SHOCKED BY BANK FUNDING SHOCKS: EVIDENCE FROM 500 MILLION CONSUMER CREDIT CARDS*

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Abstract

Using comprehensive credit card–borrower–bank matched data of approximately 500 million credit cards in the U.S., we analyze how a sharp unexpected decline in banks' short-term wholesale funding in 2008 affected their consumers. We decompose credit supply and demand effects using the sudden dry-up of short-term wholesale funding (which accounted for 17.8% of bank funding pre-2008) and account-level data on credit card limits and balances. For the *same* consumer, credit card issuers experiencing a 10% greater decline in wholesale funding reduced credit limits by 0.9% more relative to other issuers. Consumers' aggregate card balances decreased by 0.32% for a 1% reduction in aggregate limits induced by the wholesale funding liquidity shock. We document significant heterogeneity in the pass-through of the bank liquidity shocks with banks cutting credit limits by more for credit-constrained consumers (e.g., lower credit-score and higher credit utilization consumers). These consumers respond by cutting their consumption as they are less able to borrow from alternate sources. Moreover, this consumption decline is long-lasting for these credit-constrained consumers. Our results highlight that when banks face liquidity shocks, they are more likely to pass on these shocks to consumers who are least able to hedge against them. Consequently, our results show *who* bears the real costs of fragile bank funding structures. Our results also contribute to the debate on post-crisis regulatory reform on banks' funding structures that are dependent on wholesale funding by providing consumer-level elasticities of credit limits and balances to bank wholesale funding across different consumer groups.

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1 Introduction

Uninsured short-term wholesale liabilities such as repos and commercial paper are an important source of funding for many banks, but a reliance on this funding source can expose banks to significant roll-over risks and runs (Diamond and Dybvig, 1983; Bhattacharya et al., 1998; Hanson et al., 2011). These funding markets dried up suddenly at the onset of the 2008 financial crisis, causing negative shocks to bank liquidity (Gorton and Metrick, 2012; Tarullo, 2014; Pérignon et al., 2018). In this paper, we show a specific channel—namely, credit card limits, through which banks transmitted their wholesale funding liquidity shocks to their consumers and affected their consumption. Importantly, we show that banks transmitted their liquidity shocks unequally across consumers, which sheds light on *who* bears the real costs of fragile bank funding structures.

While credit cards are an important source of marginal financing for many households in the U.S.,[1] it is not obvious that the wholesale funding shock affects consumer spending. If banks can substitute their wholesale funding with another funding source on similar terms, they may not need to pass on their funding shocks to their consumers. Alternatively, if consumers can switch costlessly among multiple credit cards[2] or if they have sufficient unused credit even after their credit limits are reduced, then the transmission of bank liquidity shocks through credit cards should not have an effect on total credit card spending. Thus, frictions that constrain both banks and their consumers in the credit market are necessary for the wholesale funding shock to have a real impact through credit cards.

Using 500 million credit cards from a major credit bureau, which include *all* the credit cards for any given individual, we highlight which consumer- and bank-level frictions drive the transmission of bank liquidity shocks through credit cards. Using a *within*-consumer empirical design, we show that banks that faced a sudden decline in wholesale funding reduced the credit limits on their consumer credit cards, and this reduction consequently forced some consumers to reduce their consumption.

[1]Of the 40% of U.S. households that cannot cover an unexpected emergency expense of $400, 43% said they use credit cards to cover these unexpected expenses and will pay it off over time. Source: `https://www.federalreserve.gov/publications/files/2017-report-economic-well-being-us-households-201805.pdf`.

[2]According to the 2007 Survey of Consumer Finance, 59.8% of households held two or more credit cards, and these households utilize less than half of their available credit limit, on average.

However, there is significant heterogeneity in how banks pass on their funding shocks across their consumers. Banks reduced credit limits more sharply for consumers with lower credit scores and higher utilization ratios. At the same time, these consumers also faced greater credit market frictions and were unable to substitute their credit card debt with other sources of credit, thus forcing them to reduce their consumption. Our evidence suggests that when banks are faced with liquidity shocks, they are more likely to pass on these shocks to those consumers who are less able to cope with them. Further, we also show that the negative effect of the bank wholesale funding liquidity shock on consumption through credit cards was long lasting. Thus, our evidence suggests that the borrowing constraints on credit cards induced by the funding shock were likely an important contributor to the decline in non-durable consumption during the Great Recession and its sluggish recovery thereafter (Pistaferri, 2016).

The short-term wholesale funding market for banks collapsed in September 2008. We refer to the time period before (after) September 2008 as the *pre-shock* (*post-shock*) period. We measure a bank's exposure to the short-term wholesale funding liquidity shock by the bank's dependence on short-term wholesale funding in the pre-shock period. Thus, the intensity of the wholesale funding liquidity shock varies across banks as the banks varied in their dependence on this funding source in the pre-shock period, and because the collapse of the short-term wholesale funding markets was largely unanticipated.

One of the main identification challenges is to isolate the changes in credit supply from the changes in credit demand, because the economic forces that affect a bank's funding liquidity can also affect consumer demand. We have data on credit card limits, which reflects a bank's credit supply function, as well as credit card balances, which reflect consumer demand. These data allow us to use the approach of Agarwal et al. (2017) and decompose the effect of the liquidity shocks to banks into supply and demand components. The supply component, which is a change in credit limits, represents a bank's marginal propensity to lend in response to the liquidity shock. The demand component, which is a change in credit card balances, represents a consumer's marginal propensity to borrow given the change in credit limits induced by the liquidity shock.[3]

We first focus on individuals who have credit cards from multiple banks to implement a fixed-effects methodology similar to that of Khwaja and Mian (2008). Our fixed-effects methodology compares how the credit limits on credit cards issued to the same individual change as a function of the issuing bank's exposure to the liquidity shock. By comparing *within*-individual credit limit changes, we control for time-varying individual-specific demand factors such as income changes, which can affect a bank's credit extension to an individual.

Using the fixed-effects *within*-individual estimator, we find that a bank with a one standard deviation greater dependence on wholesale funding in the pre-shock period cuts its credit limits by 4.75%, or equivalently by $434, based on the average credit limit across consumers. We ensure that our "within-individual" results are robust to a battery of robustness tests. We show that our results are not likely to be driven by bank-specific individual demand or by the household balance sheet channel. Our findings are also not driven by any particular bank or bank type, such as large banks, risk banks, or risk-averse banks.

We also find support for our baseline results using publicly available bank-level data from regulatory filings. We show that a bank's greater dependence on wholesale funding in the pre-shock period is associated with a reduction in credit card loans on its balance sheet in the post-shock period. Further, we validate our exposure measure by showing that banks that had a greater dependence on short-term wholesale funding indeed experienced a greater decline in short-term wholesale funding in the post-shock period. Moreover, this decline in short-term wholesale funding was not offset by changes in the other sources of bank funding such as deposits and equity.

Next, we document that the liquidity crunch induced by the wholesale funding market had real consequences on aggregate credit card borrowing using the near universe of approximately 500 million credit cards issued to 134 million consumers. We show that individuals who had a greater exposure to the funding shock through their banks experienced a greater reduction in their total credit limits.

[3]The effect of the liquidity shock S on credit card borrowing B through credit limits CL is $\frac{\partial B}{\partial S} = \frac{\partial CL}{\partial S} \times \frac{\partial B}{\partial CL}$. $\frac{\partial CL}{\partial S}$ represents a bank's marginal propensity to lend in response to the shock S, and $\frac{\partial B}{\partial CL}$ represents the consumer's marginal propensity to borrow in response to the shock-induced change in her credit limits.

Furthermore, a reduction in the total credit limits available to consumers forced consumers to cut back on their total credit card balances. We find that, on average, a 1% wholesale funding shock induced reduction in an individual's total credit limit reduced the individual's total credit card balance by 0.32%.

We find heterogeneous effects of the short-term wholesale funding shock on consumers. First, at the credit card level, we find that banks do not transmit shocks equally across consumers. Conditional on the same liquidity shock, banks reduced credit limits by more for consumers with lower credit scores and higher credit card utilization. We find that consumers who had a credit card utilization of 90% or more experienced a $970 reduction in their credit limits, on average. While, consumers with less than 50% credit card utilization experienced a credit limit reduction of $370. These results are consistent with the increased cost of lending to such borrowers due to information frictions (e.g., moral hazard, adverse selection) when a bank's cost of funding increases (Stiglitz and Weiss, 1981; Agarwal et al., 2017). At the individual level, and conditional on the same magnitude of the funding shock transmitted by banks, we find that consumers who had higher aggregate credit card utilization and lower credit scores cut back more on their credit card balances. These results are consistent with credit-constrained consumers being unable to hedge themselves from the transmitted bank shocks. Overall, our results at the credit card level and the consumer level show that consumers who face more constraints in the credit market bear greater costs of bank fragility.

We find that, in the long run, the total credit extended by credit card issuers returns to pre-shock levels at the bank level. However, the effect of the wholesale funding shock was persistent for individuals who had lower credit scores. That is, among consumers with low credit scores, the consumers who were more exposed to their banks' wholesale funding shock had lower total credit limits than the low-exposure consumers even in the long run. As a result, we find that the high-exposure consumers were more limited in their ability to borrow on their credit cards than the low-exposure consumers even in the long run. In contrast, the effect of the wholesale funding shock dissipated relatively quickly over time for the consumers with higher credit scores. These results suggest that either (i) financing frictions for lower-quality borrowers were binding for a very long time or (ii) the funding shock itself weakened borrowers' fundamentals, thereby limiting their access to credit in the future. Regardless of the underlying channel, our results underscore the long-term real consequences of a bank's fragile funding structure across different types of consumers.

Our paper contributes to the literature on the transmission of bank shocks to firms (Khwaja and Mian, 2008; Chava and Purnanandam, 2011; Lin and Paravisini, 2012; Schnabl, 2012; Chodorow-Reich, 2014) and households (Puri et al., 2011; Ramcharan et al., 2016; Benmelech et al., 2017; Jensen and Johannesen, 2017). We document a new channel, namely the credit card channel, through which bank shocks are transmitted to households and affect their aggregate consumption. Using detailed microdata on credit card limits, we can distinguish credit supply effects from credit demand effects for different types of consumers.

Importantly, our paper contributes to the post-crisis regulatory reform that has focused on addressing the vulnerabilities of a bank's funding structure that is especially reliant on wholesale funding (Tarullo, 2014). For instance, the Federal Reserve has proposed to tie the risk-based capital surcharges for the systemically important U.S. banks to their reliance on wholesale funding.[4] Our results enrich this debate by providing elasticities of aggregate credit limits and credit balances to wholesale funding and also the heterogeneity of these elasticities across different types of consumers. In doing so, we shed light on the distributional consequences of bank funding shocks – i.e., who bears the cost of bank fragility.

Our paper relates to the research on the consumption and debt response to changes in credit supply using credit card data. Gross and Souleles (2002a), Agarwal et al. (2017), Aydin (2018) document that households borrow more immediately after increases in credit card limits. We complement this strand of literature, but we focus on how banks' dependence on a fragile funding source (i.e., wholesale funding) and the consequent *reduction* in credit card limits affects households' consumption through credit cards. While Agarwal et al. (2017) show that banks are *less likely* to pass on credit expansions to credit-constrained consumers, our results add to theirs as we show that banks are *more likely* to pass on credit contractions to credit-constrained consumers. Together, these results suggest that in a credit boom-bust cycle credit-constrained consumers enjoy less of the gains in the boom period and suffer more of the costs in the bust period. Thus, these results shed light on who are the

[4] See https://www.federalreserve.gov/newsevents/speech/tarullo20141120a%20.htm#fn10

winners and losers in a credit boom-bust cycle.

Our paper also adds to the literature on the sharp decline in household consumption during the recent financial crisis. Mian and Sufi (2010); Mian et al. (2013, 2017) attribute the consumption decline to the poor state of household balance sheets, which were impaired by the sharp decline in house prices. We show how the impaired balance sheets of financial intermediaries affected the credit supply to the economy and the consumption of goods. Further, while consumption recovered slowly in the post-crisis period, this recovery was puzzlingly slow for non-durable goods and services relative to durable goods, despite the recovery in households' net worth (Pistaferri, 2016). Our evidence suggests that borrowing constraints on credit cards, which are used to consume non-durable goods and services (e.g., food, apparel, gasoline, transportation, health care) played a significant role in the decline of consumption during the Great Recession and its sluggish recovery in the post-crisis period. While Mian et al. (2013) show the importance of household balance sheets, our results highlight the importance of banks' balance sheets for aggregate consumption. Instead of helping households smooth consumption during the crisis, banks can pass on their own shocks to households and may also amplify them.

The rest of the paper proceeds as follows. Section 2 discusses identification challenges and empirical methodology. Section 3 describes the data and summary statistics. Section 4 presents the main results. Section 5 presents results on the heterogeneity of the funding shock, and Section 6 presents the long-run effects. We conclude the paper in Section 7.

2 Identification challenges and empirical methodology

This section discusses the identification challenges and the empirical specification used to identify the transmission of the short-term wholesale funding shock to consumers through credit cards. The aggregate trends of credit card limits and balances indicate that such a transmission channel through credit cards may exist. Time-series patterns shown in Figure 1 reveal that credit card limits declined by approximately 25% between January 2008 and January 2010. Similarly, during the same time period, aggregate credit card balances declined by approximately 16.7%. This figure appears to suggest that the drop in aggregate credit card limits precedes the drop in credit card balances, which is consistent with households being unable to smooth their consumption through credit cards due to a reduction in their credit limits. However, such aggregate trends can be confounded by various credit demand factors.

[**Figure 1 here**]

Consequently, the main identification challenge is to isolate the changes in credit supply from the changes in credit demand. Our data offer unique advantages in this regard; namely, we observe data on credit card limits along with credit card balances. Credit card limits measure the amount that a lender is willing to lend to a consumer–i.e., they measure the supply-side of credit to a consumer. Whereas, credit card balances are a measure of a consumer's credit demand. Credit limits can increase if an account holder requests an increase in her credit limit (i.e., a demand-driven increase), but it is less likely that an account holder requests a reduction in credit limit.[5] Therefore, reductions in credit limits are more likely to be credit supply-driven effects, which allows us to distinguish credit supply effects from credit demand effects. Consequently, we utilize a cleaner measure of credit supply for our tests, which contrasts with most previous studies that typically infer changes in credit supply by using changes in loan balances.

Although credit limits are a cleaner measure of credit supply, our empirical exercise could be subject to potential endogeneity concerns if credit card issuers change credit limits in anticipation of changes in credit demand. For instance, credit card issuers can reduce credit limits in anticipation of lower consumer demand (e.g., an increase in unemployment in the aftermath of the 2008–2009 financial crisis) if maintaining unused credit lines is costly for credit card issuers.[6]

Our identification strategy allows us to mitigate such endogeneity concerns. We use an unanticipated funding shock to banks resulting from the dry-up of the short-term wholesale funding market at the end of 2008. Banks varied substantially in their dependence on short-term wholesale funding. Thus, banks that depended more on short-term wholesale funding experienced greater unanticipated

[5]From the consumer's perspective, higher credit card limits are generally preferable, even if these higher limits come from unused credit cards, since higher limits provide greater financial slack. Moreover, for a given aggregate individual credit card balance, higher credit limits translate to lower utilization ratios and higher credit scores in general.

[6]For example, banks are required to hold capital even on unused credit card commitments.

funding liquidity shocks. Next, we use the granular credit card account–level data to estimate the impact of the funding shock on the credit limits extended by the banks to their credit card borrowers. For identification, we construct our tests similar to Khwaja and Mian (2008) (see also Schnabl, 2012; Chernenko and Sunderam, 2014), in which we isolate changes in credit limits at the credit card account level in the presence of *Individual* fixed effects. We estimate the following specification:

$$\Delta CreditLimit_{i,c,b} = \alpha + \beta Exposure_b + f(\mathbf{X}_{i,c,b}) + \eta_i + \varepsilon_{i,c,b} \tag{1}$$

where i, c, and b index individuals, credit cards, and banks, respectively. $\Delta CreditLimit_{i,c,b}$ is the log-change in credit limits for individual i's credit card c with bank b from the pre-shock to the post-shock period.

The log-change in credit limits for each credit card is computed by first collapsing the time-series credit card– level data by averaging across time to obtain a single credit card–level cross-section separately in the pre-shock and post-shock period. Pre-shock and post-shock periods are symmetric, with each consisting of three semiannual archives. Each archive is a snapshot of the credit limit and the balance on each credit card in our sample. The pre-shock period includes semiannual archives for January 2007, July 2007, and January 2008. The post-shock period includes semiannual archives for January 2009, July 2009, and January 2010.

The variable $Exposure_b$ measures the exposure of a bank to the wholesale funding shock. It is constructed as the pre-shock value of the short-term wholesale funding-to-deposit ratio, thus it captures the proportion of a bank's runnable funding to its stable funding. The main coefficient of interest is β, which measures the impact of a bank's wholesale funding shock on the credit limits of its borrowers. η_i is the individual fixed-effects, which controls for confounding individual-specific demand factors (e.g., income changes) that could bias our results. However, bank-specific consumer demand factors can still confound our analysis, especially if consumers are incentivized to use some of their credit cards exclusively for purchasing certain kinds of goods.[7] In such cases, the changes in the demand for those goods can drive credit limit changes. We address this plausible concern

[7] For instance, consumers may be rewarded with cash-back or points that are redeemable for cash on certain credit cards if they use them for purchasing gasoline.

in Section 4.1.4 by constructing a "leave-out-mean" credit limit for each bank–consumer pair. This measure captures the average credit limits extended by the bank across all credit cards after excluding the bank's credit limit extended to that consumer.

