

Bank Size and Household Financial Sentiment Surprising Evidence from University of Michigan Surveys of Consumers*

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

Felix Irresberger
University of Leeds
f.irresberger@leeds.ac.uk

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

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Abstract

We analyze comparative advantages/disadvantages of small and large banks in improving household financial sentiment, with real economic implications. Matching University of Michigan Surveys of Consumers sentiment data with local banking market data from 2000-2014, we find surprising results – large banks have significant comparative advantages in boosting sentiment. Findings are robust to instrumental variables and other methods. Additional analyses using RateWatch and Home Mortgage Disclosure Act (HMDA) data are consistent with scale economies and superior safety of large banks as channels behind the findings, more than offsetting stronger relationships with and greater trust in small banks. We also discuss policy implications.

JEL Classification Codes: G21, G28, G34.

Keywords: Households, Financial Sentiment, Small Banks, Large banks, Banking Market Structure.

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1. Introduction

Financial institutions and markets exist in large part to improve the economic and financial conditions of firms and households. In particular, banks are thought to play special roles in the economic and financial lives of firms and households by providing credit, deposit, and other financial services more efficiently than other institutions and markets. Some of the banking literature emphasizes banks' special abilities to gather private information and serve large publicly traded firms (e.g., James, 1987; Billett, Flannery, and Garfinkel, 2006). Other banking literature emphasizes the relative abilities of banks of different sizes to serve small businesses, which are generally more informationally opaque than large publicly traded firms. The latter studies generally find that small banks have comparative advantages over large banks in using relationship lending to alleviate small business financial constraints (e.g., Cole, Goldberg, and White, 2004; Berger, Miller, Petersen, Rajan, and Stein, 2005).

In contrast to this vast literature on the specialness and importance of banks in serving firms, there is a void in the literature on the abilities of banks of different sizes in serving the economic and financial needs of households. We take on this challenge with the first study on the comparative advantages of small and large banks in improving household sentiment regarding personal and national economic and financial conditions. For convenience, we henceforth simply summarize this as household financial sentiment.

This sentiment is important to study and may be even more economically consequential than small business financial perceptions studied in the literature. Consumer spending accounts for about 70% of U.S. Gross Domestic Product (GDP),¹ so household financial sentiment has important macroeconomic implications. In addition, many small businesses rely on owners, family, and friends for critical funding (e.g., Berger and Udell, 1998), so household financial problems may also adversely affect financially constrained small businesses. Moreover, public confidence in the financial system stems largely from how effectively banks and other intermediaries provide households with access to safe, secure, and affordable financial services (FDIC, 2015). Many households lack sufficient banking services. The FDIC finds that about 90

¹ See, e.g., <https://fred.stlouisfed.org/graph/?g=hh3>.

million Americans or about 27% of U.S. households are unbanked or underbanked.² Other research summarized in our literature review below finds that household financial sentiment is a key predictor of macroeconomic outcomes, including GDP, consumption, and inflation.

We employ household responses to the University of Michigan Surveys of Consumers from 2000-2014. The Surveys of Consumers gives each household in the coterminous U.S. (48 states plus the District of Columbia) an equal probability of being selected, and interviews are conducted each month by telephone.³ Households are asked about their personal finances, outlooks for the economy, and perspectives on buying conditions for durables. Their answers are analyzed in different combinations to capture household financial sentiment. These sentiment measures are strong proxies for actual economic and financial conditions and are shown in other research to be powerful predictors of economic agents' behavior.⁴

Our unique dataset matches the household survey responses with bank information for the households' counties from Call Reports and Summary of Deposits. These data allow us to test how banks of different sizes affect household financial sentiment.⁵ We are the first, to our knowledge, to match the Michigan Surveys responses with banking and other economic data at the county level, and among the first to explore determinants of the survey responses.⁶ Research using Michigan Surveys data typically employs responses consolidated at the national level as a macroeconomic explanatory variable. In contrast, we use individual household responses as dependent variables and employ county small bank market share as the key independent variable.

Based on small business finance research, we might expect small banks to have comparative advantages over large banks in improving household financial sentiment. Small banks are found to have comparative advantages in improving small business managerial perceptions of

² <https://www.fdic.gov/news/news/speeches/spapr2617.pdf>

³ Information on the Surveys of Consumers as well as the aggregate index data can be found on the University of Michigan's website at: <https://data.sca.isr.umich.edu/>.

⁴ The use of sentiment or perceptions to proxy for financial conditions is also used in the small business financial constraints literature (e.g., Berger, Bouwman, and Kim, 2017).

⁵ Our initial data sample of county-level bank and other county characteristics are available for each county in the U.S. The sample was then sent to the University of Michigan where it was matched to the individual responses in a given county and subsequently anonymized. Therefore, to preserve respondent-level confidentiality, all conclusions in this paper cannot be derived from specific knowledge of the respondents or their counties.

⁶ One of the few exceptions is a report by Toussaint-Comeau and McGranahan (2006), which explains survey responses with demographic data from respondents.

financial constraints and other conditions through relationship lending. Households face similar informational opacity problems and constraints as small businesses. Thus, small banks may be better able to use relationship lending to improve household financial sentiment (*Relationship Channel*). Households may also trust small banks more than large banks (*Trust Channel*).

However, it is alternatively possible that large banks are advantaged in dealing with households. Large banks have economies of scale that may allow them to offer more attractive deposit and loan rates to consumers (*Economies of Scale Channel*). Large banks may also be better able to relieve household concerns about bank safety and continuity of services because they generally are better diversified, are subject to more prudential regulation and supervision, and have greater access to implicit government guarantees than small banks (*Safety Channel*).

We formulate and test between hypotheses representing these opposing views. Our main dependent variable is the *Index of Consumer Sentiment (ICS)* created by the University of Michigan, compiled from households' responses to five questions about their perceptions of personal and national economic and financial conditions. We regress *ICS* on *Small Bank Share*, the ratio of small bank branches to total bank branches in the household's county. The *Small Bank Share* coefficient captures the comparative advantages/disadvantages of small banks relative to large banks in improving household financial sentiment. A positive coefficient on *Small Bank Share* would suggest small bank comparative advantages in improving household financial sentiment, and a negative coefficient would suggest large bank advantages.

Our results are quite surprising. We find that higher small bank share statistically and economically significantly *negatively* affects household financial sentiment, consistent with comparative advantages for large banks. This finding holds across household demographic groups.

Important challenges to our analysis are potential endogeneity concerns from driven by omitted variables related to demand for and supply of banking services. To tackle these, we include numerous controls for demand, including a broad set of respondent characteristics, county characteristics, and year-quarter and county fixed effects. We also control for measures of banking supply other than *Small Bank Share*, including other local bank characteristics and market characteristics. We also use two sets of instrumental variables and other approaches to help further mitigate endogeneity concerns, and find that our results continue to hold.

To ensure robustness, we re-run our tests using alternative proxies for household financial sentiment, alternative proxies for small bank share and access, and alternative estimation methods and controls. We also conduct cross-sectional analyses to address bank, household, local market structure, and economic conditions heterogeneity. Our main results hold in each of these checks.

We additionally investigate the channels behind these findings using two additional datasets. Results suggest that both of the hypothesized channels through which large banks may have comparative advantages are likely operative. Using RateWatch interest rate data from individual banks, we find that large banks offer more favorable prices to consumers on relatively safe consumer deposit and loan products, consistent with the *Economies of Scale Channel*, while small banks offer more favorable prices on relatively risky consumer deposit and loan products, consistent with the *Safety Channel*. Call Report data on the quantities of these products are similarly consistent with these channels. We also use Home Mortgage Disclosure Act (HMDA) data on residential mortgage applications and find that large banks are more likely to approve mortgage applications, offer lower mortgage interest rates, and provide large amounts of credit, controlling for other bank and borrower characteristics. This gives more support to the *Economies of Scale Channel*. Together, the *Economies of Scale* and *Safety Channels* that favor large banks appear to more than offset the *Relationship* and *Trust Channels* that favor small banks.

The stark difference between our results for households and those in the literature on small businesses may be due to differences in the relative importance of the channels for the two groups. Households may value the *Economies of Scale* and *Safety Channels* more highly, while small businesses may place more importance on the *Relationship* and *Trust Channels*.

Our paper contributes to several strands of literature. First, we add another dimension to the literature on bank specialness by showing that large banks are better able than small banks to improve household financial sentiment. In addition, we extend the literature on the comparative advantages of banks of different sizes from small businesses to households. We also expand the literature on the University of Michigan Surveys of Consumers, which normally uses the data aggregated at the national level, by using individual household data. Finally, we add to the literature on the real effects of the banking industry by showing that the mix of small and large banks affects households' financial sentiment, which is shown in prior research to be a key factor in consumer spending decisions.

As discussed in the conclusions, our findings have implications regarding two sets of policy levers to improve household financial sentiment and potentially improve the real economy. Policy makers can directly affect banking market structure through merger and acquisition approval policies, regulations affecting interstate branching, and legal requirements on banks that differ by bank size. The second set of levers involves reducing compliance costs for small banks that may impinge on their abilities to serve consumers.

The remainder of the paper is organized as follows. In Section 2, we review the related literature. Section 3 discusses our channels and hypotheses, and Section 4 describes the data. Section 5 presents our main results, while Section 6 presents robustness checks. In Section 7, we investigate the channels that may explain our results. Section 8 concludes.

2. Literature Review

Our paper is related to several distinct literatures, which we group into five categories: 1) bank specialness; 2) small bank comparative advantages in relationship lending and consumer trust; 3) large bank comparative advantages in economies of scale and safety, 4) household sentiment and surveys of consumers, and 5) real effects of the banking industry.

2.1 Bank Specialness Literature

Banks are often considered to be “special” in their abilities to gather and use private information to screen and monitor borrowers. Banks are considered to have comparative advantages over others in these endeavors because of specialization in performing these functions, economies of scale in gathering and processing credit information, and relationships with borrowers that provide additional information from prior loan, deposit, and other accounts. Specialness is usually tested by evaluating the abnormal stock returns of publicly traded loan customers around the time of loan announcements, and the results in this literature are mixed (e.g., James, 1987; Billett, Flannery, and Garfinkel, 2006; Maskara and Mullineaux, 2011; Li and Ongena, 2015; Saheruddin, 2017). In contrast to this literature’s focus on publicly traded corporations, we analyze for the first time the extent to which banks may be special in boosting household financial sentiment.

2.2 Small Bank Comparative Advantages: Relationship Lending and Consumer Trust

2.2.1 Relationship Lending

The banking literature discusses comparative advantages of small and large banks in alleviating

firm financial constraints using different lending technologies. The conventional wisdom is that large banks specialize in hard, quantitative information technologies – such as financial statement lending, credit scoring, and fixed-asset lending technologies. Large banks have comparative advantages in lending to less opaque, larger, and/or older firms with more hard, quantitative information available. In contrast, small banks specialize in soft, qualitative information technologies, such as relationship lending, and have comparative advantages in lending to more opaque, smaller, and younger firms. Small banks are considered superior at using soft information that is more easily transmitted within a less complex organization with fewer managerial layers (e.g., Berger and Udell, 2002; Stein, 2002; Liberti and Mian, 2009).

A significant amount of empirical research supports this conventional wisdom (e.g., Petersen and Rajan, 1994; Berger and Udell, 1995; Berlin and Mester, 1999; Boot and Thakor, 2000; Stein, 2002; Cole, Goldberg, and White, 2004; Berger, Miller, Petersen, Rajan, and Stein, 2005; Liberti and Mian, 2009; Canales and Nanda, 2012; Kysucky and Norden, 2016). Notwithstanding this conventional view, other research suggests that technological progress in hard information technologies such as credit scoring and fixed-asset lending helped large U.S. banks overcome any comparative advantage of small banks for at least some small business borrowers. This led to an increase in lending distances over time and made it easier for the large banks to serve small, opaque firms using hard information (e.g., Petersen and Rajan, 2002; Hannan, 2003; Brevoort and Hannan, 2006; DeYoung, Frame, Glennon, and Nigro, 2011).

Some papers also suggest that the importance of small banks' comparative advantage in relationship lending may have diminished over time and business customers may now value more the relative convenience of the different types of banks (e.g., Berger, Rosen, and Udell, 2007; Berger, Goulding, and Rice, 2014). In contrast, two recent studies suggest that small businesses have significantly better outcomes when there is a greater local presence of small banks. Berger, Cerqueiro, and Penas (2015) find that greater small bank presence leads to significantly more lending to recent start-ups and slightly lower firm failure rates during normal times. Berger, Bouwman, and Kim (2017) use small business managerial perceptions of financial constraints and find that small banks still have comparative advantages in alleviating these constraints.

2.2.2 Consumer Trust

Evidence from the *Chicago Booth / Kellogg School Financial Trust Index Survey* suggests that

small banks may also have comparative advantages in being trusted more by households than large banks. Figure 1, which uses that survey, shows that about twice as many people trust local banks (typically small) than trust national banks (typically large). This margin is also relatively constant over time. Trust is defined as the expectation that the institution will perform actions beneficial or at least not detrimental to others.

2.3 Large Bank Comparative Advantages: Economies of Scale and Safety

2.3.1 Economies of Scale for Large Banks

Early research on scale economies for U.S. banks in the 1980s and early 1990s typically finds scale diseconomies past moderate bank sizes, while research starting in the mid-1990s finds scale economies even at the sizes of the largest institutions (e.g., Berger and Mester, 1997). The change might be explained in part by movement to more advanced functional forms, such as the Fourier-flexible function, or nonparametric techniques. The early research more often employs the translog function, which essentially imposes a U-shape on the average cost curve, yielding economies of scale at smaller sizes and diseconomies at larger sizes. There may also be more actual scale economies in banking in later periods because of technological progress in information and lending technologies, as well as geographic and other deregulation that allows banks to operate more efficiently at larger scales. More recent research continues to find scale economies at large bank sizes (e.g., Wheelock and Wilson, 2012, Hughes and Mester, 2013). This literature is consistent with the *Economies of Scale Channel*, under which large banks use their economies of scale to offer superior deposit and loan rates to households.

2.3.1 Safety of Large Banks

Large banks may be better able to relieve household concerns about bank safety and continuity of services than small banks because of: 1) better diversification, 2) more prudential regulation and supervision, and 3) greater access to implicit government bailout guarantees. We provide evidence on each of these in turn.

First, large banks are more diversified than small banks, but this diversification does not necessarily result in lower risk because large banks tend to hold less capital, and so may offset any reductions in credit risk with increases in leverage risk (e.g., Hughes and Mester, 2013). In addition, diversification may not always reduce credit risk as it may involve more investment into riskier assets. Finally, banks that engage in a broader set of activities may be more subject to

managerial agency problems. There is significant research on three types of diversification of large U.S. banks – geographic diversification into multiple states, geographic diversification into different countries, and product diversification into nontraditional commercial bank activities, such as investment banking and off-balance sheet activities. The literature is mixed on the effects of geographic diversification into multiple states on bank risk, with some finding essentially no overall effect (e.g., Demsetz and Strahan, 1997), but others finding reduced risk (e.g., Deng and Elyasiani, 2008; Goetz, Laeven, and Levine, 2016). International diversification by U.S. banks is found to increase bank risk, with the magnitude being more pronounced during financial crises (e.g., Berger, El Ghouli, Guedhami, and Roman, 2017). Finally, product diversification is found to have mixed effects on risk and performance (e.g., Laeven and Levine, 2007).

Second, large banks are subject to more prudential regulation and supervision than small banks. While most U.S. banks are annually examined, federal supervisors typically keep offices in and continuously examine the largest banks.⁷ Bank holding companies with over \$100 billion in assets are subject to the stress tests starting in 2009 (aka Supervisory Capital Assessment Program (SCAP) and Comprehensive Capital Analysis and Review (CCAR)), and those with over \$10 billion in assets have to undergo versions of the stress tests starting in 2014, the last year of our sample.⁸ Some research suggests that the stress tests are successful in encouraging large U.S. banks to reduce their risks (Acharya, Berger, and Roman, 2018). In contrast, others find that banks may be managing financial performance to look more attractive to regulators and investors (Cornett, Minnick, Schorno, and Tehranian, forthcoming).

Finally, large banks may also be perceived as more likely to receive government bailouts, especially the very largest banks that are sometimes considered to be too-big-to-fail (TBTF). Supporting this, nine very large financial institutions were essentially “forced” to take the initial Troubled Asset Relief Program (TARP) bailouts in October 2008, before all the other banks were able to apply for these funds. Some literature finds positive stock and bond effects for the TBTF banks (e.g., O'Hara and Shaw, 1990; Santos, 2014; Gandhi and Lustig, 2015). These banks may also be less subject to deposit withdrawals and bank runs and may even benefit from inflows of

⁷ There is some recent movement at the Office of the Comptroller of the Currency (OCC) and Federal Reserve Bank of New York toward centralizing the supervision of large institutions, rather than keeping offices at the banks. See <https://www.americanbanker.com/articles/new-occ-head-scrap-plant-to-move-big-bank-examiners-off-site>

⁸ Other recently passed legislation would increase the stress-test minimum size requirement to \$250 billion in assets.

deposits during financial crises (e.g., Martinez-Peria and Schmukler, 2001; Iyer and Puri, 2012; Osili and Paulson, 2014; Oliveira, Schiozer, and Barros, 2015).⁹

2.4 Literature on Household Sentiment and the Surveys of Consumers

Aggregate *ICS* is shown to be a significant predictor of economic outcomes in a variety of settings, such as marketing and consumption behavior (e.g., Carroll, Fuhrer, and Wilcox, 1994; Gaski and Etzel, 1986; Souleles, 2004), asset prices in financial markets (e.g., Lemmon and Portniaguina, 2006), and macroeconomic outcomes such as GDP and inflation (Batchelor and Dua, 1998).

