analysis is 2019:Q2–2020:M9. All variables using dollar amounts are expressed in real 2016:Q4 dollars for the TARP analysis and in real 2020:Q3 dollars for the PPP analysis, both using the implicit GDP price deflator.

Panel A: Variable Definitions and Sources for the TARP and PPP Analyses

Variable	Definition	Sources
<u>Bailout Variables</u>		
TARP (10 mile radius)	Weighted proportion of TARP banks in the 10-mile radius of the consumer zip code.	U.S. Treasury, Call Reports, SoD
Post-TARP1 ('09-'12)	Indicator equal to 1 from 2009:Q1 to 2012:Q4, and 0 otherwise.	CCP
Post-TARP2 ('13-'16)	Indicator equal to 1 from 2013:Q1 to 2016:Q4, and 0 otherwise.	CCP
PPP (10-mile radius)	Weighted proportion of PPP banks ($\geq 50^{\text{th}}$ pctl in PPP Loans/Total Loans over 2020:Q2-2020:Q3) in the 10-mile radius of the consumer zip code.	Call Reports, SoD
PPP2 (10-mile radius)	Weighted proportion of PPP banks (PPP Loans/Total Loans > 0 over 2020:Q2-2020:Q3) in the 10-mile radius of the consumer zip code.	
PPP3 (PPP Loans/Total Loans, 10-mile radius)	Weighted proportion of the bank PPP loans ratio (PPP Loans/Total Loans) in the 10-mile radius of the consumer zip code.	
Post-PPP (2020 'M4-'M9)	Indicator equal to 1 from April 2020 to September 2020, and 0 otherwise.	CCP
<u>Key Dependent Variables:</u>		
<u>Consumer Debt</u>		
Ln (1+Total Consumer Debt)	The natural logarithm of one plus total consumer debt.	CCP
Ln (1+Total Consumer Debt2)	The natural logarithm of one plus total consumer debt, including private student loans.	CCP
Ln (1+ Mortgage Debt)	The natural logarithm of one plus mortgage debt.	CCP
Ln (1+ HELOAN Debt)	The natural logarithm of one plus HELOAN debt.	CCP
Ln (1+ HELOC Debt)	The natural logarithm of one plus HELOC debt.	CCP
Ln (1+ Card Debt)	The natural logarithm of one plus credit card debt.	CCP
Ln (1+ Auto Debt)	The natural logarithm of one plus auto debt.	CCP
Ln (1+ Student Debt)	The natural logarithm of one plus student debt.	CCP
Ln (1+ Private Student Debt)	The natural logarithm of one plus private student debt.	CCP
Ln (1+Other Consumer Debt)	The natural logarithm of one plus other consumer debt.	CCP
<u>Consumer Characteristics</u>		
Equifax Risk Score	Equifax Risk Score of the consumer taking values from 300 to 900, with higher values indicating higher credit worthiness.	CCP
Subprime (<580)	Indicator equal to one if Equifax Risk Score is 580 or less.	CCP
Consumer Age	Consumer age in years based on the birth year.	CCP
Joint Account	Indicator for accounts with joint ownership.	CCP
Ln (1+ No. Credit Inquiries last 12mos)	The natural logarithm of one plus the total number of credit inquiries by the consumer in the last 12 months.	CCP
<u>Bank Characteristics (lagged 4 quarters)</u>		
Capital Adequacy	The weighted proportion of the bank capitalization ratio (capital/gross total assets (GTA)) in the consumer local market.	Call Reports, SoD
Asset Quality	The weighted proportion of the bank asset quality (nonperforming loans/total loans) in the consumer local market.	Call Reports, SoD
Management Quality	The weighted proportion of the bank management quality (negative of the number of regulatory enforcement actions against the bank or its executive) in the consumer local market.	Call Reports, SoD
Earnings	The weighted proportion of the bank ROA (annualized net income/GTA) in the consumer local market.	Call Reports, SoD
Liquidity	The weighted proportion of the bank liquidity (bank cash to deposits) in the consumer local market.	Call Reports, SoD
Sensitivity to Market Risk	The weighted proportion of the bank sensitivity to interest rate risk (ratio of the absolute difference (gap) between short-term assets and short-term liabilities to GTA) in the consumer local market.	Call Reports, SoD
Bank Size	The weighted proportion of the bank size in the consumer local market. Bank size is the natural logarithm value of GTA.	Call Reports, SoD
Discount Window Participant	The weighted proportion of banks receiving Discount Window loans funding during the crisis in the consumer local market.	Berger, Black, Bouwman, Dlugosz (2017)
Term Auction Facility Participant	The weighted proportion of banks receiving Term Auction Facility (TAF) funding during the crisis in the consumer local market.	Berger, Black, Bouwman, Dlugosz (2017)

FDIC TAGP Participant	The weighted proportion of banks in the FDIC Temporary Liquidity Guarantee program (TAGP) during the crisis in the consumer local market.	SNL Financial/S&P Global Market Intelligence
FDIC TDGP Participant	The weighted proportion of banks in the FDIC Temporary Debt Guarantee program (TDGP) during the crisis in the consumer local market.	SNL Financial/S&P Global Market Intelligence
SBLF Participant	The weighted proportion of banks in the Small Business Guarantee Fund (SBLF) program during the crisis in the consumer local market.	SNL Financial/S&P Global Market Intelligence
FHLB Member	The weighted proportion of Federal Home Loan Bank (FHLB) member banks during the crisis in the consumer local market.	SNL Financial/S&P Global Market Intelligence

County-Level Characteristics (lagged based on data availability)

County Unemployment Rate (UR)	Quarterly unemployment rate in the local market, lagged 4 quarters.	US Census Bureau/ Haver Analytics
County HPI Rate	Quarterly House Price Index (HPI) in the consumer local market, lagged 4 quarters.	CoreLogic Solutions
Forbearance Rate Mortgage	Mortgage forbearance rate in the consumer local market, lagged 1 quarter/1 month.	CCP
Forbearance Rate Home Equity	Home equity forbearance rate in the consumer local market, lagged 1 quarter/1 month.	CCP
Forbearance Rate Credit Card	Credit card forbearance rate in the consumer local market, lagged 1 quarter/1 month.	CCP
Forbearance Rate Auto	Auto forbearance rate in the consumer local market, lagged 1 quarter/1 month.	CCP

Panel B: Summary Statistics for the TARP Analysis (2001:Q1–2016:Q4)

Variable	mean	stdv	min	max	N
<u>Bailout Variables</u>					
TARP (10-mile radius)	0.523	0.243	0.000	1.000	5,647,134
Post-TARP1 ('09-'12)	0.250	0.433	0.000	1.000	5,647,134
Post-TARP2 ('13-'16)	0.260	0.438	0.000	1.000	5,647,134
<u>Key Dependent Variables: Consumer Debt</u>					
Ln (1+Total Consumer Debt)	8.009	4.098	0.000	16.390	5,647,134
Ln (1+Total Consumer Debt2)	7.657	4.247	0.000	16.390	5,647,134
Ln (1+ Mortgage Debt)	3.387	5.220	0.000	16.322	5,647,134
Ln (1+ HELOAN Debt)	0.425	1.995	0.000	14.960	5,647,134
Ln (1+ HELOC Debt)	0.656	2.485	0.000	15.546	5,647,134
Ln (1+ Card Debt)	4.764	3.905	0.000	14.779	5,647,134
Ln (1+ Auto Debt)	2.842	4.263	0.000	15.237	5,647,134
Ln (1+ Student Debt)	1.324	3.305	0.000	14.263	5,647,134
Ln (1+ Private Student Debt)	0.176	1.258	0.000	13.124	5,647,134
Ln (1+Other Consumer Debt)	2.856	3.651	0.000	16.106	5,647,134
<u>Consumer Characteristics</u>					
Equifax Risk Score	690.101	107.968	300.000	845.000	5,647,134
Subprime (<580)	0.179	0.384	0.000	1.000	5,647,134
Consumer Age	49.096	18.364	18.000	115.000	5,647,134
Joint Account	0.429	0.495	0.000	1.000	5,647,134
Ln (1+ No. Credit Inquiries last 12mos)	0.755	0.693	0.000	4.454	5,647,134
<u>Bank Characteristics (lagged 4 quarters)</u>					
Capital Adequacy	0.103	0.013	0.009	0.533	5,647,134
Asset Quality	0.020	0.016	0.000	0.371	5,647,134
Management Quality	-2.193	2.672	-65.000	0.000	5,647,134
Earnings	0.009	0.012	-4.473	0.361	5,647,134
Liquidity	0.085	0.280	0.001	71.410	5,647,134
Sensitivity to Market Risk	0.138	0.060	0.000	0.667	5,647,134
Bank Size	18.871	1.761	7.655	21.539	5,647,134
Discount Window Participant	0.717	0.228	0.000	1.000	5,647,134
Term Auction Facility Participant	0.535	0.248	0.000	1.000	5,647,134
FDIC TAGP Participant	0.356	0.213	0.000	1.000	5,647,134
FDIC TDGP Participant	0.629	0.207	0.000	1.000	5,647,134
SBLF Participant	0.020	0.054	0.000	1.000	5,647,134
FHLB Member	0.037	0.073	0.000	1.000	5,647,134
<u>County-Level Characteristics (lagged 4 quarters)</u>					
County Unemployment Rate (UR)	6.352	2.538	1.000	31.533	5,647,134
County HPI Rate	143.402	37.891	47.941	361.807	5,647,134

Panel C: Summary Statistics for the PPP Analysis (2019:Q2-2019:Q4 & 2020:M1-2020:M9)

Variable	mean	stdv	min	max	N
<u>Bailout Variables</u>					
PPP (10-mile radius)	0.437	0.224	0.000	1.000	5,518,082
PPP2 (10-mile radius)	0.962	0.071	0.000	1.000	5,518,082
PPP3 (Loans/Total Loans in 10-mile radius)	0.063	0.021	0.000	0.482	5,518,082
Post-PPP (2020 'M4-'M9)	0.500	0.500	0.000	1.000	5,518,082
<u>Key Dependent Variables: Consumer Debt</u>					
Ln (1+Total Consumer Debt)	8.422	3.817	0.000	16.300	5,518,082
Ln (1+Total Consumer Debt2)	7.965	4.021	0.000	16.300	5,518,082
Ln (1+ Mortgage Debt)	3.305	5.224	0.000	16.133	5,518,082
Ln (1+ HELOAN Debt)	0.219	1.436	0.000	14.201	5,518,082
Ln (1+ HELOC Debt)	0.441	2.046	0.000	15.727	5,518,082
Ln (1+ Card Debt)	5.010	3.767	0.000	14.637	5,518,082
Ln (1+ Auto Debt)	3.483	4.508	0.000	14.867	5,518,082
Ln (1+ Student Debt)	1.796	3.815	0.000	13.788	5,518,082
Ln (1+ Private Student Debt)	0.265	1.549	0.000	13.788	5,518,082
Ln (1+Other Consumer Debt)	2.584	3.619	0.000	15.140	5,518,082
<u>Consumer Characteristics</u>					
Equifax Risk Score	710.399	104.626	300.000	846.000	5,518,082
Subprime (<580)	0.137	0.343	0.000	1.000	5,518,082
Consumer Age	50.885	18.758	18.000	119.000	5,518,082
Joint Account	0.384	0.486	0.000	1.000	5,518,082
Ln (1+ No. Credit Inquiries last 12mos)	0.536	0.608	0.000	4.277	5,518,082
<u>Bank Characteristics (lagged 4 quarters)</u>					
Capital Adequacy	0.117	0.009	0.010	0.347	5,518,082
Asset Quality	0.008	0.003	0.000	0.191	5,518,082
Management Quality	-0.877	0.804	-10.000	0.000	5,518,082
Earnings	0.013	0.003	-0.156	0.090	5,518,082
Liquidity	0.249	0.047	0.012	0.927	5,518,082
Sensitivity to Market Risk	0.104	0.038	0.000	0.727	5,518,082
Bank Size	17.194	1.770	8.940	21.607	5,518,082
<u>County Characteristics (lagged 4 quarters or 1 quarter)</u>					
County Unemployment Rate (UR)	3.825	1.158	1.167	21.433	5,518,082
County HPI Rate	197.572	52.240	82.020	395.531	5,518,082
Forbearance Rate Mortgage	0.027	0.038	0.000	1.000	5,518,082
Forbearance Rate Home Equity	0.009	0.027	0.000	1.000	5,518,082
Forbearance Rate Credit Card	0.001	0.004	0.000	0.194	5,518,082
Forbearance Rate Auto	0.025	0.034	0.000	1.000	5,518,082

Table 2: Effects of TARP Bailouts on Subprime Consumer Debt – Main Evidence

This table reports difference-in-difference-in-difference (DIDID) regression estimates for analyzing the effects of TARP bailouts on debt of subprime consumers (Equifax Risk Score < 580) relative to other consumers. The table uses a 1% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period is 2001:Q1–2016:Q4. Panel A presents main results in column (1), while showing various robustness tests in columns (2)–(14). These robustness tests are: alternative dependent variables for total consumer debt, which use only private student debt or exclude student debt in columns (2)–(3), including only consumers who exist in both pre- and post-TARP periods in column (4), clustering by county and consumer in column (5), using high-dimensional County×Time fixed effects in column (6), excluding various controls in columns (7)–(9), alternative post-TARP period in column (10), and alternative radius/area close to the consumer zip code: 5, 25, or 50-mile radius, or the county of the consumer in columns (11)–(14). Panel B decomposes total consumer debt into its subcomponents. The dependent variables are $Ln(1+Total\ Consumer\ Debt)$, the natural logarithm of one plus total consumer debt in Panel A, and $Ln(1+Total\ Consumer\ Debt)$, $Ln(1+Total\ Mortgage\ Debt)$, $Ln(1+Total\ HELOAN\ Debt)$, $Ln(1+Total\ HELOC\ Debt)$, $Ln(1+Total\ Card\ Debt)$, $Ln(1+Total\ Auto\ Debt)$, $Ln(1+Total\ Student\ Debt)$, $Ln(1+Total\ Private\ Student\ Debt)$, and $Ln(1+Other\ Consumer\ Debt)$, representing the natural logarithm of one plus total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer). *TARP* is the weighted proportion of banks receiving TARP bailouts in the 10-mile radius of the consumer zip code. *Subprime* is an indicator that equals one if the consumer has an Equifax Risk Score below 580. *Post-TARP1* and *Post-TARP2* are indicators equal to one in 2009–2012 and 2013–2016, respectively, both periods after the TARP program initiation. We also include other consumer controls: *Consumer Age*, *Joint Account*, and $Ln(1+No.\ Credit\ Inquiries\ last\ 12\ mos)$. We also include several bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size and controls for other government programs other than TARP (Discount Window, Term Auction Facility, FDIC TAGP, FDIC TDGP, SBLF, and FHLB programs). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Total Consumer Debt for Individuals

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Dependent Variable: Ln (1+ Total Consumer Debt)													
	Main	Alt. Dep Variable: Consumer Debt w/ Private Student	Alt. Dep Variable: Consumer Debt w/o Student	Include only Consumers in Both Pre & Post Periods	Cluster by County & Consumer	Add County× Year-Quarter FE	Exclude Bank Proxies for CAMELS	Exclude All Bank Controls	Exclude all Bank & County Controls	Alt. Post-TARP: 2018:Q4 Onward	Alternative Radius: 5 MILES	Alternative Radius: 25 MILES	Alternative Radius: 50 MILES	Alternative Radius: COUNTY
Independent Variables														
TARP	0.090* (1.746)	0.121** (2.323)	0.128** (2.449)	0.0180 (0.340)	0.090 (1.478)	-0.009 (-0.100)	0.084 (1.629)	0.139*** (3.135)	0.137*** (3.087)	0.090* (1.741)	0.047 (1.118)	0.210*** (3.087)	0.182** (2.306)	0.136*** (2.702)
Subprime (<580)	-0.360*** (-11.401)	-0.324*** (-10.267)	-0.309*** (-9.772)	-0.463*** (-14.332)	-0.360*** (-9.357)	-0.398*** (-12.265)	-0.361*** (-11.416)	-0.359*** (-11.455)	-0.358*** (-11.438)	-0.354*** (-11.088)	-0.419*** (-14.075)	-0.295*** (-8.317)	-0.264*** (-6.903)	-0.347*** (-11.092)
TARP × Subprime (<580)	-0.508*** (-8.046)	-0.629*** (-9.955)	-0.654*** (-10.322)	-0.483*** (-7.564)	-0.508*** (-6.026)	-0.472*** (-7.288)	-0.507*** (-8.030)	-0.508*** (-8.118)	-0.509*** (-8.132)	-0.527*** (-8.198)	-0.379*** (-6.666)	-0.651*** (-8.881)	-0.728*** (-8.959)	-0.649*** (-8.508)
TARP × Post-TARP1 ('09-'12)	-0.046 (-1.130)	-0.056 (-1.354)	-0.071* (-1.725)	-0.059 (-1.454)	-0.046 (-1.039)	0.042 (0.406)	-0.032 (-0.838)	-0.031 (-0.807)	-0.061 (-1.616)	-0.046 (-1.131)	-0.021 (-0.569)	-0.099** (-2.086)	-0.196*** (-3.677)	-0.098** (-2.160)
TARP × Post-TARP2 ('13-'16)	-0.034 (-0.763)	-0.049 (-1.095)	-0.042 (-0.933)	0.066 (1.449)	-0.034 (-0.688)	0.025 (0.216)	-0.014 (-0.311)	-0.010 (-0.243)	-0.024 (-0.558)	-0.035 (-0.776)	-0.000 (-0.011)	-0.070 (-1.372)	-0.121** (-2.136)	-0.104** (-2.083)
Subprime (<580) × Post-TARP1	-0.065 (-1.193)	-0.292*** (-5.258)	-0.365*** (-6.542)	0.085 (1.567)	-0.065 (-1.137)	-0.066 (-1.157)	-0.066 (-1.188)	-0.066 (-1.223)	-0.067 (-1.240)	-0.083 (-1.538)	0.013 (0.261)	-0.108* (-1.770)	-0.159** (-2.400)	-0.046 (-0.884)
Subprime (<580) × Post-TARP2	0.085 (1.453)	-0.387*** (-6.495)	-0.434*** (-7.275)	0.431*** (7.113)	0.085 (1.391)	0.096 (1.585)	0.086 (1.472)	0.083 (1.421)	0.082 (1.414)	0.078 (1.334)	0.108** (1.968)	0.046 (0.703)	0.009 (0.125)	0.074 (1.331)
TARP × Subprime (<580) × Post-TARP1	0.644*** (7.080)	0.609*** (6.556)	0.561*** (6.001)	0.617*** (6.766)	0.644*** (6.588)	0.659*** (6.954)	0.643*** (7.069)	0.645*** (7.107)	0.645*** (7.108)	0.658*** (7.222)	0.485*** (5.854)	0.747*** (7.172)	0.858*** (7.465)	0.740*** (7.206)
TARP × Subprime (<580) × Post-TARP2	0.527*** (5.411)	0.293*** (2.949)	0.234** (2.346)	0.412*** (4.074)	0.527*** (5.050)	0.511*** (-5.055)	0.526*** (5.393)	0.529*** (5.453)	0.528*** (5.440)	0.547*** (5.554)	0.454*** (5.093)	0.625*** (5.613)	0.711*** (5.809)	0.663*** (6.110)
Other Consumer Characteristics														
Consumer Age	-0.035*** (-86.228)	-0.015*** (-35.399)	-0.011*** (-26.640)	-0.037*** (-81.274)	-0.035*** (-46.550)	-0.035*** (-84.991)	-0.035*** (-86.231)	-0.035*** (-86.220)	-0.035*** (-86.229)	-0.035*** (-86.230)	-0.035*** (-85.551)	-0.035*** (-86.382)	-0.035*** (-86.419)	-0.035*** (-86.381)
Joint Account	3.779*** (323.277)	4.185*** (350.864)	4.252*** (353.902)	3.628*** (292.342)	3.779*** (179.330)	3.779*** (318.689)	3.779*** (323.285)	3.779*** (323.488)	3.779*** (323.495)	3.779*** (323.270)	3.778*** (319.074)	3.778*** (324.462)	3.778*** (324.544)	3.779*** (324.601)
Ln (1+ No. Credit Inquiries last 12mos)	1.474*** (194.064)	1.675*** (220.020)	1.709*** (223.635)	1.406*** (174.810)	1.474*** (116.020)	1.490*** (191.784)	1.474*** (194.066)	1.474*** (194.318)	1.474*** (194.376)	1.474*** (194.051)	1.475*** (191.387)	1.473*** (194.835)	1.473*** (194.876)	1.474*** (194.914)
Bank Characteristics (lagged 4 quarters)														