Finally, $f(\mathbf{X}_{i,c,b})$ is a vector of control variables at the bank level, the individual–bank level, and the credit card level, as measured in the pre-shock period. The bank-level variables control for differences in characteristics across credit card issuers that can confound our analysis, such as size, performance, and lending quality. For instance, the credit extended by large banks and small banks might differ in the post-2008 period, because large banks and small banks were subject to different intensities of regulatory oversight. We control for the consumer's bank-specific demand and supply factors that can affect credit limits by including individual–bank variables (e.g., the number of credit-related accounts with the bank) and credit card–level variables (e.g., the age of the account). The error term is $\varepsilon_{i,c,b}$.

To estimate the effect of the banks' wholesale funding shock on credit card balances, we estimate a two-stage least squares regression model. The first stage is estimated using Equation (1), which captures the change in credit limits (i.e., the bank's credit supply) that resulted from the wholesale funding shock. In the second stage, we estimate the effect of credit limit changes on credit balance changes by instrumenting the credit limit changes with the bank's exposure to the wholesale funding shock. We estimate the following second-stage regression:

$$\Delta CreditBalance_{i,c,b} = \alpha' + \beta' \Delta \widehat{CreditLimit}_{i,c,b} + f(\mathbf{X}_{i,c,b}) + \eta'_i + \varepsilon'_{i,c,b} \tag{2}$$

where $\Delta \widehat{CreditLimit}_{i,c,b}$ are the fitted values from Equation (1). For β' to be consistent, the instrument $Exposure_b$ must satisfy the exclusion restriction. That is, a bank's wholesale funding exposure should affect only the changes in their borrowers' credit balances through credit limit changes. This seems plausible, since most borrowers are unlikely to be familiar with their banks' funding structure for it to directly affect their credit card consumption.[8] An important caveat in our analysis of credit

[8]However, it is possible that a reduction in bank funding can reduce a bank's investment in its service quality, which can in turn affect the usage of their issued credit card. We test this possibility by regressing the change in a bank's noninterest expense-to-assets ratio from the pre- to the post-shock period on the *Exposure* measure (similar to Table 2 regressions). The noninterest expense includes advertising, promotional, public relations, business development

card balances is that we observe the snapshot of balances in each archive, which can differ from the true borrowing on those credit cards. However, since the credit card spending of unconstrained borrowers should not be systematically affected by credit limit changes, β' should capture the changes in credit card borrowing from the pre- to the post-shock period due to the short-term wholesale funding shock.

An alternate method to conduct our analysis is by using the time-series panel data and including $Individual \times Archive$ fixed effects. However, this is more challenging, as it entails a larger number of fixed effects. Further, collapsing the time-series and estimating cross-sectional regressions mitigates the econometric issues related to the underestimation of standard errors in the panel data that have short time dimensions (Bertrand et al., 2004; Angrist and Pischke, 2009). Thus, our procedure provides us with conservative standard errors.

2.1 The short-term wholesale funding shock

A bank's funding sources can be broadly divided into *deposits* and *wholesale funding*. Wholesale funding consists of non-deposit financing such as repos and commercial paper. These funding are provided mainly by institutional investors such as money market funds (MMFs) and other banks. Deposits are insured by the Federal Deposit Insurance Corporation (FDIC) and are thus a cheaper source of funding than wholesale funding. By the virtue of being insured, deposits are also less sensitive to a bank's financial health than other uninsured sources of bank funding. As a result, deposits are more stable and less prone to runs (Berlin and Mester, 1999). However, banks generally find it costly to raise deposits quickly to cover any funding gap because the supply of deposits is highly inelastic with respect to the deposit rates offered (Amel and Hannan, 1999). Therefore, banks turn to non-deposit or wholesale funding as an alternative to deposits when they need to quickly cover any funding gap.

Figure 2 shows the change in bank funding measures over time as a fraction of total assets. Consistent with wholesale funding and deposits being substitutes, Subfigures 2a, 2b, and 2c show

expenses, and salaries. We do not find any evidence that banks with a greater dependence on wholesale funding reduced their noninterest expense per unit of assets.

their negative correlation over time. Subfigure 2d gives credence to the substitution argument by showing that the total liabilities are either relatively stable (before 2008) or decreasing (after 2008) across time.

[Figure 2 here]

The total wholesale funding consists of all funding sources of banks other than deposits and equity. This funding can be broadly divided into short-term and long-term wholesale funding. Short-term wholesale funding consists of funding liabilities that have a maturity of less than one year, such as repos, commercial paper, and interbank borrowing. However, long-term wholesale funding consists of other funding liabilities that have a maturity of greater than one year. Furthermore, among the total wholesale funding, the short-term wholesale funding is more sensitive to a bank's financial condition. This is because the shorter the maturity of the wholesale funding, the more exposed it is to rollover risks. Therefore, a decline in a bank's financial health can quickly make short-term wholesale funding prone to runs and liquidity shocks if the lenders who provide the short-term funding choose not to rollover their funding (Gorton and Metrick, 2012; Acharya et al., 2013).[9] Figure 3 shows the change in the components of wholesale funding over time as a fraction of total assets. The rise and fall of wholesale funding—especially the short-term funding—is apparent.

[Figure 3 here]

We measure a bank's exposure to the short-term wholesale funding shock as the short-term wholesale funding-to-deposits ratio. Recall that this ratio is a measure of a bank's runnable funds (i.e., short-term wholesale funding) as a proportion of its non-runnable funds (i.e., deposits). A bank with a higher value of this measure should be more prone to the short-term wholesale funding shock. In Figure 4, we plot our main bank exposure variable—i.e., the ratio of the short-term wholesale funding to deposits over time. Figure 4 shows that short-term wholesale funding increased with respect to deposits from 2004 to 2008, then fell dramatically after 2008. This is consistent with

[9]For instance, the maturity of certain short-term wholesale liabilities (e.g., repos, commercial paper) can be as short as a day or a week.

the drying up of the wholesale funding market which was documented in previous studies (Pérignon et al., 2018).

[Figure 4 here]

3 Data and summary statistics

3.1 Data

We use data from Equifax, which is one of the three major credit bureaus in the U.S. All the data described below are used purely for academic purposes, and they contain anonymized information. The credit bureau's data provide comprehensive records of the various credit accounts opened by every U.S. resident. These credit accounts span credit cards, mortgage, auto, student loans, and personal/business loans.

We identify the 25 bank holding companies (BHCs) from the credit bureau's data files that contain credit card issuers and also have a non-zero dependence on wholesale funding. These 25 BHCs account for 75% of the market in terms of open credit cards. From this set of 25 credit card issuers, we omit six issuers that differ from the rest of the sample of banks, and we omit one issuer because of insufficient data coverage during our sample period. Of the six issuers we omit , four are foreign credit card issuers, one issuer specializes in retail store credit cards, and one issuer targets a particular segment of the U.S. population. By omitting these six issuers, we mitigate potential credit card–specific demand factors that can confound our analysis. For instance, if consumers use retail store credit cards exclusively to borrow and purchase expensive luxury goods, then reductions in the credit limits and balances of the retail store credit cards could reflect the lower demand for luxury goods in the post-2008 period. Our final dataset consists of 18 credit card issuers that cover seven of the top 10 credit card issuers and account for 65% of the market share.

Next, from the entire U.S. population, we identify all individuals who have active credit card accounts issued by at least one of the 18 credit card issuers in our sample, as of January 2008. We then obtain their credit card limit and balance information. As mentioned previously, this information on credit card limits and balances is available at a semiannual frequency. Further, we omit credit cards that are closed in the post-shock period. This filter ensures that we do not pick up changes in credit card limits and balances due to credit card cancellations or personal bankruptcies. As a result, the majority of our analysis focuses on tracking changes in credit cards along the intensive margin. We also limit our analysis to credit cards that have at least one nonmissing pre-shock and one nonmissing post-shock limit and balance observation. We winsorize both measures at the 1% and 99% levels. Finally, we average the credit limits on credit cards separately in the pre- and post-shock periods to capture the average credit supply on individual credit cards before and after the shock. We do the same for credit card balances before and after the shock.

Our baseline credit card–level analysis with individual fixed effects relies on comparing changes in credit card limits and balances *within* individuals. Thus, our baseline analysis includes only individuals who have two or more credit cards issued by banks that are exposed to the short-term wholesale funding shock, in which the banks differ in their exposure to the funding shock. After this final filter, we are left with 158 million credit cards issued to 54 million individuals. Importantly however, we use our entire dataset of 500 million credit cards issued to 134 million individuals for our individual-level analysis.[10] This analysis aggregates credit limits and balances across all credit cards for each consumer and allows us to test the overall effect of the short-term wholesale funding shock at the individual level.

3.2 Bank-level summary statistics

We use a bank's dependence on wholesale funding as a measure of the bank's exposure to the unexpected liquidity shock. Therefore, we use the cross-sectional variation in the dependence on short-term wholesale funding across banks as a measure of the variation in the exposure of a bank to the unexpected liquidity shock. Table 1 shows how the exposure to liquidity shocks varies cross-

[10] Table A.1 reports the summary statistics at the consumer level for the full sample (134 individuals) and the fixed effect model (FE) sample (54 million individuals). This table shows that individuals in the FE sample have similar credit score, monthly income, debt-to-income ratio, credit card utilization, and mortgage balance as individuals in the full sample. Individuals in the FE sample have more credit card accounts, more debt related accounts, and higher credit card balances. However, the difference is mechanically driven by the fact that we require individuals in the FE sample have at least two credit cards.

sectionally across the banks in our sample. To show this, we first collect data from the quarterly BHC Y-9C regulatory filings for each of our credit card–issuing banks at the bank holding company level from 2006–2010.[11] We define the pre-shock period from 2006Q1 to 2007Q4, and we define the post-shock period from 2009Q1 to 2010Q4. Then, we collapse the quarterly bank-level data to obtain a single bank-level cross-section separately in the pre-shock and post-shock periods by averaging across time.

Table 1, Panel A presents summary statistics for the bank-level characteristics after splitting the pre-shock cross-section into banks that had a high exposure (above median) and banks that had a low exposure (below median) to the wholesale funding liquidity shock based on the bank's short-term wholesale funding-to-deposits ratio. We report means and medians for the bank-level characteristics where the medians are reported in square brackets. Column (3) reports the difference between the means for the high– and low–shock exposure banks, and also tests for its statistical significance.

[Table 1 here]

Table 1, Panel A, shows that the mean exposure (i.e., the dependence on short-term wholesale funding) for the banks in the high-exposure group is three times greater than the mean exposure for banks in the low-exposure group. The total wholesale funding as a fraction of assets is also about 2.5 times greater for the high-exposure group than the low-exposure group. The total wholesale funding consists of all funding sources of banks other than deposits and equity, and this funding can be broadly divided into short-term and long-term wholesale funding. Short-term wholesale funding consists of funding liabilities that have a maturity of less than one year, such as repos, commercial paper, and inter-bank borrowings. Long-term wholesale funding consists of other funding liabilities that have a maturity of greater than one year.

Table 1, Panel A, also shows summary statistics for the individual components of wholesale funding for the high- and low-exposure bank groups. Except for the federal funds purchased, the

[11] We can collect data at the holding company level for 17 out of the 18 credit card–issuing banks. We supplement our data with the quarterly call report data for the remaining credit card–issuing bank. Our results are robust even after excluding this bank from our analysis. However, we choose to retain it for our analysis because it is an economically important bank that ranks among the top five credit card–issuing banks in terms of market share.

high-exposure banks have a significantly greater dependence (by about 2.5–3 times) on all components of the wholesale funding compared to the low-exposure banks. High-exposure banks are also significantly larger than low-exposure banks, and they have a smaller deposit base as a fraction of their assets. This is consistent with previous literature that argues that a bank can substitute deposit funding with wholesale funding either (a) because of the bank's inability to raise deposits quickly when it must expand lending, or (b) in response to an outflow of deposits (see Choi and Choi, 2017). Moreover, Choi and Choi (2017) also suggest that, when required, large banks (as opposed to small banks) are better able to substitute deposits with wholesale funding because they face lower financial frictions. As a result, they obtain wholesale funding at a lower cost. Our results are consistent with the observed size differential between high- and low-exposure banks in our sample.

Further, Table 1, Panel A, shows that the high- and low-exposure banks are not statistically different in terms of their equity capital, which is an alternate source of bank funding. The high- and low-exposure banks are also similar in terms of their business mix, which measures the extent to which the banks engage in credit card, mortgage, and commercial and industrial (C&I) lending. The covariate balance along each component of the business-mix dimension also mitigates the concern that a shock to a particular industry in which banks operate drives the drop in credit card lending.

Finally, Table 1, Panel A, shows that the high- and low-exposure banks have similar performance-based measures. Importantly, given that credit cards are the focus of our study, we find no statistical difference in the performance of credit card loans between the high- and low- exposure banks. If anything, the point estimates suggest that the credit card loans of the high-exposure banks performed better than the low-exposure banks in the pre-shock period. The high-exposure banks had 0.4 percentage points fewer non-performing credit card loans as a fraction of their total credit card loans (or 17.4% lower than the low-exposure banks).

3.3 Credit card–level summary statistics

Table 1, Panel B, presents summary statistics for the quality of borrowers to whom banks issue credit cards, after splitting banks into high- and low-exposure banks. We follow the same procedure as shown in Table 1, Panel A. We first collapse the data to obtain a single bank-level cross-section in the pre-shock period by averaging across the semiannual archives. Next, we obtain the statistics reported in the table by dividing the cross-section into the same high- and low-exposure banks as defined in Table 1, Panel A.

Table 1, Panel B, shows that the high-exposure banks do in fact lend to borrowers who have better credit quality and stronger fundamentals. The borrowers of the high-exposure banks have higher credit scores and a higher monthly income. The percentage of subprime credit card borrowers (i.e., borrower credit scores < 620) for the high-exposure banks is lower than that of the low-exposure banks. While borrowers of the high- and low-exposure banks have a similar number of credit card accounts, the borrowers of the high-exposure banks have a significantly higher credit card balance (by \$1,192.50) and a lower utilization ratio (by 2.36 percentage points) than the low-exposure banks. This implies that borrowers of the high-exposure banks have, on average, significantly higher credit card limits.

Further, Table 1, Panel B, shows that, despite higher credit card balances and similar debt-to-income ratios, borrowers of the high-exposure banks have a lower delinquency rate on their credit cards relative to the borrowers of the low-exposure banks. In terms of other debt, the borrowers of the high-exposure banks have about one more debt-related account, a higher mortgage balance, and a lower auto balance than the borrowers of the low-exposure banks. Despite the differences in the composition of debt, it is important to note that the overall debt-to-income ratios are similar for the borrowers in both groups.

Overall, the summary statistics in Table 1, Panel B, are consistent with the statistics in Table 1, Panel A and show that the high-exposure banks had a better lending quality than the low-exposure banks. To the extent that better-quality borrowers can handle adverse shocks that are correlated with the negative shock to their bank's wholesale funding, the summary statistics imply that the wholesale funding supply shock transmitted from the banks to their borrowers is negatively correlated with the borrowers' demand shocks. In other words, any confounding borrower-related demand shocks that can bias our results should work against finding the proposed relationship between a bank's short-term wholesale funding shock exposure and the cut in credit limits.

3.4 Preliminary bank-level results

Figure 5 provides evidence for our baseline result at the bank level using the BHC Y-9C regulatory filings data. Figure 5 shows that banks that have a greater dependence on short-term wholesale funding experienced a greater reduction in credit card loans on their balance sheets from the pre- to the post-shock period. To plot the relationships in Figure 5, we partial out (orthogonalize) our exposure measure, and the log-change in credit card loans with respect to bank size by regressing them against the log of total assets and obtaining the residuals. This procedure adjusts for the fact that banks that have a greater dependence on wholesale funding are significantly larger, as reported in the summary statistics in Table 1. However, the relation shown in Figure 5, which uses aggregated bank-level data, cannot distinguish between credit supply and credit demand effects. Thus, we rely on the credit card–level data that include information on credit limits and balances to infer the credit supply–driven effects of the short-term wholesale funding liquidity shock.

[Figure 5 here]

Figure 6 provides evidence for the necessary conditions for our empirical tests. First, Subfigure 6a provides supporting evidence for our main assertion that banks with a greater dependence on short-term wholesale funding experienced a greater reduction in short-term wholesale funding in the post-shock period. Subfigures 6b, 6c, and 6d plot changes in the total wholesale funding, total liabilities, and equity capital. These figures indicate that banks could not make up for the funding gap using other sources of funding after the loss of short-term wholesale funding.

[Figure 6 here]

Table 2 shows the statistical significance of the relationships plotted in Figure 5 and 6. The regression results are estimated by weighting each observation by bank size, thus these results are economically more relevant. We standardize the exposure and the control variables in the regression for the ease of interpretation. Table 2, Panel A, shows the relation between the dependence on short-term wholesale funding and the change in bank funding measures in the post-shock period after controlling for the size of the bank. Column (1) in Panel A shows that a one standard deviation increase in a bank's dependence on wholesale funding in the pre-shock period led to a 42.5% reduction in short-term wholesale funding in the post-shock period. This result is both statistically and economically significant. The last row in Panel A shows the explanatory power (i.e., R^2) of using only our funding shock exposure measure (i.e., the short-term wholesale funding dependence) on the changes in the bank's funding measures after partialing out the effect of bank size. Column (1) shows that our exposure measure explains more than half (53.1%) of the cross-sectional variation in the decline of short-term wholesale funding in the post-shock period, which is again economically significant. Columns (2) and (3) suggest a 32.4% and 27.2% reduction in the total wholesale funding and total liabilities, respectively. These funding measures include short-term wholesale funding. Column (4) does not show any significant change in the total equity capital of banks. In sum, the exposure variable best explains the cross-sectional variation in the decline of short-term wholesale funding compared to other broader measures of funding that either contain it (e.g., total liabilities) or are unrelated to it (e.g., total equity capital).