While *ICS* is used in other studies as an independent variable on a national level, we are among the first to examine its determinants on an individual household level. The two studies that come closest are as follows. One explains the components of *ICS* using respondent heterogeneity (Lahiri and Zhao, 2016). However, their data are on a U.S. region level (West, North Central, Northeast, Central, etc.) and they do not make extensive use of the household characteristics. Another study provides an overview of *ICS* for different subgroups of the population (Toussaint-Comeau and McGranaham, 2006). They find that from 1978 to 2003, elderly respondents were more pessimistic in their survey answers than younger people, while male, college educated, and high-income respondents were more likely to be optimistic over this time period.

There are also studies proposing deriving text-based measures of consumer sentiment, from newspapers and other media outlets (e.g., Baker and Wurgler, 2006; Tetlock, 2007; Barber and Odean, 2008). A recent approach employed by a number of authors is the use of internet search volume data to proxy for household-level and retail investor attention and sentiment. For example, Ginsberg, Mohebbi Patel, Brammer, Smolinski and Brilliant (2009) use the search volume from Google's search engine on influenza symptoms and detect nationwide epidemics. Da, Engelberg and Gao (2015) create an index of negative household sentiment with Google Trends data and relate this index to asset prices. The disadvantages of such measures is that we often do not know for sure which part of the population or which regions are driving the resulting economic attitudes. One counterexample is the study of Soo (2018), which constructs regional housing sentiment indices for major metropolitan areas based on local newspapers. However, such a (text based)

⁹ Some of these benefits may have been reduced by the Dodd-Frank Act Orderly Liquidation Authority (OLA) for the very largest institutions.

measure is not able to capture sentiment in, e.g., rural areas where such data are not available or cover extended time periods again because of limited data availability. By using the granularity of county-level data, the household sentiment data we use from the *Michigan Surveys of Consumers* are able to cover very large parts of the United States' population and regions. In addition, they are well established, being available for a long-time horizon, and incorporate direct answers from households on a monthly basis.

2.5 Literature on Real Effects of the Banking Industry

Finally, we more broadly add to the literature on the effects of the banking industry on the real economy. This literature includes but is not limited to studies on bank geographic deregulation (e.g., Jayaratne and Strahan, 1996; Morgan, Rime, and Strahan, 2004; Huang, 2008; Levine, Levkov, and Rubinstein, 2008; Beck, Levine, and Levkov, 2010), other bank regulation such as capital standards (e.g., Allen, 2004), bank bailouts (e.g., Duchin and Sosyura, 2014; Berger and Roman, 2017), and shocks to bank deposits that affect the real economy (e.g., Gilje, Loutskina, and Strahan, 2016). We contribute to this research by showing that bank size structure also influences the real economy by affecting households' sentiment via their prevailing attitudes towards personal and national financial conditions.

3. Hypothesis Development

We next examine channels through which small banks may have comparative advantages or disadvantages in improving household financial sentiment and develop two competing hypotheses from these channels.

Small banks may have comparative advantages in improving household financial sentiment through the *Relationship Channel* and the *Trust Channel*. Under the *Relationship Channel*, small banks may be better able than large banks to build soft information-based relationships with households that result in more lending and other financial services to these households. This follows directly from the literature above in which small banks are found to have comparative advantages in providing credit to small businesses and alleviating their financial constraints. Similarly, households may benefit from banking credit and deposit relationships. Under the *Trust Channel*, small banks have comparative advantages in serving households because they may have greater trust in small banks, as suggested by the *Chicago Booth / Kellogg School Financial Trust*

Index Survey discussed previously. This may occur at least in part because small banks are more often controlled locally. Our first hypothesis is based on these two channels:

Hypothesis H1: Small banks have comparative advantages over large banks in improving household financial sentiment.

We also offer two channels under which large banks have comparative advantages. Under the *Economies of Scale Channel*, large banks have lower unit costs which allow them to offer more favorable deposit and loan prices. As discussed earlier, the economies of scale literature finds that such economies exist during our sample period and are substantial. Under the *Safety Channel*, large banks may be better able to provide households safety for their savings and assurances of continuity of other services. As discussed above, large banks may provide better safety because of superior diversification, more prudential regulation and supervision, and/or greater access to implicit government bailout guarantees. Based on these two channels, we form our second hypothesis:

Hypothesis H2: Large banks have comparative advantages relative to small banks in improving household financial sentiment.

Each hypothesis may apply for different households. For example, banking relationships may be relatively important for some households, so **Hypothesis H1** likely holds for them. For other households, continuity of services may be more pertinent, in which case **Hypothesis H2** is more likely to hold. Each hypothesis may also hold more for some subgroups of the population, consistent with findings in the literature. Our empirical analysis addresses which of the two hypotheses empirically dominates the other overall and also examines which dominates for different respondent groups by age, education, gender, home ownership, and income. Additional analyses test whether the comparative advantages or comparative disadvantages differ by bank condition, time, and local market characteristics.

4. Data

We next introduce our main dataset. Table 1 Panel A shows variable definitions and data sources. Our key endogenous variables measuring household financial sentiment are collected monthly from the University of Michigan Surveys of Consumers from 2000:M1 to 2014:M12. We obtain

commercial bank balance sheet and income data from quarterly Call Reports from 2000:Q1 to 2014:Q4.¹⁰ We normalize all financial variables using the seasonally-adjusted GDP deflator to be in real 2014:Q4 dollars. We convert these data to the county level based on the FDIC's Summary of Deposits (SoD) database. Further, we collect county-level characteristics from the U.S. Census Bureau and the U.S. Treasury. The RateWatch and HMDA databases used in our channels analyses are discussed later.

4.1 Michigan Consumer Sentiment Surveys

The *Index of Consumer Sentiment (ICS)* is based on the University of Michigan's *Surveys of Consumers*. The surveys started in 1946, and was annual until 1952, but increased its frequency to quarterly, and eventually to monthly from 1978 to the present (Ludvigson, 2004). Each month, about 500 households in the conterminous U.S. are interviewed via telephone (of which about 300 are new respondents and attempted to be re-interviewed after six months) on personal finances, general economic outlook, and individual characteristics such as age, education, gender, home ownership, and income (Curtin, 2013). The *ICS* is calculated from responses to the following five questions (abbreviations in parentheses):

- 1) "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?" (*PAGO*)
- 2) "Now looking ahead — do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?" (*PEXP*)
- 3) "Now turning to business conditions in the country as a whole — do you think that during the next twelve months we'll have good times financially, or bad times, or what?" (*BUS12*)
- 4) "Looking ahead, which would you say is more likely — that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?" (*BUS5*)
- 5) "About the big things people buy for their homes — such as furniture, a refrigerator, stove,

¹⁰ We exclude firm-quarter observations that do not refer to commercial banks (RSSD9331 different from 1), have missing or incomplete financial data for assets or equity, or have missing data for our key variables.

television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?” (*DUR*)

Questions 1 and 5 correspond to perceptions about the present, while Questions 2 to 4 capture perceptions about the future.

For each question, a positive, neutral, or negative answer is recorded, and their relative scores ($X_1 \dots X_5$) are coded as 200, 100, and 0, respectively.¹¹ The *ICS* for each household in a given month is calculated by summing the five relative scores, dividing by the 1966 base period total of 6.7558, and adding a constant of 2.0 to correct for sample design changes from the 1950s:¹²

$$ICS = \frac{X_1 + X_2 + X_3 + X_4 + X_5}{6.7558} + 2.0. \quad (1)$$

By construction, higher values of *ICS* represent a more positive household sentiment.

As a robustness check, we alternatively use the *Index of Consumer Expectations (ICE)*, constructed from the responses to Questions 2, 3, and 4. *ICE* is calculated by summing the relative scores for the three questions (X_2 , X_3 , and X_4), dividing by the 1966 base period total of 4.1134, and adding a constant of 2.0 to correct for sample design changes from the 1950s:

$$ICE = \frac{X_2 + X_3 + X_4}{4.1134} + 2.0. \quad (2)$$

Analogous to *ICS*, higher values of *ICE* represent an overall more positive sentiment.

ICS and *ICE* are continuous variables used as dependent variables in OLS regressions. We also use the responses to the five questions individually as proxies for household sentiment in OLS, ordered logit, IV, and Heckman’s (1979) correction models in Section 5.3. For these purposes, the scores for *PAGO*, *PEXP*, and *DUR* take the values of 3, 2, and 1, respectively, representing positive, neutral, and negative responses. Scores for *BUS12* and *BUS5* take integer values from 5 to 1, with 5 being the most positive, 3 being neutral, and 1 being the most negative.

¹¹ Answers that are missing or “I don’t know” are counted as neutral answers if respondent answers other questions.

¹² There was no constant added until 1972:M4 (except for 1972:M1). The constant was 2.7 from 1972:M4 until 1981:M11 and has been 2.0 from 1981:M12 to the present.

We employ data from all survey respondents with respondent identifier and anonymized county location information from the University of Michigan from 2000:M1 to 2014:M12. The start of the sample corresponds with the first month with the county location of the respondents. For each month, we match respondent identifiers with data downloaded from the *Surveys of Consumers – Survey Documentation and Analysis (SDA) Archive*.¹³ We extract *ICS*, *ICE*, and the five individual responses, as well as information on respondent age, education, gender, home ownership, and income. These are converted to quarterly data to match our banking data. We restrict our sample to counties with at least two household responses in the same quarter. We have 61,320 respondent-county-quarter observations for 2000:Q1 to 2014:Q4. For each respondent, we have an anonymized Federal Information Processing Standards (FIPS) code representing the respective county of residence.

Table 1 Panel B shows summary statistics. *ICS* and *ICE* statistics are difficult to interpret on an absolute basis because they are scaled variables. However, *ICS* varies significantly over time. The statistics on the individual components are more straightforward to interpret. *PAGO*, *PEXP*, and *DUR*, which range from 3 to 1, all have means exceeding 2, although only slightly so for *PAGO*, suggesting some optimism on net. However, *BUS12* and *BUS5*, which range from 5 to 1, both have means below 3, suggesting net negative sentiment for future national conditions.

We use several dummies for respondent characteristics to test whether the findings differ by demographic group. *Senior* indicates that a respondent is 65 or older. *College* denotes college graduates and *Male* indicates that the respondent is male. *Homeowner* designates homeowners, and *High Income* indicates those with incomes above the sample median.

The summary statistics in Table 1 Panel B show that 25.1% of all respondents are senior citizens, 50.2% have a college degree, 45.4% are male, and 77.7% are homeowners. High-income earners make up 58.6% of our sample.

4.2 Bank Data

4.2.1 Key Independent Variable, Small Bank Share

Our main independent variable of interest is the share of small bank branches in the respondent's

¹³ The respective data can be downloaded at https://data.sca.isr.umich.edu/sda-public/cgi-bin/hsda?harc_sda+sca, while general information on the data is available at: <https://data.sca.isr.umich.edu/sda-public/>.

county. We define “small banks” as those with gross total assets (GTA¹⁴) below \$1 billion in real 2014:Q4 dollars, corresponding to the usual research definition of “community banks” (e.g., DeYoung, Hunter, and Udell, 2004). In additional checks, we use alternative cutoffs of \$3 billion, \$5 billion, and \$10 billion. To calculate *Small Bank Share*, we count the number of branches of small banks in the county divided by the total number of branches in the county.

Table 1 Panel B shows *Small Bank Share* (based on the \$1 billion GTA cutoff) has a mean of 35.9%, with a standard deviation of 17.3%. Using a higher cutoff for the definition of small banks naturally yields a higher average *Small Bank Share*, which is 49.6% using the \$10 billion cutoff. Figure 2 shows an overview of the geographical distribution of the small bank share (using the \$1 billion GTA cutoff) for all U.S. counties in 2000 and 2014. The heat maps show striking differences in small bank share across U.S. counties. In 2000, we observe stark contrasts between western U.S. states – where few counties have high shares of small bank branches – and Midwest states – which often exhibit small bank shares above 75%. Eastern states are more mixed. Not surprisingly, most of the counties with small bank shares above 75% are located in rural areas. We further observe that the footprints of small banks have changed immensely over time. The density of small banks within U.S. counties was much lower in 2014 than in 2000, the result of ongoing consolidation. For example, most Midwest counties exhibited *Small Bank Share* above 75% in 2000, but many were below 50% by 2014.

As an alternative to *Small Bank Share*, we calculate a proxy for access to small banks in a county. *Small Bank Access* is the ratio of small bank branches over the county’s total population (in 1000s). The effect of this variable measures the *absolute* ability of small banks to alleviate household concerns, as opposed to the *comparative* advantage measured by *Small Bank Share*. In additional tests, we also include *Large Bank Access*, defined analogously.

4.2.2 Other Banking Variables

As controls, we include proxies for CAMELS examination ratings, the financial outcome variables used for regulators to evaluate banks (e.g., Duchin and Sosyura, 2014). The acronym CAMELS

¹⁴ Gross total assets (GTA) equals total assets plus the allowance for loan and lease losses and the allocated transfer risk reserve (a reserve for certain foreign loans). Total assets on Call Reports deduct these two reserves, which are held to cover potential credit losses. We add these reserves back to measure the full value of the assets financed.

comes from the six variables: *Capital Adequacy*(C) is the ratio of equity over GTA.¹⁵ *Asset Quality*(A) is the fraction of nonperforming loans. *Management Quality*(M) is the ratio of overhead costs to GTA, and *Earnings*(E) is return on assets. For *Liquidity*(L), we use the bank’s ratio of liquid assets over GTA. Finally, for *Sensitivity to Market Risk*(S), we use the absolute difference between short and long-term liabilities divided by GTA. To obtain county-level values of the CAMELS proxies, we calculate weighted averages of each proxy across banks in a given county, based on the bank branches in local markets.

We also employ as controls other bank characteristics for the county – average bank age (*Bank Age*); proportion of banks owned by bank holding companies (*BHC*); proportion of foreign-owned banks (*Foreign Ownership*); ratio of noninterest income to total income (*Fee Income*); ratio of bank deposits to GTA (*Deposits Ratio*), and bank concentration based on branch deposits (*Herfindahl-Hirschman Index* or *HHI*). For the county, we also include a dummy for whether a county is located in a Metropolitan Statistical Area (MSA) or New England County Metropolitan Area (NECMA) (*Metro*), as well as county fixed effects. We also include year-quarter fixed effects to control for many factors that change over time.

4.3 Combining the Data Sets

We first collect our data sample of bank and county characteristics and aggregate these at the county level for each quarter. This panel is then matched by the University of Michigan with the survey respondent data as follows. For each month, a respondent identifier is assigned to the county of residence and the respective quarter within a given year. All original county identifiers are replaced with fictional county codes to protect the respondents’ personal information. Using the given respondent identifiers, we match our bank and county characteristics to the *Surveys of Consumers* dataset, obtained from the SDA archive.

5. Empirical Results

5.1 Main Regression Analysis

We describe regression results from estimating models of the following form:

¹⁵ To avoid distortions for the equity to GTA ratio, for all observations with equity less than 1% of GTA, we replace equity with 1% of GTA (as in Berger and Bouwman, 2009).

$$\begin{aligned}
\text{Household Financial Sentiment}_{j,i,t} = & \beta \times \text{Small Bank Share}_{i,t-4} + \gamma \times \text{Respondent Characteristics}_{j,t} \\
& + \delta \times (\text{Small Bank Share}_{i,t-4} \times \text{Respondent Characteristics}_{j,t}) \quad (1) \\
& + \theta \times \text{Controls}_{i,t-4} + \mu_t + v_i + \varepsilon_{i,t}.
\end{aligned}$$

The dependent variable measuring *Household Financial Sentiment* is *ICS*, with higher values indicating more positive sentiment. All regressions include year-quarter dummies μ_t (one for every date) and county-fixed effects v_i . Heteroskedasticity-robust standard errors are clustered at the county level. All controls except for respondent characteristics are lagged by four quarters.

Table 2 shows our main regression results which test our two hypotheses. Column (1) includes *Small Bank Share* and all of the control variables, while columns (2) – (7) include interaction terms of *Small Bank Share* with respondent demographic characteristics to explore for which groups of households the different hypotheses hold. Throughout all specifications in Table 2, **Hypothesis H2** empirically dominates **Hypothesis H1** (i.e., the negative coefficients on *Small Bank Share* suggests that *large banks* have comparative advantages in boosting household financial sentiment). This main result holds for each of the regression models and is statistically significant at the one percent level. Results are also economically significant. In model (7), our most complete specification, the coefficient on *Small Bank Share* is -15.082. Moving *Small Bank Share* from zero to 100 percent, with all of the respondent characteristics set to zero, decreases *ICS* by about 12.473 (from 83.321 to 70.848).

