Deleveraging and Consumer Credit Supply in the Wake of the 2008–09 Financial Crisis*

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We explore the sources of the decline in household non-mortgage debt following the collapse of the housing market in 2006. First, we use data from the Federal Reserve Board's Senior Loan Officer Opinion Survey to document that, post-2006, banks tightened consumer lending standards more in counties that experienced a more pronounced house price decline (the pre-2006 "boom" counties). We then use the idea that renters did not experience an adverse wealth or collateral shock when the housing market collapsed to identify a general consumer credit supply shock. Our evidence suggests that a tightening of the supply of non-mortgage credit that was independent of the direct effects of lower housing collateral values played an important role in households' non-mortgage debt reduction. Renters decreased their non-mortgage debt more in boom counties than in non-boom counties, but homeowners did not. We argue that this wedge between renters and homeowners can only have arisen from a general tightening of banks' consumer lending stance. Using an IV approach, we trace this effect back to a reduction in bank capital of banks in boom counties.

JEL Codes: E21, G21.

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1. Introduction

Between 2008 and 2012, total household debt fell by about 6 percent, and debt-to-income by about 10 percent.[1] These household balance sheet adjustments are thought to have weighed on aggregate consumption as the U.S. economy struggled to emerge from the downturn. Mian, Rao, and Sufi (2012) (MRS hereafter) use regional variation to assemble evidence on the links between declines in housing wealth, deleveraging, and changes in consumption expenditures after the 2008–09 financial crisis. MRS argue that the combination of a large accumulation of household debt in counties with high house price appreciation before the mortgage crisis (here, "boom" counties) and the subsequent sharp decline in house prices in roughly the same counties resulted in household deleveraging and a concomitant reduction of household consumption expenditure. In support of their story, MRS show that household consumption expenditures declined more in boom counties than in non-boom counties.

One question that remains in this line of research is how the household deleveraging was accomplished. MRS mention two possible, not necessarily mutually exclusive, mechanisms of deleveraging. One possible mechanism for consumer deleveraging stems from a demand-side story. In a simple model of household consumption planning, homeowners would optimally choose to reduce their lifetime consumption, and thereby reduce their household debt, upon perceiving a negative and permanent shock to their housing wealth.[2] The second mechanism for household deleveraging focuses on credit supply. MRS's story here is that homeowners are forced to delever because banks are less willing to lend to them, refinance their mortgages, or roll over existing debt because the value of their collateral has declined.[3] Our story is different. We show that credit supply was

[1] Federal Reserve Flow of Funds and National Income and Product Accounts, 2008:Q3–2012:Q1.

[2] One alternative demand story is that homeowners with limited self-control may increase home equity borrowing when house prices climb in order to finance greater current consumption (Laibson 1997) and then cut back on current consumption and borrowing, perhaps out of remorse or excess prudence, when house prices fall.

[3] Mortgage refinancing usually decreases mortgage debt. But it can also be accompanied by an increase in total household debt through, for example, a more than offsetting increase in credit card spending.

tightened even for households without housing collateral. Hence, we document an overall credit supply effect as an important factor in the deleveraging process of households in the wake of the crisis.[4]

To set the stage for our analysis, figure 1 presents the cumulative tightening from 2008 through 2012 of lending standards in boom versus non-boom counties for consumer installment loans and credit card loans from the Federal Reserve Board's Senior Loan Officer Opinion Survey (SLOOS).[5] For both loan categories, banks tightened lending standards markedly more in boom counties than in non-boom counties.[6] This evidence supports the notion that non-mortgage credit extension to consumers tightened significantly

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[4]One other source of deleveraging came through the mortgage foreclosure process. More than 4 million foreclosures took place in the housing crisis, with the houses backing the defaulted mortgages remaining vacant or sold for considerably lower amounts. This process had a large impact on bank profits, but economic growth in the recovery was more closely linked to the decisions of non-defaulting households regarding desired spending and borrowing and the willingness of banks to lend to this population.

[5]Even in the credit card market, there is scope for geographic variation in credit standards. Stango (2002) finds empirical evidence of switching costs for consumers in the credit card market. In addition, only the top 50 of the 250 largest credit card issuers operate nationally. (Stango 2002, p. 481.)

[6]Figure 1 was prepared as follows: Every quarter, the SLOOS asks a panel of large and medium-sized banks how their credit standards and terms have changed over the past three months. Banks are asked to rate the direction and extent of any change by picking one of five qualitative answers. For example, banks are asked to pick one of the following answers characterizing the change in their willingness to lend since the preceding survey: much less willing, somewhat less willing, no change, somewhat more willing, or much more willing. For one consumer installment loan question (asking about the bank's change in its willingness to make such loans) and one credit card loan question (asking about the bank's change in lending standards on such loans), we assigned numerical values to each of the five choices and constructed, for each county, an index equal to the sum of the SLOOS banks' responses, with each bank's response weighted by the proportion of the total deposits at SLOOS banks' branches in the county that is held by that bank. Our values range from -2, for the most easing of credit conditions, to 2, for the most tightening of credit conditions. For each county, we then calculated running totals of these weighted sums over time to construct the cumulative change in lending conditions since the beginning of 2008. So, although in any single period, the weighted sum of responses can range between -2 and 2, if banks are tightening or easing over consecutive time periods, the value of our cumulative weighted sum can move outside of this range. The graphs in figure 1 depict the mean values of these running totals for boom and non-boom counties.

We note the sharp increase in the cumulative tightening of consumer installment loan credit standards in the fourth quarter of 2011 in non-boom counties.

more in boom counties than in non-boom counties in the aftermath of the 2008–09 financial crisis. However, a tightening of credit standards by itself does not tell us whether those standards were tightened mostly for homeowners due to declines in the value of their housing collateral.

In this paper we attempt to identify a role for a general tightening of credit supply in explaining the decline in household debt. Using individual credit file data from 1999 through 2008, we estimate a model of the level of debt in which we control for many factors likely to affect the demand for such debt. We confirm the reasonableness of the empirical results we obtain from estimating that model. We then estimate a model of the probability of a consumer living in a boom county, using the same controls as in our debt-level regressions. Following this, we construct a sample of matched consumers, with each consumer in a boom county matched to the consumer in the non-boom county that has the closest *predicted probability* of living in the boom county as the consumer in the non-boom county. Within slices of the distribution of predicted debt for 2008:Q3, we then compare the change in non-mortgage debt between 2008 and 2011 for the non-boom sample with the change in non-mortgage debt for the boom sample.[7] Finally, using the matched sample, we

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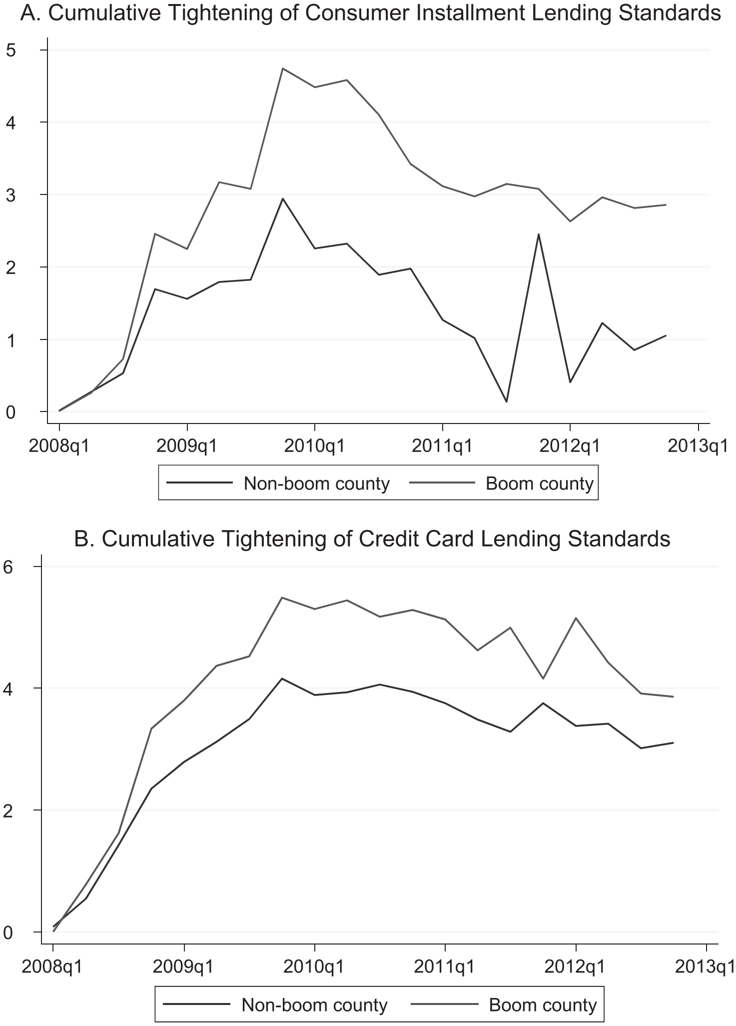
The underlying data indicate fairly widespread tightening across the relevant banks. Therefore, we simply accept the sharp increase as a feature of the data.

We also note that each bank's response to the survey likely is weighted by the distribution of its own deposits across boom versus non-boom counties. In principle, this could temper any correlation between boom counties and changes in credit standards as we measure them. For example, a bank may have a large share of the total deposits in a boom county, but the share of its own deposits in boom counties overall may be small. If such were the case, even though the bank likely would respond on the basis of its being, in general, a non-boom county lender, its response would be heavily weighted in our index for the particular boom county. We observe, however, a strong correlation between county types and changes in credit standards, in the expected direction. A contributing factor may be that, in practice, banks that have large shares of the total deposits in boom counties tend to also have large shares of their own deposits in boom counties.

[7]Since house price changes during the crisis were highly correlated with pre-crisis house price appreciation (that is, whether or not a county was a boom county (figure 7)), we are, in essence, assessing the effect of house price changes between 2008 and 2011 on the change in debt between 2008 and 2011. We follow MRS in differentiating counties according to their degree of pre-crisis house price appreciation (high versus low) instead of according to their crisis-era house price changes.

Figure 1. Cumulative Tightening of Lending Standards in Boom and Non-boom Counties

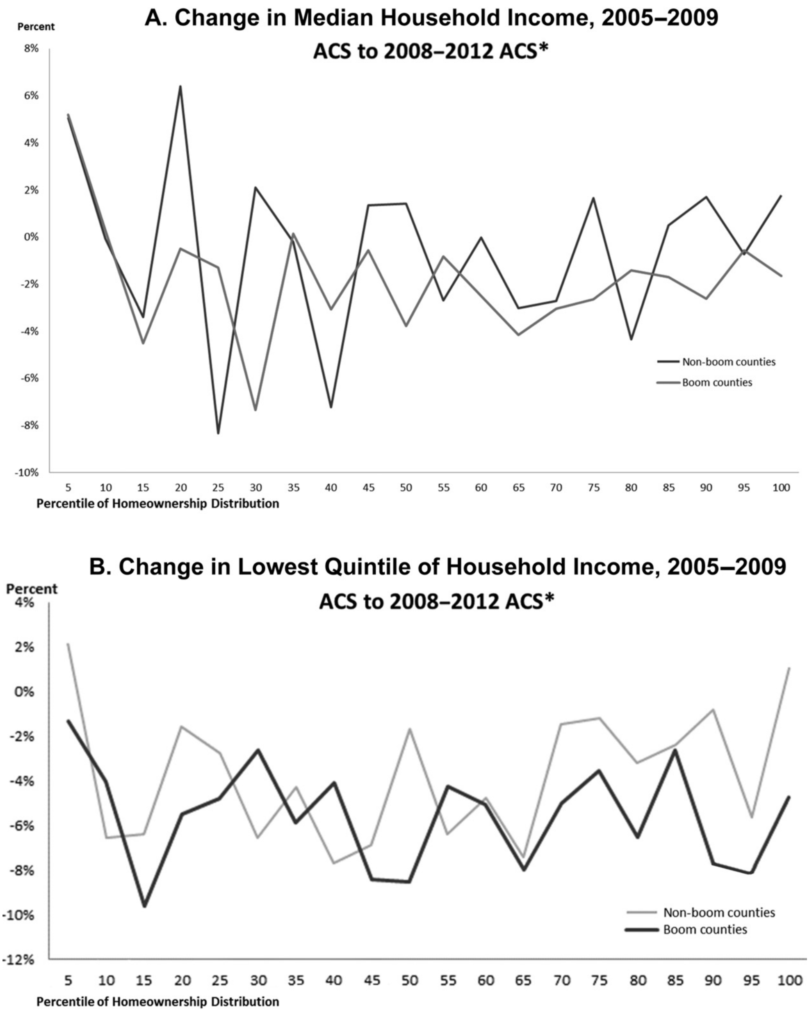


Source: Senior Loan Officer Opinion Survey and authors' calculations (see text).

estimate regressions of the change in non-mortgage debt, controlling for boom county and interacting boom county with the homeowner status of the consumer.

