

Bank Stress Tests and Consumer Credit Markets: Credit and Real Impacts*

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June 2023

Abstract

Using Federal Reserve (Fed) confidential stress-test data, we exploit the gap between the Fed's and banks' capital projections as an exogenous shock to banks and analyze how this shock is transmitted to consumer credit markets. First, we find banks in the 90th percentile of the "capital gap" reduce their new supply of risky credit by about 14 percent compared to the 10th percentile and cut their overall credit card risk exposure following stress tests. Second, we show these banks offer attractive rewards and promotions to select groups of borrowers they do lend to. Finally, we also find that stress tests have real effects: consumers at banks with larger "capital gap" have higher credit card spending, demonstrate stronger debt payment and credit performance, and are more often transactors. Results provide new insights into banks' risk management practices following stress tests and reveal a positive feedback loop among credit supply, credit usage, and credit performance.

Keywords: Bank stress tests, household finance, consumer credit supply, spending, debt management, payment behavior, consumer credit performance, credit cards, mortgages

JEL Classification Codes: G21, G28, Z1

* We thank Gene Amromin, Jose Berrospide, Souphala Chomsisengphet, Matt Frame, Bob Hunt, Sasha Indarte, Andy Kish, Wenlan Qian, David Reeb, Richard Rosen, Bill Spaniel, Jialan Wang, Bill Wisser, Calvin Zhang, and participants at the Western Finance Association Conference and the Federal Reserve Stress Testing Conference for insightful comments and suggestions. We also thank Joanne Chow, Jie Feng, Liang Geng, Bill Hewitt, Hannah Kronenberg, and Kenuo Pan for kind data help, and Alysa Blakeney for excellent research assistance. Editorial assistance from Barbara Brynko and Ruth Parker is also gratefully acknowledged.

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Introduction

Watchdog institutions, regulators, and rating agencies routinely grade firms, securities, and even countries. Sometimes it is as simple as pass/fail, but more often it is more complex, in which they assign various shades of passing grades. Businesses and even countries optimize on these grades to produce the highest valuation for their investors, provide the best value for customers, and attempt to promote favorable government policies.¹

Over the sample period in our study, U.S. bank stress testing is an example of a *pass/fail* grading scheme that has far-reaching impacts. . The Federal Reserve (Fed) has the authority to limit bank capital distributions should a bank fail the test.² In addition to pass/fail grades, stress tests also reveal Fed projected minimum capital ratios at banks under severely adverse states of the economy, which can indicate shortfalls at the institutions. Therefore, markets pay serious attention to stress tests. As one piece of evidence from common stock returns, in Appendix Table A.1 we show that banks that failed the stress tests experienced significant negative abnormal stock returns following the release of the test results. It is noteworthy that stress test results are confidential prior to the Fed's public release, meaning that test results can come as shocks to banks.

Thus, questions arise as to how banks respond to stress tests' shocks and how the shocks affect consumer markets in terms of both credit and real behavior. These questions are important due to a number of reasons: first, consumer markets constitute a large share of economic activity in the U.S. economy; second, credit is critical to mitigate consumer financial constraints; third, little is known about how the banking regulatory forces shape consumer behavior (e.g., Gross and Souleles, 2002; Brown, Stein, and Zafar, 2015; Brown, Grigsby, van der Klaauw, Wen, and Zafar, 2016). In this paper, we exploit the Fed's confidential stress tests data and loan-level consumer credit data to study these questions.

We note a number of difficulties in analyzing the effects of stress tests on consumer credit and households. First, besides stress tests, many socioeconomic factors affect borrower and bank

¹ For example, oil and coal industries try to make pollution levels lower, countries work to improve their sovereign debt ratings, and banks alter lending practices to comply with regulations.

² The Fed can also limit capital distributions to preserve bank capital under special circumstances such as the COVID-19 pandemic. See, e.g., <https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200625c.htm>.

behaviors at the same time, so it is challenging to disentangle the effect of stress tests. Second, identification is challenging. For example, the existing literature uses stressed capital ratio erosion as a measure of “shock” to banks. However, the projected capital ratio erosion is partially driven by banks’ risk appetite unrelated to stress tests, which affects credit supply and consumer outcomes, raising endogeneity concerns. Third, stress tests are intended to work through changing bank behavior, such as their risk management strategies in the supply of credit, which must be disentangled from the choices of their customers (i.e., credit demand).

To disentangle the effects of stress tests from other confounding effects and to resolve the endogeneity issue, we exploit an exogenous variation in shocks to banks due to stress tests — the difference between capital projections made by the banks and those by the Fed.³ Banks and the Fed have separate models concerning how much banks’ capital will decline under the “severely adverse” scenario prescribed by the Fed. Since banks’ passage of the stress tests is ultimately determined by the Fed’s model, banks with a higher, more optimistic, capital ratio projection relative to the Fed’s may face the risk of not passing the stress test the next year, limiting their ability to make capital distributions or expand lending. Thus, a positive difference between the bank and the Fed capital projections represents a negative *shock* to the banks, and they may act on this gap by reducing the risk exposure of their portfolios.⁴ In that regard, we examine banks’ supply of credit and consumer outcomes in the months subsequent to the revelation of the difference (i.e., the release of the Fed’s stress test results).

Besides the capital-ratio information, we use consumer credit data on credit cards and mortgages collected monthly by the Fed on its regulatory FR Y-14M schedule pursuant to the Dodd–Frank Wall Street Reform and Consumer Protection Act.⁵ Our data are at the loan level and contain detailed information on the quantity of credit granted by banks; price of credit including interest rates, rewards, and promotions; consumers’ credit spending, such as credit card new purchases and cash advances; consumer debt management behavior such as repayments and indebtedness; and

³ Note that the Fed’s stress tests apply to bank holding companies (BHCs), but for generality, we use the terms “banks” and “banking organizations” henceforth to refer to BHCs. More information about stress tests is in Section 2.

⁴ It is important to note the gap does not imply that the bank has failed the stress test as it is possible that both bank’s and the Fed’s projected minimum capital ratios are above minimum requirements.

⁵ The data dictionaries on the variables collected are summarized in the following report <https://www.federalreserve.gov/apps/reportforms/reporthistory.aspx?sOoYJ+5BzDYnbIw+U9pka3sMtCMopzoV>.

credit performance, such as delinquencies and bankruptcies. The granular loan-level data allow us to control for consumer demand in several ways, including using a rich set of consumer and loan characteristics in our estimation. In addition, we obtain bank financial data from FR Y-9C reports to account for varying financial conditions across banks and over time.

The main part of our analysis focuses on credit cards, which represent the largest consumer market in terms of total users, affecting about 175 million consumers (see Consumer Financial Protection Bureau, 2021). To banks, what distinguishes credit cards from many other retail products is their unsecured nature, which means that lenders could incur significant losses in the case of borrower default.⁶ In fact, in recent years, credit cards have been the single largest loss generator in the stress tests.⁷ Credit card balances are also retained on bank balance sheets for capital purposes; even securitized credit card lending is consolidated on balance sheets under generally accepted accounting principles (GAAP) and regulatory accounting.⁸ Therefore, banks should be especially sensitive to their credit card risk exposure. In supplementary analyses, we also study secured credit in the form of mortgage loans.

Stress tests involve a forward-looking projection of banks' capital ratios over a nine-quarter capital-planning horizon under the baseline, adverse, and severely adverse scenarios of key macroeconomic factors prescribed by the Fed. We define our *shock* measure as the difference between banks' own minimum projected capital ratio and the Fed's under the severely adverse scenario, which we label *Capital GAP*. A positive Capital GAP represents a negative shock to the bank. It can constrain future growth opportunities and capital distributions. In each of the years we study, about 80 percent of banks have a positive Capital GAP. Since banks do not have access to the proprietary models the Fed uses for capital projections,⁹ the Capital GAP represents an exogenous shock to banks. The Capital GAP in our data shows that: In the cross-section, the gap varies randomly by bank. In the time series, the gap varies randomly by year for each bank.

⁶ Harris, Kahn, and Nissim (2018) show that credit card losses account for most of consumer credit losses over their sample period 1996–2015, while Surane (2019) estimates these to be over 80 percent of total consumer credit costs.

⁷ From 2017 to 2019, losses on credit cards in the severely adverse scenario of the Fed's stress tests ranged from \$100 billion to \$113 billion, larger than commercial and industrial loan losses or trading and counterparty losses.

⁸ Because of recourse agreements on credit card securitizations, the Financial Accounting Services Board (FASB) ruled that banks must consolidate credit card asset-backed securities (ABS) on balance sheets under generally accepted accounting principles (GAAP). Regulatory Accounting Principles (RAP) follow GAAP on this.

⁹ The Fed does not disclose model parameters, and the models can evolve from year to year.

Moreover, the gap does not converge to zero over time for any particular bank. The random nature of the Capital GAP allows us to estimate a simple model in which we study the variables of interest as a function of the gap and other controls. Therefore, the underlying thought experiment is: If a bank experiences a shock in the form of a large Capital GAP, does it then try to close the gap by altering the credit risk of its portfolio?

In our first set of analyses, we find that stress-tested banks with a larger Capital GAP subsequently issue both lower credit limits for new credit card issuance and reduce the number of new credit card accounts they issue, with the latter being the bigger effect. The combined credit quantity effects are economically significant: If the Capital GAP increases from the 10th percentile to the 90th percentile, credit quantity declines by about 14 percent. The reduction in credit supply is primarily to non-prime and lower-income consumers. These findings suggest that banks reduce their risk exposure after experiencing a negative shock through stress tests.

We further investigate the timing and persistency of the effects. We find that the curtailment of credit emerges immediately after the release of stress test results and peaks in the second quarter after the release. The reduction becomes weaker in the third quarter after the release and diminishes in the fourth quarter before the next stress test cycle starts, which brings in a new round of effects on banks' credit supply. The timing of the effects, in addition to our exogenous shock measure, supports our causal inference of stress tests on credit supply.

While the credit quantity effects we find are generally consistent with those found in the literature on business loans, we find interesting pricing results that differ from those in the existing literature. The existing literature that focuses on business loans finds an increase in interest rates following stress tests (See, e.g., Acharya, Berger, and Roman, 2018 and Cortés, Demyanyk, Li, Loutskina, and Strahan, 2020). When examining credit card interest rates as well as rewards and promotions, we find that, *ceteris paribus*, banks that encounter a larger stress test shock offer more competitive pricing incentives to their customers. They specifically give more cash rewards to lower-credit score or lower-income borrowers, but more miles rewards to borrowers with higher-credit score and higher-income borrowers. These results seem counterintuitive, but they can be explained by changes in the demand curve as well as changes in banks' profit margin due to banks' engagement in finer risk management and pricing in response to stress tests. Those banks that experience bigger

negative shocks move strategically with their pricing incentives to attract high-quality credit customers while trying to address their capital gaps by cutting the supply of *risky* credit. In addition, banks that encounter a larger stress test shock offer more interest rate promotions to their lower-credit score and lower-income borrowers, which provides borrowers more opportunities to repay their credit card debts and thus improve banks' loan portfolio performance.¹⁰

We then turn to real effects of stress test shocks on consumer behavior. We start with the post-origination consumer spending in these new credit card accounts issued after each stress test, given that credit card supply is important in shaping equilibrium credit card borrowing and consumer performance (e.g., Herkenhoff and Raveendranathan, 2019; Bornstein and Indarte, 2020). We find that credit card accounts issued by banks with larger stress test shocks are associated with higher spending, i.e., bigger new purchases, and more cash advances, convenience checks, and balance transfers. Accordingly, those accounts have higher utilization rates, *ceteris paribus*. However, additional analyses show that those accounts are also associated with higher-debt repayment and lower overall debt. While the effects are all significant among high- and low-credit score borrowers, the new purchase effects are bigger among the higher-credit score borrowers, and the cash advance effects are bigger among the lower-credit score borrowers. We find that, controlling for other risk factors, accounts issued by banks with larger stress test shocks performed better, measured mainly by two-year cumulative 60-day delinquencies and average number of days past due. The performance improvements are applicable to both low- and high-credit score borrowers. Overall, the credit spending, payment, and credit performance results indicate that borrowers who benefit from better pricing incentives in the credit card market use their credit cards more without increasing delinquencies or total debt. We also look at post-origination consumer behavior that jointly considers consumer spending and debt repayment. We find that, for banks with higher capital shocks, more of the new credit card originations in their portfolio end up being safer inelastic transactors, *ceteris paribus*, consistent with potential shift towards more financially sophisticated households (Ru and Schoar, 2016).

Additional analyses of residential mortgages show that banks experiencing larger stress test shocks

¹⁰ This may also reflect that credit card quantities directly affect bank stress tests' credit risk exposure, while pricing incentives generally do not.

reduce the number of mortgage loans they originate but issue larger loan amounts and longer loan terms to their prime borrowers, *ceteris paribus*. We also find decreases in the three-year cumulative 90-day delinquencies and higher payoff for new mortgages. These findings suggest that banks employ similar risk management strategies in response to stress tests for secured consumer credit — those experiencing larger stress test shocks rebalance their mortgage lending toward less-risky customers to reduce their risk exposure.

The results continue to hold in a variety of robustness tests. For example, bank-level analysis shows that banks experiencing larger stress test shocks reduce their credit card lending as a share of their overall lending or as a share of total assets. This is consistent with those banks' risk reduction motive for credit cards, which are higher risk compared to other types of credit, such as mortgages. Our results are unaffected by excluding any one bank or any one stress test from our sample. Our results are also robust to alternative shock or exposure measures, even though we think our current measure provides sharper identification. The stress test effects also vary across different neighborhoods (e.g., urban neighborhoods see significantly bigger effects).

An additional analysis looking at time heterogeneity around the COVID-19 crisis suggests that banks with higher capital shocks reduce credit supply even more during the COVID-19 pandemic, particularly during the first part of the pandemic up to 2020:Q2, when the economic conditions were worse and the uncertainty was highest.

Finally, we show some contrasts between new originations and existing credit card accounts. For existing accounts, we find that banks experiencing larger stress test shocks engage in more line increases to existing customers and earn higher interest rates on their higher-credit score borrowers, possibly because of the stickiness of those borrowers. In fact, we show that existing borrowers with older accounts pay higher interest rates, *ceteris paribus*, which supports the borrower stickiness explanation.

Our paper's three most important contributions can be summarized as follows: 1) our unique confidential supervisory data allows us to devise a clean identification of stress test impact by exploiting the gap between the Fed's and banks' capital projections as an exogenous shock to banks; 2) we depart from the vast literature that investigates how stress tests affect businesses or the banks

themselves by instead focusing on consumer markets; 3) we not only investigate effects of stress tests on credit supply but also analyze consumers' behaviors after stress tested banks issued new credit to those consumers. This last aspect is important because little is known about the real effects of stress tests, or more generally how banking regulation impacts consumer behavior.

Specifically, our work contributes to several strands of the literature. First, we add to the burgeoning literature on the effects of stress tests on lending which mostly focuses on businesses, as described in more detail in Appendix A (e.g., Acharya, Berger, and Roman, 2018; Bassett and Berrospide, 2019; Cortés, Demyanyk, Li, Loutskina, and Strahan, 2020). This study is among the first to investigate the effects of stress tests on consumer credit markets.

The growing literature on bank stress tests generally focuses on three main areas: stress test theory and design,¹¹ the effects of stress tests disclosure,¹² and the effects of stress tests on small and large businesses.¹³ Little is known about the effects of stress tests on consumer banking and households, despite that household spending has vast macroeconomic implications as it accounts for about 70 percent of U.S. Gross Domestic Product (GDP).¹⁴ Paradkar (2019) is the only other paper we know that has looked at the consumer credit effects of stress tests.¹⁵ While the effects of stress tests on credit supply we find for consumers are generally similar to what researchers find for businesses in terms of extensive margin, our unique supervisory loan-level data allows us to also document compositional effects (average credit limits vs. number of accounts; high risk vs. low risk customers), effects on the intensive margin (price, rewards, and promotions), and the persistence of the effects. Moreover, we go beyond just the credit supply effects of stress tests on consumers and reveal significant real effects of stress tests on consumers' subsequent behaviors in

¹¹ See, e.g., Tarullo (2010); Bernanke (2013); Acharya, Engle, and Pierret (2014); Goldstein and Sapra (2013); Kapinos and Mitnik (2014); and Goldstein and Leitner (2018).

¹² See, e.g., Peristiani, Morgan, and Savino (2010); Glasserman and Tangirala (2015); and Flannery, Hirtle, and Kovner (2017).

¹³ See, e.g., Acharya, Berger, and Roman (2018); Connolly (2018); Covas (2018); Bassett and Berrospide (2019); and Cortés, Demyanyk, Li, Loutskina, and Strahan (2020).

¹⁴ See, e.g., <https://fred.stlouisfed.org/graph/?g=hh3>.

¹⁵ The biggest difference between our papers is that we exploit an exogenous shock to banks by employing the confidential Federal Reserve stress test results compared with banks' stress test results, and then analyze the size of the shock on originations, pricing, credit spending, payments, and performance of newly issued accounts. Paradkar (2019) focuses on *existing* accounts with credit bureaus data. In Section 7, we analyze existing accounts and find results similar to his when analyzing credit supply quantities. However, unlike the credit bureaus, we have access to pricing information, and we find banks increased annual percentage rates (APRs) on these *existing* accounts, suggesting risks were captured in pricing.

spending, payment, and credit performance.

We also add to the literature on the drivers of consumer credit and behavior. This literature investigates various factors of consumer-behavioral changes, such as negative equity and liquidity constraints (e.g., Gross and Souleles, 2002; Elul, Souleles, Chomsisengphet, Glennon, and Hunt, 2010; An, Deng and Gabriel, 2021); monetary policy (Indarte, 2021); behavioral bias (see, e.g., Laibson, 1998; Heidhues, Kőszegi, 2010; Keys and Wang, 2019); interest rate sensitivity (e.g., Alan and Loranth, 2013; Stango and Zinman, 2016); financial literacy (e.g., Brown, Grigsby, van der Klaauw, Wen, and Zafar, 2016); foreclosure laws (e.g., Chan, Haughwout, Hayashi, and van der Klaauw, 2016); and Fintech (e.g., Danisewicz and Elard, 2020). We contribute to this literature by showing how banking regulation, here stress tests, affects consumer credit, spending, payment, and credit performance post-origination.

Finally, we also add to the broader literature on banks and the real economy. This literature includes but is not limited to research that found real effects of banking deregulation, Basel Accord capital standards and countercyclical capital buffers, Community Reinvestment Act, bank bailouts, bank mergers, and shocks to bank deposits on firms and the real economy (e.g., Jayaratne and Strahan, 1996; Morgan, Rime, and Strahan, 2004; Rice and Strahan, 2010; Beck, Levine, and Levkov, 2010; Krishnan, Nandy, and Puri, 2014; Allen, 2004; Uluc and Wieladek, 2016; Auer and Ongena, 2019; Agarwal, Benmelech, Bergman, and Seru, 2015; Duchin and Sosyura, 2014; Berger and Roman, 2017; Garmaise and Moskowitz, 2006; Gilje, Loutskina, and Strahan, 2016; Gilje, 2019). We add to this strand of research by showing that banks' responses to stress tests can have important real effects for consumer markets.

The remainder of the paper proceeds as follows. Section 2 discusses the institutional background. Section 3 describes the data and our empirical strategy. Sections 4 and 5 present our main results on new credit cards issuance. Section 6 provides robustness tests. Sections 7 and 8 provide additional analyses on existing credit card accounts and mortgages. Section 9 concludes.

1. Institutional Background

Stress tests are a policy instrument that regulators use to promote safety and soundness of financial

institutions. Under stress tests, large banking institutions have their capital adequacy assessed to ensure they can absorb losses and continue operating and lending to households and businesses during a severe economic downturn. In the U.S., the Fed’s stress testing program consists of two primary components: the Dodd–Frank Act Stress Tests (DFAST) and the Comprehensive Capital Analysis and Review (CCAR) Program.

Under DFAST, the Fed uses a set of confidential supervisory models developed by its staff to make forward-looking projections of banks’ potential losses to their loan portfolios and other banking activities, such as securities investment and trading.¹⁶ Based on those projections and other inputs, capital ratios are calculated for each bank. At the same time, banks use their own models to project potential losses and capital ratios over the same time horizon. Both the Fed’s and banks’ projections use a set of hypothetical scenarios including a baseline, a severe, and a severely adverse scenario prescribed by the Fed.^{17,18} The most critical scenario in terms of the capital ratios is the severely adverse scenario, which is characterized by a severe recession with significant increases in unemployment rates and declines in house prices and equity market prices, among other stresses. The Fed projections use each bank’s specific loan portfolio information (i.e., credit cards, mortgages) together with a broad array of consumer and loan characteristics from banks’ Y-14M loan-level submissions.

The DFAST model results feed into CCAR, the other component of the stress-testing program. In particular, banks’ model results are submitted to the Fed (in the Federal Reserve Y-14A schedule) along with detailed model documentation and capital plans as part of the Fed’s *qualitative* review for CCAR. Over the 2013–2017 period of our study, the Fed’s model results, together with banks’ capital plans, were used in the *quantitative* part of CCAR to determine whether a bank “passes” or

¹⁶ Note that the stress tests only apply to large banking organizations. For example, the first stress test, the Supervisory Capital Assessment Program (SCAP) implemented in 2009 applied to the 19 largest bank holding companies (BHCs) with consolidated assets exceeding \$100 billion. CCAR and DFAST started in 2011 and applied to BHCs with consolidated assets exceeding \$50 billion and the intermediate holding companies (IHCs) of foreign banks. The 2018 Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA) provided immediate regulatory relief from DFAST for banks with assets less than \$100 billion.

¹⁷ The EGRRCPA removed the *adverse* scenario, reducing the number of DFAST scenarios from three to two.

¹⁸ In the company-run stress tests, banks are required to use additional scenarios (baseline and stress scenarios) developed by the banks themselves to reflect their idiosyncratic risks.

“fails” the stress test.^{19,20} Specifically, the quantitative test compares the minimum projected capital ratios during a nine-quarter capital-planning horizon with a set of predetermined minimum capital ratio requirements.²¹ If a bank’s minimum projected capital ratio falls short of the minimum requirement, then in the immediate term, the bank is given a one-time opportunity before the public release of CCAR results to revise its capital plan to meet minimum requirements. In the following year, the bank may need to raise more capital or reduce its risk exposure, if the bank wants to execute its capital plans on dividend payments and common stock repurchases without Fed restrictions.²²

Our identification grows out of this dual modeling exercise by the Fed and the CCAR banks, which we explain in Section 3. Meanwhile, a number of other institutional details are important to our study. First, stress tests are conducted annually, and banks first submit their DFAST and CCAR results to the Fed in early April, which has been the case since 2016. Then, the Fed releases DFAST and CCAR results three months later in late June.²³ Second, while the Fed obtains details about banks’ models, banks only receive high-level summary information and do not have details about the Fed’s models. In recent years, for transparency purposes, the Fed has released enhanced disclosures on their stress test models, but the full models of the Fed remain confidential supervisory information. Third, from the quantitative side, the results of the Fed’s DFAST models serve as a binding constraint on whether a bank *passes* the stress tests.

2. Data and Methodology

¹⁹ Until 2019, the Fed could object to banks’ capital plan (banks’ *failing* of a stress test) for insufficient capital (quantitative assessment in CCAR), inadequate capital planning practices (qualitative assessment in CCAR), or both. In 2019, the Fed issued a final rule exempting from the qualitative portion banks that participated in CCAR for four past consecutive years and passed the final year’s qualitative component without objection, unless they are “large and complex” institutions. There are four IHCs that are still subject to the qualitative objection/non-objection decision for CCAR 2020. In March 2020, the Fed signed a final rule that would replace the quantitative portion of CCAR with stress capital buffer requirements tailored to individual banks so that banks would have to keep year-round capital ratios above the stress buffer requirements to avoid restrictions on capital distributions and compensation. However, this rule was put on hold due to the pandemic and was not implemented yet.

²⁰ See the Federal Reserve’s Stress Tests and Capital Planning (<https://www.federalreserve.gov/supervisionreg/stress-tests-capital-planning.htm>) for a general overview of the relationship between DFAST and CCAR.

²¹ For example, the minimum requirement on Common Equity Tier 1 (CET1) capital ratio is 4.5 percent.

²² After the one-time resubmission of its capital plan, if a bank still *fails* the stress test, it cannot take any capital action such as dividend payment and common stock repurchase unless authorized by the Federal Reserve Board.

²³ Pre-2015, banks submitted their CCAR results in early January, and the Fed released the DFAST results in March.

3.1 Data sources and sample construction

We compile our data from several sources. We acquire loan-level data on consumer credit cards from monthly Federal Reserve Y-14M reports. The Y-14M is the schedule for bank holding companies (BHCs) that are required to participate in the CCAR and DFAST stress tests to submit detailed loan-level information on credit cards and mortgages. This data set is available from June 2013 and includes a rich set of consumer and loan characteristics, as well as consumers' geographic location down to the zip code, while consumer identity is anonymized. The credit card data set is very large, with each individual month having more than 500 million observations. In most of our analyses, we employ one percent random samples of the loan-level data. When analyzing credit supply, we also aggregate the loan-level data at the firm-county-month level based on the full sample. The one percent random samples allow us to segment data using various risk indicators and estimate individual loan performance over a 24-month period following origination. Note: stress-tested banks are dominant players in the credit card market, holding a market share of over 80 percent,²⁴ which allows us to draw conclusions that are relevant for the market as a whole.