The interactions of *Small Bank Share* and each respondent characteristic are insignificantly different from zero except for *Homeowner* and *Male*. Thus, the estimated large bank comparative advantages do not significantly differ for seniors, college degree holders, or high-income households relative to their opposites. However, for homeowners and males, the negative effect of *Small Bank Share* is less strong. Thus, **Hypothesis H2** is widely supported.

Turning to the controls, most of the (uninteracted) respondent characteristics are statistically significant in specifications (2)–(7), and are generally consistent with Toussaint-Comeau and McGranaham (2006). Most CAMELS proxies and other bank controls are not statistically significant. An exception is *Foreign Ownership* with a negative sign, suggesting that foreign-owned institutions are associated with less positive household financial sentiment. Also, *Deposits Ratio* is consistently statistically significant at the 10% level, suggesting that counties

with mostly deposit-taking banks may help boost household financial sentiment.

In Table 2 Panel B, we report the same specifications, but replace county fixed effects with state dummies. Allowing for within-state variation in our variables does not alter our findings.

For brevity, in all of the following analyses except when noted otherwise, we show only the full specification from column (7).

5.2 Instrumental Variable (IV) Regressions

We next address a potential endogeneity concern regarding our key independent variable, *Small Bank Share*. Large banks may avoid entering counties with poor economic outlooks, increasing *Small Bank Share*, causing a spurious negative relation between *ICS* and *Small Bank Share*. To mitigate this potential bias, we employ an instrumental variable (IV) approach.

In our complete specification, we include *Small Bank Share* alone and interacted with five demographic characteristics, requiring six instruments. Ideally, our instruments vary by county and over time and are plausibly exogenous to the number of small bank branches per county. We employ two different IV approaches.

In our first IV approach, we use *Church/Population*, the number of churches over population (in thousands) in the county in 1980, as an instrument for *Small Bank Share*. For the interaction terms, we use *Church/Population* interacted with each of the five demographic characteristics.¹⁶ This strategy assumes that *Church/Population* is correlated with *Small Bank Share* (instrument relevance) but does not directly affect *ICS* (exclusion restriction). *Church/Population* seems to meet these conditions. *Church/Population* represents stronger community ties through religious activities. Karlan (2005) shows that such activities influence the development of social capital. Small bank owners might feel less pressure to sell their businesses to larger banking organizations in counties with high *Church/Population*. The instrument is measured in 1980 to reduce the possibility that it directly influences *ICS*. It seems unlikely that access to churches directly affects time-varying household attitudes more than 20 years later. In addition, *Small Bank Share* changed significantly after 1980 because of geographic deregulation

¹⁶ It is not correct to view *Small Bank Share* as the endogenous right-hand-side variable, create a predicted value of *Small Bank Share* in the first stage and then interact it with the five respondent demographic dummies in the second stage. Wooldridge (2002, p. 236) and Angrist and Pischke (2009, pp. 190-192) call this the “forbidden regression”.

in the 1980s and 1990s that resulted in bank consolidation. We argue that this consolidation is likely to have been affected by the social capital associated with the instrument. The downside of this approach is that we cannot use county fixed effects for the IV estimates given that *Church/Population* instrument is at the county level for a single time period (1980) and thus, would be absorbed by these fixed effects. Instead, we show results with state fixed effects.¹⁷

To circumvent this problem, in our second IV approach, we construct instruments based on bank branch divestitures. The U.S. Department of Justice (DoJ) and the bank regulatory agencies often require merging banks to divest some branches in overlapping markets due to anti-trust concerns. Other banks, including some small banks, can acquire divested branches of the merging banks and grow substantially in a short period of time, sometimes becoming large banks and decreasing small bank shares in their markets. While the decision to acquire new bank branches is endogenous, the timing, location, and extent of these banks' asset growth is plausibly exogenous to their activities in existing markets. That is, these divestiture shocks may decrease *Small Bank Share* in the following years as their branches are reassigned to those of large banks.

We obtain data documented in Williams (2018) on bank branch divestitures, including the total amount of deposits divested to other banks, and identify whether these banks are small. The larger are the deposits divested to these banks, the more likely it is that their branches will be designated as branches of large banks. For each small bank acquiring divested branches, we identify the states in which it has other branches at the time of the divestiture. We then assign to each county in our sample within the state the amount of deposits divested and scale it by total deposits in the county to measure the relative size increase. We use the state to preserve anonymity of the respondents' counties.¹⁸ Our instrument, *Divested Deposits to Small Banks*, has the advantage that it varies by county and over time, allowing for county-fixed effects, and is plausibly exogenous to our key independent variable, *Small Bank Share*. We acknowledge that the number of bank branch divestitures to small banks is limited (less than 40 over our time period), so its predictive power may be limited.

¹⁷ In unreported results, we also run the IV analysis without state or county fixed effects and results are consistent.

¹⁸ Furthermore, in our matched sample, we assign the respective values to the county if the divestiture occurred up to two years ago to mitigate the possibility that a market affected by a divestiture is not chosen by the rotating survey panel design at the given time.

Table 3 compares OLS estimates and IV estimates. In both panels, column (1) shows the OLS results, columns (2)-(7) show the first-stage IV regressions, and column (8) shows the second stage IV estimates. Control variable coefficients are suppressed for brevity.

In the first stage regression in Panel A column (2), *Small Bank Share* is the dependent variable, and the coefficient on the corresponding instrument (*Church/Population*) is positive and highly significant. Similarly, when *Small Bank Share* \times *Senior* is the endogenous variable, the coefficient on the corresponding instrument (*Church/Population* \times *Senior*) is positive and highly significant. We obtain similar results on the diagonal terms for the other endogenous variables in first-stage regressions (4)-(7). We conduct two tests to check the suitability of our instruments. First, we find that the Kleibergen-Paap rk *LM* test (K-P test) rejects the null hypothesis (rk *LM* has a *p*-value less than 0.001), suggesting that our model is well identified. Second, we conduct an *F*-test of the excluded exogenous variables in the first stage regression, in which the null hypothesis is that the instruments do not explain the variation in the *Small Bank Share* and *Small Bank Share* interacted with the five demographic characteristics. We reject this null hypothesis (Cragg-Donald *F* has a *p*-value less than 0.001 and the Anderson-Rubin (1949) *F*-test also with a *p*-value less than 0.001),¹⁹ suggesting that we do not have a weak instrument problem.

In the second stage in Panel A column (8), the effects of *Small Bank Share* on *ICS* are negative and statistically significant and the comparative advantages of large banks again extend to all demographic groups. One difference, however, is that the IV coefficients are larger than the OLS coefficients, a common finding in the literature (e.g., Levitt, 1996). In addition, the effects are approximately cut in half for the male respondents. Nonetheless, our main results hold.

Panel B shows that the instrument *Divested Deposits to Small Banks* is negatively related to *Small Bank Share*, as predicted. The *K-P* test and *F*-test statistics fail to reliably reject weakness of instrument in this specification. However, the instrument weak IV-robust Anderson-Rubin (1949) *F*-test statistics strongly rejects our instruments' joint equality to zero (having a *p*-value less than 0.001) and the Stock and Wright (2000) rank test rejects underidentification of our model (having a *p*-value of 0.053) (for a similar case, see Prilmeier, 2017). Reassuringly, in the second stage regression, we obtain a negative effect of *Small Bank Share* on households' financial

¹⁹ We obtain similar results using individual equations first-stage *F*-statistics, all having a *p*-value less than 0.001.

sentiment, consistent with our main findings.

5.3 Decomposition Analysis of the Index of Consumer Sentiment

In Table 4, we evaluate comparative advantages of banks of different sizes using the five different components of *ICS*. As noted previously, *PAGO*, *PEXP*, and *DUR* take the values 3, 2, and 1, and *BUS12* and *BUS5* take the values 5, 4, 3, 2, and 1 in descending order from the most positive to the most negative. Because these are discrete dependent variables, we run the regressions in three ways²⁰ – OLS in Panel A columns (1)-(5), ordered logit model in Panel A columns (6)-(10), and a Heckman’s (1979) sample correction model including the self-selection parameter (inverse Mills’ ratio) in Panel B column (1)-(5) to account for selection bias,²¹ as some individual questions were not answered by the households (which are treated as neutral in the calculation of *ICS*). We examine whether the coefficients in our OLS and Heckman selection models are positive or negative and test them for equality to zero, whereas we evaluate whether the odds ratios in the ordered probit are above or below one and test them for equality to one. For brevity, we show only the most complete specification from Table 2 with all controls and interaction terms. In all cases, we run the strongest specification possible. For the OLS and Heckman selection models, we use county fixed effects and for the ordered probit, we use state fixed effects.²²

Using all of the estimation methods, we find that for all demographic groups, households in counties with greater *Small Bank Share* report worse expected future conditions, i.e., worse personal finances next year (*PEXP*), worse national conditions in the next 12 months (*BUS12*), and worse national conditions in the next five years (*BUS5*). However, the findings for current conditions differ, with statistically insignificant effects on the change in personal finances since last year (*PAGO*) and national conditions for buying durables (*DUR*). Thus, our main finding of more negative financial sentiment for households from higher county presence of small banks is driven primarily by pessimism about the future, which may be related to households’ concerns about small banks’ safety in the long term.

²⁰ We also run IV models based on our two instrumental variable approaches – including state FE and county FE, respectively.

²¹ The coefficients on the inverse Mills’ ratio are not statistically significant in all cases, suggesting that sample selection bias may not be an issue.

²² In unreported results, we also ran all tests without county or state fixed effects and results are consistent.

6. Robustness Checks and Subset Analyses

6.1 Alternative Definitions of Small Bank Presence

6.1.1 Different Cutoffs for Small Bank Share Definition

In Table 5 columns (2) - (4), we redefine *Small Bank Share* using alternative cutoffs of \$3 billion, \$5 billion, and \$10 billion in GTA instead of \$1 billion in our main analysis, which is replicated for convenience in column (1). Results continue to show that large banks have a comparative advantage in boosting households' financial sentiment.²³

6.1.2 Small and Large Bank Access

In Table 5 Panel B columns (1)-(4), we replace the *Small Bank Share* variables with *Small Bank Access* and in columns (5)-(8), we add *Large Bank Access*. *Small Bank Access* is the ratio of small bank branches to county population measured in thousands. *Large Bank Access* is defined analogously. We use the same four GTA cutoffs of \$1 billion, \$3 billion, \$5 billion, and the \$10 billion. The effects of these variables on *ICS* measure the absolute abilities of small and large banks to improve household financial sentiment, as opposed to the comparative advantages/disadvantages of small banks. Small banks may be particularly bad at alleviating households' financial concerns, large banks may be particularly good, or both. The results in Table 5 Panel B suggest that most of the comparative disadvantages for small banks are due to absolute disadvantages for small banks. Two exceptions are seniors and college graduates, for which large banks appear to have absolute advantages.

6.2 Alternative Sentiment Proxy: Index of Consumer Expectations (ICE)

In Table 6 column (1), we replace the *Index of Consumer Sentiment (ICS)* with the alternative sentiment measure *Index of Consumer Expectations (ICE)*. The finding is consistent with our main results – large banks have comparative advantages that are reduced for males and homeowners.

6.3 Alternative Econometric Specifications and Bank Characteristics

In Table 6 column (2), we show results from two-way clustering at the county and year-quarter level (e.g., Thompson, 2011). In column (3), we weight based on the proportions of bank deposits

²³ In unreported results, we also ran the tests with the share of large bank branches instead of the share of small bank branches in a given county based on the four cutoffs and results are very similar except that the signs are reversed, showing that large banks have comparative advantages in improving household financial sentiment.

in a county instead of by the number of branches.²⁴ Column (4) shows results including CAMELS proxies separately for small and large banks. In both cases, the key coefficients remain statistically significant. Column (5) also controls for *Credit Union Branches/Total Bank Branches*, credit union branches divided by the number of traditional bank branches.²⁵ We find that our main coefficient of interest *Small Bank Share* remains statistically significant at the 1% level and economically relevant, and credit unions also negatively affect *ICS*. Column (6) shows a model with *State × Year-Quarter* fixed effects instead of county and year-quarter dummies to absorb any state-level effects that vary over time, and our main findings continue to hold.

6.4 Subsample Evidence

We next provide evidence on how bank size comparative advantages differ for counties with different banking market characteristics. We split our sample above and below median values for market concentration (HHI), number of bank branches, number of young bank branches, and degree of regulation at the state level. Table 7 Panel A, columns (1)-(8) show these regressions. Large banks have comparative disadvantages in every group, but there are some minor differences. The negative influence of *Small Bank Share* is more slightly pronounced in markets with less bank competition (higher HHI) and with fewer overall bank branches. That is, when there are only few bank branches available and competition is low, households respond more negatively, indicating a higher comparative advantage of large banks. The advantages of large banks with respect to boosting household financial sentiment are greater where banks are younger, suggesting that *de novo* small banks are particularly poor at serving households. Further, our results are slightly stronger in less regulated, open banking markets.

In Table 7 Panel B, we split our sample with respect to different national economic conditions. Again, the results are robust across subsamples, with some notable differences. The results are particularly strong during times of financial crises, when unemployment is rising, or when national GDP growth is stagnating. All these subsample results support the safety channel,

²⁴ The number of branches used in our main analysis is an indicator for the supply of banking services, whereas deposits are more indicative of demand.

²⁵ We obtain data on credit union branches from the National Credit Union Administration (NCUA) website. Complete data on county level location of credit union branches is only available starting with 2010:Q3, when we count the total number of credit union branches in a given county. Before 2010:Q3, we only have information on credit union's headquarters proving the credit union existence, and thus for these time periods we approximate the credit union number of total branches in a given county by taking the number of branches it has in 2010:Q3.

which may be of particular importance for households during troubled times. Finally, we split our sample at the median of the economic policy and monetary policy uncertainty indices, respectively, as introduced in Baker, Bloom, and Davis (2016). The effects are stronger in times of uncertainty, again supporting the safety channel.

The results in Table 8 suggest that the comparative advantages of large banks in improving household financial sentiment hold relatively broadly, but they are stronger in less competitive environments and those in which economic and financial conditions are weaker or more uncertain.

7. Channels Analysis

Our main empirical analysis clearly favors **Hypothesis H2** – the large banks have comparative advantages. We next try to determine which or both of the channels underlying this hypothesis – the *Economies of Scale Channel* and/or the *Safety Channel* – are consistent with some additional data on bank prices and quantities and mortgage application outcomes.

Table 8 Panel A compares the means of consumer deposit rates for small and large banks using RateWatch branch-level data for 2000:Q1-2014:Q4 based on the \$1 billion GTA cutoff between small and large banks. The data suggest that large banks pay statistically significantly better deposit rates to their customers for \$100,000 certificates of deposit (CDs) with 3, 6, and 12-month maturity, supporting the *Economies of Scale Channel*. However, for \$100,000 CDs with 24, 36, 48, and 60-month maturity, \$100,000 Savings Accounts, and \$250,000 CDs of all maturities, for which bank safety may be more of a consideration, small banks pay statistically significantly higher deposit rates. These results support the *Safety Channel* – small banks may need to offset their safety disadvantages with better deposit rates. The results in Panel B on quantities of insured and uninsured consumer deposits further support this conclusion.²⁶ They

²⁶ To calculate uninsured deposits, we take all the funds in accounts that are partially insured and subtract off the amount that is insured. This requires separate treatment for several time periods because of the changes in deposit insurance limits over time. For the period 2000:Q1-2006:Q1, we calculate the uninsured deposits as the amount of bank deposit accounts (demand, savings, and time) with a balance on the report date of more than \$100,000 minus the number of such deposit accounts multiplied by \$100,000. For the period 2006:Q2-2009:Q2, we take into account the different treatment of deposit retirement accounts versus the rest. Thus, we calculate the uninsured deposits as the amount of bank deposit accounts (demand, savings, and time, excluding retirement accounts) with a balance on the report date of more than \$100,000 minus the number of such deposit accounts multiplied by \$100,000 plus the amount of bank deposit retirement accounts with a balance on the report date of more than \$250,000 minus the number of such deposit accounts multiplied by \$250,000. For the period 2009:Q3 onwards, we account for the deposit insurance limit increase from \$100,000 to \$250,000 for all deposits except foreign ones. Thus, we calculate the uninsured deposits as the amount of bank deposit accounts (demand, savings, and time, including retirement accounts) with a

suggest that households strongly prefer large banks for their uninsured deposits.

Table 8 Panel C shows consistent results on consumer loan rates. Large banks give statistically significantly lower loan rates to their household customers for a large variety of important household loans, including mortgages, auto loans, and credit cards, supporting the *Economies of Scale Channel*. However, for home equity lines of credit, particularly those with longer terms, safety may be more of an issue because these lines only have value to the extent that the providing bank remains solvent. The data suggest that small banks charge statistically significantly lower rates of these lines, consistent with the arguments behind the *Safety Channel*. The results in Panel D on household loan quantities further corroborate the loan rate evidence. In most cases, it appears that households choose large banks because of their better rates or greater safety. Thus, the evidence on consumer deposit and loan prices and quantities support both the *Economies of Scale* and *Safety Channels* as underlying our main results.