[Table 2 here]

Similarly, Table 2, Panel B, shows the cross-sectional relation between the exposure variable and the change in credit card loans from the pre- to post-shock period. Column (1) shows that a one standard deviation increase in the dependence on wholesale funding led to a 21.1% reduction in the amount of credit card loans issued by banks. The last row in Table 2 shows that the exposure measure explains 41.1% of the cross-sectional variation in the reduction of credit card loans in the post-shock period, and this is economically significant. The results are robust in Column (2), which controls for the extent of credit card business conducted by banks to mitigate the concern that the results are driven by shocks to the credit card industry. Column (3) controls for the quality of the credit loans issued by banks, and it shows that the point estimates are unchanged, but are estimated more precisely. This result suggests that it is less likely for the differential lending quality at banks to explain the decline in credit card lending.

4 Results

A funding shock increases a bank's marginal cost of extending credit because it increases the bank's funding costs. Banks can pass on their higher funding costs to consumers either through price (e.g., increasing interest rates on credit card borrowing) or through quantity (e.g., reducing credit limits). However, interest rates on credit cards tend to be relatively inelastic (Ausubel, 1991; Calem and Mester, 1995). Moreover, an increase in interest rates can lead to adverse selection issues since only the riskier borrowers are willing to borrow (Stiglitz and Weiss, 1981). Thus, credit limits, as opposed to interest rates, are more likely to be the primary margin of adjustment for banks as they transmit their funding shocks to consumers through credit cards. We first estimate the average effect of the wholesale funding shock on individuals. Next, we examine the heterogeneous effects of the wholesale funding shock across individuals because the heterogeneity of information issues (e.g., moral hazard, adverse selection) can affect the cost of extending credit differentially across consumers (Agarwal et al., 2017).

4.1 Credit card–level results

4.1.1 Effect of the funding shock on credit limits

In this section, we use the granular credit card–level data to estimate the effect of the wholesale funding shock on a bank's credit supply. As described in Section 2, we isolate changes in credit limits at the credit card–level in the presence of *Individual* fixed effects. Table 3 documents these results, which are obtained by estimating Equation 1. Our regression sample consists of 158 million credit card accounts belonging to 54 million individuals after omitting singleton observations (i.e., individuals who have only one credit card) and after applying the filters described in Section 3 to the raw data from the credit bureau, which cover the entire U.S. population.[12] We also standardize the exposure variable for ease of interpretation. Finally, all control variables are constructed by averaging over the pre-shock period.

[12] The singleton observations do not contribute to the estimation of the fixed-effects estimator, but they can lead to an underestimation of standard errors.

[Table 3 here]

The summary statistics in Table 1 show that larger banks, in general, have a greater fraction of wholesale funding. Therefore, in Table 3, Column (1), we control for bank size by including the logarithm of bank assets and its square to account for any nonlinear effects due to bank size in our analysis. Column (1) also controls for a bank's ability to sustain losses by including the risk-based capital ratio. To mitigate the concern that our results are driven by correlated shocks to the credit card industry, we also include the amount of credit card loans as a fraction of the bank's assets as a control in Column (1). After controlling for these initial sets of bank characteristics, we find that the coefficient of interest, which is associated with the *Exposure* variable, is negative and statistically significant. This indicates that the banks that had a greater dependence on short-term wholesale funding in the pre-shock period reduced credit limits more in the post-shock period. In Column (2) and Column (3), we show that our point estimates remain virtually unchanged even after controlling for the performance and lending quality of the bank. These specifications suggest that our results are unlikely to be driven by banks with poor fundamentals such as poor performance, more risk-taking, or a low-quality customer base.

In Column (4), we also control for credit card–specific and individual–bank-specific characteristics than can affect credit limits, such as the age of the credit card account and the relationship between an individual and her credit card–issuing bank. We measure the relationship between an individual and her credit card–issuing bank by observing the number of open accounts (e.g., mortgage loans, auto loans) that the individual has with the bank. Column (4) show that our results remain unchanged, indicating that such individual–bank-specific factors are less likely to confound our results. The coefficient estimated in Column (4) suggests that a one standard deviation increase in the dependence on short-term wholesale funding in the pre-shock period leads to a 4.75% decline in credit card limits from the pre- to post-shock period. Given that the average pre-shock credit limit is $9,131.60, a one standard deviation increase in a bank's exposure to the short-term wholesale funding shock decreases the credit limit by $434, on average.

In Column (5), we re-estimate the specification in Column (4) without individual fixed effects.

We note that the coefficient associated with the *Exposure* variable is relatively unchanged. This implies that the individual demand factors, which we absorb using the fixed-effects specifications in Column (4), is mostly uncorrelated with the *Exposure* variable. This result is useful when we attempt to trace the impact of the wholesale funding shock on an individual's aggregate credit card balances through the changes in credit limits.

[**Figure 7 here**]

In Figure 7, we provide evidence for *parallel trends* in the credit limits extended by the high- and low-exposure banks. Figure 7 attempts to replicate the cross-sectional "within" individual analysis in Table 3 over time (see Khwaja and Mian, 2008). The plot in Figure 7 is equivalent to first obtaining the residual from regressing credit limits on $Individual \times Archive$ fixed effects, then plotting the residual after sorting it based on whether it is associated with a high- or a low-exposure bank. However, given the large number of fixed effects that must be employed in such a regression, we choose to implement this task in the following equivalent manner.[13] For each individual in every semiannual archive, we compute the deviation of each credit card's credit limit from the individual's mean credit limit in that archive. Next, we sort the deviations into two groups based on whether the individual's credit card was issued by a high- or a low-exposure bank. Then, we plot the mean of the deviations computed for each group–archive in Figure 7. The high- and low-exposure bank groups are defined "within" individual, based on the mean of our wholesale funding exposure measure computed for each individual.

Figure 7 shows parallel trends for the (within-individual) credit limits extended by the high- and low-exposure banks in the pre-shock period. However, in the post-shock period, the credit limits for the cards issued by high-exposure banks trend lower relative to the mean individual credit limit. The within-individual credit limits trend for credit cards issued by the low-exposure banks is a mirror image of the trend for high-exposure banks because we sum up the deviations within each individual and archive. The unconditional mean change in credit limits from the pre- to post-shock period is -3.95% for the high-exposure banks and -0.30% for the low-exposure banks. These unconditional

[13] Our sample consists of 54 million credit card consumers and covers seven semiannual archives during our sample period from 2007–2010 to plot Figure 7. Thus, we have $54 \times 7 = 378$ million fixed effects.

means indicate that our results are not driven by credit limit increases on cards issued by the low-exposure banks. Rather, these changes occur due to the credit limit reductions on cards issued by the high-exposure banks.

4.1.2 Effect of the funding shock on credit balances

Ex ante, controlling for individual demand factors, it is not obvious how changes in credit limits should affect credit card balances. For instance, if consumers are not liquidity constrained then a change in credit limits should not lead to a change in credit card balances.[14] Table 4 shows how consumers change their their credit card usage when it experiences a credit limit cut. In Column (1) we estimate the OLS regression to obtain the relation between credit limit changes and credit balance changes at the credit card level. We find that a 1% reduction in credit limits leads to a 0.74% increase in credit card balances. It is important to note that Column (1) does not include Individual fixed effects and thus captures the cross-sectional variation across individuals.

Clearly, endogenous demand factors can bias the results in Column (1) because consumer demand is arguably the primary driver of changes in credit balances. For example, consumers can receive an increase in credit limits by applying for it with the intention of utilizing more credit in the future. Similarly, if lenders anticipate future demand changes (e.g., a reduction in future income), then they could reduce credit limits in anticipation of such demand factors. Therefore, in Column (2), we re-estimate our specification in Column (1) with *Individual* fixed effects. This allows us to control for individual demand factors and compare how credit limit changes affect credit balance changes within individuals who use multiple credit cards. The *Individual* fixed effects estimator in Column (2) shows that a 1% change in credit limits leads to a 0.85% change in credit card balances. The positive relationship between credit limit changes and balance changes is consistent with Gross and Souleles (2002a).

[Table 4 here]

[14] For instance, under the permanent income hypothesis, an increase in credit limits should not affect credit balances or consumption. However, if liquidity constraints bind currently, or if they are expected to bind in the future (buffer stock models), then credit limit changes can lead to changes in credit balances or consumption.

Columns (3) and (4) estimate the OLS and the *Individual* fixed effects estimator using our bank *Exposure* variable to the short-term wholesale funding shock. Both columns suggest that the credit card consumers of banks that had a greater exposure to the short-term wholesale funding shock reduced balances on those credit card to a greater extent. The *Individual* fixed effects estimator in Column (4), which corrects for changes in individual demand factors, indicates that a one standard deviation increase in a bank's exposure to the short-term wholesale funding shock leads to reduction of 9.81% in balances on the credit cards issued by the bank. A comparison of the estimates in Columns (3) and (4) reveals that the individual demand factors are positively correlated with our bank *Exposure* variable resulting in a positively biased coefficient in Column (3). This suggests that omitting demand factors should work against finding the negative relation between a bank's exposure to the liquidity shock and the reduction in the balances on the credit cards issued by the bank.

In Column (5), we estimate the 2SLS specification in Equation 2, which instruments the change in credit card limits from the pre- to post-shock period with our bank *Exposure* variable. Therefore, the estimate in Column (5), which captures the local average treatment effect (LATE), shows that a 1% reduction in credit limits due to the short-term wholesale funding shock reduces credit card balances by 2.06%.

4.1.3 Elasticity of credit card limits and balances to short-term wholesale funding

Next, in Table 5, we estimate the elasticity of credit card limits and balances directly to short-term wholesale funding. The point estimate in Column (1), which includes *individual* fixed effects suggests that banks that experienced a 1% decrease in short-term wholesale funding from the pre- to the post-shock period reduced credit limits by 0.056% (i.e., an elasticity of 0.056). In Column (2), we instrument the change in short-term wholesale funding with our exposure measure. We find that the elasticity of credit card limits to short-term wholesale funding increases to 0.090. Consistent with all our prior results, the results in Columns (1) and (2) suggest that the point estimate in Column (1) was negatively biased. The mean reduction in short-term wholesale funding for the banks in our sample is 11.3%, which accounts for a 1.02% (11.3×0.090) decline in credit limits on the credit cards issued by these banks.

In Columns (3) and (4), we estimate the elasticity of credit card balances to short-term wholesale funding. The OLS regression in Column (3) suggests an elasticity of 0.093, while the instrumented regression in Column (4) suggests a higher elasticity of 0.186. This elasticity suggests a 2.10% (11.3×0.186) decline in credit card balances due to the wholesale funding shock for the mean bank in our sample.

[Table 5 here]

4.1.4 Are the results being driven by bank-specific consumer demand?

If endogenous demand factors exist only at the individual level, then our fixed-effects specification can control for them entirely. However, if there are confounding demand factors at the credit card level, then our results could still be biased. For instance, if individuals prefer to use certain credit cards over others, then the true measure of individual demand will be reflected only through those frequently used credit cards. Moreover, if banks tend to reduce credit limits for those cards that are infrequently used, then our results should matter less economically. Therefore, in Table 6, Panel A, we consider only the active credit cards in our sample. These are cards that had a nonzero balance in both the pre- and the post-shock period. This additional condition results in dropping approximately 24% of the credit card accounts in our sample.

Column (1) shows how a bank's exposure to the short-term wholesale funding shock affects the change in credit limits for the subsample of active cards. We find a stronger effect compared to the baseline results in Table 3. Namely, a one standard deviation increase in the dependence on short-term wholesale funding leads to a 5.20% reduction in the credit limits of an actively used card. This suggests that the credit cards that were in greater use saw a larger reduction in credit limits in the post-shock period, which makes our analysis economically relevant. Column (3) re-estimates the IV specification in Table 4, Column (5). We find that a 1% reduction in credit limits for active cards due to the short-term wholesale funding shock leads to a 3.42% decrease in credit card balances for active cards. This effect is about 1.6 times greater than the estimate in Table 4, Column (5), which also includes cards that are not actively used. Moreover, recall that the fixed-effects specification for the actively used cards should be better able to control for the endogenous changes in the demand-side factors at the individual level. Thus, it is likely that the higher IV estimate for the active credit cards subsample better reflects the LATE stemming from the financially constrained individuals.

[Table 6 here]

To further mitigate endogeneity concerns due to card-specific demand factors, we construct a "leave-out-mean" credit limit change for each credit card. For every individual i's credit card c issued by bank b, we first compute the "leave-out-mean" credit limit $CreditLimit_{i,-c,b}$ as the average credit limit using all the credit cards issued by bank b except credit card c. Next, we compute the change in this "leave-out-mean" credit limit for each credit card.[15] By construction, this measure excludes the credit limits changes made by a bank due to individual demand factors such as individual requests for increases in credit limits. At the same time, this measure captures the bank's average change in credit supply through its credit cards.

We re-estimate our baseline model with the leave-out mean credit limit change measure in Table 6, Panel B. The point estimate in Column (1) indicates that a one standard deviation increase in bank exposure to short-term wholesale funding led to a -4.30% reduction in credit limits. This point estimate is remarkably similar to the point estimate of -4.75% in the comparable specification shown in Table 3, Column (4), with individual fixed effects. This further suggests that bank-specific individual demand factors are less likely to influence our results, and individual fixed effects seem to adequately control for confounding demand-related factors in our setting. Similarly, for the credit card balance regressions, the point estimates in Columns (2) and (3) of Table 6, Panel B, are similar to the point estimates with comparable specifications shown in Table 4, Columns (4) and (5), with individual fixed effects.

In Table 6, Panel C, we mitigate the concern that our results might still be demand driven due to household balance sheet effects in the post-2008 period after the housing market crash. Mian et al.

[15] The change in credit limit for the new supply measure for an individual i's credit card c is given by the log difference: $\Delta CreditLimit_{i,-c,b} = Log\left(\sum_{c\neq j} CreditLimit_{i,j,b}^{post-shock}\right) - Log\left(\sum_{c\neq j} CreditLimit_{i,j,b}^{pre-shock}\right)$.

(2013) show that areas with greater house price declines and more levered households reduced their consumption more in the post-2008 period. Their results highlight the role of negative housing-wealth shocks and debt overhang in reducing household consumption (see also Pistaferri, 2016). Thus, our results might be confounded by the household balance sheet effect if homeowners are more likely to borrow from banks that have a greater dependence on short-term wholesale funding. To address this concern, we re-estimate the model in Table 4, Column (5), by splitting the sample based on whether an individual owns a home. Table 6, Panel C, shows that the point estimates for homeowners and non-homeowners are similar, suggesting that our results are less likely to be confounded by the household balance sheet channel.

4.1.5 Are the results driven by other differences across banks?

A potential concern is that our results are driven by differences in other characteristics between the high- and low-exposure banks, as opposed to their differential exposure to the short-term wholesale funding shock. For instance, the summary statistics in Table 1 show that banks dependent on wholesale funding were larger banks. It is plausible that larger banks were subject to greater scrutiny and regulation in the post-2008 period, which led them to be more conservative while extending credit. To mitigate such a concern, we classify the banks into large (above median) and small (below median) size groups, and we include the interactions of the size indicator variable with the *Individual* fixed effects in our regression specification (i.e., $Individual \times SizeGroup$ fixed effects). First, these fixed effects control for any differences in the credit extended by smaller and larger banks to consumers in a flexible and nonparametric manner. Moreover, the coefficient of interest, which is associated with *Exposure*, is also identified *within* large and small banks. In other words, if the reduction in credit limits in the post-shock period is in fact driven by differences in bank size, then the $Individual \times SizeGroup$ fixed effects should subsume all the variation in the *Exposure* variable across banks and render its estimated coefficient statistically insignificant.

Table A.2, Column (1), presents the results after including the $Individual \times SizeGroup$ fixed effects. The coefficient associated with *Exposure* in Table A.2, Column (1), is -4.79. This coefficient is practically unchanged when compared to the coefficient of -4.75 in our baseline specification in Table 3, Column (4), with *Individual* fixed effects and the same set of control variables. Thus, our baseline results, which show a reduction in credit limit due to the wholesale funding liquidity shock, are unlikely to be driven by differences in size between the high- and low-exposure banks. Similarly, based on the summary statistics in Table 1, one might argue that the high-exposure banks were riskier because they had lower capital ratios, on average, and they suffered greater losses in the post-shock period as a consequence. Table 1 also shows that high-exposure banks have lower utilization ratios, and they may have sought to reduce their unused credit card commitments in the post-shock period because such commitments are costly to maintain. Table 1 also shows that the high-exposure banks were lending to relatively safer consumers in the pre-shock period. Thus, it is plausible that the high-exposure banks were more risk-averse and consequently reduced credit limits more in the post-shock period.

In order to mitigate the above potential concerns, we follow the same empirical strategy as we did with bank size in Table A.2, Column(1). We classify banks into above-median and below-median groups based on their capital ratios, their unused credit card commitments, and their percentage of subprime consumers. Next, we interact the *Individual* fixed effects with the aforementioned group indicator variables, and include them in our analysis. These results are presented in Table A.2, Columns (2)–(4), and they remain qualitatively unchanged when compared to our baseline specification in Table 3, Column (4). Overall, our results are robust to controlling for the potential differences in bank characteristics that could drive our results.

We also show that our results are not driven by any particular bank. We re-estimate the baseline regression specification shown in Table 3, Column (4), by excluding one bank from the analysis each time and estimating the regression on the sample consisting of the remaining 17 banks. Consequently, there are 18 such regressions, and we plot the 18 estimated coefficients of interest associated with $Exposure$, along with their standard errors, in Figure 8. As can be seen, the estimated coefficients are significantly negative and relatively stable across all the 18 specifications, which indicates that our results are not driven by any particular bank.