]To this loan-level data, we add BHC financial information from the quarterly FR Y-9C reports collected as part of banking supervision. To construct stress test measures discussed next, we combine DFAST/CCAR public release and confidential supervisory information contained in the Federal Reserve Y-14A reports on projected capital ratios. We also use data from other sources for additional controls and analyses, such as the U.S. Census Bureau, the Federal Deposit Insurance Corporation (FDIC), and the Federal Financial Institutions Examination Council (FFIEC).

Our main data set covers the period of June 2013–December 2017. From the original credit card data, we omit non-consumer cards and consumer charge cards, for which the balance is paid in full in each billing cycle, having different business models from consumer credit cards. We also omit purchased-impaired loans that have different accounting treatment. Next, we remove any loan-level observations that have missing or incomplete information on basic loan and consumer characteristics such as credit limit, account balance, credit score, consumer income, purchase APR, or for which we do not have the consumer county of residence. To remove observations with

²⁴ This is based on market-share assessments of these banks in Y-14M compared with the Federal Reserve Bank of New York (FRBNY) Consumer Credit Panel (CCP), which has information on the total credit card market.

incorrect credit scores, we restrict consumer credit scores to be between 300 and 900. We adjust BHC financial variables to be in real 2017Q4 terms using the GDP price deflator. These screens leave us with 1,686,990 loan-level observations for the one percent random sample and 1,335,178 firm–month–county observations for the aggregate sample based on the full population for 16 BHCs, 3,142 U.S. counties, and 55 months over the entire sample period from June 2013–December 2017.

Table 1 provides variable definitions, mean, median, standard deviation, and various percentiles across our sample for the variables used in our analyses. Panel A reports statistics for our firm–county–month sample, while Panel B reports statistics for our loan-level sample. In terms of consumer and loan characteristics, Panel A shows that the consumers in our sample have an average current consumer credit score of 732.²⁵ The mean and median borrower annual income at origination in logarithmic form (actual) are 11.0 (\$96,490) and 11.1 (\$66,929), respectively. The average utilization rate is 9.7 percent. On average, about 4.2 percent of the consumers have joint accounts and about 20.6 percent have a prior banking relationship with the lender, while 89.4 percent of the credit card accounts have variable interest rates.²⁶

The sample covers a set of very large BHCs (all CCAR banks with material credit card portfolios), with a mean bank size of \$1,166.9 billion (average log of bank size is 20.4). Other financial characteristics are consistent with other studies exploring large BHCs. The mean *Capital Adequacy* is 11.8 percent, the mean nonperforming loan ratio (Asset Quality) is 2.1 percent, the mean return on equity (Earnings) is 10.5 percent, and the mean liquidity ratio is 8.6 percent. The BHCs in our sample have an average share of consumer loans of 26.8 percent, an average share of residential real estate loans of 24.1 percent, and an average share of trading assets of 6.3 percent. The summary statistics in Panel B for our one percent loan-level sample are generally similar to those for our firm–county–month sample.

²⁵ The vast majority (over 80 percent) of the credit card accounts in Y-14M over our sample period have FICO, but a small number have other types of credit scores.

²⁶ Most credit card accounts have their APR indexed to prime rate, so they are variable-rate accounts. Historically, prior to the Credit Card Accountability Responsibility and Disclosure (Credit CARD) Act of 2009, there were more fixed-rate accounts.

3.2 Measures of stress tests shocks

We construct measures of shocks induced by stress tests using the different model results produced by the Fed and each bank. Leveraging the supervisory data we have on banks' model results, we calculate *Capital GAP* as the difference between the minimum nine-quarter capital ratio projected in the BHC's own internal stress test model (from the Y-14A Schedule) and the minimum nine-quarter capital ratio projected by the Fed's supervisory stress test model (publicly disclosed), both using the Fed's DFAST severely adverse scenario. The gap can only be constructed starting in 2013 when banks were required to release their own capital projections and is given by equation (1) below and illustrated in Figure 1 Panel A:

$$Capital\ GAP = \min[(Capital\ Ratio_{BHC})_{Q_1, \dots, Q_9}] - \min[(Capital\ Ratio_{FR})_{Q_1, \dots, Q_9}] \quad (1)$$

Given that BHCs' passage of stress tests is determined by the Fed's model results, a positive *Capital GAP* (i.e., a lower capital ratio projection made by the Fed relative to that by BHCs) puts regulatory pressure on the BHCs. For example, banks with a too-optimistic projection relative to the Fed's can face the risk of not passing the stress test the following year, limiting their ability to make dividend distributions and/or common stock share repurchases if they do not reduce their risk exposure in the 12 months after the Fed model results are revealed.²⁷ Therefore, a positive *Capital GAP* represents a negative *shock* to the BHC. The larger the gap, the bigger a shock it is to the BHC. A similar capital gap measure is used in Bassett and Berrospide (2019).

As a comparison, what has been most used in the literature as a measure of stress test impact is the projected capital ratio erosion over the capital-planning horizon. It is calculated as the stress test starting capital ratio minus the projected minimum nine-quarter capital ratio. The issue with this measure is that it is endogenous — banks with a strong risk appetite are most likely to have a bigger projected capital ratio erosion. In contrast, our shock measure is exogenous because banks do not know the exact size of the Fed projection, *Capital Ratio_{FR}*, ahead of time. In addition, the Fed's models are evolving year over year to include new salient risks or to improve upon the existing models, making the Fed's model results less predictable. In fact, Schneider, Strahan, and

²⁷ Between two stress test cycles, the Fed and banks conduct *off-cycle* runs of the stress test model as a portfolio monitoring exercise. The bank results are submitted to the Fed, but the Fed's off-cycle run results are not disclosed.

Yang (2020) find no evidence that banks could reverse-engineer the Fed’s models. Finally, the Fed’s model is an overall banking industry model, and thus, the Fed’s model results for specific firms are not likely to be correlated with idiosyncratic practices of a particular BHC.

The capital measure used in our main analyses is *Tier 1 Capital GAP*. Table 1 reports summary statistics. The *Tier 1 Capital GAP* measure averages 0.796 percentage points (median of 0.760). These numbers capture how much of a gap exists between the BHC’s and the Fed’s capital projections for a typical bank. They are economically significant, as they are approximately 72 percent in magnitude, of the one-standard-deviation change in the corresponding capital ratio. The *Tier 1 Capital GAP* varies considerably across banks as well, having a standard deviation of 1.053 percentage points. We report robustness of our results using alternative shock measures such as *Total Capital GAP* and *Max Capital GAP* (the maximum of three different capital ratio gaps) in Appendix tables.

Panel B of Figure 1 plots the cross-sectional distribution of the *Tier 1 Capital GAP* from 2013 to 2017 in a box plot. In each of the years, we find that about 80 percent of banks had their gap as positive, meaning bank projections are more optimistic than the Fed’s. These figures show that there is substantial variation in the cross-section. Meanwhile, there is also some time series variation. Overall, there does not appear to be a trend in either the level or variation of the gaps across BHCs. We also make scatterplots of the *Capital GAP* for each year and find the gaps to be evenly distributed (i.e., no clustering). Further analyses of the time series for each bank show no serial correlation or time trend. In addition, we group banks by S&P bond credit rating or size and find no clear pattern in terms of their *Capital GAP*. Finally, we test if the market is able to predict the *Capital GAP* by correlating our gap measure and the cumulative abnormal return (CAR) of bank stocks around the release date of stress test results. We find no meaningful correlation.²⁸ All these analyses indicate the exogeneity of the *Capital GAP*.²⁹

Figure 2 plots a U.S. county heat map with the correlations of our first measure of stress test shocks,

²⁸ Regressions of bank CARs on *Capital GAP* over rolling 3 months, 6 months, 12 months, or 24 months periods also do not show significant relations between Capital GAP and bank stock returns. To preserve data confidentiality, we do not include these results in the paper. They are available upon request under a confidentiality agreement.

²⁹ We also run additional regressions in which we examine effects of the stress tests *Capital GAP* on changes in bank funding such as changes in deposits, non-deposits, subordinated debt, equity, and Discount Window loans. These tests yield insignificant results, too.

Tier 1 Capital GAP, with our main credit quantity proxy, sum of all credit card credit limits divided by county population (*Credit Limit/County Population*). We observe, for most counties, negative correlations over our sample period, suggesting that higher BHC Capital GAPs associated with lower credit supply. This is suggestive that capital constraints from stress tests may induce BHCs to reduce credit card risk exposure by reducing credit quantities to consumers. While this is suggestive, it will be more formally tested using multivariate regression analysis in the next section.

3.3 Regression framework

To examine the relationship between stress tests and consumer credit supply, we estimate the following model based on the full population of Y-14M credit card issuances aggregated at the bank–county–month level:

$$Y_{c,b,t} = \beta_0 + \beta_1 \text{BHC Capital GAP}_{b,t-k} + \beta_2 \text{Consumer \& Loan Characteristics}_{c,t} + \beta_3 \text{BHC Characteristics}_{b,t-1} + \beta_4 \text{BHC FE}_b + \beta_5 \text{County} \times \text{Month FE}_{c,t} + \varepsilon_{c,b,t}, \quad (2)$$

where c indexes the county, b indexes the bank, and t indexes the month–year. $Y_{c,b,t}$ refers to credit supply by bank b in county c at month-year t , measured with the sum of all new issuance credit limit in the county divided by county population *Credit Limit/County Population*. *BHC Capital GAP* $_{b,t-k}$ is the BHC’s *Capital GAP* (*Tier 1 Capital GAP* in our main analysis or *Total Capital GAP* and other capital measures in robustness tests) in the last stress test, where k ranges between 1 and a maximum of 12 months before the current reporting month.³⁰ Negative coefficients on the *Capital GAP* terms would show reductions in credit resulting from stress tests, and vice versa for positive coefficients.

To assess the impact of stress tests on the credit limits of individual accounts, consumer credit pricing incentives, post-origination consumer spending on credit cards, debt repayment, and credit performance we run regressions at the account-level using our one percent random sample:

³⁰ An exception is the 2016 stress test year, when the disclosure month changed from March in 2015 to June in 2016, lengthening the in-between period for these two tests by three additional months for 2016.

$$\begin{aligned}
Y_{i,j,c,b,t/t...t+24} = & \varphi_0 + \varphi_1 BHC \text{ Capital GAP}_{b,t-k} + \\
& \varphi_2 \text{Consumer Characteristics}_{j,c,t} + \varphi_3 \text{Loan Characteristics}_{i,c,t} \\
& \varphi_4 BHC \text{ Characteristics}_{b,t-1} + \varphi_5 BHC \text{ FE}_b + \\
& \varphi_6 \text{County} \times \text{Month FE}_{c,t} + \eta_{i,j,c,b,t},
\end{aligned} \tag{3}$$

where i indexes the loan, j indexes the consumer, c indexes the county, b indexes the bank, and t indexes the month–year. $Y_{i,j,c,b,t}$ refers to the interest rate or other pricing terms for consumer j 's account i with bank b in county c at month-year t . $Y_{i,j,c,b,t...t+24}$ refers to post-origination consumer credit card spending, debt repayment behavior, and credit performance within 24 months (2 years) of issuance of the account. $BHC \text{ Capital GAP}_{b,t-k}$ is defined the same as above.

To mitigate the potential for credit demand driving our results, we include a strong set of consumer and loan characteristics at the consumer-level in equation (3) and county-level in equation (2). These variables include: consumer credit score, log of consumer annual income, consumer utilization rate, percent of consumers with joint accounts, percent of consumers with relationship lending, and percent of variable interest rate accounts. To account for demand factors in the local markets over time, we include high granularity *County* \times *Month* fixed effects, which help capture local economic conditions affecting consumer credit demand.³¹ This allows us to compare banks operating in similar markets and serving similar borrowers but facing different stress test shocks.

To account for supply factors affecting BHC credit decisions other than the *Capital GAP*, we include several BHC characteristics and they are: capital adequacy, share of nonperforming loans, earnings proxied by return on equity, BHC size proxied by the log of total assets, the share of consumer loans, the share of residential real estate loans, and the share of trading assets. All BHC characteristics are lagged one quarter to avoid reverse causality. We also include BHC fixed effects to account for other BHC-level unobservable factors; $\varepsilon_{c,b,t}$ and $\eta_{i,j,c,b,t}$ are error terms allowed to cluster at the county level.³² Therefore, we report heteroskedasticity-robust standard errors along with parameter point estimates.

3. Credit Effects

³¹ Results are robust to an alternative specification in which we use *Zip Code* \times *Month* fixed effects instead of *County* \times *Month* fixed effects.

³² Alternative errors clustered at *Bank* \times *Month* level in robustness checks yield consistent results.

It is unclear *ex ante* whether bank stress tests would improve or worsen credit supply to consumers. On the one hand, banks with higher capital shocks may restrict consumer credit supply particularly to riskier customers to reduce both stress test-projected losses and risk-weighted assets to improve risk-based capital ratios. Alternatively, stress-tested banks with higher capital shocks may increase credit supply at the extensive margin, particularly for riskier borrowers who pay more, to engage in reaching-for-yield behavior to boost their earnings. In fact, findings in the existing literature are mixed. For example, Flannery, Hirtle, and Kovner (2017) and Bassett and Berrospide (2019) find little to no effects on credit supply. Others such as Acharya, Berger, and Roman (2018) and Cortés, Demyanyk, Li, Loutskina, and Strahan (2020) find reductions in credit supply (See more discussion in Appendix A.1.).

4.1 Aggregate credit supply

Table 2 Panel A presents our main results for the effects of stress tests on the quantity of credit supply using equation (2). We report results from regressing our aggregate credit limit measure, *Credit Limit / County Population*, on *Tier 1 Capital GAP* and different sets of controls. Model 1 controls only for BHC fixed effects and *County × Month* fixed effects at the time of credit card issuance. Model 2 additionally controls for consumer and loan characteristics. Model 3, our main specification, additionally controls for one quarter lagged BHC characteristics.

Throughout all specifications in Table 2, the coefficients on the *Capital GAP* terms (shown in the shaded area), are negative and statistically significant. Controlling for a battery of other variables, including high granularity *County × Month* fixed effects, a bigger *Capital GAP* is associated with smaller per capita new issuance credit card limit. This suggests that banks which experience a bigger shock from the stress tests may be managing credit card risk more carefully by reducing their credit card risk exposures.

The reductions in credit limits are also economically significant. Using the full set of control variables, the coefficient on *Tier 1 Capital GAP* of -0.2306 in Model 3 suggests that changing *Tier 1 Capital GAP* from the 10th percentile to the 90th percentile, with all the other characteristics set

to their mean, results in a reduction in the credit limit of 14.1 percent.³³ Calculating it differently, changing *Tier 1 Capital GAP* by a one standard deviation leads to a 5.4 percent reduction in aggregate credit limit per capita.³⁴

We also test for non-linearity in the relationship between credit supply and the stress test shock. In that regard, we run similar regressions but with fifth-order polynomial terms of the *Capital GAP* as explanatory variables. In Appendix A Figure A.1, we plot the relationship between new issuance credit limit and the *Tier 1 Capital GAP*. We see clear non-linearity — the relation becomes concave when the gap becomes larger, suggesting that the response from banks with particularly large shocks is stronger.³⁵ It is worth pointing out that when the *Capital GAP* is negative, meaning that when banks find their own estimates to be more conservative, they tend to lend more, which is consistent with the intuition that there is room for banks to take additional risk in that case. However, we see the sensitivity is smaller in those negative gap cases than in the positive gap cases, judged by the slopes of the curve.³⁶

Turning to the control variables, we find coefficient signs consistent with expectations and prior research. Starting with consumer and loan controls, we find that across all models in Table 2, borrowers and accounts that are less risky (higher credit score, higher income, lower utilization rate, joint accounts, fixed rate accounts, relationship consumers) are associated with higher credit limits. For BHC controls, we see that BHCs with more economies of scale and more capacity to increase lending (i.e., larger size, higher capital ratios, lower share of non-performing loans, higher earnings, higher liquidity ratios) provide their borrowers with larger credit limits. In addition, BHCs with higher shares of consumer and residential real estate loans, and thus with more of specialization in consumer finance, also tend to provide higher credit card limits. Finally, BHCs with higher shares of trading assets are associated with lower credit limits, likely to offset their

³³ Calculated as $(-0.2306 \times 2.780 (90^{\text{th}}\text{-}10^{\text{th}} \text{ percentile}) \div 1.053) \div 4.304 = -14.2\%$. See Table 1 for summary stats of *Tier 1 Capital GAP* and *Credit Limit / County Population*.

³⁴ Since the focus variable is already standardized in the regression, this is calculated as $-0.2306 \div 4.304 = -5.4\%$. See Table 1 for summary stats of *Tier 1 Capital GAP* and *Credit Limit / County Population*.

³⁵ We also run quantile regressions and find the coefficient of the upper quartile to be bigger than that of the lower quartile. For brevity, those results are available upon request.

³⁶ We also run a regression to separate the effects for those that had positive gaps versus those that had negative gaps. The results are consistent with what we see in Appendix A Figure A.1. For brevity, those results are not included in the paper but are available upon request.

higher risks from trading activities.

4.2 Decomposing the credit-supply effect

To obtain a deeper understanding of the credit-supply effect, we decompose the credit supply quantities into average credit limit per account and number of new accounts (normalized by county population). Banks can cut credit supply by reducing the credit limit of individual *existing* accounts, by issuing fewer new credit cards, or both. We want to see where the effects come from exactly. Table 2 Panel B show regression results for *AvgCredit Limit* and *No. New Accounts/County Population*. Here we have the full set of controls as in Panel A Model 3. Column 1 shows that higher capital shocks from the stress tests are associated with decreases in the average credit limit for newly originated credit card accounts. Column 2 shows a similar relation between stress test capital shocks and per capita number of new credit cards issued in each county.

What is interesting is the economic significance: Based on our calculation, the effect on the number of new credit card accounts is more than four times of that on the average credit limit.³⁷ Therefore, these results suggest that the decreases in aggregate credit supply appear to be driven by both lower average credit limits as well as lower numbers of new accounts issued by the lenders, with the latter being a bigger effect.

4.3 Credit supply effect by risk segments

As we just discussed, the effect of stress test on average credit limit is relatively small. However, the effect might be uneven for different segments of the credit market. Our detailed account-level data enable us to study the heterogenous impacts. We rerun our credit quantity analysis using our one percent random sample instead of the aggregated firm–county–month sample above. Now the focus is on individual credit limits, and we use *Credit Limit* for new originations as the dependent variable following equation (3) above. We segment our sample based on *Consumer Credit Score*, and we divide borrowers into six credit score buckets.³⁸

³⁷ The effect on the number of new credit cards $(-0.0229 \times 2.780 (90^{\text{th}}-10^{\text{th}} \text{ percentile}) \div 1.053) \div 0.9 = -6.7\%$, while the effect on average credit limit is $(-36.0472 \times 2.780 (90^{\text{th}}-10^{\text{th}} \text{ percentile}) \div 1.053) \div 6,044.9 = -1.6\%$. Using the derivative product rule, the combined effect is about -14%.

³⁸ To overcome concerns about making inferences by comparing regression coefficients from different FICO subsamples whose magnitudes depend on the scale of both the dependent and independent variables, we run these regressions using a standardizing procedure as suggested in Bennett, Sias, and Starks (2003). Specifically, we

We present our regression results in Table 3. Now we see that the coefficient of the capital shock variable is negative and statistically significant for subprime ($\text{Score} < 620$), prime ($720 \leq \text{Score} < 760$), and super prime ($\text{Score} \geq 800$) borrower segments while that for near prime ($680 < \text{Score} < 720$) and high prime ($760 < \text{Score} < 800$) borrowers are insignificant. More importantly, if we examine the economic significance when changing *Tier 1 Capital GAP* from the 10th percentile to the 90th percentile, with all the other characteristics set to their means, we find that the impact is highest for the subprime segment, where we observe about 22% decrease in average credit limit.³⁹ The same shock is only associated with a 1.7% decrease in average credit limit for the super prime segments.⁴⁰ In Appendix Table A.3, we segment by borrower income and find that credit limit decreases are larger in magnitude for the bottom quintiles (Quintile1–Quintile3) and become insignificant for the top quintile.

Results of these segmentation analyses suggest that banks with a larger Capital GAP, compared to their peers, not only reduce their overall credit supply, but also target specifically the riskiest segments of their customer base in their credit supply reduction.

4.4 Persistence of stress test effects on credit supply

We examine whether there is persistence of the stress test effects on credit card credit supply. We do so by conducting regression analyses as previously stated but including a series of dummy variables in the regressions to trace the effects of each individual quarter after the results are disclosed. Specifically, we replace the *Capital GAP* terms with interactions of the *Capital GAP* measures with dummies for each of the quarters since the Fed’s stress test results disclosure. In these tests, we exclude month 12 to avoid the confounding effect from next year’s stress test results release.⁴¹ We plot the interaction coefficient estimates as well as their confidence intervals in Figure 3.

As we see in Panel A of Figure 3, the results are consistent with our main findings, stress-tested

standardize the key independent variable coefficients on *Tier 1 Capital GAP*, so the interpretation of the coefficients is the expected change in the dependent variable given a one standard deviation change in the independent variable.

³⁹ Calculated as $(-62.461 \times 2.780 \text{ (90}^{\text{th}}\text{-10}^{\text{th}} \text{ percentile)}) \div 1.053 \div 745.73 = -22.1\%$.

⁴⁰ Calculated as $(-60.473 \times 2.780 \text{ (90}^{\text{th}}\text{-10}^{\text{th}} \text{ percentile)}) \div 1.053 \div 9,636.72 = -1.7\%$.

⁴¹ For the 2015 stress test, we exclude months 13, 14, and 15, which appear in the year following the 2015 stress test because of changes in the results disclosure month from March to June from the 2015 stress test to the 2016 stress test lengthening the in-between period for these two tests.

banks with higher-capital shocks reduce credit risk exposure after the stress tests disclosure as indicated by negative and statistically significant coefficients in all quarters since the tests' disclosure. More interesting, there are differences in intensity over different periods. Specifically, credit supply begins to decline in the first quarter immediately after disclosure and become most pronounced in the second quarter. After that, the credit supply effect weakens in the third quarter and diminishes in intensity in the last quarter as BHCs enter another stress test cycle.⁴²

4.5 Interest rate of credit cards

Stress-tested banks may constrict credit supply at the intensive margin (prices) as well to further manage risk by charging customers more or offering fewer rewards/promotions to earn more on loans that pay back to cover losses on defaulted loans. Alternatively, banks may be concerned with maintaining their competitive stance in the consumer market to earn more profits while complying with the stress tests. Thus, banks may try to attract less-risky consumers or induce credit card spending by improving credit at the intensive margin (i.e., interest rate, rewards, and promotions). In fact, in the credit card market, lenders often use prices and other terms as a marketing device to attract new customers.

We examine the effects of stress tests on credit card interest rates and then on rewards and promotions. Table 4 presents the results for credit card annual percentage rate (APR) based on the one percent random sample pooled and by FICO segments.⁴³

Column 1 shows a statistically significant reductions in credit card *Cycle APRs* associated with a higher *Capital GAP*. However, the economic significance is really small: A model coefficient of -0.1176 suggests that, on average, a firm with a one standard deviation greater *Tier 1 Capital GAP* would provide only a 12 basis points (bps) lower APR for new issuances, which, compared to the average new issuance APR of over 18 percent, is not economically meaningful. In the rest of Table 4, we show results for *Cycle APR* for subsamples of riskier and less-risky consumers partitioned based on *Consumer Credit Score*. Results show that the stress test effect on APR is not statistically

⁴² Banks in fact submit results of their new round of firm-run stress test at the beginning of the last quarter.

⁴³ Again, in order to overcome concerns about making inferences by comparing regression coefficients from different FICO subsamples, we standardize the independent variables, such that the interpretation of the coefficients is the expected change in the dependent variable given a one standard deviation change in the independent variable.

significant for subprime (credit score <620) consumers. The effect is statistically significant for other segments, but similar to overall results, are not economically meaningful.⁴⁴

4.6 Credit card rewards and promotions

APR is only one dimension of credit card pricing. Banks usually use rewards and promotions along with APR for pricing, and from the perspective of consumers, promotions and rewards should be considered in the true cost of credit. Our data allow us to study two important credit card reward programs, cash back and airline miles, as well as credit card promotions.

Table 5 presents regression results for total rewards and promotions, miles rewards, cash-back rewards, and credit card promotions, respectively. Panel A presents the results for the effects of bank stress tests on these rewards and promotions combined. Column 1 shows statistically significantly more rewards and promotions at banks with a larger Capital GAP, and columns 2 to 7 show that the effects are prevalent in all credit score buckets. The stress test impacts on rewards and promotions are also economically significant. The coefficient of *Tier 1 Capital GAP* of 0.0192 in the pooled sample suggests that, when changing a firm's *Tier 1 Capital GAP* from the 10th percentile to the 90th percentile, with all the other characteristics set to their means, the firm would be 19.1 percent more likely to offer rewards or promotions for new originations. Decomposing on various types of rewards and promotions, effects can be quite sizable for some groups. Thus, there is a 80 percent higher likelihood for miles rewards overall, ranging between 50 percent for near subprime to 103 percent for the super prime group. There is a 9 percent higher likelihood for cash rewards overall, ranging between 4 percent for the high prime group to 27 percent for the subprime group.⁴⁵ For promotions, moving a firm's *Tier 1 Capital GAP* from the 10th percentile to the 90th percentile, with all the other characteristics set to their means, results in an overall 5 percent increase in the likelihood of credit card promotions, with the effects being largest in the subprime group of about 13 percent.⁴⁶

⁴⁴ To facilitate comparison among different segments, we standardize all the continuous variables including our focus variable in each sub-sample regression.