In our final channels analysis, we analyze the comparative advantages of small and large banks in serving households using a dataset with extensive information that allows us to control for a number of household characteristics as well as individual bank data. Specifically, we use data on over 20 million mortgage applications and over 5,000 individual banks from the HMDA Loan Application Registry. We run OLS regressions of mortgage application outcomes on bank size and other bank characteristics, as well as additional borrower characteristics (*Loan-to-Income* which proxies for loan risk, race, and gender).²⁷ As dependent variables, we employ 1) a dummy indicating whether the loan was approved by the bank (*Approved Application*), 2) loan size proxied by the natural log of the dollar amount ($\ln(\text{Loan Amount})$), and 3) the loan spread (*Loan Spread*). Our measure of bank size is *Small Bank*, a dummy for banks with GTA below \$1 billion, and alternatively \$3 billion, \$5 billion, or \$10 billion.

balance on the report date of more than \$250,000 minus the number of such deposit accounts multiplied by \$250,000. While the last change in deposit insurance took place in October 2008, the Call Report did not change to reflect it until 2009:Q3. For all time periods, we also add the foreign deposits to the uninsured deposits because foreign deposits are not covered by the FDIC deposit insurance.

²⁷ HMDA data covers about 90% of mortgage lending in the U.S. We match Call Report bank data with the HMDA mortgage application data using the lender file developed by Robert Avery. We follow prior literature to filter the mortgage applications data (e.g., Duchin and Sosyura, 2014; Chu and Zhao, 2018). Specifically, we exclude: (1) loans to finance non-one-to-four family houses, (2) loans insured by government agencies (i.e., FHA, VA, FAS, or RHS), (3) refinancing loans, (4) loans neither approved nor rejected, (5) loans to finance non-owner-occupied units. Our final sample has 23,514,180 applications to 5,541 banks.

Table 9 shows results of the OLS regressions using the three dependent variables, each using one of the four bank size cutoffs on the right-hand side.²⁸ The coefficient estimate in column (1) using our main bank size cutoff of \$1 billion suggests that small banks are associated with an estimated 2.8% lower probability of mortgage application approval, all else equal, consistent with large bank comparative advantages. This credit availability at the extensive margin is likely more important to households than credit terms at the intensive margin. We further see in columns (2) and (3) that at the intensive margin, small banks provide lower loan amounts and charge higher rate spreads, also consistent with large bank comparative advantages.²⁹ Columns (4)-(12) generally provide consistent evidence using the alternative bank size cutoffs, although in some cases with less statistical or economic significance. These results support the *Economies of Scale Channel*, in which large banks are more efficient in providing residential mortgage services, given that we control for bank risk using CAMELS proxies.

8. Conclusions

We formulate and test hypotheses about whether small versus large banks have comparative advantages in boosting household financial sentiment, which is shown in other research to be economically consequential. We also investigate the channels behind the findings. Our analysis is the first to use individual household data from the University of Michigan Surveys of Consumers and match household survey responses with data on banks in their local markets.

The evidence strongly suggests that large banks have comparative advantages relative to small banks in relieving household financial concerns and boosting positive sentiment regarding their personal finances and the nationwide economy. The findings apply across all demographic groups, market types, and time periods considered and are robust to many different measurements and econometric methods. Further analyses support both the *Economies of Scale* and *Safety Channels* as underlying the findings. Large banks provide superior pricing for households for relatively safe deposit and loan products by large banks, evidence of the *Economies of Scale*

²⁸ We use the OLS method for all outcomes, including *Approved Application*. Our choice of a linear rather than nonlinear model of loan approvals is in line with recent research (e.g. Puri, Rocholl, and Steffen, 2011; Duchin and Sosyura, 2014), and is motivated by the fact that nonlinear models tend to produce biased estimates in panel data sets with many fixed effects, leading to incidental parameter problems and inconsistent estimates (e.g., Lancaster, 2000; Greene, 2004).

²⁹ These models have fewer observations because only approved applications have loan amounts and spreads. The number of observations on spreads is further limited as they are reported only for loans above certain thresholds.

Channel, and small banks are associated with more favorable prices for riskier products, evidence of the *Safety Channel*. Large banks are also found to approve higher proportions of mortgage applications and provide more and cheaper funds to home purchasers, further evidence of the *Economies of Scale Channel*.

These findings may seem surprising in that they appear to conflict with the results in the literature that small banks have comparative advantages in alleviating small business financial constraints. The difference between the small business and household results likely stems from emphases on different banking features – small businesses may value the relationships with and trust in small banks more highly, while households may place greater values on the benefits associated with the economies of scale and safety of large banks.

Our paper contributes to the literatures on bank specialness, the comparative advantages and disadvantages and social benefits and costs of small and large banks, household sentiment, and the real effects of the banking industry. We add to the research using the University of Michigan Surveys of Consumers, which usually focuses on household sentiment at the national level. We investigate the determinants of financial sentiment at the household level.

The results in our paper suggest that both government regulators and researchers may take into account these previously unknown social benefits of large banks in improving household financial sentiment. Given the importance of this sentiment to the real economy established elsewhere, the paper has implications regarding two sets of policy levers. The first set involves ways that policy makers can affect banking market structure. Bank mergers and acquisitions (M&As) require federal regulatory approval, giving regulators a vote in consolidation decisions that affect local small bank market shares. Under the Riegle-Neal Act, states can also choose their restrictions on interstate branching (Rice and Strahan, 2010). In addition, under the Dodd-Frank Act and other post-crisis legislation, many regulations become effective at certain size thresholds, potentially deterring M&As that would otherwise reduce small bank market shares.

However, this first set of policy levers that allows for more bank consolidation and reduced small bank market shares may have both positive and negative impacts on the real economy. While household sentiment may be improved, the increased consolidation may have negative effects on small businesses because small banks are shown in other research to be better at reducing small

business financial constraints through relationship lending.

The second set of policy levers concern reducing regulatory compliance costs on both small and large banks that draw resources away from serving consumers. For small banks, in particular, some of the relatively fixed reporting requirements impose costs that cannot be spread over very many assets, possibly making these banks less efficient at serving consumers. Policies that lower these compliance costs may improve household financial sentiment, but could also result in social costs in terms of greater risk in the banking system.

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Figure 1: Chicago Booth/Kellogg School Financial Trust Index (2009-2015)

This figure shows the percentage of people trusting various types of banks as per the *Chicago/Booth/Kellogg School Trust Index* – Wave 24 available at <http://www.financialtrustindex.org/>.

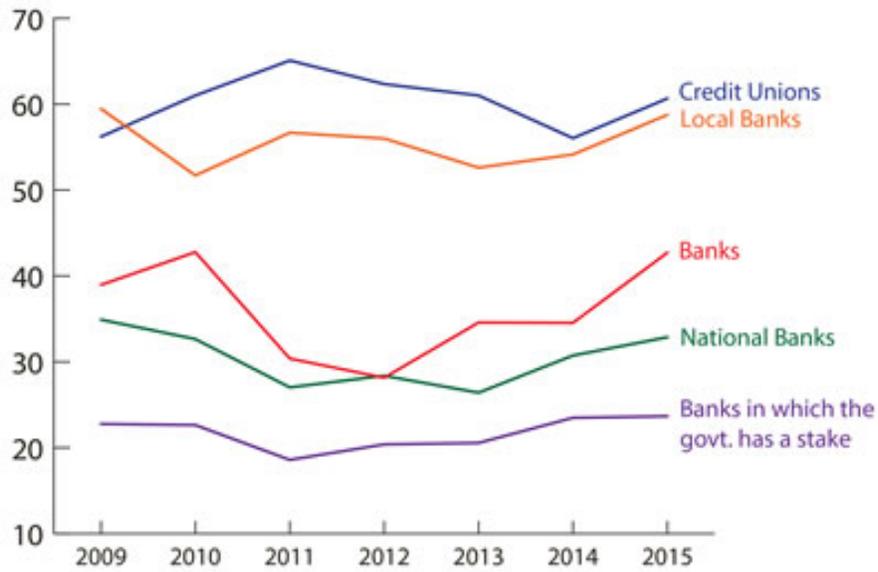
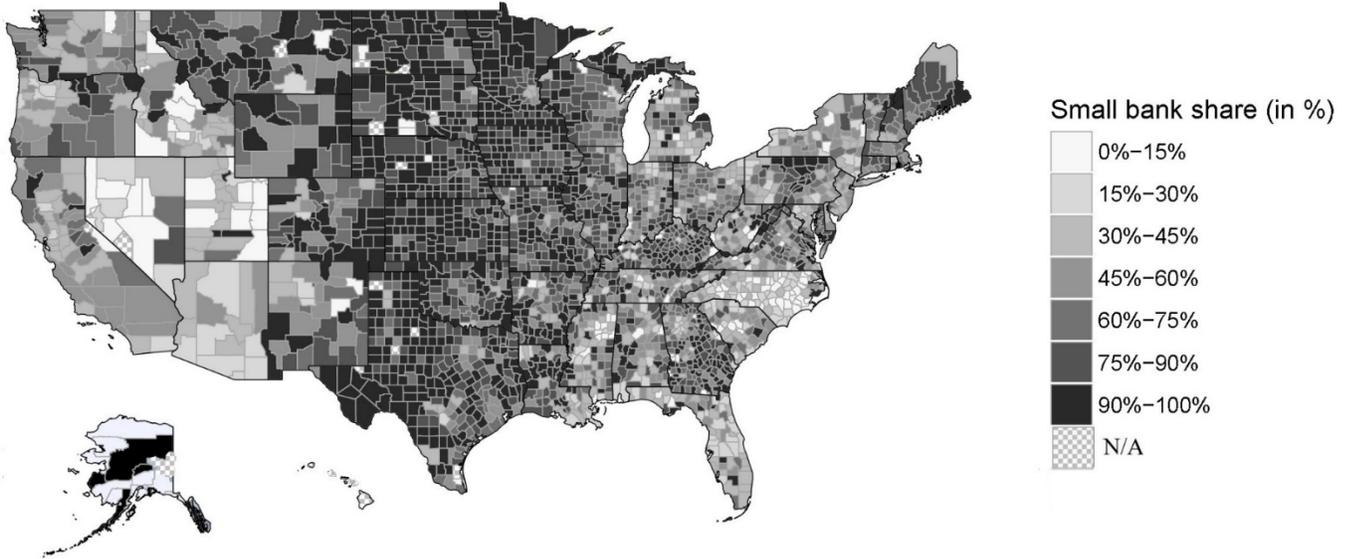


Figure 2: Small Banks in the United States (2000 and 2014)

This figure shows the distribution of the small banks (*Small Bank Share*) across the counties in the U.S. in 2000 and 2014.

Panel A: Small Bank Share by U.S. Counties (2000)



Panel B: Small Bank Share by U.S. Counties (2014)

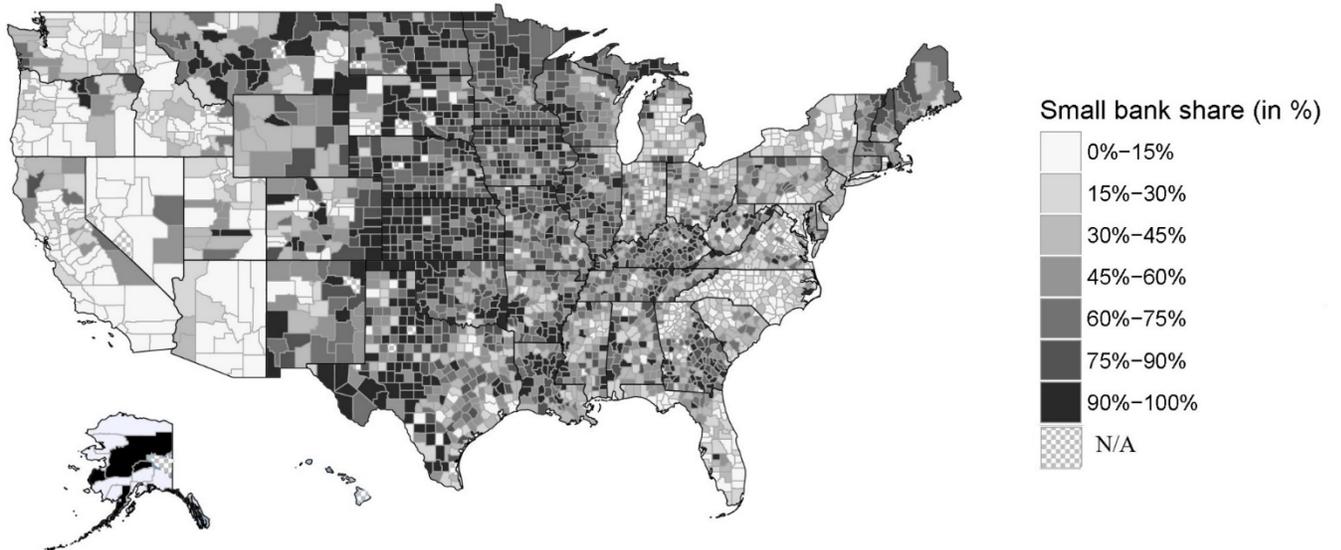


Table 1: Variable Definitions and Summary Statistics*Panel A: Variable Definitions*

This panel provides definitions for all variables used in our analysis.

Group	Definition	Source
Dependent Variables		
Household Sentiment:		
<i>Index of Consumer Sentiment (ICS)</i>	The county-level aggregate Index of Consumer Sentiment from University of Michigan Surveys of Consumers computed using a formula based on responses to the five survey questions.	<i>UMichigan Surveys of Consumers</i>
<i>Index of Consumer Expectations (ICE)</i>	The county-level aggregate Index of Consumer Expectations from University of Michigan Surveys of Consumers computed using a formula based on responses to three of the survey questions.	<i>UMichigan Surveys of Consumers</i>
<i>Finances vs. 1 Year Ago (PAGO)</i>	The survey responses to the following question at the county level: "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?" Possible answers: Better, Same, Worse, Don't know. Responses are transformed into a discrete variable that takes on the integer values 3, 2, or 1, with 3 being positive, 2 being neutral and 1 being negative, respectively.	<i>UMichigan Surveys of Consumers</i>
<i>Finances Expected 1 Year Ahead (PEXP)</i>	The survey responses to the following question at the county level: "Now looking ahead — do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?" Possible answers: Better, Same, Worse, Don't know. Responses are transformed into a discrete variable that takes on the integer values 3, 2, or 1, with 3 being positive, 2 being neutral and 1 being negative, respectively.	<i>UMichigan Surveys of Consumers</i>
<i>National Conditions over Next Year (BUS12)</i>	The survey responses to the following question at the county level: "Now turning to business conditions in the country as a whole — do you think that during the next twelve months we'll have good times financially, or bad times, or what?" Possible answers: Good times, Uncertain, Bad times, Don't know. Responses are transformed into a discrete variable that takes on integer values from 5 to 1, with 5 being the most positive, 3 being neutral, and 1 being the most negative response.	<i>UMichigan Surveys of Consumers</i>
<i>National Conditions over Next 5 Years (BUS5)</i>	The survey responses to the following question at the county level: "Looking ahead, which would you say is more likely — that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of widespread unemployment or depression, or what?" Possible answers: Good times, Uncertain, Bad times, Don't know. Responses are transformed into a discrete variable that takes on integer values from 5 to 1, with 5 being the most positive, 3 being neutral, and 1 being the most negative response.	<i>UMichigan Surveys of Consumers</i>
<i>Conditions for Purchase of Durables (DUR)</i>	The survey responses to the following question at the county level: "About the big things people buy for their homes — such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?" Possible answers: Good, Uncertain, Bad, Don't know. Responses are transformed into a discrete variable that takes on the integer values 3, 2, or 1, with 3 being positive, 2 being neutral and 1 being negative respectively.	<i>UMichigan Surveys of Consumers</i>
Key Explanatory Variables		
<i>Small Bank Share (Main Measure): Small Bank Share (\$1 Billion Cutoff)</i>	The proportion of small bank branches to total bank branches in the county of the household using the \$1 Billion GTA cutoff measured in real 2014:Q4 dollars.	<i>Call Reports, SoD</i>
<i>Small Bank Share (Other Measures) Small Bank Share (\$3 Billion Cutoff)</i>	The proportion of small bank branches to total bank branches in the county of the household using the \$3 Billion GTA cutoff measured in real 2014:Q4 dollars.	<i>Call Reports, SoD</i>
<i>Small Bank Share (\$5 Billion Cutoff)</i>	The proportion of small bank branches to total bank branches in the county of the household using the \$5 Billion GTA cutoff measured in real 2014:Q4 dollars.	<i>Call Reports, SoD</i>
<i>Small Bank Share (\$10 Billion Cutoff)</i>	The proportion of small bank branches to total bank branches in the county of the household using the \$10 Billion GTA cutoff measured in real 2014:Q4 dollars.	<i>Call Reports, SoD</i>
Control Variables		
Respondent Characteristics:		
<i>Senior</i>	Binary variable equal to one if age of respondent is 65 or over.	<i>UMichigan Surveys of Consumers</i>
<i>Male</i>	Binary variable equal to one if sex of respondent is male.	<i>UMichigan Surveys of Consumers</i>
<i>College</i>	Binary variable equal to one if education of respondent is college degree or more.	<i>UMichigan Surveys of Consumers</i>
<i>Homeowner</i>	Binary variable equal to one if respondent is homeowner.	<i>UMichigan Surveys of Consumers</i>
<i>High Income</i>	Binary variable equal to one if household income of respondent is greater or equal to the median.	<i>UMichigan Surveys of Consumers</i>
Bank Condition Variables (CAMELS Proxies):		
<i>Capital Ratio (C)</i>	The average equity ratio, the total equity to gross total assets (GTA) of banks in the county of the household.	<i>Call Reports, SoD</i>
<i>Asset Quality (A)</i>	Proxy: nonperforming loans to total loans of banks in the county of the household.	<i>Call Reports, SoD</i>
<i>Management Quality (M)</i>	Proxy: overhead costs ratio of banks in the county of the household.	<i>Call Reports, SoD</i>
<i>Earnings (E)</i>	Proxy: return on assets (ROA) of banks in the county of the household.	<i>Call Reports, SoD</i>
<i>Liquidity (L)</i>	Proxy: the ratio of liquid assets to GTA of banks in the county of the household.	<i>Call Reports, SoD</i>
<i>Sensitivity to Market Risk (S)</i>	Proxy: the ratio of the absolute difference (gap) between short-term assets and short-term liabilities to GTA of banks in the county of the household.	<i>Call Reports, SoD</i>

Group	Definition	Source
Control Variables (cont.):		
Other Bank & County Characteristics:		
Bank Age	The average bank age in the county of the household.	<i>Call Reports, SoD</i>
BHC Indicator	Proportion of banks that are BHC or part of a BHC in the county of the household.	<i>Call Reports, SoD</i>
Foreign Ownership	Proportion of banks that are foreign owned in the county of the household.	<i>Call Reports, SoD</i>
Fee Income	Non-interest to total income of banks in the county of the household.	<i>Call Reports, SoD</i>
Deposits Ratio	Deposits ratio to GTA in the county of the household.	<i>Call Reports, SoD</i>
Herfindahl-Hirschman Index	The Herfindahl-Hirschman Index (HHI) based upon branch deposits in the county of the household.	<i>Call Reports, SoD</i>
Metro	Binary variable equal to one if the household is located in a metropolitan statistical area (MSA) or New England county metropolitan area (NECMA), and zero otherwise.	<i>Call Reports, SoD</i>
Other Variables Used in Robustness Tests:		
Instrumental Variable:		
Church/Population	The county-level number of church per 1,000 population in 1990.	<i>The Association of Religion Data Archives (ARDA)</i>
Divestiture Deposits to Small Banks	The total amount of deposits divested from M&A banks to small banks during a bank merger process – as identified in Williams (2018), assigned to each count located in a state where the acquiring bank has active bank branches up to two years after the divestiture— scaled by total deposits in the given county (multiplied by 1000).	<i>Williams (2018), SoD</i>
Small Bank Access (\$1 Billion Cutoff)	The ratio of small bank branches to total population in the county of the household scaled by 1,000,000 using the \$1 Billion GTA cutoff measured in real 2014: Q4 dollars.	<i>Call Reports, SoD, US Census</i>
Small Bank Access (\$3 Billion Cutoff)	The ratio of small bank branches to total population in the county of the household scaled by 1,000,000 using the \$3 Billion GTA cutoff measured in real 2014: Q4 dollars.	<i>Call Reports, SoD, US Census</i>
Small Bank Access (\$5 Billion Cutoff)	The ratio of small bank branches to total population in the county of the household scaled by 1,000,000 using the \$5 Billion GTA cutoff measured in real 2014: Q4 dollars.	<i>Call Reports, SoD, US Census</i>
Small Bank Access (\$10 Billion Cutoff)	The ratio of small bank branches to total population in the county of the household scaled by 1,000,000 using the \$10 Billion GTA cutoff measured in real 2014: Q4 dollars.	<i>Call Reports, SoD, US Census</i>
Large Bank Access (\$1 Billion Cutoff)	The ratio of large bank branches to total population in the county of the household scaled by 1000 using the \$1 Billion GTA cutoff measured in real 2014:Q4 dollars.	<i>Call Reports, SoD, US Census</i>
Large Bank Access (\$3 Billion Cutoff)	The ratio of large bank branches to total population in the county of the household scaled by 1000 using the \$3 Billion GTA cutoff measured in real 2014:Q4 dollars.	<i>Call Reports, SoD, US Census</i>
Large Bank Access (\$5 Billion Cutoff)	The ratio of large bank branches to total population in the county of the household scaled by 1000 using the \$5 Billion GTA cutoff measured in real 2014:Q4 dollars.	<i>Call Reports, SoD, US Census</i>
Large Bank Access (\$10 Billion Cutoff)	The ratio of large bank branches to total population in the county of the household scaled by 1000 using the \$10 Billion GTA cutoff measured in real 2014:Q4 dollars.	<i>Call Reports, SoD, US Census</i>
Credit Unions Control Variable:		
Credit Union Branches / Total Bank Branches	Number of credit union branches to total bank branches in the county of the household.	<i>Call Reports, SoD, NCUA</i>
Additional Variables Used in Cross-Sectional Tests:		
No. Branches County	The natural logarithm of the number of bank branches in the county of the household.	<i>Call Reports, SoD</i>
No. Young Branches County	The number of branches of young banks (less than 5 years old) in the county of the household.	<i>Call Reports, SoD</i>
Bank Deregulation Index	Bank competition proxied by the index of interstate bank branching deregulation at the state level, based on Rice and Strahan (2010), plus the additional restriction for reciprocity between states, and subsequent updates from individual state statutes. It ranges from zero (deregulated) to five (highly regulated) based on the regulation changes in a state.	<i>Rice and Strahan (2010)</i>
Financial Crises	An indicator equal to 1 in all financial crises periods as per Berger and Bouwman (2013) and 0 otherwise.	<i>Berger and Bouwman (2013)</i>
National Unemployment Growth	Unemployment rate at the national level.	<i>Bureau of Labor Statistics</i>
National GDP Growth	GDP growth at the national level.	<i>Bureau of Labor Statistics</i>
U.S. Economic Policy Uncertainty	The arithmetic average of the overall U.S. economic policy uncertainty measure developed by Baker, Bloom, and Davis (2016) over each month.	<i>Baker, Bloom, and Davis (2016)</i>
U.S. Monetary Policy Uncertainty	The arithmetic average of the U.S. monetary policy uncertainty measure developed by Baker, Bloom, and Davis (2016) over each month.	<i>Baker, Bloom, and Davis (2016)</i>

Panel B: Summary Statistics – Full Sample (2000-2014)

This panel reports summary statistics of the variables for our analysis for the period 2000:Q1-2014:Q4. All variables using dollar amounts are expressed in real 2014:Q4 dollars using the implicit GDP price deflator. It contains number of observations, means, standard deviations and several quartiles (min, p25, median, p75, and max) on all the regression variables used to examine the relationship between share of or access to small banks and the sentiment of the consumers in the markets that these banks serve.

<i>Group: Statistics:</i>	<i>Main Statistics</i>			<i>Quantiles</i>					<i>Source</i>
	<i>N</i>	<i>Mean</i>	<i>S.d.</i>	<i>Min</i>	<i>p25</i>	<i>Median</i>	<i>p75</i>	<i>Max</i>	
<i>Dependent Variables</i>									
<i>Household Sentiment:</i>									
<i>Index of Consumer Sentiment (ICS)</i>	61,320	83.321	39.455	2.000	46.000	91.000	120.000	150.000	<i>UMichigan Surveys of Consumers</i>
<i>Index of Consumer Expectations (ICE)</i>	61,320	76.482	47.008	2.000	26.000	75.000	124.000	148.000	<i>UMichigan Surveys of Consumers</i>
<i>Finances vs. 1 Year Ago (PAGO)</i>	61,204	2.005	0.847	1.000	1.000	2.000	3.000	3.000	<i>UMichigan Surveys of Consumers</i>
<i>Finances Expected 1 Year Ahead (PEXP)</i>	59,841	2.207	0.656	1.000	2.000	2.000	3.000	3.000	<i>UMichigan Surveys of Consumers</i>
<i>National Conditions over Next Year (BUS12)</i>	56,073	2.833	1.914	1.000	1.000	2.000	5.000	5.000	<i>UMichigan Surveys of Consumers</i>
<i>National Conditions over Next 5 Years (BUS5)</i>	58,752	2.899	1.783	1.000	1.000	3.000	5.000	5.000	<i>UMichigan Surveys of Consumers</i>
<i>Conditions for Purchase of Durables (DUR)</i>	58,270	2.452	0.864	1.000	2.000	3.000	3.000	3.000	<i>UMichigan Surveys of Consumers</i>
<i>Key Explanatory Variables</i>									
<i>Small Bank Share (Main Measure):</i>									
<i>Small Bank Share (\$1 Billion Cutoff)</i>	61,320	0.359	0.173	0.000	0.226	0.347	0.462	1.000	<i>Call Reports, SoD</i>
<i>Small Bank Share (Other Measures):</i>									
<i>Small Bank Share (\$3 Billion Cutoff)</i>	61,320	0.429	0.179	0.000	0.295	0.421	0.540	1.000	<i>Call Reports, SoD</i>
<i>Small Bank Share (\$5 Billion Cutoff)</i>	61,320	0.458	0.182	0.000	0.323	0.451	0.580	1.000	<i>Call Reports, SoD</i>
<i>Small Bank Share (\$10 Billion Cutoff)</i>	61,320	0.496	0.187	0.000	0.351	0.493	0.619	1.000	<i>Call Reports, SoD</i>
<i>Control Variables</i>									
<i>Respondent Characteristics:</i>									
<i>Senior</i>	61,320	0.251	0.434	0.000	0.000	0.000	1.000	1.000	<i>UMichigan Surveys of Consumers</i>
<i>Male</i>	61,320	0.454	0.498	0.000	0.000	0.000	1.000	1.000	<i>UMichigan Surveys of Consumers</i>
<i>College</i>	61,320	0.502	0.500	0.000	0.000	1.000	1.000	1.000	<i>UMichigan Surveys of Consumers</i>
<i>Homeowner</i>	61,320	0.777	0.416	0.000	1.000	1.000	1.000	1.000	<i>UMichigan Surveys of Consumers</i>
<i>High Income</i>	61,320	0.586	0.493	0.000	0.000	1.000	1.000	1.000	<i>UMichigan Surveys of Consumers</i>
<i>Bank Condition Variables (CAMELS Proxies):</i>									
<i>Capital Ratio (C)</i>	61,320	0.091	0.014	0.062	0.080	0.085	0.102	0.305	<i>Call Reports, SoD</i>
<i>Asset Quality (A)</i>	61,320	0.012	0.014	0.000	0.001	0.003	0.025	0.058	<i>Call Reports, SoD</i>
<i>Management Quality (M)</i>	61,320	0.011	0.004	-0.052	0.009	0.011	0.013	0.032	<i>Call Reports, SoD</i>
<i>Earnings (E)</i>	61,320	0.010	0.005	-0.107	0.007	0.011	0.013	0.094	<i>Call Reports, SoD</i>
<i>Liquidity (L)</i>	61,320	0.057	0.024	0.011	0.039	0.051	0.069	0.220	<i>Call Reports, SoD</i>
<i>Sensitivity to Market Risk (S)</i>	61,320	0.162	0.084	0.000	0.098	0.176	0.222	0.663	<i>Call Reports, SoD</i>
<i>Other Bank & County Characteristics:</i>									
<i>Bank Age</i>	61,320	72.984	19.697	4.727	59.728	73.451	87.073	147.333	<i>Call Reports, SoD</i>
<i>BHC Indicator</i>	61,320	0.478	0.199	0.000	0.335	0.475	0.623	1.000	<i>Call Reports, SoD</i>
<i>Foreign Ownership</i>	61,320	0.057	0.073	0.000	0.000	0.027	0.102	0.604	<i>Call Reports, SoD</i>
<i>Fee Income</i>	61,320	0.322	0.834	-98.374	0.277	0.330	0.389	9.504	<i>Call Reports, SoD</i>
<i>Deposits Ratio</i>	61,320	0.665	0.052	0.293	0.632	0.662	0.697	0.917	<i>Call Reports, SoD</i>
<i>Herfindahl-Hirschman Index</i>	61,320	0.155	0.087	0.042	0.101	0.133	0.181	0.900	<i>Call Reports, SoD</i>
<i>Metro</i>	61,320	0.955	0.206	0.000	1.000	1.000	1.000	1.000	<i>Call Reports, SoD</i>
<i>Other Variables used in Robustness Tests:</i>									
<i>Instrumental Variable:</i>									
<i>Church/Population</i>	61,316	0.719	0.401	0.320	0.483	0.583	0.823	7.658	<i>ARDA</i>
<i>Divested Deposits to Small Banks</i>	61,320	0.000	0.0004	0.000	0.000	0.000	0.000	0.080	<i>Williams (2018), SoD</i>

<i>Group Statistics</i>	<i>Main Statistics</i>			<i>Quantiles</i>					<i>Source</i>
	<i>N</i>	<i>Mean</i>	<i>S.d.</i>	<i>Min</i>	<i>p25</i>	<i>Median</i>	<i>p75</i>	<i>Max</i>	
<i>Other Variables used in Robustness Tests (cont.):</i>									
<i>Alternative Bank Share/Access Variables:</i>									
<i>Small Bank Access (\$1 Billion Cutoff)</i>	61,316	0.719	0.401	0.320	0.483	0.583	0.823	7.658	<i>Call Reports, SoD, US Census</i>
<i>Small Bank Access (\$3 Billion Cutoff)</i>	61,320	0.110	0.081	0.000	0.060	0.091	0.141	1.481	<i>Call Reports, SoD, US Census</i>
<i>Small Bank Access (\$5 Billion Cutoff)</i>	61,320	0.132	0.087	0.000	0.073	0.111	0.169	1.481	<i>Call Reports, SoD, US Census</i>
<i>Small Bank Access (\$10 Billion Cutoff)</i>	61,320	0.140	0.089	0.000	0.079	0.120	0.181	1.481	<i>Call Reports, SoD, US Census</i>
<i>Large Bank Access (\$1 Billion Cutoff)</i>	61,320	0.185	0.068	0.000	0.135	0.182	0.231	0.716	<i>Call Reports, SoD, US Census</i>
<i>Large Bank Access (\$3 Billion Cutoff)</i>	61,320	0.164	0.064	0.000	0.117	0.162	0.205	0.645	<i>Call Reports, SoD, US Census</i>
<i>Large Bank Access (\$5 Billion Cutoff)</i>	61,320	0.155	0.062	0.000	0.108	0.153	0.196	0.645	<i>Call Reports, SoD, US Census</i>
<i>Large Bank Access (\$10 Billion Cutoff)</i>	61,320	0.143	0.062	0.000	0.098	0.142	0.184	0.645	<i>Call Reports, SoD, US Census</i>
<i>Credit Unions Control Variable:</i>									
<i>Credit Union Branches/Total Bank Branches</i>	59,819	0.093	0.079	0.000	0.038	0.074	0.127	1.769	<i>Call Reports, SoD, NCUA</i>
<i>Additional Cross-Sectional Tests:</i>									
<i>No. Branches County</i>	61,320	5.147	1.083	0.693	4.466	5.247	5.814	7.495	<i>Call Reports, SoD</i>
<i>No. Young Branches County</i>	61,320	7.091	12.266	0.000	0.000	3.000	8.000	111.000	<i>Call Reports, SoD</i>
<i>Bank Deregulation Index</i>	61,320	2.999	1.090	1.000	2.000	3.000	4.000	5.000	<i>Rice and Strahan (2010)</i>
<i>Financial Crises</i>	61,320	0.329	0.470	0.000	0.000	0.000	1.000	1.000	<i>Berger and Bouwman (2013)</i>
<i>National Unemployment Growth</i>	61,320	0.007	0.056	-0.066	-0.025	-0.011	0.031	0.203	<i>Bureau of Labor Statistics</i>
<i>National GDP Growth</i>	61,320	1.125	1.711	-3.624	0.815	1.542	2.397	3.490	<i>Bureau of Labor Statistics</i>
<i>U.S. Economic Policy Uncertainty</i>	61,320	114.844	38.442	57.203	85.188	104.305	142.171	245.127	<i>Baker, Bloom, and Davis (2016)</i>
<i>U.S. Monetary Policy Uncertainty</i>	61,320	129.616	65.256	30.799	86.088	113.328	162.382	377.410	<i>Baker, Bloom, and Davis (2016)</i>

Table 4: Comparative Advantages of Small and Large Banks in Boosting Household Financial Sentiment – Index of Consumer Sentiment (ICS) Decomposition This table reports regression estimates for analyzing small and large bank comparative advantages in boosting household financial sentiment using a decomposition of the *Index of Consumer Sentiment (ICS)* into its subcomponent survey questions: *PAGO*, *PEXP*, *BUS12*, *BUS5*, and *DUR*, described in detail in Appendix A. Panel A shows estimates using an OLS model with county fixed effects in columns (1)-(5), and an ordered logit model with state fixed effects which reports odds ratios in columns (6)-(10). Panel B reports results the second stage estimates of the Heckman’s selection corrected model with county fixed effects to account for missing responses to single questions of the survey in columns (1)-(5), and the second-stage estimates of the instrumental variable (IV) 2SLS regressions with state fixed effects in columns (6)-(10). The dependent variable is the household’s *ICS* from University of Michigan Surveys of Consumers. The key explanatory variable is *Small Bank Share*, the ratio of small bank branches to total bank branches in the county of the household using the \$1 Billion GTA cutoff measured in real 2014:Q4 dollars. Respondent characteristics are senior status, college degree, male, homeowner, and high income. Bank characteristics at the county level include CAMELS proxies, capital adequacy, asset quality, management quality, earnings, liquidity, and sensitivity to market risk; other bank and county characteristics are bank age, BHC status, foreign ownership, fee income, deposits ratio, Herfindahl-Hirschman Index, and an indicator of metropolitan presence. All models include year-quarter fixed effects and either county or state fixed effects, the strongest specification possible in each case. Variable definitions are given in Table 1. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: ICS Index Decomposition – OLS and Ordered Logit Models

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	OLS with County Fixed Effects					Ordered Logit with State Fixed Effects				
	<i>PAGO</i>	<i>PEXP</i>	<i>BUS12</i>	<i>BUS5</i>	<i>DUR</i>	<i>PAGO</i>	<i>PEXP</i>	<i>BUS12</i>	<i>BUS5</i>	<i>DUR</i>
Independent Variables										
<i>Small Bank Share</i>	-0.079 (-0.885)	-0.127* (-1.892)	-0.643*** (-2.947)	-1.026*** (-5.033)	-0.018 (-0.198)	0.918 (-0.589)	0.583*** (-3.841)	0.557*** (-3.615)	0.369*** (-6.317)	1.199 (1.081)
Interactions with Respondent Characteristics										
<i>Small Bank Share</i> × <i>Senior</i>	-0.012 (-0.247)	-0.011 (-0.255)	0.197 (1.634)	0.207* (1.855)	0.008 (0.155)	0.966 (-0.352)	0.965 (-0.308)	1.265* (1.907)	1.193 (1.542)	0.964 (-0.282)
<i>Small Bank Share</i> × <i>Male</i>	0.023 (0.531)	0.064* (1.856)	0.183* (1.907)	0.272*** (2.768)	-0.047 (-0.930)	1.053 (0.551)	1.188* (1.718)	1.268** (2.339)	1.392*** (3.220)	0.929 (-0.589)
<i>Small Bank Share</i> × <i>College</i>	0.015 (0.342)	-0.046 (-1.171)	-0.175 (-1.510)	0.003 (0.029)	-0.072 (-1.501)	1.052 (0.522)	0.950 (-0.450)	0.851 (-1.379)	1.012 (0.100)	0.814* (-1.781)
<i>Small Bank Share</i> × <i>Homeowner</i>	0.033 (0.589)	0.040 (0.917)	0.332** (2.426)	0.360*** (2.768)	-0.013 (-0.220)	1.128 (0.983)	1.139 (1.036)	1.365** (2.249)	1.497*** (2.989)	0.930 (-0.500)
<i>Small Bank Share</i> × <i>High Income</i>	-0.030 (-0.669)	0.072* (1.887)	-0.091 (-0.774)	0.059 (0.538)	-0.052 (-1.015)	0.951 (-0.526)	1.175 (1.453)	0.917 (-0.734)	1.072 (0.621)	0.875 (-1.048)
Respondent Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank & County Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	NO	NO	NO	NO	NO
State FE	NO	NO	NO	NO	NO	YES	YES	YES	YES	YES
Clusters by County	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	61,204	59,841	56,073	58,752	58,270	61,204	59,841	56,073	58,752	58,270
Adjusted R-squared	0.111	0.103	0.108	0.076	0.073	0.918	0.583***	0.557***	0.369***	1.199

Panel B: ICS Index Decomposition – Heckman’s Selection Corrected Model (2nd Stage)

Dependent Variable:	(1)	(2)	(3)	(4)	(5)
	Heckman’s Selection Model with County Fixed Effects (2 nd Stage)				
	<i>PAGO</i>	<i>PEXP</i>	<i>BUS12</i>	<i>BUS5</i>	<i>DUR</i>
Independent Variables					
<i>Small Bank Share</i>	-0.123 (-1.288)	-0.125* (-1.850)	-0.644*** (-2.949)	-1.025*** (-5.029)	-0.018 (-0.198)
Interactions with Respondent Characteristics					
<i>Small Bank Share</i> × <i>Senior</i>	-0.015 (-0.295)	-0.007 (-0.172)	0.186 (1.525)	0.225** (1.970)	0.012 (0.221)
<i>Small Bank Share</i> × <i>Male</i>	0.047 (0.997)	0.063* (1.827)	0.185* (1.916)	0.269*** (2.732)	-0.047 (-0.942)
<i>Small Bank Share</i> × <i>College</i>	0.031 (0.663)	-0.050 (-1.255)	-0.174 (-1.498)	-0.002 (-0.015)	-0.072 (-1.505)
<i>Small Bank Share</i> × <i>Homeowner</i>	0.033 (0.575)	0.039 (0.884)	0.333** (2.438)	0.358*** (2.752)	-0.013 (-0.233)
<i>Small Bank Share</i> × <i>High Income</i>	-0.024 (-0.495)	0.071* (1.873)	-0.091 (-0.774)	0.059 (0.541)	-0.051 (-1.009)
<i>Inverse Mills Ratio</i>	-0.528 (-0.465)	0.784 (1.599)	-0.705 (-0.436)	-0.686 (-0.723)	-0.501 (-0.537)

Respondent Characteristics	YES	YES	YES	YES	YES
Bank & County Characteristics	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES
State FE	NO	NO	NO	NO	NO
Clusters by County	YES	YES	YES	YES	YES
Observations	52,910	59,841	56,073	58,752	58,270
Adjusted R-squared	0.110	0.103	0.108	0.076	0.073

Table 5: Comparative Advantages of Small and Large Banks in Boosting Household Financial Sentiment – Bank Share and Access Robustness Tests This table reports robustness tests for analyzing small and large bank comparative advantages in boosting household financial sentiment using various definitions of our main explanatory variable. Panel A reports robustness tests when the key explanatory variable is *Small Bank Share*, the ratio of small/large bank branches to total bank branches in the county of the household. Columns (1)-(4) reports regression estimates when using the alternative cutoffs of small banks' size (in billions): \$1, \$3, \$5, and \$10 Billion GTA in real 2014:Q4 dollars. Panel B reports robustness tests when the key explanatory variable is *Small/Large Bank Access*, the ratio of small/large bank branches to total population in the county of the household scaled by 1,000 (in billions) using the \$1, \$3, \$5, and \$10 GTA cutoffs measured in real 2014:Q4 dollars. The dependent variable is the household's *Index of Consumer Sentiment (ICS)* from University of Michigan Surveys of Consumers. Respondent characteristics are senior status, college degree, male, homeowner, and high income. Bank characteristics at the county level include CAMELS proxies, capital adequacy, asset quality, management quality, earnings, liquidity, and sensitivity to market risk; other bank and county characteristics are bank age, BHC status, foreign ownership, fee income, deposits ratio, Herfindahl-Hirschman Index, and an indicator of metropolitan presence. All models include year-quarter fixed effects and county fixed effects. Variable definitions are given in Table 1. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Bank Share Cutoffs – Robustness Tests

	(1)	(2)	(3)	(4)
	Small Bank Share			
GTA Cutoff (\$):	\$1Bn	\$3Bn	\$5Bn	\$10Bn
Dependent Variable:	<i>Index of Consumer Sentiment (ICS)</i>			
Independent Variables				
<i>Small/Large Bank Share</i>	-15.082*** (-3.497)	-13.917*** (-3.550)	-12.351*** (-3.219)	-16.591*** (-4.349)
Interactions with Respondent Characteristics				
<i>Small/Large Bank Share</i> × <i>Senior</i>	2.305 (0.961)	3.525 (1.572)	2.635 (1.201)	2.190 (1.046)
<i>Small/Large Bank Share</i> × <i>Male</i>	3.912* (1.934)	3.370* (1.690)	2.821 (1.411)	2.761 (1.451)
<i>Small/Large Bank Share</i> × <i>College</i>	-2.822 (-1.269)	-2.775 (-1.287)	-3.180 (-1.483)	-1.458 (-0.707)
<i>Small/Large Bank Share</i> × <i>Homeowner</i>	6.068** (2.320)	5.907** (2.410)	5.713** (2.417)	6.126*** (2.649)
<i>Small/Large Bank Share</i> × <i>High Income</i>	-0.322 (-0.142)	-0.734 (-0.340)	-0.686 (-0.322)	-1.252 (-0.598)
Respondent Characteristics	YES	YES	YES	YES
Bank & County Characteristics	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Clusters by County	YES	YES	YES	YES
Observations	61,320	61,320	61,320	61,320
Adjusted R-squared	0.128	0.128	0.128	0.128

Table 6: Comparative Advantages of Small and Large Banks in Boosting Household Financial Sentiment – Other Robustness Tests This table reports regression estimates for analyzing small and large bank comparative advantages in boosting household financial sentiment using several robustness tests. Column (1) reports regression estimates when considering the dependent variable to be the county-level *Index of Consumer Expectations (ICE)* from University of Michigan Surveys of Consumers. Column (2) reports regression estimates when using alternative model specifications: a model with errors clustered by county and time. Column (3) and (4) employ a different calculation of our bank control variables: First, we employ deposit-weighted average instead of branch-weighted averages of bank characteristics to obtain county-level values. Second, we calculate the county-level values of CAMELS proxies separately for small and large banks (using the \$1 billion GTA cutoff definition) and include them as control variables. The model estimates in column (5) additionally include a variable measuring the presence of credit unions in a given county. Column (6) shows our baseline specification using state-year-quarter fixed effects instead of year-quarter and county fixed effects. Respondent characteristics are senior status, college degree, male, homeowner, and high income. Bank characteristics at the county level include CAMELS proxies, capital adequacy, asset quality, management quality, earnings, liquidity, and sensitivity to market risk; other bank and county characteristics are bank age, BHC status, foreign ownership, fee income, deposits ratio, Herfindahl-Hirschman Index, and an indicator of metropolitan presence. All models except (6) include year-quarter fixed effects and county fixed effects. The details of definitions and measurements of all variables are reported in Table 1. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Robustness Test:	Alternative Dependent Variable	Two- Way Clustering	Deposit- Weighted Bank Variables	CAMELS for Small & Large Banks	Control for Credit Unions	State × Year- Quarter FE
Dependent Variable:	<i>Index of Consumer Expectations (ICE)</i>	<i>Index of Consumer Sentiment (ICS)</i>				
Independent Variables						
<i>Small Bank Share</i>	-22.404*** (-4.264)	-15.082*** (-3.398)	-12.280*** (-2.961)	-14.164*** (-3.215)	-13.841*** (-3.148)	-9.494*** (-3.156)
Interactions with Respondent Characteristics						
<i>Small Bank Share × Senior</i>	3.965 (1.356)	2.305 (0.905)	2.348 (0.981)	3.346 (1.373)	2.514 (1.018)	2.369 (1.012)
<i>Small Bank Share × Male</i>	7.165*** (2.933)	3.912** (2.122)	3.838* (1.897)	3.156 (1.515)	3.377 (1.614)	3.930** (1.990)
<i>Small Bank Share × College</i>	-3.406 (-1.183)	-2.822 (-1.293)	-2.846 (-1.280)	-3.416 (-1.496)	-3.955* (-1.728)	-2.760 (-1.287)
<i>Small Bank Share × Homeowner</i>	9.156*** (2.828)	6.068** (2.038)	6.136** (2.338)	6.063** (2.248)	6.519** (2.413)	5.459** (2.172)
<i>Small Bank Share × High Income</i>	1.458 (0.519)	-0.322 (-0.136)	-0.330 (-0.146)	-0.135 (-0.058)	0.055 (0.024)	-0.628 (-0.295)
<i>Credit Union Branches / Total Bank Branches</i>					-15.647** (-2.249)	
Respondent Characteristics	YES	YES	YES	YES	YES	YES
Bank & County Characteristics	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	NO
County FE	YES	YES	YES	YES	YES	NO
State × Year-Quarter FE	NO	NO	NO	NO	NO	YES
Clusters by County	YES	YES	YES	YES	YES	YES
Observations	61,320	61,316	61,320	60,250	59,819	61,320
Adjusted R-squared	0.089	0.128	0.128	0.128	0.128	0.127

Table 7: Comparative Advantages of Small and Large Banks in Boosting Household Financial Sentiment – Cross-Sectional Evidence This table reports regression estimates for analyzing small bank comparative advantages/disadvantages in boosting household financial sentiment using different subsamples. Panel A reports subsamples by banking market characteristics and Panel B splits the sample according to national economic indicators. Columns (1)-(2) of Panel A report regression estimates when considering counties with high bank HHI (\leq median) versus those with high bank HHI ($>$ median). Columns (3)-(4) report regression estimates using subsamples of counties with a low (\leq median) or high ($>$ median) number of bank branches while the sample used in columns (5)-(6) is split according to the median of the number of young bank branches (below 5 years old). Columns (7)-(8) show results of regressions using subsamples of counties in states with a low/high bank deregulation index. The subsamples used in Panel B are based on splits according to crisis versus normal times, high versus low national unemployment growth, high versus low national GDP growth, and high versus low U.S. economic or monetary policy uncertainty. The dependent variable is the household's *Index of Consumer Sentiment (ICS)* from University of Michigan Surveys of Consumers. The key explanatory variable is *Small Bank Share*, the ratio of small bank branches to total bank branches in the county of the household using the \$1 Billion GTA cutoff measured in real 2014:Q4 dollars. Respondent characteristics are senior status, college degree, male, homeowner, and high income. Bank characteristics at the county level include CAMELS proxies, capital adequacy, asset quality, management quality, earnings, liquidity, and sensitivity to market risk; other bank and county characteristics are bank age, BHC status, foreign ownership, fee income, deposits ratio, Herfindahl-Hirschman Index, and an indicator of metropolitan presence. All models include year-quarter fixed effects and county fixed effects. The details of definitions and measurements of all variables are reported in Table 1. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Banking Market Structure

Subsample: Group: Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HHI Index		No. Branches County		No. Young Bank Branches County		Bank Deregulation Index	
	\leq median	$>$ median	\leq median	$>$ median	\leq median	$>$ median	\leq median	$>$ median
Independent Variables	<i>Index of Consumer Sentiment (ICS)</i>							
<i>Small Bank Share</i>	-14.595** (-2.254)	-17.114*** (-2.861)	-17.417*** (-2.611)	-13.049** (-2.211)	-12.073** (-2.143)	-17.203** (-2.187)	-15.503*** (-2.918)	-13.738* (-1.652)
Interactions with Respondent Characteristics								
<i>Small Bank Share</i> \times <i>Senior</i>	4.428 (1.215)	2.606 (0.806)	-2.954 (-0.749)	4.408 (1.464)	0.857 (0.271)	2.615 (0.652)	3.857 (1.350)	3.270 (0.691)
<i>Small Bank Share</i> \times <i>Male</i>	-0.130 (-0.043)	6.506** (2.246)	7.164** (2.222)	2.471 (0.910)	6.437** (2.367)	2.399 (0.806)	2.655 (1.058)	7.190* (1.829)
<i>Small Bank Share</i> \times <i>College</i>	-3.010 (-0.950)	-1.124 (-0.356)	1.668 (0.461)	-6.817** (-2.308)	-2.662 (-0.910)	-4.282 (-1.291)	-1.119 (-0.417)	-2.317 (-0.550)
<i>Small Bank Share</i> \times <i>Homeowner</i>	8.912** (2.568)	3.688 (0.975)	5.044 (1.203)	8.502** (2.500)	5.898* (1.742)	7.457* (1.764)	4.713 (1.611)	5.660 (0.981)
<i>Small Bank Share</i> \times <i>High Income</i>	-0.338 (-0.111)	0.977 (0.313)	0.396 (0.104)	-0.973 (-0.352)	-0.565 (-0.186)	-0.287 (-0.081)	0.217 (0.085)	1.000 (0.215)
Respondent Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Bank & County Characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Clusters by County	YES	YES	YES	YES	YES	YES	YES	YES
Observations	30,980	30,340	18,978	42,342	30,650	30,670	41,048	20,272
Adjusted R-squared	0.136	0.124	0.142	0.123	0.131	0.130	0.134	0.117

Panel B: National Economic Conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Financial Crisis vs. Normal Times		National Unemployment Growth		National GDP Growth		U.S. Economic Policy Uncertainty		U.S. Monetary Policy Uncertainty	
Subsample: Group:	Crisis	Normal	≤ zero	> zero	≤ median	> median	≤ median	> median	≤ median	> median
Dependent Variable:	<i>Index of Consumer Sentiment (ICS)</i>									
Independent Variables										
<i>Small Bank Share</i>	-15.540** (-2.484)	-10.612* (-1.713)	-12.979** (-2.141)	-14.515** (-2.327)	-18.928*** (-2.730)	-10.962** (-2.100)	-12.954** (-2.219)	-16.827*** (-2.825)	-10.436* (-1.869)	-17.890*** (-2.831)
Interactions with Respondent Characteristics										
<i>Small Bank Share × Senior</i>	1.284 (0.280)	2.638 (0.845)	3.197 (1.022)	-0.328 (-0.076)	3.588 (1.065)	2.610 (0.828)	2.895 (0.867)	2.801 (0.830)	2.386 (0.732)	2.183 (0.590)
<i>Small Bank Share × Male</i>	8.390** (2.301)	2.892 (1.154)	1.802 (0.717)	7.877** (2.259)	6.307** (2.176)	2.476 (0.904)	3.918 (1.363)	3.914 (1.436)	3.972 (1.415)	2.689 (0.915)
<i>Small Bank Share × College</i>	-0.173 (-0.047)	-1.944 (-0.668)	-0.765 (-0.264)	-3.422 (-0.935)	-4.722 (-1.441)	-1.345 (-0.436)	-2.631 (-0.812)	-3.238 (-0.961)	-3.123 (-1.136)	-2.561 (-0.743)
<i>Small Bank Share × Homeowner</i>	-1.005 (-0.225)	6.589** (2.049)	8.587** (2.493)	-1.077 (-0.258)	4.672 (1.122)	6.811* (1.899)	7.205* (1.760)	2.820 (0.749)	4.249 (1.133)	7.153* (1.731)
<i>Small Bank Share × High Income</i>	6.862* (1.890)	-0.913 (-0.322)	-0.891 (-0.319)	3.620 (1.015)	-0.778 (-0.239)	-1.445 (-0.492)	-3.357 (-1.037)	0.178 (0.052)	-0.345 (-0.122)	-2.942 (-0.892)
Respondent Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank & County Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clusters by County	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	20,172	41,148	39,638	21,682	29,251	32,069	30,826	30,494	34,749	26,571
Adjusted R-squared	0.201	0.098	0.109	0.164	0.115	0.124	0.113	0.101	0.126	0.112

Table 8: Small and Large Banks and Household Financial Sentiment – Potential Channels (RateWatch and Call Report Evidence) This table reports univariate analyses for analyzing channels for the effects of the small and large bank comparative advantages in boosting household financial sentiment for 2000-2014. *Small Bank* is a bank with a GTA (measured in real 2014:Q4 dollars) of \$1 Billion or less. Panel A reports consumer deposit rates. Panel B reports deposit quantities. Panel C reports consumer loan rates. Panel D reports consumer loan quantities. The details of definitions and measurements of all are reported in Table 1 and Appendix A. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Consumer Deposit Rates

Variable	Small Banks		Large Banks		Difference in Means (Large-Small)	
	(1) N	(2) Mean	(3) N	(4) Mean	(5) Difference	(6) t-Stat
100K Deposits						
03MCD100K	117,368	0.8405	147,319	1.0170	0.1765***	35.2
06MCD100K	131,979	1.1025	181,450	1.1529	0.0504***	10.2
12MCD100K	133,964	1.3650	186,114	1.3857	0.0207***	4.0
24MCD100K	113,860	1.4060	157,762	1.3574	-0.0486***	-10.4
36MCD100K	98,619	1.5033	136,795	1.4290	-0.0741***	-16.6
48MCD100K	81,478	1.6379	116,458	1.5388	-0.0991***	-21.9
60MCD100K	82,120	1.8850	121,472	1.8257	-0.0593***	-12.7
SAV100K	71,442	0.2131	108,317	0.1800	-0.0331***	-30.5
250K Deposits						
03MCD250K	65,420	0.2380	79,011	0.1896	-0.0484***	-55.0
06MCD250K	72,195	0.3636	103,503	0.3047	-0.0588***	-51.9
12MCD250K	72,489	0.5419	104,931	0.4527	-0.0892***	-64.6
24MCD250K	69,051	0.7862	99,742	0.6713	-0.1149***	-68.2
36MCD250K	64,869	1.0170	93,337	0.8750	-0.1419***	-70.3
48MCD250K	55,320	1.2127	80,988	1.0534	-0.1592***	-65.7
60MCD250K	55,206	1.4332	82,571	1.2898	-0.1434***	-53.4

Panel B: Deposit Quantities

Variable	Small Banks		Large Banks		Difference in Means (Large-Small)	
	(1) N	(2) Mean	(3) N	(4) Mean	(5) Difference	(6) t-Stat
Insured Deposits / GTA	431,993	0.6373	34,029	0.4779	-0.1594***	-97.9
Uninsured Deposits / GTA	431,993	0.3184	34,029	0.3616	0.0432***	29.4

Panel C: Consumer Loan Rates

Variable	Small Banks		Large Banks		Difference in Means (Large-Small)	
	(1) N	(2) Mean	(3) N	(4) Mean	(5) Difference	(6) t-Stat
Mortgages						
1 Year ARM @ 175K - Rate	17,464	5.7430	39,053	5.2927	-0.4503***	-31.2
3 Year ARM @ 175K - Rate	20,069	5.9506	46,053	5.2891	-0.6615***	-51.0
5 Year ARM @ 175K - Rate	17,304	6.0738	48,334	5.2438	-0.8301***	-60.7
15 Yr Fxd Mtg @ 175K - Rate	37,941	5.6743	97,794	5.3298	-0.3445***	-36.8
30 Yr Fxd Mtg @ 175K - Rate	27,562	5.8727	85,392	5.8119	-0.0608***	-6.5
Auto Loans						
Auto New - 36 Mo Term	99,546	6.6974	204,812	5.6914	-1.0059***	-150.0
Auto New - 48 Mo Term	99,693	6.8000	205,525	5.7974	-1.0025***	-150.0
Auto New - 60 Mo Term	99,159	6.9141	205,619	5.9114	-1.0026***	-150.0
Auto Used 2 Yrs - 36 Mo Term	87,976	7.2779	187,500	6.0322	-1.2457***	-160.0
Auto Used 2 Yrs - 48 Mo Term	84,971	7.3187	185,123	6.0917	-1.2270***	-160.0
Auto Used 2 Yrs - 60 Mo Term	55,667	7.1053	160,012	5.9369	-1.1684***	-130.0
Auto Used 4 Yrs - 36 Mo Term	70,990	7.8033	153,494	6.2994	-1.5038***	-170.0
Auto Used 4 Yrs - 48 Mo Term	52,999	7.6119	138,112	6.1769	-1.4350***	-140.0
Auto Used 4 Yrs - 60 Mo Term	20,842	7.1023	100,899	5.7555	-1.3468***	-80.3
Credit Cards						
Credit Cards - Annual Fee	4,922	6.6522	26,892	3.5051	-3.1471***	-16.8
Credit Cards - Cash Adv Fee	8,061	2.7212	47,654	2.4210	-0.3001***	-10.6
Credit Cards - Intro Rate	3,348	1.8031	22,053	1.5556	-0.2476***	-4.9
Credit Cards - MasterCard	4,329	13.0926	22,610	12.5937	-0.4990***	-7.3
Credit Cards - Visa	8,219	12.7194	53,821	12.3491	-0.3703***	-9.8
Credit Cards - Gold	4,803	12.1544	30,880	11.2691	-0.8853***	-17.8
Credit Cards - Platinum	3,671	10.1306	36,566	9.6647	-0.4658***	-12.5
Home Equity Loans						
H.E. Loan Up to 80% LTV @ 20K - 60 Mo Term	61,860	6.8602	159,965	6.6153	-0.2449***	-27.4
H.E. Loan Up to 80% LTV @ 20K - 120 Mo Term	35,653	6.5079	143,275	6.8697	0.3618***	22.7
H.E. Loan Up to 80% LTV @ 20K - 180 Mo Term	19,427	7.2371	114,179	7.2596	0.0225***	1.3
H.E. Loan 81-90% LTV @ 20K - 60 Mo Term	31,461	7.0865	102,164	7.1914	0.1049***	7.9
H.E. Loan 81-90% LTV @ 20K - 120 Mo Term	17,645	6.5543	91,083	7.4409	0.8866***	35.5

	9,202	7.1281	72,243	7.8175	0.6894***	16.8
<i>H.E. Loan 81-90% LTV @ 20K - 180 Mo Term</i>						
Group:	Small Banks		Large Banks		Difference in Means (Large-Small)	
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	N	Mean	N	Mean	Difference	t-Stat
<i>H.E. Loan 91-100% LTV @ 20K - 120 Mo Term</i>	5,483	6.3536	50,961	8.3069	1.9532***	33.8
<i>H.E. Loan 91-100% LTV @ 20K - 180 Mo Term</i>	3,216	6.7420	41,128	8.6531	1.9111***	20.6

Panel D: Consumer Loan Quantities

	Small Banks		Large Banks		Difference in Means (Large-Small)	
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	N	Mean	N	Mean	Difference	t-Stat
<i>Residential Real Estate Loans / GTA</i>	431,993	0.1725	34,029	0.1761	0.0036***	5.2
<i>Consumer Credit Card Loans / GTA</i>	431,993	0.0025	34,029	0.0248	0.0223***	33.9
<i>Other Consumer Loans / GTA</i>	431,993	0.0519	34,029	0.0464	-0.0055***	-12.4
<i>Residential Real Estate Unused Commitments / GTA</i>	431,993	0.0113	34,029	0.0291	0.0178***	87.2
<i>Consumer Credit Card Unused Commitments / GTA</i>	431,993	0.6602	34,029	0.3095	-0.3507***	-8.9

Table 9: Small and Large Banks and Household Financial Sentiment – Potential Channels (HMDA Mortgage Originations Loan-Level Evidence) This table reports loan-level regression analyses for analyzing channels for the effects of the large bank comparative advantages in boosting household financial sentiment. The individual loan application data come from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry and cover the period 2000–2014. Panels A and B report regression estimates from a linear probability model explaining the relation between small banks and mortgage origination decisions. The dependent variables are: *Approved Application*, an indicator that equals one if a loan was approved and zero if it was denied; *Ln(Loan Amount)*, the natural logarithm of the loan amount for approved applications; and *Loan Spread*, the spread on the mortgage for approved applications. The key explanatory variable is *Small Bank*, a dummy equal to one if a bank is small using the \$1 Billion GTA cutoff measured in real 2014:Q4 dollars (our main proxy) in columns (1)-(3) and alternative proxies (in billions) of \$3, \$5, and \$10 GTA cutoffs, all measured in real 2014:Q4 dollars in columns (4)-(12). Bank characteristics at the bank level include CAMELS proxies, capital adequacy, asset quality, management quality, earnings, liquidity, and sensitivity to market risk; other bank and county characteristics are bank age, BHC status, foreign ownership, fee income, deposits ratio, and the Herfindahl-Hirschman Index. Borrower characteristics are loan-to-income, gender, and race dummies. All models include year fixed effects and county fixed effects. The details of definitions and measurements of all variables are reported in Table 1 and Appendix A. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Small Bank: Different Cutoffs												
Small Bank Proxy:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1bn GTA Cutoff (\$)			3bn GTA Cutoff (\$)			5bn GTA Cutoff (\$)			10bn GTA Cutoff (\$)		
Dependent Variable:	<i>Approved Application</i>	<i>Ln(Loan Amount)</i>	<i>Loan Spread</i>	<i>Approved Application</i>	<i>Ln(Loan Amount)</i>	<i>Loan Spread</i>	<i>Approved Application</i>	<i>Ln(Loan Amount)</i>	<i>Loan Spread</i>	<i>Approved Application</i>	<i>Ln(Loan Amount)</i>	<i>Loan Spread</i>
Independent Variables												
<i>Small Bank</i>	-0.028*** (-11.365)	-0.253*** (-17.154)	0.184*** (7.281)	-0.005** (-2.113)	-0.272*** (-17.484)	0.199*** (7.707)	-0.004 (-1.413)	-0.286*** (-18.495)	0.201*** (6.436)	0.013*** (5.300)	-0.278*** (-19.130)	0.000 (0.004)
Bank Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower Characteristics	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clusters by County	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	23,514,180	19,718,830	1,598,689	23,514,180	19,718,830	1,598,689	23,514,180	19,718,830	1,598,689	23,514,180	19,718,830	1,598,689
Adjusted R-squared	0.030	0.164	0.263	0.029	0.165	0.263	0.029	0.166	0.263	0.029	0.166	0.262

Appendix A: Additional Variable Definitions and Summary Statistics

Panel A: Additional Variable Definitions

This panel provides definitions for additional variables used in our channels analysis.

Group	Definition	Source
Other Variables Used in Channel Tests (RateWatch and Call Report):		
Consumer Deposit Rates		
03MCD100K	Deposit rate on 3 month CD of \$100,000.	RateWatch
06MCD100K	Deposit rate on 6 month CD of \$100,000.	RateWatch
12MCD100K	Deposit rate on 12 month CD of \$100,000.	RateWatch
24MCD100K	Deposit rate on 24 month CD of \$100,000.	RateWatch
36MCD100K	Deposit rate on 36 month CD of \$100,000.	RateWatch
48MCD100K	Deposit rate on 48 month CD of \$100,000.	RateWatch
60MCD100K	Deposit rate on 60 month CD of \$100,000.	RateWatch
SAV100K	Deposit rate on savings account of \$100,000.	RateWatch
03MCD250K	Deposit rate on 3 month CD of \$250,000.	RateWatch
06MCD250K	Deposit rate on 6 month CD of \$250,000.	RateWatch
12MCD250K	Deposit rate on 12 month CD of \$250,000.	RateWatch
24MCD250K	Deposit rate on 24 month CD of \$250,000.	RateWatch
36MCD250K	Deposit rate on 36 month CD of \$250,000.	RateWatch
48MCD250K	Deposit rate on 48 month CD of \$250,000.	RateWatch
60MCD250K	Deposit rate on 60 month CD of \$250,000.	RateWatch
Deposit Quantities		
Insured Deposits / GTA	The ratio of bank insured deposits to GTA.	Call Reports
Uninsured Deposits / GTA	The ratio of bank uninsured deposits to GTA.	Call Reports
Consumer Loan Rates		
Mortgages		
1 Year ARM @ 175K - Rate	Loan rate on 1-year adjustable rate mortgage of \$175,000.	RateWatch
3 Year ARM @ 175K - Rate	Loan rate on 3-year adjustable rate mortgage of \$175,000.	RateWatch
5 Year ARM @ 175K - Rate	Loan rate on 5-year adjustable rate mortgage of \$175,000.	RateWatch
15 Yr Fxd Mtg @ 175K - Rate	Loan rate on 15-year fixed rate mortgage of \$175,000.	RateWatch
30 Yr Fxd Mtg @ 175K - Rate	Loan rate on 30-year fixed rate mortgage of \$175,000.	RateWatch
Auto Loans		
Auto New - 36 Mo Term	Loan rate on new auto for 36 month term.	RateWatch
Auto New - 48 Mo Term	Loan rate on new auto for 48 month term.	RateWatch
Auto New - 60 Mo Term	Loan rate on new auto for 60 month term.	RateWatch
Auto Used 2 Yrs - 36 Mo Term	Loan rate on 2-year used auto for 36 month term.	RateWatch
Auto Used 2 Yrs - 48 Mo Term	Loan rate on 2-year used auto for 48 month term.	RateWatch
Auto Used 2 Yrs - 60 Mo Term	Loan rate on 2-year used auto for 60 month term.	RateWatch
Auto Used 4 Yrs - 36 Mo Term	Loan rate on 4-year used auto for 36 month term.	RateWatch
Auto Used 4 Yrs - 48 Mo Term	Loan rate on 4-year used auto for 48 month term.	RateWatch
Auto Used 4 Yrs - 60 Mo Term	Loan rate on 4-year used auto for 60 month term.	RateWatch
Credit Cards		
Credit Cards - Annual Fee	Credit card annual fee.	RateWatch
Credit Cards - Cash Adv Fee	Credit card cash advance fee.	RateWatch
Credit Cards - Intro Rate	Credit card introductory rate.	RateWatch
Credit Cards - MasterCard	Standard MasterCard credit card rate.	RateWatch
Credit Cards - Visa	Standard Visa credit card rate.	RateWatch
Credit Cards - Gold	Gold credit card rate.	RateWatch
Credit Cards - Platinum	Platinum credit card rate.	RateWatch
Home Equity Loans		
H.E. Loan Up to 80% LTV @ 20K	Rate on home equity loan up to 80% loan to value of \$20,000.	RateWatch
H.E. Loan Up to 80% LTV @ 20K - 120 Mo Term	Rate on home equity loan up to 80% loan to value of \$20,000 for 120-month term.	RateWatch
H.E. Loan Up to 80% LTV @ 20K - 180 Mo Term	Rate on home equity loan up to 80% loan to value of \$20,000 for 180-month term.	RateWatch
H.E. Loan 81-90% LTV @ 20K - 60 Mo Term	Rate on home equity loan up to 81-90% loan to value of \$20,000 for 60-month term.	RateWatch
H.E. Loan 81-90% LTV @ 20K - 120 Mo Term	Rate on home equity loan up to 81-90% loan to value of \$20,000 for 120-month term.	RateWatch
H.E. Loan 81-90% LTV @ 20K - 180 Mo Term	Rate on home equity loan up to 81-90% loan to value of \$20,000 for 180-month term.	RateWatch
H.E. Loan 91-100% LTV @ 20K - 60 Mo Term	Rate on home equity loan up to 91-100% loan to value of \$20,000 for 60-month term.	RateWatch
H.E. Loan 91-100% LTV @ 20K - 120 Mo Term	Rate on home equity loan up to 91-100% loan to value of \$20,000 for 120-month term.	RateWatch
H.E. Loan 91-100% LTV @ 20K - 180 Mo Term	Rate on home equity loan up to 91-100% loan to value of \$20,000 for 180-month term.	RateWatch
Consumer Loan Quantities		
Residential Real Estate Loans / GTA	The ratio of bank residential real estate loans to GTA.	Call Reports
Consumer Credit Card Loans / GTA	The ratio of bank residential credit card loans to GTA.	Call Reports
Other Consumer Loans / GTA	The ratio of other bank consumer loans to GTA.	Call Reports
Residential Real Estate Unused Commitments / GTA	The ratio of bank residential real estate unused commitments to GTA.	Call Reports
Consumer Credit Card Unused Commitments / GTA	The ratio of bank residential credit card unused commitments to GTA.	Call Reports

Group	Definition	Source
Other Variables Used in Channel Tests (HMDA):		
Dependent Variables		
<i>Approved Application</i>	A dummy equal to one if a loan application is approved and zero otherwise.	<i>HMDA</i>
<i>Ln(Loan Amount)</i>	The natural logarithm of the loan amount for approved applications.	<i>HMDA</i>
<i>Loan Spread</i>	The loan spread on the loan for approved applications.	<i>HMDA</i>
Explanatory Variables		
<i>Small Bank (\$1 Billion Cutoff)</i>	A dummy equal to one for small banks using the \$1 Billion GTA cutoff measured in real 2014:Q4 dollars.	<i>Call Reports</i>
<i>Small Bank (\$3 Billion Cutoff)</i>	A dummy equal to one for small banks using the \$3 Billion GTA cutoff measured in real 2014:Q4 dollars.	<i>Call Reports</i>
<i>Small Bank (\$5 Billion Cutoff)</i>	A dummy equal to one for small banks using the \$5 Billion GTA cutoff measured in real 2014:Q4 dollars.	<i>Call Reports</i>
<i>Small Bank (\$10 Billion Cutoff)</i>	A dummy equal to one for small banks using the \$10 Billion GTA cutoff measured in real 2014:Q4 dollars.	<i>Call Reports</i>
<i>Bank Size</i>	The natural logarithm of the bank GTA measured in real 2014:Q4 dollars.	<i>Call Reports</i>
Bank Characteristics (CAMELS Proxies):		
<i>Capital Ratio (C)</i>	Banks' equity ratio calculated as total equity over gross total assets (GTA).	<i>Call Reports</i>
<i>Asset Quality (A)</i>	Proxy: nonperforming loans to total loans of a bank.	<i>Call Reports</i>
<i>Management Quality (M)</i>	Proxy: overhead costs ratio of banks.	<i>Call Reports</i>
<i>Earnings (E)</i>	Proxy: return on assets (ROA) of a bank.	<i>Call Reports</i>
<i>Liquidity (L)</i>	Proxy: liquid assets to GTA of a bank.	<i>Call Reports</i>
<i>Sensitivity to Market Risk (S)</i>	Proxy: the ratio of the absolute difference (gap) between short-term assets and short-term liabilities to GTA.	<i>Call Reports</i>
<i>Bank Age</i>	Bank age in years.	<i>Call Reports</i>
<i>BHC Indicator</i>	Indicator that is one for banks that are a BHC or part of a BHC and zero otherwise.	<i>Call Reports</i>
<i>Foreign Ownership</i>	Dummy variable indicating foreign ownership of a bank.	<i>Call Reports</i>
<i>Fee Income</i>	Ratio of non-interest to total income.	<i>Call Reports</i>
<i>Deposits Ratio</i>	Ratio of deposits to GTA.	<i>Call Reports</i>
<i>Herfindahl-Hirschman Index</i>	The Herfindahl-Hirschman Index (HHI) based upon branch deposits in the county of the bank/loan.	<i>SoD</i>
Borrower Characteristics		
<i>Loan-to-Income</i>	Loan amount requested in a mortgage application divided by applicant's annual income.	<i>HMDA</i>
<i>Borrower Race Dummies</i>	Dummies for borrower race categories as reported in HMDA.	<i>HMDA</i>
<i>Borrower Sex Dummies</i>	Dummies for borrower sex categories as reported in HMDA.	<i>HMDA</i>

Panel B: Additional Summary Statistics – Full Sample (2000-2014)

This panel reports summary statistics of additional variables for our channels analysis for the period 2000:Q1-2014:Q4. All variables using dollar amounts are expressed in real 2014:Q4 dollars using the implicit GDP price deflator. It contains number of observations, means, standard deviations and several quartiles (min, p25, median, p75, and max) on all the regression variables used to examine channels for the relationship between share of or access to small banks and the sentiment of the consumers in the markets that these banks serve.

<i>Group Statistics</i>	<i>Main Statistics</i>			<i>Quantiles</i>					<i>Source</i>
	<i>N</i>	<i>Mean</i>	<i>S.d.</i>	<i>Min</i>	<i>p25</i>	<i>Median</i>	<i>p75</i>	<i>Max</i>	
<i>Other Variables Used in Channels Tests (RateWatch):</i>									
<i>Consumer Deposit Rates</i>									
<i>03MCD100K</i>	264,687	0.939	1.322	0.001	0.150	0.300	1.050	70.000	<i>RateWatch</i>
<i>06MCD100K</i>	313,429	1.132	1.410	0.001	0.250	0.500	1.340	30.616	<i>RateWatch</i>
<i>12MCD100K</i>	320,078	1.377	1.483	0.001	0.400	0.750	1.730	48.000	<i>RateWatch</i>
<i>24MCD100K</i>	271,622	1.378	1.240	0.010	0.580	0.950	1.722	27.000	<i>RateWatch</i>
<i>36MCD100K</i>	235,414	1.460	1.113	0.010	0.750	1.100	1.800	37.000	<i>RateWatch</i>
<i>48MCD100K</i>	197,936	1.580	1.035	0.010	0.927	1.277	1.982	41.710	<i>RateWatch</i>
<i>60MCD100K</i>	203,592	1.850	1.083	0.010	1.139	1.550	2.255	12.935	<i>RateWatch</i>
<i>SAV100K</i>	179,759	0.193	0.233	0.001	0.058	0.148	0.250	5.372	<i>RateWatch</i>
<i>03MCD250K</i>	144,431	0.212	0.168	0.001	0.100	0.170	0.250	5.950	<i>RateWatch</i>
<i>06MCD250K</i>	175,698	0.329	0.240	0.001	0.192	0.288	0.415	6.125	<i>RateWatch</i>
<i>12MCD250K</i>	177,420	0.489	0.295	0.001	0.300	0.450	0.650	6.250	<i>RateWatch</i>
<i>24MCD250K</i>	168,793	0.718	0.350	0.010	0.488	0.690	0.950	6.770	<i>RateWatch</i>
<i>36MCD250K</i>	158,206	0.933	0.407	0.010	0.650	0.900	1.190	6.350	<i>RateWatch</i>
<i>48MCD250K</i>	136,308	1.118	0.454	0.010	0.800	1.096	1.392	6.350	<i>RateWatch</i>
<i>60MCD250K</i>	137,777	1.347	0.507	0.010	1.000	1.300	1.688	6.500	<i>RateWatch</i>
<i>Group Statistics</i>									
<i>Main Statistics</i>									
<i>Quantiles</i>									
<i>Source</i>									
<i>Uninsured Deposits / GTA</i>	466,022	0.322	0.326	-0.185	0.108	0.181	0.350	1.302	<i>Call Reports</i>
<i>Consumer Loan Rates</i>									
<i>Mortgages</i>									
<i>1 Year ARM @ 175K - Rate</i>	56,517	5.432	1.568	0.000	4.375	5.500	6.500	41.250	<i>RateWatch</i>
<i>3 Year ARM @ 175K - Rate</i>	66,122	5.490	1.565	0.000	4.500	5.583	6.500	31.250	<i>RateWatch</i>
<i>5 Year ARM @ 175K - Rate</i>	65,638	5.463	1.599	0.000	4.375	5.583	6.500	17.656	<i>RateWatch</i>
<i>15 Yr Fxd Mtg @ 175K - Rate</i>	135,735	5.426	1.497	0.000	4.375	5.542	6.375	44.000	<i>RateWatch</i>
<i>30 Yr Fxd Mtg @ 175K - Rate</i>	112,954	5.827	1.338	-2.292	4.792	6.000	6.625	46.750	<i>RateWatch</i>
<i>Auto Loans</i>									
<i>Auto New - 36 Mo Term</i>	304,358	6.020	1.945	0.000	4.750	6.240	7.350	24.900	<i>RateWatch</i>
<i>Auto New - 48 Mo Term</i>	305,218	6.125	1.925	0.000	4.950	6.250	7.495	18.000	<i>RateWatch</i>
<i>Auto New - 60 Mo Term</i>	304,778	6.238	1.923	0.000	5.000	6.455	7.500	18.000	<i>RateWatch</i>
<i>Auto Used 2 Yrs - 36 Mo Term</i>	275,476	6.430	2.129	-7.900	5.000	6.623	7.917	36.600	<i>RateWatch</i>
<i>Auto Used 2 Yrs - 48 Mo Term</i>	270,094	6.478	2.097	-4.500	5.083	6.677	7.950	60.000	<i>RateWatch</i>
<i>Auto Used 2 Yrs - 60 Mo Term</i>	215,679	6.239	2.081	-1.833	4.850	6.417	7.680	33.000	<i>RateWatch</i>
<i>Auto Used 4 Yrs - 36 Mo Term</i>	224,484	6.775	2.286	0.000	5.250	7.000	8.350	40.000	<i>RateWatch</i>
<i>Auto Used 4 Yrs - 48 Mo Term</i>	191,111	6.575	2.233	0.000	5.000	6.750	8.065	85.000	<i>RateWatch</i>
<i>Auto Used 4 Yrs - 60 Mo Term</i>	121,741	5.986	2.205	-4.800	4.310	6.016	7.500	90.000	<i>RateWatch</i>
<i>Credit Cards</i>									
<i>Credit Cards - Annual Fee</i>	31,814	3.992	10.521	0.000	0.000	0.000	0.000	200.000	<i>RateWatch</i>
<i>Credit Cards - Cash Adv Fee</i>	55,715	2.464	2.465	0.000	0.000	3.000	3.500	40.000	<i>RateWatch</i>
<i>Credit Cards - Intro Rate</i>	25,401	1.588	2.397	0.000	0.000	0.000	2.990	15.900	<i>RateWatch</i>
<i>Credit Cards - MasterCard</i>	26,939	12.674	3.898	0.000	10.900	12.990	14.900	25.240	<i>RateWatch</i>
<i>Credit Cards - Visa</i>	62,040	12.398	2.898	0.000	10.240	12.650	13.990	25.240	<i>RateWatch</i>
<i>Credit Cards - Gold</i>	35,683	11.388	2.776	0.000	9.900	11.250	12.900	43.875	<i>RateWatch</i>

<i>Group</i>	<i>Main Statistics</i>			<i>Quantiles</i>					<i>Source</i>	
	<i>Statistics</i>	<i>N</i>	<i>Mean</i>	<i>S.d.</i>	<i>Min</i>	<i>p25</i>	<i>Median</i>	<i>p75</i>	<i>Max</i>	<i>N</i>
<i>Other Variables Used in Channels Tests (RateWatch)</i>										
<i>cont.:</i>										
<i>Credit Cards - Platinum</i>	40,237	9.707	1.873	0.000	8.790	9.900	10.150	24.900		<i>RateWatch</i>
<i>Home Equity Loans</i>										
<i>H.E. Loan Up to 80% LTV @ 20K - 60 Mo Term</i>	221,825	6.684	1.806	0.000	5.750	6.750	7.750	44.850		<i>RateWatch</i>
<i>H.E. Loan Up to 80% LTV @ 20K - 120 Mo Term</i>	178,928	6.798	2.124	-7.580	5.990	7.000	8.000	48.000		<i>RateWatch</i>
<i>H.E. Loan Up to 80% LTV @ 20K - 180 Mo Term</i>	133,606	7.256	1.805	0.000	6.350	7.250	8.240	80.000		<i>RateWatch</i>
<i>H.E. Loan 81-90% LTV @ 20K - 60 Mo Term</i>	133,625	7.167	1.895	0.000	6.250	7.250	8.250	60.000		<i>RateWatch</i>
<i>H.E. Loan 81-90% LTV @ 20K - 120 Mo Term</i>	108,728	7.297	2.307	0.000	6.500	7.500	8.550	100.000		<i>RateWatch</i>
<i>H.E. Loan 81-90% LTV @ 20K - 180 Mo Term</i>	81,445	7.740	2.403	-9.740	6.950	7.865	8.803	95.000		<i>RateWatch</i>
<i>H.E. Loan 91-100% LTV @ 20K - 60 Mo Term</i>	65,538	8.032	2.188	0.000	7.083	8.240	9.308	42.083		<i>RateWatch</i>
<i>H.E. Loan 91-100% LTV @ 20K - 120 Mo Term</i>	56,444	8.117	2.582	0.000	7.410	8.500	9.550	42.083		<i>RateWatch</i>
<i>H.E. Loan 91-100% LTV @ 20K - 180 Mo Term</i>	44,344	8.515	2.716	0.000	7.750	8.750	9.773	100.000		<i>RateWatch</i>
<i>Consumer Loan Quantities</i>										
<i>Residential Real Estate Loans / GTA</i>	466,022	0.173	0.112	0.000	0.091	0.159	0.235	0.987		<i>Call Reports</i>
<i>Residential Credit Card Loans / GTA</i>	466,022	0.004	0.044	0.000	0.000	0.000	0.000	0.993		<i>Call Reports</i>
<i>Other Consumer Loans / GTA</i>	466,022	0.052	0.059	0.000	0.016	0.037	0.068	0.997		<i>Call Reports</i>
<i>Residential Real Estate Unused Commitments / GTA</i>	466,022	0.013	0.022	0.000	0.000	0.003	0.017	0.948		<i>Call Reports</i>
<i>Other Variables Used in Channels Tests (HMDA):</i>										
<i>Dependent Variables</i>										
<i>Approved Application</i>	23,500,000	0.839	0.368	0.000	1.000	1.000	1.000	1.000		<i>HMDA</i>
<i>Ln(Loan Amount)</i>	19,718,830	4.903	0.912	0.000	4.407	4.977	5.505	11.513		<i>HMDA</i>
<i>Loan Spread</i>	1,598,689	4.961	1.721	1.500	3.560	4.950	6.130	94.540		<i>HMDA</i>
<i>Explanatory Variables</i>										
<i>Small Bank (\$1 Billion Cutoff)</i>	23,500,000	0.097	0.296	0.000	0.000	0.000	0.000	1.000		<i>Call Reports</i>
<i>Small Bank (\$3 Billion Cutoff)</i>	23,500,000	0.154	0.361	0.000	0.000	0.000	0.000	1.000		<i>Call Reports</i>
<i>Small Bank (\$5 Billion Cutoff)</i>	23,500,000	0.174	0.379	0.000	0.000	0.000	0.000	1.000		<i>Call Reports</i>
<i>Small Bank (\$10 Billion Cutoff)</i>	23,500,000	0.218	0.413	0.000	0.000	0.000	0.000	1.000		<i>Call Reports</i>
<i>Bank Size</i>	23,500,000	18.1695	2.604259	9.690811	16.76983	18.86921	20.05078	21.77056		<i>Call Reports</i>
<i>Bank & Borrower Characteristics:</i>										
<i>Capital Ratio (C)</i>	23,500,000	0.104	0.040	-0.024	0.084	0.093	0.113	1.687		<i>Call Reports</i>
<i>Asset Quality (A)</i>	23,500,000	0.006	0.009	0.000	0.001	0.002	0.006	0.295		<i>Call Reports</i>
<i>Management Quality (M)</i>	23,500,000	0.013	0.006	-0.038	0.010	0.012	0.016	0.155		<i>Call Reports</i>
<i>Earnings (E)</i>	23,500,000	0.011	0.011	-0.530	0.009	0.012	0.015	0.313		<i>Call Reports</i>
<i>Liquidity (L)</i>	23,500,000	0.048	0.035	0.000	0.029	0.039	0.057	0.683		<i>Call Reports</i>
<i>Sensitivity to Market Risk (S)</i>	23,500,000	0.150	0.101	0.000	0.064	0.143	0.223	0.764		<i>Call Reports</i>
<i>Bank Age</i>	23,500,000	102.203	50.567	0.000	72.000	110.000	149.000	229.000		<i>Call Reports</i>
<i>BHC Indicator</i>	23,500,000	0.733	0.442	0.000	0.000	1.000	1.000	1.000		<i>Call Reports</i>
<i>Foreign Ownership</i>	23,500,000	0.102	0.303	0.000	0.000	0.000	0.000	1.000		<i>Call Reports</i>
<i>Fee Income</i>	23,500,000	0.277	0.957	0.000	0.177	0.264	0.357	37.000		<i>Call Reports</i>
<i>Deposits Ratio</i>	23,500,000	0.655	0.120	0.079	0.581	0.649	0.749	0.967		<i>Call Reports</i>
<i>Herfindahl-Hirschman Index</i>	23,500,000	0.091	0.060	0.011	0.064	0.077	0.100	0.709		<i>SoD</i>
<i>Loan-to-Income</i>	23,500,000	2.272	4.945	0.001	1.310	2.143	2.987	6000.000		<i>HMDA</i>