Capital Adequacy	-0.649 (-1.255)	-0.732 (-1.395)	-0.915* (-1.734)	-0.847 (-1.590)	-0.649 (-1.139)	-2.564** (-2.539)				-0.659 (-1.274)	-0.745* (-1.670)	-0.085 (-0.134)	0.254 (0.343)	-0.477 (-1.206)
Asset Quality	0.515 (0.919)	0.100* (1.758)	1.033* (1.814)	1.038* (1.824)	0.515 (0.708)	-2.023 (-1.572)				0.512 (0.919)	-0.823* (-1.675)	0.921 (1.315)	1.714** (2.122)	1.387** (2.317)
Management Quality	0.004*** (2.709)	0.005*** (3.687)	0.005*** (3.772)	0.004*** (3.040)	0.004** (2.210)	0.001 (0.120)				0.004*** (2.663)	0.005*** (3.316)	0.003** (2.323)	0.004*** (2.815)	0.005*** (3.383)
Earnings	-0.231* (-1.690)	-0.170 (-1.146)	-0.151 (-1.024)	-0.155 (-1.109)	-0.231 (-0.957)	-0.153 (-0.800)				-0.228* (-1.666)	-0.118 (-1.289)	-0.737*** (-2.594)	-1.153*** (-2.745)	-0.242 (-0.862)
Liquidity	-0.008 (-1.389)	-0.009 (-1.389)	-0.008 (-1.335)	-0.011* (-1.856)	-0.008* (-1.882)	-0.005 (-0.445)				-0.008 (-1.387)	-0.006* (-1.677)	-0.015 (-1.640)	0.000 (0.031)	0.174 (1.388)
Sensitivity to Market Risk	-0.131 (-1.101)	-0.121 (-1.003)	-0.115 (-1.000)	-0.059 (-0.480)	-0.131 (-0.875)	-0.627** (-2.274)				-0.134 (-1.127)	-0.081 (-0.761)	0.180 (1.261)	0.342** (2.129)	-0.044 (-0.511)
Bank Size	0.016** (2.229)	0.011 (1.566)	0.011 (1.432)	0.019** (2.531)	0.016** (2.012)	0.024*** (2.650)	0.015** (2.069)			0.016** (2.223)	0.006 (0.947)	0.030** (2.567)	-0.006 (-0.352)	-0.013* (-1.747)
Discount Window Participant	0.041 (0.838)	0.043 (0.870)	0.052 (1.053)	0.067 (1.329)	0.041 (0.727)	0.063 (0.901)	0.041 (0.850)			0.041 (0.842)	-0.018 (-0.469)	0.041 (2.071)	0.148** (1.985)	0.185** (0.677)
Term Auction Facility Participant	0.007 (0.132)	-0.008 (-0.148)	-0.010 (-0.184)	0.012 (0.225)	0.007 (0.101)	0.112 (1.401)	0.000 (0.003)			0.007 (0.133)	-0.078* (-1.895)	-0.129* (-1.821)	-0.222*** (-2.596)	-0.061 (-0.857)
FDIC TAGP Participant	0.002 (0.039)	-0.027 (-0.574)	-0.025 (-0.516)	-0.006 (-0.125)	0.002 (0.034)	0.111 (1.572)	0.006 (0.131)			0.001 (0.029)	0.010 (0.279)	-0.205*** (-3.104)	-0.167** (-2.095)	-0.084 (-1.535)
FDIC TDGP Participant	0.035 (0.820)	0.011 (0.265)	-0.010 (-0.219)	0.020 (0.456)	0.035 (0.718)	0.049 (0.717)	0.037 (0.881)			0.036 (0.832)	0.037 (1.084)	-0.027 (-0.470)	0.035 (0.522)	0.024 (0.477)
SBLF Participant	-0.288** (-1.973)	-0.234 (-1.587)	-0.191 (-1.288)	-0.250 (-1.632)	-0.288* (-1.877)	-0.419** (-2.166)	-0.290** (-1.987)			-0.288** (-1.971)	-0.097 (-0.887)	-0.045 (-0.193)	-0.060 (-0.161)	-0.111 (-0.619)
FHLB Member	0.182* (1.813)	0.196* (1.914)	0.210** (2.038)	0.176* (1.669)	0.182 (1.528)	0.245* (1.816)	0.176* (1.755)			0.182* (1.814)	0.111 (1.412)	0.137 (0.809)	0.186 (0.784)	0.202 (1.556)
County-Level Characteristics (lagged 4 quarters)														
County Unemployment Rate	-0.012*** (-3.604)	-0.007** (-2.011)	-0.006* (-1.833)	-0.012*** (-3.672)	-0.012** (-2.541)		-0.011*** (-3.334)	-0.011*** (-3.462)		-0.012*** (-3.590)	-0.010*** (-3.075)	-0.013*** (-4.074)	-0.013*** (-4.122)	-0.011*** (-3.512)
County HPI	0.001** (2.419)	0.001*** (5.676)	0.001*** (5.968)	0.001*** (3.646)	0.001 (1.489)		0.000** (2.251)	0.001** (2.3550)		0.001** (2.406)	0.000* (1.770)	0.000** (2.294)	0.000* (1.735)	0.000** (2.327)
County FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
County × Year-Quarter FE							X							
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Errors Clustered by County					X									
Observations	5,647,134	5,647,134	5,647,134	5,180,773	5,647,134	5,629,782	5,647,134	5,657,056	5,657,056	5,647,134	5,476,101	5,692,572	5,696,772	5,697,891
R-squared	0.348	0.365	0.37	0.344	0.348	0.360	0.348	0.348	0.348	0.348	0.348	0.348	0.348	0.348

Panel B: Decomposition by Product

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
TARP	0.090* (1.746)	0.303*** (4.012)	0.004 (0.111)	0.245*** (6.475)	-0.125** (-2.102)	0.028 (0.484)	0.012 (0.256)	0.013 (0.802)	0.003 (0.051)
Subprime (<580)	-0.360*** (-11.401)	-1.332*** (-33.617)	0.0510** (2.306)	-0.123*** (-8.167)	-0.306*** (-8.149)	-0.791*** (-22.007)	-0.091*** (-2.900)	-0.038*** (-3.664)	0.624*** (18.365)
TARP × Subprime (<580)	-0.508*** (-8.046)	-1.230*** (-15.775)	-0.249*** (-6.108)	-0.666*** (-22.014)	-0.345*** (-4.664)	0.654*** (9.176)	0.388*** (6.092)	0.051** (2.475)	-0.192*** (-2.873)
TARP × Post-TARP1 ('09-'12)	-0.046 (-1.130)	-0.297*** (-5.410)	-0.063** (-2.385)	-0.061** (-1.986)	0.144*** (3.245)	-0.200*** (-4.201)	0.029 (0.812)	0.0330** (2.118)	0.060 (1.498)
TARP × Post-TARP2 ('13-'16)	-0.034 (-0.763)	-0.5880*** (-9.501)	0.023 (0.828)	-0.388*** (-12.143)	0.288*** (5.949)	-0.218*** (-4.233)	0.102** (2.497)	0.002 (0.116)	0.140*** (3.246)
Subprime (<580) × Post-TARP1	-0.065 (-1.193)	0.160** (2.448)	-0.170*** (-5.310)	-0.029 (-1.146)	-0.878*** (-14.661)	0.080 (1.310)	0.539*** (9.089)	0.182*** (6.750)	0.064 (1.129)
Subprime (<580) × Post-TARP2	0.0850 (1.453)	-0.070 (-1.017)	-0.177*** (-5.956)	-0.021 (-0.863)	-1.149*** (-18.190)	0.215*** (3.211)	0.911*** (12.633)	0.129*** (4.638)	0.033 (0.561)
TARP × Subprime (<580) × Post-TARP1	0.644*** (7.080)	0.861*** (7.879)	0.392*** (7.419)	0.294*** (6.648)	0.469*** (4.651)	0.341*** (3.349)	0.091 (0.943)	0.067 (1.525)	-0.144 (-1.531)
TARP × Subprime (<580) × Post-TARP2	0.527*** (5.411)	0.404*** (3.510)	0.338*** (6.732)	0.378*** (8.903)	0.350*** (3.283)	0.024 (0.215)	0.595*** (5.075)	0.082* (1.822)	-0.333*** (-3.349)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134
R-squared	0.348	0.260	0.042	0.077	0.143	0.210	0.140	0.030	0.153

Table 3: Effects of TARP Bailouts on Subprime Consumer Debt – Endogeneity and Sample Selection Tests

This table reports difference-in-difference-in-difference (DIDID) regression estimates for analyzing the effects of TARP bailouts on debt of subprime consumers (Equifax Risk Score < 580) relative to other consumers when using endogeneity and sample selection tests. The table uses a 1% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period is 2001:Q1–2016:Q4. In Panel A, we report estimates from the last stage of an instrumental variable analysis as in Wooldridge Section 18.4.1, and in Panel B, we report estimates for the outcome equation from the Heckman (1979)'s selection model. We use as an instrument a political connections variable: *Subcommittees on Financial Institutions or Capital Markets*. *Subcommittees on Financial Institutions or Capital Markets* is a variable, which takes a value of 1 if a firm is headquartered in a district of a House member, who served on the Capital Markets Subcommittee or the Financial Institutions Subcommittee of the House Financial Services Committee in 2008 or 2009. The dependent variables are $\ln(1+ \text{Total Consumer Debt})$, $\ln(1+ \text{Total Mortgage Debt})$, $\ln(1+ \text{Total HELOAN Debt})$, $\ln(1+ \text{Total HELOC Debt})$, $\ln(1+ \text{Total Card Debt})$, $\ln(1+ \text{Total Auto Debt})$, $\ln(1+ \text{Total Student Debt})$, $\ln(1+ \text{Total Private Student Debt})$, and $\ln(1+ \text{Other Consumer Debt})$, representing the natural logarithm of one plus total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer). *TARP* is the weighted proportion of banks receiving TARP bailouts in the 10-mile radius of the consumer zip code. *Subprime* is an indicator that equals one if the consumer has an Equifax Risk Score below 580. *Post-TARP1* and *Post-TARP2* are indicators equal to one in 2009-2012 and 2013-2016, respectively, both periods after the TARP program initiation. We also include other consumer controls: *Consumer Age*, *Joint Account*, and $\ln(1+ \text{No. Credit Inquiries last 12mos})$. We also include a number of bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size and controls for other government programs other than TARP (Discount Window, Term Auction Facility, FDIC TAGP, FDIC TDGP, SBLF, and FHLB programs). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV Last Stage – Consumer Debt for Individuals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
TARP	0.386** (2.345)	0.214 (0.889)	0.233** (2.153)	0.147 (1.142)	0.410** (2.196)	-0.230 (-1.255)	0.223 (1.358)	0.049 (0.813)	-0.463*** (-2.858)
Subprime (<580)	-0.354*** (-7.196)	-1.063*** (-17.414)	0.098*** (2.873)	0.0423* (1.952)	-0.512*** (-8.743)	-1.033*** (-18.669)	-0.161*** (-3.354)	-0.027* (-1.717)	0.610*** (11.567)
TARP × Subprime (<580)	-0.523*** (-4.936)	-1.837*** (-14.047)	-0.354*** (-5.079)	-1.035*** (-21.664)	0.113 (0.902)	1.196*** (10.093)	0.544*** (5.223)	0.027 (0.803)	-0.160 (-1.420)
TARP × Post-TARP1 ('09-'12)	-0.063 (-0.999)	-0.589*** (-6.932)	-0.109*** (-2.649)	-0.072 (-1.616)	0.297*** (4.300)	-0.192*** (-2.619)	0.052 (0.940)	0.0560** (2.499)	0.264*** (4.174)
TARP × Post-TARP2 ('13-'16)	-0.041 (-0.628)	-0.997*** (-10.907)	0.025 (0.575)	-0.478*** (-10.512)	0.445*** (6.127)	-0.246*** (-3.234)	0.208*** (3.535)	0.042* (1.804)	0.312*** (4.742)
Subprime (<580) × Post-TARP1	-0.172** (-2.446)	-0.208** (-2.489)	-0.257*** (-6.069)	-0.149*** (-4.968)	-0.854*** (-10.982)	0.175** (2.199)	0.418*** (5.687)	0.125*** (3.667)	0.157** (2.107)
Subprime (<580) × Post-TARP2	-0.025 (-0.330)	-0.401*** (-4.453)	-0.252*** (-6.071)	-0.144*** (-4.756)	-1.219*** (-14.595)	0.234*** (2.647)	0.824*** (9.043)	0.088** (2.575)	0.096 (1.201)
TARP × Subprime (<580) × Post-TARP1	0.825*** (6.462)	1.634*** (10.654)	0.563*** (7.287)	0.590*** (10.203)	0.312** (2.166)	0.044 (0.305)	0.251* (1.940)	0.171*** (2.886)	-0.307** (-2.262)
TARP × Subprime (<580) × Post-TARP2	0.713*** (5.172)	1.115*** (6.809)	0.488*** (6.297)	0.682*** (11.772)	0.348** (2.261)	-0.150 (-0.944)	0.697*** (4.413)	0.155*** (2.608)	-0.442*** (-3.054)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,635,680	5,635,680	5,635,680	5,635,680	5,635,680	5,635,680	5,635,680	5,635,680	5,635,680
R-squared	0.330	0.232	0.021	0.053	0.110	0.189	0.107	0.015	0.123

Panel B: Heckman Outcome Equation – Consumer Debt

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
TARP	0.064 (1.082)	0.461*** (5.293)	0.051 (1.223)	0.286*** (6.408)	-0.180*** (-2.647)	0.039 (0.575)	-0.024 (-0.438)	0.001 (0.049)	-0.062 (-1.035)
Subprime (<580)	-0.362*** (-11.394)	-1.464*** (-38.182)	0.052** (2.367)	-0.122*** (-8.106)	-0.315*** (-8.343)	-0.793*** (-21.969)	-0.090*** (-2.852)	-0.037*** (-3.531)	0.627*** (18.367)
TARP × Subprime (<580)	-0.506*** (-7.987)	-1.375*** (-18.346)	-0.251*** (-6.154)	-0.666*** (-21.915)	-0.330*** (-4.443)	0.658*** (9.203)	0.3860*** (6.033)	0.049** (2.365)	-0.197*** (-2.942)
TARP × Post-TARP1 ('09-'12)	-0.044 (-1.088)	-0.330*** (-5.701)	-0.070*** (-2.606)	-0.061** (-1.991)	0.148*** (3.332)	-0.203*** (-4.233)	0.035 (0.962)	0.036** (2.309)	0.070* (1.725)
TARP × Post-TARP2 ('13-'16)	-0.032 (-0.721)	-0.657*** (-10.014)	0.018 (0.641)	-0.386*** (-12.090)	0.291*** (5.981)	-0.223*** (-4.296)	0.106*** (2.576)	0.003 (0.151)	0.149*** (3.434)
Subprime (<580) × Post-TARP1	-0.071 (-1.294)	0.129** (2.205)	-0.172*** (-5.337)	-0.0260 (-1.022)	-0.879*** (-14.604)	0.081 (1.321)	0.535*** (8.985)	0.186*** (6.830)	0.065 (1.135)
Subprime (<580) × Post-TARP2	0.085 (1.449)	-0.120* (-1.910)	-0.181*** (-6.037)	-0.013 (-0.510)	-1.147*** (-18.051)	0.212*** (3.153)	0.908*** (12.503)	0.127*** (4.559)	0.036 (0.594)
TARP × Subprime (<580) × Post-TARP1	0.652*** (7.132)	0.727*** (7.457)	0.395*** (7.444)	0.290*** (6.538)	0.469*** (4.624)	0.337*** (3.298)	0.097 (0.999)	0.062 (1.399)	-0.144 (-1.525)
TARP × Subprime (<580) × Post-TARP2	0.526*** (5.370)	0.516*** (4.893)	0.344*** (6.807)	0.366*** (8.582)	0.345*** (3.221)	0.026 (0.234)	0.600*** (5.085)	0.084* (1.852)	-0.335*** (-3.351)
Lambda	0.017 (0.610)	-0.000 (-0.003)	-0.037** (-2.000)	-0.038* (-1.772)	0.037 (1.158)	-0.003 (-0.107)	0.026 (0.979)	0.010 (1.049)	0.048* (1.727)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,635,680	5,635,680	5,635,680	5,635,680	5,635,680	5,635,680	5,635,680	5,635,680	5,635,680
R-squared	0.348	0.269	0.042	0.077	0.143	0.210	0.140	0.030	0.153

Table 4: Effects of TARP Bailouts on Subprime Consumer Debt: Alternative Definition of Subprime