⁴⁵ For the super prime group, the likelihood of getting cash rewards is actually lower when the *Tier 1 Capital GAP* increases.

⁴⁶ As we did previously, all calculations discussed in this paragraph are following approach discussed above (regression coefficient \times 2.780 (90th-10th percentile) \div 1.053) \div mean of the dependent variable, given that we have standardized the focus *Tier 1 Capital GAP* variable.

To summarize our results on individual components of rewards and promotions: Effects on cash-back rewards tend to apply to all other than very safe customers (credit score 800+ borrowers), and the magnitudes are generally larger among lower-credit score groups. In contrast, the effects of stress test on miles rewards tend to be more frequent among lower-risk customers (higher credit score borrowers). Promotions effects are more common again among riskier customers, generally non-prime and near prime (credit score <720) groups. Segmentation based on borrower income shows similar patterns in Appendix Table A.3 Panel C, which are: cash-back rewards and promotions are more prevalent among lower-income borrowers while miles rewards are more prevalent among higher-income borrowers.

Intuitively, borrowers in the lower end of the income and risk spectrum care more about cash-back rewards and promotions while those in the upper end of the income and risk spectrum care more about miles rewards. Therefore, a reasonable interpretation of these regression results is: stress-tested banks with larger capital shocks cut back their exposure to risky customers, however, they find alternative ways to remain competitive by using more rewards and promotions to entice consumers of relatively good credit quality. Those rewards and promotions not only could help them attract new customers, but also could stimulate more credit card spending post-origination.

We also investigate the persistence of the impacts of stress tests on credit card price incentives, similar to what we do for credit limits. As shown in Figure 3, the effect on cash rewards is the most pronounced in the second quarter after the stress tests results' release. It then becomes smaller in the third and fourth quarter. Promotions and miles rewards show similar patterns.

4.7 Reconciling the price-quantity relation

In a fully competitive partial equilibrium, a shift up in the supply curve (reduction in supply) will lead to a decline in quantity and increase in price, if we fix the demand curve. This seems to be the documented effects of stress tests on business loans (See, e.g., Acharya, Berger, and Roman, 2018; and Cortés, Demyanyk, Li, Loutskina, and Strahan, 2020). In contrast, what we find in consumer credit cards is both a decline in credit supply quantities and a decline in price in the form of rewards and promotions. We think this can be explained by several factors.

First, rewards and promotions are not normal pricing factors. By giving out rewards and

promotions, consumer credit card issuers could actually build loyalty and improve longer-term consumer performance. In other words, the more rewards and promotions the stress tested firms give out are not pure price reductions. They also affect consumer demand and affect firms' profit margin. Second, the consumer credit card market is not full competitive. In fact, it is dominated by a handful of large card issuers. For example, the stress tested firms have over 80 percent of the market in terms of outstanding consumer credit card balances. As further evidence of a lack of full competition, existing studies have also found significant profitability in consumer credit cards (see, e.g., Sinkay and Nash, 1993; Nash and Sinkay, 1997; Agarwal, Chomsisengphet, Mahoney, and Stroebel, 2015; Berger, Bouwman, Norden, Roman, Udell, and Wang, 2021). Finally, compared to business loans, consumer credit cards are less sticky as consumers can easily switch lenders without switching costs much. Therefore, it is reasonable for banks to strive to maintain their competitiveness in the consumer credit card market by providing more rewards and promotions to attract customers and incentivize them to increase their credit card spending (which will be discussed later).

4. Real Effects

Changes in credit supply and pricing are likely to have real economic impacts on consumers. For example, many consumers are liquidity constrained (e.g. Hayashi, 1985; Gross and Souleles, 2002; Hurst and Lusardi, 2004; Agarwal, Liu, Souleles, 2007). An increase in credit supply, either on the intensive or extensive margin, could alleviate liquidity constraints and thus boost consumption. Conversely, a reduction in credit supply could lead to a reduction in consumption. However, for risky borrowers, more credit could lead to over-spending and debt accumulation (Laibson, 1998; Livshits, Mac Gee, and Tertilt, 2016). Less credit could protect risky borrowers from excessive debt and subsequent delinquencies and bankruptcies. In addition, lower cost of credit, especially in the form of credit card promotional rates and rewards, could encourage more consumer spending (e.g., Borzekowski, Kiser and Ahmed, 2008; Arango, Huynh and Sabetti, 2011).

5.1 Credit card purchases and other spending

Existing data on consumer credit such as that from credit bureaus tend to comingle credit usage and debt repayment, and thus, lack the detailed information to separately identify the effects on

spending and debt management. We leverage the Y-14M data that contain separate spending and payment information. We first examine consumer credit card purchases for accounts newly issued after the stress tests. We run regressions described in equation (3). Here the dependent variable is the natural log of one plus the average consumer purchase volume over 24 months since card issuance, $24mos \text{ Ln}(1 + \text{Avg Purchase Volume})$. Panel A of Table 6 contains point estimates of the coefficient of our focus variable, *Tier 1 Capital GAP*, for the full one percent random sample of accounts and subsamples by credit score bucket. As we see from column 1, there is a significant relation between *Capital GAP* and credit card purchases – consumers of credit cards issued by higher *Capital GAP* banks spend more, everything else equal. Moving a firm’s *Tier 1 Capital GAP* from the 10th percentile to the 90th percentile, with all the other characteristics set to their means, results in a 3.9 percent stronger spending overall for new issuances. Columns 2 to 7 shows that the effect exists across the full credit spectrum, even though it is largest for prime and super-prime borrowers (5.5 percent, and 6.8 percent, respectively).

In Panels B-D, we report results for other forms of credit card spending such as cash advances, convenience checks, and balance transfers. Overall, we see more cash advances, convenience checks, and balance transfers for accounts issued by banks with higher *Tier 1 Capital GAP*. The effects on cash advances and convenience checks are stronger for subprime borrowers than for prime borrowers. Balance transfer effects exist across the board.

Results here on spending are consistent with the story of lower costs of credit incentivizing borrowers to use credit cards more. What is interesting is that borrowers across the risk spectrum experience stronger or weaker effects when they were provided more or less rewards and promotions.

5.2 Debt payoff

Our credit card data contain not only detailed spending information but also borrowers’ payment information in each month, which enables us to study consumer debt repayment behavior in the context of stress testing. In Panel A of Table 7, we report regression results on monthly payment. Here the dependent variable is the natural log of one plus the average consumer monthly payment in the 24 months since card issuance, $24mos \text{ Ln}(1 + \text{Avg Payment})$. Column 1 in the panel is for all borrowers in our sample and columns 2 to 7 are for subsets of borrowers in different *Consumer*

Credit Score buckets. The coefficient of our focus variable, *Tier 1 Capital GAP*, is positive and statistically significant for the overall sample and for each credit score segment of the sample. Moving *Tier 1 Capital GAP* from the 10th percentile to the 90th percentile, with all the other characteristics set to their means, results in a 3.6 percent stronger balance payment overall for new issuances. Payment behavior is slightly nonlinear across various credit score buckets, with subprime and high prime and super prime showing the strongest payment effects.

We also look at how indebted the consumer is after origination. Panel B of Table 7 contains our regression results for $24mos \ln(1+Sum \ Total \ Debt)$, the natural log of one plus the total consumer debt over 24 months since origination, where total debt is balance plus payments minus new purchases. Again, we report results for the overall sample and for different credit score segments. From column 1, we see that a higher *Tier 1 Capital GAP* is associated with lower total debt, suggesting that customers of more stress test affected banks accumulate less debt in the two years after card issuance. Specifically, based on the regression coefficients, we find that, changing *Tier 1 Capital GAP* from the 10th percentile to the 90th percentile, with all the other characteristics set to their means, yields a 5.4 percent lower debt overall for new issuances. Indebtedness is particularly reduced most strongly in the riskier consumers, with the subprime ones showing the strongest reduction of 13.4 percent.

Besides analyzing consumer credit card spending and repayment separately, another way to understand consumer behavior after origination is to jointly examine the history of debt and payment behavior of the consumer. Based on this, credit card accounts can be broadly categorized as “transactors,” where consumers pay the balance each month and do not incur finance charges, posing lower credit risk to the bank, while others can be categorized as “revolvers,” where consumers tend to maintain an unpaid balance from month to month and incur finance charges and other fees, in which case banks may get higher profits but incur higher credit risk. Consistently, under the Basel III regulatory framework, revolvers carry higher-risk weights than transactor accounts.⁴⁷ We are particularly interested in understanding whether banks with higher capital shocks may have strategically shifted away from risky “revolvers” and oriented themselves more towards safe inelastic “transactors.” The idea is that having a higher proportion of transactor

⁴⁷ See details for example at: https://www.bis.org/bcbs/publ/d424_hlsummary.pdf.

accounts in their portfolio can help banks reduce credit risk exposure and comply with bank stress test requirements. The change in rewards documented earlier coupled with a higher proportion of consumers ending up being transactors is consistent with banks' shifting towards more financially sophisticated households (Ru and Schoar, 2016).

Table 7 Panel C presents the results for likelihood that new account originations are transactors after origination. Namely, we use *24mos Transactor*, a variable equal to one if a credit card account behaves as a transactor over two years after origination, and zero otherwise. We show results both pooled and by credit score groups. Results show that banks with higher capital shocks tend to end up having a higher proportion of transactor accounts in their portfolio two years after origination.

The increases in transactor accounts are also economically significant. When changing *Tier 1 Capital GAP* from the 10th percentile to the 90th percentile, with all the other characteristics set to their means, we observe an almost 10% percent higher likelihood that new originations turn out to be transactors. The effects are generally increasing with the credit score, with the high prime category showing highest likelihood increase by 16.4 percent.

5.3 Delinquency and bankruptcy

Table 8 provides evidence on consumer delinquency and bankruptcy, pooled and by credit score groups. Panel A shows results with the *24mos 60 Days Past Due (DPD)/Bankruptcy* dummy equal to one if a credit card account was 60 or more days past due or in severe delinquency within 24 months since origination and/or consumers entered bankruptcy, respectively, and zero otherwise. Panel B shows results with *24mos Avg Days Past Due*, the average of days past due for the credit card account within 24 months of the loan's life. The evidence shows that loans originated by BHCs with high capital shocks are less likely to become delinquent and have a smaller number of days past due.

Results are statistically and economically significant. For brevity, we discuss the economic significance on *60 Days Past Due (DPD)/Bankruptcy*. Looking at Model 1 of Panel A, the coefficient on *Tier 1 Capital GAP* of 0.0123 suggests that changing *Tier 1 Capital GAP* from the 10th percentile to the 90th percentile, with all the other characteristics set to their means, results in a 13.7 percent lower likelihood to become delinquent 24 months since origination.

5. Robustness Tests and Additional Analyses

In addition to the previously mentioned tests, we present a number of robustness checks, all of which produce similar results to what we have discussed.

6.1 Alternative capital shock measures

First, in Appendix Table A4, we run credit and real effects results using alternative capital shock measures used in the literature. For brevity, we focus on results on several key dependent variables for credit supply and consumer real outcomes as follows: *Credit Limit/County Population*, *Cycle APR*, *% Rewards/Promotions*, *24mos Ln(1+Avg Purchase Volume)*, *24mos 60DPD*, and *24mos Transactor*. Panels A and B replace *Tier 1 Capital GAP* used in our main analysis with alternative gap variables, *Total Capital GAP*, and *Max Capital GAP*, the maximum out of three capital ratio gaps (tier 1 capital ratio, total capital ratio, and bank leverage ratio), where each gap is the lowest capital ratio projected in the BHC's own exercise (Y-14A) minus the lowest projected total capital ratio in the Fed's stress test exercise (publicly announced), both under the severely adverse scenario.

Finally, instead of our capital shocks that are based on confidential supervisory information, Panels C and D replace *Tier 1 Capital GAP* with alternative capital exposure measures based on public data employed in prior bank stress tests research (e.g., Paradkar, 2019; Cortés, Demyanyk, Li, Loutskina, and Strahan, 2020). In these tests, the key explanatory variables are *Total Capital Exposure*, *Max Capital Exposure*, and the maximum out of three capital ratio exposure measures (tier 1 capital ratio, total capital ratio, and bank leverage ratio), where each of the exposures are based on the difference between the BHC's initial capital ratio and the lowest implied capital ratio expected under the severely adverse stress-test scenario. As we explained earlier, these capital exposure variables are likely subject to endogeneity concerns, making causal inference of the results challenging, while our preferred capital shocks constructed based on confidential supervisory information are likely exogenous to bank credit decisions and consumer behavior. Nevertheless, even with these limitations, we find consistent results with our main findings despite the magnitudes being smaller at times, likely because of biases in the measures.

6.2 Falsification Test

We address potential endogeneity concerns related to unobservable omitted shocks or factors that may occur at the same time as our Capital GAP shocks and may drive our results by conducting a falsification test. Specifically, we obtain an empirical distribution of the GAP shocks and randomly assign the Capital GAPs to banks following the empirical distribution and construct a *Pseudo Tier 1 Capital GAP* and rerun our main regressions. This method preserves the distribution of the capital shocks from our baseline specification, but it disrupts the proper assignment of the shocks to the banks. If unobservable shocks occur at approximately the same time as the capital shocks, they would still exist in the testing framework and could drive the results. However, if no such shocks exist, our placebo assignments should weaken our main results. Results reported in Appendix Table A5 Panel A shows that the coefficient estimates of the placebo capital shocks in this falsification test are statistically insignificant and not different from zero, suggesting that our main results are not driven by alternative shocks.

6.3 Alternative clustering of error terms

We next test the sensitivity of our main results to an alternative specification with a more stringent clustering of the error terms at the $BHC \times Month$ level instead of at the $County \times Month$ level. This can account for any within BHC times month correlations and better account for the level of variation in the capital shocks. However, one concern is that our sample consists of a small number of BHCs, so these newly reported standard errors could be biased with too few clusters. Nevertheless, our results in Appendix Table A5 Panel B show robust significance estimates.

6.4 Potential impact of individual firms

One BHC in our credit card sample was revealed to have a very different business model from the other BHCs. To attenuate concerns that these differences may trigger our main results, we exclude this one BHC and rerun our results. The coefficient estimates on our capital shock variables remain significant and qualitatively similar to our main findings, as shown in Appendix Table A5 Panel C.

BHCs that failed the stress tests may be severely constrained and thus may be more likely to take actions to mitigate their capital deficiencies and a concern is that our results may be particularly driven by them. To alleviate such concerns, we exclude observations of BHCs that failed the

previous stress test. As we can see from Table 9 Panel D, the results are robust.

The number of banks participating in different stress tests has increased over time up to December 2017, the end of our sample period, because of changes in asset thresholds in the CCAR/DFAST stress test requirements. To ensure our results are unbiased by these changes, in an additional robustness test, we only include BHCs that exist in all stress test years. We find our results continue to hold and are not driven by different BHC sorting across different stress years, as shown in Appendix Table A5 Panel E.

To ensure the results are not driven by one particular BHC, in unreported tests we reestimate results by excluding one bank at a time and re-estimating results with the remaining BHCs. Across all specifications, we continue to find that coefficient estimates on our capital shocks remain similarly statistically and economically significant, suggesting that no particular bank appears to be driving the documented results.⁴⁸

6.5 Starting capital level

To ensure our results reflect new effects about stress tests rather than simply effects of the BHCs capital levels unrelated to stress tests, in all our results we include the BHC capital ratio in the previous quarter as a control variable. However, one may argue that the initial capital ratio at the beginning of a stress test better reflects the BHCs capital levels and constraints. Thus, in an additional test, we control for this initial stress test capital ratio instead of the capital ratio in the previous quarter. This test leaves our main results unchanged, as shown in Appendix Table A5 Panel F, suggesting our results are not sensitive to this alternative capital control.

6.6 Potential impact of individual stress test years

To ensure the results are not driven by one particular stress test that may be particularly stringent on the banks, we rerun results excluding one stress test year at a time and using all the other tests. We find our results shown in Appendix Table A5 Panel G on the main outcome variables are robust to this test.

⁴⁸ To ensure confidentiality, results are available upon request with a confidentiality agreement.

6.7 Excluding potential outlier counties

To ensure that our results are not driven by some counties with the smallest or highest credit card market share, we rerun our tests when excluding bottom 5% and top 5% counties, respectively, in terms of credit card limit market share. These tests are shown in Appendix Table A5 Panels H and I and show that our main results continue to hold and remain similar in significance and magnitudes. In unreported results, we also alternatively try excluding bottom 1% and top 1% counties or bottom 10% and top 10% counties, respectively, all yielding consistent results.

6.8 Alternative random samples

Given that some of our analyses discussed previously are based on a random sample of credit card accounts, in Appendix A Figure A.2, we plot coefficient estimates from rerunning regressions using 10 different one percent random samples for key credit and real outcome dependent variables as above to ensure our results are not driven by the random sample selection. These results show qualitatively similar results across different random samples. Estimates in almost all cases are within the 95 percent confidence intervals of the one percent random sample used in our main analyses.

6.9 Alternative measures of credit supply

First, as shown in in Appendix A Table A.6, we rerun our regressions using alternative dependent variables for credit quantities and alternative measures for pricing *in lieu of* those used in our main analyses. Thus, in Panel A, the dependent variables are *Cash Advance Limit/County Population*, credit card cash-advance limit at the firm-county level divided by the county population for new originations; *Log (1+ Total Cash Advance Limit)*, the natural logarithm of the credit card cash-advance limit at the firm-county level for new originations; *Credit Limit/BHC Total Loans*, the credit card limit at the firm-county level for new originations divided by the BHC total loans; and *Δ CC Credit Limit*, the annual change in credit card limit for new originations at the firm-county level. In Panel B, the dependent variables are *Cycle APR (weighted)*, APR weighted by credit limit used for the cycle for consumer retail purchases for new originations; *Cash APR*, APR used for the cycle for cash advances for new originations; *Max APR*, the maximum or default APR (rate cap) allowed to be used for the cycle for both retail purchases and cash advances; *Interest Rate Margin*, the purchase APR margin reflecting the number of percentage points that credit card

lenders add to the prime rate (or other index) to calculate the variable interest rate. Across all these different measures, we continue to find statistically and economically significant effects of the capital shocks on consumer credit supply, similar to our main findings.

6.10 Firm-level analysis

We also conduct a BHC-level analysis. Here we take a holistic view of firms' loans and assets and consider credit cards as one of the firms' consumer lending products. The key question is whether firms reshuffle their loan portfolios after stress tests.

For this analysis, we construct two credit card credit limit measures at the BHC level for newly issued credit cards: One is total credit card limit divided by firm's total loans, *Total Card Limit/Total Loans*, and the other is total credit card limit divided by firm's total assets, *Total Card Limit/Total Assets*. These are our dependent variables. In terms of key independent variables, we use the same capital shock variable, *Tier 1 Capital GAP*, as well as the same controls for BHC characteristics as before. In addition, we include BHC fixed effects and month-year fixed effects.

Results for the BHC-level regressions are reported in Table 9. In column 1, we see that the firms' newly committed credit card limit as a share of its total loans has a negative relation with our capital gap measure, suggesting that firms that experience a negative shock due to stress tests reduce their exposure to credit cards, which is consistent with our prior findings about firms' reduction in risk exposure, as credit cards, compared to other loan types such as mortgages, are relatively riskier. Column 2 shows similar results when we calculate credit card limit as a share of firms' total assets. Columns 3 and 4 report results of regressions that allow error terms to be clustered at bank \times year level.⁴⁹ These results are consistent with those in columns 1 and 2.⁵⁰

6.11 Neighborhood and time heterogeneity

We also conduct a number of tests to better understand how our main consumer credit and real outcome findings vary with consumer neighborhood characteristics. Additionally, we test how the

⁴⁹ Changing *Tier 1 Capital GAP* from the 10th percentile to the 90th percentile, with all characteristics set to their means, results in about 10% percent decrease in the share of credit card limits using either BHC total loans or assets.

⁵⁰ In unreported results, we also tried additional credit supply measures such as the national logarithms of the new credit limit issued or number of new accounts issued or changes in credit limit and number of accounts, or the total bank credit card balances scaled by total loans, all yielding consistent results.

effects have changed during the COVID-19 pandemic. Results are reported in Appendix Tables A.7 through A.8.

6.11.1 Cross-sectional evidence — Splits by neighborhood characteristics

Appendix Table A.8 Panels A–E show cross-sectional evidence for the main results when splitting the data by several local market/neighborhood characteristics, all based on the FFIEC Home Mortgage Disclosure Act (HMDA)/Community Reinvestment Act (CRA) local market demographics data: 1) urban versus rural consumer local market; 2) high versus low percent of minorities in the county (using the upper and bottom halves); 3) high versus low income (based on whether the ratio of the tract family income/MSA income is greater or less than one); 4) HMDA/CRA low-income local market binary indicator; and 5) high versus low unemployment rate (using the upper and bottom halves).

Results again hold in various subsamples, but credit quantity declines are more pronounced for urban local markets, low-income markets, and high unemployment markets, while effects on high-minority neighborhoods are roughly similar to those on low-minority neighborhoods, suggesting no concerns of consumer discrimination. Prices decline more in low-minority, rural, and high-income areas, the latter being consistent with increased risk management and safety, while high- and low-unemployment areas yield roughly comparable declines. Offerings of rewards and promotions are more common in urban areas, slightly higher in low-income areas, but about the same in high versus low minority and high versus low unemployment areas.

As regards real effects, again results hold in various subsamples. Purchases 24 months after origination are somewhat higher in urban and low minority areas, but also in lower income and high unemployment rate areas, results reflecting either price declines or rewards and promotions being higher in some of these neighborhoods. Low delinquencies are more pronounced in rural and high-income areas but also in areas with higher unemployment rate but are about the same in low and high minority areas. Prevalence of transactors is somewhat higher in low minority and low unemployment rate areas, but about the same or mixed in urban and rural as well as in high- and low-income areas.

6.11.3 Time heterogeneity: Effects during the COVID-19 pandemic

Finally, the current COVID-19 pandemic caused a very severe recession in the U.S. by 2020:Q2, and significantly impacted consumers. It is important to understand from both a policy and research perspective how effects of stress tests capital gaps may be different during this crisis.

We conduct a separate analysis for our main credit supply effects using the sample period January 2019 to March 2021 and the same econometric model as in equation (1) to which we add interactions between our Capital GAP measure and indicators for the COVID-19 crisis (crisis Phase 1: M3-M6 2020 and Phase 2:M7-M12 2020, or individual months in the crisis), where the COVID-19 crisis covers the period March 2020 through December 2020. The coefficients of interest are on the interaction terms and capture changes in the effects of the bank stress test capital gaps during the COVID-19 crisis relative to the pre-crisis period.

Results are reported in Appendix Table A.9, where Panel A shows results by crisis phases and Panel B shows dynamic month-by-month crisis effects. Our Capital GAP coefficient estimates – denoting pre-COVID-19 effects – continue to show that banks with higher stress test capital gaps decrease credit card limits but reduce APR and increase rewards and promotions to consumers, consistent with our main effects. Then, focusing on the interaction terms between the Capital GAP and the COVID-19 crisis dummies for phases and months, results suggest that, in general, banks with higher capital gaps reduced their credit risk exposure and supply more during the crisis (lower credit limits, higher pricing, and reduced offerings of rewards and promotions relative to the pre-crisis period), however variations exist across different crisis phases and months. Thus, the highest declines in limits occurred in the first most acute part of the crisis up to June 2020 (Phase 1: M3-M6 2020), when the economic and health uncertainty was highest, GDP experienced its highest decline, and unemployment rate was at its highest.

This period is followed by months of recovery in the crisis, when banks appear to increase limits or decrease them less than they would otherwise. To avert potential negative spillovers from the real economy to the banking sector via loan losses from businesses and households, from June 2020 onwards, the Federal Reserve capped dividends and restricted stock buybacks by the stress-

tested banks, which may have helped keep their bank capital at healthy levels.⁵¹ Other measures such as the CARES Act forbearance accommodations and various income support measures for households and businesses also helped reduce the probability that banks would incur high loan losses. All these allowed these banks to lend more in some of the months of recovery. However, we do observe later again some declines in limits in some of the months as banks may prepare for a new stress test cycle and/or due to other crisis developments. But, crisis months with increases in credit limits are almost always accompanied by increases in APR, likely to compensate for credit risks. We also observe that during the COVID-19 crisis, credit cards are associated with less rewards and promotions, and this is a relatively steady phenomenon. This latter effect may be due to banks becoming more cautious about giving cash away to consumers during a crisis and/or there may be lower demand for rewards and promotions by consumers in a period in which travel, tourism, and overall spending declined significantly due to the pandemic.

6. Evidence from Existing Accounts

As mentioned in the Introduction, a contemporaneous paper, Paradkar (2019), used credit bureau data and investigated effects of stress tests on *existing* credit card accounts. The author finds that the earlier rounds of stress tests induced high-exposure banks to reduce credit limits, especially for risky borrowers, while the later rounds of stress tests caused high-exposure banks to increase credit limits for risky consumers. The author conjectures a reaching-for-yield story for the effect of later rounds of stress tests. Our additional tests for existing accounts yield similar results as Paradkar (2019) on card credit limits. However, beyond what is in Paradkar (2019), we find banks increased APRs on these borrowers, which suggests these risks were priced into the accounts.