[Figure 8 here]

4.1.6 Other robustness tests

Table A.3 shows that our baseline results in Table 3 are robust to using alternate measures of bank exposure and using different levels of clustering. We use short-term wholesale funding as a fraction of total assets as an alternate measure for bank exposure in Columns (2) and (4), and we find that our results are unchanged. Consistent with Figure 2, this suggests that our results capture the variation in the numerator of the bank exposure measure (i.e., a bank's dependence on short-term wholesale funding) as opposed to the denominator. We also cluster the standard errors at the bank level instead of the bank–state level as in Columns (3) and (4), and we find that our results are robust. Although the bank-level cluster is larger and can completely account for within-bank correlations, we cluster at the bank–state level for the rest of the analysis because we have only 18 banks and the standard errors can be biased when there are too few clusters (Angrist and Pischke, 2009; Cameron and Miller, 2015).

So far, our analysis has focused on the effects of the sudden decline in short-term wholesale funding on the credit limits extended on the intensive margin. Next, we estimate the effect of the bank liquidity shock on the extensive margin. Specifically, we test whether banks that were more affected by the shock are less likely to issue new credit cards and more likely to close existing credit card accounts. In Table A.4, Columns (1) and (2), we consider all new credit card accounts that were opened by the banks in our sample in the post-shock period, but did not exist in the pre-shock period. We define an indicator variable $New_{i,c,b}$, which takes the value 1 if a new card c is issued to individual i by bank b in our post-shock period, and takes the value 0 otherwise. Column (1) estimates the OLS regression and shows that a one standard deviation increase in a bank's dependence on short-term wholesale funding reduces its likelihood of issuing new credit cards by 1.97%. In Column (2), we include *Individual* fixed effects to control for individual demand factors that might affect the issuance of credit cards to an individual. The fixed effects estimator in Column (2) is slightly higher and indicates that banks are 2.34% less likely to issue new credit cards in the post-shock period if they had a one standard deviation greater dependence on short-term wholesale funding in the pre-shock period.

Similarly, we define an indicator variable $Closed_{i,c,b}$, which takes the value 1 if a card c issued to individual i by bank b was closed in the post-shock after the sudden decline in short-term wholesale funding, and takes the value 0 otherwise.[16] Columns (3) and (4) present results for the closed credit card accounts. The point estimates with *Individual* fixed effects (Column (4)) and without them (Column (3)) are similar. These results suggests that a bank with one standard deviation greater exposure to the short-term wholesale funding shock was 4.35% more likely to close credit cards in the post-shock period. Overall, our extensive margin results suggest that banks that were more exposed to the short-term wholesale funding shock were more likely to close existing cards and less likely to open new credit cards.

4.2 Individual-level results: Does the funding shock affect ***total*** credit card balances?

So far, we have provided evidence for how negative liquidity shocks to banks transmit through credit limits and result in lower balances on the affected credit card. In this section, we test whether the liquidity shocks to banks that are transmitted through credit limits have an aggregate effect on credit card borrowing and spending by consumers.

If credit card consumers are hedged with respect to their bank's liquidity shocks, then the bank liquidity shocks transmitted through credit limits should not affect consumers' total credit card balances. However, if consumers are constrained, either due to high aggregate credit card utilization ratios or due to high costs of switching from one credit card to another, then the liquidity shocks transmitted from banks can have real consequences by reducing consumers' total credit card balances and consumption through credit cards. Our data allow us to test for the impact of the short-term wholesale funding shock on total credit card balances, because we can observe balances and credit

[16] Creditors can close a credit card account with no advance notice if (a) the card is inactive, (b) the creditor no longer offers the same terms on the credit card, or (c) the borrower has defaulted. Creditors can also close credit card accounts for undisclosed reasons (see https://blog.equifax.com/credit/credit-tips-what-to-do-when-an-issuer-closes-your-credit-card/)

limits on all the credit cards of a consumer in our pre- and post-shock period. Therefore, we aggregate the credit limits and credit balances for all the credit cards at the consumer level for the pre- and post-shock period, then we take the log-difference to construct the change in total credit card limits and balances from the pre- to the post-shock period.

Next, we construct a weighted average exposure measure at the consumer level called *Weighted Exposure*, which measures the exposure of a consumer to the funding shock through their credit limits. *Weighted Exposure* is constructed by weighting the bank's exposure variable (i.e., the ratio of short-term wholesale funding to deposits) associated with a credit card by its credit limit as a proportion of the consumer's total credit limit. For the credit card–issuing banks that are not among the 18 banks in our sample, we assume that their exposure to the short-term wholesale funding (and thus their exposure to the liquidity shock) is zero. If we rely on this assumption, we could misclassify some banks as unexposed banks when in fact they experienced a liquidity shock due to the contraction of short-term wholesale funding. As a result, some individuals would be misclassified as unexposed or low-exposure individuals when they are actually high-exposure individuals. However, such a misclassification will only underestimate any effect on the change in aggregate credit card limits and spending.[17]

Table 7 presents results for the impact of the short-term wholesale funding shock on total credit card balances. The coefficient associated with the *Weighted Exposure* variable in Column (1) captures the aggregate effect of the funding shock on total credit card balances. If credit card consumers are hedged with respect to their bank's liquidity shocks, then the coefficient associated with the *Weighted Exposure* should be close to zero and statistically insignificant.

It is also important to note that in Table 7, we do not control for *Individual* fixed effects because our unit of observation is at the individual level rather than at the credit card level. As a consequence, our results in Table 7 rely on a stronger identification assumption that credit demand and supply

[17]This underestimation occurs for two reasons. First, the changes in credit limits and balances for the low-exposure individuals will be biased downwards. This should be the case, because our prior "within" individual credit card–level analysis, which was confined to the set of 18 banks that had a nonzero exposure to the short-term wholesale funding shock, shows that a high exposure to the liquidity shock negatively affects credit limits and balances. Second, the coefficient on the weighted average exposure measure captures the change in aggregate credit limits and balances for the high-exposure individuals relative to the low-exposure individuals.

factors are uncorrelated. However, our credit card–level analysis shows that it is less likely that credit demand factors confound our analysis, because the coefficient associated with the exposure variable is similar with or without the addition of *Individual* fixed effects (see Table 4), and this coefficient also remains unchanged when we construct a leave-out mean credit supply measure for a credit card account by excluding that credit card's credit limit (see Table 6).

In any case, to control for unobserved confounding factors, we include the 5-digit ZIP code fixed effects and controls for the individual's credit quality, such as the individual's pre-shock credit score, debt-to-income ratio, credit card utilization, credit card and mortgage balances, and the number of credit-related accounts. The ZIP code fixed effects allow us to compare the changes in credit limits and balances for two individuals *within* the same ZIP code. As a result, we can control for any common shocks at the ZIP code level (e.g., changes in unemployment, house prices) that can affect an individual's total credit card balance.

[Table 7 here]

Table 7, Column (1) and Column (2), show that a one standard deviation increase in the weighted exposure measure reduces an individual's total credit limit by 3.83% and the individual's total credit card balance by 1.22% . Column (3) shows the OLS regression of the change in total credit balance on the change in total credit limit. The result in Column (3) indicates that a 1% reduction in total credit limits leads to a 0.86% reduction in total credit card balances. Table 7, Column (4), estimates the IV regression for the total credit balance changes on the total credit limit changes by instrumenting the total credit limit by the weighted exposure variable. The point estimates in Column (4) indicate that a 1% reduction in total credit limits leads to a 0.32% reduction in total credit card balances. This estimate is smaller than the IV estimates in Table 4, Column (5), which suggests that the effect of transmitted bank shock is smaller at the consumer level. However, the estimate in Column (5) is economically significant and thus suggests that the consumers were not able to completely hedge away the short-term wholesale funding shock.

5 Heterogeneity of the funding shock: Are all consumers equally affected?

5.1 Credit card–level limits

In this section, we examine whether banks transmit their funding shocks equally across all consumers. The cost of extending credit may vary significantly in the cross-section due to information issues such as moral hazard and adverse selection (Agarwal et al., 2017). For instance, the marginal cost of extending credit should be higher for those individuals who are more likely to borrow out of it and then default.[18] Table 8 examines the heterogeneous effect of the short-term wholesale funding shock on credit limits across credit cards. In Panel A, we explore the cross-sectional cuts across credit cards that have different utilization ratios, because the marginal cost of extending credit to such consumers should be higher, since they are more likely to borrow on it. We group the credit cards in our sample into three groups based on their pre-shock utilization ratios: *low* ($\leq$ 50%), *high* (50–90%), and *very high* (> 90%). Table 8 examines the heterogeneous effect of the short-term wholesale funding shock on credit limits across credit cards. In Panel A, we explore the cross-sectional cuts across credit cards that have different utilization ratios, because the marginal cost of extending credit to such consumers should be higher, since they are more likely to borrow on it. We group the credit cards in our sample into three groups based on their pre-shock utilization ratios: *low* ($\leq$ 50%), *high* (50–90%), and *very high* (> 90%). The results in Table 8, Panel A, show that a one standard deviation increase in a bank's exposure to the wholesale funding shock reduces credit card limits by 4.30% and 6.59% more for the high- and very high-utilization ratio credit cards, respectively, relative to the low-utilization credit cards. Overall, the results in Table 8, Panel A, suggest that banks transmitted the short-term wholesale funding shock disproportionately more to credit cards with a higher utilization ratio.

In Table 8, Panels B, we perform cross-sectional cuts at the individual-level utilization ratio, which is computed as the ratio of an individual's total credit balance to the individual's total credit

[18] For example, higher debt levels for consumers can cause higher defaults, because either (a) higher debt levels increase a consumer's sensitivity to liquidity shocks, (b) the consumer has an incentive to default strategically (i.e., moral hazard), or (c) consumers overborrow and default due to behavioral biases.

limit. The results Panel B are similar, but stronger when compared Table 8, Panel A. For instance, the results in Panel B indicate that a one standard deviation increase in a bank's exposure to the wholesale funding shock reduces credit card limits by 8.19% more for consumers with a total utilization ratio of greater than 90% relative to the consumer with a total utilization ratio of less than 50%. In Table 8, Panel C, we find similar results when we conduct cross-sectional cuts on the credit scores of consumers. Banks pass on their liquidity shocks to a greater extent to the subprime consumers (FICO <620) than the prime consumers (FICO>680).

[Table 8 here]

5.2 Credit card–level balances

Next, we examine the heterogeneous effect of credit limit cuts on credit balances across individuals in Table 9, Panel A, at the credit card level. Consumers can substitute their affected credit cards (i.e., cards with a credit limit cut) for other credit cards or other sources of credit (e.g., personal loans, home equity line of credit). However, the ability to substitute away from an affected card can vary across individuals. For instance, consumers with a high total credit card utilization across all their cards should be less able to substitute away from their affected credit cards to their other credit cards. As a result, for such individuals, a credit limit cut on their affected cards should have a smaller effect on the credit balance on that card.

[Table 9 here]

In Table 9, Panel A, we re-estimate our instrumented specification from Equation 2 by splitting our sample based on how easily a consumer can substitute away from an affected credit card. Table 9, Panel A, shows that the relation between changes in credit limits and changes in credit balances at the credit card level is positive and stronger for individuals with lower aggregate utilization. For instance, consumers with a low aggregate credit card utilization ratio (0–50%) reduce their balances on affected credit cards by 2.65% for a 1% reduction in the credit limit on that card. However, consumers with a higher aggregate credit card utilization appear to be unable to reduce their spending in response to a credit limit cut. We also split our sample based on a consumer's creditworthiness (measured by the FICO score), which proxies for the consumer's ability to switch from the affected credit card to other credit cards. Consistent with the results for aggregate utilization, the elasticity of credit balances to credit limits at the credit card level increases with the creditworthiness of the consumer.

5.3 Individual-level total credit card balances

Table 7 shows the average impact of the short-term wholesale funding shock on total credit card balances. However, as discussed previously, the impact of the funding shock should be greater for consumers who are more constrained and cannot costlessly substitute away from an affected bank's credit card. For instance, the transmission of the funding shock should have a greater impact on the total credit card balances of individuals who have higher aggregate credit card utilization. Thus, for such consumers, in contrast to the credit card–level analysis, a greater cut in their total credit card limits should also lead to a greater reduction in their total credit card balances—i.e., we should expect a positive relation between total credit limit changes and total balance changes at the consumer level for consumers who *cannot* easily substitute away from their affected credit cards. In Table 9, Panel B, we study the heterogeneous response of the total credit card balances to changes in total credit limits due to the transmission of the short-term wholesale funding shock by splitting the sample based on the aforementioned factors similar to Table 9, Panel A.

Consistent with our expectation, Columns (1)–(3) show that the relation between total credit limit changes and total credit balance changes at the consumer level monotonically increases with the aggregate utilization ratio. For instance, consumers with a low aggregate utilization ratio (0–50%) do not change their total credit card balances despite experiencing credit limit cuts due to the transmission of the short-term wholesale funding liquidity shock from their credit card–issuing bank. That is, consumers with lower aggregate credit card utilization ratios are hedged from bank liquidity shocks. However, for consumers with high aggregate utilization ratios ($> 90\%$), a 1% cut in total credit limits resulting from the transmission of the bank liquidity shock leads to an equivalent 1.33% reduction in total credit card balances.

In Columns (4)–(6), we split our sample based on a consumer's creditworthiness and her ability to access other less affected or unaffected credit cards proxied by her credit score. Consistent with the results for the sample split on aggregate credit utilization, we find that the elasticity of total credit balances to total credit limits at the consumer level monotonically decreases with the creditworthiness of the consumer. While prime borrowers' credit card balances are unaffected by the transmitted funding shocks, subprime borrowers reduce their total credit card balances by 1.48% for every 1% reduction in total credit limits.

5.4 Individual-level total debt balances

Section 5.3 indicates that the liquidity shocks to banks that are transmitted through credit card limits have an effect on the total credit card balances of consumers. This effect is more pronounced for credit-constrained consumers who have higher credit card utilization ratios or lower credit scores. In this section, we examine whether consumers seek other sources of credit to finance their consumption and offset their credit limit cuts. If so, who is able to hedge away the liquidity shocks transmitted through credit card limits by substituting to other sources of credit? We answer these questions by studying the change in total debt balances aggregated over all credit accounts for an individual. For instance, the total debt balance for an individual includes debt balances for home equity line of credit (HELOC) and personal installment loans, which are likely substitutes for credit card debt. We use the individual-level change in total debt balances as our dependent variable and conduct a similar IV analysis as in Table 9, Panel B.

Table 9, Panel C, reports the results. Column (1) shows that consumers with a low aggregate credit card utilization ratio (0–50%) do not exhibit a reduction in total debt balances, even though they experience credit card limit cuts due to the funding shock. However, Column (3), which analyzes the high aggregate credit card utilization ratio ($> 90\%$) consumers, indicates that a 1% reduction in total credit card limit resulting from the transmission of the funding shock leads to a 0.20% reduction in total debt balances. We find similar results when splitting the sample based on credit scores in Columns (4)–(6). Subprime consumers have a 0.6% reduction in total debt balances for a

1% reduction in total credit card limits, while near-prime and prime consumers do not exhibit any reduction in their total debt balances in response to the short-term wholesale funding shock induced credit limit cuts.

Overall, these results show that the elasticity of total debt balances decreases in consumers' ability to hedge. Our results on total debt balances show that some individuals, such as consumers with higher utilization ratios or lower credit scores, were not able to hedge away the wholesale funding shock to their banks. As a result, these consumers were forced to reduce their aggregate borrowing, which lowers their ability to smooth consumption.

There is an important caveat for the exclusion restriction of the IV analysis in the total debt balance regressions in Table 9, Panel C. The IV's exclusion restriction may be violated if the short-term wholesale funding liquidity shock to banks also affects the credit supply of other types of consumer credit. That is, if consumers also borrow other types of credit from their credit card lenders, then the bank liquidity shock may be transmitted to the consumers' total debt balances through other types of credit in addition to credit card limits. However, this concern is somewhat mitigated since we use credit card limits as weights to compute our weighted exposure. Regardless, we present the reduced form analysis for Table 9, Panel C in Table A.5 where we regress the total debt balance change on our weighted exposure measure directly. The main takeaways from Table A.5 are unchanged as Table A.5 again shows that the high aggregate utilization ratio consumers and the subprime consumers could not hedge away from their banks' wholesale funding liquidity shock.

6 Long run effect of funding shock

Figure 9 plots the average credit limits extended by the high- and low-exposure banks relative to the pre-shock period. The average credit limits are computed by averaging the total credit limits extended by banks to all consumers across the high exposure (above median) and the low exposure (below median) bank groups. The figure shows that, relative to pre-shock levels, the aggregate credit limits extended by the high-exposure banks reduced more than the low-exposure banks in the first two years after the short-term wholesale funding liquidity shock. This trend is consistent with the high-exposure banks facing greater liquidity constraints than the low-exposure banks due to their greater exposure to the short-term wholesale funding liquidity shock. After the first two years, the aggregate credit limits extended by both types of banks recover close to their pre-shock levels within 10 years after the wholesale funding shock.

[Figure 9 here]

Figure 10 plots the long-run effect of the funding shock on total credit card balances for the subprime, near-prime, and prime individuals. The coefficients in the plot are the elasticities estimated using the specifications in Columns (4)–(6) in Table 9, Panel B, for each category of borrower quality over time. We plot the negative elasticites (as opposed to elasticities) for the ease of interpreting the coefficients as the change in total credit card balances for a 1% reduction in the total credit limits induced by the short-term wholesale funding shock. For each period, the changes in total credit limits and total credit balances for each individual are computed relative to their pre-shock period values. Figure 10 shows a striking result — the effect of the short-term wholesale funding shock was persistent for the subprime and the near-prime consumers. That is the credit balances for the more-exposed subprime and near-prime consumers were lower than the less-exposed subprime and near-prime consumers even in the long run. However, Figure 10 shows that the effect of the transmitted bank funding shock gradually dissipated over time for the prime consumers. Our results suggest that either financing frictions for lower-quality borrowers are binding for a very long time, or that the transmitted funding shock can itself weaken a borrower's fundamentals, thereby limiting her access to credit in the future.