This table reports difference-in-difference-in-difference (DIDID) regression estimates for analyzing the effects of TARP bailouts on debt of subprime consumers using an alternative definition, namely Equifax Risk Score < 620. The table uses a 1% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period is 2001:Q1–2016:Q4. The dependent variables are $\text{Ln}(1 + \text{Total Consumer Debt})$, $\text{Ln}(1 + \text{Total Mortgage Debt})$, $\text{Ln}(1 + \text{Total HELOAN Debt})$, $\text{Ln}(1 + \text{Total HELOC Debt})$, $\text{Ln}(1 + \text{Total Card Debt})$, $\text{Ln}(1 + \text{Total Auto Debt})$, $\text{Ln}(1 + \text{Total Student Debt})$, $\text{Ln}(1 + \text{Total Private Student Debt})$, and $\text{Ln}(1 + \text{Other Consumer Debt})$, representing the natural logarithm of one plus total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer). *TARP* is the weighted proportion of banks receiving TARP bailouts in the 10-mile radius of the consumer zip code. *Subprime* is an indicator that equals one if the consumer has an Equifax Risk Score below 620. *Post-TARP1* and *Post-TARP2* are indicators equal to one in 2009–2012 and 2013–2016, respectively, both periods after the TARP program initiation. We also include other consumer controls: *Consumer Age*, *Joint Account*, and $\text{Ln}(1 + \text{No. Credit Inquiries last 12mos})$. We also include a number of bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size and controls for other government programs other than TARP (Discount Window, Term Auction Facility, FDIC TAGP, FDIC TDGP, SBLF, and FHLB programs). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
TARP	0.166*** (3.178)	0.468*** (6.076)	0.031 (0.829)	0.326*** (8.327)	-0.100* (-1.661)	-0.031 (-0.525)	0.010 (0.195)	0.013 (0.777)	0.017 (0.329)
Subprime (<620)	-0.533*** (-17.982)	-1.458*** (-38.165)	0.056*** (2.722)	-0.172*** (-11.321)	-0.519*** (-14.732)	-0.709*** (-21.135)	-0.163*** (-5.762)	-0.052*** (-5.829)	0.548*** (17.426)
TARP × Subprime (<620)	-0.599*** (-10.168)	-1.384*** (-18.523)	-0.260*** (-6.860)	-0.728*** (-23.674)	-0.306*** (-4.444)	0.650*** (9.872)	0.267*** (4.776)	0.035** (2.023)	-0.181*** (-2.974)
TARP × Post-TARP1 ('09-'12)	-0.041 (-0.978)	-0.336*** (-5.804)	-0.094*** (-3.342)	-0.081** (-2.436)	0.147*** (3.192)	-0.183*** (-3.661)	0.018 (0.466)	0.025 (1.564)	0.086** (2.068)
TARP × Post-TARP2 ('13-'16)	-0.092** (-2.000)	-0.664*** (-10.165)	-0.009 (-0.296)	-0.434*** (-12.565)	0.259*** (5.130)	-0.197*** (-3.635)	0.052 (1.214)	-0.004 (-0.209)	0.144*** (3.201)
Subprime (<620) × Post-TARP1	-0.084* (-1.723)	0.123** (2.123)	-0.173*** (-6.056)	-0.014 (-0.556)	-0.851*** (-16.074)	0.131** (2.451)	0.401*** (8.080)	0.135*** (6.153)	0.045 (0.909)
Subprime (<620) × Post-TARP2	-0.015 (-0.293)	-0.136** (-2.180)	-0.169*** (-6.058)	-0.014 (-0.573)	-1.056*** (-18.683)	0.220*** (3.745)	0.678*** (11.274)	0.106*** (4.658)	0.013 (0.246)
TARP × Subprime (<620) × Post-TARP1	0.425*** (5.210)	0.737*** (7.591)	0.373*** (7.932)	0.275*** (6.449)	0.321*** (3.602)	0.170* (1.902)	0.115 (1.432)	0.076** (2.128)	-0.197** (-2.397)
TARP × Subprime (<620) × Post-TARP2	0.554*** (6.323)	0.541*** (5.148)	0.343*** (7.346)	0.413*** (9.667)	0.3600*** (3.773)	-0.051 (-0.522)	0.567*** (5.790)	0.073** (1.999)	-0.239*** (-2.730)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134
R-squared	0.352	0.269	0.042	0.080	0.148	0.210	0.138	0.030	0.152

Table 5: Effects of TARP Bailouts on Subprime Consumer Debt: Placebo Experiment and Matched Sample

This table reports difference-in-difference-in-difference (DIDID) regression estimates for analyzing the effects of TARP bailouts on debt of subprime consumers (Equifax Risk Score < 580) relative to other consumers when using a placebo experiment and a propensity score matched (PSM) sample. The table uses a 1% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period is 2001:Q1–2016:Q4. In Panel A, we report estimates from a placebo experiment in which we randomly assign consumers into the subprime designation and reestimate our main specification, and in Panel B, we report estimates from a sample obtained from propensity score matching using nearest-neighbor matching: N=1 without replacement in which we match each period subprime with non-subprime consumers with similar characteristics. The dependent variables are $\ln(1+ \text{Total Consumer Debt})$, $\ln(1+ \text{Total Mortgage Debt})$, $\ln(1+ \text{Total HELOAN Debt})$, $\ln(1+ \text{Total HELOC Debt})$, $\ln(1+ \text{Total Card Debt})$, $\ln(1+ \text{Total Auto Debt})$, $\ln(1+ \text{Total Student Debt})$, $\ln(1+ \text{Total Private Student Debt})$, and $\ln(1+ \text{Other Consumer Debt})$, representing the natural logarithm of one plus total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer). *TARP* is the weighted proportion of banks receiving TARP bailouts in the 10-mile radius of the consumer zip code. *Subprime* is an indicator that equals one if the consumer has an Equifax Risk Score below 580. *Post-TARP1* and *Post-TARP2* are indicators equal to one in 2009–2012 and 2013–2016, respectively, both periods after the TARP program initiation. We also include other consumer controls: *Consumer Age*, *Joint Account*, and $\ln(1+ \text{No. Credit Inquiries last 12mos})$. We also include a number of bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size and controls for other government programs other than TARP (Discount Window, Term Auction Facility, FDIC TAGP, FDIC TDGP, SBLF, and FHLB programs). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Placebo Experiment (Randomly Assign Consumers into Subprime Designation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
Placebo TARP	-0.004 (-0.070)	0.056 (0.750)	-0.044 (-1.232)	0.110*** (3.023)	-0.201*** (-3.403)	0.169*** (2.963)	0.110** (2.324)	0.027 (1.603)	-0.045 (-0.883)
Subprime (<580)	0.008 (0.744)	-0.013 (-0.829)	0.009 (1.142)	-0.002 (-0.258)	0.022* (1.768)	0.005 (0.368)	-0.003 (-0.290)	-0.006* (-1.906)	-0.005 (-0.378)
Placebo TARP × Subprime (<580)	-0.014 (-0.618)	0.031 (0.994)	-0.010 (-0.645)	0.014 (0.861)	-0.038 (-1.486)	0.008 (0.307)	0.001 (0.060)	0.007 (1.127)	0.021 (0.865)
Placebo TARP × Post-TARP1 ('09-'12)	0.067* (1.720)	-0.132*** (-2.579)	0.011 (0.430)	0.001 (0.020)	0.228*** (5.274)	-0.155*** (-3.402)	0.020 (0.553)	0.045*** (2.867)	0.060 (1.543)
Placebo TARP × Post-TARP2 ('13-'16)	0.060 (1.412)	-0.483*** (-8.349)	0.083*** (3.161)	-0.304*** (-10.614)	0.361*** (7.694)	-0.245*** (-4.944)	0.157*** (3.788)	0.012 (0.739)	0.109*** (2.590)
Subprime (<580) × Post-TARP1	-0.001 (-0.026)	0.016 (0.536)	0.003 (0.205)	0.008 (0.546)	-0.032 (-1.286)	0.023 (0.888)	-0.009 (-0.417)	0.005 (0.623)	0.026 (1.097)
Subprime (<580) × Post-TARP2	-0.004 (-0.169)	-0.014 (-0.484)	-0.008 (-0.649)	-0.004 (-0.264)	-0.037 (-1.519)	0.012 (0.467)	-0.007 (-0.351)	0.012 (1.425)	0.026 (1.150)
Placebo TARP × Subprime (<580) × Post-TARP1	-0.011 (-0.276)	-0.068 (-1.301)	-0.005 (-0.198)	-0.017 (-0.638)	0.041 (0.961)	-0.060 (-1.359)	0.017 (0.481)	-0.017 (-1.180)	-0.052 (-1.328)
Placebo TARP × Subprime (<580) × Post-TARP2	0.015 (0.414)	0.026 (0.516)	0.015 (0.714)	0.004 (0.157)	0.059 (1.449)	-0.026 (-0.598)	0.008 (0.230)	-0.019 (-1.373)	-0.048 (-1.256)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134
R-squared	0.346	0.245	0.042	0.074	0.135	0.209	0.132	0.029	0.150

Panel B: Propensity Score Matching (1:1 Nearest Neighbor Matching without Replacement)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
TARP	0.313*** (4.509)	0.668*** (6.991)	0.113** (2.454)	0.295*** (8.024)	0.053 (0.667)	0.011 (0.135)	-0.056 (-0.692)	-0.008 (-0.277)	0.089 (1.193)
Subprime (<580)	-0.293*** (-9.107)	-1.362*** (-32.934)	0.064*** (2.873)	-0.200*** (-13.317)	-0.270*** (-7.018)	-0.578*** (-14.914)	0.0550 (1.585)	-0.004 (-0.305)	0.628*** (17.627)
TARP × Subprime (<580)	-0.600*** (-9.271)	-1.087*** (-13.148)	-0.303*** (-7.262)	-0.559*** (-17.687)	-0.470*** (-6.174)	0.373*** (4.822)	0.281*** (3.973)	0.046* (1.926)	-0.192*** (-2.731)
TARP × Post-TARP1 ('09-'12)	-0.297*** (-4.506)	-0.627*** (-7.235)	-0.087** (-2.371)	-0.205*** (-5.650)	0.147** (2.026)	-0.436*** (-5.426)	-0.086 (-1.180)	0.026 (0.803)	-0.050 (-0.740)
TARP × Post-TARP2 ('13-'16)	-0.188*** (-2.743)	-0.947*** (-10.070)	-0.0257 (-0.670)	-0.482*** (-13.515)	0.370*** (4.885)	-0.496*** (-5.697)	0.176** (2.169)	-0.015 (-0.430)	0.071 (0.979)
Subprime (<580) × Post-TARP1	-0.203*** (-3.518)	0.191*** (2.661)	-0.113*** (-3.319)	0.016 (0.602)	-0.653*** (-10.018)	-0.126* (-1.863)	0.162** (2.425)	0.103*** (3.481)	-0.075 (-1.220)
Subprime (<580) × Post-TARP2	-0.050	0.096	-0.148***	0.036	-0.905***	-0.154**	0.640***	0.046	-0.084

	(-0.818)	(1.276)	(-4.682)	(1.472)	(-13.322)	(-2.067)	(8.137)	(1.466)	(-1.293)
TARP × Subprime (<580) × Post-TARP1	0.838***	0.989***	0.389***	0.422***	0.343***	0.535***	0.298***	0.060	0.006
	(8.590)	(8.138)	(6.915)	(8.842)	(3.125)	(4.703)	(2.714)	(1.237)	(0.056)
TARP × Subprime (<580) × Post-TARP2	0.654***	0.623***	0.351***	0.455***	0.189*	0.269**	0.554***	0.091*	-0.193*
	(6.397)	(4.930)	(6.561)	(10.384)	(1.652)	(2.165)	(4.291)	(1.785)	(-1.776)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	2,026,327	2,026,327	2,026,327	2,026,327	2,026,327	2,026,327	2,026,327	2,026,327	2,026,327
R-squared	0.215	0.228	0.054	0.065	0.136	0.205	0.129	0.037	0.145

Table 6: TARP - Mechanisms Investigation

This table reports difference-in-difference-in-difference (DIDID) regression estimates for credit mechanisms of the effects of TARP bailouts on debt of subprime consumers (Equifax Risk Score < 580) relative to other consumers. The table uses a 1% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period is 2001:Q1–2016:Q4. The dependent variables are $\ln(1+Total\ Consumer\ Credit)$, $\ln(1+Total\ Consumer\ Credit_2)$, $\ln(1+Total\ HELOC\ Limit)$, $\ln(1+Total\ CC\ Limit)$, representing the natural logarithm of one plus total consumer credit amount (with total student credit amount or private student credit amount) or credit limit or credit utilization in one of its subcomponents (HELOC, credit card) in Panel A, and total payment rate or payment rates by individual products in Panel B. *TARP* is the weighted proportion of banks receiving TARP bailouts in the 10-miles radius of the consumer zip code. *Subprime* is an indicator that equals one if the consumer has an Equifax Risk Score below 580. *Post-TARP1* and *Post-TARP2* are indicators equal to one in 2009–2012 and 2013–2016, respectively, both periods after the TARP program initiation. We also include other consumer controls: *Consumer Age*, *Joint Account*, and $\ln(1+No.\ Credit\ Inquiries\ last\ 12\ mos)$. We also include a number of bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size and controls for other government programs other than TARP (Discount Window, Term Auction Facility, FDIC TAGP, FDIC TDGP, SBLF, and FHLB programs). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Credit Limits, Amounts, Utilization Rate for Individual Products

	(1)	(2)	(3)	(4)	(5)
	Total Consumer Credit & Some Individual Products				
Dependent Variable:	Ln (1+ Total Consumer Credit)	Ln (1+ HELOC Limit)	Ln (1+ Card Limit)	HELOC Utilization Rate	Card Utilization Rate
Independent Variables					
TARP	0.074 (1.546)	0.306*** (6.804)	-0.125* (-1.860)	1.584* (1.746)	0.024* (1.887)
Subprime (<580)	-1.304*** (-43.288)	-0.168*** (-9.554)	-1.939*** (-49.673)	0.708 (1.412)	0.706*** (4.198)
TARP × Subprime (<580)	-0.489*** (-8.130)	-0.909*** (-25.546)	-0.501*** (-6.536)	-1.003 (-1.243)	-0.366 (-1.542)
TARP × Post-TARP1 ('09-'12)	-0.067 (-1.636)	-0.081** (-2.334)	0.244*** (4.724)	4.750* (1.788)	-0.011* (-1.704)
TARP × Post-TARP2 ('13-'16)	0.009 (0.197)	-0.500*** (-13.343)	0.383*** (6.828)	-5.222 (-1.316)	-0.009 (-0.703)
Subprime (<580) × Post-TARP1	0.170*** (3.223)	-0.041 (-1.445)	-0.615*** (-9.989)	0.540 (0.635)	-0.539*** (-3.065)
Subprime (<580) × Post-TARP2	0.455*** (8.080)	-0.025 (-0.899)	-0.810*** (-12.267)	-4.220 (-1.267)	-0.603*** (-3.495)
TARP × Subprime (<580) × Post-TARP1	0.596*** (6.760)	0.331*** (6.777)	0.413*** (3.994)	-1.682 (-0.756)	0.434* (1.777)
TARP × Subprime (<580) × Post-TARP2	0.439*** (4.671)	0.499*** (10.250)	0.305*** (2.754)	6.320 (1.397)	0.444* (1.863)
Consumer, Bank, County Characteristics	X	X	X	X	X
County FE	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X
Observations	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134
R-squared	0.262	0.091	0.186	0.000	0.003

Panel B: Payments: Total and by Individual Products

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Payment: Decomposition by Individual Products								
Dependent Variable:	Total Consumer Payment Rate	Mortgage Payment Rate	HELOAN Payment Rate	HELOC Payment Rate	Card Payment Rate	Auto Payment Rate	Student Payment Rate	Private Student Payment Rate	Other Consumer Payment Rate
Independent Variables									
TARP	0.210 (0.997)	0.009 (0.743)	-0.002 (-0.506)	0.006 (1.417)	-0.052 (-1.608)	0.196 (0.887)	-0.003 (-1.236)	0.001* (1.648)	0.007 (0.302)
Subprime (<580)	0.073* (1.767)	0.008 (1.055)	0.007 (1.080)	0.002 (0.558)	-0.049* (-1.732)	0.095 (1.374)	0.005*** (3.373)	0.001*** (4.961)	0.028** (2.368)
TARP × Subprime (<580)	-0.118 (-0.731)	-0.006 (-0.346)	-0.010 (-1.212)	-0.011 (-1.259)	0.061 (1.174)	-0.163 (-0.903)	0.016*** (4.206)	0.000 (0.058)	-0.017 (-0.798)
TARP × Post-TARP1 ('09-'12)	-0.075 (-0.561)	-0.008 (-0.534)	-0.000 (-0.046)	-0.018* (-1.742)	0.079 (1.412)	-0.269 (-1.595)	0.005* (1.955)	0.000 (0.034)	0.032 (1.325)
TARP × Post-TARP2 ('13-'16)	-0.120 (-0.946)	-0.008 (-0.676)	0.003 (1.223)	-0.017 (-1.609)	0.075 (1.357)	-0.182 (-1.370)	0.003 (1.198)	-0.001** (-2.217)	0.004 (0.341)
Subprime (<580) × Post-TARP1	0.004 (0.198)	-0.002 (-0.065)	-0.006 (-0.919)	-0.002 (-0.326)	0.063* (1.825)	-0.074 (-1.089)	0.013*** (3.708)	0.003*** (3.878)	0.046 (0.808)
Subprime (<580) × Post-TARP2	-0.010 (-0.253)	0.015 (0.613)	-0.002 (-0.287)	-0.007 (-1.576)	0.051 (1.552)	0.049 (0.456)	-0.008** (-2.106)	0.001 (1.189)	-0.014 (-1.019)
TARP × Subprime (<580) × Post-TARP1	0.028 (0.315)	0.066 (1.192)	0.008 (0.873)	0.018* (1.672)	-0.086 (-1.584)	0.138 (1.233)	-0.019*** (-3.441)	-0.002 (-1.250)	-0.092 (-1.102)
TARP × Subprime (<580) × Post-TARP2	0.085 (0.677)	0.049 (1.125)	0.006 (0.564)	0.015* (1.762)	-0.068 (-1.183)	0.067 (0.352)	-0.006 (-0.749)	0.001 (0.984)	-0.002 (-0.069)

Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134
R-squared	0.002	0.000	0.000	0.001	0.006	0.002	0.000	0.001	0.002

Table 7: Effects of TARP Bailouts on Subprime Consumer Debt – Bank Cross-Sectional Tests