Given the very large credit card data, for this additional analysis, we use a 0.02 percent loan-level random sample of the Y-14M existing account population and keep only accounts with ages that are 24 months or more, to avoid potential overlap with our new accounts analysis and their performance. We apply equation (3) to the existing accounts and use the same comprehensive set of controls including *County* \times *Month* fixed effects as for our main analysis to estimate effects of

⁵¹ <https://www.federalreserve.gov/newsevents/pressreleases/bcreg20200625c.html>;
<https://www.federalreserve.gov/newsevents/pressreleases/bcreg20210325a.html>.

capital shocks on credit supply for existing accounts. Specifically, we regress an indicator for *Line Increase* (equal to one if the line was increased by the lender in the respective month) and *Cycle APR* (capturing any APR changes by the lender in the credit cycle) on our measure of capital shock, *Tier 1 Capital GAP*.

Results are presented in Table 10. Panel A is for credit limit and Panel B is for APR. Model 1 in Panels A and B shows the main results — increases in credit limits from BHCs with higher capital constraints for the existing accounts; however, these credit quantity changes appear to be at least partially offset by increases in APR. Thus, lenders may react differently to existing accounts than new accounts by increasing pricing on existing accounts to manage their credit risks. Models 2–7 show subsamples by broad credit score categories and suggest higher line increases for prime customers relative to near prime and subprime ones, which are accompanied by higher APR. Interestingly, for subprime accounts, we see a significant reduction in APR, possibly due to good performance of those accounts as they become seasoned.

Credit effects could vary with different account ages. Hence, we rerun the regressions by account age and report results in Appendix Table A.9. Evidence suggests an interesting lender strategy pattern by age. Relatively younger accounts, up to five years old, are more likely to get higher line increases and lower APRs, while older accounts, particularly those over 10 years old, obtain lower line increases and are charged higher APRs. The more favorable terms for younger accounts may be because these borrowers do not have a long history with the bank so are managed more directly by increasing lines when borrowers exhibit strong performance; older accounts have likely gone through this process so have more lines at optimal levels. and may require better terms to be retained. The higher charges for older accounts may be because of consumer stickiness.

7. Evidence from New Originations of Mortgages

We next address the possibility that stress tests may also affect other consumer products such as first-lien mortgages.

8.1 Data and econometric approach for the first-lien mortgages

Similar to our analysis on credit cards, we conduct analyses looking at effects of BHC capital

shocks on new first-lien mortgage originations using monthly Y-14M mortgage data, which covers the period of June 2012–December 2017.⁵² Specifically, we use bank–county–month aggregated samples for the full population as well as a 10 percent random sample of the loan-level population. The 10 percent random samples allow us to segment data using various risk indicators and estimate individual loan performance over 24 months after origination. We merge the Y-14M loan-level data with BHC financial information from the quarterly FR Y-9C reports and measures of capital gaps constructed from combined public disclosure and supervisory capital projections information (Y-14A) over a nine-quarter horizon from the DFAST/CCAR stress tests results.

From the original Y-14M mortgage data, we keep portfolio loan observations, which matter for bank portfolio risk while excluding commercial loans and purchased impaired loans, both of which have different portfolio or accounting treatments. We also exclude all government loans from our data sets since they are insured against credit risk. We also remove any loan-level observations that have missing, incomplete, or erroneous information on basic loan and consumer characteristics. We adjust BHC financial variables to be in real 2017:Q4 terms using the GDP price deflator.

We use the same econometric models described previously for credit cards (equations (2) and (3)) with slight modifications noted next. We use mortgage loan amount, interest rate, and maturity for new originations as dependent variables, along with the same controls for BHC characteristics lagged one quarter, and county-level and loan-level characteristics at origination specific to mortgages (consumer credit score, LTV ratio, property type dummies (single family 2-4 units, condo, planned unit development, other); occupancy type dummies (primary home, secondary home, investment, other), loan purpose type (refinance, cash-out, other)) as well as high granularity *County* × *Month* fixed effects and BHC fixed effects. Our focus variable is the BHC’s Capital GAP (*Tier 1 Capital GAP*) in the most recent stress test. Specifications for interest rates and mortgage maturity also control for $\ln(1+Loan\ Amount)$ for mortgages.

8.2 Empirical evidence from first-lien mortgages

For mortgages, after applying the filters discussed previously, we have a final aggregated bank–county–month regression sample of 341,355 observations for 29 BHCs, 2,784 U.S. counties, and

⁵² Note that mortgage and home equity data are available from June 2012 rather than June 2013 for credit cards.

67 months covering the full population over the entire sample period. The final 10 percent loan-level random sample has 337,457 observations for 28 banks, 1,981 counties, and 67 months over the entire sample period of June 2012–December 2017.

Table 11 presents the results for the effects of stress tests on new mortgage originations, where Panels A and B show aggregate sample regression results and loan-level regression results, respectively, and they jointly show the effects on credit supply — quantities, interest rates, and maturities – and credit performance such as 90 days past due, and the payoff of the loan, of the newly originated loans 36 months after their origination.⁵³

The evidence in Panels A and B shows that higher capital shocks are associated with decreased overall mortgage credit quantities, driven primarily by a reduction in the number of new loans originated, while the average mortgage loan amount originated and maturity is actually higher. Results also indicate higher mortgage interest rates on new originations. The overall decreased credit quantities and the increased interest rates on new mortgage originations can reflect some risk management to allow banks to manage credit risk by reducing exposures and/or earnings more on loans that pay back to cover losses on the unsuccessful loans.⁵⁴

Results are all statistically and economically significant for credit quantities and pricing. For example, the result in Panel A Model 1 suggests that changing *Tier 1 Capital GAP* from the 10th percentile to the 90th percentile, with all the other characteristics set to their means, results in a decrease in the aggregate mortgage credit for new originations of 4.9 percent. Similarly, the result in Panel A Model 4 suggests that firms with a similar increase in *Tier 1 Capital GAP* have about 6.3 percent lower number of new mortgages originated after stress tests. In addition, results in Panel B show that the reduction in 90-day delinquency rate is 4.6 percent and the increase in payoff rate is about 7.8 percent for loans originated by firms moving their *Tier 1 Capital GAP* from the 10th percentile to the 90th percentile in stress tests.

⁵³ We consider a 36-month period here rather than 24-month period as it can be argued that it may take longer for a consumer to become delinquent on a mortgage, enter foreclosure, and/or repay the loan relative to a credit card. Our results are generally similar when we use a 24-month period instead.

⁵⁴ Higher yields on those loans are possible due to inefficient rate shopping in the mortgage market (see, e.g., Bhutta, Fuster, and Hizmo, 2019).

8. Conclusions

Bank stress tests are important forward-looking capital requirements used by the Federal Reserve for supervising large banking organizations. It has been over a decade since the first bank stress test was implemented in 2009, and a growing extant literature has analyzed many aspects and goals of stress tests, including optimal stress tests design and disclosure and improved credit risk management by banks. This paper is among the first to examine their effects on consumer credit markets.

Moreover, some critical unanswered questions remain as to whether stress tests improved or worsened credit conditions for average American consumers. Increases in consumer spending can drive economic growth, while decreases in spending can have negative effects on the economy. In addition, in recent years, U.S. consumer debt reached record highs (\$15.6 trillion in 2021Q4⁵⁵), worrying policymakers, especially if losses are to follow. In this paper, we investigate whether stress tests affect credit supply and have real effects for consumers. To do so, we use unique supervisory data at the consumer loan level that are used directly in the BHC's and Fed's DFAST models. For identification, we exploit an exogenous shock to BHCs induced by the Capital GAP between the Fed's and the BHC's stress tests model results.

We have several findings. First, we find that stress-tested banks with higher capital gaps significantly reduce limits for new card originations and reduce the number of new accounts. The quantity decline is primarily among riskier consumers (non-prime and lower income), consistent with banks with higher capital shocks engaging in risk management and reducing exposure to these higher risk groups. The timing of the effects, in addition to our exogenous shock measure, further backs our causal inference of the effects of bank stress tests on credit card supply.

Second, despite the large declines in credit quantities, we find that banks with larger capital shocks find alternative ways to remain competitive and attract good customers by improving pricing, mainly through rewards and promotions, while staying in compliance with stress test capital requirements.

⁵⁵ See Center for Microeconomic Data, Household Debt and Credit Report (Q4 2021), Available at: <https://www.newyorkfed.org/microeconomics/hhdc.html>.

Third, we follow the new card accounts issued over 24 months after origination to evaluate real outcomes for consumers. We find that, controlling for other risk factors, consumers with new card originations by banks with higher-capital shocks performed better, and improvements are applicable to both low- and high-credit score and low- and high-income borrowers. With regard to credit card spending, debt repayment, and credit performance, we find that consumers with new originations from banks with larger shocks tend to make larger new purchases and increase their spending; they also tend to make higher debt repayments and are less likely to become delinquent over 24 months after card issuance. Effects apply and are significant for both low- and high-credit score and low- and high-income borrowers. However, the new purchase effects are larger among higher-credit score groups, and the debt repayment effects are bigger among the lower-credit score group. Overall, these results show that customers who benefit from better pricing incentives i.e., higher rewards and promotions in the credit card market, engage in more credit card usage without increasing delinquencies or total debt. We also find evidence that higher capital gap banks end up having more credit card transactors on their portfolio. These transactor accounts bear lower risk weights according to the Basel III capital requirements and more often reflect higher-credit score and higher-income borrowers.

Finally, our additional analyses on mortgages further show that banks with higher capital shocks from stress tests also employ finer risk management after stress tests for these other consumer products.

In terms of consumer welfare, based on our results it might be true that some risky borrowers are rationed out of the market made by the largest creditors as an impact of stress test requirements. However, borrowers who are granted credit are benefiting from more rewards and promotions.

The paper contributes to several strands of research, including the literature on bank stress tests, the literatures on consumer credit and behavior, and the broader literature on effects of banks on the real economy. The paper also yields policy implications by showing that stress tests may be able to steer both bank and consumer behavior toward their intended goals of improved credit risk management. Our results demonstrate a positive feedback loop among consumer credit supply, credit card spending, and credit performance due to the stress tests.

]In addition, recent heated debates discuss what are the appropriate levels of stress test transparency and disclosure to the public and the banks, making these important policy issues. Our results add to these discussions and suggest that there may be value in maintaining a certain level of opacity and keeping the stress tests less predictable to the banks. Our paper shows positive benefits from an exogenous capital shock to the banks from the Fed stress tests' unpredictable components, such as changes in stress scenarios due to new salient risks captured in the Fed's stress tests supervisory models. As noted in Flannery (2019) and Glasserman and Tangirala (2015), leaving the banks unsure about DFAST model parameters may be able to reduce their heavy reliance on the DFAST model in making their own portfolio choices, thus diversifying the banking system's risk exposure, and reducing the risk of having banks set capital policies against one single model. After all, a key purpose of capital is to protect against *unexpected* losses. This capital protection was highly evident in the banking sector condition witnessed during the recent economic crisis caused by the unexpected COVID-19 pandemic.⁵⁶

⁵⁶ See e.g., Blank, Hanson, Stein, and Sunderam (2020) for a discussion on this.

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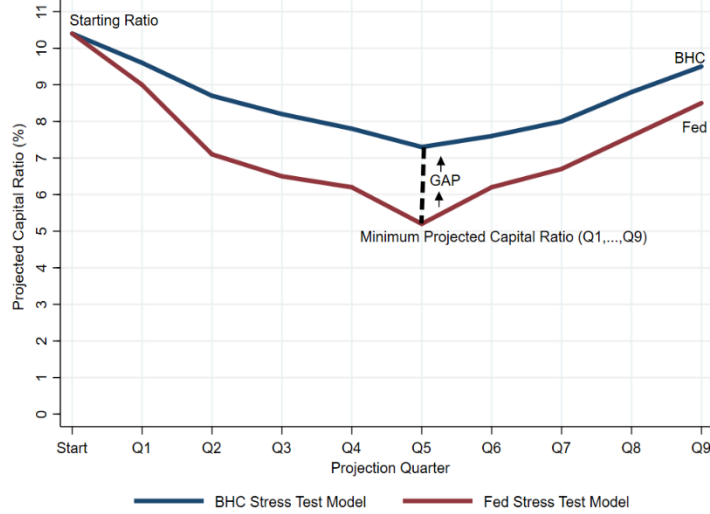
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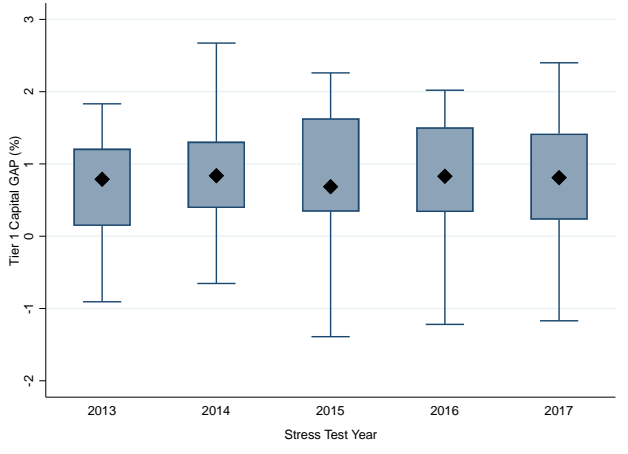
Figure 1: Distribution of Our Shock Measure — Stress Tests Capital ‘GAPs’ (2013–2017)

Panel A is a graphical illustration of a typical 9-quarter projection of the stressed capital ratio based on stress tests independently done by the bank holding companies (BHCs) and the Federal Reserve. The *GAP* is calculated as the difference between firm’s lowest projected capital ratio and the Federal Reserve (Fed)’s lowest projected capital ratio during the 9-quarter capital planning horizon under a severely adverse scenario. A positive *GAP* means that the firm’s projection is more optimistic than the Fed’s, so the Fed’s result would come in as a negative *shock* to the firm. Panels B and C show the cross-sectional distribution of the *Tier 1 Capital GAP* and *Total Capital GAP* for each year between 2013 and 2017 in our sample. Outliers are not shown in these charts to protect confidentiality of the BHCs.

Panel A: An Illustration of Stress Tests Capital Ratio Projections



Panel B: Distribution of Tier 1 Capital GAP



Panel C: Distribution of Total Capital GAP

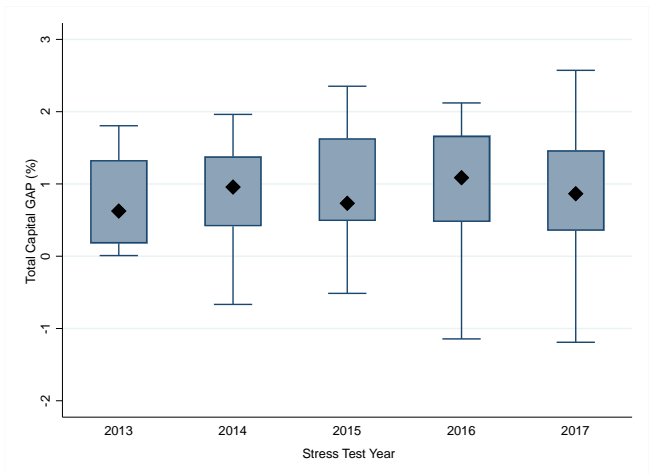


Figure 2: Correlations of Stress Test Shocks and Consumer Credit Supply by County

This figure shows the correlation of the *Tier 1 Capital GAP* with the newly issued credit card (CC) credit limit per capita (*Credit Limit/County Population*) across the counties in the U.S. The sample spans the periods June 2013–December 2017.

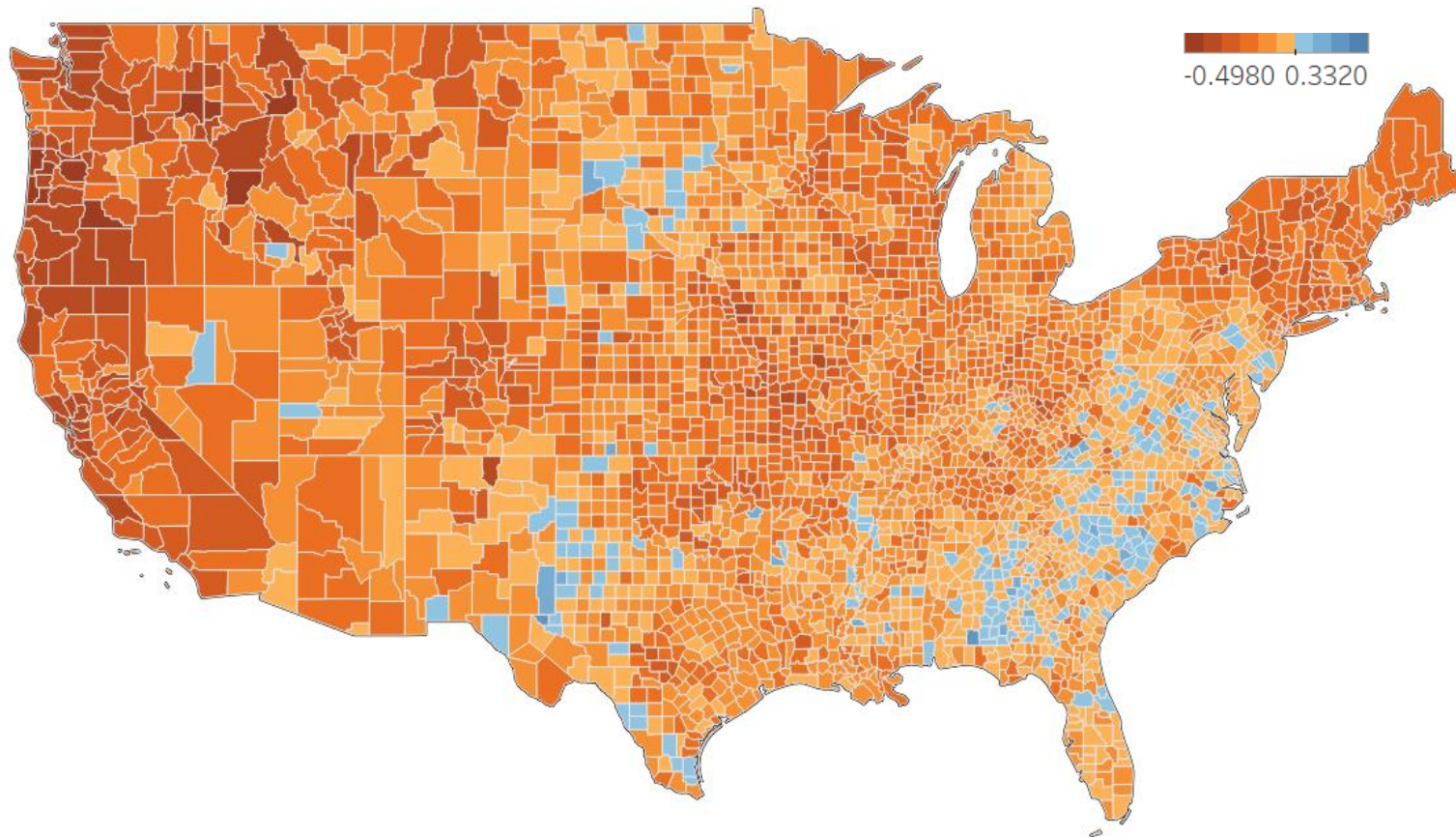


Figure 3: Persistence of Stress Test Effects on Consumer Credit Supply

This figure plots the regression coefficients for the effects of stress tests Capital GAPs on consumer credit quantities in Panel A, % rewards and promotions in Panel B, % miles rewards in Panel C, % cash rewards in Panel D, and % promotions in Panel E, for each quarter since the Fed's stress test disclosure. The coefficients are plotted together by their 95% confidence intervals represented by the blue-gray dashed areas. Results are for new originations over June 2013–December 2017.

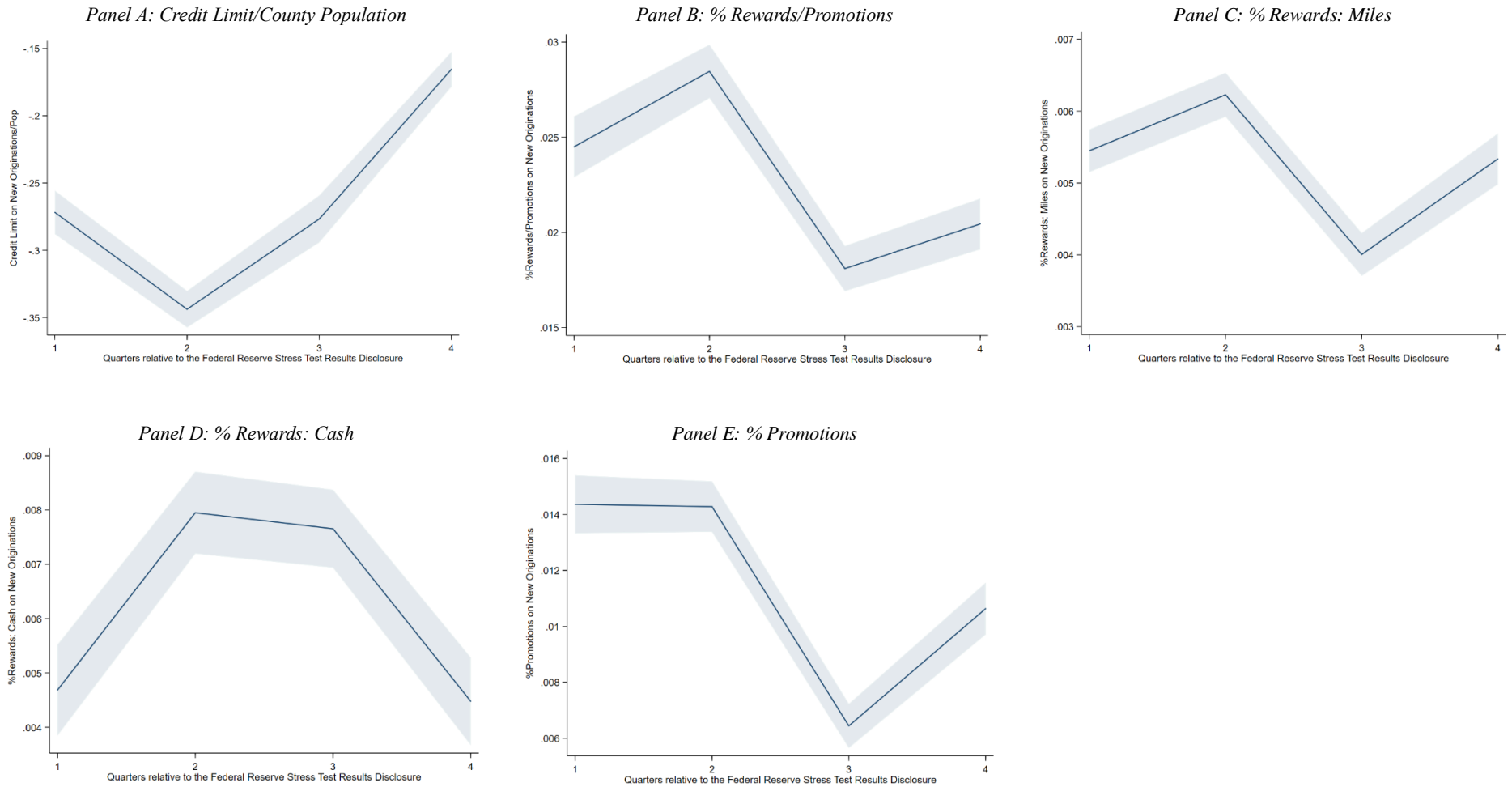


Table 1: Variable Definitions and Summary Statistics

This table provides summary statistics and definitions for the variables used in our analysis. Panel A presents statistics from FR Y-14M credit card new originations data aggregated at the firm–county–month level and public Y-9C BHC information. Panel B presents statistics from a 1% random sample of the FR Y-14M credit card new originations data and public Y-9C BHC information. Variables using dollar amounts are expressed in real 2017:Q4 dollars using the implicit GDP price deflator. The 10th and 90th percentiles of Tier 1 Capital GAP are -0.58 and 2.20, respectively.

Variable	Mean	10th Percentile	Median	90th Percentile	Standard Deviation	No. of Observations	Definition
Panel A: FR Y-14M firm-county-month data							
Stress Test Variables (lagged pertaining to last disclosure, FR Y-14M and Public Reports)							
Tier 1 Capital GAP	0.796	-0.580	0.760	2.200	1.053	1,335,178	Lowest projected tier1 capital ratio projected in the BHC’s own exercise (Y-14A) minus the lowest projected tier1 capital ratio in the Fed’s stress test exercise (publicly announced), both under the severely adverse scenario.
Credit Supply (at origination) (Y-14M)							
Credit Limit/County Population	4.304	0.295	2.502	10.647	5.331	1,335,178	Credit card limit at the firm-county level adjusted for inflation divided by the county population.
Avg. Credit Limit No New Accounts /County Population	6,067.9	1,545.9	5,559.9	10,459.3	3,741.9	1,335,178	Average credit card limit at the firm-county level adjusted for inflation.
	0.865	0.057	0.545	2.090	0.960	1,335,178	The log of one plus total credit card limit at the firm-county level adjusted for inflation.
Consumer Characteristics (at origination or origination month-end) (FR Y-14M)							
Consumer Credit Score Ln(1+ Consumer Income)	731.523	680.250	735.376	773.735	39.469	1,335,178	The consumer credit score or FICO.
Consumer Utilization Rate	11.043	10.575	11.133	11.690	1.090	1,335,178	The natural logarithm of one plus the consumer income.
% Consumers with Joint Accounts	0.097	0.000	0.075	0.220	0.113	1,335,178	The utilization rate on the account calculated as the outstanding balance divided by the credit card limit.
% Variable Interest Rate Accounts	0.042	0.000	0.000	0.136	0.121	1,335,178	Percent of consumer joint accounts.
% Relationship Consumers	0.894	0.600	1.000	1.000	0.235	1,335,178	Percent of consumer variable interest rate accounts.
	0.206	0.000	0.012	0.900	0.332	1,335,178	Percent of accounts from consumers with a prior relationship with the lender.
BHC Characteristics (lagged 1 quarter) (Y9-C)							
Capital Adequacy	0.118	0.102	0.116	0.140	0.015	1,335,178	BHC capital adequacy, proxied by the ratio of BHC equity to total assets.
Nonperforming Loans	0.021	0.009	0.017	0.037	0.011	1,335,178	BHC’s ratio of nonperforming loans to total loans.
Earnings	0.105	0.050	0.093	0.146	0.061	1,335,178	Earnings proxied by ROE (return on equity), the ratio of BHC annualized net income to total equity.
Liquidity	0.086	0.021	0.081	0.162	0.053	1,335,178	Liquidity proxied by the ratio of BHC liquid assets to total assets.
BHC Size	20.436	18.916	21.176	21.672	1.110	1,335,178	The natural logarithm of the BHC total assets.
Consumer Loans	0.268	0.132	0.197	0.564	0.161	1,335,178	The ratio of consumer loans to total loans.
Residential RE Loans	0.241	0.084	0.277	0.363	0.110	1,335,178	The ratio of residential real estate loans to total loans.
Trading Assets	0.063	0.002	0.041	0.154	0.064	1,335,178	The ratio of trading assets to total assets.