[Figure 10 here]

7 Conclusion

In this paper, we show that liquidity shocks to banks can transmit to consumers with significant distributional consequences. We use micro data on credit limits (banks' credit supply) and credit balances (consumers' demand) for the near universe of 500 million credit cards issued to 134 million consumers to show how the dry-up of the short-term wholesale funding for banks transmitted to consumers through credit cards. We document a new channel – namely, credit card limits, through which banks transmitted their short-term wholesale funding liquidity shocks to their consumers and affected their consumption through credit cards.

We document significant heterogeneity in how banks transmit their liquidity shocks to consumers through credit card limits. In general, banks passed on their liquidity shock to a greater extent to credit-constrained consumers (e.g., consumers with lower credit scores and higher credit card utilization). As credit-constrained consumers generally face greater credit market frictions, they were unable to hedge away from the transmitted bank liquidity shocks and were forced to reduce their consumption. Our results show that when banks face liquidity shocks, they are more likely to pass on these shocks to those consumers who are least able to cope with them. Consequently, our results show *who* bears the real costs of fragile bank funding structures.

Our results also contribute to the debate on post-crisis regulatory reform on banks' funding structures that have become heavily reliant on wholesale funding. Our analysis provides estimates for the elasticities of consumer-level credit limits and credit balances to wholesale funding across different consumer groups, such as prime, subprime, and near-prime consumer groups. Thus, by providing these elasticities, our results enrich the debate on the distributional effects of banks' funding fragility on consumers.

Overall, our results contribute to the literature on how banks pass on credit expansions and contractions *across* consumers. We show that banks are more likely to pass on credit contractions to credit constrained consumers. This result complements previous studies that show that banks are less likely to pass on credit expansions to credit constrained consumers (Agarwal et al., 2017). Together, these findings imply that credit-constrained consumers enjoy less of the gains in the boom period and suffer more of the costs in the bust period. Thus, we shed light on who are the winners and loser in a credit boom-bust cycle.

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Figure 1: Aggregate changes in credit limits and credit balances

The figure presents the aggregate trend in credit limits and credit balances over time. Our data are available at a semiannual frequency from 2007–2010 from one of the three major credit bureaus in the U.S. The solid blue line represents the trend in aggregate credit limits over time. The dashed red line represents the trend in aggregate credit balances over time. The dashed vertical black line represents July 2008, which demarcates the pre- and post-shock period in our analysis. While both aggregate credit limits and balances decline in the post-shock period, the changes in aggregate credit balances seem to follow changes in credit limits.

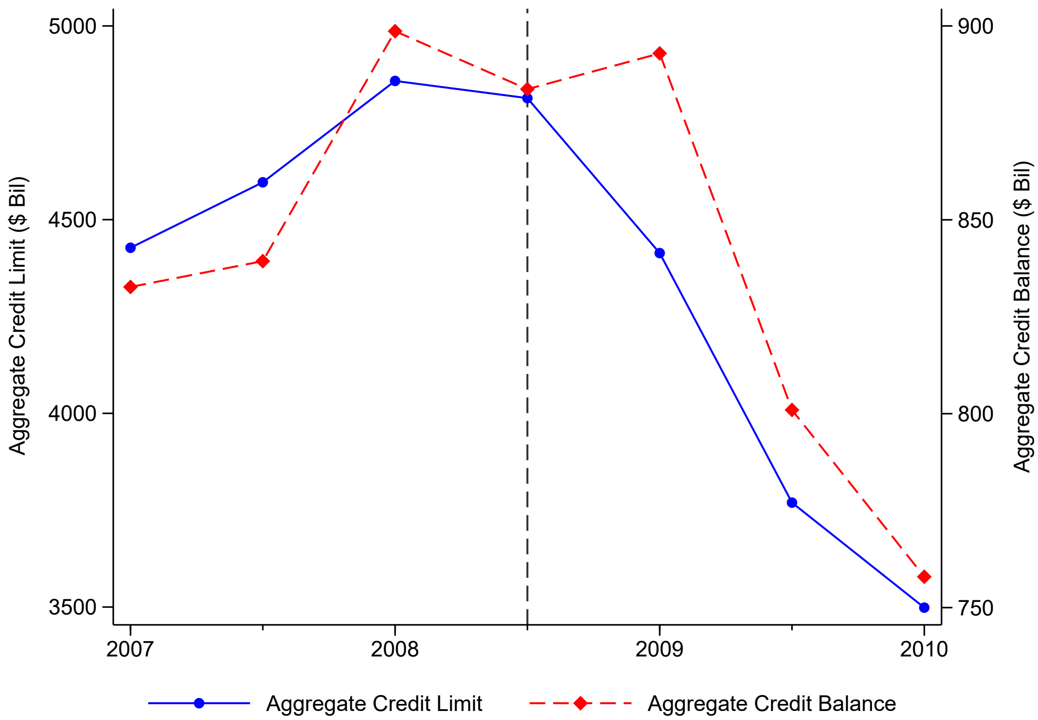
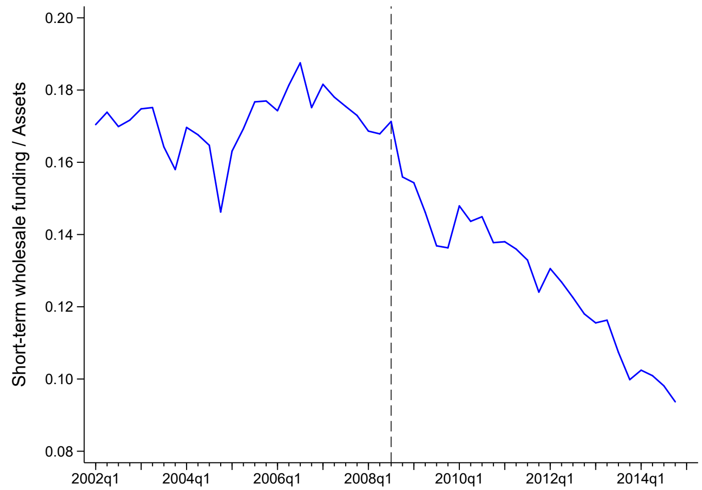


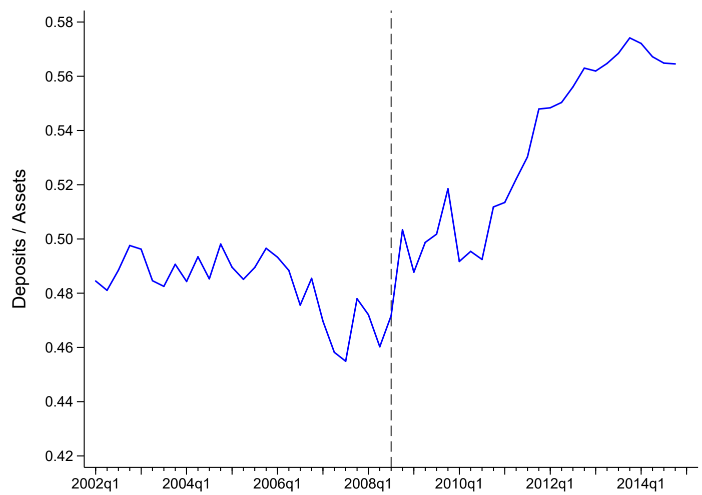
Figure 2: Bank funding measures over time

The figure presents the trend of the various sources of funding as a proportion of assets for the banks in our sample over time. These data are gathered from the quarterly Y-9C filings of U.S. bank holding companies (BHCs).

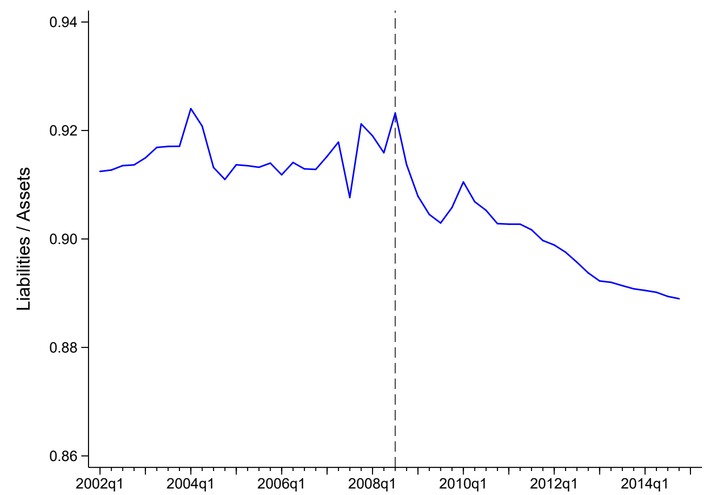


(a) *Short-term wholesale funding*

(b) *Wholesale funding*



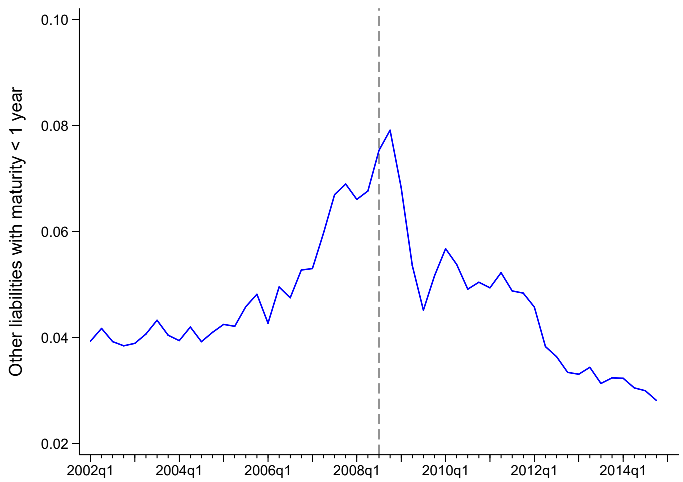
(c) *Deposits*



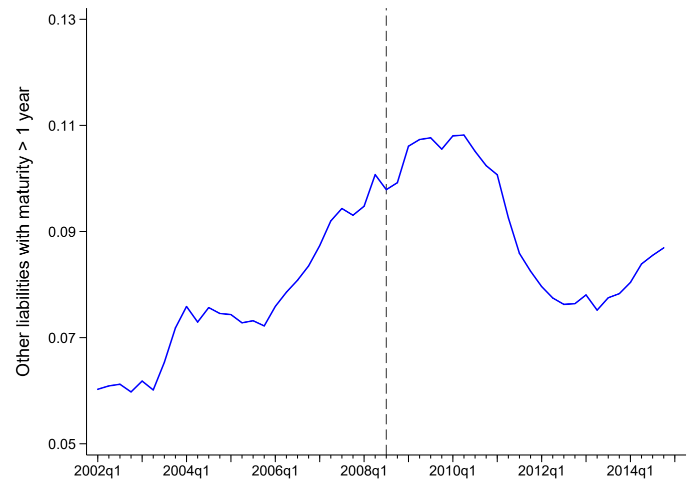
(d) *Total liabilities*

Figure 3: Components of wholesale funding over time

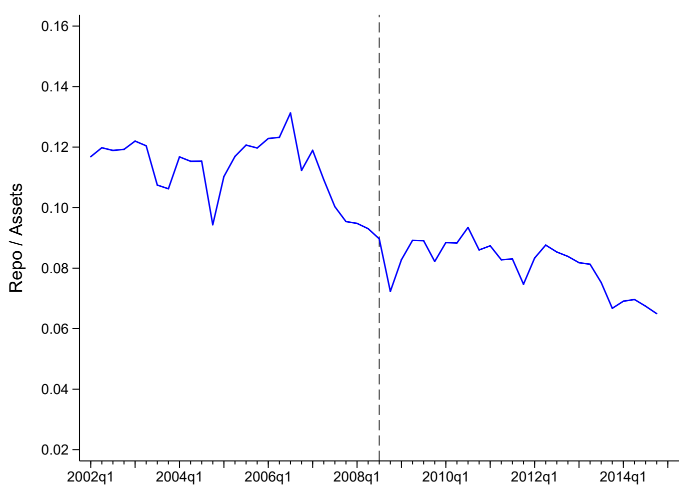
The figure presents the trend of the various components of wholesale funding as a proportion of assets for the banks in our sample over time. These data are gathered from the quarterly Y-9C filings of U.S. BHCs.



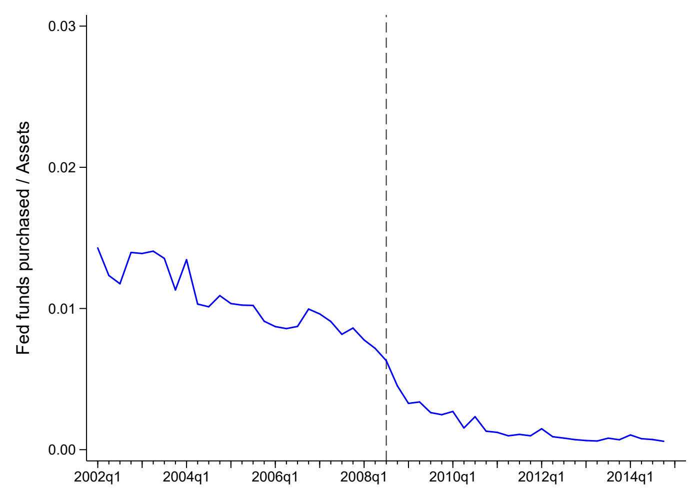
(a) *Liabilities with maturity < 1 year*



(b) *Liabilities with maturity > 1 year*



(c) *Repos*



(d) *Fed funds purchased*

Figure 4: Exposure measure over time

The figure presents the time trend of our main independent variable of interest, *Exposure*, which is defined as the ratio of a bank's short-term wholesale funding to its total deposits. The figure is plotted by averaging the *Exposure* variable across the banks in our sample in each quarter. The data for the plot below are gathered from the quarterly Y-9C filings of U.S. BHCs.

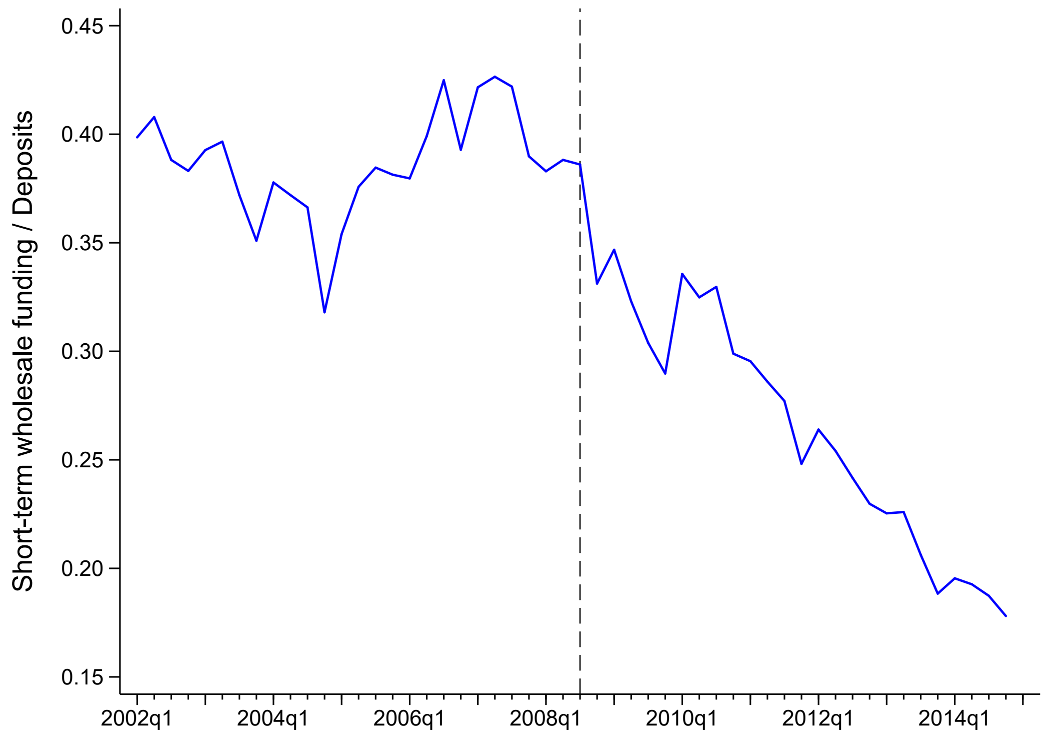


Figure 5: Bank exposure and change in credit card loans

The figure plots the change in credit card loans from the pre-shock to the post-shock period as a function of our main independent variable of interest, *Exposure*, which is defined as the ratio of a bank's short-term wholesale funding to its total deposits. However, before plotting, we partial out (orthogonalize) *Exposure* and the log-change in credit card loans with respect to the log of total bank assets to account for the fact that larger banks, in general, have a greater dependence on wholesale funding (see Table 1). The pre-shock period ranges from 2006Q1 to 2007Q4, and the post-shock period ranges from 2009Q1 to 2010Q4. The points on the graph are plotted proportional to bank size as measured by the average total assets in the pre-shock period. The data for the plot below are gathered from the quarterly Y-9C filings of U.S. BHCs.

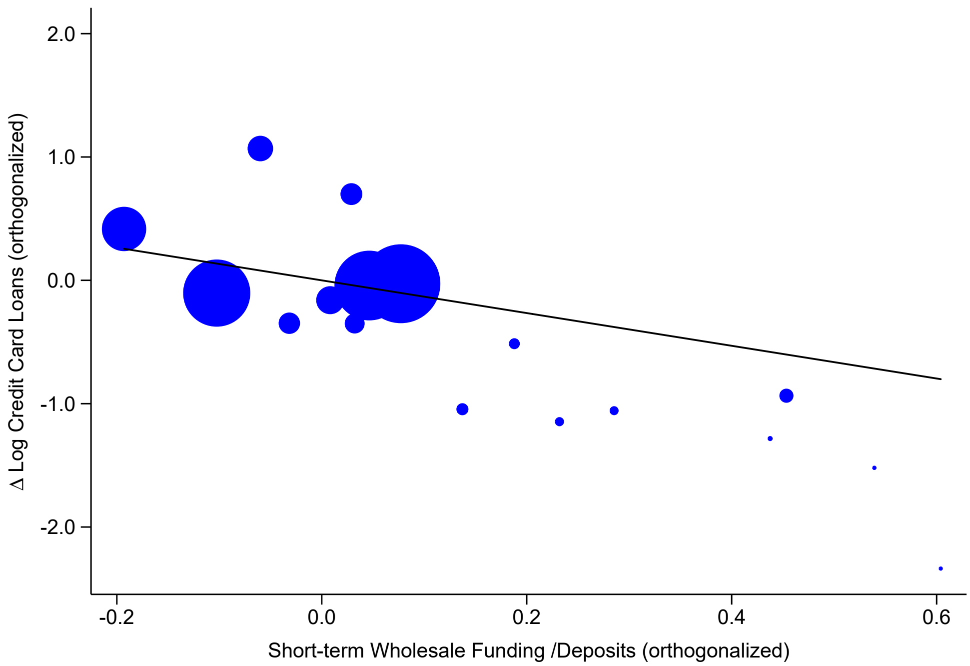
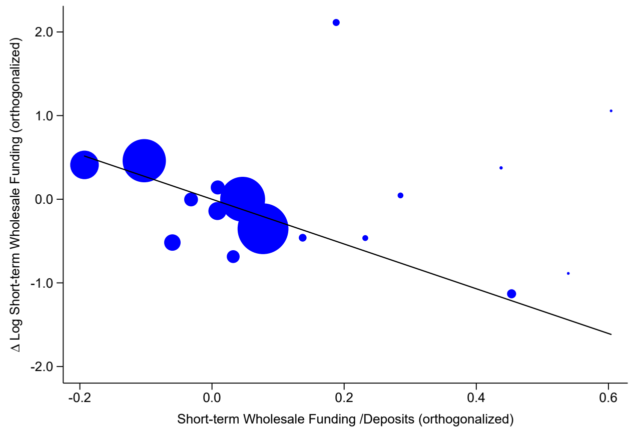
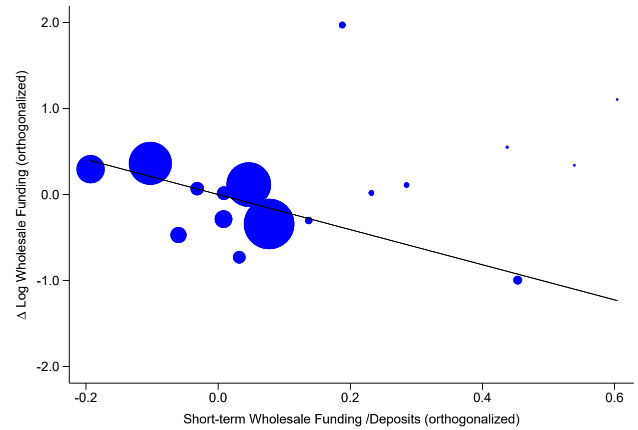


Figure 6: Bank exposure and change in bank funding

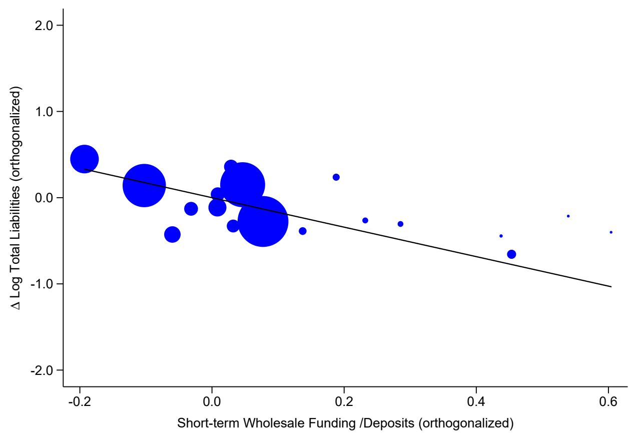
The figure plots the change in bank funding measures from the pre-shock to the post-shock period as a function of our main independent variable of interest, *Exposure*, which is defined as the ratio of a bank's short-term wholesale funding to its total deposits. However, before plotting, we partial out (orthogonalize) *Exposure* and bank funding measures with respect to bank assets to account for the fact that larger banks, in general, have a greater dependence on wholesale funding (see Table 1). The pre-shock period ranges from 2006Q1 to 2007Q4, and the post-shock period ranges from 2009Q1 to 2010Q4. The points on the graph are plotted proportional to bank size as measured by the average total assets in the pre-shock period. The data for the plot below are gathered from the quarterly Y-9C filings of U.S. BHCs.



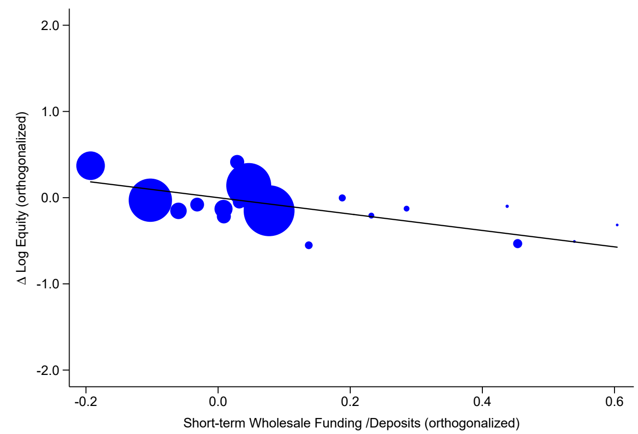
(a) Δ*Short-term wholesale funding*



(b) Δ*Wholesale funding*



(c) Δ*Total Liabilities*



(d) Δ*Equity capital*

Figure 7: Credit limits extended *within*-individual over time

The figure plots the mean credit limit deviations computed "within" individual for the low- and high-exposure banks over time. For each individual in every semiannual archive, we compute the deviation of each credit card's credit limit from the individual's mean credit limit in that archive. Next, we sort the deviations into two groups based on whether the individual's credit card was issued by a high- or a low-exposure bank. Banks are classified as low- and high-exposure banks within each individual based on the mean exposure computed at the individual level. The figure plots the mean of the deviations computed across all credit cards in each semiannual archive for the low- and high-exposure banks separately. Our data sample is gathered from one of the three major credit bureaus in the U.S. and ranges from 2007–2010 at a semiannual frequency.

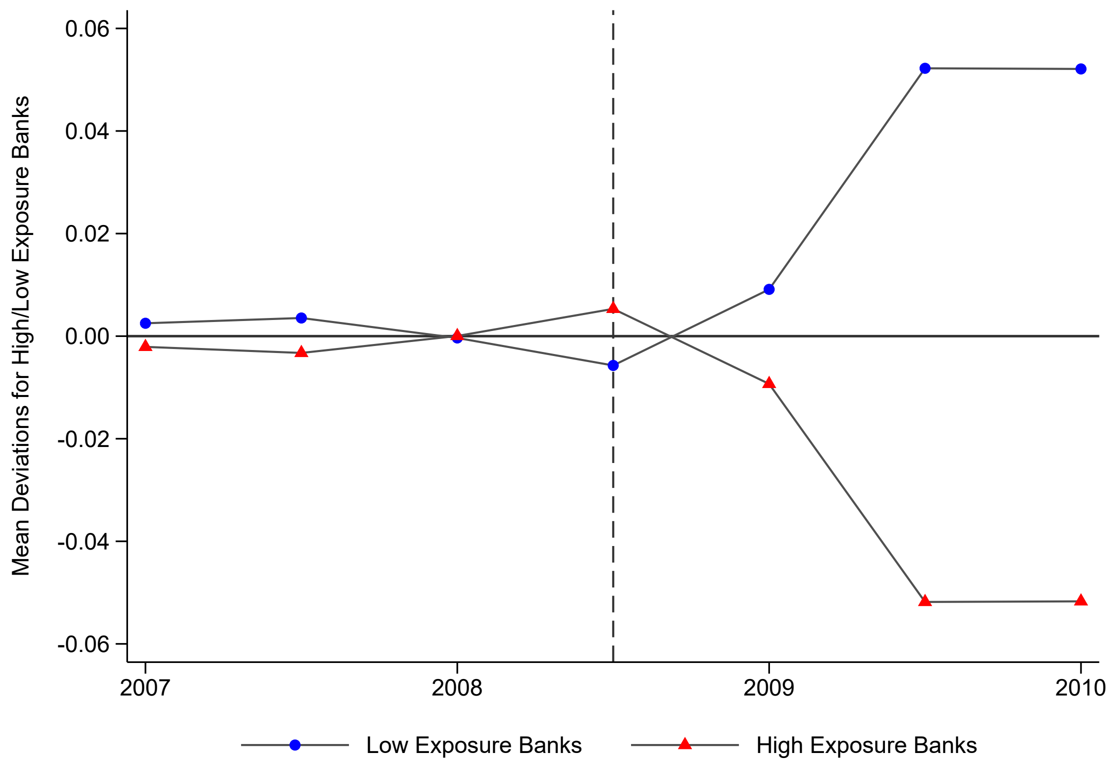


Figure 8: Estimation excluding each bank

This figure shows the coefficient β associated with our variable of interest, *Exposure*, from Equation 1 estimated by excluding each BHC from our sample to address the potential concern that a particular BHC might be driving our results. *Exposure* is defined as the ratio of a bank's short-term wholesale funding to its total deposits. The circles in the plot represent the coefficient estimate β associated with the *Exposure* variable from estimating Equation 1 after excluding the bank shown below the plotted point on the x-axis. The solid vertical lines represent the 95% confidence intervals for the estimated coefficients. The point estimates are ordered based on bank size. Thus, "Bank 1" represents the coefficient estimate after removing the largest bank in our sample, and "Bank 18" represents the coefficient estimate after removing the smallest bank in our sample.

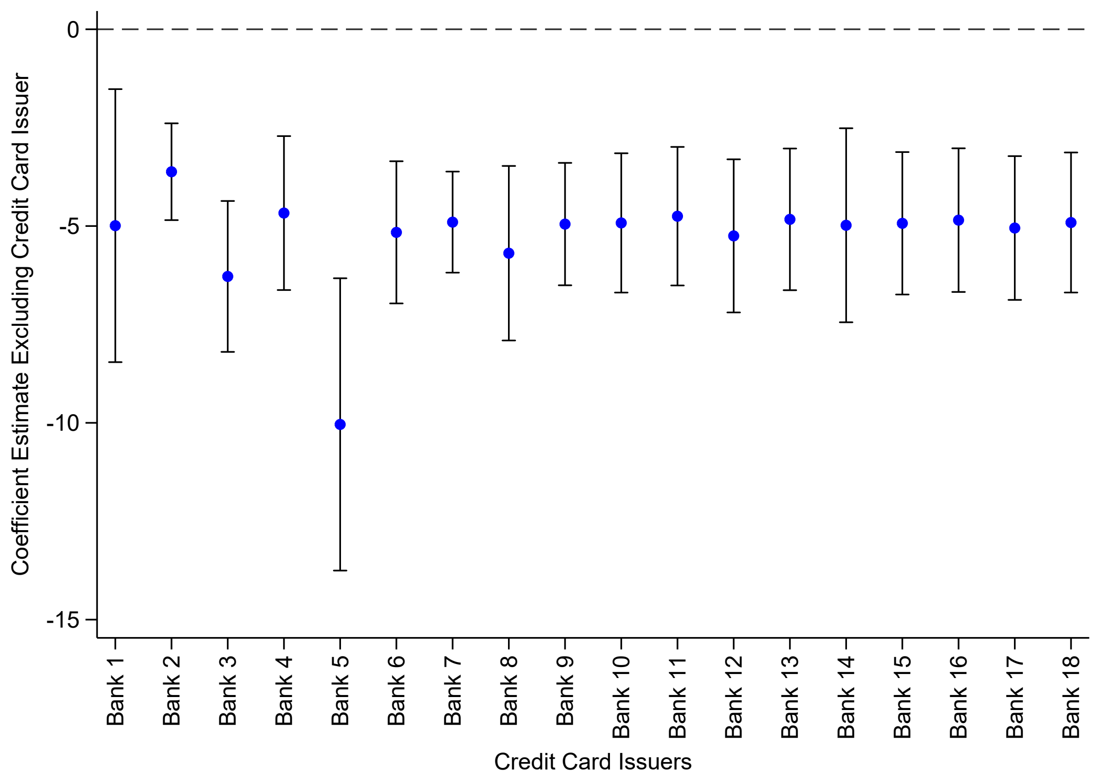


Figure 9: Long-run effect of the funding shock on aggregate credit supply

This figure plots the average credit limits extended by the high- and low-exposure banks relative to the pre-shock period. The average credit limits are computed by averaging the total credit limits extended by banks to all consumers across the high exposure (above median) and the low exposure (below median) bank groups.

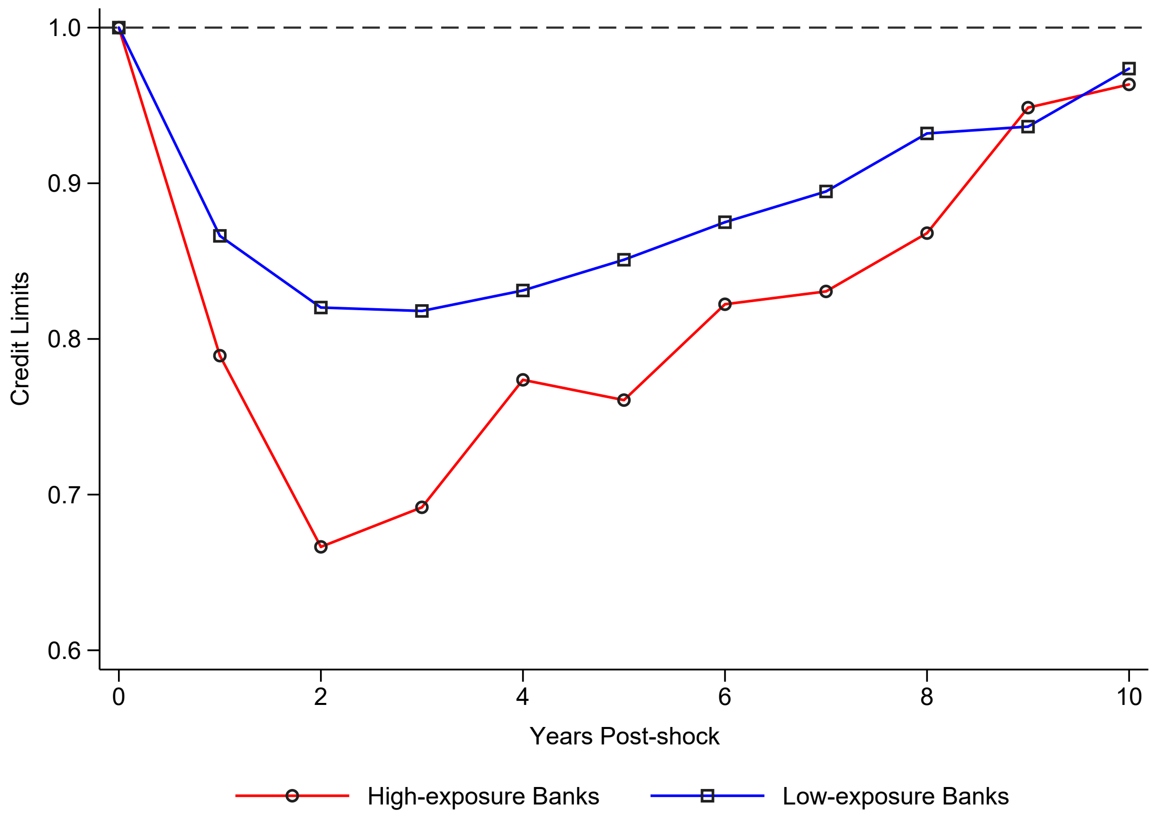


Figure 10: Long-run effect of the funding shock on total credit card balances

This figure plots the negative elasticities of total credit card balances to total credit card limits for subsamples of individuals with subprime (< 620), near-prime (≥ 620 and < 680), and prime (≥ 680) credit scores. To obtain these elasticities, total credit card limits are instrumented by the individual's pre-shock weighted exposure to the short-term wholesale funding shock using the specification in Table 7, Column (4). The regressions are estimated at the individual level. An individual's weighted exposure is computed by aggregating the weighted *Exposure* measure at the credit card level, where the weights assigned to a credit card are proportional to its credit limit. The points represent coefficient estimates, and the dashed vertical lines represent the 95% confidence intervals for the estimated coefficients.