This table reports difference-in-difference-in-difference (DIDID) regression estimates for analyzing the effects of TARP bailouts on debt of subprime consumers (Equifax Risk Score < 580) relative to other consumers when using cross-sectional tests by TARP bank size (using \$10 billion as the cutoff for groups), bank capital (using median as the cutoff for groups), and bank liquidity (using median as the cutoff for groups). The table uses a 1% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period is 2001:Q1–2016:Q4. The dependent variables are $\ln(1+ \text{Total Consumer Debt})$, $\ln(1+ \text{Total Mortgage Debt})$, $\ln(1+ \text{Total HELOAN Debt})$, $\ln(1+ \text{Total HELOC Debt})$, $\ln(1+ \text{Total Card Debt})$, $\ln(1+ \text{Total Auto Debt})$, $\ln(1+ \text{Total Student Debt})$, $\ln(1+ \text{Total Private Student Debt})$, and $\ln(1+ \text{Other Consumer Debt})$, representing the natural logarithm of one plus total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer). TARP is the weighted proportion of banks receiving TARP bailouts in the 10-mile radius of the consumer zip code. *Subprime* is an indicator that equals one if the consumer has an Equifax Risk Score below 580. *Post-TARP1* and *Post-TARP2* are indicators equal to one in 2009-2012 and 2013-2016, respectively, both periods after the TARP program initiation. We also include other consumer controls: *Consumer Age*, *Joint Account*, and $\ln(1+ \text{No. Credit Inquiries last 12mos})$. We also include a number of bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size, and controls for other government programs other than TARP (Discount Window, Term Auction Facility, FDIC TAGP, FDIC TDGP, SBLF, and FHLB programs). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Bank Size (Large: \geq \$10 Billion; Small < \$10 Billion)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+Other Consumer Debt)
Independent Variables									
TARP Large	0.130** (2.368)	0.455*** (5.664)	0.009 (0.257)	0.290*** (7.109)	-0.104* (-1.651)	-0.034 (-0.544)	-0.000 (-0.007)	0.018 (0.992)	0.024 (0.429)
TARP Small	-0.007 (-0.081)	-0.167 (-1.380)	-0.029 (-0.513)	0.114* (1.823)	-0.105 (-1.106)	0.174* (1.873)	0.100 (1.359)	0.016 (0.649)	-0.032 (-0.379)
Subprime (<580)	-0.360*** (-11.407)	-1.337*** (-33.726)	0.050** (2.263)	-0.124*** (-8.241)	-0.305*** (-8.122)	-0.788*** (-21.926)	-0.088*** (-2.806)	-0.038*** (-3.617)	0.624*** (18.348)
TARP Large \times Subprime (<580)	-0.514*** (-7.647)	-1.342*** (-16.131)	-0.280*** (-6.601)	-0.697*** (-21.659)	-0.333*** (-4.249)	0.752*** (9.953)	0.478*** (7.028)	0.064*** (2.963)	-0.202*** (-2.852)
TARP Small \times Subprime (<580)	-0.478*** (-3.841)	-0.673*** (-4.426)	-0.096 (-1.173)	-0.514*** (-8.073)	-0.412*** (-2.765)	0.184 (1.326)	-0.050 (-0.399)	-0.010 (-0.219)	-0.143 (-1.054)
TARP Large \times Post-TARP1 ('09-'12)	-0.074* (-1.715)	-0.402*** (-6.959)	-0.077*** (-2.815)	-0.085*** (-2.620)	0.176*** (3.769)	-0.203*** (-4.047)	0.027 (0.694)	0.034** (2.096)	0.078* (1.868)
TARP Small \times Post-TARP1 ('09-'12)	0.096 (1.229)	0.160 (1.508)	0.021 (0.393)	0.035 (0.571)	-0.023 (-0.265)	-0.150 (-1.613)	0.093 (1.339)	0.031 (1.060)	-0.076 (-0.963)
TARP Large \times Post-TARP2 ('13-'16)	-0.057 (-1.227)	-0.718*** (-11.137)	0.017 (0.572)	-0.426*** (-12.788)	0.320*** (6.334)	-0.232*** (-4.299)	0.120*** (2.810)	0.006 (0.345)	0.143*** (3.171)
TARP Small \times Post-TARP2 ('13-'16)	0.096 (1.026)	0.070 (0.542)	0.058 (0.988)	-0.179*** (-2.609)	0.121 (1.193)	-0.056 (-0.519)	0.041 (0.484)	-0.019 (-0.591)	0.108 (1.189)
Subprime (<580) \times Post-TARP1	-0.056 (-1.027)	0.168*** (2.577)	-0.166*** (-5.155)	-0.025 (-0.982)	-0.875*** (-14.596)	0.089 (1.455)	0.552*** (9.316)	0.185*** (6.839)	0.054 (0.957)
Subprime (<580) \times Post-TARP2	0.096* (1.647)	-0.066 (-0.958)	-0.174*** (-5.821)	-0.018 (-0.722)	-1.143*** (-18.057)	0.228*** (3.406)	0.927*** (12.849)	0.130*** (4.689)	0.027 (0.451)
TARP Large \times Subprime (<580) \times Post-TARP1	0.703*** (7.372)	1.000*** (8.715)	0.446*** (8.129)	0.345*** (7.436)	0.483*** (4.579)	0.313*** (2.934)	0.100 (0.991)	0.073 (1.578)	-0.192* (-1.949)
TARP Small \times Subprime (<580) \times Post-TARP1	0.237 (1.252)	0.122 (0.548)	0.078 (0.719)	0.007 (0.070)	0.355* (1.712)	0.307 (1.507)	-0.188 (-0.965)	-0.001 (-0.013)	0.223 (1.129)
TARP Large \times Subprime (<580) \times Post-TARP2	0.588*** (5.785)	0.503*** (4.190)	0.382*** (7.363)	0.416*** (9.430)	0.380*** (3.420)	-0.004 (-0.035)	0.603*** (4.926)	0.081* (1.738)	-0.354*** (-3.424)
TARP Small \times Subprime (<580) \times Post-TARP2	0.038 (0.181)	-0.079 (-0.326)	0.088 (0.8216)	0.155 (1.624)	0.085 (0.376)	-0.123 (-0.526)	0.219 (0.865)	0.050 (0.528)	-0.113 (-0.522)

Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134
R-squared	0.348	0.260	0.042	0.077	0.143	0.210	0.140	0.030	0.153

Panel B: Bank Capital (Above and Below Median of Bank Equity Capital Ratio)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
TARP HighEq	0.160** (2.571)	0.330*** (3.629)	-0.0543 (-1.204)	0.373*** (7.733)	0.018 (0.250)	0.040 (0.544)	-0.082 (-1.463)	0.007 (0.370)	0.043 (0.676)
TARP LowEq	0.067 (1.277)	0.280*** (3.647)	0.017 (0.461)	0.212*** (5.468)	-0.150** (-2.465)	0.029 (0.489)	0.039 (0.788)	0.015 (0.874)	-0.010 (-0.186)
Subprime (<580)	-0.363*** (-11.479)	-1.335*** (-33.621)	0.050** (2.290)	-0.126*** (-8.344)	-0.312*** (-8.292)	-0.792*** (-22.018)	-0.090*** (-2.852)	-0.038*** (-3.647)	0.619*** (18.205)
TARP HighEq × Subprime (<580)	-0.920*** (-9.540)	-1.618*** (-13.485)	-0.258*** (-4.054)	-1.090*** (-21.538)	-1.107*** (-9.947)	0.483*** (4.247)	0.632*** (6.492)	0.060* (1.798)	-0.788*** (-7.589)
TARP LowEq × Subprime (<580)	-0.415*** (-6.184)	-1.142*** (-13.825)	-0.244*** (-5.780)	-0.571*** (-17.917)	-0.174** (-2.208)	0.693*** (9.189)	0.334*** (4.941)	0.049** (2.269)	-0.056 (-0.797)
TARP HighEq × Post-TARP1 ('09-'12)	-0.112* (-1.947)	-0.295*** (-3.759)	-0.014 (-0.348)	-0.213*** (-4.818)	-0.016 (-0.258)	-0.191*** (-2.715)	0.048 (0.946)	0.020 (0.938)	0.067 (1.140)
TARP LowEq × Post-TARP1 ('09-'12)	-0.031 (-0.659)	-0.308*** (-4.915)	-0.060** (-1.992)	-0.008 (-0.210)	0.191*** (3.762)	-0.219*** (-3.995)	0.099** (2.356)	0.054*** (2.990)	0.023 (0.506)
TARP HighEq × Post-TARP1 ('13-'16)	-0.005 (-0.081)	-0.545*** (-6.015)	0.087** (2.024)	-0.420*** (-8.509)	0.194*** (2.765)	-0.264*** (-3.381)	0.212*** (3.613)	0.004 (0.166)	0.158** (2.432)
TARP LowEq × Post-TARP1 ('13-'16)	-0.111** (-2.089)	-0.637*** (-8.708)	0.010 (0.328)	-0.453*** (-11.964)	0.268*** (4.674)	-0.184*** (-3.022)	0.068 (1.397)	0.005 (0.271)	0.098* (1.944)
Subprime (<580) × Post-TARP1	-0.062 (-1.137)	0.163** (2.496)	-0.170*** (-5.297)	-0.026 (-1.029)	-0.873*** (-14.575)	0.081 (1.332)	0.538*** (9.080)	0.183*** (6.762)	0.068 (1.191)
Subprime (<580) × Post-TARP2	0.090 (1.543)	-0.069 (-1.008)	-0.177*** (-5.940)	-0.017 (-0.692)	-1.140*** (-18.042)	0.218*** (3.249)	0.912*** (12.637)	0.128*** (4.624)	0.040 (0.667)
TARP HighEq × Subprime (<580) × Post-TARP1	1.151*** (9.302)	1.586*** (10.539)	0.422*** (5.651)	0.785*** (12.393)	1.081*** (7.820)	0.603*** (4.264)	0.004 (0.033)	0.170*** (2.988)	0.326** (2.530)
TARP LowEq × Subprime (<580) × Post-TARP1	0.440*** (4.159)	0.377*** (3.000)	0.365*** (6.077)	0.123** (2.362)	0.477*** (4.122)	0.194* (1.666)	-0.040 (-0.352)	-0.062 (-1.200)	-0.132 (-1.225)
TARP HighEq × Subprime (<580) × Post-TARP2	0.654*** (4.781)	0.995*** (6.037)	0.350*** (4.677)	0.626*** (9.757)	0.725*** (4.817)	0.027 (0.170)	0.118 (0.734)	0.107* (1.736)	0.028 (0.195)
TARP LowEq × Subprime (<580) × Post-TARP2	0.734*** (6.034)	0.094 (0.673)	0.332*** (5.791)	0.465*** (9.007)	0.588*** (4.513)	0.168 (1.227)	0.897*** (5.953)	0.048 (0.835)	-0.221* (-1.815)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134
R-squared	0.348	0.260	0.042	0.077	0.143	0.210	0.140	0.030	0.153

Panel C: Bank Liquidity (Above and Below Median of Bank Liquidity Ratio)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								

Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
TARP HighLiq	0.063 (1.001)	0.351*** (3.843)	0.043 (0.994)	0.168*** (3.762)	-0.130* (-1.800)	-0.051 (-0.725)	0.027 (0.463)	0.038* (1.820)	0.073 (1.163)
TARP LowLiq	0.093 (1.385)	0.133 (1.331)	-0.078* (-1.673)	0.359*** (6.782)	-0.010 (-0.128)	0.126* (1.647)	-0.056 (-0.904)	-0.018 (-0.819)	-0.055 (-0.801)
Subprime (<580)	-0.356*** (-11.258)	-1.352*** (-34.017)	0.042* (1.895)	-0.103*** (-6.881)	-0.282*** (-7.493)	-0.775*** (-21.497)	-0.095*** (-2.999)	-0.036*** (-3.398)	0.635*** (18.627)
TARP HighLiq × Subprime (<580)	-0.464*** (-6.501)	-1.386*** (-15.920)	-0.318*** (-7.263)	-0.496*** (-14.673)	-0.139* (-1.674)	0.795*** (9.977)	0.368*** (5.106)	0.077*** (3.456)	-0.083 (-1.110)
TARP LowLiq × Subprime (<580)	-0.604*** (-6.617)	-0.863*** (-7.476)	-0.084 (-1.400)	-1.054*** (-22.629)	-0.821*** (-7.625)	0.335*** (3.229)	0.442*** (4.652)	-0.005 (-0.152)	-0.435*** (-4.433)
TARP HighLiq × Post-TARP1 ('09-'12)	-0.095** (-2.063)	-0.387*** (-6.299)	-0.108*** (-3.722)	-0.010 (-0.277)	0.208*** (4.149)	-0.213*** (-3.972)	-0.036 (-0.892)	0.026 (1.517)	0.035 (0.782)
TARP LowLiq × Post-TARP1 ('09-'12)	0.035 (0.663)	-0.107 (-1.472)	0.028 (0.785)	-0.166*** (-4.024)	0.007 (0.115)	-0.201*** (-3.134)	0.150*** (3.157)	0.048** (2.366)	0.102* (1.933)
TARP HighLiq × Post-TARP1 ('13-'16)	-0.096* (-1.915)	-0.704*** (-10.161)	-0.016 (-0.515)	-0.445*** (-12.501)	0.336*** (6.184)	-0.237*** (-4.109)	0.055 (1.200)	-0.018 (-1.018)	0.103** (2.143)
TARP LowLiq × Post-TARP1 ('13-'16)	0.070 (1.158)	-0.344*** (-4.007)	0.107*** (2.737)	-0.319*** (-6.847)	0.156** (2.359)	-0.207*** (-2.884)	0.199*** (3.526)	0.037 (1.600)	0.190*** (3.213)
Subprime (<580) × Post-TARP1	-0.068 (-1.250)	0.179*** (2.748)	-0.161*** (-5.025)	-0.049* (-1.925)	-0.901*** (-15.051)	0.065 (1.066)	0.543*** (9.184)	0.180*** (6.668)	0.054 (0.961)
Subprime (<580) × Post-TARP2	0.074 (1.277)	-0.048 (-0.697)	-0.170*** (-5.680)	-0.044* (-1.824)	-1.181*** (-18.709)	0.196*** (2.927)	0.913*** (12.685)	0.126*** (4.546)	0.013 (0.218)
TARP HighLiq × Subprime (<580) × Post-TARP1	0.753*** (7.261)	0.9557*** (7.7283)	0.4780*** (8.2331)	0.304*** (5.806)	0.550*** (4.818)	0.360*** (3.128)	0.115 (1.057)	0.092* (1.865)	-0.065 (-0.610)
TARP LowLiq × Subprime (<580) × Post-TARP1	0.488*** (3.999)	0.5961*** (4.0079)	0.2007*** (2.7121)	0.392*** (6.513)	0.474*** (3.473)	0.396*** (2.858)	0.027 (0.210)	0.040 (0.659)	-0.215* (-1.676)
TARP HighLiq × Subprime (<580) × Post-TARP2	0.751*** (6.641)	0.4918*** (3.7499)	0.4396*** (7.9598)	0.425*** (8.766)	0.472*** (3.842)	0.026 (0.203)	0.654*** (4.756)	0.067 (1.310)	-0.073 (-0.637)
TARP LowLiq × Subprime (<580) × Post-TARP2	0.245* (1.853)	0.1227 (0.7774)	0.1297* (1.8059)	0.448*** (7.414)	0.370** (2.537)	0.138 (0.907)	0.486*** (3.057)	0.119* (1.920)	-0.605*** (-4.434)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134
R-squared	0.348	0.260	0.042	0.077	0.143	0.210	0.140	0.030	0.153

Table 8: Effects of TARP Bailouts on Subprime Consumer Debt – Cross-Sectional Tests by Consumer Education and Financial Literacy

This table reports difference-in-difference-in-difference (DIDID) regression estimates for analyzing the effects of TARP bailouts on debt of subprime consumers (Equifax Risk Score < 580) relative to other consumers when using cross-sectional tests by county-level consumer education (percent of population with a Bachelor's degree) and state-level financial literacy (based on state literacy and economics mandates across time), both using median as the cutoff for the groups. The table uses a 1% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period is 2001:Q1–2016:Q4. The dependent variables are $\ln(1+ \text{Total Consumer Debt})$, $\ln(1+ \text{Total Mortgage Debt})$, $\ln(1+ \text{Total HELOAN Debt})$, $\ln(1+ \text{Total HELOC Debt})$, $\ln(1+ \text{Total Card Debt})$, $\ln(1+ \text{Total Auto Debt})$, $\ln(1+ \text{Total Student Debt})$, $\ln(1+ \text{Total Private Student Debt})$, and $\ln(1+ \text{Other Consumer Debt})$, representing the natural logarithm of one plus total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer). *TARP* is the weighted proportion of banks receiving TARP bailouts in the 10-mile radius of the consumer zip code. *Subprime* is an indicator that equals one if the consumer has an Equifax Risk Score below 580. *Post-TARP1* and *Post-TARP2* are indicators equal to one in 2009–2012 and 2013–2016, respectively, both periods after the TARP program initiation. We also include other consumer controls: *Consumer Age*, *Joint Account*, and $\ln(1+ \text{No. Credit Inquiries last 12mos})$. We also include a number of bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size, and controls for other government programs other than TARP (Discount Window, Term Auction Facility, FDIC TAGP, FDIC TDGP, SBLF, and FHLB programs). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Low and High Education (Based on % Population with Bachelor's Degree)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
TARP	0.091* (1.769)	0.292*** (3.873)	-0.002 (-0.058)	0.237*** (6.280)	-0.121** (-2.037)	0.040 (0.697)	0.023 (0.489)	0.015 (0.872)	0.004 (0.078)
TARP × Post-TARP1 ('09-'12)	-0.045 (-1.110)	-0.301*** (-5.503)	-0.061** (-2.291)	-0.055* (-1.798)	0.148*** (3.336)	-0.210*** (-4.408)	0.025 (0.700)	0.032*** (2.084)	0.064 (1.586)
TARP × Post-TARP2 ('13-'16)	-0.033 (-0.751)	-0.593*** (-9.613)	0.028 (1.010)	-0.383*** (-12.035)	0.293*** (6.067)	-0.229*** (-4.458)	0.098** (2.410)	0.002 (0.147)	0.143*** (3.324)
Subprime (<580)_lowEDUC	-0.369*** (-11.389)	-1.302*** (-32.161)	0.042* (1.893)	-0.133*** (-8.808)	-0.334*** (-8.729)	-0.778*** (-21.161)	-0.105*** (-3.259)	-0.041*** (-3.845)	0.619*** (17.808)
Subprime (<580)_highEDUC	0.150 (1.075)	-1.325*** (-7.617)	-0.126 (-1.623)	-0.088 (-1.106)	0.662*** (3.753)	-0.741*** (-4.416)	0.533*** (2.696)	0.012 (0.156)	0.655*** (3.929)
TARP × Subprime (<580)_lowEDUC	-0.549*** (-8.465)	-1.225*** (-15.335)	-0.235*** (-5.682)	-0.661*** (-21.653)	-0.390*** (-5.161)	0.610*** (8.346)	0.354*** (5.418)	0.049** (2.340)	-0.228*** (-3.329)
TARP × Subprime (<580)_highEDUC	-0.213 (-0.806)	-1.487*** (-4.593)	0.030 (0.205)	-0.563*** (-3.749)	-0.344 (-1.046)	1.171*** (3.701)	0.421 (1.130)	0.087 (0.608)	0.307 (0.976)
Subprime (<580)_lowEDUC × Post-TARP1	-0.067 (-1.218)	0.156** (2.369)	-0.169*** (-5.247)	-0.015 (-0.586)	-0.856*** (-14.084)	0.070 (1.124)	0.520*** (8.708)	0.184*** (6.752)	0.059 (1.029)
Subprime (<580)_highEDUC × Post-TARP1	0.330 (1.083)	-0.157 (-0.385)	-0.182 (-1.147)	0.152 (0.759)	-0.951*** (-2.576)	0.195 (0.578)	1.504*** (3.586)	0.232 (1.178)	-0.088 (-0.258)
Subprime (<580)_lowEDUC × Post-TARP2	0.073 (1.239)	-0.090 (-1.294)	-0.172*** (-5.704)	-0.014 (-0.558)	-1.131*** (-17.652)	0.207*** (3.043)	0.880*** (12.077)	0.121*** (4.325)	0.045 (0.735)
Subprime (<580)_highEDUC × Post-TARP2	0.632* (1.933)	-0.174 (-0.415)	0.077 (0.435)	-0.008 (-0.039)	-0.862** (-2.187)	0.142 (0.379)	2.439*** (4.815)	0.799*** (3.104)	-0.659** (-2.056)
TARP × Subprime (<580)_lowEDUC × Post-TARP1	0.634*** (6.828)	0.824*** (7.421)	0.387*** (7.253)	0.263*** (5.941)	0.432*** (4.208)	0.355*** (3.424)	0.093 (0.958)	0.060 (1.329)	-0.114 (-1.193)
TARP × Subprime (<580)_highEDUC × Post-TARP1	0.231 (0.499)	1.677*** (2.755)	0.424* (1.794)	0.254 (0.838)	0.751 (1.340)	-0.018 (-0.035)	-0.937 (-1.507)	0.070 (0.237)	-0.303 (-0.585)
TARP × Subprime (<580)_lowEDUC × Post-TARP2	0.536*** (5.389)	0.395*** (3.384)	0.322*** (6.308)	0.367*** (8.690)	0.320*** (2.953)	0.024 (0.208)	0.624*** (5.238)	0.080* (1.757)	-0.324*** (-3.197)
TARP × Subprime (<580)_highEDUC × Post-TARP2	-0.125 (-0.254)	0.883 (1.402)	0.092 (0.348)	0.407 (1.383)	0.248 (0.415)	0.194 (0.338)	-1.271* (-1.694)	-0.627* (-1.699)	0.371 (0.735)

Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134
R-squared	0.348	0.260	0.042	0.077	0.143	0.210	0.141	0.031	0.153

Panel B: Low and High Financial Literacy (Based on State Financial Literacy and Economics Education Mandates)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
TARP	0.094* (1.835)	-0.118** (-1.975)	0.030 (0.512)	0.012 (0.252)	0.013 (0.762)	0.002 (0.030)	0.309*** (4.099)	0.005 (0.124)	0.247*** (6.531)
TARP × Post-TARP1 ('09-'12)	-0.053 (-1.301)	0.134*** (3.026)	-0.205*** (-4.289)	0.026 (0.707)	0.033** (2.126)	0.064 (1.604)	-0.306*** (-5.581)	-0.065** (-2.428)	-0.064** (-2.083)
TARP × Post-TARP2 ('13-'16)	-0.040 (-0.889)	0.279*** (5.760)	-0.2214*** (-4.2915)	0.101** (2.476)	0.002 (0.138)	0.142*** (3.296)	-0.596*** (-9.626)	0.022 (0.800)	-0.390*** (-12.223)
Subprime (<580)_lowEDUCMANDATE	-0.359*** (-11.009)	-0.313*** (-8.081)	-0.7906*** (-21.2351)	-0.080** (-2.452)	-0.043*** (-3.874)	0.651*** (18.535)	-1.336*** (-32.819)	0.046** (2.047)	-0.123*** (-8.040)
Subprime (<580)_highEDUCMANDATE	-0.397*** (-3.991)	-0.276** (-2.322)	-0.8255*** (-7.5502)	-0.226** (-2.480)	0.004 (0.136)	0.346*** (3.222)	-1.319*** (-10.737)	0.095 (1.328)	-0.130*** (-2.615)
TARP × Subprime (<580)_lowEDUCMANDATE	-0.504*** (-7.726)	-0.305*** (-3.984)	0.6683*** (9.0443)	0.357*** (5.418)	0.060*** (2.769)	-0.233*** (-3.366)	-1.220*** (-15.199)	-0.241*** (-5.781)	-0.662*** (-21.421)
TARP × Subprime (<580)_highEDUCMANDATE	-0.601*** (-3.079)	-0.960*** (-4.221)	0.4319** (1.9858)	0.813*** (3.958)	-0.036 (-0.566)	0.147 (0.702)	-1.388*** (-5.753)	-0.301** (-2.271)	-0.742*** (-7.939)
Subprime (<580)_lowEDUCMANDATE × Post-TARP1	-0.054 (-0.906)	-0.880*** (-13.441)	0.1499** (2.2531)	0.620*** (9.333)	0.197*** (6.458)	-0.012 (-0.199)	0.175** (2.453)	-0.166*** (-4.810)	-0.041 (-1.492)
Subprime (<580)_highEDUCMANDATE × Post-TARP1	-0.067 (-0.519)	-0.851*** (-5.796)	-0.1559 (-1.0917)	0.297** (2.353)	0.097* (1.744)	0.533*** (3.827)	0.114 (0.754)	-0.214*** (-2.611)	0.030 (0.537)
Subprime (<580)_lowEDUCMANDATE × Post-TARP2	0.102 (1.561)	-1.174*** (-16.765)	0.2678*** (3.5882)	1.047*** (12.705)	0.169*** (5.134)	-0.065 (-0.988)	-0.078 (-1.030)	-0.153*** (-4.761)	-0.015 (-0.577)
Subprime (<580)_highEDUCMANDATE × Post-TARP2	0.053 (0.390)	-1.091*** (-7.124)	0.0781 (0.5074)	0.579*** (3.759)	-0.025 (-0.503)	0.534*** (3.678)	-0.062 (-0.376)	-0.2829*** (-3.542)	-0.035 (-0.612)
TARP × Subprime (<580)_lowEDUCMANDATE × Post-TARP1	0.687*** (6.943)	0.565*** (5.178)	0.280** (2.548)	-0.019 (-0.177)	0.033 (0.675)	-0.035 (-0.339)	0.930*** (7.833)	0.393*** (6.990)	0.338*** (7.074)
TARP × Subprime (<580)_highEDUCMANDATE × Post-TARP1	0.513** (2.232)	0.463* (1.771)	0.716*** (2.815)	0.240 (1.015)	0.263** (2.545)	-0.754*** (-3.076)	0.642** (2.354)	0.410*** (2.860)	0.162 (1.599)
TARP × Subprime (<580)_lowEDUCMANDATE × Post-TARP2	0.606*** (5.629)	0.489*** (4.187)	-0.036 (-0.291)	0.485*** (3.651)	0.019 (0.356)	-0.222** (-2.031)	0.535*** (4.285)	0.311*** (5.816)	0.415*** (9.008)
TARP × Subprime (<580)_highEDUCMANDATE × Post-TARP2	0.4053* (1.690)	0.452* (1.672)	0.398 (1.463)	0.640** (2.317)	0.335*** (3.6211)	-0.901*** (-3.5316)	0.171 (0.586)	0.456*** (3.194)	0.343*** (3.397)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134	5,647,134
R-squared	0.348	0.143	0.210	0.140	0.030	0.153	0.260	0.042	0.077

Table 9: Effects of TARP Bailouts on Subprime Consumer Leverage – Additional Evidence from Full Anonymized CCP Aggregated at County Level

This table reports difference-in-difference-in-difference (DIDID) regression estimates for analyzing the effects of TARP bailouts on leverage ratios of subprime consumers (Equifax Risk Score < 580) relative to other consumers when using an additional analysis in which we aggregate the full anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP) at county level. The anonymized CCP data are a

representative panel of individual credit records from Equifax. The unit of observation in this table is a county-quarter. The sample period is 2001:Q1–2016:Q4. The dependent variables are $Ln(1+Total\ Consumer\ Debt)$, $Ln(1+Total\ Consumer\ Debt_2)$ with Private Student Debt, $Ln(1+Total\ Consumer\ Debt_3)$ without Student Debt, Total Consumer Debt/Total Income, Total Consumer Debt₂ (with Private Student)/Total Income, Total Consumer Debt₃ (without Student Debt)/Total Income, Mortgage Debt/Total Income, HELOAN Debt/Total Income, HELOC Debt/Total Income, Card Debt/Total Income, Auto Debt/Total Income, Student Debt/Total Income, Private Student Debt/Total Income, and Other Consumer Debt/Total Income, representing the total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer) scaled by total county consumer income from BEA. TARP is the weighted proportion of banks receiving TARP bailouts in the consumer county. Pct Subprime is the percent of consumers with an Equifax Risk Score below 580 in the county. Post-TARP1 and Post-TARP2 are indicators equal to one in 2009-2012 and 2013-2016, respectively, both periods after the TARP program initiation. We also include other consumer controls in the county: Consumer Age, Joint Account, and $Ln(1+No.\ Credit\ Inquiries\ last\ 12\ mos)$. We also include a number of bank characteristics in the county of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size, and controls for other government programs other than TARP (Discount Window, Term Auction Facility, FDIC TAGP, FDIC TDGP, SBLF, and FHLB programs). Finally, we control for unemployment rate and HPI in the consumer county. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust t -statistics clustered at county level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Full CCP Population Aggregated at County Level: County-Level Consumer Leverage										
Dependent Variable	Consumer Leverage										
Dependent Variable:	Total Consumer Debt/Total Income	Total Consumer Debt (w/ Private Student)/Total Income	Total Consumer Debt (w/o Student) / Total Income	Mortgage Debt/Total Income	HELOAN Debt/Total Income	HELOC Debt/Total Income	Card Debt/Total Income	Auto Debt/Total Income	Student Debt/Total Income	Private Student Debt /Total Income	Other Consumer Debt/Total Income
Independent Variables											
TARP	0.043*** (2.617)	0.038** (2.374)	0.037** (2.263)	0.013 (1.057)	0.009*** (4.878)	0.011*** (5.045)	0.004 (1.552)	0.000 (0.153)	0.006* (1.704)	0.002*** (3.435)	0.000 (1.624)
Pct Subprime	0.488*** (12.112)	0.458*** (11.967)	0.454*** (11.964)	0.219*** (7.704)	0.054*** (13.726)	0.040*** (9.388)	0.076*** (15.133)	0.007 (1.170)	0.034*** (4.578)	0.004*** (2.821)	0.000 (0.841)
TARP × Pct Subprime	-0.193*** (-2.788)	-0.176** (-2.561)	-0.171** (-2.482)	-0.057 (-1.102)	-0.045*** (-5.316)	-0.037*** (-4.116)	-0.022** (-2.109)	0.003 (0.281)	-0.022 (-1.211)	-0.005* (-1.883)	-0.000 (-1.635)
TARP × Post-TARP1 ('09-'12)	-0.024 (-1.290)	-0.019 (-1.061)	-0.018 (-1.012)	-0.024 (-1.556)	-0.006*** (-3.458)	0.006*** (3.423)	0.003 (1.441)	-0.004* (-1.892)	-0.006* (-1.711)	-0.001 (-1.613)	0.000* (1.930)
TARP × Post-TARP2 ('13-'16)	-0.167*** (-8.762)	-0.161*** (-8.488)	-0.160*** (-8.440)	-0.119*** (-7.763)	-0.005** (-2.320)	-0.022*** (-6.874)	-0.004* (-1.773)	-0.006** (-2.356)	-0.008* (-1.860)	-0.001 (-1.579)	0.000*** (3.208)
Pct Subprime × Post-TARP1	-0.279*** (-7.035)	-0.288*** (-7.385)	-0.296*** (-7.607)	-0.155*** (-4.362)	-0.044*** (-15.514)	-0.010*** (-3.618)	-0.027*** (-7.777)	-0.019*** (-4.637)	0.017*** (2.894)	0.007*** (6.671)	0.000*** (6.378)
Pct Subprime × Post-TARP2	-0.073** (-2.161)	-0.137*** (-4.229)	-0.143*** (-4.440)	-0.006 (-0.229)	-0.043*** (-12.364)	-0.007 (-1.366)	-0.026*** (-6.060)	0.028*** (4.947)	0.070*** (7.503)	0.006*** (4.160)	0.000*** (6.100)
TARP × Pct Subprime × Post-TARP1	0.292*** (3.380)	0.253*** (3.015)	0.242*** (2.904)	0.215*** (2.923)	0.027*** (3.424)	-0.010 (-1.057)	0.004 (0.392)	0.008 (0.823)	0.051*** (2.850)	0.011*** (3.197)	-0.000** (-2.375)
TARP × Pct Subprime × Post-TARP2	0.665*** (6.939)	0.575*** (6.058)	0.561*** (5.906)	0.383*** (5.170)	0.019* (1.939)	0.092*** (3.969)	0.032*** (2.857)	-0.011 (-0.900)	0.105*** (4.124)	0.014*** (3.626)	-0.000*** (-3.545)
County, Bank Controls	X	X	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X	X	X
Errors Clustered by County	X	X	X	X	X	X	X	X	X	X	X
Observations	194,231	194,231	194,231	194,231	194,231	194,231	194,231	194,231	194,231	194,231	194,231
R-squared	0.915	0.915	0.915	0.931	0.691	0.819	0.812	0.863	0.861	0.611	0.941

Table 10: Effects of PPP Bailouts on Subprime Consumer Debt – Main Evidence

This table reports difference-in-difference (DID) regression estimates for analyzing the effects of PPP bailouts on debt of subprime consumers (Equifax Risk Score < 580) relative to other consumers. The table uses a 5% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period covers 2019:Q2-2019:Q4 (three quarterly periods) + 2020:M1-2020:M9 (nine monthly periods). Panel A presents main results in column (1), while showing various robustness tests in columns (2)-(14). These robustness are: alternative dependent variables for total consumer which use only private student debt or exclude student debt in columns (2)-(3), including only consumers that exist in both pre- and post-TARP periods in column (4), clustering by county and consumer in column (5), using high-dimensional County×Time fixed effects in column (6), excluding various controls in columns (7)-(9), controlling for county median household income in column (10), and alternative radius/area close to the consumer zip code: 5, 25, or 50 miles radius or the county of the consumer in columns (11)-(14). Panel B decomposes total consumer debt into its subcomponents. The dependent variables are $Ln(1+Total\ Consumer\ Debt)$, the natural logarithm of one plus total consumer debt in Panel A, and $Ln(1+Total\ Consumer\ Debt)$, $Ln(1+Total\ Mortgage\ Debt)$, $Ln(1+Total\ HELOAN\ Debt)$, $Ln(1+Total\ HELOC\ Debt)$, $Ln(1+Total\ Card\ Debt)$, $Ln(1+Total\ Auto\ Debt)$, $Ln(1+Total\ Student\ Debt)$, and $Ln(1+Other\ Consumer\ Debt)$, representing the natural logarithm of one plus total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer). PPP is the weighted proportion of high PPP lending banks (those with PPP Loans/Total Loans \geq 50th percentile) in the 10-mile radius of the consumer zip code. Subprime is an indicator that equals one if the consumer has an Equifax Risk Score below 580. Post-PPP is an indicator equal to one from April 2020 (2020:M4) onwards, after the PPP program initiation. We also include other consumer controls: *Consumer Age*, *Joint Account*, and $Ln(1+No. Credit\ Inquiries\ last\ 12\ mos)$. We also include a number of bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size and controls for other government programs other than PPP (CARES Act forbearances using forbearance rates for individual products in the consumer county). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Total Consumer Debt for Individuals

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	Dependent Variable: $Ln(1+Total\ Consumer\ Debt)$													
	Main Spec	Alt. Dep Variable: Consumer Debt w/ Private Student	Alt. Dep Variable: Consumer Debt w/o Student	Include only Consumers in Both Pre & Post Periods	Cluster by County & Consumer	Add County× Year-Quarter FE	Exclude Bank Proxies for CAMELS	Exclude All Bank Controls	Exclude All Bank & County Controls	Control for County Income	Alternative Radius: 5 MILES	Alternative Radius: 25 MILES	Alternative Radius: 50 MILES	Alternative Radius: COUNTY
Independent Variables														
PPP	0.025 (0.582)	0.019 (0.425)	0.018 (0.400)	0.028 (0.643)	0.025 (0.483)	0.073 (1.505)	0.011 (0.254)	-0.042 (-0.994)	-0.048 (-1.156)	0.028 (0.641)	0.043 (1.385)	-0.019 (-0.211)	0.066 (0.472)	0.051 (0.975)
Subprime (<580)	-0.136*** (-5.583)	-0.597*** (-22.937)	-0.581*** (-22.318)	-0.171*** (-7.018)	-0.136*** (-2.788)	-0.128*** (-5.210)	-0.137*** (-5.621)	-0.137*** (-5.620)	-0.137*** (-5.664)	-0.136*** (-5.569)	-0.142*** (-6.444)	-0.103*** (-3.622)	-0.082*** (-2.616)	-0.152*** (-6.573)
PPP × Subprime (<580)	-0.231*** (-4.704)	-0.242*** (-4.649)	-0.229*** (-4.391)	-0.228*** (-4.642)	-0.231*** (-2.709)	-0.235*** (-4.754)	-0.230*** (-4.679)	-0.230*** (-4.675)	-0.232*** (-4.990)	-0.232*** (-4.711)	-0.222*** (-5.079)	-0.304*** (-5.112)	-0.352*** (-5.304)	-0.238*** (-4.294)
PPP × Post-PPP (M4-M9)	0.105*** (7.619)	0.106*** (7.438)	0.105*** (7.332)	0.089*** (6.723)	0.105*** (5.808)	0.027 (0.875)	0.120*** (9.142)	0.119*** (9.064)	0.126*** (9.698)	0.098*** (7.102)	0.084*** (6.867)	0.127*** (7.349)	0.140*** (7.064)	0.129*** (8.657)
Subprime (<580) × Post-PPP	0.142*** (7.127)	0.230*** (10.869)	0.243*** (11.442)	0.171*** (8.786)	0.142*** (6.232)	0.123*** (6.071)	0.143*** (7.200)	0.143*** (7.192)	0.146*** (7.371)	0.141*** (7.080)	0.130*** (7.226)	0.166*** (7.159)	0.180*** (7.025)	0.145*** (7.800)
PPP × Subprime (<580) × Post-PPP	-0.123*** (-3.137)	-0.168*** (-4.021)	-0.168*** (-4.026)	-0.124*** (-3.212)	-0.123*** (-2.905)	-0.118*** (-2.912)	-0.125*** (-3.190)	-0.125*** (-3.179)	-0.134*** (-3.448)	-0.122*** (-3.117)	-0.095*** (-2.698)	-0.176*** (-3.744)	-0.207*** (-3.904)	-0.159*** (-3.658)
Other Consumer Characteristics														
Consumer Age	-0.031*** (-120.486)	-0.007*** (-26.491)	-0.003*** (-11.511)	-0.031*** (-118.328)	-0.031*** (-45.009)	-0.031*** (-120.306)	-0.031*** (-120.500)	-0.031*** (-120.558)	-0.031*** (-121.556)	-0.031*** (-120.478)	-0.031*** (-118.398)	-0.031*** (-121.001)	-0.031*** (-121.064)	-0.031*** (-121.080)
Joint Account	3.238*** (422.953)	3.701*** (470.873)	3.773*** (477.485)	3.179*** (412.504)	3.238*** (131.851)	3.238*** (422.348)	3.238*** (422.963)	3.238*** (422.946)	3.238*** (428.407)	3.238*** (422.814)	3.239*** (416.658)	3.239*** (424.692)	3.239*** (424.855)	3.238*** (424.855)
$Ln(1+No. Credit\ Inquiries\ last\ 12\ mos)$	1.278*** (187.489)	1.604*** (224.634)	1.644*** (229.396)	1.259*** (184.242)	1.278*** (109.079)	1.279*** (187.274)	1.278*** (187.482)	1.278*** (187.492)	1.279*** (190.773)	1.278*** (187.435)	1.279*** (184.247)	1.279*** (188.369)	1.279*** (188.415)	1.278*** (188.372)
Bank Characteristics (lagged 4 quarters)														
Capital Adequacy	0.109 (0.141)	0.066 (0.083)	0.194 (0.242)	0.042 (0.055)	0.109 (0.118)	-0.199 (-0.235)				0.079 (0.102)	-0.492 (-0.961)	0.946 (0.617)	0.197 (0.092)	3.080*** (4.041)
Asset Quality	0.020 (0.011)	0.767 (0.399)	0.809 (0.419)	0.289 (0.154)	0.020 (0.008)	0.655 (0.289)				-0.034 (-0.018)	0.259 (0.186)	1.423 (0.454)	-9.933** (-2.230)	-4.572*** (-3.242)
Management Quality	-0.010*** (-3.493)	-0.008*** (-2.590)	-0.008*** (-2.612)	-0.007** (-2.576)	-0.010*** (-2.584)	-0.027* (-1.847)				-0.010*** (-3.565)	-0.006* (-1.852)	-0.007** (-2.409)	-0.002 (-0.622)	-0.010*** (-3.675)
Earnings	-1.692 (-0.989)	-0.357 (-0.199)	-0.662 (-0.367)	-1.499 (-0.872)	-1.692 (-0.913)	-1.400 (-0.571)				-1.668 (-0.975)	0.783 (0.595)	-0.158 (-0.060)	-1.423 (-0.451)	-2.407** (-2.311)