Variable	Mean	10th Percentile	Median	90th Percentile	Standard Deviation	No. of Observations	Definition
Panel B: FR Y14 account-level data (1% random sample)							
Credit Supply (at origination) (FR Y-14M)							
Credit Limit	5,679.9	529.0	3,716.4	12,742.1	6438.588	1,686,990	The credit card credit limit at the loan level adjusted for inflation.
Ln(1+Credit Limit)	8.039	6.273	8.221	9.453	1.192	1,686,990	The natural logarithm of one plus credit limit adjusted for inflation.
Cycle APR	18.436	0.000	22.240	26.240	9.235	1,686,990	APR used for the cycle for consumer retail purchases.
Rewards/Promotions	0.287	0.000	0.000	1.000	0.497	1,686,990	An indicator for accounts with rewards (cash-back and miles) or start-up promotions.
Rewards: Miles	0.039	0.000	0.000	0.000	0.194	1,686,990	An indicator for accounts with miles rewards.
Rewards: Cash Back	0.111	0.000	0.000	1.000	0.314	1,686,990	An indicator for accounts with cash-back rewards.
Promotions	0.137	0.000	0.000	1.000	0.344	1,686,990	An indicator for accounts with start-up promotions.
Consumer Real Effects Variables (FR Y-14M calculated over 24mos since origination)							
<i>Consumer Spending Behavior</i>							
24mos Ln(1+Avg Purchase Volume)	3.792	0.000	4.187	6.757	2.416	1,651,935	The natural logarithm of one plus the average purchase volume over 24mos since origination adjusted for inflation.
24mos Ln(1+Avg Cash Advance Volume)	0.157	0.000	0.000	0.000	0.736	1,594,692	The natural logarithm of one plus the average cash advance volume over 24mos since origination adjusted for inflation.
24mos Ln(1+Avg Convenience Check Volume)	0.047	0.000	0.000	0.000	0.485	1,584,295	The natural logarithm of one plus the average convenience check volume over 24mos since origination adjusted for inflation.
24mos Ln(1+Avg Balance Transfer Volume)	0.285	0.000	0.000	0.000	1.192	1,594,848	The natural logarithm of one plus the average balance transfer volume over 24mos since origination adjusted for inflation.
<i>Consumer Payment, Debt, and Transactor Behavior</i>							
24mos Ln(1+Avg Payment)	4.114	0.365	4.311	6.700	2.102	1,662,836	The natural logarithm of one plus average payment over the 24mos since origination adjusted for inflation.
24mos Ln(1+SumTotal Debt)	7.371	0.000	8.586	11.150	3.764	1,673,129	The natural logarithm of one plus the total debt over 24mos since origination (total debt = balance + payments - new purchases) adjusted for inflation.
24mos Transactor	0.472	0.000	0.000	1.000	0.499	1,662,883	An indicator for whether the account was transactor (balance greater than zero and payment of balance in full each month) over the 24mos since origination.
<i>Consumer Credit Performance</i>							
24mos 60DPD/Bankruptcy	0.052	0.000	0.000	0.000	0.221	1,686,990	An indicator for whether the account was ever in 60DPD or bankruptcy over the 24mos since origination.
24mos Avg. Days Past Due	1.540	0.000	0.000	1.500	7.424	1,662,883	The average days past due over the 24mos since origination.
Consumer Characteristics (at origination or origination month-end) (FR Y-14M)							
Consumer Credit Score	732.200	634.000	733.000	830.000	74.778	1,686,990	The consumer credit score.
Ln(1+ Consumer Income)	10.971	10.146	11.018	11.934	1.061	1,686,990	The natural logarithm of one plus the consumer income.
Consumer Utilization Rate	0.101	0.000	0.000	0.370	0.223	1,686,990	The utilization rate on the account calculated as the outstanding balance divided by the credit card limit.
Joint Account	0.014	0.000	0.000	0.000	0.117	1,686,990	Indicator for consumer joint accounts.
Variable Interest Rate Account	0.897	0.000	1.000	1.000	0.303	1,686,990	Indicator for consumer variable interest rate accounts.
Relationship Consumer	0.173	0.000	0.000	1.000	0.378	1,686,990	Indicator for accounts of consumers with a prior relationship with the lender.

Table 2: Effects of Stress Tests on Aggregate Credit Limit of Credit Cards

This table reports regression estimates for analyzing the effects of stress tests on consumer credit card quantities for new originations. The loan origination data come from the supervisory FR Y-14M data set and covers the period June 2013–December 2017. In both panels, we use standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. Panels A and B use aggregated sample using the full Y-14M sample aggregated at the BHC-county-month level. The dependent variables are *Credit Limit/County Population*, credit card limit at the firm-county level divided by the county population for new originations in Panel A. Panel B decomposes credit supply effects into individual components and uses two additional measures: *Avg. Credit Limit*, the average credit card limit at the firm-county level for new originations; and *Number of New Accounts/County Population*, the number of new credit card accounts divided by county population at the firm-county level for new originations. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced) both under the severely adverse scenario for tier 1 capital. We include a broad set of consumer and loan controls measured at the origination time or origination month end: *Consumer Credit Score*, $\ln(1+ \text{Consumer Income})$, *Consumer Utilization Rate*, the percent of consumers with joint accounts, the percent of variable interest rate accounts, and the percent of relationship consumers. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County \times Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively. For Panel A, the dependent variable mean is 4.304. The standard deviation of the focus variable Tier 1 Capital GAP is 1.053, and the 10th and 90th percentiles of Tier 1 Capital GAP are -0.58 and 2.20, respectively.

Panel A: Effect on Aggregate Credit Limit

Independent Variables:	(1)	(2)	(3)
	Dependent Variable = (Credit Limit/County Population) for New Originations		
Stress Test Measures			
Tier 1 Capital GAP	-0.2126*** (0.006)	-0.2133*** (0.006)	-0.2306*** (0.006)
Consumer, Loan Characteristics			
Consumer Credit Score		0.0148*** (0.000)	0.0153*** (0.000)
Ln(1+ Consumer Income)		0.1038*** (0.005)	0.0689*** (0.005)
Consumer Utilization Rate		-0.5043*** (0.038)	-0.4802*** (0.038)
% Consumers with Joint Accounts		0.5394*** (0.050)	0.5045*** (0.050)
% Variable Interest Rate Accounts		-0.4637*** (0.051)	-0.5930*** (0.056)
% Relationship Consumers		2.8618*** (0.078)	2.9153*** (0.079)
BHC Characteristics			
Capital Adequacy			14.7820*** (1.025)
Non-performing Loans			-27.3659*** (0.838)
Earnings			5.5795*** (0.112)
Liquidity			1.5836*** (0.262)
BHC Size			2.0529*** (0.116)
Consumer Loans			4.5922*** (0.143)
Residential RE Loans			18.7070*** (0.364)
Trading Assets		-25.2021*** (0.662)	9,673.2297*** (676.330)
County \times Month-Year FE	YES	YES	YES
BHC FE	YES	YES	YES
Observations	1,337,577	1,335,178	1,335,178
Adj R-squared	0.504	0.521	0.526
<i>Dependent variable mean</i>	<i>4.304</i>	<i>4.304</i>	<i>4.304</i>

Panel B: Decomposition of the Credit Supply Effect

(1) (2) (3)

Independent Variables:	Credit Limit/ County Population	Avg. Credit Limit	No. of New Accounts/County Population
Stress Test Measures			
Tier 1 Capital GAP	-0.2306*** (0.006)	-36.0472*** (3.692)	-0.0229*** (0.001)
Borrower & Loan Characteristics	YES	YES	YES
BHC Characteristics	YES	YES	YES
County × Month-Year FE	YES	YES	YES
BHC FE	YES	YES	YES
Observations	1,335,178	1,335,178	1,335,178
Adj R-squared	0.561	0.561	0.669
<i>Dependent variable mean</i>	<i>4.304</i>	<i>6,067.9</i>	<i>0.865</i>
<i>Derivative product rule</i>	<i>-0.17</i>	<i>-0.03</i>	<i>-0.14</i>
<i>Component contribution</i>		18.4%	81.6%

Table 3: Effects of Stress Tests on Individual Credit Card Limit (1% Random Sample)

This table reports regression estimates for analyzing the effects of stress tests on consumer credit card limit for new originations segmented by credit score groups using 1% random loan-level sample and standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The loan origination data come from the supervisory FR Y-14M data set and covers the period June 2013–December 2017. We report both main effects and risk segmentation by FICO. The dependent variable is *Credit Limit*, the credit card limit for new originations. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced) both under the severely adverse scenario for tier 1 capital. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score*, $\ln(1 + \text{Consumer Income})$, *Consumer Utilization Rate*, the percent of consumers with joint accounts, the percent of variable interest rate accounts, and the percent of relationship consumers. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County \times Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable = Credit Limit for New Originations					
Independent Variables:	FICO <620	FICO [620, 680)	FICO [680, 720)	FICO [720, 760)	FICO [760, 800)	FICO ≥ 800
Stress Test Measures						
Tier 1 Capital GAP	-62.4610*** (17.035)	10.1219 (8.907)	-25.1247 (15.657)	-37.6219* (21.587)	-11.6921 (25.213)	-60.4730** (26.900)
Consumer & Loan Characteristics	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES
Observations	84,103	332,761	269,774	258,159	245,882	361,361
Adj R-squared	0.288	0.345	0.282	0.302	0.313	0.365
<i>Dependent variable mean</i>	<i>745.7</i>	<i>1,961.1</i>	<i>3,947.7</i>	<i>5,993.8</i>	<i>8,291.6</i>	<i>9,636.7</i>

Table 4: Effects of Stress Tests on Credit Card APR (1% Random Sample)

This table reports regression estimates for analyzing the effects of stress tests on consumer credit card pricing for new originations overall and segmented by credit score groups using a 1% random loan-level sample and standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The loan origination data come from the supervisory FR Y-14M data set and cover the period June 2013–December 2017. We report both main effects and risk segmentation by FICO. The dependent variable is *Cycle APR*, the cycle APR used for consumer credit card retail purchases at the account-level for new originations. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced), both under the severely adverse scenario for tier 1 capital. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score*, $\ln(1 + \text{Consumer Income})$, *Consumer Utilization Rate*, an indicator for consumers with joint accounts, an indicator for interest rate accounts, and an indicator for relationship consumers. In addition, in all pricing tables, we include $\ln(1 + \text{Credit Limit})$ as a control variable. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County \times Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable = Cycle APR for New Originations						
Independent Variables:	All	FICO <620	FICO [620, 680)	FICO [680, 720)	FICO [720, 760)	FICO [760, 800)	FICO ≥ 800
Stress Test Measures							
Tier 1 Capital GAP	-0.1176*** (0.019)	-0.0190 (0.075)	-0.1282*** (0.037)	-0.1751*** (0.032)	-0.2048*** (0.032)	-0.2152*** (0.034)	0.4416*** (0.034)
Ln(1+ Credit Limit)	YES	YES	YES	YES	YES	YES	YES
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,686,990	84,103	332,761	269,774	258,159	245,882	361,361
Adj R-squared	0.284	0.288	0.345	0.282	0.302	0.313	0.365
<i>Dependent variable mean</i>	<i>18.439</i>	<i>18.728</i>	<i>19.582</i>	<i>18.427</i>	<i>18.237</i>	<i>17.679</i>	<i>17.995</i>

Table 5: Effects of Stress Tests on Credit Card Rewards and Promotions (1% Random Sample)

This table reports regression estimates for analyzing the effects of stress tests on consumer credit card rewards and promotions for new originations overall and segmented by credit score groups using a 1% random loan-level sample and standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The loan origination data come from the supervisory FR Y-14M data set and cover the period June 2013–December 2017. We report both main effects and risk segmentation by FICO. The dependent variables are *Rewards/Promotions*, *Rewards: Miles*, *Rewards: Cash Back*, and *Promotions*, indicators for new credit cards with rewards and promotions, miles rewards, cash-back rewards, or start-up promotions at the account level. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced), both under the severely adverse scenario for tier 1 capital. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score*, $\ln(1 + \text{Consumer Income})$, *Consumer Utilization Rate*, an indicator for consumers with joint accounts, an indicator for interest rate accounts, and an indicator for relationship consumers. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County \times Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Independent Variables:	Rewards/Promotions, Miles Rewards, Cash Rewards, and Promotions for New Originations						
	All	FICO<620	FICO [620, 680)	FICO [680, 720)	FICO [720, 760)	FICO [760, 800)	FICO \geq 800
<u>Dependent Variable = Rewards/Promotions for New Originations</u>							
Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	0.0192*** (0.001)	0.0174*** (0.003)	0.0160*** (0.001)	0.0168*** (0.002)	0.0152*** (0.002)	0.0188*** (0.002)	0.0191*** (0.002)
Observations	1,686,990	84,103	332,761	269,774	258,159	245,882	361,361
Adj R-squared	0.235	0.145	0.244	0.269	0.250	0.242	0.239
Dependent variable mean	0.266	0.208	0.258	0.291	0.284	0.284	0.245
<u>Dependent Variable = Rewards: Miles for New Originations</u>							
Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	0.0118*** (0.001)	0.0044*** (0.001)	0.0045*** (0.001)	0.0061*** (0.001)	0.0097*** (0.001)	0.0146*** (0.001)	0.0231*** (0.001)
Observations	1,686,990	84,103	332,761	269,774	258,159	245,882	361,361
Adj R-squared	0.074	0.053	0.060	0.050	0.055	0.076	0.080
Dependent variable mean	0.039	0.005	0.020	0.032	0.042	0.053	0.059
<u>Dependent Variable = Rewards: Cash Back for New Originations</u>							
Panel C	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	0.0038*** (0.001)	0.0095*** (0.002)	0.0103*** (0.001)	0.0081*** (0.001)	0.0037** (0.001)	0.0019 (0.002)	-0.0108*** (0.001)
Observations	1,686,990	84,103	332,761	269,774	258,159	245,882	361,361
Adj R-squared	0.232	0.121	0.220	0.253	0.252	0.245	0.257
Dependent variable mean	0.111	0.093	0.103	0.126	0.123	0.126	0.092
<u>Dependent Variable = Promotions for New Originations</u>							
Panel D	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	0.0025*** (0.000)	0.0071** (0.003)	0.0023* (0.001)	0.0023** (0.001)	-0.0007 (0.001)	-0.0020* (0.001)	-0.0002 (0.001)
Observations	1,686,990	84,103	332,761	269,774	258,159	245,882	361,361
Adj R-squared	0.297	0.210	0.309	0.374	0.337	0.323	0.282
Dependent variable mean	0.137	0.141	0.155	0.154	0.140	0.126	0.112
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES

Table 6: Effects of Stress Tests on Consumer Spending (24 months since origination)

This table reports regression estimates for analyzing the effects of stress tests on consumer credit card credit spending post-origination using a 1% random loan-level sample overall and segmented by credit score groups and standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The loan origination data come from the supervisory FR Y-14M data set and cover the period June 2013–December 2017. We report both pooled main effects and risk segmentation by FICO. The dependent variables include several consumer credit spending indicators such as average purchase volume, average cash advance volume, average convenience check volume, and average balance transfer volume, all computed over 24 months since origination. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced) both under the severely adverse scenario for the tier 1 capital ratio. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score*, $\ln(1 + \text{Consumer Income})$, *Consumer Utilization Rate*, an indicator for consumers with joint accounts, an indicator for interest rate accounts, and an indicator for relationship consumers. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County \times Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Independent Variables:	24mos Purchase Volume, Cash Advance Volume, Convenience Checks, and Balance Transfers						
	All	FICO<620	FICO [620, 680)	FICO [680, 720)	FICO [720, 760)	FICO [760, 800)	FICO≥800
Panel A Dependent Variable = 24mos Ln(1+Avg Purchase Volume)							
Stress Test Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	0.0554*** (0.004)	0.0332** (0.015)	0.0330*** (0.007)	0.0148* (0.008)	0.0527*** (0.009)	0.0773*** (0.010)	0.0916*** (0.010)
Observations	1,651,935	82,830	328,167	264,712	252,357	239,482	350,289
Adj R-squared	0.193	0.153	0.154	0.155	0.195	0.217	0.261
Dependent variable mean	3.785	3.846	3.917	3.943	3.817	3.725	3.540
Panel B Dependent Variable = 24mos Ln(1+Avg Cash Advance Volume)							
Stress Test Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	0.0170*** (0.001)	0.0418*** (0.009)	0.0253*** (0.004)	0.0168*** (0.004)	0.0079** (0.004)	0.0104*** (0.003)	-0.0000 (0.002)
Observations	1,594,692	72,012	305,771	257,484	244,245	233,028	351,292
Adj R-squared	0.044	0.083	0.051	0.036	0.028	0.016	0.004
Dependent variable mean	0.159	0.332	0.240	0.216	0.159	0.098	0.043
Panel C Dependent Variable = 24mos Ln(1+Avg Convenience Check Volume)							
Stress Test Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	0.0084*** (0.001)	0.0026* (0.001)	0.0087*** (0.002)	0.0157*** (0.003)	0.0074** (0.003)	0.0101*** (0.003)	0.0023 (0.002)
Observations	1,584,295	71,979	304,520	255,537	242,068	230,724	348,800
Adj R-squared	0.016	-0.016	-0.002	0.007	0.028	0.030	0.015
Dependent variable mean	0.047	0.003	0.023	0.065	0.081	0.064	0.029
Panel D Dependent Variable = 24mos Ln(1+Avg Balance Transfer Volume)							
Stress Test Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	0.0181*** (0.002)	0.0038 (0.004)	0.0132*** (0.004)	0.0312*** (0.005)	0.0277*** (0.006)	0.0294*** (0.006)	0.0143*** (0.003)
Observations	1,594,848	72,011	305,791	257,520	244,285	233,056	351,318
Adj R-squared	0.053	0.008	0.042	0.067	0.075	0.058	0.028
Dependent variable mean	0.285	0.031	0.176	0.426	0.473	0.360	0.148
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES

Table 7: Effects of Stress Tests on Consumer Payment Behavior (24 months since origination)

This table reports regression estimates for analyzing the effects of stress tests on consumer credit card payment behavior post-origination (payment, total debt, and transactor behavior) overall and segmented by credit score groups using a 1% random loan-level sample and In all panels, we use standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The loan origination data come from the supervisory FR Y-14M data set and cover the period June 2013–December 2017. We report both pooled main effects and risk segmentation by FICO. The dependent variables are average actual payment, total consumer debt (balance+payments-new purchases), and an indicator for transactor behavior over 24 months since origination. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced) both under the severely adverse scenario for the tier 1 capital ratio. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score*, $\ln(1+ \text{Consumer Income})$, *Consumer Utilization Rate*, an indicator for consumers with joint accounts, an indicator for interest rate accounts, and an indicator for relationship consumers. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County \times Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Independent Variables:	24mos Payment, Debt, and Transactor Behavior						
	All	FICO<620	FICO [620, 680)	FICO [680, 720)	FICO [720, 760)	FICO [760, 800)	FICO \geq 800
Panel A							
	Dependent Variable = 24mos Ln(1+Avg Payment)						
Stress Test Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	0.0556*** (0.004)	0.0300** (0.014)	0.0263*** (0.006)	0.0207*** (0.008)	0.0478*** (0.008)	0.0698*** (0.009)	0.1210*** (0.009)
Observations	1,662,836	82,972	329,272	266,187	254,188	241,351	354,608
Adj R-squared	0.203	0.138	0.160	0.165	0.216	0.233	0.275
<i>Dependent variable mean</i>	<i>4.105</i>	<i>3.745</i>	<i>3.976</i>	<i>4.220</i>	<i>4.260</i>	<i>4.249</i>	<i>4.017</i>
Panel B							
	Dependent Variable = 24mos Ln(1+Sum Total Debt)						
Stress Test Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	-0.1519*** (0.008)	-0.3626*** (0.024)	-0.3182*** (0.013)	-0.1795*** (0.015)	-0.1294*** (0.015)	-0.0130 (0.016)	0.1314*** (0.015)
Observations	1,673,129	83,755	331,261	267,949	255,666	243,091	356,707
Adj R-squared	0.246	0.258	0.300	0.223	0.262	0.258	0.219
<i>Dependent variable mean</i>	<i>7.365</i>	<i>7.104</i>	<i>7.753</i>	<i>7.961</i>	<i>7.499</i>	<i>7.084</i>	<i>6.713</i>
Panel C							
	Dependent Variable = 24mos Transactor						
Stress Test Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	0.0177*** (0.001)	-0.0018 (0.003)	0.0055*** (0.002)	0.0161*** (0.002)	0.0288*** (0.002)	0.0355*** (0.002)	0.0308*** (0.002)
Observations	1,662,883	82,972	329,288	266,197	254,196	241,356	354,616
Adj R-squared	0.125	0.140	0.098	0.060	0.056	0.063	0.063
<i>Dependent variable mean</i>	<i>0.469</i>	<i>0.152</i>	<i>0.314</i>	<i>0.444</i>	<i>0.522</i>	<i>0.570</i>	<i>0.610</i>
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES

Table 8: Effects of Stress Tests on Consumer Credit Performance (24 months since origination)

This table reports regression estimates for analyzing the effects of stress tests on consumer credit card performance of new originations overall and segmented by credit score groups using a 1% random loan-level sample and standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The loan origination data come from the supervisory FR Y-14M data set and cover the period June 2013–December 2017. We report both pooled main effects and risk segmentation by FICO. The dependent variables are *24mos 60DPD/Bankruptcy*, indicator for consumers that are 60 days past due or enter bankruptcy and *24mos Avg Days Past Due*, the average number of days past due, calculated over 24 months since origination. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced), both under the severely adverse scenario for the tier 1 capital ratio. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score*, $\ln(1 + \text{Consumer Income})$, *Consumer Utilization Rate*, an indicator for consumers with joint accounts, an indicator for interest rate accounts, and an indicator for relationship consumers. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County \times Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Independent Variables:	24mos 60DPD/Bankruptcy and Days Past Due						
	All	FICO<620	FICO [620, 680)	FICO [680, 720)	FICO [720, 760)	FICO [760, 800)	FICO≥800
	<u>Dependent Variable = 24mos 60DPD/Bankruptcy</u>						
Stress Test Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	-0.0027*** (0.000)	0.0042 (0.003)	-0.0045*** (0.001)	-0.0036*** (0.001)	-0.0003 (0.001)	-0.0001 (0.000)	0.0001 (0.000)
Observations	1,686,990	84,103	332,761	269,774	258,159	245,882	361,361
Adj R-squared	0.095	0.115	0.051	0.023	0.007	0.002	0.000
<i>Dependent variable mean</i>	<i>0.052</i>	<i>0.243</i>	<i>0.109</i>	<i>0.046</i>	<i>0.022</i>	<i>0.010</i>	<i>0.004</i>
	<u>Dependent Variable = 24mos Avg Days Past Due</u>						
Stress Test Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	-0.0747*** (0.011)	0.1686 (0.122)	-0.1197*** (0.028)	-0.0862*** (0.023)	-0.0265* (0.015)	-0.0105 (0.010)	-0.0055 (0.006)
Observations	1,662,883	82,972	329,288	266,197	254,196	241,356	354,616
Adj R-squared	0.119	0.142	0.078	0.025	0.004	-0.007	-0.005
<i>Dependent variable mean</i>	<i>1.556</i>	<i>9.503</i>	<i>2.878</i>	<i>1.069</i>	<i>0.575</i>	<i>0.292</i>	<i>0.163</i>
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES

Table 9: Effects of the Stress Tests Capital Gap on Consumer Credit — Firm-Level Analysis