We rely on the following idea to identify general credit supply effects. We make use of the fact that renters experienced neither an adverse housing wealth shock in boom counties nor a drop in collateral values. Hence, if the difference in debt reduction between renters in boom counties and renters in non-boom counties is greater than or equal to the difference between homeowners in boom counties and homeowners in non-boom counties, this would indicate the presence of general credit supply effects that are independent of house value effects. If, on the other hand, the difference between renters in non-boom counties and renters in boom counties is smaller than the difference between the debt reduction of homeowners in boom counties versus that of homeowners in non-boom counties, we cannot identify supply effects. Hence, our identification of credit supply effects relies on a double difference-in-differences term. The first difference is the one between boom and non-boom counties and the second is the difference between homeowners and renters. One possible challenge to our empirical approach is that the economic downturn affected renters more in boom than in non-boom counties. For example, the shock to consumer fundamentals (consumer expectations, incomes, unemployment) may have been more severe for renter households than for homeowner households. We check for this possibility and find that boom versus non-boom county changes in median income over this period across U.S. counties appear to be uncorrelated with the percentile of the homeownership rate (see figure 2A). In addition, examining changes in the 20th percentile of income, we find that counties at the *higher* end of the homeownership rate distribution show a more consistent pattern of deeper declines in income in boom than in non-boom counties than do counties at the lower end of the homeownership rate distribution. We also use Panel Study of Income Dynamics (PSID) data to show that renter income growth over our period did not vary significantly with pre-recession house price growth across different markets (see figure 3). We take this finding as supportive of our overall approach of using renters as a control group for studying the impact of the housing bust on credit supply.

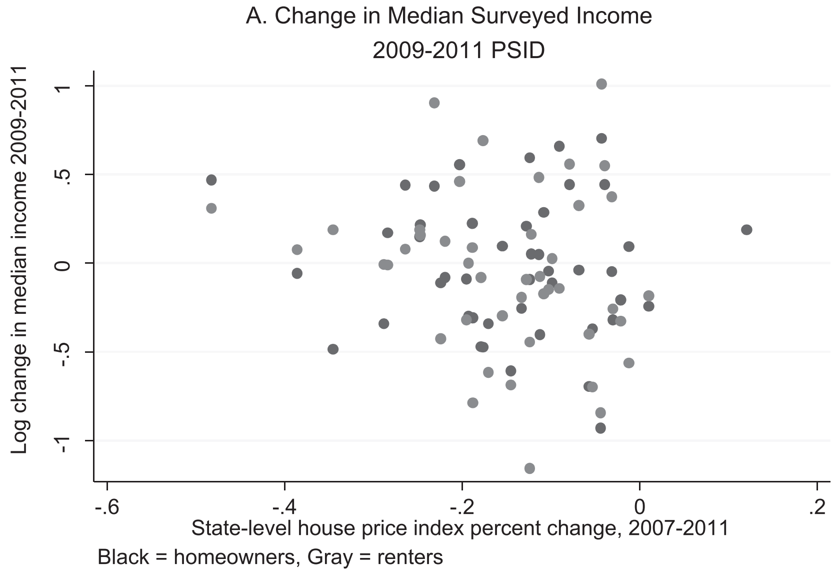
Figure 2. Changes in Median and 20th Percentile of Household Income

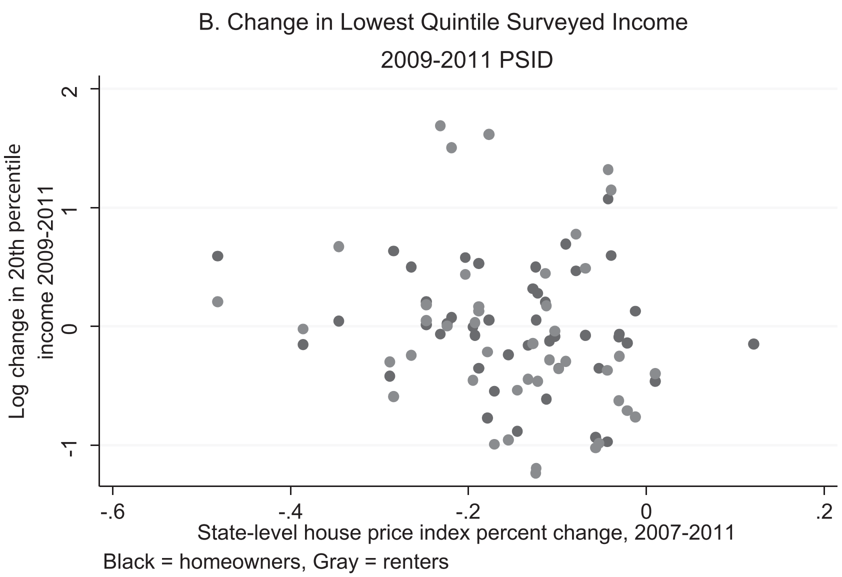


Source: American Community Survey and Federal Reserve Bank of San Francisco calculations.

Our results indicate the presence of general credit supply effects. Controlling for demand for debt using our methodology, we find stronger deleveraging in boom counties after the crisis, consistent with MRS. However, this difference appears only for renters. We

Figure 3. Changes in Median and 20th Percentile Surveyed Income





argue that, as renters were not hit by an adverse wealth shock, this finding must be due to differences in the availability of credit in boom versus non-boom counties. Finally, we trace the effect back to weaker bank balance sheets in boom counties compared with non-boom counties, using an instrumental-variables (IV) approach, and map out the transmission channel from bank balance sheets to household consumer borrowing.

This paper is an empirical microeconomic investigation. However, in the background, on the demand side, we have in mind a general consumption-smoothing framework. A sharp unanticipated drop in house prices may cause leveraged households to want to reduce debt by way of a standard wealth effect. On the supply side, the drop in collateral values may reduce the provision of credit to households, which may result in a larger reduction in debt than the wealth effect alone would have generated. Decreases in the provision of credit due to the collateral channel are consistent with arguments in Eggertsson and Krugman (2012) and Midrigan and Philippon (2011). Of interest to us are various other sources of reduced credit provision during this period. For example, see Damar, Gropp, and Mordell (2012) for an empirical investigation using Canadian data of the effect of bank financial distress on household consumption. In addition, see Dynan and Edelberg (2013) for a comprehensive list of potential supply and demand factors that may affect household leverage, and Bhutta (2013) for evidence of decreases in the supply of mortgage credit since the housing bust. Brown, Stein, and Zafar (2015) also use the Federal Reserve Bank of New York's (FRBNY's) Consumer Credit Panel to report interesting differences in the way different demographic groups (e.g., older and prime homeowners) substituted between home equity and credit card debt over the sample period.

We complement the large literature that links household debt, household wealth, and consumption with a focus on the Great Recession. For example, Carroll (2013), Eggertsson and Krugman (2012), Guerrieri and Lorenzoni (2011), Hall (2011), and Midrigan and Philippon (2011) all point to a high level of household debt as an important precursor of the Great Recession. In these expositions, a negative shock to homeowner collateral values causes lenders to restrict credit to homeowners. We show, however, that the effect coming from bank balance sheets and the consequent general restriction in credit supply for all borrowers may have been at least as important as the channel these papers point to. Additional empirical evidence linking high levels of household debt to economic downturns in a macroeconomic context can be found in Glick and Lansing (2009, 2010), Jordà, Schularick, and Taylor (2012), and Mian and Sufi (2010).

The paper is organized as follows. In section 2 we describe the data. In section 3, we present the results of our pre-crisis debt-level regressions. In section 4, we present the results of our post-crisis debt-change regressions. Section 5 concludes.

2. Data

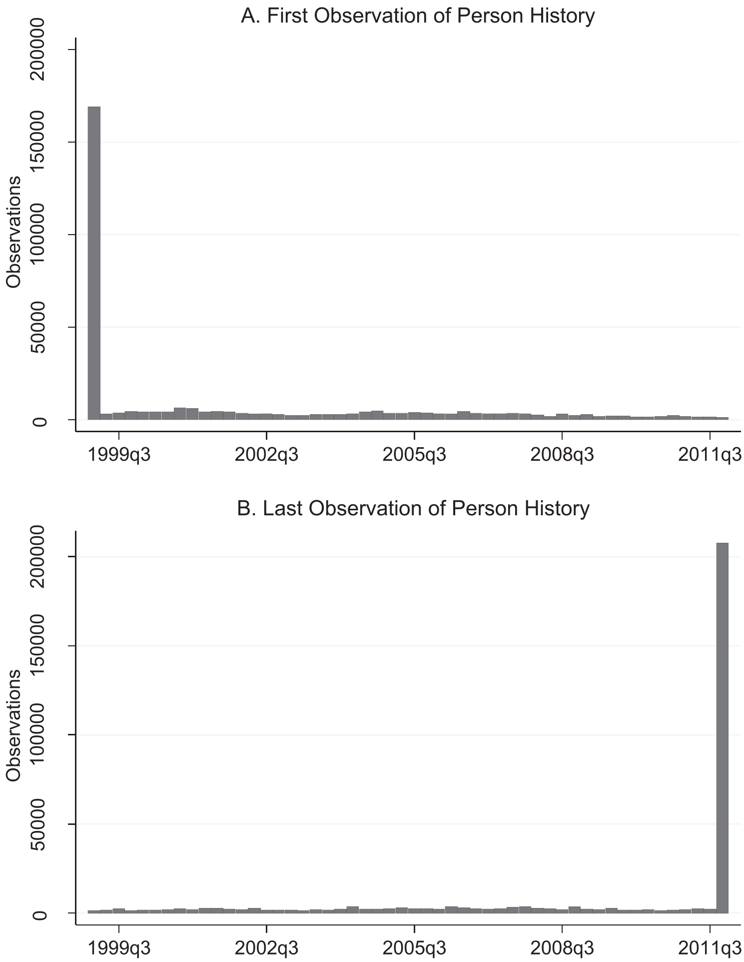
The data come from Equifax, a large credit-reporting agency. The data span 1999:Q1 to 2011:Q4 and contain a large amount of information on consumer liabilities—mortgage, home equity, auto, credit card, etc., and some borrower characteristics such as age, risk score, and delinquency status on their liabilities.[8] All analysis is based on data from the Federal Reserve Bank of New York's Consumer Credit Panel, which is a 5 percent random sample of consumers with credit histories that is nationally representative in a given quarter and also designed to reproduce the transitions of young and old into and out of the credit pool.[9] To make the data set more manageable, we used a 10 percent random sample of the Consumer Credit Panel, implying a .5 percent random sample of the U.S. population with credit histories. Consumers are located by the Zip code of their home mailing address. After identifying the county of each residence and merging with house price indexes available from CoreLogic, our sample consists of over 900,000 individuals living in more than 1,100 counties across the country.