Liquidity	-0.350**	-0.443**	-0.459**	-0.331*	-0.350*	-0.374**		-0.355**	-0.258**	-0.178	-0.188	-0.365*
	(-1.979)	(-2.427)	(-2.505)	(-1.861)	(-1.680)	(-1.967)		(-2.002)	(-2.021)	(-0.519)	(-0.352)	(-1.770)
Sensitivity to Market Risk	0.462**	0.726***	0.774***	0.457**	0.462**	0.438*		0.439**	0.042	0.691**	1.613***	0.490***
	(2.312)	(3.529)	(3.747)	(2.277)	(2.065)	(1.800)		(2.179)	(0.280)	(2.134)	(4.285)	(2.911)
Bank Size	0.035***	0.034***	0.033***	0.036***	0.035***	0.031***	0.036***	0.035***	0.008	0.093***	0.091***	-0.015**
	(4.631)	(4.360)	(4.231)	(4.702)	(3.335)	(3.674)	(4.929)	(4.604)	(1.467)	(6.482)	(3.680)	(-2.173)
County-Level Characteristics (lagged 4 or 1 quarter)												
County Unemployment Rate	-0.000	-0.001	-0.001	0.000	-0.000	-0.000	-0.001	-0.001	-0.001	0.000	0.000	-0.001
	(-0.100)	(-0.211)	(-0.306)	(0.087)	(-0.096)	(-0.153)	(-0.297)	(-0.379)	(-0.484)	(0.050)	(0.059)	(-0.316)
County HPI	0.003***	0.002***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(4.449)	(3.927)	(4.552)	(5.213)	(2.288)	(4.471)	(4.544)	(4.340)	(4.466)	(4.306)	(4.160)	(4.388)
Constant	0.034	-0.006	-0.000	0.076*	0.034	0.129***	0.027	0.023	0.022	-0.007	0.044	0.040
	(0.742)	(-0.130)	(-0.008)	(1.726)	(0.668)	(3.337)	(0.602)	(0.505)	(0.493)	(-0.161)	(0.967)	(0.893)
Forbearance Rate Mortgage	-0.065	-0.076*	-0.090**	-0.064	-0.065	-0.007	-0.064	-0.063	-0.063	-0.070	-0.054	-0.052
	(-1.564)	(-1.743)	(-2.050)	(-1.585)	(-1.336)	(-0.223)	(-1.531)	(-1.619)	(-1.511)	(-1.624)	(-1.291)	(-1.249)
Forbearance Rate Home Equity	1.455***	1.333***	1.235***	1.322***	1.455***	0.690*	1.597***	1.620***	1.405***	1.623***	1.159***	1.168***
	(3.659)	(3.214)	(2.958)	(3.412)	(3.235)	(1.958)	(4.029)	(4.091)	(3.538)	(3.882)	(2.977)	(2.990)
Forbearance Rate Credit Card	-0.071	-0.107*	-0.110*	-0.022	-0.071	-0.111***	-0.100*	-0.099*	-0.052	-0.081	-0.045	-0.056
	(-1.284)	(-1.868)	(-1.925)	(-0.404)	(-0.868)	(-2.620)	(-1.832)	(-1.815)	(-0.955)	(-1.447)	(-0.811)	(-1.015)
Forbearance Rate Auto	-0.000	-0.001	-0.001	0.000	-0.000	-0.000	-0.001	-0.001	-0.001	-0.001	0.000	0.000
	(-0.100)	(-0.211)	(-0.306)	(0.087)	(-0.096)	(-0.153)	(-0.297)	(-0.379)	(-0.484)	(0.050)	(0.059)	(-0.316)
Ln(1+ County Income)												
County FE	X	X	X	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X	X	X	X
County × Year-Quarter FE							X					
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X	X	X	X
Errors Clustered by County							X					
Observations	5,518,082	5,518,082	5,518,082	5,461,694	5,518,082	5,517,947	5,518,082	5,518,596	5,669,006	5,515,189	5,343,623	5,563,622
R-squared	0.264	0.288	0.293	0.261	0.264	0.263	0.264	0.264	0.264	0.264	0.263	0.265

Panel B: Decomposition by Product

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
PPP	0.025	-0.141**	-0.016	0.052*	0.069	0.152***	0.152***	0.028	-0.011
	(0.582)	(-2.229)	(-0.740)	(1.955)	(1.374)	(2.819)	(2.819)	(0.608)	(-0.576)
Subprime (<580)	-0.136***	-2.328***	-0.077***	-0.243***	-0.518***	0.426***	0.426***	1.257***	0.004
	(-5.583)	(-79.524)	(-8.852)	(-26.691)	(-17.907)	(13.241)	(13.241)	(36.189)	(0.299)
PPP × Subprime (<580)	-0.231***	0.298***	-0.070***	0.008	-0.736***	-0.747***	-0.747***	-0.301***	-0.075***
	(-4.704)	(5.053)	(-3.837)	(0.452)	(-12.617)	(-11.612)	(-11.612)	(-4.353)	(-3.000)
PPP × Post-PPP (M4-M9)	0.105***	0.017	-0.012*	-0.001	0.115***	0.011	0.011	0.010	0.001
	(7.619)	(0.923)	(-1.920)	(-0.141)	(7.645)	(0.632)	(0.632)	(0.821)	(0.177)
Subprime (<580) × Post-PPP	0.142***	-0.064***	-0.001	0.029***	0.368***	0.065**	0.065**	-0.195***	-0.036***
	(7.127)	(-2.841)	(-0.120)	(4.391)	(15.502)	(2.433)	(2.433)	(-7.614)	(-3.621)
PPP × Subprime (<580) × Post-PPP	-0.123***	-0.016	0.006	-0.002	-0.204***	0.005	0.005	0.092*	0.007
	(-3.137)	(-0.343)	(0.375)	(-0.177)	(-4.363)	(0.104)	(0.104)	(1.851)	(0.355)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082
R-squared	0.264	0.237	0.020	0.054	0.078	0.223	0.223	0.127	0.019

Table 11: Effects of PPP Bailouts on Subprime Consumer Debt – Endogeneity and Sample Selection Tests

This table reports difference-in-difference-in-difference (DIDID) regression estimates for analyzing the effects of PPP bailouts on debt of subprime consumers (Equifax Risk Score < 580) when using endogeneity and sample selection tests. The table uses a 5% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period covers 2019:Q2-2019:Q4 (three quarterly periods) + 2020:M1-2020:M9 (nine monthly periods). In Panel A, we report estimates from the last stage of an instrumental variable analysis as in Wooldridge Section 18.4.1 and in Panel B, we report estimates for the outcome equation from the Heckman (1979)'s selection model. We use as an instrument: *SBA 7(a) 2019*. *SBA 7(a) 2019* is a variable which takes a value of 1 if a bank was involved in SBA 7(a) lending prior to the launch of the PPP in 2019. The dependent variables are $\ln(1 + \text{Total Consumer Debt})$, $\ln(1 + \text{Total Mortgage Debt})$, $\ln(1 + \text{Total HELOAN Debt})$, $\ln(1 + \text{Total HELOC Debt})$, $\ln(1 + \text{Total Card Debt})$, $\ln(1 + \text{Total Auto Debt})$, $\ln(1 + \text{Total Student Debt})$, $\ln(1 + \text{Total Private Student Debt})$, and $\ln(1 + \text{Other Consumer Debt})$, representing the natural logarithm of one plus total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer). *PPP* is the weighted proportion of high PPP lending banks (those with PPP Loans/Total Loans $\geq 50^{\text{th}}$ percentile) in the 10-mile radius of the consumer zip code. *Subprime* is an indicator that equals one if the consumer has an Equifax Risk Score below 620. *Post-PPP* is an indicator equal to one from April 2020 (2020:M4) onward, after the PPP program initiation. We also include other consumer controls: *Consumer Age*, *Joint Account*, and $\ln(1 + \text{No. Credit Inquiries last 12mos})$. We also include a number of bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size and controls for other government programs other than PPP (CARES Act forbearances using forbearance rates for individual products in the consumer county). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV Last Stage – Consumer Debt for Individuals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
PPP	-0.782*** (-3.404)	-0.003 (-0.010)	0.113 (1.062)	0.077 (0.584)	-1.688*** (-5.864)	-0.759*** (-2.662)	-0.728*** (-3.154)	-0.169* (-1.751)	-0.517** (-2.070)
Subprime (<580)	-0.044 (-0.355)	-1.279*** (-8.455)	-0.058 (-1.202)	0.191*** (3.961)	-1.284*** (-8.791)	-0.900*** (-5.668)	0.036 (0.213)	0.049 (0.816)	1.066*** (7.590)
PPP × Subprime (<580)	4.103*** (5.397)	-0.112 (-0.123)	-0.276 (-0.879)	0.425 (1.114)	8.606*** (8.376)	3.896*** (4.148)	3.376*** (4.910)	0.450 (1.615)	3.868*** (4.619)
PPP × Post-PPP (M4-M9)	-0.401 (-1.439)	-2.070*** (-6.056)	-0.118 (-1.092)	-0.973*** (-8.945)	1.086*** (3.286)	2.290*** (6.373)	2.509*** (6.585)	-0.173 (-1.265)	-0.941*** (-2.963)
Subprime (<580) × Post-PPP	0.741*** (2.678)	-3.337*** (-9.853)	0.033 (0.306)	-0.501*** (-4.860)	3.653*** (11.084)	4.134*** (11.432)	2.307*** (6.032)	-0.034 (-0.257)	1.077*** (3.418)
PPP × Subprime (<580) × Post-PPP	-1.539** (-2.501)	7.264*** (9.647)	-0.060 (-0.255)	1.182*** (5.150)	-7.704*** (-10.514)	-9.141*** (-11.380)	-5.582*** (-6.559)	-0.006 (-0.019)	-1.899*** (-2.711)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,517,173	5,517,173	5,517,173	5,517,173	5,517,173	5,517,173	5,517,173	5,517,173	5,517,173
R-squared	0.240	0.215	0.010	0.039	0.000	0.196	0.104	0.009	0.089

Panel B: Heckman Outcome Equation – Consumer Debt

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
PPP	-0.005 (-0.087)	-0.032 (-0.376)	-0.003 (-0.104)	0.032 (0.869)	-0.050 (-0.739)	0.172** (2.349)	0.172** (2.349)	0.055 (0.885)	-0.022 (-0.809)
Subprime (<580)	-0.136*** (-5.583)	-2.330*** (-79.553)	-0.077*** (-8.857)	-0.243*** (-26.703)	-0.518*** (-17.899)	0.428*** (13.308)	0.428*** (13.308)	1.257*** (36.152)	0.004 (0.322)
PPP × Subprime (<580)	-0.231*** (-4.702)	0.302*** (5.117)	-0.070*** (-3.826)	0.009 (0.502)	-0.735*** (-12.598)	-0.752*** (-11.683)	-0.752*** (-11.683)	-0.300*** (-4.346)	-0.076*** (-3.018)
PPP × Post-PPP (M4-M9)	0.107*** (7.734)	0.017 (0.947)	-0.012* (-1.914)	0.000 (0.015)	0.117*** (7.777)	0.011 (0.648)	0.011 (0.648)	0.011 (0.861)	0.001 (0.225)
Subprime (<580) × Post-PPP	0.142*** (7.139)	-0.060*** (-2.672)	-0.001 (-0.137)	0.030*** (4.426)	0.368*** (15.489)	0.062** (2.330)	0.062** (2.330)	-0.194*** (-7.580)	-0.036*** (-3.650)
PPP × Subprime (<580) × Post-PPP	-0.123*** (-3.144)	-0.021 (-0.468)	0.006 (0.399)	-0.003 (-0.230)	-0.204*** (-4.373)	0.011 (0.211)	0.011 (0.211)	0.091* (1.824)	0.007 (0.381)
Lambda	0.016 (0.608)	-0.071* (-1.853)	-0.009 (-0.656)	0.012 (0.714)	0.072** (2.370)	-0.015 (-0.458)	-0.019 (-0.668)	0.006 (0.503)	-0.049* (-1.716)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,517,173	5,517,173	5,517,173	5,517,173	5,517,173	5,517,173	5,517,173	5,517,173	5,517,173
R-squared	0.264	0.237	0.020	0.054	0.078	0.223	0.223	0.127	0.019

Table 12: Effects of PPP Bailouts on Subprime Consumer Debt: Alternative Definitions of Subprime

This table reports difference-in-difference-in-difference (DIDID) regression estimates for analyzing the effects of PPP bailouts on debt of subprime consumers using an alternative definition, namely Equifax Risk Score < 620. The table uses a 5% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period covers 2019:Q2-2019:Q4 (three quarterly periods) + 2020:M1-2020:M9 (nine monthly periods). The dependent variables are $\ln(1+ \text{Total Consumer Debt})$, $\ln(1+ \text{Total Mortgage Debt})$, $\ln(1+ \text{Total HELOAN Debt})$, $\ln(1+ \text{Total HELOC Debt})$, $\ln(1+ \text{Total Card Debt})$, $\ln(1+ \text{Total Auto Debt})$, $\ln(1+ \text{Total Student Debt})$, $\ln(1+ \text{Total Private Student Debt})$, and $\ln(1+ \text{Other Consumer Debt})$, representing the natural logarithm of one plus total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer). PPP is the weighted proportion of high PPP lending banks (those with PPP Loans/Total Loans $\geq 50^{\text{th}}$ percentile) in the 10-mile radius of the consumer zip code. Subprime is an indicator that equals one if the consumer has an Equifax Risk Score below 620. Post-PPP is an indicator equal to one from April 2020 (2020:M4) onward, after the PPP program initiation. We also include other consumer controls: Consumer Age, Joint Account, and $\ln(1+ \text{No. Credit Inquiries last 12mos})$. We also include a number of bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size, and controls for other government programs other than PPP (CARES Act forbearances using forbearance rates for individual products in the consumer county). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust t -statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Use < 620 as Subprime

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
PPP	0.053 (1.205)	-0.152** (-2.387)	-0.011 (-0.476)	0.055** (2.014)	0.142*** (2.821)	0.172*** (3.158)	0.172*** (3.158)	0.027 (0.582)	-0.010 (-0.489)
Subprime (<620)	-0.331*** (-15.077)	-2.449*** (-92.233)	-0.073*** (-9.059)	-0.268*** (-30.288)	-0.578*** (-22.879)	0.357*** (12.920)	0.357*** (12.920)	0.934*** (32.337)	-0.017 (-1.616)
PPP \times Subprime (<620)	-0.264*** (-5.965)	0.274*** (5.090)	-0.071*** (-4.107)	-0.003 (-0.162)	-0.800*** (-15.649)	-0.585*** (-10.563)	-0.585*** (-10.563)	-0.192*** (-3.336)	-0.056*** (-2.617)
PPP \times Post-PPP (M4-M9)	0.116*** (8.082)	0.022 (1.120)	-0.011 (-1.640)	0.000 (0.010)	0.126*** (8.066)	0.031* (1.662)	0.031* (1.662)	0.013 (1.025)	0.004 (0.688)
Subprime (<620) \times Post-PPP	0.168*** (10.148)	-0.046** (-2.436)	0.009 (1.523)	0.033*** (5.420)	0.360*** (18.925)	0.087*** (4.069)	0.087*** (4.069)	-0.075*** (-3.882)	-0.007 (-0.923)
PPP \times Subprime (<620) \times Post-PPP	-0.134*** (-4.054)	-0.018 (-0.474)	-0.002 (-0.189)	-0.007 (-0.572)	-0.188*** (-4.960)	-0.078* (-1.823)	-0.078* (-1.823)	0.034 (0.894)	-0.011 (-0.711)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082
R-squared	0.265	0.246	0.020	0.055	0.081	0.223	0.223	0.126	0.019

Panel B: Define Subprime Based on Score over the Pre-PPP/Pre-CARES Act Period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
PPP	0.040 (0.911)	-0.149** (-2.339)	-0.015 (-0.690)	0.056** (2.074)	0.112** (2.219)	0.160*** (2.933)	0.160*** (2.933)	0.033 (0.714)	-0.010 (-0.483)
Subprime Pre (<580)	-0.152*** (-6.477)	-2.318*** (-77.674)	-0.072*** (-7.878)	-0.249*** (-25.875)	-0.502*** (-18.015)	0.412*** (13.351)	0.412*** (13.351)	1.155*** (35.252)	0.015 (1.162)
PPP \times Subprime Pre (<580)	-0.222*** (-4.713)	0.284*** (4.721)	-0.058*** (-3.001)	-0.007 (-0.353)	-0.746*** (-13.257)	-0.610*** (-9.894)	-0.610*** (-9.894)	-0.246*** (-3.784)	-0.066*** (-2.701)
PPP \times Post-PPP (M4-M9)	0.094*** (6.820)	0.024 (1.316)	-0.007 (-1.048)	-0.002 (-0.292)	0.114*** (7.657)	0.021 (1.205)	0.021 (1.205)	0.015 (1.223)	0.005 (0.887)
Subprime Pre (<580) \times Post-PPP	0.076*** (4.885)	-0.002 (-0.104)	0.003 (0.486)	0.017*** (3.197)	0.201*** (11.312)	0.089*** (4.329)	0.089*** (4.329)	0.021 (1.209)	0.009 (1.216)
PPP \times Subprime Pre (<580) \times Post-PPP	-0.081*** (-2.598)	-0.061* (-1.792)	-0.010 (-0.907)	0.007 (0.612)	-0.102*** (-2.895)	-0.027 (-0.669)	-0.027 (-0.669)	-0.005 (-0.131)	-0.018 (-1.246)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,494,194	5,494,194	5,494,194	5,494,194	5,494,194	5,494,194	5,494,194	5,494,194	5,494,194
R-squared	0.265	0.241	0.020	0.055	0.080	0.223	0.223	0.131	0.019

Table 13: Effects of PPP Bailouts on Subprime Consumer Debt: Placebo Experiment and Matched Sample

This table reports difference-in-difference-in-difference (DIDID) regression estimates for analyzing the effects of PPP bailouts on debt of subprime consumers when using a placebo experiment and a propensity score matched (PSM) sample. The table uses a 5% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period covers 2019:Q2-2019:Q4 (three quarterly periods) + 2020:M1-2020:M9 (nine monthly periods). In Panel A, we report estimates from a placebo experiment in which we randomly assign consumers into the subprime designation and reestimate our main specification, and in Panel B, we report estimates from a sample obtained from propensity score matching using nearest-neighbor matching: N=1 without replacement in which we match each period subprime with non-subprime consumers with similar characteristics. The dependent variables are $\ln(1+ \text{Total Consumer Debt})$, $\ln(1+ \text{Total Mortgage Debt})$, $\ln(1+ \text{Total HELOAN Debt})$, $\ln(1+ \text{Total HELOC Debt})$, $\ln(1+ \text{Total Card Debt})$, $\ln(1+ \text{Total Auto Debt})$, $\ln(1+ \text{Total Student Debt})$, $\ln(1+ \text{Total Private Student Debt})$, and $\ln(1+ \text{Other Consumer Debt})$, representing the natural logarithm of one plus total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer). PPP is the weighted proportion of high PPP lending banks (those with PPP Loans/Total Loans $\geq 50^{\text{th}}$ percentile) in the 10-mile radius of the consumer zip code. Subprime is an indicator that equals one if the consumer has an Equifax Risk Score below 580. Post-PPP is an indicator equal to one from April 2020 (2020:M4) onward, after the PPP program initiation. We also include other consumer controls: *Consumer Age*, *Joint Account*, and $\ln(1+ \text{No. Credit Inquiries last 12mos})$. We also include a number of bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size, and controls for other government programs other than PPP (CARES Act forbearances using forbearance rates for individual products in the consumer county). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Placebo Experiment (Randomly Assign Consumers into Subprime Designation)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	$\ln(1+ \text{Total Consumer Debt})$	$\ln(1+ \text{Mortgage Debt})$	$\ln(1+ \text{HELOAN Debt})$	$\ln(1+ \text{HELOC Debt})$	$\ln(1+ \text{Card Debt})$	$\ln(1+ \text{Auto Debt})$	$\ln(1+ \text{Student Debt})$	$\ln(1+ \text{Private Student Debt})$	$\ln(1+ \text{Other Consumer Debt})$
Independent Variables									
PPP	-0.008 (-0.188)	-0.116* (-1.847)	-0.028 (-1.280)	0.050* (1.920)	-0.043 (-0.857)	0.036 (0.676)	-0.012 (-0.256)	-0.023 (-1.190)	-0.028 (-0.608)
Subprime Pre (<580)	0.011 (1.025)	-0.016 (-1.107)	-0.001 (-0.253)	-0.005 (-0.888)	0.014 (1.233)	0.003 (0.243)	0.002 (0.176)	0.000 (0.063)	0.006 (0.529)
PPP \times Subprime Pre (<580)	-0.017 (-0.781)	0.028 (0.932)	-0.001 (-0.060)	0.008 (0.609)	-0.035 (-1.463)	0.016 (0.618)	0.014 (0.621)	0.003 (0.287)	-0.001 (-0.040)
PPP \times Post-PPP ('M4-'M9)	0.095*** (6.688)	0.021 (1.132)	-0.011* (-1.821)	-0.001 (-0.154)	0.104*** (6.688)	0.023 (1.262)	0.028** (2.070)	0.003 (0.532)	0.040** (2.495)
Subprime Pre (<580) \times Post-PPP	-0.009 (-0.575)	0.027 (1.285)	-0.004 (-0.658)	-0.002 (-0.240)	-0.016 (-0.948)	-0.021 (-1.160)	-0.015 (-0.923)	-0.001 (-0.194)	0.011 (0.694)
PPP \times Subprime Pre (<580) \times Post-PPP	0.001 (0.042)	-0.051 (-1.199)	0.006 (0.462)	0.003 (0.191)	0.017 (0.491)	0.012 (0.314)	-0.030 (-0.929)	-0.005 (-0.342)	-0.034 (-1.064)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082
R-squared	0.264	0.218	0.019	0.053	0.074	0.223	0.119	0.018	0.124

Panel B: Propensity Score Matching (1:1 Nearest Neighbor Matching without Replacement)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	$\ln(1+ \text{Total Consumer Debt})$	$\ln(1+ \text{Mortgage Debt})$	$\ln(1+ \text{HELOAN Debt})$	$\ln(1+ \text{HELOC Debt})$	$\ln(1+ \text{Card Debt})$	$\ln(1+ \text{Auto Debt})$	$\ln(1+ \text{Student Debt})$	$\ln(1+ \text{Private Student Debt})$	$\ln(1+ \text{Other Consumer Debt})$
Independent Variables									
PPP	0.152** (2.120)	-0.152 (-1.581)	0.008 (0.256)	0.009 (0.347)	0.229*** (2.638)	0.428*** (4.322)	0.078 (0.795)	-0.010 (-0.264)	0.016 (0.189)
Subprime Pre (<580)	-0.042 (-1.484)	-1.986*** (-55.732)	-0.090*** (-8.278)	-0.205*** (-19.579)	-0.594*** (-17.657)	0.445*** (11.527)	1.246*** (30.361)	0.011 (0.675)	0.657*** (19.753)
PPP \times Subprime Pre (<580)	-0.344*** (-5.948)	-0.018 (-0.240)	-0.022 (-0.975)	-0.018 (-0.839)	-0.414*** (-5.990)	-0.852*** (-10.823)	-0.281*** (-3.394)	-0.067** (-2.171)	-0.056 (-0.829)
PPP \times Post-PPP ('M4-'M9)	0.111** (2.330)	0.027 (0.426)	-0.018 (-0.888)	-0.002 (-0.085)	0.160*** (3.058)	0.015 (0.233)	0.024 (0.429)	0.018 (0.711)	0.075 (1.404)
Subprime Pre (<580) \times Post-PPP	0.094*** (3.193)	-0.206*** (-5.561)	0.001 (0.073)	0.003 (0.296)	0.370*** (11.067)	0.081** (2.064)	-0.197*** (-5.241)	-0.039** (-2.499)	0.294*** (8.690)
PPP \times Subprime Pre (<580) \times Post-PPP	-0.117** (-1.997)	0.004 (0.052)	0.010 (0.431)	-0.002 (-0.078)	-0.232*** (-3.432)	0.000 (0.006)	0.074 (0.992)	-0.014 (-0.444)	-0.130* (-1.902)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	1,489,801	1,489,801	1,489,801	1,489,801	1,489,801	1,489,801	1,489,801	1,489,801	1,489,801
R-squared	0.147	0.193	0.025	0.039	0.098	0.219	0.088	0.019	0.141

Table 14: Effects of PPP Bailouts on Subprime Consumer Debt: Alternative Definitions of PPP

This table reports difference-in-difference-in-difference (DIDID) regression estimates for analyzing the effects of PPP bailouts on debt of subprime consumers using alternative definitions/thresholds for PPP: PPP2 (PPP Loans/Total Loans > 0) and PPP3 (PPP Loans/Total Loans). The table uses a 5% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period covers 2019:Q2-2019:Q4 (three quarterly periods) + 2020:M1-2020:M9 (nine monthly periods). The dependent variables are $\ln(1+ \text{Total Consumer Debt})$, $\ln(1+ \text{Total Mortgage Debt})$, $\ln(1+ \text{Total HELOAN Debt})$, $\ln(1+ \text{Total HELOC Debt})$, $\ln(1+ \text{Total Card Debt})$, $\ln(1+ \text{Total Auto Debt})$, $\ln(1+ \text{Total Student Debt})$, $\ln(1+ \text{Total Private Student Debt})$, and $\ln(1+ \text{Other Consumer Debt})$, representing the natural logarithm of one plus total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer). PPP is the weighted proportion of high PPP lending banks (those with PPP Loans/Total Loans \geq 50th percentile) in the 10-mile radius of the consumer zip code. Subprime is an indicator that equals one if the consumer has an Equifax Risk Score below 580. Post-PPP is an indicator equal to one from April 2020 (2020:M4) onward, after the PPP program initiation. We also include other consumer controls: Consumer Age, Joint Account, and $\ln(1+ \text{No. Credit Inquiries last 12mos})$. We also include a number of bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size, and controls for other government programs other than PPP (CARES Act forbearances using forbearance rates for individual products in the consumer county). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust t -statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Use PPP2 (PPP Loans/Total Loans Is Nonzero)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
PPP2	0.237*** (3.547)	0.383*** (4.060)	0.073** (2.297)	0.065* (1.700)	0.009 (0.113)	0.117 (1.424)	0.117 (1.424)	-0.016 (-0.240)	0.009 (0.329)
Subprime (<580)	-0.227* (-1.942)	-1.675*** (-11.781)	-0.042 (-0.910)	-0.264*** (-6.369)	-1.174*** (-8.531)	-0.113 (-0.743)	-0.113 (-0.743)	1.081*** (7.013)	0.008 (0.140)
PPP2 \times Subprime (<580)	-0.011 (-0.091)	-0.550*** (-3.690)	-0.069 (-1.400)	0.026 (0.609)	0.352** (2.440)	0.224 (1.401)	0.224 (1.401)	0.047 (0.290)	-0.039 (-0.653)
PPP2 \times Post-PPP ('M4-'M9)	0.212*** (3.824)	0.312*** (4.248)	0.005 (0.183)	-0.003 (-0.104)	0.016 (0.258)	-0.083 (-1.186)	-0.083 (-1.186)	-0.087* (-1.665)	0.010 (0.439)
Subprime (<580) \times Post-PPP	0.506*** (3.309)	0.573*** (3.279)	0.033 (0.515)	0.073 (1.410)	0.461*** (2.579)	-0.173 (-0.882)	-0.173 (-0.882)	-0.530*** (-2.795)	-0.081 (-1.168)
PPP2 \times Subprime (<580) \times Post-PPP	-0.435*** (-2.769)	-0.647*** (-3.602)	-0.032 (-0.487)	-0.047 (-0.879)	-0.207 (-1.129)	0.232 (1.155)	0.232 (1.155)	0.383** (1.963)	0.049 (0.694)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082
R-squared	0.264	0.237	0.020	0.054	0.078	0.223	0.223	0.127	0.019

Panel B: Use PPP3 (PPP Loans/Total Loans)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	Ln (1+ Total Consumer Debt)	Ln (1+ Mortgage Debt)	Ln (1+ HELOAN Debt)	Ln (1+ HELOC Debt)	Ln (1+ Card Debt)	Ln (1+ Auto Debt)	Ln (1+ Student Debt)	Ln (1+ Private Student Debt)	Ln (1+ Other Consumer Debt)
Independent Variables									
PPP3	0.568 (1.381)	-0.182 (-0.308)	0.001 (0.004)	0.468* (1.877)	0.626 (1.330)	0.947* (1.861)	0.947* (1.861)	0.396 (0.921)	0.014 (0.082)
Subprime (<580)	-0.127*** (-3.690)	-2.252*** (-55.447)	-0.074*** (-5.969)	-0.277*** (-22.620)	-0.433*** (-10.548)	0.447*** (9.938)	0.447*** (9.938)	1.263*** (26.238)	-0.013 (-0.749)
PPP3 \times Subprime (<580)	-1.777*** (-3.414)	0.878 (1.422)	-0.543*** (-2.801)	0.615*** (3.360)	-6.537*** (-10.475)	-5.593*** (-8.233)	-5.593*** (-8.233)	-2.204*** (-3.050)	-0.256 (-0.983)
PPP3 \times Post-PPP ('M4-'M9)	0.868*** (6.070)	0.272 (1.454)	-0.141** (-2.135)	0.079 (1.006)	0.889*** (5.749)	-0.034 (-0.185)	-0.034 (-0.185)	0.065 (0.506)	0.008 (0.138)
Subprime (<580) \times Post-PPP	0.147*** (5.087)	-0.061* (-1.900)	0.001 (0.125)	0.035*** (3.678)	0.378*** (11.017)	0.048 (1.223)	0.048 (1.223)	-0.200*** (-5.482)	-0.028** (-2.095)
PPP3 \times Subprime (<580) \times Post-PPP	-0.939** (-2.187)	-0.129 (-0.268)	0.008 (0.048)	-0.116 (-0.840)	-1.523*** (-3.000)	0.335 (0.574)	0.335 (0.574)	0.731 (1.368)	-0.079 (-0.407)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082
R-squared	0.264	0.237	0.020	0.054	0.078	0.223	0.223	0.127	0.019

Table 15: Effects of PPP Bailouts on Consumer Debt: Dynamic Effects

This table reports difference-in-difference-in-difference (DIDID) regression estimates for analyzing the effects of PPP bailouts on debt of subprime consumers (Equifax Risk Score < 580), using a month-by-month analysis. The table uses a 5% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period covers 2019:Q2-2019:Q4 (three quarterly periods) + 2020:M1-2020:M9 (nine monthly periods). The dependent variables are $\ln(1 + \text{Total Consumer Debt})$, $\ln(1 + \text{Total Mortgage Debt})$, $\ln(1 + \text{Total HELOAN Debt})$, $\ln(1 + \text{Total HELOC Debt})$, $\ln(1 + \text{Total Card Debt})$, $\ln(1 + \text{Total Auto Debt})$, $\ln(1 + \text{Total Student Debt})$, $\ln(1 + \text{Total Private Student Debt})$, and $\ln(1 + \text{Other Consumer Debt})$, representing the natural logarithm of one plus total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer). *PPP* is the weighted proportion of high PPP lending banks (those with PPP Loans/Total Loans $\geq 50^{\text{th}}$ percentile) in the 10-mile radius of the consumer zip code. *Subprime* is an indicator that equals one if the consumer has an Equifax Risk Score below 580. *Post-PPP* (*M4-M9*) are indicators equal to one for each of the months from April 2020 (2020:M4) onward, after the PPP program initiation. We also include other consumer controls: *Consumer Age*, *Joint Account*, and $\ln(1 + \text{No. Credit Inquiries last 12mos})$. We also include a number of bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size, and controls for other government programs other than PPP (CARES Act forbearances using forbearance rates for individual products in the consumer county). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Consumer Debt: Decomposition by Individual Products								
Dependent Variable:	$\ln(1 + \text{Total Consumer Debt})$	$\ln(1 + \text{Mortgage Debt})$	$\ln(1 + \text{HELOAN Debt})$	$\ln(1 + \text{HELOC Debt})$	$\ln(1 + \text{Card Debt})$	$\ln(1 + \text{Auto Debt})$	$\ln(1 + \text{Student Debt})$	$\ln(1 + \text{Private Student Debt})$	$\ln(1 + \text{Other Consumer Debt})$
Independent Variables									
PPP	0.026 (0.593)	-0.142** (-2.245)	-0.016 (-0.747)	0.052* (1.929)	0.068 (1.353)	0.155*** (2.869)	0.155*** (2.869)	0.027 (0.589)	-0.012 (-0.592)
Subprime (<580)	-0.136*** (-5.585)	-2.328*** (-79.517)	-0.077*** (-8.852)	-0.243*** (-26.686)	-0.518*** (-17.902)	0.425*** (13.233)	0.425*** (13.233)	1.257*** (36.188)	0.004 (0.299)
PPP × Subprime (<580)	-0.231*** (-4.704)	0.298*** (5.055)	-0.070*** (-3.836)	0.008 (0.455)	-0.736*** (-12.614)	-0.747*** (-11.616)	-0.747*** (-11.616)	-0.300*** (-4.351)	-0.075*** (-2.998)
PPP × Post-PPP (M4)	0.076*** (5.666)	0.008 (0.439)	-0.016*** (-2.720)	0.012* (1.692)	0.146*** (9.907)	-0.049*** (-2.817)	-0.049*** (-2.817)	0.001 (0.111)	0.003 (0.648)
PPP × Post-PPP (M5)	0.047*** (3.482)	0.022 (1.249)	-0.015** (-2.495)	0.002 (0.297)	0.054*** (3.682)	-0.054*** (-3.183)	-0.054*** (-3.183)	-0.006 (-0.485)	0.001 (0.226)
PPP × Post-PPP (M6)	0.135*** (9.660)	0.006 (0.312)	-0.018*** (-2.918)	-0.017** (-2.130)	0.161*** (10.527)	0.046*** (2.615)	0.046*** (2.615)	-0.005 (-0.370)	-0.004 (-0.695)
PPP × Post-PPP (M7)	0.103*** (5.952)	0.029 (1.269)	-0.004 (-0.487)	0.012 (1.198)	0.087*** (4.589)	0.015 (0.683)	0.015 (0.683)	0.027* (1.675)	0.006 (0.826)
PPP × Post-PPP (M8)	0.121*** (6.966)	0.035 (1.484)	-0.007 (-0.817)	0.002 (0.152)	0.119*** (6.254)	0.030 (1.336)	0.030 (1.336)	0.014 (0.850)	0.000 (0.050)
PPP × Post-PPP (M9)	0.142*** (8.074)	0.015 (0.625)	-0.012 (-1.500)	-0.008 (-0.776)	0.139*** (7.218)	0.038* (1.691)	0.038* (1.691)	0.041** (2.541)	0.004 (0.517)
Subprime (<580) × Post-PPP (M4)	0.162*** (8.514)	-0.007 (-0.300)	-0.002 (-0.245)	0.030*** (4.490)	0.454*** (20.094)	-0.024 (-0.890)	-0.024 (-0.890)	-0.187*** (-7.635)	-0.030*** (-3.187)
Subprime (<580) × Post-PPP (M5)	0.160*** (7.552)	0.005 (0.209)	-0.000 (-0.058)	0.028*** (3.915)	0.416*** (16.571)	-0.030 (-1.002)	-0.030 (-1.002)	-0.202*** (-7.373)	-0.039*** (-3.690)
Subprime (<580) × Post-PPP (M6)	0.154*** (6.680)	-0.068** (-2.570)	-0.006 (-0.731)	0.023*** (2.993)	0.370*** (13.449)	0.088*** (2.803)	0.088*** (2.803)	-0.195*** (-6.567)	-0.043*** (-3.761)
Subprime (<580) × Post-PPP (M7)	0.115*** (4.536)	-0.099*** (-3.397)	-0.004 (-0.449)	0.037*** (4.256)	0.293*** (9.759)	0.073** (2.152)	0.073** (2.152)	-0.170*** (-5.198)	-0.036*** (-2.869)
Subprime (<580) × Post-PPP (M8)	0.131*** (4.935)	-0.107*** (-3.493)	0.004 (0.431)	0.028*** (3.195)	0.294*** (9.332)	0.145*** (4.052)	0.145*** (4.052)	-0.161*** (-4.663)	-0.034** (-2.555)
Subprime (<580) × Post-PPP (M9)	0.122*** (4.439)	-0.125*** (-3.945)	0.004 (0.358)	0.029*** (3.224)	0.367*** (11.255)	0.156*** (4.199)	0.156*** (4.199)	-0.258*** (-7.233)	-0.033** (-2.370)
PPP × Subprime (<580) × Post-PPP (M4)	-0.120*** (-3.188)	-0.038 (-0.849)	0.007 (0.456)	-0.025* (-1.916)	-0.227*** (-5.110)	0.030 (0.571)	0.030 (0.571)	0.146*** (3.070)	0.007 (0.407)
PPP × Subprime (<580) × Post-PPP (M5)	-0.091** (-2.170)	-0.065 (-1.326)	0.005 (0.283)	-0.015 (-1.090)	-0.139*** (-2.796)	0.050 (0.869)	0.050 (0.869)	0.154*** (2.883)	0.010 (0.508)
PPP × Subprime (<580) × Post-PPP (M6)	-0.154*** (-3.389)	-0.018 (-0.348)	0.014 (0.794)	0.004 (0.270)	-0.258*** (-4.749)	-0.059 (-0.950)	-0.059 (-0.950)	0.101* (1.760)	0.017 (0.760)
PPP × Subprime (<580) × Post-PPP (M7)	-0.108** (-2.153)	0.006 (0.108)	0.013 (0.667)	-0.013 (-0.747)	-0.145** (-2.442)	0.040 (0.592)	0.040 (0.592)	0.030 (0.474)	-0.002 (-0.074)
PPP × Subprime (<580) × Post-PPP (M8)	-0.137*** (-2.601)	0.002 (0.026)	-0.004 (-0.222)	0.014 (0.802)	-0.205*** (-3.293)	-0.049 (-0.696)	-0.049 (-0.696)	0.024 (0.361)	0.008 (0.295)
PPP × Subprime (<580) × Post-PPP (M9)	-0.122** (-2.237)	0.033 (0.525)	-0.001 (-0.050)	0.023 (1.276)	-0.250*** (-3.859)	0.025 (0.346)	0.025 (0.346)	0.089 (1.274)	-0.001 (-0.051)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082
R-squared	0.264	0.237	0.020	0.054	0.078	0.223	0.223	0.127	0.019

Table 16: PPP: Mechanisms Investigation

This table reports difference-in-difference-in-difference (DIDID) regression estimates for mechanisms of the effects of PPP bailouts on debt of subprime consumers (Equifax Risk Score < 580) relative to other consumers. The table uses a 5% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP), a representative panel of individual credit records from Equifax. The unit of observation in this table is a consumer-quarter. The sample period covers 2019:Q2-2019:Q4 (three quarterly periods) + 2020:M1-2020:M9 (nine monthly periods). The dependent variables are $\ln(1+Total\ Consumer\ Credit)$, $\ln(1+Total\ Consumer\ Credit^2)$, $\ln(1+Total\ HELOC\ Limit)$, $\ln(1+Total\ CC\ Limit)$, representing the natural logarithm of one plus total consumer credit amount (with total student credit amount or private student credit amount) or credit limit or credit utilization in one of its subcomponents (HELOC, credit card) in Panel A and total payment rate or payment rates by individual products in Panel B. *PPP* is the weighted proportion of high PPP lending banks (those with PPP Loans/Total Loans $\geq 50^{th}$ percentile) in the 10-mile radius of the consumer zip code. *Subprime* is an indicator that equals one if the consumer has an Equifax Risk Score below 580. *Post-PPP* is an indicator equal to one from April 2020 (2020:M4) onward, after the PPP program initiation. We also include other consumer controls: *Consumer Age*, *Joint Account*, and $\ln(1+No.\ Credit\ Inquiries\ last\ 12\ mos)$. We also include a number of bank characteristics in the relevant radius or area of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size, and controls for other government programs other than PPP (CARES Act forbearances using forbearance rates for individual products in the consumer county). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Credit Limits, Amounts, Utilization Rate for Individual Products

	(1)	(2)	(3)	(4)	(5)
Total Consumer Credit & Some Individual Products					
Dependent Variable:	Ln (1+ Total Consumer Credit)	Ln (1+ HELOC Limit)	Ln (1+ Card Limit)	HELOC Utilization Rate	Card Utilization Rate
Independent Variables					
PPP	-0.026 (-0.649)	0.057* (1.722)	0.013 (0.223)	0.094 (1.235)	0.022*** (4.120)
Subprime (<580)	-1.044*** (-45.848)	-0.368*** (-34.961)	-2.290*** (-77.474)	0.047 (0.669)	0.355*** (76.118)
PPP × Subprime (<580)	0.016 (0.352)	0.023 (1.077)	-0.461*** (-7.684)	-0.026 (-0.122)	-0.155*** (-16.034)
PPP × Post-PPP (M4-M9)	0.024* (1.908)	0.003 (0.371)	-0.010 (-0.621)	-0.206 (-1.086)	0.007*** (3.877)
Subprime (<580) × Post-PPP	-0.060*** (-3.240)	0.022*** (2.997)	0.078*** (3.290)	-0.137 (-0.987)	0.018*** (4.693)
PPP × Subprime (<580) × Post-PPP	-0.010 (-0.281)	-0.001 (-0.062)	-0.051 (-1.090)	0.152 (0.602)	-0.019** (-2.415)
Consumer, Bank, County Characteristics	X	X	X	X	X
County FE	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X
Observations	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082
R-squared	0.193	0.066	0.135	0.002	0.100

Panel B: Payments: Total and by Individual Products

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Consumer Payment: Decomposition by Individual Products									
Dependent Variable:	Total Consumer Payment Rate	Mortgage Payment Rate	HELOAN Payment Rate	HELOC Payment Rate	Card Payment Rate	Auto Payment Rate	Student Payment Rate	Private Student Payment Rate	Other Consumer Payment Rate
Independent Variables									
PPP	0.001 (0.373)	-0.000 (-0.172)	-0.007 (-1.052)	-0.007 (-0.687)	0.004 (1.426)	-0.014 (-1.263)	-0.000 (-0.299)	-0.000 (-0.421)	-0.001 (-0.247)
Subprime (<580)	0.002 (0.570)	-0.003*** (-3.818)	-0.002 (-1.262)	-0.000 (-0.503)	-0.014*** (-2.788)	0.007 (1.579)	-0.002*** (-3.403)	-0.000 (-0.345)	-0.009 (-1.200)
PPP × Subprime (<580)	0.006 (1.305)	0.001 (0.848)	-0.002 (-0.916)	-0.003 (-1.115)	0.003 (0.318)	-0.008 (-1.178)	0.001 (0.849)	0.000 (0.371)	0.026 (1.236)
PPP × Post-PPP (M4-M9)	-0.004 (-1.396)	0.001 (0.719)	-0.001 (-0.294)	-0.007 (-1.413)	-0.004 (-1.497)	-0.016 (-1.083)	0.001 (0.716)	0.000 (0.433)	0.004 (0.885)
Subprime (<580) × Post-PPP	-0.016*** (-4.382)	0.001 (0.858)	-0.000 (-0.020)	-0.003 (-1.459)	-0.017*** (-13.998)	-0.021** (-2.294)	0.002* (1.716)	0.000 (0.111)	0.008 (1.154)
PPP × Subprime (<580) × Post-PPP	0.017*** (3.371)	-0.001 (-0.998)	-0.000 (-0.134)	0.006 (1.504)	0.009*** (3.534)	0.028* (1.742)	-0.002 (-0.932)	-0.000 (-0.181)	-0.013 (-0.587)
Consumer, Bank, County Characteristics	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X
Errors Clustered by Consumer	X	X	X	X	X	X	X	X	X
Observations	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082	5,518,082
R-squared	0.001	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.000

Table 17: Effects of PPP Bailouts on Subprime Consumer Debt – Additional Evidence from Full Anonymized CCP Aggregated at County Level

This table reports difference-in-difference-in-difference (DIDID) regression estimates for analyzing the effects of PPP bailouts during the COVID-19 crisis on leverage ratios of subprime consumers (Equifax Risk Score < 580) relative to other consumers when using an additional analysis in which we aggregate the full anonymized FRBNY Consumer Credit Panel/Equifax Data (CCP) at county level. The CCP data are a representative panel of individual credit records from Equifax. The unit of observation in this table is a county-time period. The sample period covers 2019:Q2-2019:Q4 (three quarterly periods) + 2020:M1-2020:M9 (nine monthly periods). The dependent variables are *Total Consumer Debt/Total Income*, *Total Consumer Debt (with Private Student)/Total Income*, *Total Consumer Debt (without Student Debt)/Total Income*, *Mortgage Debt/Total Income*, *HELOAN Debt/Total Income*, *HELOC Debt/Total Income*, *Card Debt/Total Income*, *Auto Debt/Total Income*, *Student Debt/Total Income*, *Private Student Debt/Total Income*, and *Other Consumer Debt/Total Income*, representing the total consumer debt or debt in one of its subcomponents (mortgage, HELOAN, HELOC, credit card, auto, student (total and private), and other consumer) scaled by total county consumer income from BEA. *PPP* is the weighted proportion of high PPP lending banks (those with *PPP Loans/Total Loans* ≥ 50th percentile) in the consumer county. *Pct Subprime* is the percent of consumers with an Equifax Risk Score below 580 in the county. *Post-PPP* is an indicator equal to one from April 2020 (2020:M4) onward, after the PPP program initiation. We also include other consumer controls: *Consumer Age*, *Joint Account*, and *Ln (1+ No. Credit Inquiries last 12mos)*. We also include a number of bank characteristics in the county of the consumer, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size, and controls for other government programs other than PPP (CARES Act forbearances using forbearance rates for individual products in the consumer county). Finally, we control for unemployment rate and HPI in the county of the consumer. All regressions include County and Year-Quarter FE unless noted otherwise. All variables are defined in Table 1. Heteroskedasticity-robust *t*-statistics clustered at consumer level are reported in parentheses unless noted otherwise in the specification. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Full CCP Population Aggregated at County Level: County-Level Consumer Leverage										
Dependent Variable	Consumer Leverage										
	Total Consumer Debt/ Total Income	Total Consumer Debt (w/ Private Student)/ Total Income	Total Consumer Debt (w/o Student) / Total Income	Mortgage Debt/Total Income	HELOAN Debt/Total Income	HELOC Debt/Total Income	Card Debt/Total Income	Auto Debt/Total Income	Student Debt/Total Income	Private Student Debt/Total Income	Other Consumer Debt/Total Income
Dependent Variable:											
Independent Variables											
PPP	0.130 (0.553)	0.116 (0.488)	0.118 (0.494)	0.109 (0.918)	0.109 (0.980)	0.110 (0.993)	0.163* (1.646)	-0.002 (-0.161)	0.009* (1.744)	-0.005 (-0.445)	-0.004 (-0.212)
Pct Subprime	-0.065 (-0.665)	-0.081 (-0.795)	-0.079 (-0.777)	-0.057 (-1.381)	-0.054 (-1.393)	-0.051 (-1.320)	-0.048 (-1.428)	0.001 (0.154)	0.001 (0.632)	0.017*** (3.706)	-0.030*** (-3.535)
PPP × Pct Subprime	0.316 (0.244)	0.241 (0.187)	0.263 (0.205)	0.163 (0.252)	0.067 (0.111)	0.068 (0.113)	-0.318 (-0.600)	0.010 (0.176)	-0.020 (-0.757)	0.028 (0.552)	0.111 (1.138)
PPP × Post-PPP ('M4-'M9)	0.178** (2.558)	0.175** (2.400)	0.180** (2.452)	0.107*** (2.855)	0.102*** (2.893)	0.102*** (2.922)	0.090*** (2.639)	-0.000 (-0.036)	0.000 (0.100)	-0.002 (-0.534)	0.027*** (2.595)
Pct Subprime × Post-PPP	0.104*** (3.659)	0.090*** (2.837)	0.090*** (2.832)	0.060*** (4.273)	0.050*** (3.696)	0.049*** (3.666)	0.0340*** (2.838)	0.002 (0.748)	0.000 (0.132)	0.009*** (5.288)	0.010** (2.331)
PPP × Pct Subprime × Post-PPP	-1.089*** (-2.873)	-1.012** (-2.321)	-1.045** (-2.390)	-0.682*** (-3.505)	-0.628*** (-3.339)	-0.629*** (-3.371)	-0.531*** (-3.164)	0.018 (0.490)	-0.007 (-0.450)	0.004 (0.182)	-0.163*** (-2.606)
County, Bank Controls	X	X	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X	X	X
Year-Quarter FE	X	X	X	X	X	X	X	X	X	X	X
Errors Clustered by County	X	X	X	X	X	X	X	X	X	X	X
Observations	35,397	35,397	35,397	35,385	35,385	35,385	35,385	35,385	35,385	35,385	35,385
R-squared	1.000	1.000	1.000	0.991	0.991	0.991	0.993	0.969	0.935	0.954	0.986

Appendix for A Tale of Two Bailouts: Effects of TARP and PPP on Subprime Consumer Debt

Table A.1: Effects of TARP Bailouts on Subprime Consumer Debt: Probit Bank-Level Model (1st Stage for IV Analysis and Heckman Selection Model)

This table reports first stage probit-regression estimates for analyzing the effects of TARP bailouts on debt of subprime consumers (Equifax Risk Score < 580) relative to other consumers when using endogeneity and sample selection tests. The table uses Call Report financial data aggregated at the bank holding company level and the unit of observation in this table is a bank-quarter. The sample period is 2001:Q1–2016:Q4. We report probit estimates from the first stage of an instrumental variable analysis as in Wooldridge Section 18.4.1, which also serves as the first stage equation from the Heckman (1979)'s selection model. The dependent variable is *TARP*, an indicator equal to 1 for banks that received TARP capital injections. We use as an instrument a political connections variable: *Subcommittees on Financial Institutions or Capital Markets*. *Subcommittees on Financial Institutions or Capital Markets* is a variable, which takes a value of 1 if a firm is headquartered in a district of a House member, who served on the Capital Markets Subcommittee or the Financial Institutions Subcommittee of the House Financial Services Committee in 2008 or 2009. We also include other bank controls, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), bank size, and controls for other government programs other than TARP (Discount Window, Term Auction Facility, FDIC TAGP, FDIC TDGP, SBLF, and FHLB programs). The probit regressions also include Year-Quarter FE. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Dependent Variable:	(1) TARP
Independent Variables	
Subcommittee Financial Institutions & Capital Markets	0.096*** (10.121)
Bank Characteristics (lagged 4 quarters)	
Capital Adequacy	-0.456*** (-4.089)
Asset Quality	0.863*** (5.700)
Management Quality	0.0310*** (3.735)
Earnings	-7.092*** (-17.081)
Liquidity	-0.001 (-0.287)
Sensitivity to Market Risk	-0.106*** (-2.810)
Bank Size	0.402*** (117.652)
Discount Window Participant	0.250*** (30.460)
Term Auction Facility Participant	0.269*** (16.714)
FDIC TAGP Participant	0.258*** (24.789)
FDIC TDGP Participant	0.380*** (46.476)
SBLF Participant	1.469*** (111.384)
FHLB Member	0.037*** (2.739)
Year-Quarter FE	X
Observations	321,444
Pseudo-R-squared	0.292
First Stage Statistics	
Kleibergen-Paap rk Wald <i>F</i> -statistic	2011***
Kleibergen-Paap rk <i>LM</i> -statistic	9922***

Table A.2: Effects of PPP Bailouts on Subprime Consumer Debt: Probit Bank-Level Model (1st Stage for IV Analysis and Heckman Selection Model)

This table reports first stage probit-regression estimates for analyzing the effects of PPP bailouts on debt of subprime consumers (Equifax Risk Score < 580) relative to other consumers when using endogeneity and sample selection tests. The table uses Call Report financial data aggregated at the bank holding company level and the unit of observation in this table is a bank-quarter. The sample period is 2019:Q2–2020:Q3. We report probit estimates from the first stage of an instrumental variable analysis as in Wooldridge Section 18.4.1, which also serves as the first stage equation from the Heckman (1979)'s selection model. The dependent variable is *PPP*, an indicator equal to 1 for high PPP lending banks (those with PPP Loans/Total Loans \geq 50th percentile). We use as an instrument: *SBA_7(a)_2019*. *SBA_7(a)_2019* is the natural logarithm of one plus the total dollar amount of SBA loans a bank made via the SBA 7(a) lending platform in 2019. We also include other bank controls, all lagged four quarters: proxies for CAMELS (capital, asset quality, management quality, earnings, and sensitivity to market risk), and bank size. The probit regressions also include Year-Quarter FE. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Dependent Variable:	(1) PPP
Independent Variables	
SBA_7(a)_2019	0.101*** (41.438)
Bank Characteristics (lagged 4 quarters)	
Capital Adequacy	-5.189*** (-14.407)
Asset Quality	-7.581*** (-12.039)
Management Quality	0.524*** (7.039)
Earnings	-0.320 (-1.043)
Liquidity	0.570*** (10.309)
Sensitivity to Market Risk	-0.227*** (-2.881)
Bank Size	0.114*** (15.293)
Year-Quarter FE	X
Observations	26,944
Pseudo-R-squared	0.118
First Stage Statistics	
Kleibergen-Paap rk Wald <i>F</i> -statistic	30.5***
Kleibergen-Paap rk <i>LM</i> -statistic	123.6***