This table reports regression estimates for analyzing the effects of stress tests on consumer credit cards using aggregated loan-level data at firm-month level and standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The data come from the supervisory FR Y-14M data set and cover the period June 2013–December 2017. The dependent variables are: *Total Card Limit/ Total Loans*, the ratio of total credit card limit (new accounts) to BHC total loans; *Total Card Limit/ Total Assets*, the ratio of total credit card limit (new accounts) to BHC total assets at the firm level. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced) both under the severely adverse scenario for the tier 1 capital ratio. We include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include BHC fixed effects. The variables are defined in Table A.2. Heteroskedasticity-robust standard errors are reported in parentheses in columns (1)-(2) and robust standard errors clustered at bank \times year level in columns (3)-(4). Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Independent Variables:	Total Card Limit	Total Card Limit	Total Card Limit	Total Card Limit
Stress Test Measures	/Total Loans	/Total Assets	/Total Loans	/Total Assets
Tier 1 Capital GAP	-0.0830** (0.034)	-0.0426*** (0.016)	-0.0830* (0.043)	-0.0426* (0.022)
BHC Characteristics				
Capital Adequacy	15.9247** (7.742)	10.2517** (4.915)	15.9247 (10.498)	10.2517 (6.265)
Nonperforming Loans	-13.9870** (5.911)	-4.7616 (3.481)	-13.9870 (9.209)	-4.7616 (5.566)
Earnings	1.9070 (2.655)	0.4001 (1.813)	1.9070 (2.325)	0.4001 (1.451)
Liquidity	0.7352 (2.429)	0.8752 (1.581)	0.7352 (3.268)	0.8752 (1.773)
Bank Size	-1.1151** (0.491)	-0.8070*** (0.294)	-1.1151 (0.835)	-0.8070 (0.505)
Consumer Loans	-6.5184** (2.715)	-5.2883*** (1.913)	-6.5184 (4.247)	-5.2883* (2.890)
Residential RE Loans	9.2118*** (2.056)	4.9638*** (1.043)	9.2118*** (2.848)	4.9638*** (1.696)
Trading Assets	-3.5548 (5.353)	0.8685 (2.591)	-3.5548 (9.679)	0.8685 (4.225)
BHC FE	YES	YES	YES	YES
Month-Year FE	YES	YES	YES	YES
Error Term Clustering			Bank \times Year	Bank \times Year
Observations	862	862	862	862
Adj R-squared	0.901	0.850	0.901	0.850
Dependent variable mean	2.230	1.156	2.230	1.156

Table 10: Effects of Stress Tests on Existing Credit Card Accounts

This table reports regression estimates for analyzing the effects of stress tests on credit card consumer credit for existing accounts (24 months or older) using a 0.2% random loan-level sample and standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The loan-level data come from the supervisory FR Y-14M data set and cover the period June 2013–December 2017. We report both pooled main effects and segmentation by FICO. The dependent variables are: *Line Increase*, an indicator equal to one if the credit card limit was increased on the account; *Cycle APR*, the average APR used for the cycle for consumer retail purchases at the firm-county level. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced) both under the severely adverse scenario for the tier 1 capital ratio. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score* (refreshed score), $\ln(1 + \text{Consumer Income})$, *Consumer Utilization Rate*, an indicator for consumers with joint accounts, an indicator for interest rate accounts, and an indicator for relationship consumers. In the pricing regressions, we also include $\ln(1 + \text{Credit Limit})$ as a control variable. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County \times Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Independent Variables:	Line Increase and Cycle APR for Existing Accounts						
	All	FICO<620	FICO [620, 680)	FICO [680, 720)	FICO [720, 760)	FICO [760, 800)	FICO \geq 800
	<u>Dependent Variable = Line Increase</u>						
Stress Test Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	0.0008*** (0.000)	0.0014*** (0.000)	0.0002 (0.000)	0.0002** (0.000)	0.0005*** (0.000)	0.0017*** (0.000)	0.0017*** (0.000)
Observations	15,930,012	1,277,909	2,852,296	2,785,721	3,143,363	2,343,629	2,343,629
Adj R-squared	0.005	0.011	0.001	0.002	0.002	0.010	0.010
Dependent variable mean	0.009	0.015	0.014	0.012	0.009	0.006	0.005
	<u>Dependent Variable = Cycle APR</u>						
Stress Test Measures	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier 1 Capital GAP	-0.0002 (0.006)	-0.2514*** (0.027)	0.0150 (0.012)	-0.0003 (0.011)	0.0607*** (0.010)	0.0547*** (0.010)	0.0782*** (0.011)
Observations	15,930,012	1,277,909	2,852,296	2,785,721	3,143,363	3,360,458	2,343,629
Adj R-squared	0.423	0.170	0.284	0.337	0.386	0.460	0.615
Dependent variable mean	17.897	20.430	20.499	18.434	16.890	15.971	17.258
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES

Table 11: Effects of Stress Tests on Other Consumer Products: New Mortgage Originations

This table reports regression estimates for analyzing the effects of stress tests on consumer mortgage credit supply for new originations using an aggregated firm–county–month sample in Panel A and effects on account-level credit supply and credit performance using a 10% random loan-level sample in Panel B. In all panels, we use standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The loan origination data come from the supervisory FR Y-14M data set and cover the period June 2012–December 2017. In Panel A using the aggregated sample, the dependent variables are several measures for mortgage credit supply including *Loan Amount / County Population*, *Ln(1+Loan Amount)*, *Ln(1+AvgLoan Amount)*, and *Ln(1+No. New Loans)*. In Panel B using the 10% random loan-level sample, the dependent variables are account-level measures of credit supply, such as *Ln(1+Loan Amount)*, *Mortgage Interest Rate*, and *Log (1+ Mortgage Maturity) (months)*, as well as measures of credit performance indicators such as 90 days past due, and paid off, calculated over 36 months since origination. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced) both under the severely adverse scenario for the tier 1 capital ratio. We include a broad set of consumer and loan controls specific to mortgages measured at the origination time: consumer credit score, LTV ratio, property type dummies (single family 2-4 units, condo, planned unit development; other), occupancy type dummies (primary home, secondary home, investment, other), loan purpose type dummies (refinance, cash-out, other)). In the pricing and maturity regressions, we also include *Ln(1+ Loan Amount)* as a control variable. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County × Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Credit Effects for New Mortgage Originations (Aggregate Sample)

Independent Variables:	(1) Dependent Variable = Loan Amount / Population	(2) Dependent Variable = Ln(1+Loan Amount)	(3) Dependent Variable = Ln(1+AvgLoan Amount)	(4) Dependent Variable = No New Loans/ Population
Stress Test Measures				
Tier 1 Capital GAP	-2.3666*** (0.100)	-0.0965*** (0.005)	0.0271*** (0.002)	-0.0114*** (0.000)
Consumer, Loan Characteristics	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES
Observations	341,355	341,355	341,355	341,355
Adj R-squared	0.379	0.607	0.675	0.415
Dependent variable mean	12.834	13.477	12.370	0.048

Panel B: Credit Effects for New Mortgage Originations (10% Random Sample)

Independent Variables:	(1) Dependent Variable = Ln(1+Loan Amount)	(2) Dependent Variable = Mortgage Interest Rate	(3) Dependent Variable = Ln(1+Mortgage Maturity (Months))	(4) Dependent Variable = 36mos 90DPD	(5) Dependent Variable = 36mos Paidoff
Stress Test Measures					
Tier 1 Capital GAP	0.0319*** (0.004)	0.0012*** (0.000)	0.0051*** (0.001)	-0.0007* (0.000)	0.0057*** (0.002)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Observations	337,457	337,457	337,457	185,087	185,087
Adj R-squared	0.569	0.293	0.361	0.074	0.082
Dependent variable mean	12.480	0.035	5.656	0.004	0.194

Appendix for Online Publication Only
**for “Bank Stress Test Results and
Consumer Credit Markets: Credit and Real Impacts”**

A.1 Literature Review on Stress Testing

There is a growing literature on the bank stress tests. One strand of the literature focuses on the theoretical benefits and costs, and the methodology/design of stress tests. For example, Hirtle, Schuermann, and Stiroh (2009) argue that the 2009 U.S. stress test was credible and stabilizing for the banking system. Schuermann (2014) finds to the contrary that stress tests are counterproductive because they force banks to use similar models in passing the stress tests, which may set the system up for a subsequent crisis. Goldstein and Sapra (2013) provide a complete overview of the benefits and costs of the stress tests and their disclosure and conclude that benefits may outweigh the costs. Goldstein and Leitener (2015) develop a model for optimal stress tests disclosure policy for the regulators during normal and bad times.

Other papers look at stress tests disclosure specifically. For example, Peristiani, Morgan, and Savino (2010) find that SCAP results were informative, as banks with larger capital gaps registered more negative abnormal stock returns and negative credit default swap (CDS) spreads around release of SCAP results and other disclosures. Bird, Karolyi, and Ruchti (2020) find that CCAR has information content for banks. They report significant abnormal stock trading volume and returns, which are correlated with the unexpected component of the disclosure. Glasserman and Tangirala (2015) find stress tests outcomes have become more predictable and less informative over time. For example, they find that projected stress losses in the 2013 and 2014 stress tests are nearly perfectly correlated for banks that participated in both rounds.

A number of papers assess whether stress tests made banks less risky and find mostly positive effects. Acharya, Engle, and Pierret (2014) find that projected capital shortfalls from stress tests relative to banks’ total assets and contributions to systemic risk match well, suggesting stress tests are helpful preparing banks for actual losses. Schneider, Strahan, and Yang (2020) find larger stress-tested banks make more conservative capital plans as a result of the stress tests (i.e., are reluctant to commit to an aggressive dividend increase for fear of failing CCAR tests). Clark, Francis, Garcia, and Steele (2020) document that non-stress tested (non-treated) banks also react to the stress tests by increasing capital and risk by 60 percent, while stress-tested banks decrease these by a similar percentage. In contrast, Cornett, Minnick, Schorno, and Tehranian (2018) suggest that stress-tested banks may be window dressing to look more attractive to regulators and investors: They show higher capital ratios than their peers in the CCAR starting quarter,

which get reversed in later quarters. Finally, a number of the papers discussed next focus on lending and derive effects for portfolio risk, a component of banks' overall risk.

An increasing number of papers focus on the effects of stress tests on large and small businesses and find either decreases or insignificant effects on credit supply. Acharya, Berger, and Roman (2018) find that stress-tested banks reduced credit supply at the intensive and extensive margins particularly to relatively risky business borrowers. Consistently, Lambertini and Mukherjee (2016) and Connolly (2018) also find reductions in credit supply at the intensive margin for large corporate borrowers in the syndicated loan market for various stress test years, but some were offset by credits from other institutions. Berrospide and Edge (2019) document significantly reduced commercial and industrial (C&I) lending to large firms by the stress-tested banks, but economic effects are inconsequential. Several papers, including Acharya, Berger, and Roman (2018), document significant decreases in lending to small businesses, often regarded as riskier customers. Cortés, Demyanyk, Li, Loutskina, and Strahan (2020) find that banks affected by stress tests reduce credit supply and raise interest rates on small business loans, while Covas (2018) finds that stress tests constrain the availability of small business loans secured by nonfarm nonresidential properties.⁵⁷ Doerr (2021) find stress tests led to strong cuts in small business loans secured by home equity, an important source of financing for entrepreneurs, with negative effects on entrepreneurship and innovation. Finally, Flannery, Hirtle, and Kovner (2017) and Bassett and Berrospide (2019) find little to no effects on credit supply in broad loan categories using a sample covering mostly stress-tested banks.

Literature on the effects of stress tests on consumers is scarce. To the best of our knowledge, only three papers have some evidence on consumer credit and only one looks at credit cards. Calem, Correa, and Lee (forthcoming) find the CCAR 2011 test reduced jumbo mortgage approvals and originations. Morris-Levenson, Sarama, and Ungener (2017) document that non-banks are able to increase mortgage shares as a result of stress tests. There is only one paper focusing on credit cards and closest to ours. Paradkar (2019) analyzes effects of bank stress tests on credit limit changes for existing accounts using credit bureau data and reports that stress tests induce banks to increase credit limits to non-prime consumers, inconsistent with the credit-risk management goals of the stress tests.

⁵⁷ Related to this, Bordo and Duca (2018) document that the small loan share of C&I loans at large banks and banks with \$300 million or more in assets has fallen by 9 percentage points since the 2010 Dodd–Frank Act.

Figure A.1: Non-linearity of the Relation between Credit Limit and Capital GAP

This figure illustrates the relation between credit card limits scaled by county population and Tier 1 Capital GAP. The *GAP* is calculated as the difference between firm's lowest projected capital ratio and the Federal Reserve (Fed)'s lowest projected capital ratio during the 9-quarter capital planning horizon under a severely adverse scenario. A positive *GAP* means that the firm's projection is more optimistic than the Fed's, so the Fed's result would come in as a negative *shock* to the firm.

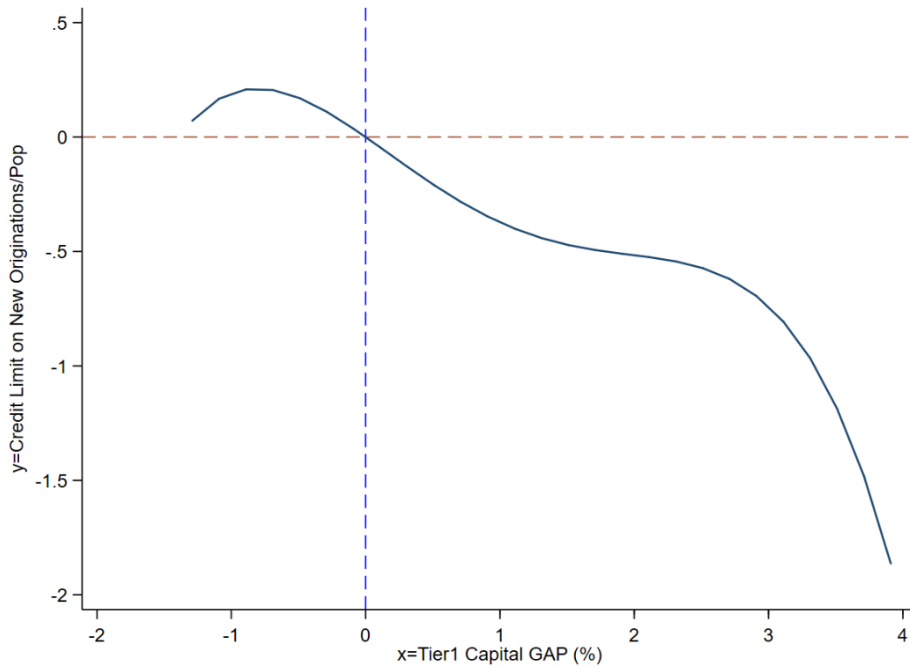
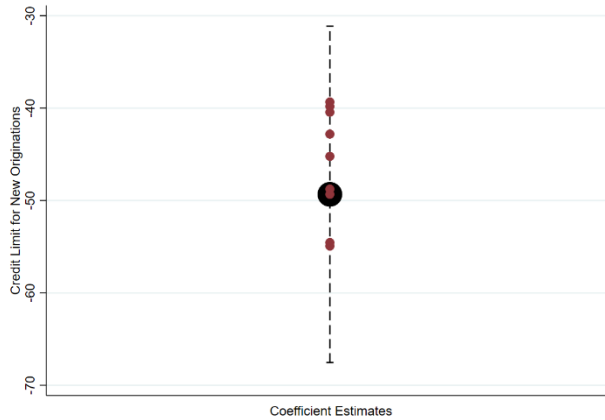


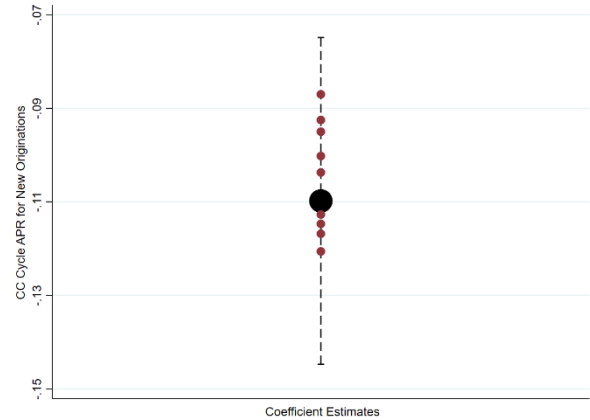
Figure A.2: 1% Random Sample Robustness Tests

This figure plots the regression coefficient estimates for the effects of bank stress tests Capital Gaps on consumer credit card limit in Panel A, cycle APR in Panel B, rewards and promotions in Panel C, natural logarithm of one plus the average purchase volume over 24 months since origination in Panel D, natural logarithm of one plus the average payment over 24 months since origination in Panel E, and transactor indicator over 24 months since origination in Panel F, using our 1% random sample shown in the paper tables and represented by a big black dot together with the afferent 95% confidence intervals represented by dotted lines, and estimates from 9 additional 1% random samples represented by smaller red dots. Results are for new originations over June 2013 to December 2017.

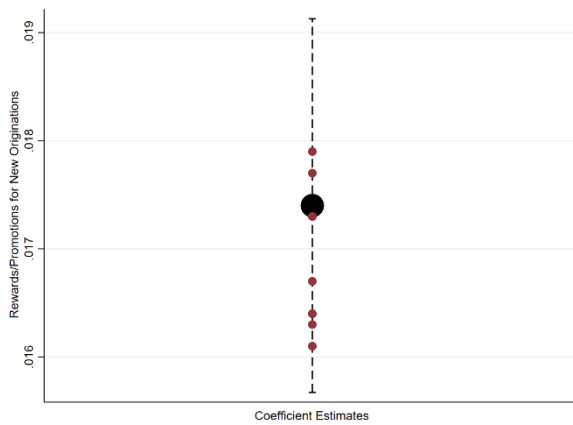
Panel A: Credit Limit



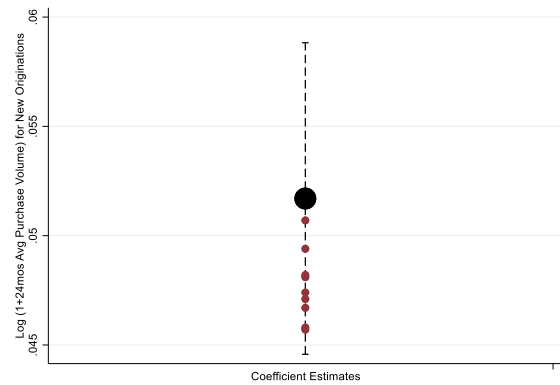
Panel B: Cycle APR



Panel C: Rewards/Promotions

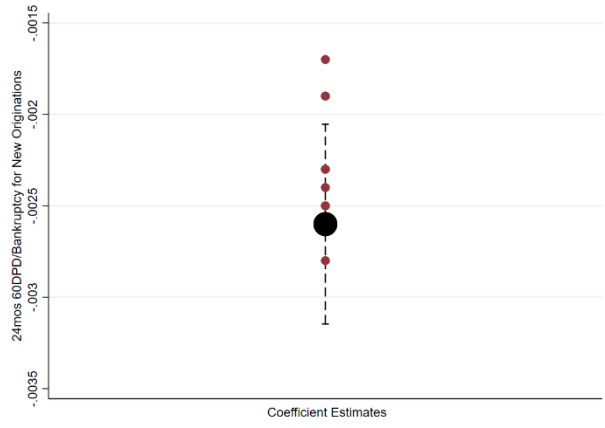
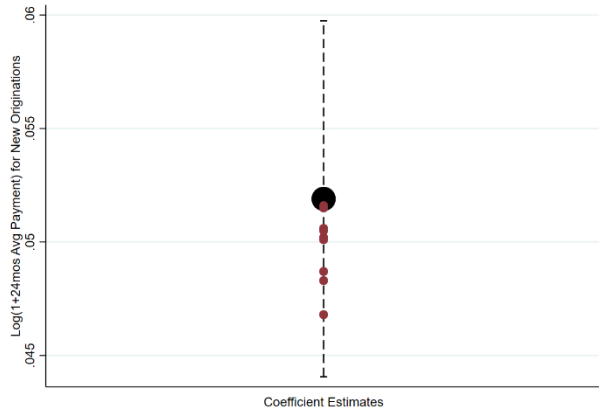


Panel D: 24mos Ln(1+ Avg Purchase Volume)



Panel E: 24mos Ln(1+ Avg Payment)

Panel F: 24mos 60DPD/Bankruptcy



Panel G: 24mos Transactor

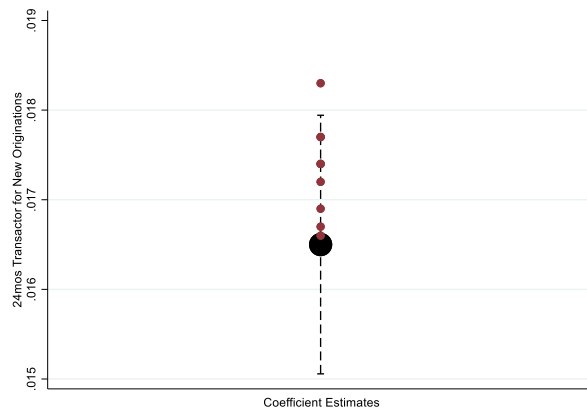


Table A.1: Stock Market Response to Banks' Stress Test Results

In this table, we report the mean abnormal returns (ARs) and cumulative abnormal returns (CARs) surrounding the CCAR results announcements (in percent) for credit card banks in our sample over stress tests 2013 to 2017. Banks that failed CCAR include banks that received objections and those that received conditional objection to their capital plans.⁵⁸ We use a pre-intervention estimation window starting 100 trading days before each event date and ending 50 days before each event date. The returns are calculated using the Fama-French Three-Factor model.⁵⁹ *, ** and *** indicate significance 10%, 5% and 1% level.

<i>Bank Type</i>	Banks that Passed CCAR			Banks that Failed CCAR		
	All Firm-Disclosure Events			All Firm-Disclosure Events		
<i>Estimation</i>	Mean AR	Patell Z	Obs.	Mean AR	Patell Z	Obs.
Event Window (Day)						
-1	0.197	1.190	72	0.030	0.094	5
0	0.242	0.389	72	0.497	1.403	5
1	0.662***	5.142	72	-2.358***	-8.254	5
Event Window (Days)	Mean CAR	Patell Z	Obs.	Mean CAR	Patell Z	Obs.
[-1, 1]	0.662***	3.880	72	-2.358***	-4.010	5
[0, 1]	0.459***	3.926	72	-2.406***	-4.878	5

⁵⁸ In unreported results, we also look at CCAR banks that failed with straight objection only (excluding conditional objection cases), and they register even stronger negative stock returns.

⁵⁹ Returns using Carhart Four-Factor model yield qualitative similar results.

Table A.2: Additional Summary Statistics and Variable Definitions

This table provides additional summary statistics and definitions for Y-14M credit card new originations data aggregated at the firm–county–month level and Y-14M portfolio data at the firm–month level as well as public Y-9C BHC information. Variables using dollar amounts are expressed in real 2017:Q4 dollars using the implicit GDP price deflator.

Variable	Mean	10th Percentile	Median	90th Percentile	Standard Deviation	No. of Observations	Definition
Additional Variables Used in Other Analyses (FR Y-14M firm-county-month data)							
Additional Credit Supply Variables							
Cash Advance Limit/ County Population	0.906	0.034	0.506	2.247	1.238	1324071	Credit card cash advance limit at the firm-county level adjusted for inflation divided by the county population.
Δ Credit Limit	0.026	-0.857	0.025	0.918	0.701	1009570	Annual change in credit card limit at the firm-county level.
Ln(1+ Total Cash Advance Limit) / Credit Limit / BHC Total Loans	9.411	6.753	9.581	12.365	2.684	1343679	The log of one plus total cash advance limit at the firm-county level adjusted for inflation.
Cycle APR	17.462	10.644	17.768	23.900	5.456	1355032	Credit card cash advance limit at the firm-county level divided by the BHC total loans.
Cycle APR (weighted)	16.454	10.379	16.234	23.400	5.472	1355032	Average APR used for the cycle for consumer retail purchases.
Cash APR	23.992	20.386	24.990	27.226	4.220	1250067	Average APR weighted by credit limit used for the cycle for consumer retail purchases.
Max APR	28.671	19.392	29.990	30.900	11.472	1151402	Average APR used for the cycle for cash advances.
Interest Rate Margin	15.482	10.990	14.866	21.221	4.181	1311295	The average maximum or default APR (rate cap) allowed to be used for the cycle for both retail purchases and cash advances.
% Rewards/Promotions	0.382	0.000	0.250	1.000	0.394	1355032	The average purchase APR margin, the number of percentage points that credit card lenders add to the prime rate (or other index) to calculate the variable interest rate. Issuers must disclose the margin at account-opening and in each monthly statement.
Additional Real Effects Variables							
24mos Ln(1+Avg Purchase Volume)	5.141	3.766	5.315	6.543	1.337	1351398	Percent of accounts with rewards (cash back and miles) or startup promotions.
24mos Ln(1+Avg Payment)	8.032	6.697	8.184	9.458	1.466	1351226	The natural logarithm of one plus the average purchase volume over 24mos since origination adjusted for inflation.
24mos 60DPD/Bankruptcy	0.075	0.000	0.040	0.189	0.128	1352321	The natural logarithm of one plus average payment over the 24mos since origination adjusted for inflation.
24mos Transactor	0.440	0.000	0.432	1.000	0.340	884749	Percent of accounts that were ever in 60DPD or bankruptcy over the 24mos since origination.
Additional Stress Test Variables (lagged pertaining to last disclosure, FR Y-14M or Public Reports)							
Total Capital GAP	0.867	-0.514	0.726	2.325	1.058	1,355,032	The lowest projected total capital ratio (tier1+tier2) projected in the BHC's own exercise (Y-14a) minus the lowest projected total capital ratio in the Fed's stress test exercise (publicly announced), both under the severely adverse scenario.
Max Capital GAP	1.044	0.076	0.879	2.325	0.956	1,355,032	The maximum out of three capital ratio gaps (tier 1 capital ratio, total capital ratio, and bank leverage ratio), where each gap is based on the lowest capital ratio projected in the BHC's own exercise (Y-14a) minus the lowest projected total capital ratio in the Fed's stress test exercise (publicly announced), both under the severely adverse scenario.
Tier 1 Capital Exposure	3.547	1.500	3.600	5.200	1.689	1,355,032	The difference between the BHC's initial tier 1 capital ratio and the lowest implied tier 1 capital ratio expected under the severely adverse stress-test scenario.
Max Capital Exposure	3.764	1.800	3.600	5.400	1.715	1,355,032	The maximum out of three capital ratio exposure measures (tier 1 capital ratio, total capital ratio, and bank leverage ratio), where each of the exposures are based on difference between the BHC's initial capital ratio and the lowest implied capital ratio expected under the severely adverse stress-test scenario.