The distribution of entry into and exit from our sample may be seen in figure 4. On average, about 3,000 new credit histories appear in our sample each quarter, offset somewhat by about 2,300

[8] The risk score is the Equifax Risk Score.

[9] See Lee and Van der Klaauw (2010) for a description of the sampling methodology used in the construction of the Consumer Credit Panel.

Figure 4. Distribution of Entry into and Exit from Sample



Source: FRBNY Consumer Credit Panel/Equifax.

history terminations each quarter, so that our sample is slowly growing over time.[10] The commencement of a borrower history, however,

[10]Termination of a borrower record could take place for a variety of reasons, including death or instances where a trade line (credit type) has no recorded activity for a length of time greater than Equifax's predefined limits. Also, the

does appear closely related to age. The new borrowers entering the sample had a median age of about twenty-eight, a number which trended downward over the sample period. Newly appearing borrowers had median risk scores of about 660, well below the overall sample median of 712.

Only one-third of our sample of consumer histories spans the full 1999:Q1–2011:Q4 period. While this is still a substantial amount of data, in this analysis we use the entire, unbalanced panel to allow some of the compositional changes that we experienced over the 2000s to enter into the analysis. As alluded to above, many of the new entrants to the panel were young households with low risk scores. These household borrowers were particularly susceptible to the economic volatility that occurred at the end of our sample, and we will want their credit experiences present in our data. In many ways, this group bore the brunt of the shock that hit the U.S. housing market starting in 2006. By contrast, a more seasoned homeowner that bought in 1999 and stayed in the house most likely experienced net house price appreciation over the entire period.[11] Indeed, average risk scores for borrowers present for the entire sample period actually increased over the thirteen-year period, whereas average risk scores for the population at large fell quite notably.

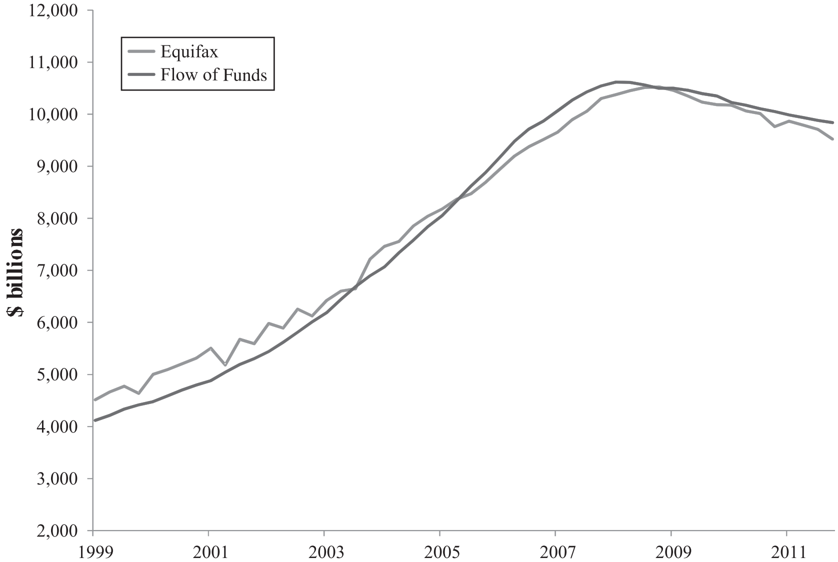
For a first glimpse at the loan balance data, we compare the Flow of Funds data with the aggregated totals in our sample. While the match is not perfect, the correlation of our total mortgage series (figure 5) and total non-mortgage debt series (figure 6) with the Flow of Funds counterpart is quite high. Throughout, we define non-mortgage debt as the sum of auto, credit card, and other non-mortgage consumer loan balances outstanding, excluding student debt.[12] This particular concept of non-mortgage debt does not match

Consumer Credit Panel draws from borrowers with specific sequences of digits in their social security numbers. If an individual changes their social security number, they could drop out of the sample.

[11]Of course, the same homeowner may still have changed leverage over the period and become underwater relative to their mortgage debt despite the overall price appreciation.

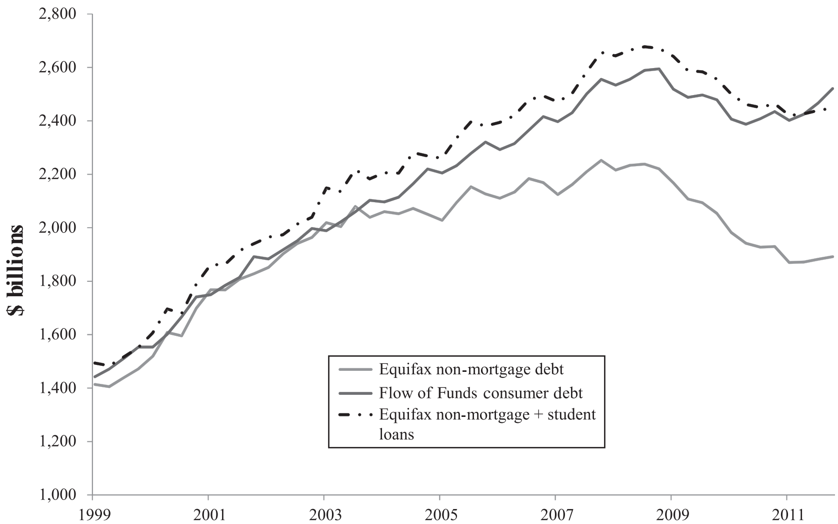
[12]Our non-mortgage consumer debt excludes any consumer debt secured by a house, so it excludes, for example, home equity debt. In the appendix, we discuss results obtained when we add home equity debt to total non-mortgage debt.

Figure 5. Total Mortgage Debt (includes home equity)



Source: Federal Reserve Board, FRBNY Consumer Credit Panel/Equifax.

Figure 6. Non-mortgage Debt



Source: Federal Reserve Board, FRBNY Consumer Credit Panel/Equifax.

the dynamics of the Flow of Funds, because we do not include student loans in our measure. This choice was made because of the uncertainties of measuring student loan debt as well as our desire to focus on a non-mortgage debt series that is plausibly linked to debt put in place to finance consumption.

As seen in figures 5 and 6, through the course of our sample period, total mortgage debt more than doubled, peaking in 2008 and then falling by about 10 percent. Non-mortgage debt declined somewhat more, as balances fell 15 percent from the peak.

Following MRS, our debt-level regressions use the estimates from Saiz (2010) of the elasticity of local housing supply with respect to price as a way of controlling for exogenous features of the land that might lead to differential house price levels and, hence, differences in debt. For example, MRS present empirical evidence that, in counties with highly inelastic housing supply and rapidly increasing house prices during the boom, homeowners were especially likely to increase their debt. We manually link the 806 MSA-level elasticity estimates in Saiz (2010) to the counties in our data set. About 10 percent of our observations are from locales not covered by Saiz (2010). Inspection reveals that the vast majority of these match failures are in less-populated areas. To conserve data, we assigned an imputed elasticity equal to the sample maximum to these observations and included a missing elasticity dummy variable in all our debt-level regression specifications.

At the individual borrower level, our debt-level regressions include the number of inquiries made to Equifax over the preceding four quarters regarding the consumer's credit record as well as the borrower's age and risk score. The inquiries are usually made as a result of the consumer seeking more credit and therefore are a useful gauge of overall credit demand.

We also use information from the U.S. Census Bureau's American Community Survey (ACS), based on pooled data from 2006 through 2010. These demographic data are at the census tract level. All of the variables here are meant to proxy for income, wealth, family attributes, and the many other factors that would be expected to influence an individual's demand for credit independent of their influence through changes in credit record inquiries. Finally, we use the unemployment rate, from the Bureau of Labor Statistics, which is monthly and is at the county level. Many of our demographic variables are the same as those in Cohen-Cole (2011) and Musto and Souleles (2006).

Table 1 gives some summary statistics on the demographic variables we use in the analysis.

3. Pre-crisis Debt-Level Regressions

The first step in establishing a benchmark for the demand for credit takes the form of debt-level regressions as given by

$$D_i = \alpha + f(X_i) + \Gamma X + \varepsilon, \tag{1}$$

where D_i is an individual debt category for individual i, X_i consists of borrower i's age and risk score and the number of inquiries requesting borrower i's credit report in the previous twelve months, and X is a vector of control variables at the census tract or county level.[13] We estimate the above equation as a pooled regression on a subsample of our data using observations from 1999:Q1 to 2008:Q2, the quarter at which total household debt peaked in our overall sample. All debt categories are in logs. The results from the OLS specifications may be found in table 2.

The number of credit report inquiries comes in strongly positive in all categories, as expected. Interestingly, we do not find a particularly strong role for the supply elasticity in explaining cross-sectional differences in consumer debt. Only for home equity does the elasticity coefficient estimate have both the expected sign and statistical and economic significance that would be fully consistent with MRS. Since we are looking at the individual borrower level and focusing on debt levels—not debt-to-income ratios—this result is not necessarily a contradiction of the results in the MRS paper. In addition, we include more control variables than MRS. This is an important result for our study in that the supply elasticity is one of only two variables in our set of controls that vary meaningfully

[13]The regression in equation (1) also contains a complete set of time dummies to capture macroeconomic fluctuations over the period. The individual's age and risk score enter the equation as piecewise linear splines. Explanatory variables also include squared terms of all the other non-categorical variables. We do not report the coefficients on the time dummies, on the age or risk score splines, or on the squared terms.

Table 1. Summary Statistics

	Mean	Std. Dev.	p25	p50	p75
Age	48.1	17.84	34	46	60
Credit Inquiries (Trailing Twelve Month)	2.598	6.722	1	3	4
Risk Score	688.5	107.4	610	710	781
County Unemployment	6.107	2.61	4.3	5.4	7.4
Housing Supply Elasticity	1.729	0.95	0.998	1.645	2.175
High Small Business Percent	23.614	10.867	15.878	24.924	29.427
Median Age	37.96	6.673	33	38	42
Median Homeownship Costs (Monthly)	1,391	628.1	925	1,267	1,710
Median Rent (Monthly)	836.5	368.5	568	749	1,010
Median Tract Income (Annual)	60,048	27,504	41,103	54,561	73,150
Median Year Moved into Housing Unit	2001	3.423	1999	2001	2003
Percent Black	12.72	21.6	0.856	3.608	12.882
Percent College Education	29.88	18.63	15.37	25.549	41.146
Percent Food Stamps	9.546	9.231	3.005	6.671	13.048
Percent High School Only	27.92	10.64	20.525	28.436	35.524
Percent Hispanic	8.816	13.08	1.248	3.802	10.367
Percent Homeowner	66.39	21.45	52.99	70.729	83.521
Percent in Labor Force	66.14	8.403	61.52	66.887	71.604
Percent Male	0.487	0.037	0.466	0.487	0.508
Percent Married	49.48	12.93	41.453	50.95	59.097
Percent One Vehicle	95.2	10.06	95.643	98.273	99.426
Percent Some High School	14.15	11.29	6.084	11.087	18.904
Percent Working	78.48	7.787	74.452	79.756	83.893
Total Tract Population	4,990	2,038	3,618	4,799	6,115
Observations	16,024,144				

Source: FRBNY Consumer Credit Panel/Equifax, Saiz (2010), and the 2010 American Community Survey.
Notes: The table shows the summary statistics (means and percentiles) of the explanatory variables used in the debt-level and debt-change regressions. The sample period is from 1999:Q1 to 2011:Q4. Age, credit inquiries, and risk score are observed at the consumer level. The housing supply elasticity is taken from MSA-level estimates in Saiz (2010) and mapped to the county level by the authors. All other variables are observed at the county or census tract level.

Table 2. Debt-Level Regressions

	Total Debt (1)	**Mortgage (2)**	**Home Equity (3)**	**Non-mortgage (4)**	**Auto (5)**	**Credit Card (6)**
Housing Supply Elasticity	0.021***	0.052***	−0.014***	0.008***	0.001	−0.008***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Missing Elasticity Dummy	−0.008	−0.014*	−0.145***	−0.031***	−0.125***	−0.031***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
Credit Inquiries (Trailing Twelve Month)	0.335***	0.184***	0.100***	0.321***	0.346***	0.204***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.011)
County Unemployment	0.010***	−0.017***	0.048***	0.027***	0.034***	0.033***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Median Tract Income	−4.089***	−15.373***	−2.114***	−0.854***	0.265	−1.371***
	(0.195)	(0.237)	(0.166)	(0.191)	(0.215)	(0.191)
Percent College Education	−0.003***	0.002*	0.003***	0.000	−0.010***	0.007***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Percent Black	−0.007***	−0.005***	−0.001***	−0.003***	0.002***	−0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Percent Hispanic	0.002***	0.003***	−0.009***	0.006***	0.015***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
High Small Business Percent	−0.174***	−0.247***	−0.151***	−0.072***	−0.336***	0.077***
	(0.015)	(0.019)	(0.013)	(0.015)	(0.017)	(0.015)
Percent One Vehicle	−0.008*	−0.051***	0.016***	−0.005	0.002	−0.024***
	(0.004)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)
Percent Married	0.004***	−0.008***	−0.003***	0.007***	0.010***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Percent Food Stamps	−0.012***	0.001	−0.002***	−0.019***	−0.018***	−0.018***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Percent Working	−0.018***	−0.024***	0.014***	−0.013***	−0.008**	−0.023***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Percent Homeowner	0.012***	0.023***	0.011***	0.001**	−0.000	−0.002***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)

(*continued*)

Table 2. (Continued)

	Total Debt (1)	**Mortgage (2)**	**Home Equity (3)**	**Non-mortgage (4)**	**Auto (5)**	**Credit Card (6)**
Median Age	−0.002***	−0.012***	−0.002***	0.004***	−0.006***	0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Tract Population	−0.676***	−1.331***	0.086	−0.073	−0.884***	0.227**
(in logs)	(0.080)	(0.097)	(0.068)	(0.079)	(0.088)	(0.079)
Median Rent (in logs)	0.195	3.169***	1.063***	0.308**	0.948***	1.001***
	(0.108)	(0.132)	(0.093)	(0.107)	(0.120)	(0.107)
Median Homeowner Cost	−0.210*	1.219***	−0.463***	0.308**	1.342***	0.958***
(in logs)	(0.101)	(0.123)	(0.086)	(0.099)	(0.112)	(0.099)
Percent Some High School	−0.019***	−0.013***	−0.0000	−0.021***	−0.019***	−0.021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Percent High School Only	−0.008***	−0.013***	0.003***	−0.005***	−0.002***	−0.006***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	15.993***	58.421***	0.698	−2.533*	−20.309***	1.011
	(1.155)	(1.403)	(0.987)	(1.135)	(1.277)	(1.136)
Observations	6,351,515	6,351,515	6,351,515	6,351,515	6,351,515	6,351,515
R-squared Adjusted	0.211	0.172	0.056	0.161	0.103	0.122
Log Likelihood	−1.722e+07	−1.845e+07	−1.622e+07	−1.710e+07	−1.785e+07	−1.711e+07

Source: FRBNY Consumer Credit Panel/Equifax.
Notes: This table depicts the debt-level regressions using data from 2004:Q2 to 2008:Q2. These specifications will be used to generate predicted debt levels for consumers living in boom and non-boom counties in 2008:Q3. Debt levels enter specification in logs. Explanatory variables also include squared terms of all the non-categorical variables, as well as splines for age and risk score as described in the text.

across counties. As we will see, there are not large differences in our distribution of predicted debt levels across counties when we sort by house price appreciation during the housing boom. This finding is consistent with our finding of a muted role for cross-county variation in supply elasticity.

The other variable in our set of controls that varies meaningfully across counties is the current unemployment rate. As with all the other controls, the presence of credit report inquiries in the regression complicates interpretation of the coefficients on the unemployment rate. However, we do note that the unemployment coefficient for all but the mortgage category is positive. This finding is consistent with the results in Hurst and Stafford (2004), who document household consumption smoothing in the face of income shocks by way of drawing on credit lines—particularly home equity credit.

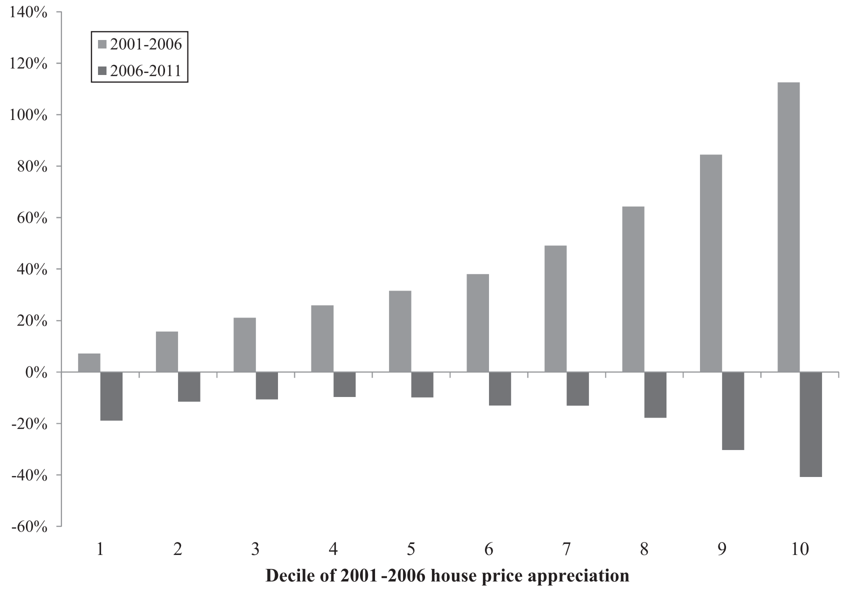
4. Post-crisis Debt-Change Analysis

4.1 Empirical Setup

The ultimate objective of this paper is to ascertain whether a contributing factor to households in counties with particularly strong pre-crisis house price appreciation reducing their debt was because they were unable to obtain the desired amount of credit. Following MRS, we break our sample up into regional groupings according to county house price appreciation during the 2001–06 period (figure 7). We form a group of low-appreciation counties that were in the bottom two deciles of boom-period house price appreciation ("non-boom" counties). We also form a group of high-appreciation counties from the top two deciles of this same distribution ("boom" counties).

Disentangling the demand for credit from the supply of credit is no easy task. Ideally, we would be able to identify consumers with identical demand for credit but living in counties with different exposures to house price shocks. Further, despite differing house price shocks, we would like all other economic conditions in these different counties to evolve in exactly the same way. In this idealized setting, with underlying credit demand controlled for, differences in household debt changes across the counties would be interpreted as

Figure 7. County-Level Deciles of House Price Appreciation Rates



Source: CoreLogic.

differences in credit availability. Using matching techniques and taking advantage of one group of households not directly affected by an adverse housing shock, renters, we feel we come quite close to such an idealized setting.

We proceed as follows. First, the data set does not contain a variable identifying consumers as "homeowners" or "renters" directly. Instead, we classify consumers with a mortgage outstanding as "homeowners" and those that do not have mortgages as "renters."[14] This classifies those consumers that paid off their mortgages fully as

[14]Thus, a "renter" is a long-term renter, and similarly for homeowners. When working with a renter- and homeowner-only sample, this means that we will be dropping consumers who switch tenure choice during our window of analysis. The assumption also implies that our total sample size (column 1 of table 3) will be greater than the sum of sample sizes of the renter- and homeowner-only samples (columns 2 and 3 of table 3).

renters, causing some measurement error. However, with a fully paid-off mortgage, it does seem reasonable to classify these consumers as not being subject to a severe housing shock, as while the value of their home may have declined recently, they are likely to have owned their home for a long time. In any case, the data suggest that the values of the homes of these consumers were above the purchase levels even after the collapse of the housing market in 2009–10.

Next, we perform a propensity-score matching exercise that pairs consumers that are similar in terms of their probability of living in a boom county but are different according to whether they actually live in a boom county or not. We perform the matching exercise separately for homeowners and for renters. We then take a difference-in-differences approach among the matched consumers within their predicted 2008:Q2 total debt-level category, to investigate whether we observe differences in deleveraging following the post-2008 boom. Finally, we estimate a set of regressions of changes in debt at the individual consumer level that allows us to control not just for proxies for initial-period consumer-specific credit demand but also for differences in subsequent changes in the economic environment that might have led to changes in demand as the housing bust and recession set in in mid-2008.

Before presenting the results, we note that our identification strategy requires that, conditional on our matching routine, renters in boom counties differ from their counterparts in non-boom counties only by their county of residence. One concern might be that once the recession was under way, the effects of the economic slowdown were stronger in boom counties, and renters there were disproportionately affected compared with renters in non-boom counties. In the robustness section we show that there is no evidence for such differential exposure to the recession. Among other tests, we use data from the PSID to show that renters did not suffer significantly larger income declines in boom markets than in non-boom markets; nor did they suffer significantly higher incidences of unemployment.[15] Compared with homeowners, renters did indeed suffer larger income declines.

[15] The PSID does not allow us to identify individuals at the same county level we use in our analysis, so we base our tests on whether renter income growth in the states containing boom counties was different than growth in states containing non-boom counties.

But these growth rates do not vary across markets or with measures of pre-recession house price growth, leaving our identification strategy intact.

The matching routine is based on a probit model of the assignment of consumers into boom versus non-boom counties, estimated separately for homeowners and renters.[16] Our predictors in the probit model are the same variables as are in the debt-level regressions, with the exception that we omit the squared terms for the demographic variables and we replace the spline terms for age and risk score with the level of these variables. The fitted probabilities of living in a boom county are estimated over all consumers present in the data in 2008:Q2. Homeowners (renters) in the boom counties are matched to homeowners (renters) in the non-boom counties by virtue of the similarity of their fitted probabilities of living in the boom county. We match with replacement.

Using this matched sample, we then take slices of the predicted total debt distribution in our base year (2008:Q2) to focus on how non-mortgage debt changed amongst the consumers as a function of their overall level of indebtedness. In this spirit we focus on consumers with low debt (less than 20th percentile of total predicted debt in 2008:Q2), medium debt (40th–60th percentile of total predicted debt in 2008:Q2), and high debt ranges (greater than 80th percentile). The predictions of total debt in 2008:Q3 are based on the estimates of the debt-level regressions in column 1 of table 2.

Finally, we then compare the change in non-mortgage debt from 2008:Q3 to 2011:Q4 for residents of boom counties with the same difference for their matches in non-boom counties, again comparing renters who, even in boom counties, were not subject to an adverse housing wealth shock with homeowners who were.

4.2 Matching Results

The results from the probit estimation may be found in table 3. The results suggest that consumers living in boom counties have a higher rate of credit inquiries, on average. Homeowners in boom counties also have higher risk scores than those in non-boom counties. As of

[16]We omit borrowers living in counties other than the bottom two and top two deciles from all of the empirical analyses from here on in the paper.

Table 3. Probability of Living in High-Appreciation County

	All Consumers	Homeowners	Renters
	b/se	b/se	b/se
Age	0.001***	0.006***	0.001*
	(0.000)	(0.001)	(0.000)
Credit Inquiries (Trailing Twelve Month)	0.031***	0.071***	0.026***
	(0.002)	(0.007)	(0.003)
Risk Score	0.077	0.914***	0.006
	(0.054)	(0.164)	(0.069)
County Unemployment	−0.151***	−0.216***	−0.143***
	(0.003)	(0.008)	(0.004)
High Small Business Percent	0.856***	0.364***	0.941***
	(0.044)	(0.104)	(0.057)
Median Age	0.046***	0.060***	0.041***
	(0.001)	(0.003)	(0.001)
Median Homeowner Cost (in logs)	1.244***	1.981***	1.102***
	(0.022)	(0.070)	(0.028)
Median Rent (in logs)	1.775***	1.409***	1.871***
	(0.019)	(0.044)	(0.026)
Median Tract Income	1.240***	1.237***	1.168***
	(0.036)	(0.101)	(0.045)
Median Year Moved into Housing Unit	−0.001	−0.019***	0.004
	(0.002)	(0.005)	(0.003)
Percent Black	−0.002***	−0.004***	−0.001***
	(0.000)	(0.001)	(0.000)
Percent College Education	−0.049***	−0.057***	−0.045***
	(0.001)	(0.002)	(0.001)
Percent Food Stamps	−0.040***	−0.033***	−0.041***
	(0.001)	(0.003)	(0.001)
Percent High School Only	−0.015***	−0.022***	−0.014***
	(0.001)	(0.003)	(0.001)
Percent Hispanic	0.050***	0.065***	0.046***
	(0.001)	(0.002)	(0.001)
Percent Homeowner	−0.019***	−0.022***	−0.017***
	(0.001)	(0.002)	(0.001)
Percent in Labor Force	−0.026***	−0.024***	−0.026***
	(0.001)	(0.003)	(0.001)
Percent Male	−1.562***	−2.264***	−1.468***
	(0.140)	(0.399)	(0.175)

(*continued*)

Table 3. (Continued)

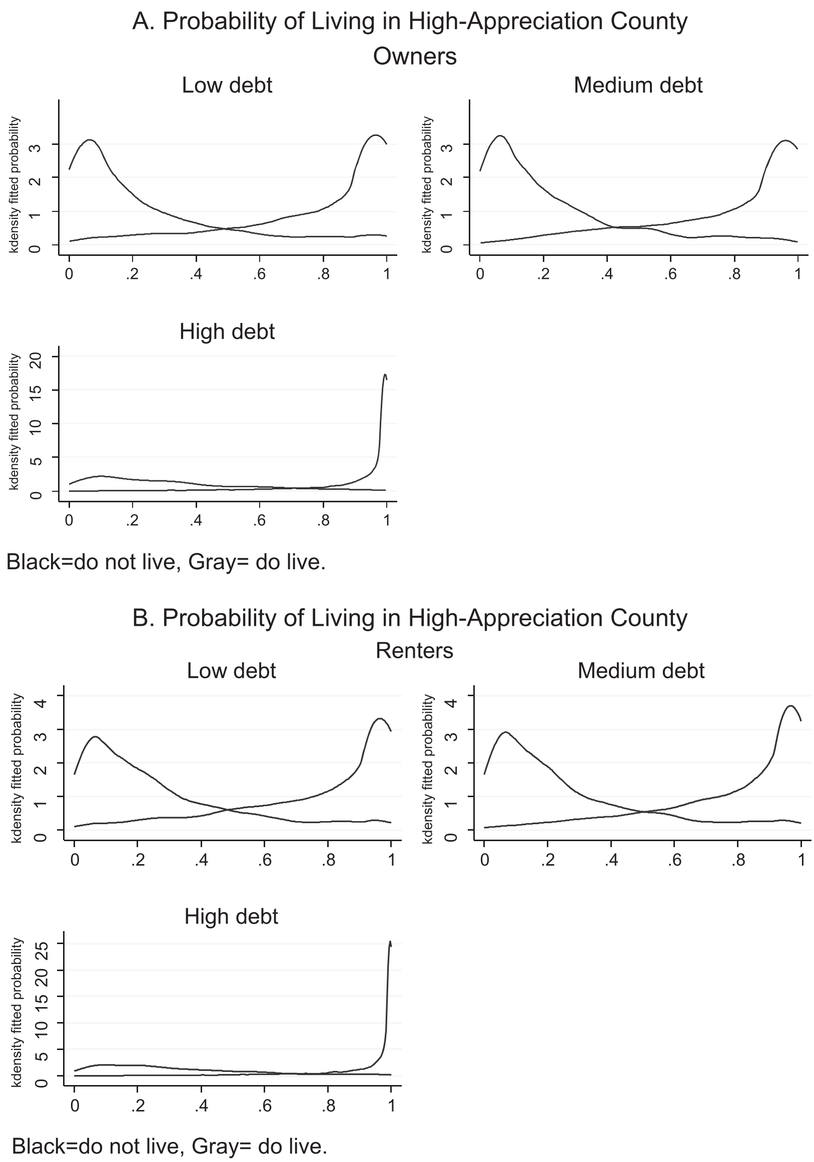
	All Consumers	Homeowners	Renters
	b/se	**b/se**	**b/se**
Percent Married	−0.028***	−0.041***	−0.024***
	(0.001)	(0.002)	(0.001)
Percent One Vehicle	−0.058***	−0.050***	−0.061***
	(0.001)	(0.004)	(0.001)
Percent Some High School	0.008***	0.004	0.010***
	(0.001)	(0.003)	(0.001)
Percent Working	−0.027***	−0.036***	−0.025***
	(0.001)	(0.004)	(0.002)
Total Tract Population (in logs)	0.386***	0.366***	0.402***
	(0.013)	(0.034)	(0.017)
Constant	−22.303***	11.205	−30.062***
	(4.172)	(10.815)	(5.299)
Observations	143,523	22,998	87,801
Log Likelihood	−42,789.858	−6,764.014	−26,074.814

Notes: This table presents the results from the probit model that forms the basis for the propensity-score matching routine. The dependent variable is the binary variable taking the value of one if a consumer lives in a high-appreciation boom county in 2008:Q2, and zero if the consumer lives in a low-appreciation non-boom county. Among the covariates, inquiries, age, and risk score are observed at the individual level. All other controls are observed at the county or census tract level. The "All Consumers" column reflects all records of consumers living in the boom and non-boom counties in 2008:Q2. The "Homeowner" ("Renter") column reflects all consumers who have had a mortgage (no mortgage) continuously for three years leading up to 2008:Q2. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

2008, the geographic controls identify the boom counties as having census tracts with somewhat better economic conditions as given by a higher incidence of small business activity, lower unemployment, and lower shares of households living on food stamps.

In figure 8, we plot the kernel density estimates of the fitted probabilities of living in a boom county, conditional on actual county of residence and conditional on our estimate of predicted total debt. We focus on low-debt consumers (in the 20th percentile of the predicted debt distribution), consumers with predicted total debt in a middle range (40th–60th percentile), and consumers with high levels

Figure 8. Probability of Living in High-Appreciation County: Owners and Renters



Source: FRBNY Consumer Credit Panel/Equifax.

of predicted debt (above the 80th percentile of predicted total debt). We generally have ample common support for the two distributions of fitted probabilities, meaning that for most of the boom county consumers in these particular slices of the predicted total debt distribution, there exists a counterpart actually living in a non-boom county with a similar propensity to live in a boom county. This observation is equally valid for the sample of homeowners (figure 8A) as it is for the renter sample (figure 8B). For consumers with high predicted levels of total debt, however, we see that there is less common support in the distribution of fitted probabilities of living in the boom counties. As can readily be seen in both the homeowner and renter figures, there are relatively few individuals with high predicted debt who live in a non-boom county but have attributes that give them a high probability of living in a boom county. We have 1,284 renters with high predicted debt in non-boom counties matched to the renters with high predicted debt in boom counties. We have 192 homeowners with high predicted debt in non-boom counties matched to the homeowners with high predicted debt in boom counties.

In tables 4–6, we summarize the demographic variables in our matched sample. As we would expect, once we have matched on the consumer attributes from the probit regression (see tables 4–6), the average characteristics of consumers in the remaining sample look quite similar. This basic conclusion holds when we restrict our matching according to whether we observe a mortgage on the consumers' balance sheets (homeowners in table 4 and renters in table 5). The main exception to this result, however, is the percent Hispanic variable. Even after controlling for observables, our matched sample consists of a higher percentage of borrowers in the boom counties that live in census tracts with relatively high Hispanic representation.[17]

With matches in hand we can then test for differences in debt changes across counties and across different types of borrowers (homeowners and renters). Before we do this, however, we note in figure 9 that, unconditionally and in aggregate, we do see a noticeable difference in declines in non-mortgage debt across non-boom

[17] This is not surprising, given the prevalence of boom counties in California and other parts of the southwestern United States.

Table 4. Characteristics of Matched Sample of Consumers: All Borrowers

	Non-boom Counties		Boom Counties	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Age	49.32	18.3	48.41	18.05
Credit Inquiries (Trailing Twelve Month)	1.639	2.691	1.645	2.492
Risk Score	690.2	114.1	687.4	111.6
County Unemployment Rate	5.672	1.462	5.649	1.67
High Small Business Percent	22.2	14.5	23.6	10.6
Median Age	38.57	6.491	37.45	7.401
Median Ownership Costs	7.073	0.338	7.323	0.423
Median Rent	6.595	0.354	6.872	0.358
Median Tract Income	10.87	0.454	10.95	0.435
Median Year Moved into Housing Unit	2001	3.468	2001	3.384
Percent Black	15.52	24.95	13.52	22.02
Percent College Education	29.6	18.62	28.78	18.08
Percent Food Stamps	9.707	9.908	8.744	8.721
Percent High School Only	28.25	10.55	26.17	9.727
Percent Hispanic	6.088	9.865	14.32	15.81
Percent Homeowner	68.71	21.64	62.11	23.19
Percent in Labor Force	65.52	8.629	65.44	8.725
Percent Male	48.5	4.17	48.7	3.75
Percent Married	49.11	14.93	47.93	12.17
Percent One Vehicle	96.5	5.759	93.45	12.25
Percent Some High School	12.93	10.14	16.93	13.37
Percent Working	78.14	8.369	76.59	7.708
Total Population	8.385	0.422	8.467	0.411
Observations	13,517		96,639	

Source: FRBNY Consumer Credit Panel/Equifax.
Notes: This table presents the summary statistics for the matched sample of boom and non-boom county consumers. All consumers in the boom counties are matched to corresponding non-boom county consumers. The matching is done through a propensity-score matching routine. The matching is done with replacement. Non-matched consumers are dropped from the sample for purposes of calculating the summary tables.

Table 5. Characteristics of Matched Sample of Consumers: Homeowners

	Non-boom Counties		Boom Counties	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Age	51.05	11.51	51.87	11.77
Credit Inquiries (Trailing Twelve Month)	1.34	2.013	1.372	1.878
Risk Score	749.9	84.69	758.3	80.8
County Unemployment Rate	5.485	1.386	5.527	1.715
High Small Business Percent	23.5	15.5	24.6	10.2
Median Age	39.8	5.933	39.01	6.814
Median Ownership Costs	7.198	0.314	7.443	0.381
Median Rent	6.684	0.367	6.968	0.373
Median Tract Income	11.06	0.417	11.15	0.406
Median Year Moved in	2000	3.272	2000	3.513
Percent Black	9.234	18.11	8.463	15.47
Percent Food Stamps	6.588	7.208	5.796	6.118
Percent High School Only	25.84	10.56	23.89	9.873
Percent Hispanic	5.078	8.082	11.86	13.43
Percent Homeowner	75.48	18.49	71.84	18.88
Percent in Labor Force	66.75	7.851	66.21	7.907
Percent Male	48.8	3.79	48.9	3.25
Percent Married	54.63	13.23	53.18	10.76
Percent One Vehicle	97.96	3.552	96.89	6.615
Percent Some High School	9.753	8.384	12.6	11.16
Percent Working	79.92	6.522	78.13	6.575
Percent Colege Education	35.02	18.42	34.41	18.93
Total Population	4,962	1,949	5,336	2,307
Observations	2,143		14,809	

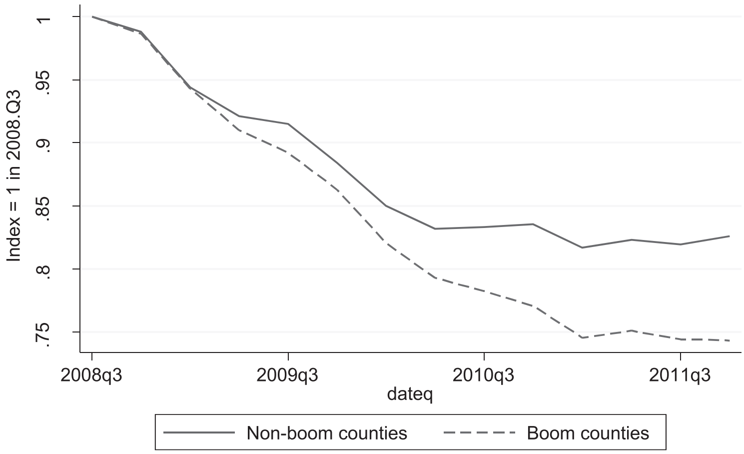
Source: FRBNY Consumer Credit Panel/Equifax.
Notes: This table presents the summary statistics for the matched sample of boom and non-boom county consumers. All consumers in the boom counties are matched to corresponding non-boom county consumers. The matching is done through a propensity-score matching routine. The matching is done with replacement. Non-matched consumers are dropped from the sample for purposes of calculating the summary tables. Homeowners are identified as consumers with positive mortgage balances over the preceding twelve quarters.

Table 6. Characteristics of Matched Sample of Consumers: Renters

	Non-boom Counties		Boom Counties	
	Mean	Std. Dev.	Mean	Std. Dev.
Age	52.05	19.47	50.64	18.9
Credit Inquiries (Trailing Twelve Month)	1.553	2.685	1.514	2.442
Risk Score	679.9	115.2	678.1	112.5
County Unemployment Rate	5.729	1.47	5.676	1.633
High Small Business Percent	22	14.2	23.5	10.6
Median Age	38.34	6.622	37.27	7.533
Median Ownership Costs	7.026	0.339	7.292	0.433
Median Rent	6.558	0.339	6.849	0.354
Median Tract Income	10.81	0.448	10.9	0.431
Median Year Moved in	2001	3.533	2001	3.364
Percent Black	17.76	26.94	14.88	23.55
Percent College Education	27.72	18.5	27.57	17.66
Percent Food Stamps	10.95	10.68	9.425	9.127
Percent High School Only	29.1	10.46	26.67	9.649
Percent Hispanic	6.357	10.49	14.76	16.14
Percent Homeowner	66.6	21.8	59.77	23.48
Percent in Labor Force	64.79	8.805	65.12	8.96
Percent Male	48.4	4.31	48.6	3.86
Percent Married	47.1	14.84	46.58	12.15
Percent One Vehicle	96.02	6.201	92.64	13.02
Percent Some High School	14.2	10.58	17.88	13.56
Percent Working	77.36	8.9	76.19	7.952
Total Population	8.358	0.423	8.452	0.407
Observations	8,231		59,120	

Source: FRBNY Consumer Credit Panel/Equifax.
Notes: This table presents the summary statistics for the matched sample of boom and non-boom county consumers. All consumers in the boom counties are matched to corresponding non-boom county consumers. The matching is done through a propensity-score matching routine. The matching is done with replacement. Non-matched consumers are dropped from the sample for purposes of calculating the summary tables. Renters are identified as consumers with zero mortgage balances over the preceding twelve quarters.

Figure 9. Non-mortgage Debt in Matched Sample



Source: FRBNY Consumer Credit Panel/Equifax.

and boom counties. Consumers in the boom counties reduced non-mortgage debt at a faster pace early on in the recession, and continued to reduce debt for a longer period than their matched counterparts in the non-boom counties.

The results of difference-in-difference tests are found in table 7, where we report the difference in changes in debt levels between the matched individuals. Negative numbers mean that individuals living in boom counties reduced their debt levels more than did their matched counterparts in non-boom counties. With the exception of low-debt homeowners, all statistically significant difference-in-difference estimates are negative, and all of these indicate economically important effects. In particular, for consumers with high levels of predicted total debt (top two deciles of the predicted debt distribution), we see more evidence of greater non-mortgage debt reductions in boom counties than in non-boom counties for renters than for homeowners.

4.3 Post-crisis Regressions on the Matched Sample

The results in table 7 suggest the possibility that an inward shift in credit supply played an important role in the deleveraging of

Table 7. Difference-in-Difference Results for Non-mortgage Debt

Percentile of Total Predicted Debt 2008:Q2	20th Percentile	40th–60th Percentile	80th Percentile
All Consumers	.088	0.029	−.190***
	(.061)	(.060)	(.021)
Homeowners	.265*	−.735***	−.536***
	(.137)	(.107)	(.040)
Renters	−0.010	−.144*	−.814***
	(.075)	(.077)	(.027)

Source: FRBNY Consumer Credit Panel/Equifax.
Notes: This table presents the results of differences-in-means t-tests of changes in non-mortgage debt from 2008:Q3 to 2011:Q4 among consumers living in boom counties vs. consumers living in non-boom counties. All results are based on a sample of matched consumers as described in the propensity-score matching method. With consumers matched by propensity scores, we also filter by restricting the sample to consist of matched consumers belonging to specific quantiles of the distribution of predicted total debt in 2008:Q2. A negative difference in mean debt change signifies that debt declined more in the boom counties than in the non-boom counties. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

households in boom counties. However, even though we control for debt demand and household- and tract-level characteristics, we would like to rule out that *changes* in these characteristics between 2008 and 2011 drive the differences in deleveraging of renters between boom and non-boom counties. Specifically, it is possible that renters fared worse from 2008 to 2011 in boom counties than in non-boom counties and that this underlies our differences in deleveraging. In order to address this point, we estimate variants of the following regression:

$$\Delta D_{i,2011-2008} = \alpha + \rho_1 BC + \rho_2 BC * Renter_i + \rho_3 BC * risk_i + \Pi X_i + \Theta X + \xi \Delta ue + \varepsilon, \tag{2}$$

where $\Delta D_{i,2011-2008}$ represents, for individual i, the difference between their 2008:Q3 non-mortgage debt level and their 2011:Q4 non-mortgage debt level.[18] The coefficients ρ_1, ρ_2, and ρ_3 on the indicator variable BC ("boom county") are of most interest. The first is intended to measure the degree to which households in boom counties reduce debt more than those in non-boom counties, controlling for changes in the non-house-price elements of the demand for debt. The second allows us to see how that differential depends on whether the borrower is a renter. The third allows us to see how that differential depends on the risk score of the borrower. We also include a triple interaction of boom county, renter status, and risk score to further explore the patterns in consumer debt reduction.

In all of the changes in debt regressions to follow, we work with the matched sample of borrowers from the propensity-score matching analysis above. That is, while we have both homeowners and renters from the two groups of counties, a non-boom homeowner only appears if it is matched to a homeowner in a boom county, and similarly for renters. The controls in X_i include, analogous to equation (1), the individual's age and risk score, and the number of credit report inquiries on the individual over the previous twelve months, all as of 2008:Q3. In addition, X_i includes the change in the individual's risk score between 2008 and 2011, whether the individual is a homeowner, and the individual's actual level of total debt, as of 2008:Q3. The controls in X also include the census tract and county level control variables as they appear in equation (1), with the exception of the unemployment rate, which, instead, enters equation (2) as a change between 2008 and 2011.

Table 8 presents the results for non-mortgage debt-change regressions. The coefficients on each of the individual level controls are highly statistically significant. As expected, consumers with a low risk score (<650) in 2008 tended to reduce non-mortgage debt more than those with a higher risk score. However, those consumers with risk scores that improved (i.e., a positive change in risk score) reduced debt more than consumers whose risk score worsened.[19]

[18] Our regression sample consists of pairs of individuals, matched on their probability of living in a boom county, within predicted 2008:Q2 debt ranges, as described in the text above.

[19] In part this may just be due to reverse causality, as those who reduced debt more may have been rewarded with a higher risk score.

Table 8. Change in Non-mortgage Debt Regressions

	(1)	(2)	(3)	(4)	(5)
Boom County	−.076**	−0.050	0.081	0.093	0.107
	(0.039)	(0.049)	(0.065)	(0.063)	(0.067)
Borrower Age in 2008:Q3		−0.018***	−0.018***	−0.018***	−0.018***
		(0.001)	(0.001)	(0.001)	(0.001)
Borrower Credit Inquiries in 2008:Q3		0.071***	0.070***	0.070***	0.070***
		(0.007)	(0.007)	(0.007)	(0.007)
Borrower Total Debt in 2008:Q3		−0.340***	−0.340***	−0.340***	−0.340***
		(0.005)	(0.005)	(0.005)	(0.005)
Change in Risk Score (2008:Q3–2011:Q4)		−0.007***	−0.007***	−0.007***	−0.007***
		(0.000)	(0.000)	(0.000)	(0.000)
Low Risk Score (<650) in 2008:Q3		−1.250***	−1.249***	−1.167***	−0.954***
		(0.031)	(0.031)	(0.071)	(0.235)
Renter (2008:Q3–2011:Q4)		−1.819***	−1.673***	−1.694***	−1.652***
		(0.052)	(0.057)	(0.059)	(0.067)
Boom County × Renter			−0.170**	−0.146*	−0.167*
			(0.064)	(0.068)	(0.078)
Boom County × Low Risk Score				−0.094	−0.186
				(0.074)	(0.252)
Renter × Low Risk					−0.245
					(0.253)
Boom County × Renter × Low Risk					0.109
					(0.274)
Constant	−0.562***	14.892	14.639	14.575	14.562
	(0.036)	(10.663)	(10.673)	(10.682)	(10.678)
Observations	76,437	76,437	76,437	76,437	76,437
R-squared Adjusted	.000	0.162	0.162	0.162	0.162

Notes: This table presents the results from the regressions of changes in non-mortgage debt on the boom county dummy and control variables. The change in non-mortgage debt is computed over 2008:Q3–2011:Q4. Among the covariates, age, credit inquiries, risk score, and total debt are calculated for each consumer for the base year 2008:Q3. We also compute a change in risk score over the 2008:Q3–2011:Q4 period. All regressions include tract- and county-level controls, and clustered standard errors at the county level. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Individuals with more inquiries tended to reduce debt less, as expected. More debt in 2008 was correlated with greater reductions in debt. All other factors held constant, renters reduced debt more than homeowners. Again, this result points to the role of restricted credit supply during the 2008:Q3–2011:Q4 period. Controlling for the demographics we have available to us, we would naturally expect renters to reduce debt by less because their demand would not have been affected by the negative wealth shock to housing.

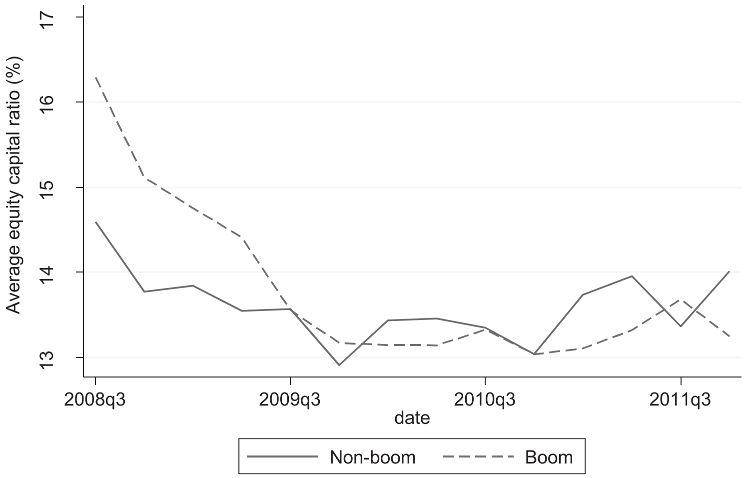
The coefficients on the interaction between boom county and renter in table 8, in columns 3–5, are negative and statistically significant. Living in a boom county strengthens the positive association between renters and reduction in non-mortgage debt. This contrasts with the lack of statistical significance of the effect of boom county on homeowners (the coefficient on boom county by itself) in the same specifications.

These results about the relationship between boom county and debt reduction point towards a more subtle interpretation of the determinants of household deleveraging during the aftermath of the housing boom than is typically reported. We generally corroborate the results in MRS with the positive association between boom county and deleveraging and also the finding that borrowers entering our analysis period with relatively large overhangs of total debt tended to delever more. However, the important point here is that the effect of residence in a boom county on any non-mortgage debt reduction tends to be larger for renters than for equivalent homeowners. This is indicated by the negative coefficient on the interaction between renter and boom county. This suggests that a general negative credit supply shock contributed to debt reduction in the post-2008 period. In addition, the lack of statistical significance of the coefficient on the three-way interaction between boom county, renter, and low risk score indicates that the cutback in supply was not confined to the borrowers with the highest levels of credit risk.

4.4 IV Results

The findings above naturally suggest a story where a bank lending channel restricted consumers' ability to borrow in the aftermath of the housing boom. To explore this idea more fully, we compare measures of bank conditions across the boom and non-boom counties during the 2008:Q3–2011:Q4 period. We associate banks with local markets on the basis of their headquarters of operation as reported in the Federal Reserve's Call Reports. When we restrict our analysis to include only those commercial banks with less than $1 billion in assets in 2008, we can be reasonably confident that our banks are

Figure 10. Average Equity Capital Ratios by County



small enough to be lending primarily in the counties where they are headquartered.[20]

As a first pass, in figure 10 we plot the average equity capital ratio of our sample of banks in both the boom and non-boom counties. As the figure indicates, local banks in the boom counties suffered losses during the recession and experienced a decline in their equity capital ratios. Since new lending must be supported by equity capital, the boom county banks were progressively more constrained in terms of capital as the analysis period rolled forward from 2008:Q3 and into 2011. The figure also makes clear that if we find any evidence of bank effects on consumer deleveraging, then the channel will be through a change in bank conditions. Indeed, the figure shows that average equity capital ratios in the boom counties declined to become more similar to the equity capital ratios observed in the non-boom counties. Thus, our sample of banks clearly indicates that boom county banks suffered a shock, but there is much less evidence of the non-boom county banks experiencing a similar shock.

Proceeding more formally, we estimate an IV model, in which we use boom county residence as an instrument for changes in bank

[20]The $1 billion asset threshold is a commonly used definition of a "community bank" in the U.S. banking sector.

capital of local banks. The model permits us to map out the transmission channel from banks' balance sheets to deleveraging. The approach should map out the part of extra deleveraging in boom counties due to differential changes in bank capital. Hence, a significant coefficient in the IV model shows the relative differences in deleveraging between homeowners and renters in boom versus non-boom counties limited to differences in credit supply of banks. As we are interested in the relative effect for homeowners and renters, we estimate the model separately for the two groups.

The results are presented in table 9. Columns 1 and 3 show that our instrument is strong: we obtain negative coefficients on the boom county indicator and large negative t-statistics for both the homeowner and renter samples. Economically, being headquartered in a boom county is highly correlated with a strong decline in bank capital in the 2008 to 2011 period. In the second stage (columns 2 and 4 of table 9), we find that changes in bank capital and changes in debt exhibit a negative and insignificant correlation for homeowners and a positive and significant correlation for renters. This evidence suggests that credit supply was important in the deleveraging of renters and not in the deleveraging of homeowners. This confirms our earlier findings that a significant part of the deleveraging process of households in the wake of the real estate boom before the crisis resulted from more restrictive lending of banks that were trying to rebuild capital after sustaining large losses.

5. Robustness

We conduct several robustness checks on our results. First, we investigate whether our results may be due to renters' demand for debt being more negatively affected by residence in a boom county than homeowners' demand for debt. Recall that it is not a problem if renters overall (regardless of being in a boom or non-boom county) were more affected by the economic downturn that followed the crisis than homeowners. What is important for our identification strategy to hold is that renters in boom counties were not more affected than renters in non-boom counties. Hence, we examine this question in detail here. Start with the observation that, according to the debt-level regression results in table 2, income is correlated with auto debt (positively) and credit card debt (negatively). No doubt some

Table 9. Local Bank Conditions and Changes in Non-mortgage Debt

	Homeowners Only		Renters Only	
	First Stage	Second Stage	First Stage	Second Stage
Dependent Variable	Change in Bank Equity	Change in Non-mortgage Debt	Change in Bank Equity	Change in Non-mortgage Debt
Boom County	-0.014^{***}		-0.016^{***}	
	(0.002)		(0.001)	
Predicted Change in Bank Equity Capital		-5.462		5.871^{*}
		(5.543)		(2.935)
Constant		1.610		25.117
		(24.098)		(12.985)
Borrower Age in 2008:Q3		-0.011^{***}		-0.019^{***}
		(0.002)		(0.001)
Borrower Credit Inquiries in 2008:Q3		-0.015		0.085^{***}
		(0.014)		(0.006)
Borrower Total Debt in 2008:Q3		-0.141^{***}		-0.344^{***}
		(0.028)		(0.004)
Change in Risk Score (2008:Q3–2011:Q4)		-0.005^{***}		-0.007^{***}
		(0.000)		(0.000)
Low Risk Score (<650) in 2008:Q3		-1.021^{***}		-1.280^{***}
		(0.083)		(0.034)
Demographic Controls	Yes	Yes	Yes	Yes
Observations	16,121	16,121	60,263	60,263
R-squared	0.024	0.016	0.026	0.175

Notes: The table reports the results of an instrumental-variables regression of the change in non-mortgage debt (2008:Q3–2011:Q4) on a local banking conditions variable and controls. The first stage is a regression of change in bank equity on the boom county indicator variable and demographic controls. The second stage is a regression of change in non-mortgage debt on the instrumented change in equity and the control variables. The control variables include county- and tract-level demographic variables used in table 8 and throughout the paper. The banking conditions variable is the average change in equity capital ratio (2008:Q3–2011:Q4) for banks headquartered in the consumer's county of residence. The average equity capital ratio is instrumented using the boom county indicator. A positive coefficient on the predicted change in equity capital variable indicates that growth in non-morntgage debt is positively associated with growth in local bank equity ratios. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

of this correlation is coming from the demand side and some from the supply side. In any case, if there were an association between boom versus non-boom county residence and changes in income, and if such an association showed a differential boom effect for renters versus homeowners, then our results might be due to differential demand changes, not the presence of credit supply shocks.

As a first piece of evidence consider figure 2. Figure 2 gives no evidence of differential boom effects that would confound the interpretation of our results. The figure uses data from the ACS vintages that correspond most closely with 2008, the beginning of the window over which we measure debt changes, and 2011, the end of the debt-change window. In figure 2A, we plot changes in median household income at the county level. In figure 2B, we plot changes in the 20th percentile of household income. On the horizontal axis of the two panels we plot the percentiles of the county homeownership rate, increasing from left to right. In figure 2A, there is no association between homeownership rate and any differences between changes in income in boom versus non-boom counties. Changes in incomes for boom counties that are systematically lower than changes in incomes for non-boom counties (the gray line below the black line) *along with* a shrinkage in this differential from left to right would support a view of differential demand changes that would be detrimental to our argument. Figure 2A shows no such pattern. Neither does figure 2B. In fact, figure 2B shows the opposite pattern. For households at the 20th percentile of income, there appears to be a more consistent pattern of deeper declines in income in boom than in non-boom counties on the right side of the graph than on the left, but the right side of the graph represents the *high*-homeownership counties, not the low-homeownership counties.

We also conducted a similar exercise to the one depicted in figures 2A and 2B using data from the Panel Study of Income Dynamics (PSID). The PSID allows us to look at the actual income distributions for both renters and homeowners, instead of using the local homeownership rates as proxies for renting versus owning. One drawback to the PSID, however, is that it only identifies the state of residence of the survey respondents. Thus, we cannot look at how income changed for renters and owners in our specific boom and non-boom *counties*, but are forced to analyze this at the state level. We use observations on total family income from the family files in 2009 and 2011 waves, which corresponds most closely to the sample period in our study. To parallel the analysis with the ACS data above, in each wave we calculate the median and the 20th percentile of the income distribution within each state, by renter and homeowner. Our change in income measure is the (log) difference of incomes at each of these percentiles. We then correlate these income changes with the four-year past house price appreciation in the state. We plot these relationships for the change in median income (figure 3A) and the change in income at the 20th percentile (figure 3B). In the figures, the dots depict the change in income and four-year change in house prices for each state, with black representing the observations for homeowners and gray representing the observations for renters. As we saw with the ACS data, at the aggregated market level, changes in income do not vary systematically with house price changes for renter households.

The analysis reported in figures 3A and 3B is conducted at the state level. Differences in average renter and homeowner income growth do not vary with the house price appreciation in their states of residence. This level of aggregation parallels the analysis with the ACS data in figures 2A and 2B. We can also use the PSID data to track income growth at the family unit. We restrict our sample to include observations on total family income only for individuals who identified themselves as head of household and reported no change in family composition between the 2009 and 2011 PSID waves.

In table 10 we report regressions of income growth on renter status and our proxies for exposure to the housing market wealth shock. The dependent variable is the log change in total income. All regressions include a standard set of controls observed in 2009 (log income, age, and years of education). A household is considered a renter if it rents in both the 2009 and 2011 waves. We use two measures of exposure to the housing market shock. First, we use the five-year state-level house price appreciation between 2001 and 2006, similar to the measure that we use to define the boom and non-boom counties in the main part of our analysis. We also include a "boom state" indicator variable, equal to one for states with boom counties from our earlier analysis and zero for states with non-boom counties.[21] The regressions are weighted using the PSID cross-sectional sampling weights.

In general, the results in table 10 are consistent with our earlier results. Family income growth is negatively related to renter status, suggesting that renters are more vulnerable than homeowners to income shocks over the business cycle. However, the coefficient

[21] We are forced to drop New York and North Carolina as states that have both boom and non-boom counties.

Table 10. PSID Family Income Growth Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
House Price Change, 2001–06	0.138**			0.159***		0.188***	
	(0.045)			(0.045)		(0.052)	
Boom State		0.092**			0.103**		0.130***
		(0.033)			(0.033)		(0.037)
Renter			−0.277***	−0.283***	−0.291***	−0.238***	−0.248***
			(0.051)	(0.051)	(0.072)	(0.059)	(0.073)
Renter × House Price Change						−0.090	
						(0.079)	
Renter × Boom State							−0.087
							(0.062)
Age, 2009	−0.148	−0.136	−0.574***	−0.583***	−0.574***	−0.586***	−0.581***
	(0.119)	(0.144)	(0.135)	(0.135)	(0.173)	(0.135)	(0.172)
Years Education, 2009	0.047***	0.047***	0.044***	0.044***	0.044***	0.044***	0.044***
	(0.009)	(0.011)	(0.008)	(0.008)	(0.010)	(0.008)	(0.010)
Total Income (log), 2009	−0.273***	−0.294***	−0.320***	−0.324***	−0.347***	−0.324***	−0.347***
	(0.046)	(0.062)	(0.050)	(0.050)	(0.068)	(0.049)	(0.068)
Constant	2.415***	2.638***	3.682***	3.668***	3.932***	3.652***	3.928***
	(0.416)	(0.568)	(0.577)	(0.565)	(0.790)	(0.561)	(0.788)
Observations	5,319	3,278	5,319	5,319	3,278	5,319	3,278
Log Likelihood	−4,953.620	−3,131.567	−4,878.349	−4,861.509	−3,075.109	−4,860.326	−3,073.365

Notes: This table shows regressions of 2009–11 total family income growth on renter status and housing market exposure as reported in the 2009 and 2011 PSID. All regressions are weighted using the PSID cross-sectional sampling weights in 2011. The sample is restricted to observations from the PSID individual file for individuals self-identified as head of household who reported no change in family composition over 2009–11. A family is designated as a "renter" if it was a renter in both 2009 and 2011. Housing market exposure is measured as house price appreciation between 2001 and 2006, and also with the boom state indicator variable equal to one if the state includes a boom county and zero if it includes a non-boom county. Observations are dropped from the sample if a household lives in a state with both boom and non-boom counties.

estimates on the interactions of renter status with past house price appreciation and boom state are insignificant. We do not find evidence that renter family income growth was systematically lower in states corresponding to our boom markets. Thus, weak income growth among the renter population in boom markets does not appear to explain why renter households in these markets had significantly weaker growth in credit during the economic recovery.

Perhaps renters' optimism about the future declined more than did homeowners'. Here, we do not have evidence on boom versus non-boom, but we can proxy for renter versus owner. We investigate the Michigan Index of Consumer Expectations and find no strong evidence that this was true. We assume that income is positively correlated with homeownership. We find that the change in the Index between 2008:Q3 and 2011:Q4 was −3.2 for the lowest income quartile, −2.5 for the next highest quartile, −2.3 for the next highest quartile, and −3.8 for the highest income quartile. Optimism about the future declined the most for the group most likely to be homeowners. We assume that demand for debt is positively associated with optimism. Therefore, this result does not support the view that renters' demand declined more than homeowners' demand.

There are several other assumptions in our research design that need closer examination. First, our method of identifying homeowners and renters as having (or not having) a mortgage balance is somewhat restrictive. In table 11, we loosen this assumption. We define homeowners in the usual way, as consumers who had a mortgage balance throughout the 2008:Q3–2011:Q4 period. Renters, by contrast, include everyone else in the matched sample. This definition of renters encompasses the old definition and admits in other consumers who may have transitioned between homeownership and renter status. The results in table 11 generally confirm our earlier debt-change regression results in table 8. The more expansive definition still shows that renters reduced debt significantly more than homeowners, and particularly so in the boom counties. Indeed, the boom county $\times$ renter interaction term in columns 3–5 is always negative and significant at the 1 percent confidence level.

For another robustness check we run parallel debt-change regressions using all consumers living in the boom and non-boom counties, and not just the consumers that have been matched. While we believe that using some kind of matching approach is desirable to try

Table 11. Change in Non-mortgage Debt Regressions: Alternative Definition of Renters

	(1)	(2)	(3)	(4)	(5)
Boom County	−0.092*	−0.065	0.087	0.096	0.115
	(0.037)	(0.047)	(0.062)	(0.060)	(0.065)
Borrower Age in 2008:Q3		−0.018***	−0.018***	−0.018***	−0.018***
		(0.001)	(0.001)	(0.001)	(0.001)
Borrower Credit Inquiries in 2008:Q3		0.064***	0.064***	0.064***	0.064***
		(0.007)	(0.007)	(0.007)	(0.007)
Borrower Total Debt in 2008:Q3		−0.331***	−0.331***	−0.331***	−0.331***
		(0.004)	(0.004)	(0.004)	(0.004)
Change in Risk Score (2008:Q3–2011:Q4)		−0.007***	−0.007***	−0.007***	−0.007***
		(0.000)	(0.000)	(0.000)	(0.000)
Low Risk Score (<650) in 2008:Q3		−1.289***	−1.289***	−1.228***	−0.927***
		(0.031)	(0.031)	(0.071)	(0.233)
Renter (2008:Q3–2011:Q4)		−1.669***	−1.503***	−1.517***	−1.460***
		(0.043)	(0.055)	(0.058)	(0.061)
Boom County × Renter			−0.194**	−0.177**	−0.204**
			(0.062)	(0.065)	(0.071)
Boom County × Low Risk Score				−0.069	−0.187
				(0.076)	(0.251)
Renter × Low Risk					−0.343
					(0.238)
Boom County × Renter × Low Risk					0.138
					(0.259)
Constant	−0.567***	15.422	15.140	15.088	15.084
	(0.035)	(10.736)	(10.746)	(10.756)	(10.751)
Observations	83,071	83,071	83,071	83,071	83,071
R-squared Adjusted	0.000	0.157	0.157	0.157	0.157

Notes: This table presents the results from the regressions of changes in non-mortgage debt on the boom county dummy and control variables. In this table the definition of renter is expanded to include all consumers who do not have a mortgage balance for the entire 2008:Q3–2011:Q4 sample period. Partial spells with mortgages are classified as renters. The change in non-mortgage debt is computed over 2008:Q3–2011:Q4. Among the covariates, age, credit inquiries, risk score, and total debt are calculated for each consumer for the base year 2008:Q3. We also compute a change in risk score over the 2008:Q3–2011:Q4 period. All regressions include tract- and county-level controls, and clustered standard errors at the county level. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

to put consumers on an even footing as of 2008:Q3, this robustness check helps to alleviate concerns that the matching somehow selects renters in the non-boom counties who were particularly sensitive to changes in economic conditions. The results from this exercise are in table 12. Again, we see that renters are still more likely to have reduced their non-mortgage debt during the 2008:Q3–2011:Q4 period, and particularly so in the boom counties.

Table 12. Change in Non-mortgage Debt Regressions: Non-matched Sample

	(1)	(2)	(3)	(4)	(5)
Boom County	−0.142***	−0.066	0.122*	0.149**	0.144*
	(0.024)	(0.039)	(0.055)	(0.055)	(0.058)
Borrower Age in 2008:Q3		−0.020***	−0.020***	−0.020***	−0.020***
		(0.001)	(0.001)	(0.001)	(0.001)
Borrower Credit Inquiries in 2008:Q3		0.066***	0.066***	0.065***	0.065***
		(0.006)	(0.006)	(0.006)	(0.006)
Borrower Total Debt in 2008:Q3		−0.354***	−0.354***	−0.354***	−0.354***
		(0.005)	(0.005)	(0.005)	(0.005)
Change in Risk Score (2008:Q3–2011:Q4)		−0.007***	−0.007***	−0.007***	−0.007***
		(0.000)	(0.000)	(0.000)	(0.000)
Low Risk Score (<650) in 2008:Q3		−1.176***	−1.175***	−1.052***	−1.032***
		(0.032)	(0.032)	(0.047)	(0.120)
Renter (2008:Q3–2011:Q4)		−1.810***	−1.651***	−1.681***	−1.677***
		(0.050)	(0.047)	(0.048)	(0.052)
Boom County × Renter			−0.241***	−0.192***	−0.186**
			(0.055)	(0.057)	(0.062)
Boom County × Low Risk Score				−0.181***	−0.135
				(0.052)	(0.152)
Renter × Low Risk					−0.024
					(0.123)
Boom County × Renter × Low Risk					−0.050
					(0.156)
Constant	−0.461***	7.967	7.508	7.455	7.471
	(0.020)	(8.606)	(8.627)	(8.677)	(8.690)
Observations	107,686	107,686	107,686	107,686	107,686
R-squared Adjusted	0.000	0.163	0.164	0.164	0.164

Notes: This table presents the results from the regressions of changes in non-mortgage debt on the boom county dummy and control variables. In this table the definition of renter is expanded to include all consumers who do not have a mortgage balance for the entire 2008:Q3–2011:Q4 sample period. Partial spells with mortgages are classified as renters. The change in non-mortgage debt is computed over 2008:Q3–2011:Q4. Among the covariates, age, credit inquiries, risk score, and total debt are calculated for each consumer for the base year 2008:Q3. We also compute a change in risk score over the 2008:Q– 2011:Q4 period. All regressions include tract- and county-level controls, and clustered standard errors at the county level. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

6. Conclusion

Previous empirical research has suggested that the tremendous blow to the housing market contributed to the sharp drop in aggregate consumer debt. We investigate whether such a link may be at least partially due to cutbacks in the supply of credit. First using the Federal Reserve Board's Senior Loan Officer Opinion Survey, we show that banks did indeed tighten credit standards in boom counties more than in non-boom counties. In order to further explore the role of credit supply conditions, we examine individual credit file data. Here, we find evidence suggesting that credit supply effects independent of collateral effects were important. In our estimations, we find that, for non-mortgage debt, homeowners did not reduce debt more in counties with large house price declines than in counties with small house price declines. In contrast, renters did reduce debt more in the boom counties. Using an IV estimation, we map out the transmission channel from banks with weak bank balance sheets to a higher degree of deleveraging after the crisis. Our evidence supports the view that a general tightening of credit supply that was independent of the effects of the drop in value of housing collateral contributed to cutbacks in consumer borrowing.

Appendix

As mentioned in the main text, we also conduct additional estimations of the non-mortgage debt change regressions. Table 13 shows that our main results hold up when we add home equity debt to non-mortgage debt. When we excluded home equity debt, in table 8, we saw that renters saw a negative effect on debt change from living in a boom county, but that homeowners saw no effect from living in a boom county. In most specifications in table 13, boom county has no effect on the debt change of either homeowners or renters, either by itself or in interaction with any other variable. The important point here is that homeowners did not undergo a greater reduction in debt in boom counties than in non-boom counties wherein that differential was stronger than for renters. This too suggests that a general negative credit supply shock contributed to debt reduction in the post-2008 period.

Table 13. Change in Non-mortgage + Home Equity Debt Regressions

	(1)	(2)	(3)	(4)	(5)
Boom County	−0.023	−0.189	0.132	0.136	0.188
	(0.048)	(0.106)	(0.096)	(0.093)	(0.102)
Borrower Age in 2008:Q3		−0.021***	−0.021***	−0.021***	−0.021***
		(0.001)	(0.001)	(0.001)	(0.001)
Borrower Credit Inquiries in 2008:Q3		0.067***	0.067***	0.067***	0.067***
		(0.008)	(0.008)	(0.008)	(0.008)
Borrower Total Debt in 2008:Q3		−0.437***	−0.415***	−0.415***	−0.415***
		(0.012)	(0.007)	(0.007)	(0.007)
Change in Risk Score (2008:Q3–2011:Q4)		−0.007***	−0.007***	−0.007***	−0.007***
		(0.000)	(0.000)	(0.000)	(0.000)
Low Risk Score (<650) in 2008:Q3		−1.341***	−1.340***	−1.317***	−1.002***
		(0.032)	(0.032)	(0.087)	(0.289)
Renter (2008:Q3–2011:Q4)		−2.017***	−1.885***	−1.891***	−1.831***
		(0.060)	(0.084)	(0.089)	(0.099)
Boom County × Renter			−0.153	−0.146	−0.220*
			(0.088)	(0.096)	(0.109)
Boom County × Low Risk Score				−0.027	−0.430
				(0.091)	(0.314)
Renter × Low Risk					−0.360
					(0.304)
Boom County × Renter × Low Risk					0.458
					(0.333)
Constant	−0.817***	11.137	10.898	10.880	10.799
	(0.045)	(13.509)	(13.513)	(13.517)	(13.535)
Observations	76,437	76,437	76,437	76,437	76,437
R-squared Adjusted	−0.000	0.140	0.140	0.140	0.140

Notes: This table presents the results from the regressions of changes in non-mortgage debt plus home equity debt on the boom county dummy and control variables. The change in non-mortgage debt is computed over 2008:Q3–2011:Q4. Among the covariates, age, credit inquiries, risk score, and total debt are calculated for each consumer for the base year 2008:Q3. We also compute a change in risk score over the 2008:Q– 2011:Q4 period. All regressions include tract- and county-level controls, and clustered standard errors at the county level. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level, respectively.

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