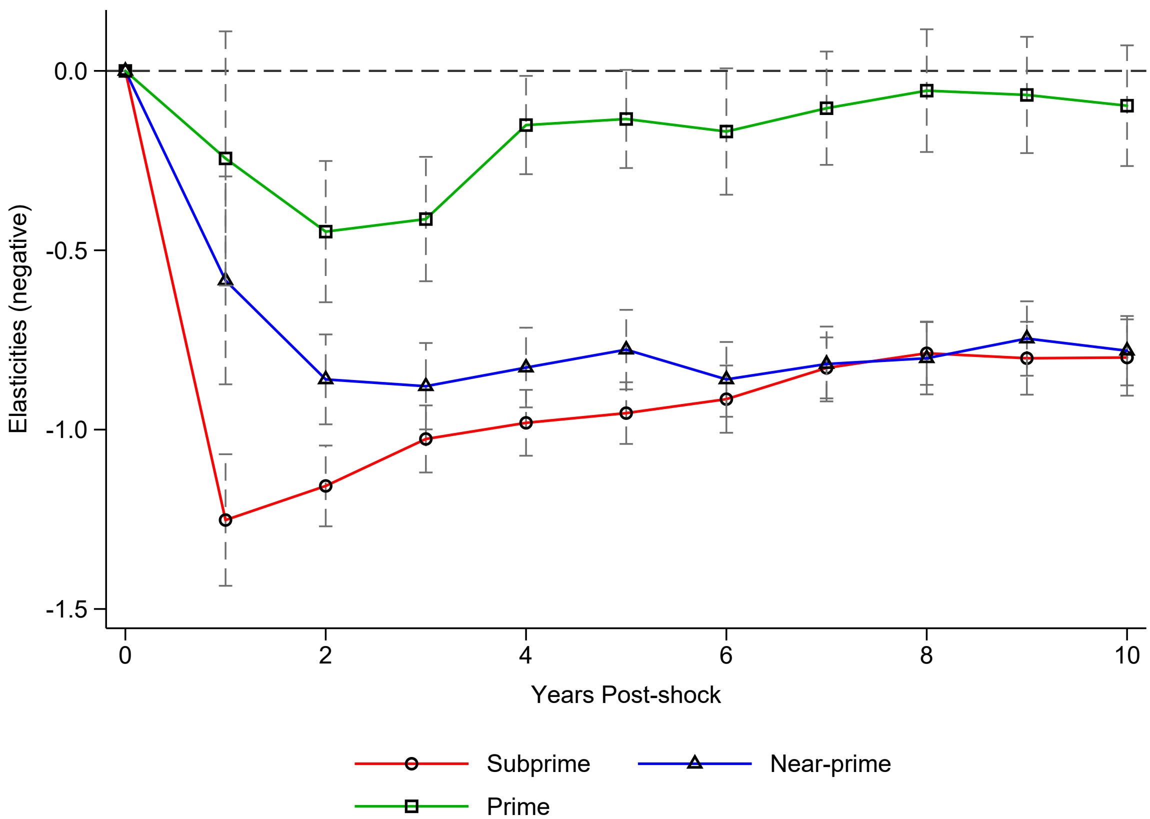


Table 1: Balancing of covariates

This table presents the summary statistics at the credit card–issuing bank level. Panel A uses quarterly BHC Y-9C and Call report regulatory filings data in the pre-shock period. The pre-shock period for regulatory filing data ranges from 2006Q1 to 2007Q4. Panel B uses credit bureau data in the pre-shock period. The pre-shock period for credit bureau data consists of three semiannual archives namely, January 2007, July 2007, and January 2008. The data are first collapsed to obtain a single bank-level cross-section in the pre-shock period by averaging across time. Next, the statistics reported in the table are obtained by dividing the cross-section based on high (above median) and low (below median) dependence on short-term wholesale funding in the pre-shock period. The dependence on short-term wholesale funding is measured as the ratio of short-term wholesale funding to total deposits. The variables in Panel A are reported as a fraction of total assets unless otherwise specified. The table reports means and medians. Medians are reported in square brackets. Column (3) reports the difference in means. The significance for the statistical test that tests the equality of means are reported using *, **, and ***, which indicate a significance greater than 10%, 5%, and 1%, respectively.

Panel A: Quarterly BHC Y-9C and Call report regulatory filing data

	Dependence on short-term wholesale funding (exposure to shock)		
	High-exposure (1)	Low-exposure (2)	Diff (3)
Wholesale funding			
Short-term wholesale funding/Deposits	0.300	0.101	0.200***
	[0.217]	[0.095]	
Wholesale funding	0.242	0.099	0.143***
	[0.218]	[0.098]	
Fed funds purchased	0.014	0.016	-0.002
	[0.009]	[0.008]	
Repo	0.074	0.026	0.048*
	[0.042]	[0.020]	
Other liabilities maturity $<$ 1 yr	0.060	0.024	0.035***
	[0.059]	[0.018]	
Other liabilities maturity $>$ 1 yr	0.094	0.033	0.061***
	[0.098]	[0.020]	
Other			
Assets (log)	19.599	16.377	3.222***
	[19.213]	[16.555]	
Deposits	0.539	0.662	-0.123*
	[0.555]	[0.713]	
Equity capital	0.096	0.177	-0.081
	[0.092]	[0.098]	
Liquid assets	0.223	0.226	-0.003
	[0.215]	[0.220]	
Business mix			
CC loans	0.041	0.070	-0.029
	[0.038]	[0.029]	
Mortgage loans	0.298	0.379	-0.081
	[0.304]	[0.442]	
C&I loans	0.115	0.100	0.015
	[0.100]	[0.095]	
Performance			
ROE	0.088	0.105	-0.018
	[0.087]	[0.080]	
Non-perf loans	0.007	0.005	0.002
	[0.006]	[0.004]	
Non-perf CC loans/Total CC loans	0.019	0.023	-0.004
	[0.021]	[0.011]	
Risk-based capital ratio	12.140	23.278	-11.139
	[11.605]	[14.221]	

Panel B: Credit bureau data

	Dependence on short-term wholesale funding (exposure to shock)		
	High-exposure	Low-exposure	Diff
	(1)	(2)	(3)
Borrower fundamentals			
Credit score	733.47	729.21	4.26
	[741.75]	[750.89]	
Monthly income ($)	3,897.39	3,868.95	28.44
	[3,985.62]	[3,994.93]	
Debt-to-income ratio (DTI)	33.49	32.55	.94
	[34.65]	[31.95]	
Subprime (%)	10.08	13.71	-3.63
	[8.39]	[5.28]	
Credit card debt			
Credit card accounts	4.49	4.17	.32
	[4.54]	[3.98]	
Credit card balance	6,936	5,743.50	1,192.50**
	[6,634.90]	[6,013.95]	
Credit card utilization	26.61	28.96	-2.36
	[23.90]	[21.74]	
Credit card delinquincy	0.75	0.86	-0.11
	[0.54]	[0.42]	
Other debt			
Total-debt related accounts	10.58	9.87	0.71
	[10.55]	[9.97]	
Mortgage balance ($)	191,283.39	170,178.43	21,104.96*
	[198,673.86]	[163,028.70]	
Auto balance ($)	16,732.41	17,077.06	-344.65
	[16,806.57]	[16,840.96]	

Table 2: Bank-level aggregate evidence

This table shows the relation between the pre-shock dependence on short-term wholesale funding, the change in bank funding, and the total credit card loans. The pre-shock period ranges from 2006Q1 to 2007Q4, and the post-shock period ranges from 2009Q1 to 2010Q4. Bank-level variables are obtained from the quarterly BHC Y-9C and Call report regulatory filings. The quarterly data are first collapsed to obtain a single bank-level cross-section separately in the pre-shock and post-shock periods by averaging across time. Then, the change in bank funding and credit card loans is computed by taking the log difference from the post- to the pre-shock period. The dependence on short-term wholesale funding (exposure) is measured as the ratio of short-term wholesale funding to total deposits. *, **, and *** indicate a significance greater than 10%, 5%, and 1%, respectively.

Panel A: Dependence on short-term wholesale funding and change in bank funding

Depvar:	ΔST Wholesale (1)	ΔWholesale (2)	ΔTot Liabilities (3)	ΔTot Equity (4)
Exposure	-0.425***	-0.324***	-0.272***	-0.151
	(-4.03)	(-2.95)	(-3.34)	(-1.75)
Assets (log)	0.946***	0.812***	0.400***	0.283*
	(3.79)	(3.57)	(3.74)	(1.80)
Constant	-0.511**	-0.324	0.148	0.254**
	(-2.39)	(-1.56)	(1.24)	(2.49)
N	18	18	18	18
Adj. R^2	0.469	0.334	0.412	0.181
Orthog-Exposure R^2	0.531	0.412	0.481	0.278

Panel B: Dependence on short-term wholesale funding and change in credit card loans

Depvar: ΔCC Loans	(1)	(2)	(3)
Exposure	-0.211*	-0.197*	-0.210**
	(-1.89)	(-1.81)	(-2.26)
Assets (log)	0.011	-0.032	0.123
	(0.04)	(-0.11)	(0.53)
CC Business (%)		-0.237	-0.251
		(-1.10)	(-1.35)
Non-perf loans (%)			0.261
			(1.61)
Constant	0.764***	0.734***	0.656***
	(3.40)	(3.41)	(3.12)
N	18	18	18
Adj. R^2	0.333	0.324	0.373
Orthog-Exposure R^2		0.411	

Table 3: Effect of funding shock on credit card limits

This table shows the relation between the pre-shock dependence on short-term wholesale funding and the change in credit card limits using the credit bureau data. Both the pre-shock and post-shock periods consist of three semiannual archives. The pre-shock period includes the January 2007, July 2007, and January 2008 semiannual archives, while the three semiannual archives for the post-shock period are January 2009, July 2009, and January 2010. Credit card–level data are first collapsed to obtain a single credit card–level cross-section separately in the pre-shock and post-shock periods by averaging across time. Then, the change in credit card limits is computed by taking the log difference from the post- to the pre-shock period. The dependence on short-term wholesale funding is measured as the ratio of short-term wholesale funding to total deposits. The standard errors are clustered at the bank–state level. *, **, and *** indicate a significance greater than 10%, 5%, and 1%, respectively.

	Individual FE				OLS
Depvar: ΔCC *Limit*	(1)	(2)	(3)	(4)	(5)
Exposure	-3.811***	-6.613***	-5.050***	-4.750***	-4.035***
	(-9.85)	(-16.11)	(-13.32)	(-12.89)	(-8.66)
Bank characteristics					
Assets (log)	-1.353***	-1.068***	-0.362***	-0.359***	-0.519***
	(-17.98)	(-33.86)	(-4.62)	(-4.85)	(-5.95)
Assets^2 (log)	0.035***	0.028***	0.010***	0.010***	0.015***
	(17.99)	(33.40)	(5.00)	(5.22)	(6.39)
Risk-based capital ratio	-0.021***	-0.020***	-0.004*	-0.004**	-0.006***
	(-14.89)	(-23.54)	(-1.74)	(-1.98)	(-2.67)
CC business (%)	-0.001***	-0.002***	-0.002***	-0.001***	-0.001***
	(-9.12)	(-16.88)	(-9.45)	(-9.35)	(-6.19)
Bank performance					
ROE		3.059***	1.351***	1.366***	0.778**
		(11.51)	(4.36)	(4.62)	(2.02)
Non-perf loans (%)		-0.182***	-0.026	-0.020	0.052
		(-5.24)	(-0.85)	(-0.66)	(1.37)
Lending quality					
Avg. credit score			-0.001*	-0.001*	-0.002***
			(-1.86)	(-1.78)	(-3.20)
Avg. DTI			-0.035***	-0.035***	-0.040***
			(-6.17)	(-6.22)	(-5.72)
Avg. CC balance (log)			0.301***	0.283***	0.196***
			(7.51)	(7.10)	(3.99)
Avg. mortgage balance (log)			0.041	0.051	-0.012
			(0.97)	(1.10)	(-0.25)
Credit card controls					
CC utilization				0.002***	0.001***
				(23.57)	(8.07)
Months CC open (log)				-0.006**	-0.016***
				(-2.13)	(-6.18)
Accounts open (log)				0.023***	-0.023***
				(6.94)	(-8.09)
N	158,432,533	158,432,533	158,432,533	158,432,533	158,432,533
Adj. R^2	0.072	0.082	0.084	0.090	0.036

Table 4: Effect of funding shock on credit card balances

The table shows the relation between the pre-shock dependence on short-term wholesale funding and the change in credit card balances at the credit card level. Both the pre-shock and post-shock periods consist of three semiannual archives. The pre-shock period includes the January 2007, July 2007, and January 2008 semiannual archives, while the three semiannual archives for the post-shock period are January 2009, July 2009, and January 2010. Credit card–level data are first collapsed to obtain a single credit card–level cross-section separately in the pre-shock and post-shock periods by averaging across time. Then, the change in credit card balance is computed by taking the log difference from the post- to the pre-shock period. The dependence on short-term wholesale funding (exposure) is measured as the ratio of short-term wholesale funding to total deposits. In Column (5), Δ *CC limit* is instrumented by the *Exposure* variable. The standard errors are clustered at the bank–state level. *, **, and *** indicate a significance greater than 10%, 5%, and 1%, respectively.

Depvar: Δ*CC Balance*	(1)	(2)	(3)	(4)	(5)
Δ CC limit	0.744***	0.854***			
	(46.40)	(25.05)			
Exposure			-3.080	-9.805***	
			(-1.02)	(-4.57)	
Δ CC limit (instrumented)					2.064***
					(4.52)
Individual FE		✓		✓	✓
Bank characteristics	✓	✓	✓	✓	✓
Bank performance	✓	✓	✓	✓	✓
Lending quality	✓	✓	✓	✓	✓
Credit card controls	✓	✓	✓	✓	✓
N	158,432,533	158,432,533	158,432,533	158,432,533	158,432,533
Adj. R^2	0.038	0.164	0.024	0.146	0.128
F-stat (Excl. instru)					97.1

Table 5: Elasticity of credit limits & balances to short-term wholesale funding

This table shows the relation between the change in short-term wholesale funding and the change in credit card limits and credit card balances using the credit bureau data. Both the pre-shock and post-shock periods consist of three semiannual archives. The pre-shock period includes the January 2007, July 2007, and January 2008 semiannual archives, while the three semiannual archives for the post-shock period are January 2009, July 2009, and January 2010. Credit card–level data are first collapsed to obtain a single credit card–level cross-section separately in the pre-shock and post-shock periods by averaging across time. Then, the change in credit card limits and the change in credit card balances is computed by taking the log difference from the post- to the pre-shock period. The standard errors are clustered at the bank–state level. *, **, and *** indicate a significance greater than 10%, 5%, and 1%, respectively.

	Δ Credit Limit		Δ Credit Balance	
	(1)	(2)	(3)	(4)
Δ Short-term wholesale funding	0.056***		0.093**	
	(5.18)		(2.32)	
Δ Short-term wholesale funding (instrumented)		0.090***		0.186***
		(10.45)		(3.70)
Individual FE	✓	✓	✓	✓
Bank characteristics	✓	✓	✓	✓
Bank performance	✓	✓	✓	✓
Lending quality	✓	✓	✓	✓
Credit card controls	✓	✓	✓	✓
N	158,432,533	158,432,533	158,432,533	158,432,533
Adj. R^2	0.090	0.091	0.146	0.148
F-stat (Excl. instru)		1699.99		1699.99

Table 6: Robustness: Effect of funding shock on credit cards

The table shows the robustness of the relation between the pre-shock dependence on short-term wholesale funding and the change in credit card limits and balances. Both the pre-shock and post-shock periods consist of three semiannual archives. The pre-shock period includes the January 2007, July 2007, and January 2008 semiannual archives, while the three semiannual archives for the post-shock period are January 2009, July 2009, and January 2010. Credit card–level data are first collapsed to obtain a single credit card–level cross-section separately in the pre-shock and post-shock periods by averaging across time. Then, the change in credit card limits and balances are computed by taking the log difference from the post- to the pre-shock period. The dependence on short-term wholesale funding (shock exposure) is measured as the ratio of short-term wholesale funding to total deposits. The standard errors are clustered at the bank level. *, **, and *** indicate a significance greater than 10%, 5%, and 1%, respectively.

Panel A: $\Delta CCLimit$ using active cards only

Depvar:	ΔCC Limit	ΔCC Balance	
	(1)	(2)	(3)
Exposure	-5.204***	-17.793***	
	(-14.58)	(-8.77)	
Δ CC limit (instrumented)			3.419***
			(8.18)
N	120,497,687	120,497,687	120,497,687
Adj. R^2	0.099	0.192	0.104
F-stat (Excl. instru)			212.629

Panel B: $\Delta CCLimit_{i,-c,b}$: computed independent of credit card-specific limits

Depvar:	ΔCC Limit	ΔCC Balance	
	(1)	(2)	(3)
Exposure	-4.254***	-9.805***	
	(-18.11)	(-4.57)	
Δ CC limit (instrumented)			2.305***
			(4.57)
N	158,432,533	158,432,533	158,432,533
Adj. R^2	0.981	0.146	0.152
F-stat (Excl. instru)			251.00

Panel C: Homeowner

Depvar:	ΔCC Balance	
Homeowner:	No	Yes
	(1)	(2)
Δ CC limit (instrumented)	1.809***	2.213***
	(2.95)	(5.36)
N	68,474,761	89,957,772
Adj. R^2	0.127	0.133
F-stat (Excl. instru)	108.469	199.268

Controls for all specifications in Panel A, B, and C	
Individual FE	✓
Bank characteristics	✓
Bank performance	✓
Lending quality	✓
Credit card controls	✓

Table 7: Effect of funding shock on *aggregate* credit card balances

The table shows the relation between funding shock-induced changes in total credit card limits on total credit card balances. Both the pre-shock and post-shock periods consist of three semiannual archives. The pre-shock period includes the January 2007, July 2007, and January 2008 semiannual archives, while the three semiannual archives for the post-shock period are January 2009, July 2009, and January 2010. Credit card–level data are first collapsed to obtain a single credit card–level cross-section separately in the pre-shock and post-shock periods by averaging across time. Then, the credit card limits and balances are aggregated at the individual level and the change in total credit card limits and total balances are computed by taking the log difference from the post- to the pre-shock period. *Weighted exposure* is computed at the individual level by aggregating the weighted *Exposure* measure at the credit card–level, where the weights assigned to a credit card are proportional to its credit limit. In Column (4), Δ *Aggregate CC limit* is instrumented by the *Weighted exposure* variable. The standard errors are clustered at the bank–state level. *, **, and *** indicate a significance greater than 10%, 5%, and 1%, respectively.