Table A.3 Segmentation by Consumer Income

This table reports regression estimates for analyzing the effects of stress tests on consumer credit for new originations by focusing on several splits by consumer income using the 1% random sample. In all panels, we use standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The loan origination data come from the supervisory FR Y-14M data set and cover the period June 2013–December 2017. We show results for consumer credit quantities in Panel A, cycle APR in Panel B, rewards and promotions in Panel C, consumer credit spending over 24 months since origination in Panel D, consumer payment behavior in Panel E and credit performance in Panel F. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced) both under the severely adverse scenario for the tier 1 capital ratio. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score*, $\ln(1 + \text{Consumer Income})$, *Consumer Utilization Rate*, an indicator for consumers with joint accounts, an indicator for interest rate accounts, and an indicator for relationship consumers. In all pricing regressions, we also include $\ln(1 + \text{Credit Limit})$ as a control variable. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County \times Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Credit Limit

Independent Variables:	(1)	(2)	(3)	(4)	(5)
	Dependent Variable = Credit Limit for New Originations				
	Consumer Income Quintile 1	Consumer Income Quintile 2	Consumer Income Quintile 3	Consumer Income Quintile 4	Consumer Income Quintile 5
Stress Test Measures					
Tier 1 Capital GAP	-94.9387*** (14.045)	-124.9237*** (10.187)	-163.5446*** (15.083)	-169.3753*** (19.230)	-126.1535*** (36.201)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Observations	310,587	324,684	301,953	344,542	290,687
Adj R-squared	0.453	0.467	0.460	0.462	0.453
<i>Dependent variable mean</i>	<i>3,113.116</i>	<i>3,735.736</i>	<i>4,801.561</i>	<i>6,574.963</i>	<i>10,455.700</i>

Panel B: Cycle APR

Independent Variables:	(1)	(2)	(3)	(4)	(5)
	Dependent Variable = Cycle APR for New Originations				
	Consumer Income Quintile 1	Consumer Income Quintile 2	Consumer Income Quintile 3	Consumer Income Quintile 4	Consumer Income Quintile 5
Stress Test Measures					
Tier 1 Capital GAP	0.0198 (0.031)	-0.0763** (0.034)	-0.0851** (0.040)	-0.2015*** (0.029)	-0.2572*** (0.032)
$\ln(1 + \text{Credit Limit})$	YES	YES	YES	YES	YES
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Observations	310,587	324,684	301,953	344,542	290,687
Adj R-squared	0.371	0.332	0.291	0.283	0.248
<i>Dependent variable mean</i>	<i>18.343</i>	<i>18.119</i>	<i>19.019</i>	<i>18.709</i>	<i>18.003</i>

Panel C: Rewards and Promotions

Independent Variables:	Rewards/Promotions, Miles Rewards, Cash Rewards, and Promotions for New Originations				
	Borrower Income Quintile 1	Borrower Income Quintile 2	Borrower Income Quintile 3	Borrower Income Quintile 4	Borrower Income Quintile 5
	<u>Dependent Variable = Rewards/Promotions for New Originations</u>				
Stress Test Measures	(1)	(2)	(3)	(4)	(5)
Tier 1 Capital GAP	0.0213*** (0.001)	0.0124*** (0.002)	0.0126*** (0.002)	0.0142*** (0.002)	0.0173*** (0.002)
Observations	310,587	324,684	301,953	344,542	290,687
Adj R-squared	0.287	0.232	0.243	0.231	0.198
<i>Dependent variable mean</i>	<i>0.266</i>	<i>0.260</i>	<i>0.252</i>	<i>0.262</i>	<i>0.291</i>
	<u>Dependent Variable = Rewards: Miles for New Originations</u>				
Stress Test Measures	(1)	(2)	(3)	(4)	(5)
Tier 1 Capital GAP	0.0037*** (0.001)	0.0052*** (0.001)	0.0091*** (0.001)	0.0139*** (0.001)	0.0216*** (0.001)
Observations	310,587	324,684	301,953	344,542	290,687
Adj R-squared	0.306	0.252	0.232	0.203	0.182
<i>Dependent variable mean</i>	<i>0.016</i>	<i>0.021</i>	<i>0.032</i>	<i>0.048</i>	<i>0.082</i>
	<u>Dependent Variable = Rewards: Cash Back for New Originations</u>				
Stress Test Measures	(1)	(2)	(3)	(4)	(5)
Tier 1 Capital GAP	0.0058*** (0.001)	0.0058*** (0.002)	0.0050*** (0.001)	0.0044*** (0.001)	-0.0011 (0.001)
Observations	310,587	324,684	301,953	344,542	290,687
Adj R-squared	0.306	0.252	0.232	0.203	0.182
<i>Dependent variable mean</i>	<i>0.127</i>	<i>0.114</i>	<i>0.105</i>	<i>0.099</i>	<i>0.105</i>
	<u>Dependent Variable = Promotions for New Originations</u>				
Stress Test Measures	(1)	(2)	(3)	(4)	(5)
Tier 1 Capital GAP	0.0134*** (0.001)	0.0009 (0.001)	-0.0041*** (0.001)	-0.0074*** (0.001)	-0.0085*** (0.001)
Observations	310,587	324,684	301,953	344,542	290,687
R-squared	0.320	0.289	0.296	0.301	0.306
<i>Dependent variable mean</i>	<i>0.145</i>	<i>0.145</i>	<i>0.135</i>	<i>0.136</i>	<i>0.126</i>
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES

Panel D: Consumer Spending

Independent Variables:	24mos Purchase Volume, Cash Advance Volume, Convenience Checks, and Balance Transfers				
	Borrower Income Quintile 1	Borrower Income Quintile 2	Borrower Income Quintile 3	Borrower Income Quintile 4	Borrower Income Quintile 5
	<u>Dependent Variable = 24mos Ln(1+Avg Purchase Volume)</u>				
Stress Test Measures	(1)	(2)	(3)	(4)	(5)
Tier 1 Capital GAP	0.0241*** (0.007)	0.0142* (0.008)	0.0297*** (0.009)	0.0577*** (0.009)	0.0967*** (0.009)
Observations	304,821	318,551	295,625	336,087	283,020
Adj R-squared	0.189	0.178	0.196	0.206	0.219
<i>Dependent variable mean</i>	<i>3.512</i>	<i>3.663</i>	<i>3.620</i>	<i>3.814</i>	<i>4.366</i>
	<u>Dependent Variable = 24mos Ln(1+Avg Cash Advance Volume)</u>				
Stress Test Measures	(1)	(2)	(3)	(4)	(5)
Tier 1 Capital GAP	0.0179*** (0.003)	0.0159*** (0.003)	0.0253*** (0.003)	0.0164*** (0.003)	0.0064* (0.003)
Observations	288,165	305,959	283,507	326,243	278,923
Adj R-squared	0.052	0.045	0.039	0.033	0.031
<i>Dependent variable mean</i>	<i>0.193</i>	<i>0.181</i>	<i>0.145</i>	<i>0.131</i>	<i>0.138</i>
	<u>Dependent Variable = 24mos Ln(1+Avg Convenience Check Volume)</u>				
Stress Test Measures	(1)	(2)	(3)	(4)	(5)
Tier 1 Capital GAP	0.0081*** (0.002)	0.0035 (0.002)	0.0149*** (0.002)	0.0087*** (0.003)	0.0059** (0.003)
Observations	285,464	304,605	281,842	323,988	276,618
Adj R-squared	0.014	0.013	0.020	0.021	0.025
<i>Dependent variable mean</i>	<i>0.030</i>	<i>0.043</i>	<i>0.048</i>	<i>0.053</i>	<i>0.062</i>
	<u>Dependent Variable = 24mos Ln(1+Avg Balance Transfer Volume)</u>				
Stress Test Measures	(1)	(2)	(3)	(4)	(5)
Tier 1 Capital GAP	0.0058* (0.003)	0.0021 (0.005)	0.0191*** (0.005)	0.0295*** (0.005)	0.0228*** (0.006)
Observations	288,186	305,985	283,547	326,277	278,959
R-squared	0.037	0.055	0.061	0.060	0.063
<i>Dependent variable mean</i>	<i>0.165</i>	<i>0.265</i>	<i>0.296</i>	<i>0.329</i>	<i>0.365</i>
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES

Panel E: Consumer Payment Behavior

Independent Variables:	24mos Payment, Debt, and Transactor Behavior				
	Borrower Income Quintile 1	Borrower Income Quintile 2	Borrower Income Quintile 3	Borrower Income Quintile 4	Borrower Income Quintile 5
	<u>Dependent Variable = 24mos Ln(1+Avg Payment)</u>				
Stress Test Measures	(1)	(2)	(3)	(4)	(5)
Tier 1 Capital GAP	0.0353*** (0.007)	0.0169** (0.007)	0.0242*** (0.008)	0.0453*** (0.008)	0.0743*** (0.008)
Observations	306,240	320,278	297,677	339,045	285,665
Adj R-squared	0.174	0.167	0.198	0.212	0.217
<i>Dependent variable mean</i>	<i>3.641</i>	<i>3.891</i>	<i>3.962</i>	<i>4.235</i>	<i>4.857</i>
	<u>Dependent Variable = 24mos Ln(1+Sum Total Debt)</u>				
Stress Test Measures	(1)	(2)	(3)	(4)	(5)
Tier 1 Capital GAP	-0.1598*** (0.013)	-0.2095*** (0.012)	-0.2141*** (0.015)	-0.1723*** (0.014)	-0.0819*** (0.014)
Observations	307,294	322,032	299,275	341,691	288,536
Adj R-squared	0.255	0.223	0.261	0.257	0.221
<i>Dependent variable mean</i>	<i>6.776</i>	<i>7.306</i>	<i>7.227</i>	<i>7.476</i>	<i>8.098</i>
	<u>Dependent Variable = 24mos Transactor</u>				
Stress Test Measures	(1)	(2)	(3)	(4)	(5)
Tier 1 Capital GAP	0.0152*** (0.002)	0.0122*** (0.002)	0.0175*** (0.002)	0.0226*** (0.002)	0.0220*** (0.002)
Observations	306,244	320,287	297,683	339,056	285,677
R-squared	0.141	0.141	0.125	0.112	0.107
<i>Dependent variable mean</i>	<i>0.431</i>	<i>0.440</i>	<i>0.458</i>	<i>0.491</i>	<i>0.532</i>
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES

Panel F: Consumer Credit Performance

Independent Variables:	24mos 60DPD/Bankruptcy and Days Past Due				
	Borrower Income Quintile 1	Borrower Income Quintile 2	Borrower Income Quintile 3	Borrower Income Quintile 4	Borrower Income Quintile 5
	<u>Dependent Variable = 24mos 60DPD/Bankruptcy</u>				
Stress Test Measures	(1)	(2)	(3)	(4)	(5)
Tier 1 Capital GAP	-0.0030*** (0.001)	-0.0036*** (0.001)	-0.0023*** (0.001)	-0.0017** (0.001)	-0.0009 (0.001)
Observations	310,587	324,684	301,953	344,542	290,687
Adj R-squared	0.124	0.100	0.081	0.068	0.049
<i>Dependent variable mean</i>	<i>0.078</i>	<i>0.067</i>	<i>0.051</i>	<i>0.037</i>	<i>0.024</i>
	<u>Dependent Variable = 24mos Avg Days Past due</u>				
Stress Test Measures	(1)	(2)	(3)	(4)	(5)
Tier 1 Capital GAP	-0.0254 (0.031)	-0.1112*** (0.026)	-0.1007*** (0.031)	-0.0712*** (0.020)	-0.0328* (0.017)
Observations	306,244	320,287	297,683	339,056	285,677
Adj R-squared	0.164	0.132	0.102	0.081	0.059
<i>Dependent variable mean</i>	<i>2.548</i>	<i>2.026</i>	<i>1.474</i>	<i>1.019</i>	<i>0.670</i>
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES

Table A.4: Effects of Stress Tests on Consumer Credit — Different Measures of Shocks to Firms

This table reports regression estimates for analyzing the effects of stress tests on credit card customers for new originations using the firm-month-county aggregated sample and alternative measures of capital gaps or capital exposure, the latter using public data only. In all panels, we use standardized coefficients on the key independent variables, bank capital gaps or exposures, for ease of interpretation. The loan origination data come from the supervisory FR Y-14M data set and cover the period June 2013–December 2017. The dependent variables are: *Credit Limit/County Population*, credit card limit at the firm-county level divided by the county population for new originations; *Cycle APR*, the average APR used for the cycle for consumer retail purchases at the firm-county level; *%Rewards/Promotions*, the percent of new credit cards with rewards and promotions; *Ln(1+Avg Purchase Volume)*, the log of one plus the average purchase volume over 24 months since origination; *24mos 60DPD*, percent of accounts 60 days or more past due over 24 months since origination; and *24mos Transactor*, percent of accounts that are transactor over 24 months since origination, all at the firm-county level. In Panels A-C, the key explanatory variables are *Tier 1 Capital GAP*, *Total Capital GAP* and *Max Capital GAP*, the latter being the maximum out of three capital ratio gaps (tier 1 capital ratio, total capital ratio, and bank leverage ratio), where each gap is the lowest capital ratio projected in the BHC's own exercise (Y-14a) minus the lowest projected total capital ratio in the Fed's stress test exercise (publicly announced), both under the severely adverse scenario. In Panels D and E, the key explanatory variables are *Total Capital Exposure* and *Max Capital Exposure*, the maximum out of three capital ratio exposure measures (tier 1 capital ratio, total capital ratio, and bank leverage ratio), where each of the exposures are based on difference between the BHC's initial capital ratio and the lowest implied capital ratio expected under the severely adverse stress-test scenario. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score*, *Ln(1+ Consumer Income)*, *Consumer Utilization Rate*, the percent of consumers with joint accounts, the percent of variable interest rate accounts, and the percent of relationship consumers. In addition, in the pricing regressions, we include *Ln(1+ Credit Limit)* as a control variable. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County \times Month-Year FE as well as BHC fixed effects. The variables are defined in Table 1 and Table A.2. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Tier1 Capital GAP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variables:	Credit Limit/ County Population	Cycle APR	% Rewards/ Promotions	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos Transactor
Stress Test Measures							
Tier 1 Capital GAP	-0.2306*** (0.006)	-0.3769*** (0.007)	0.0222*** (0.001)	0.0406*** (0.002)	0.0603*** (0.002)	-0.0016*** (0.000)	0.0114*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,335,178	1,355,032	1,355,032	1,351,398	1,351,226	1,352,321	884,749
Adjusted R-squared	0.526	0.570	0.630	0.326	0.285	0.159	0.159
<i>Dependent variable mean</i>	<i>4.304</i>	<i>17.462</i>	<i>0.382</i>	<i>5.141</i>	<i>8.032</i>	<i>0.075</i>	<i>0.440</i>

Panel B: Total Capital GAP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variables:	Credit Limit/ County Population	Cycle APR	% Rewards/ Promotions	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos Transactor
Stress Test Measures							
Total Capital GAP	-0.2390*** (0.007)	-0.3500*** (0.006)	0.0172*** (0.000)	0.0366*** (0.001)	0.0525*** (0.002)	-0.0013*** (0.000)	0.0105*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,335,178	1,355,032	1,355,032	1,351,398	1,351,226	1,352,321	884,749
Adjusted R-squared	0.526	0.570	0.629	0.326	0.285	0.159	0.159
<i>Dependent variable mean</i>	<i>4.304</i>	<i>17.462</i>	<i>0.382</i>	<i>5.141</i>	<i>8.032</i>	<i>0.075</i>	<i>0.440</i>

Panel C: Max Capital GAP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variables:	Credit Limit/ County Population	Cycle APR	% Rewards/ Promotions	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos Transactor
Stress Test Measures							
Max Capital GAP	-0.1977***	-0.4234***	0.0202***	0.0432***	0.0616***	-0.0008***	0.0124***

	(0.006)	(0.007)	(0.001)	(0.002)	(0.002)	(0.000)	(0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,335,178	1,355,032	1,355,032	1,351,398	1,351,226	1,352,321	884,749
Adjusted R-squared	0.526	0.570	0.630	0.326	0.285	0.159	0.159
<i>Dependent variable mean</i>	<i>4.304</i>	<i>17.462</i>	<i>0.382</i>	<i>5.141</i>	<i>8.032</i>	<i>0.075</i>	<i>0.440</i>

Panel D: Tier1 Capital Exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variables:	Credit Limit/ County Population	Cycle APR	% Rewards/ Promotions	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos Transactor
Stress Test Measures							
Tier 1 Capital Exposure	-0.2914*** (0.009)	-0.0550*** (0.008)	0.0360*** (0.001)	0.0713*** (0.002)	0.1176*** (0.002)	-0.0032*** (0.000)	0.0075*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,335,178	1,355,032	1,355,032	1,351,398	1,351,226	1,352,321	884,749
Adjusted R-squared	0.526	0.567	0.631	0.326	0.286	0.159	0.158
<i>Dependent variable mean</i>	<i>4.304</i>	<i>17.462</i>	<i>0.382</i>	<i>5.141</i>	<i>8.032</i>	<i>0.075</i>	<i>0.440</i>

Panel D: Max Capital Exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variables:	Credit Limit/ County Population	Cycle APR	% Rewards/ Promotions	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos Transactor
Stress Test Measures							
Max Capital Exposure	-0.3267*** (0.009)	-0.0746*** (0.008)	0.0326*** (0.001)	0.0752*** (0.002)	0.1190*** (0.002)	-0.0030*** (0.000)	0.0077*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,335,178	1,355,032	1,355,032	1,351,398	1,351,226	1,352,321	884,749
Adjusted R-squared	0.526	0.567	0.630	0.326	0.286	0.159	0.158
<i>Dependent variable mean</i>	<i>4.304</i>	<i>17.462</i>	<i>0.382</i>	<i>5.141</i>	<i>8.032</i>	<i>0.075</i>	<i>0.440</i>

Table A.5: Effects of Stress Tests on Consumer Credit and Real Outcomes – Additional Robustness Tests

This table reports regression estimates for analyzing the effects of stress tests on consumer credit card customers for new originations using the firm-county-month aggregated sample and a variety of additional robustness tests. In all panels, we use standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The tests include: a falsification test in which we allocate the capital GAPs randomly to the BHCs in Panel A; using alternative error clustering at *BHC × Month-Year* in Panel B; excluding one firm due to different business model in Panel C; excluding observations of BHCs that failed previous stress test in Panel D; including only BHCs that exist in all stress test years in Panel E; controlling for the initial stress test capital at the stress test onset instead of capital ratio in previous quarter in Panel F; excluding one stress test at a time in Panel G; and excluding bottom 5% and top 5% counties in terms of credit card limit share in Panels H and I, respectively. The loan origination data come from the supervisory FR Y-14M data set and cover the period June 2013–December 2017. The dependent variables are: *Credit Limit/County Population*, credit card limit at the firm-county level divided by the county population for new originations; *Cycle APR*, the average APR used for the cycle for consumer retail purchases at the firm-county level; *%Rewards/Promotions*, the percent of new credit cards with rewards and promotions; *Ln(1+Avg Purchase Volume)*, the log of one plus the average purchase volume over 24 months since origination; *24mos 60DPD*, percent of accounts 60 days or more past due over 24 months since origination; and *24mos Transactor*, percent of accounts that are transactor over 24 months since origination, all at the firm-county level. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced) both under the severely adverse scenario for the tier 1 capital ratio. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score*, *Ln(1+ Consumer Income)*, *Consumer Utilization Rate*, the percent of consumers with joint accounts, the percent of variable interest rate accounts, and the percent of relationship consumers. In addition, in the pricing regressions, we include *Ln(1+ Credit Limit)* as a control variable. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County × Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Random Assignment of the Capital GAPs to the BHCs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variables:	Credit Limit/ County Population	Cycle APR	% Rewards/ Promotions	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos Transactor
Stress Test Measures							
Pseudo Tier 1 Capital GAP	0.0012 (0.003)	0.0021 (0.003)	-0.0002 (0.000)	-0.0004 (0.001)	-0.0017 (0.001)	-0.0002 (0.000)	-0.0002 (0.000)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,335,178	1,355,032	1,355,032	1,351,398	1,351,226	1,352,321	884,749
Adjusted R-squared	0.525	0.567	0.628	0.325	0.284	0.159	0.158
<i>Dependent variable mean</i>	<i>4.304</i>	<i>17.462</i>	<i>0.382</i>	<i>5.141</i>	<i>8.032</i>	<i>0.075</i>	<i>0.440</i>

Panel B: Alternative Error Clustering by BHC × Month-Year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variables:	Credit Limit/ County Population	Cycle APR	% Rewards/ Promotions	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos Transactor
Stress Test Measures							
Tier 1 Capital GAP	-0.2306*** (0.066)	-0.3769*** (0.067)	0.0222*** (0.004)	0.0406*** (0.008)	0.0603*** (0.010)	-0.0016** (0.001)	0.0114*** (0.002)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,335,178	1,355,032	1,355,032	1,351,398	1,351,226	1,352,321	884,749
Adjusted R-squared	0.526	0.570	0.630	0.326	0.285	0.159	0.159
<i>Dependent variable mean</i>	<i>4.304</i>	<i>17.462</i>	<i>0.382</i>	<i>5.141</i>	<i>8.032</i>	<i>0.075</i>	<i>0.440</i>

Panel C: Exclude One Firm Due to Different Business Model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variables:	Credit Limit/ County Population	Cycle APR	% Rewards/ Promotions	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos Transactor
Stress Test Measures							
Tier 1 Capital GAP	-0.2246*** (0.007)	-0.4481*** (0.007)	0.0194*** (0.000)	0.0366*** (0.002)	0.0650*** (0.002)	-0.0015*** (0.000)	0.0127*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,215,751	1,232,479	1,232,479	1,229,121	1,229,085	1,229,960	830,491
Adjusted R-squared	0.516	0.568	0.481	0.328	0.293	0.161	0.167
<i>Dependent variable mean</i>	<i>4.386</i>	<i>17.542</i>	<i>0.313</i>	<i>5.055</i>	<i>7.934</i>	<i>0.078</i>	<i>0.434</i>

Panel D: Exclude Observations of BHCs that "Failed" Previous Stress Test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variables:	Credit Limit/ County Population	Cycle APR	% Rewards/ Promotions	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos Transactor
Stress Test Measures							
Tier 1 Capital GAP	-0.2593*** (0.006)	-0.3647*** (0.007)	0.0225*** (0.001)	0.0436*** (0.002)	0.0511*** (0.002)	-0.0017*** (0.000)	0.0105*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,293,030	1,311,821	1,311,821	1,308,235	1,308,060	1,309,137	847,433
Adjusted R-squared	0.516	0.556	0.636	0.324	0.276	0.160	0.161
<i>Dependent variable mean</i>	<i>4.157</i>	<i>17.310</i>	<i>0.389</i>	<i>5.159</i>	<i>8.061</i>	<i>0.076</i>	<i>0.442</i>

Panel E: Only Include BHCs that Exist in All Stress Test Years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variables:	Credit Limit/ County Population	Cycle APR	% Rewards/ Promotions	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos Transactor
Stress Test Measures							
Tier 1 Capital GAP	-0.2122*** (0.006)	-0.3871*** (0.006)	0.0178*** (0.000)	0.0486*** (0.001)	0.0734*** (0.002)	-0.0021*** (0.000)	0.0120*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,279,083	1,298,291	1,298,291	1,295,132	1,294,836	1,295,816	860,127
Adjusted R-squared	0.523	0.585	0.649	0.341	0.290	0.165	0.159
<i>Dependent variable mean</i>	<i>4.459</i>	<i>17.484</i>	<i>0.385</i>	<i>5.162</i>	<i>8.065</i>	<i>0.074</i>	<i>0.442</i>

Panel F: Control for Initial Stress Test Tier 1 Capital instead of Capital Ratio in Previous Quarter

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variables:	Credit Limit/ County Population	Cycle APR	% Rewards/ Promotions	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos Transactor
Stress Test Measures							
Tier 1 Capital GAP	-0.2322*** (0.006)	-0.3664*** (0.007)	0.0218*** (0.001)	0.0401*** (0.002)	0.0583*** (0.002)	-0.0016*** (0.000)	0.0109*** (0.001)
Initial Stress Test Tier 1 Capital	0.0611*** (0.008)	-0.3943*** (0.012)	0.0146*** (0.001)	0.0187*** (0.003)	0.0753*** (0.003)	0.0014*** (0.000)	0.0087*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,335,178	1,355,032	1,355,032	1,351,398	1,351,226	1,352,321	884,749

Adjusted R-squared	0.526	0.570	0.630	0.326	0.285	0.159	0.159
Dependent variable mean	4.304	17.462	0.382	5.141	8.032	0.075	0.440