Depvar:	Δ Agg. CC Limit	Δ Agg. CC Balance		
	(1)	(2)	(3)	(4)
Weighted exposure	-3.827***	-1.216**		
	(-9.56)	(-2.55)		
Δ Agg. CC limit			0.859***	
			(43.56)	
Δ Agg. CC limit (instrumented)				0.318***
				(2.87)
Zip-code FE	✓	✓	✓	✓
Consumer quality	✓	✓	✓	✓
N	133,501,009	133,501,009	133,501,009	133,501,009
Adj. R^2	0.027	0.032	0.141	0.098
F-stat (excl. instru)				91.386

Table 8: Heterogeneity in bank response to funding shock

This table shows how banks pass on the short-term wholesale funding shock differentially across consumers. The dependence on short-term wholesale funding (exposure) is measured as the ratio of short-term wholesale funding to total deposits. *CC utilization (50–90%)*, and *CC utilization (> 90%)* are indicator variables that equal 1 if the utilization ratio for a credit card is between 50% and 90% or greater than 90%, respectively, and 0 otherwise. *Agg. utilization (50–90%)*, and *Agg. utilization (> 90%)* are indicator variables that equal 1 if an individual's aggregate utilization ratios, computed using all the credit cards, is between 50% and 90% or greater than 90%, respectively, and 0 otherwise. *Near-prime*, and *Subprime* are indicator variables that equal 1 if an individual's credit score is between 620 and 680 or lower than 620, respectively, and 0 otherwise. The standard errors are clustered at the bank–state level. *, **, and ***, indicate a significance greater than 10%, 5%, and 1%, respectively.

Panel A: Credit-card level utilization		Panel B: Individual-level utilization		Panel C: Credit score	
Depvar: ΔCC Limit	(1)	*Depvar: ΔCC Limit*	(2)	*Depvar: ΔCC Limit*	(3)
Exposure	-4.052***	Exposure	-4.232***	Exposure	-4.038***
	(-10.61)		(-10.87)		(-10.26)
Exposure×CC utilization (50–90%)	-4.298***	Exposure×Agg. utilization (50–90%)	-4.994***	Exposure×Near-prime	-4.145***
	(-10.61)		(-11.68)		(-9.92)
Exposure×CC utilization (>90%)	-6.587***	Exposure×Agg. utilization (>90%)	-8.185***	Exposure×Subprime	-7.887***
	(-15.16)		(-15.37)		(-14.88)
CC utilization (50–90)	9.099***				
	(19.55)				
CC utilization (≥90)	7.997***				
	(10.32)				
Individual FE	✓		✓		✓
Bank characteristics	✓		✓		✓
Bank performance	✓		✓		✓
Lending quality	✓		✓		✓
Credit card controls	✓		✓		✓
N	158,432,533		151,449,029		158,423,518
Adj. R^2	0.089		0.089		0.089

Table 9: Heterogeneity in consumer response to funding shock

This table shows consumers' differential response to their credit limit cuts induced by their banks' short-term wholesale funding shock. Panel A shows cross-sectional variation in consumer response at the credit card-level similar to Table 4, Column (5). Panel B shows cross-sectional variation in consumer response at the individual level similar to Table 7, Column (4). Panel C is similar to Panel B, but the dependent variable is the total change in debt balances across all debt-related accounts of the consumer. Columns (1)–(3) consist of subsamples of individuals whose aggregate utilization ratios, computed using all the credit cards issued to them, is between 0–50%, 50–90%, and greater than 90%, respectively. Columns (4)–(6) consist of subsamples of subprime (< 620), near-=prime (>= 620 and < 680), and prime (>= 680) individuals, classified based on their credit score. The standard errors are clustered at the bank–state level. *, **, and ***, indicate a significance greater than 10%, 5%, and 1%, respectively.

Panel A: Credit card balances

	Utilization			Credit score		
	0-50%	50-90%	90%+	Sub-prime	Near-prime	Prime
Depvar: Δ CC Balance	(1)	(2)	(3)	(4)	(5)	(6)
Δ CC limit (instrumented)	2.650***	-0.827**	-2.393***	-2.018***	-0.172	2.959***
	(5.58)	(-2.31)	(-3.15)	(-4.16)	(-0.51)	(6.04)
Individual FE	✓	✓	✓	✓	✓	✓
Bank characteristics	✓	✓	✓	✓	✓	✓
Bank performance	✓	✓	✓	✓	✓	✓
Lending quality	✓	✓	✓	✓	✓	✓
Credit card controls	✓	✓	✓	✓	✓	✓
N	121,040,448	23,846,428	13,111,138	17,331,618	25,369,629	115,731,258
Adj. R^2	0.102	0.131	-0.284	-0.326	0.197	0.069
F-stat (Excl. instru)	158.877	156.524	43.442	70.802	244.376	136.286

Panel B: Total credit card balances

	Utilization			Credit score		
	0-50%	50-90%	90%+	Sub-prime	Near-prime	Prime
Depvar: Δ Agg. CC Balance	(1)	(2)	(3)	(4)	(5)	(6)
Δ Agg. CC limit (instrumented)	0.232	1.078***	1.325***	1.475***	0.639***	0.120
	(1.14)	(21.11)	(44.16)	(36.59)	(12.50)	(0.66)
N	98,625,046	20,357,771	14,237,721	19,181,224	19,924,108	94,395,673
Adj. R^2	0.079	0.285	0.254	0.099	0.205	0.058
F-stat (Excl. instru)	45.184	147.687	250.590	251.084	132.804	58.953

Panel C: Total debt balances

	Utilization			Credit score		
	0–50%	50–90%	>90%	Sub-prime	Near-prime	Prime
Depvar: Δ Agg. Debt Balance	(1)	(2)	(3)	(4)	(5)	(6)
Δ Agg. CC limit (instrumented)	-0.890***	-0.001	0.199***	0.596***	0.123**	-0.723***
	(-4.91)	(-0.03)	(6.48)	(10.23)	(2.13)	(-5.43)
N	99,045,677	20,421,935	14,380,579	19,551,761	20,007,886	94,598,483
Adj. R^2	-0.238	0.058	0.117	0.070	0.073	-0.128
F-stat (Excl. instr)	45.863	148.713	249.066	246.854	133.895	58.965

Controls for Panels B and C

Zip-code FE	✓	✓	✓	✓	✓	✓
Consumer quality	✓	✓	✓	✓	✓	✓

Appendix

This appendix is divided into two sections. The first section documents excerpts from news articles which provide anecdotal evidence for credit limit cuts in our post shock period which ranges from 2008–2010. The second section provides supplemental tables.

A Anecdotal evidence on credit limit cuts

1. "A July 30, 2008, report by Javelin Strategy & Research says that of the 13 top-tier credit card issuers it surveyed, eight said that as a direct result of current economic conditions, they had reduced consumers' credit lines. It's a move took Jerry Jacobs by surprise. About eight months ago, one credit card bank reduced his \$10,000 limit to \$6,200, just above his card balance. The Florida resident says he's never missed a payment or been late with a bill, and his phone calls to the company netted no real reason for the change."
   Source: `https://www.creditcards.com/credit-card-news/lending-crisis-credit-score-cut-limits-1270.php`

2. "After years of flooding Americans with credit card offers and sky-high credit lines, lenders are sharply curtailing both, just as an eroding economy squeezes consumers. The pullback is affecting even creditworthy consumers ... Capital One, another big issuer, for example, has aggressively shut down inactive accounts and reduced customer credit lines by 4.5 percent in the second quarter from the previous period, according to regulatory filings."
   Source: `https://www.nytimes.com/2008/10/29/business/29credit.html`

3. "Credit card companies are not immune to the credit crisis, and one way they're protecting themselves is by lowering credit limits wherever and whenever they can. You might have a perfect payment history and still wake up to a \$5,000 card limit that's been reduced to \$500. One of the biggest victims in this whole economic meltdown — besides the millions who've lost their jobs – is the world's financial liquidity reserve. That means there's no credit anywhere because there's no money to lend."
   Source: `https://www.gobankingrates.com/credit-cards/advice/why-credit-limits-cut/`

4. "Many Americans have come to rely on credit cards to cover everyday expenses like groceries, gasoline and medical bills, in addition to big-ticket items and luxuries. While consumer spending, the nation's economic engine, has been surprisingly resilient of late, a more sweeping reduction in credit card limits could pose serious challenges for hard-pressed consumers and, in turn, the broader economy."

   "Washington Mutual cut back the total credit lines available to its cardholders by nearly 10 percent in the first quarter of the year, according to an analysis of bank regulatory data. HSBC HOldings, Target and Wells Fargo each trimmed their credit card lines by about 3 percent."
   Source: `https://www.nytimes.com/2008/06/21/business/21credit.html`

5. "Johann Beukes, a software engineering manager for Bankrate Inc. based in North Palm Beach, Fla., logged on to American Express' Web site recently to make a payment and discovered his

credit line had been reduced by $5,000, despite the fact that he's been a cardholder for more than 10 years and has a credit score north of 800.

"I called them up the next day and asked why they were doing this, since we've never had a late payment," he says.

After lodging complaints with three company representatives, Beukes finally was told that his credit line was lowered because American Express wants to reduce its risk because of the credit crisis. Nothing personal."
Source: `https://www.bankrate.com/finance/financial-literacy/coping-with-cut-credit-1.aspx`

6. "About one in five cardholders had their credit limits reduced recently, according to a [2008] July survey by Consumer Action, a San Francisco-based consumer advocacy group."

   "Meredith Whitney, a banking analyst at Oppenheimer & Co., predicts card issuers will cut credit lines by $2 trillion-plus over the next 18 months [2008–2010]."
   Source: `https://www.bankrate.com/finance/financial-literacy/coping-with-cut-credit-1.aspx`

Table A.1: Summary statistics at the consumer level

This table presents the summary statistics at the consumer level for the full sample and fixed effects model (FE) sample using credit bureau data in the pre-shock period. The pre-shock period consists of three semiannual archives namely, January 2007, July 2007, and January 2008. The data are collapsed to obtain a single consumer-level cross-section in the pre-shock period by averaging across time.

	Full Sample				FE Sample			
	N	Mean	Median	Std. dev.	N	Mean	Median	Std. dev.
Borrower fundamentals								
Credit score	133,507,048	725	743	83.9	54,174,946	735	751	76.1
Monthly income ($)	133,507,048	3,735	3,583	1,436	53,867,498	3,963	3,750	1,388
Debt-to-income ratio (DTI)	133,507,048	28.4	23	26.8	53,127,992	31.2	27.3	25.7
Credit card debt								
Credit card accounts	133,507,048	3.7	3	2.54	54,174,952	5.34	5	2.86
Credit card balance	133,507,048	4,985	1,980	7,459	54,174,952	7,505	3,655	9,724
Credit card utilization	120,364,050	0.29	0.16	0.31	51,166,136	0.27	0.15	0.29
Other debt								
Total debt related accounts	132,104,446	8.69	7.67	5.3	53,385,332	10.8	10	5.65
Mortgage balance ($)	53,407,329	184,645	134,378	171,887	24,113,774	184,457	135,569	169,268

Table A.2: Robustness: Controlling for potential alternate channels

This table presents results assuaging concerns of a particular type of bank driving the baseline findings presented in Table 3. The table shows the relation between the pre-shock dependence on short-term wholesale funding and the change in credit card limits using the credit bureau data, where the focus is on individuals who hold multiple credit cards issued by the same 'type' of bank. In column (1), bank type is determined by the size of the bank's assets. Banks with assets larger (smaller) than the sample median are classified as large (small) banks. Similarly, in columns (2), bank type is determined through the banks' capital ratios. In column (3), the sample of banks is partitioned into high- and low- groups on the basis of unused credit card limits as a percentage of total extended credit cards limits. Finally, in column (4), bank type is identified through lending quality, as proxied by the percentage of subprime borrowers constituting the bank's clientele. Both the pre-shock and post-shock periods consist of three semiannual archives. The pre-shock period includes the January 2007, July 2007, and January 2008 semiannual archives, while the three semiannual archives for the post-shock period are January 2009, July 2009, and January 2010. Credit card–level data are first collapsed to obtain a single credit card–level cross-section separately in the pre-shock and post-shock period by averaging across time. Then the change in credit card limits is computed by taking the log difference from the post- to the pre-period. The dependence on short-term wholesale funding (exposure) is measured as the ratio of short-term wholesale funding to total deposits. The standard errors are clustered at the bank–state level. *, **, and ***, indicate a significance greater than 10%, 5%, and 1%, respectively.

Individual FE interacted with Group:	Size indicator	Cap ratio indicator	Unused CC limits indicator	% Subprime indicator
Depvar: $\Delta CC\ Limit$	(1)	(2)	(3)	(4)
Exposure	-4.792***	-5.558***	-5.911***	-3.195***
	(-15.88)	(-14.31)	(-15.76)	(-9.40)
$Individual \times Group$ FE	✓	✓	✓	✓
Bank characteristics	✓	✓	✓	✓
Bank performance	✓	✓	✓	✓
Lending quality	✓	✓	✓	✓
Credit card controls	✓	✓	✓	✓
N	131,652,681	118,081,930	155,904,113	131,574,880
Adj. R^2	0.086	0.126	0.090	0.086

Table A.3: Effect of funding shock on credit card limits: Robustness

This table presents robustness for the baseline results in Table 3 with alternate measures for bank exposure and different levels of clustering. The table shows the relation between the pre-shock dependence on short-term wholesale funding and the change in credit card limits using the credit bureau data. Both the pre-shock and post-shock periods consist of three semiannual archives. The pre-shock period includes the January 2007, July 2007, and January 2008 semiannual archives, while the three semiannual archives for the post-shock period are January 2009, July 2009, and January 2010. Credit card–level data are first collapsed to obtain a single credit card-level cross-section separately in the pre-shock and post-shock period by averaging across time. Then the change in credit card limits is computed by taking the log difference from the post- to the pre-period. The dependence on short-term wholesale funding (exposure) is measured as the ratio of short-term wholesale funding to total deposits. The standard errors are clustered at the bank–state level. *, **, and ***, indicate a significance greater than 10%, 5%, and 1%, respectively.

Depvar: Δ*CC Limit*	(1)	(2)	(3)	(4)
Exposure (w.r.t. deposits)	-4.750***		-4.750***	
	(-12.89)		(-9.04)	
Exposure (w.r.t. assets)		-4.532***		-4.532***
		(-11.72)		(-7.17)
Individual FE	✓	✓	✓	✓
Bank characteristics	✓	✓	✓	✓
Bank performance	✓	✓	✓	✓
Lending quality	✓	✓	✓	✓
Credit card controls	✓	✓	✓	✓
N	158,432,533	158,432,533	158,432,533	158,432,533
Adj. R^2	0.090	0.090	0.090	0.090
Bank×State clustering	✓	✓		
Bank clustering			✓	✓

Table A.4: Effect of funding shock on extensive margin

This table shows the relation between the pre-shock dependence on short-term wholesale funding and the opening and closure of a credit card. The regressions are estimated at the credit card level. The dependent variable in Columns (1) and (2) is *New* which is a dummy variable which takes the value 1 if a new card is issued by the bank in the post-shock period (i.e., after July 2008), and is 0 otherwise. The dependent variable in Columns (3) and (4) is *Closed* which is a dummy variable that takes the value 1 if an existing credit card in the pre-shock period (i.e., prior to July 2008) is closed in the post-shock period, and is 0 otherwise. The dependence on short-term wholesale funding (exposure) is measured as the ratio of short-term wholesale funding to total deposits. The standard errors are clustered at the bank-state level. *, **, and ***, indicate a significance greater than 10%, 5%, and 1%, respectively.

	New Cards		Closed Cards	
	(1)	(2)	(3)	(4)
Exposure	-1.974***	-2.340***	4.358***	4.345***
	(-3.68)	(-5.16)	(4.76)	(5.41)
Individual FE		✓		✓
Bank characteristics	✓	✓	✓	✓
Bank performance	✓	✓	✓	✓
Lending quality	✓	✓	✓	✓
Credit card controls			✓	✓
N	164,445,583	164,445,583	344,803,931	344,803,931
Adj. R^2	0.020	0.057	0.028	0.192

Table A.5: Reduced form: Heterogeneity in consumers' total debt response to funding shock

This table shows results from reduced form regressions that examine consumers' differential total debt response to their banks' short-term wholesale funding shock. Columns (1)–(3) consist of subsamples of individuals whose aggregate utilization ratios, computed using all the credit cards issued to them, is between 0–50%, 50–90%, and greater than 90%, respectively. Columns (4)–(6) consist of subsamples of subprime (< 620), near-=prime (>= 620 and < 680), and prime (>= 680) individuals, classified based on their credit score. The standard errors are clustered at the bank–state level. *, **, and ***, indicate a significance greater than 10%, 5%, and 1%, respectively.

	Utilization			Credit score		
	0–50%	50–90%	>90%	Subprime	Near-prime	Prime
	(1)	(2)	(3)	(4)	(5)	(6)
Weighted exposure	2.548***	0.006	-1.421***	-4.914***	-0.575**	2.318***
	(7.18)	(0.03)	(-5.76)	(-10.12)	(-2.00)	(7.35)
Zip-code FE	✓	✓	✓	✓	✓	✓
Consumer quality	✓	✓	✓	✓	✓	✓
N	99,045,677	20,421,935	14,380,579	19,551,761	20,007,886	94,598,483
Adj. R^2	0.017	0.059	0.070	0.071	0.043	0.023