Panel G: Exclude One Stress Test at a Time

Panel G1: Main Outcomes: Quantities

	(1)	(2)	(3)	(4)	(5)
Independent Variables:	Exclude 2013	Exclude 2014	Exclude 2015	Exclude 2016	Exclude 2017
Dependent Variable: Credit Limit/County Population					
Stress Test Measures					
Tier 1 Capital GAP	-0.1657*** (0.006)	-0.2782*** (0.007)	-0.2828*** (0.008)	-0.1665*** (0.006)	-0.3135*** (0.008)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Observations	1,106,339	1,053,971	974,818	1,026,079	1,179,505
Adjusted R-squared	0.519	0.522	0.521	0.551	0.524
Dependent variable mean	4.097	4.126	4.000	4.079	4.144

Panel G2: Main Outcomes: Prices

	(1)	(2)	(3)	(4)	(5)
Independent Variables:	Exclude 2013	Exclude 2014	Exclude 2015	Exclude 2016	Exclude 2017
Dependent Variable: Cycle APR					
Stress Test Measures					
Tier 1 Capital GAP	-0.4251*** (0.008)	-0.2903*** (0.007)	-0.6282*** (0.010)	-0.5558*** (0.009)	-0.2264*** (0.006)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Observations	1,122,809	1,069,795	989,351	1,041,007	1,197,166
Adjusted R-squared	0.588	0.569	0.559	0.571	0.573
Dependent variable mean	17.615	17.663	17.739	17.430	17.355

Panel G3: Main Outcomes: %Rewards/Promotions

	(1)	(2)	(3)	(4)	(5)
Independent Variables:	Exclude 2013	Exclude 2014	Exclude 2015	Exclude 2016	Exclude 2017
Dependent Variable: %Rewards/Promotions					
Stress Test Measures					
Tier 1 Capital GAP	0.0163*** (0.001)	0.0248*** (0.001)	0.0373*** (0.001)	0.0249*** (0.001)	0.0174*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Observations	1,122,809	1,069,795	989,351	1,041,007	1,197,166
Adjusted R-squared	0.647	0.634	0.622	0.630	0.633
Dependent variable mean	0.387	0.386	0.383	0.387	0.386

Panel G4: Main Outcomes: 24mos Ln(1+Avg Purchase Volume)

	(1)	(2)	(3)	(4)	(5)
Independent Variables:	Exclude 2013	Exclude 2014	Exclude 2015	Exclude 2016	Exclude 2017
Dependent Variable: 24mos Ln(1+Avg Purchase Volume)					
Stress Test Measures					
Tier 1 Capital GAP	0.0147*** (0.002)	0.0461*** (0.002)	0.0370*** (0.002)	0.0625*** (0.002)	0.0545*** (0.002)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Observations	1,119,838	1,067,316	986,457	1,038,038	1,193,943
Adjusted R-squared	0.317	0.326	0.336	0.328	0.327
Dependent variable mean	5.133	5.117	5.110	5.113	5.113

Panel G5: Main Outcomes: 24mos Ln(1+Avg Payment)

	(1)	(2)	(3)	(4)	(5)
Independent Variables:	Exclude 2013	Exclude 2014	Exclude 2015	Exclude 2016	Exclude 2017
Dependent Variable: 24mos Ln(1+Avg Payment)					
Stress Test Measures					
Tier 1 Capital GAP	0.0357*** (0.002)	0.0477*** (0.002)	0.0781*** (0.003)	0.0941*** (0.002)	0.0699*** (0.002)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Observations	1,119,762	1,067,225	986,329	1,037,891	1,193,697
Adjusted R-squared	0.283	0.283	0.300	0.283	0.282
Dependent variable mean	8.003	8.007	8.000	7.981	7.987

Panel G6: Main Outcomes: 24mos 60DPD/Bankruptcy

	(1)	(2)	(3)	(4)	(5)
Independent Variables:	Exclude 2013	Exclude 2014	Exclude 2015	Exclude 2016	Exclude 2017
Dependent Variable: 24mos 60DPD/Bankruptcy					
Stress Test Measures					
Tier 1 Capital GAP	-0.0008*** (0.000)	-0.0023*** (0.000)	-0.0025*** (0.000)	-0.0020*** (0.000)	-0.0018*** (0.000)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Observations	1,120,652	1,068,085	987,110	1,038,750	1,194,687
Adjusted R-squared	0.163	0.157	0.152	0.163	0.161
Dependent variable mean	0.078	0.076	0.073	0.073	0.074

Panel G7: Main Outcomes: 24mos Transactor

	(1)	(2)	(3)	(4)	(5)
Independent Variables:	Exclude 2013	Exclude 2014	Exclude 2015	Exclude 2016	Exclude 2017
Dependent Variable: 24mos Transactor					
Stress Test Measures					
Tier 1 Capital GAP	0.0118*** (0.001)	0.0092*** (0.001)	0.0193*** (0.001)	0.0166*** (0.001)	0.0081*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Observations	733,393	697,972	641,388	682,108	784,135
Adjusted R-squared	0.162	0.162	0.160	0.156	0.157
Dependent variable mean	0.436	0.439	0.436	0.436	0.434

Panel H: Drop Bottom 5% Counties (Credit Card Limit Share)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variables:	Credit Limit/ County Population	Cycle APR	% Rewards/ Promotions	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos Transactor
Stress Test Measures							
Tier 1 Capital GAP	-0.2382*** (0.007)	-0.3757*** (0.007)	0.0225*** (0.001)	0.0436*** (0.002)	0.0620*** (0.002)	-0.0014*** (0.000)	0.0113*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,266,600	1,285,378	1,285,378	1,282,215	1,282,060	1,282,975	873,717
Adjusted R-squared	0.543	0.591	0.644	0.323	0.285	0.159	0.157
Dependent variable mean	4.119	17.484	0.390	5.167	8.041	0.074	0.438

Panel I: Drop Top 5% Counties (Credit Card Limit Share)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Independent Variables:	Credit Limit/ County Population	Cycle APR	% Rewards/ Promotions	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos Transactor
Stress Test Measures							
Tier 1 Capital GAP	-0.2083*** (0.005)	-0.3795*** (0.007)	0.0214*** (0.001)	0.0398*** (0.002)	0.0606*** (0.002)	-0.0017*** (0.000)	0.0114*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES
Observations	1,269,535	1,289,389	1,289,389	1,285,921	1,285,776	1,286,816	827,362
Adjusted R-squared	0.557	0.565	0.625	0.318	0.281	0.158	0.150
Dependent variable mean	4.012	17.588	0.383	5.093	7.976	0.075	0.436

Table A.6: Effects of Stress Tests on Consumer Credit – Alternative Credit Supply Measures

This table reports regression estimates for analyzing the effects of stress tests on consumer credit card quantities for new originations the firm-county-month aggregated sample and alternative measures of quantities in Panel A and alternative measures of pricing in Panel B than those used in our main results. In all panels, we use standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The loan origination data come from the supervisory FR Y-14M data set and cover the period June 2013–December 2017. In Panel A, the dependent variables are: *Cash Advance Limit/County Population*, credit card cash advance limit at the firm-county level divided by the county population for new originations; *Log(1+ Total Cash Advance Limit)*, the natural logarithm of the credit card cash advance limit at the firm-county level for new originations; *Credit Limit/BHC Total Loans*, the credit card limit at the firm-county level for new originations divided by the BHC total loans; and Δ *CC Credit Limit*, the annual change in credit card limit for new originations at the firm-county level. In Panel B, the dependent variables are: *Cycle APR (weighted)*, APR weighted by credit limit used for the cycle for consumer retail purchases for new originations; *Cash APR*, APR used for the cycle for cash advances for new originations; *Max APR*, the maximum or default APR (rate cap) allowed to be used for the cycle for both retail purchases and cash advances; *Interest Rate Margin*, the purchase APR margin reflecting the number of percentage points that credit card lenders add to the prime rate (or other index) to calculate the variable interest rate. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced) both under the severely adverse scenario for the tier 1 capital ratio. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score*, $\ln(1+ \text{Consumer Income})$, *Consumer Utilization Rate*, the percent of consumers with joint accounts, the percent of variable interest rate accounts, and the percent of relationship consumers. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County \times Month-Year FE as well as BHC fixed effects. The variables are defined in Table 1 and Table A.2. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Alternative Measures of Credit Quantities

Independent Variables:	(1) Cash Advance Limit/Population	(2) Ln(1+Total Cash Advance Limit)	(3) Credit Limit/ BHC Total Loans	(4) Δ Credit Limit
Stress Test Measures				
Tier 1 Capital GAP	-0.0553*** (0.002)	-0.0695*** (0.002)	-0.0880*** (0.009)	-0.0131*** (0.002)
Consumer, Loan Characteristics	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES
Observations	1,324,071	1,343,679	1,355,032	1,009,570
Adj R-squared	0.413	0.638	0.418	0.120
<i>Dependent variable mean</i>	<i>0.906</i>	<i>9.411</i>	<i>1.400</i>	<i>0.026</i>

Panel B: Alternative Measures of Pricing

Independent Variables:	(1) Cycle APR (weighted)	(2) Cash APR	(3) Max APR	(4) Interest Rate Margin
Stress Test Measures				
Tier 1 Capital GAP	-0.3153*** (0.007)	-0.2687*** (0.004)	-0.0927*** (0.007)	-0.1925*** (0.005)
Consumer, Loan Characteristics	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES
Observations	1,355,032	1,250,067	1,151,402	1,311,295
Adj R-squared	0.446	0.652	0.793	0.659
<i>Dependent variable mean</i>	<i>16.454</i>	<i>23.992</i>	<i>28.671</i>	<i>15.482</i>

Table A.7: Effects of Stress Tests on Consumer Credit and Real Effects – Splits by Neighborhood Characteristics

This table reports regression estimates for analyzing the effects of stress tests on consumer credit for new originations by focusing on several splits by neighborhood characteristics using a 1% random sample and standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The loan origination data come from the supervisory FR Y-14M data set and cover the period June 2013–December 2017. Panel A splits the sample into urban and rural counties based on whether the consumer county of residence is in a predominantly urban area (50% or more) or not. Panel B splits the sample into counties with high (above the 50th percentile) versus small % of minorities in the consumer county of residence. Panel C splits the sample into high- and low-income counties based on whether the population-weighted ratio of tract family median to MSA median income at county level is higher or below 1. The dependent variables are: *Credit Limit/County Population*, credit card limit at the firm-county level divided by the county population for new originations; *Cycle APR*, the average APR used for the cycle for consumer retail purchases at the firm-county level; *Rewards/Promotions*, indicator for new credit cards with rewards and promotions; *Ln(1+Avg Purchase Volume)*, the log of one plus the average purchase volume over 24 months since origination; *24mos 60DPD*, percent of accounts 60 days or more past due over 24 months since origination; and *24mos Transactor*, percent of accounts that are transactor over 24 months since origination, all at the firm-county level. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced) both under the severely adverse scenario for the tier 1 capital ratio. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score*, *Ln(1+ Consumer Income)*, *Consumer Utilization Rate*, an indicator for consumers with joint accounts, an indicator for interest rate accounts, and an indicator for relationship consumers. In all pricing regressions, we also include *Ln(1+ Credit Limit)* as a control variable. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County × Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Splits by County Urban/Rural

	(1)	(2)	(3)	(4)	(5)	(6)
Independent Variables:		Credit Limit		Cycle APR		Rewards/Promotions
Group	URBAN	RURAL	URBAN	RURAL	URBAN	RURAL
Stress Test Measures						
Tier 1 Capital GAP	-52.5179*** (11.998)	-42.0249*** (15.513)	-0.0903*** (0.023)	-0.1961*** (0.024)	0.0194*** (0.001)	0.0190*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES
Observations	1,189,487	497,503	1,189,487	497,503	1,189,487	497,503
Adj R-squared	0.416	0.389	0.288	0.277	0.230	0.260
<i>Dependent variable mean</i>	<i>5919.975</i>	<i>5102.963</i>	<i>18.194</i>	<i>18.995</i>	<i>0.275</i>	<i>0.247</i>

	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Independent Variables:		24mos Ln(1+Avg Purchase Volume)		24mos Ln(1+Avg Payment)		24mos 60DPD/ Bankruptcy		24mos Transactor
Group	URBAN	RURAL	URBAN	RURAL	URBAN	RURAL	URBAN	RURAL
Stress Test Measures								
Tier 1 Capital GAP	0.0573*** (0.005)	0.0514*** (0.007)	0.0554*** (0.005)	0.0560*** (0.006)	-0.0022*** (0.000)	-0.0040*** (0.001)	0.0175*** (0.001)	0.0182*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,164,490	487,445	1,172,482	490,354	1,189,487	497,503	1,172,521	490,362
Adj R-squared	0.199	0.171	0.212	0.181	0.084	0.111	0.128	0.119
<i>Dependent variable mean</i>	<i>3.889</i>	<i>3.551</i>	<i>4.188</i>	<i>3.917</i>	<i>0.050</i>	<i>0.057</i>	<i>0.451</i>	<i>0.478</i>

Panel B: Splits by County Income (Tract/MSA Ratio)

	(1)	(2)	(3)	(4)	(5)	(6)
Independent Variables:		Credit Limit		Cycle APR		Rewards/Promotions
Group	HIGH INCOME	LOW INCOME	HIGH INCOME	LOW INCOME	HIGH INCOME	LOW INCOME
Stress Test Measures						
Tier 1 Capital GAP	-162.0726*** (19.519)	-79.2953*** (9.379)	-0.2414*** (0.022)	-0.0270 (0.025)	0.0161*** (0.001)	0.0183*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES
Observations	720,364	932,606	720,364	932,606	720,364	932,606
Adj R-squared	0.454	0.420	0.262	0.327	0.218	0.253
<i>Dependent variable mean</i>	<i>8080.688</i>	<i>3794.066</i>	<i>18.376</i>	<i>18.489</i>	<i>0.274</i>	<i>0.260</i>

	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Independent Variables:	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos Ln(1+Avg Payment)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos 60DPD/ Bankruptcy	24mos Transactor	24mos Transactor
Group	HIGH INCOME	LOW INCOME	HIGH INCOME	LOW INCOME	HIGH INCOME	LOW INCOME	HIGH INCOME	LOW INCOME
Stress Test Measures								
Tier 1 Capital GAP	0.0706*** (0.006)	0.0285*** (0.005)	0.0556*** (0.006)	0.0350*** (0.004)	-0.0013*** (0.000)	-0.0033*** (0.000)	0.0139*** (0.001)	0.0221*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	702,813	915,292	708,786	920,193	720,364	932,606	920,216	708,810
Adj R-squared	0.212	0.181	0.220	0.172	0.067	0.105	0.134	0.111
<i>Dependent variable mean</i>	<i>4.051</i>	<i>3.579</i>	<i>4.490</i>	<i>3.806</i>	<i>0.033</i>	<i>0.067</i>	<i>0.505</i>	<i>0.442</i>

Panel C: Splits by County % Minority

	(1)	(2)	(3)	(4)	(5)	(6)
Independent Variables:		Credit Limit		Cycle APR		Rewards/Promotions
Group	HIGH % MINORITY	LOW % MINORITY	HIGH % MINORITY	LOW % MINORITY	HIGH % MINORITY	LOW % MINORITY
Stress Test Measures						
Tier 1 Capital GAP	-60.3905*** (14.392)	-35.6563*** (12.202)	-0.0906*** (0.031)	-0.1474*** (0.018)	0.0208*** (0.001)	0.0179*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES
Observations	851,357	835,205	851,357	835,205	851,357	835,205
Adj R-squared	0.421	0.388	0.298	0.275	0.227	0.247
<i>Dependent variable mean</i>	<i>5762.924</i>	<i>5584.608</i>	<i>18.101</i>	<i>18.805</i>	<i>0.280</i>	<i>0.254</i>

	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Independent Variables:	24mos Ln(1+Avg Purchase Volume)	24mos Ln(1+Avg Payment)	24mos Ln(1+Avg Payment)	24mos Ln(1+Avg Payment)	24mos 60DPD/ Bankruptcy	24mos 60DPD/ Bankruptcy	24mos Transactor	24mos Transactor
Group	HIGH % MINORITY	LOW % MINORITY	HIGH % MINORITY	LOW % MINORITY	HIGH % MINORITY	LOW % MINORITY	HIGH % MINORITY	LOW % MINORITY
Stress Test Measures								
Tier 1 Capital GAP	0.0562*** (0.006)	0.0559*** (0.005)	0.0539*** (0.006)	0.0588*** (0.005)	-0.0026*** (0.000)	-0.0029*** (0.000)	0.0164*** (0.001)	0.0192*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	833,536	817,981	839,025	823,391	851,357	835,205	839,055	823,408
Adj R-squared	0.196	0.187	0.209	0.199	0.087	0.106	0.135	0.116
<i>Dependent variable mean</i>	<i>3.919</i>	<i>3.655</i>	<i>4.190</i>	<i>4.025</i>	<i>0.053</i>	<i>0.051</i>	<i>0.473</i>	<i>0.468</i>

Table A.8: Effects of Stress Test Capital Gaps on Consumer Credit — Evidence from the COVID-19 Crisis

This table reports regression estimates for analyzing the effects of stress tests on consumer credit supply using the firm-county-month aggregated sample. In all panels, we use standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. We report estimates over the COVID-19 crisis, where *COVID-19 Crisis* is an indicator equal to one from March 2020 onwards. Our focus is on the interaction terms *Tier 1 Capital GAP* × *COVID-19 Crisis*, showing the effects of the stress tests capital gaps on consumer credit during the COVID-19 crisis relative to normal times in different phases (Panel A, Phase 1:2020:M3-M6 and Phase 2: 2020:M7-M12) or individual months (Panel B). The data come from the supervisory FR Y-14M data set and cover the period January 2019–March 2021. The dependent variables are several measures of credit supply used above. The dependent variables are: *Credit Limit/County Population*, credit card limit at the firm-county level divided by the county population for new originations; *Ln(1+Total Credit Limit)*, the natural logarithm of the credit card limit at the firm-county level for new originations; *Cycle APR*, the average APR used for the cycle for consumer retail purchases at the firm-county level, and *%Rewards/Promotions*, the percent of new credit cards with rewards and promotions. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced) both under the severely adverse scenario for the tier 1 capital ratio. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score*, *Ln(1+ Consumer Income)*, *Consumer Utilization Rate*, an indicator for consumers with joint accounts, an indicator for interest rate accounts, and an indicator for relationship consumers. In all pricing regressions, we also include *Ln(1+ Credit Limit)* as a control variable. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County × Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Main Effects of the COVID-19 Crisis

Independent Variables:	(1) Credit Limit/ County Population	(2) No Loans/ County Population	(3) Ln(1+ Avg Loan Amount)	(4) Cycle APR	(5) % Rewards/ Promotions
Stress Test Measures					
Tier 1 Capital GAP	-0.1787*** (0.007)	-0.0284*** (0.001)	-0.0269*** (0.001)	-0.0613*** (0.011)	0.0182*** (0.001)
Tier 1 Capital GAP × COVID-19 Crisis: Phase 1	-0.4901*** (0.011)	-0.1379*** (0.002)	-0.0866*** (0.003)	-0.4784*** (0.017)	-0.0158*** (0.001)
Tier 1 Capital GAP × COVID-19 Crisis: Phase 2	0.1903*** (0.008)	0.0060*** (0.001)	-0.0803*** (0.002)	0.2399*** (0.012)	-0.0150*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Observations	553,289	553,289	562,110	562,110	562,110
Adjusted R-squared	0.539	0.674	0.722	0.534	0.372
<i>Dependent variable mean</i>	3.589	0.653	8.472	19.665	0.085

Panel B: Dynamic Effects of the COVID-19 Crisis

Independent Variables:	(1) Credit Limit/ County Population	(2) No Loans/ County Population	(3) Ln(1+ Avg Loan Amount)	(4) Cycle APR	(5) % Rewards/ Promotions
Stress Test Measures					
Tier 1 Capital GAP	-0.1816*** (0.008)	-0.0274*** (0.001)	-0.0241*** (0.001)	-0.0847*** (0.011)	0.0176*** (0.001)
Tier 1 Capital GAP × COVID-19 Crisis: 2020M3	-0.4550*** (0.012)	-0.0934*** (0.002)	-0.0878*** (0.004)	-0.2009*** (0.022)	0.0060*** (0.002)
Tier 1 Capital GAP × COVID-19 Crisis: 2020M4	-0.4830*** (0.016)	-0.1995*** (0.002)	-0.0177*** (0.005)	-1.6566*** (0.038)	-0.0153*** (0.003)
Tier 1 Capital GAP × COVID-19 Crisis: 2020M5	-0.4493*** (0.015)	-0.1864*** (0.002)	-0.1090*** (0.005)	-0.2378*** (0.036)	-0.0330*** (0.003)
Tier 1 Capital GAP × COVID-19 Crisis: 2020M6	-0.5512*** (0.015)	-0.1853*** (0.002)	-0.2160*** (0.005)	0.5132*** (0.028)	-0.0432*** (0.003)
Tier 1 Capital GAP × COVID-19 Crisis: 2020M7	0.3235*** (0.009)	-0.0238*** (0.002)	-0.1482*** (0.003)	0.8803*** (0.017)	-0.0205*** (0.001)
Tier 1 Capital GAP × COVID-19 Crisis: 2020M8	0.2200*** (0.009)	-0.0251*** (0.002)	-0.1243*** (0.003)	0.3024*** (0.021)	-0.0199*** (0.001)
Tier 1 Capital GAP × COVID-19 Crisis: 2020M9	0.1273*** (0.009)	-0.0557*** (0.002)	-0.1137*** (0.003)	0.5162*** (0.020)	-0.0071*** (0.001)
Tier 1 Capital GAP × COVID-19 Crisis: 2020M10	0.2152*** (0.010)	0.0263*** (0.002)	-0.0556*** (0.003)	-0.1355*** (0.020)	-0.0092*** (0.001)
Tier 1 Capital GAP × COVID-19 Crisis: 2020M11	0.0309*** (0.009)	0.0119*** (0.002)	-0.0285*** (0.002)	-0.3347*** (0.019)	-0.0158*** (0.001)
Tier 1 Capital GAP × COVID-19 Crisis: 2020M12	0.2462*** (0.010)	0.0905*** (0.002)	-0.0325*** (0.003)	0.3832*** (0.016)	-0.0160*** (0.001)
Consumer, Loan Characteristics	YES	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES	YES
County × Month-Year FE	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Observations	553,289	553,289	562,110	562,110	562,110
Adjusted R-squared	0.539	0.675	0.724	0.539	0.373
<i>Dependent variable mean</i>	3.589	0.653	8.472	19.665	0.085

Table A9: Additional Effects of Stress Tests on Existing Credit Card Accounts

This table reports regression estimates for analyzing the effects of stress tests on credit card consumer credit for existing accounts (24 months or older) using a 0.2% random loan-level sample and standardized coefficients on the key independent variable, *Tier 1 Capital GAP*, for ease of interpretation. The loan-level data come from the supervisory FR Y-14M data set and cover the period June 2013–December 2017. We report both pooled main effects and segmentation by credit card account age groups. The dependent variables are: *Line Increase*, an indicator equal to one if the credit card limit was increased on the account; *Cycle APR*, the average APR used for the cycle for consumer retail purchases at the firm-county level. The key explanatory variable is *Tier 1 Capital GAP*, which represents the lowest projected capital ratio in the BHC’s own exercise (Y-14A) minus the lowest projected capital ratio in the Fed’s stress test exercise (publicly announced) both under the severely adverse scenario for the tier 1 capital ratio. We include a broad set of consumer and loan controls measured at the origination time: *Consumer Credit Score* (refreshed score), $\ln(1 + \text{Consumer Income})$, *Consumer Utilization Rate*, an indicator for consumers with joint accounts, an indicator for interest rate accounts, and an indicator for relationship consumers. In the pricing regressions, we also include $\ln(1 + \text{Credit Limit})$ as a control variable. We also include a number of BHC characteristics, all lagged one quarter: the BHC capital adequacy, the ratio of BHC non-performing loans, earnings, the liquidity ratio, BHC size, the ratio of consumer loans, the ratio of residential real estate loans, and the ratio of trading assets. All regressions include County \times Month-Year FE as well as BHC fixed effects. All variables are defined in Table 1. Heteroskedasticity-robust standard errors clustered at county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Line Increase and Cycle APR for Existing Accounts				
Independent Variables:	CC Age [2,3 years)	CC Age [3,5 years)	CC Age [5,10 years)	CC Age ≥ 10 years
<u>Dependent Variable = Line Increase</u>				
Stress Test Measures	(1)	(2)	(3)	(4)
Tier 1 Capital GAP	0.0016*** (0.000)	0.0009*** (0.000)	0.0001* (0.000)	0.0002 (0.000)
Observations	3,447,843	4,424,521	5,453,848	2,512,022
Adj R-squared	0.005	0.004	0.003	0.001
<i>Dependent variable mean</i>	<i>0.012</i>	<i>0.011</i>	<i>0.009</i>	<i>0.006</i>
<u>Dependent Variable = Cycle APR</u>				
Stress Test Measures	(1)	(2)	(3)	(4)
Tier 1 Capital GAP	-0.1883*** (0.012)	-0.0545*** (0.011)	0.2287*** (0.009)	0.0651*** (0.011)
Observations	3,447,843	4,424,521	5,453,848	2,512,022
Adj R-squared	0.438	0.440	0.333	0.254
<i>Dependent variable mean</i>	<i>20.493</i>	<i>19.664</i>	<i>17.229</i>	<i>15.180</i>
Consumer, Loan Characteristics	YES	YES	YES	YES
BHC Characteristics	YES	YES	YES	YES
County \times Month-Year FE	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES