Population aging and bank risk-taking

Doerr, Sebastian and Kabas, Gazi and Ongena, Steven

Bank for International Settlments, University of Zurich, University of Zurich

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Sebastian Doerr
BIS

Gazi Kabaş
UZH & SFI

Steven Ongena
UZH, SFI,
KU Leuven & CEPR

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Abstract

Does population aging affect bank lending? To answer this question we exploit geographic variation in population aging across U.S. counties to provide the first evidence on its impact on bank risk-taking. We find that banks more exposed to aging counties experience deposit inflows due to seniors' higher savings rate. They consequently extend more credit, but relax lending standards: Loan-to-income ratios increase and application rejection rates decline. Exposed banks also see a sharper rise in nonperforming loans during downturns, suggesting that population aging may lead to financial instability. These results are in line with an increase in savings and a decline in investment opportunities induced by population aging.

JEL classification: G21, E51

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Sebastian Doerr is at the Bank for International Settlements (sebastian.doerr@bis.org). Gazi Kabaş is at the University of Zurich and Swiss Finance Institute (gazi.kabas@bf.uzh.ch). Steven Ongena is at the University of Zurich, Swiss Finance Institute, KU Leuven, NTNU, and CEPR (steven.ongena@bf.uzh.ch).
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1 Introduction

Persistently low interest rates have raised concerns about financial stability (CGFS, 2018), as they could encourage bank risk-taking (Dell'Ariccia et al., 2017; Heider et al., 2021). One major driver of falling interest rates is population aging, through an increase in available savings.[1] Beyond an increase in savings, demographic change could, however, also depress the demand for credit (Auclert et al., 2021).[2] A key concern is therefore whether population aging – through its effects on the supply of and demand for capital – could lead to the build-up of risks in the financial system (ECB, 2018; IMF, 2019). The U.S. population aged 65 and older will grow by 18 million (or 33%) over the next decade. Similar developments are taking place in other advanced economies. And yet, evidence on the consequences for bank lending or risk-taking, and ultimately financial stability, is scarce.

This paper empirically investigates how an aging population affects bank lending standards in the U.S. For identification, we exploit the extensive variation in aging that has already occurred across U.S. counties (Figure 1), combined with granular data on bank deposits and mortgage loans. Specifically, we focus on the time period between 1997 and 2007. This period is characterized by an increase in the senior population by around 20% and a stable regulatory environment.[3]

Our study starts by establishing that an increase in the number of seniors in a county has a positive and strongly significant effect on local bank deposits. A rise in a county's senior population by one-third is associated with an increase in county-level bank deposits by over 25%.[4] Seniors' relatively larger share of wealth held in the form of deposits explains the link between aging and deposits (Becker, 2007). Our regressions absorb

[1]See eg Carvalho et al. (2017) and Conesa and Kehoe (2018).

[2]Note that this implies that the effects of aging on banks and the economy are distinct from those of low interest rates alone: While lower interest rates make funding cheaper and lead to an increase in the demand for goods and services (and hence credit), population aging could lead to an increase in available funds but reduce the demand for credit.

[3]We focus on the 1997–2007 period for two main reasons. First, while the growth in the senior population has been even more pronounced after the Great Financial Crisis, the post-crisis period is characterized by substantial financial regulatory reform (such as the Dodd-Frank Act and regular stress tests) and encompassing government programs. Both have affected banks' lending decisions and would make it difficult to identify the respective channels through which population aging affects bank risk-taking. Second, we can exploit the Great Recession as a shock to see whether higher risk-taking during our sample period manifested itself in higher non-performing loans during the crisis.

[4]The increase of 33% in the number of seniors corresponds to the expected U.S. growth in the senior population over the next decade, from 2021 to 2030. The mean and standard deviation of the growth in the number of seniors between 1997 and 2007 equal 18% and 15%, respectively.

all observable and unobservable bank heterogeneity with bank fixed effects. They also include a large set of county-level control variables. We hence account for other bank or county characteristics that could explain the rise in deposits.

Local aging could be correlated with county characteristics that affect deposit growth. To address this concern, we develop an instrumental variable (IV) strategy that exploits the predetermined component of counties' age structure. Specifically, we instrument the change in the population of age 65 and above from 1997 to 2007 with the change in the population of age 45 to 65 from 1977 to 1987 in the same county. This approach builds on the assumption that the historical demographic structure is plausibly exogenous to *changes* in contemporaneous confounding factors. These include, for example, changes in life expectancy, in- and out-migration, or income. We find that coefficients in IV regressions are similar in terms of sign, size, and significance to those in OLS regressions.[5] Supporting the plausible exogeneity of our IV, directly controlling for contemporaneous changes in county characteristics (e.g., income per capita, the unemployment rate, or house prices) does not affect our estimates. Formally testing for the sensitivity of the exclusion restriction in the spirit of Conley et al. (2012) lends further support to our identification assumption.

In a second step, we investigate how banks' presence in aging counties affects their credit supply and lending standards. How could population aging affect bank lending and risk-taking? On the one hand, our findings show that aging increases deposits, which are a stable and cheap source of funding (Hanson et al., 2015). Higher exposure to aging counties could hence translate into an increase in lending, and reduce banks' risk-taking. On the other hand, an aging population reduces the local demand for credit. Homeownership rates and savings are highest among seniors, and they are less likely to start new companies (Azoulay et al., 2020). Both factors dampen their demand for credit. Further, an aging-induced decline in the labor force reduces firms' marginal product of capital, lowering the demand for capital (Auclert et al., 2021).[6] In line with these arguments, we provide direct evidence that aging leads to a decline in the local demand

[5]Coefficients in IV regressions are slightly larger than those in OLS regressions. This could suggest that the IV approach overcomes measurement error in the aging variable. Such mis-measurement could arise, if, for example, seniors hold deposits in bank branches outside their residence county (which happens when snowbirds permanently move from the Great Lakes region to Florida but leave their deposits in a bank branch up north in the town of origin).

[6]Gagnon et al. (2016) and Maestas et al. (2016) provide macroeconomic evidence that aging contributes to slower growth and reduces investment opportunities.

for mortgages.[7] Aging-exposed banks could hence be confronted with a decline in the demand for credit in counties where they raise deposits at a time when they experience an increase in available funds. This could lead banks to look for new and potentially riskier clients, especially in counties where they have no branch presence.

To measure banks' presence in aging counties, we define bank *exposure* as the weighted average change in seniors across counties where banks raise deposits. Weights are given by deposit shares in 1997, i.e., at the beginning of the sample period. To ensure that exposure is uncorrelated with changes in contemporary county characteristics, we construct exposure from the change in seniors predicted with the historical demographic structure. Banks with higher exposure have a larger footprint in counties that will see a stronger increase in seniors from 1997–2007. They consequently experience deposit inflows.

We show that high- and low-exposure banks are similar in terms of most initial balance sheet characteristics. For example, they have similar capital ratios, shares of non-performing loans, or return on assets. In regressions, we further show that including bank controls and fixed effects does not affect the magnitude of our coefficients of interest, despite increasing the R^2 substantially. Exposure to aging counties is hence likely uncorrelated with observable and unobservable bank characteristics. This finding reduces potential concerns about self-selection and omitted variable bias (Altonji et al., 2005; Oster, 2019). In addition, we investigate whether local aging or bank exposure predict where banks open new branches prior to our sample period. We find no such evidence. This result suggests that banks did not strategically open branches to benefit from future deposit inflows in anticipation of demographic trends.

We then establish that more-exposed banks increase their mortgage lending. Specifically, higher bank exposure by 33 percentage points (pp) leads to a relative increase in mortgage lending by around 30%.[8] The increase in loan volume is over 50% larger in counties where banks operate no branches, i.e., in counties where exposed banks are not directly affected by an aging-induced decline in credit demand.

The baseline specification uses detailed Home Mortgage Disclosure Act (HMDA) data

[7]Specifically, we decompose mortgage loan growth in each county into supply and demand factors, following Amiti and Weinstein (2018). Higher growth among seniors has a significant negative effect on the demand factor, both in OLS and IV regressions.

[8]An increase in bank exposure by 33 pp occurs for example when moving from a bank with zero exposure to a bank with 33% exposure, which is a bank exposed to counties that deposit-weighted have a growth in seniors equal to the expected growth in the U.S. over the next decade. As we will calculate later, the number of seniors increased by 16% in the average county where banks take their deposits during the sample period.

on residential mortgage lending at the bank-county level. It focuses on mortgage loans that were not sold in the respective calendar year, i.e., those that were retained on the balance sheet and thus mostly financed by deposits (Han et al., 2015). However, the results are similar for total mortgage lending, as well as for mortgages above the jumbo-loan threshold that are harder to securitize (Cortés and Strahan, 2017). We also find no evidence that the aging-induced increase in mortgage lending crowds out other forms of lending. Instead, overall lending increases.

For identification, we absorb all observable and unobservable county fundamentals, including loan demand, by including borrower-county fixed effects (Khwaja and Mian, 2008; Jiménez et al., 2014; Degryse et al., 2019). Accounting for county characteristics increases the R^2 by almost 40 pp, but does not change the estimated effect of exposure on lending. The stability of coefficients suggests that bank exposure is orthogonal to observable and unobservable county characteristics (Altonji et al., 2005; Oster, 2019).

We then investigate whether exposed banks adjust their lending standards. We find that 33 pp increase in bank exposure is associated with a significant increase in loan-to-income (LTI) ratios by around 23 pp.[9] The magnitude of the effect varies along the distribution: exposed banks increase LTI ratios at the 75^{th} percentile by significantly more than those at the 25^{th} percentile. In other words, more-exposed banks increase LTI ratios in particular among borrowers that already had high LTI ratios. We obtain similar results for the share of denied loans, which falls by more for more-exposed banks. These findings are robust to the inclusion of county fixed effects that control for unobservable factors at the borrower-county level.

Previous literature has shown that banks with lower capital ratios take more risk when their funding conditions ease (Altunbas et al., 2014; Jiménez et al., 2014; Dell'Ariccia et al., 2017). Cheaper access to funds relaxes banks' capital constraints arising from moral hazard problems (Adrian and Shin, 2010). Related work shows that banks tend to serve riskier clients in counties where they have no physical presence. A greater borrower distance to the nearest branch requires banks to rely more on hard information (DeYoung et al., 2008; Liberti and Petersen, 2019) and can thus result in less efficient screening and monitoring of borrowers (Granja et al., 2018). We find evidence consistent with these arguments. The exposure-induced increase in LTI ratios is economically and statistically more pronounced among banks with lower capital ratios and among loans granted in

[9]In HMDA, a loan's LTI ratio has been shown to be highly correlated with ex-post default (Fuster et al., 2021).

counties where banks operate no branches. Banks extending riskier loans in areas where they have no branches implies that a local increase in available funding affects *other* markets – highlighting geographic spillover effects of population aging.

The relaxation of lending standards among exposed banks suggests an increase in credit risk. To analyze whether higher credit risk had consequences for financial stability, we examine the performance of exposed banks during a negative shock. Specifically, we show that banks with higher exposure to aging counties see a significantly stronger increase in their share of nonperforming loans between 2007 and 2010. Yet, there were no discernible pre-trends in nonperforming loans across exposed and non-exposed banks prior to the crisis. Importantly, controlling for banks' exposure to the rise in house prices prior to the Great Recession does not affect our estimates. Our findings hence suggest that population aging negatively affects financial stability through laxer lending standards.

To examine the robustness of our findings, we perform a series of additional tests. To rule out any direct effect of local aging on bank lending (except through exposure) we exclude counties where banks raise deposits from the sample.[10] Coefficients do not change in any statistically or economically meaningful way. When we further exclude borrower-counties with a high employment share in tradable industries to rule out potential cross-county linkages through the demand for goods, baseline results remain unaffected. Similar results are obtained when we exclude counties that score high on the Social Connectedness Index (Bailey et al., 2018) and might be subject to spillover effects. Our findings are also robust to the exclusion of different regions, for example those with a particularly strong or weak increase in the share of seniors. Controlling for local population growth or banks' exposure to overall population growth does not affect our results, and neither does controlling for changes in the prime working age population or young population, either directly or via banks' exposure.

Further, exposed banks increase LTI ratios at higher percentiles (i.e., for loans with already high LTI ratios) by more in counties without branches than ratios at lower percentiles. They also deny fewer loans in general, as well as in counties where they have no branch. These findings are robust to the inclusion of both bank and county fixed

[10]Suppose a bank raises deposits in Los Angeles County (CA), and lends to Los Angeles County and Arlington County (VA). By construction, bank exposure is correlated with population aging in Los Angeles County. This direct effect of aging on bank lending in Los Angeles, through for example loan demand, could bias our estimation. We thus focus on lending by banks to counties where they do not raise deposits, i.e., lending by the example bank to Arlington County only.

effects, and further highlight that local aging could lead to the build-up of financial risks in other counties. Finally, at the aggregate county level, we show that counties in which exposed banks have a larger ex-ante market share see a stronger increase in household debt-to-income ratios. This is, the increase in risk-taking and *loan*-to-income ratios at the bank-county level is mirrored in an increase of households' *debt*-to-income ratios.

Our paper contributes to two strands of literature. To the best of our knowledge, we are the first to empirically investigate the effects of demographic change on bank credit and lending standards. While Becker (2007) uses the local demographic structure as an instrument for changes in bank deposits, the paper focuses on how the availability of deposits affects local entrepreneurial activity. Other papers explore how banks adjust their lending standards during credit booms (Berger and Udell, 2004; Dell'Ariccia and Marquez, 2006; Mendoza and Terrones, 2008; Dell'Ariccia et al., 2012; Justiniano et al., 2019); or whether low interest rates affect bank risk-taking (Maddaloni and Peydró, 2011; Altunbas et al., 2014; Jiménez et al., 2014; Ioannidou et al., 2015; Dell'Ariccia et al., 2017; Heider et al., 2021). These papers show that credit booms or periods of low interest rates can lead to laxer lending standards and a higher risk of financial crises. However, there exists no evidence on the effects of population aging on bank risk-taking, despite the significant policy attention devoted to this major macroeconomic trend contributing to a low interest rate environment (CGFS, 2018; ECB, 2018; IMF, 2019; OECD, 2019).[11] Our analysis aims to fill this gap in the literature, by providing novel evidence that aging affects credit demand and supply – and thereby lending standards.

Our paper is further related to literature that uses local shocks, such as natural disasters or gas shale discoveries, to show how banks use internal capital markets to adjust lending (Gilje et al., 2016; Cortés and Strahan, 2017; De Jonghe et al., 2020; Rehbein and Ongena, 2021). Our work contributes to this literature by analyzing how secular demographic change – rather than a local temporary shock to deposits – affects lending and risk-taking in connected markets. We thereby also complement results in Drechsler et al. (2021), Lin (2020) and Doerr et al. (2021) by highlighting an alternative channel through which macroeconomic changes affect the financial sector. As advanced economies face an unprecedented increase in the number of seniors over the next decade, the risk-taking channel of population aging could gain in importance for financial stability.

The rest of the paper proceeds as follows. Section 2 describes our main data sources

[11] Butler and Yi (2021) investigate the effect of an aging population on the U.S. municipal bond market.

and the construction of the main variables. Section 3 explains our empirical strategy and presents the main results. Section 4 provides additional tests, and Section 5 concludes.

2 Data and descriptive statistics

This section explains the construction of our main variables and reports descriptive statistics. For detailed variable definitions and sources, see Table OA1. Our main analysis focuses on the period from 1997 to 2007, for two main reasons. First, while the growth in the senior population has been even more pronounced after the Great Financial Crisis, the post-crisis period is characterized by substantial financial regulatory reform (such as the Dodd-Frank Act and regular stress tests) and encompassing government programs. These reforms have shaped banks' lending decisions in the post-crisis period. The absence of major financial regulatory changes during our sample period makes it well-suited to identify the effects of population aging on bank risk-taking. Second, we can exploit the Great Recession to analyse whether higher risk-taking in the years leading up to the crisis manifested itself in higher non-performing loans during the shock episode.

2.1 Main variables

County data. Our main explanatory variable at the county level is the log change in the population of age 65 and above from 1997 to 2007, denoted by Δold_c^{97-07}. In the baseline specification, we use the change in the total senior population as main explanatory variable. In line with the stylized fact that seniors hold more deposits, a change in their cohort size is expected to be directly related to a change in local deposits. We do, however, also verify our results in specifications in which we use the change in the share of the senior out of total population. Detailed population data by age cohort are provided by the National Cancer Institute Surveillance, Epidemiology, and End Results (SEER) program. We use these data also to construct changes in the size of other age cohorts.

We further collect information on debt-to-income ratios (Federal Reserve Bank of New York Consumer Credit Panel, available from 1999 onwards). As county controls we include 1997 values of log population (NCI SEER), the unemployment rate (Bureau of Labor Statistics, Local Area Unemployment Statistics (BLS LAUS)), log income per capita (Bureau of Economic Analysis, Local Area Personal Income (BEA LAPI)), house price indices (Federal Housing Finance Agency (FHFA)), as well as employment shares in manufacturing (SIC code 20), retail trade (SIC code 52), and services (SIC code 70), provided in the County Business Patterns (CBP). CBP also provide information on employment in tradable and nontradable industries.[12]

Bank-county data. To calculate banks' beginning-of-sample exposure to aging counties, we use data from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD), which provides information on the geographic distribution of bank deposits. We compute bank exposure as

$$exposure_b = \sum_c \frac{deposits^{97}_{b,c}}{deposits^{97}_b} \times \Delta \widehat{old^{97-07}_c}, \tag{1}$$

where $deposits_{b,c}$ and $deposits_b$ denote bank b's deposits in county c and its total deposits as of 1997. $\Delta \widehat{old^{97-07}_c}$ is county c's log change in the population of age 65 and older from 1997 to 2007. As local aging could be correlated with other (unobservable) county factors, we instrument Δold with the predetermined component of each counties' age structure prior to computing exposure. We will discuss this approach in more detail in the next section.

High $exposure_b$ implies that a large share of bank deposits is held in aging counties, while low exposure implies that deposits are held in counties with a low increase in seniors. Higher exposure thus corresponds to an increase in deposit-weighted average aging in banks' borrower counties. For example, if a bank lends in equal shares to two counties, and one county sees an increase in seniors (Δold) of 50% and the other county sees no change, exposure equals ($0.5 \times 0.5 + 0.5 \times 0 =$) 0.25. Exposure is constructed from beginning-of-sample deposit shares, alleviating concerns about banks selectively opening branches in aging counties.[13]

We calculate the change in bank deposits in each county between 1997 and 2007 as

$$\Delta deposits^{97-07}_{b,c} = \frac{deposits^{07}_{b,c} - deposits^{97}_{b,c}}{(deposits^{07}_{b,c} + deposits^{97}_{b,c})/2}. \tag{2}$$

To account for bank entry into and exit out of counties over the long time horizon, we

[12]Following Adelino et al. (2015), we classify two-digit NAICS code 23 as construction; codes 44, 45, and 72 as nontradable, and all others as tradable industries.

[13]In the Online Appendix we show that neither local aging nor bank exposure predict in which counties banks open new branches prior to 1997, see Table OA3.

standardize the change in deposits by the respective mid-points. This definition bounds growth rates to lie in $[-2, 2]$, where -2 implies that a bank exited a county between 1997 and 2007, and 2 that it entered.[14]

Home Mortgage Disclosure Act data provide detailed information on banks' residential mortgage lending.[15] HMDA collects home mortgage application data, covering the vast majority of applications and approved loans in the U.S. The data include the application outcome (granted or denied), loan amount, and borrower income for each loan.[16] Similar to Equation 2 we compute the 1997 to 2007 change in HMDA loans at the bank-county level as

$$\Delta HMDA_{b,c}^{97-07} = \frac{HMDA_{b,c}^{07} - HMDA_{b,c}^{97}}{(HMDA_{b,c}^{07} + HMDA_{b,c}^{97})/2}. \tag{3}$$

For our main analysis, we compute $\Delta HMDA_{b,c}^{97-07}$ based on mortgage loans that were not sold in the respective calendar year. Since these loans are mostly retained on banks' balance sheets, they are predominately funded by deposits (Han et al., 2015). For robustness tests, we also compute loan growth across all HMDA loans, as well as for mortgages above the jumbo-loan threshold that are more information sensitive and harder to securitize (Cortés and Strahan, 2017).

Our main measure of bank risk-taking is the loan-to-income ratio, defined as loan volume over applicant income. LTI ratios are a highly significant predictor of ex-post default (Fuster et al., 2021).[17] We compute the 1997 to 2007 change in the average LTI ratio, as well as at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentile in each bank-county cell. Additionally, we compute the change in the share of denied applications in each bank-county cell. For these measures of risk-taking, we are restricted to the 'intensive margin', in the sense that we can only take into account counties in which banks operated in 1997

[14]While the log difference is symmetric around zero, it is unbounded above and below, and does not easily afford an integrated treatment of entry and exit. The growth rate used in this paper is divided by the simple average in $t-1$ and t. It is symmetric around zero, lies in the closed interval [-2,2], facilitates an integrated treatment of entry and exit, and is identical to the log difference up to a second order Taylor series expansion (Davis and Haltiwanger, 1999).

[15]We follow the literature and restrict the sample to conventional or Federal Housing Administration (FHA)-insured loans, exclude multi-family properties, and keep only originated, approved, and purchased loans. We also drop all observations with missing county Federal Information Processing Standards (FIPS) codes or missing borrower income, as well as loans extended to borrowers residing outside of metropolitan statistical areas (MSAs).

[16]In 2007 mortgage lending averaged around 30% of banks' total lending, and 40% for the largest banks. Additionally, HMDA data represent the most detailed publicly available data on bank lending disaggregated at the geographical level, which is why we focus on mortgage lending in our analysis.

[17]The LTI has been widely used in the literature to measure the riskiness of loans, see Dell'Ariccia and Marquez (2006); Dell'Ariccia et al. (2012); Duchin and Sosyura (2014).

and 2007. Finally, we define the dummy *no branch* that takes on a value of one if bank b had no branch in county c in 1997 and zero otherwise.

Bank data. The FDIC provides detailed bank balance sheet data in its Statistics on Depository Institutions (SDI). We collect 1997 second quarter data on banks' total assets, Tier 1 capital ratio, nonperforming loans (NPL), return on assets, total deposits, total liabilities, share of non-interest out of total income, and overhead costs (efficiency ratio). We also include an indicator of an institution's primary specialization in terms of asset concentration that takes on ten distinct values.[18] We also collect 1997 and 2007 data on banks' total deposits, total liabilities, and total loans and compute the log change for each variable.

To remove outliers, we winsorize all variables at the 0.5^{th} and 99.5^{th} percentile. We then trim all remaining extreme values that lie at least five standard deviations above or below the mean.

2.2 Descriptive statistics

In the average county, the number of seniors (Δold_c^{97-07}) increased by 18%, with a standard deviation of 15%. There is significant variation in population aging across the U.S., as well as within states. Figure 1 provides a map of the 1997 to 2007 change in seniors across U.S. counties, where darker areas indicate higher values. Most areas see an increase in the population 65 and above, with the exception of counties in the Great Plains.

Table 1 provides descriptive statistics for our main variables. In total, our sample includes 1,843 banks. Panel (a) summarizes bank *exposure* and other balance sheet characteristics from the SDI. For the average bank, exposure equals 0.16, with a standard deviation of 0.11. As exposure reflects deposit-weighted aging, a mean of 0.16 implies that the number of seniors increased by 16% in the average county where a bank takes deposits.

Panel (b) reports summary statistics at the bank-county level. For the average bank-county pair, deposits increased by 114% over the time period (13,086 observations); mortgage lending (one- to four-family residences) increased by 103% (53,197 observations).[19]

[18] The indicator reflects, for example, whether a bank has an agricultural or a mortgage lending specialization.

[19] The difference in the number of observations reflects that the average bank lends to counties in

Along the intensive margin (disregarding bank entry and exit across counties) lending increased by 84% (17,643 observations). [20] The average bank saw little change in its LTI ratio, but there is sizeable dispersion in the change across banks, the standard deviation equals 85 pp. While LTI ratios at the 25^{th} percentile declined by 19 pp, LTI ratios increased by more than 5 pp on average at the 75^{th} percentile, and by more than 20 pp at the 90^{th} percentile. The share of denied loans increased by 7 pp on average.

Finally, panel (c) reports summary statistics for county-level variables for the set of 2,163 counties. On average, the number of seniors (Δold) increased by 18% from 1997 to 2007, which is close to the mean change in bank exposure. Its standard deviation is 15%.

Balancedness. To examine the balancedness in covariates of our sample of banks, in Table 2 we split banks into those below (low exposure) and above (high exposure) the median of the exposure distribution. High-exposure banks are slightly smaller, but have a significantly higher return on assets.[21] Yet, differences are small quantitatively, as both bank types have a 1% return on assets on average. They differ only marginally (in a statistical and economic sense) in their share of deposits out of total liabilities (94% for both), and are similar in their NPLs, Tier-1 capital ratios, share of non-interest income, overhead costs, share of C&I out of total loans, and the share of loans extended to no-branch counties.

In the Online Appendix we further show that neither local aging nor bank exposure predict in which counties banks open new branches prior to 1997 (see Table OA3). Specifically, we regress different measures that indicate whether banks opened branches on population aging or bank exposure and find no systematic relationship. This result mitigates concerns about banks strategically opening branches to benefit from future deposit inflows in anticipation of demographic trends.

which it does not raise deposits – a fact we will exploit for identification.

[20] The unweighted average increase in mortgage lending in our sample is lower than the figure based on aggregate outstanding mortgage debt (one- to four-family residences) that increased by around 190% from 1997 to 2007. See Federal Reserve Bank of St. Louis, FRED series MDOTP1T4FR.

[21] A potential concern arising from the correlation between bank size and exposure is that the estimates of exposure on bank lending and risk-taking reflect (unobservable) bank characteristics correlated with bank size. To address this concern, we estimate regressions with granular bank size*county fixed effects, where bank size corresponds to deciles of 1997 total bank assets. We thus account for any unobservable factors, including loan demand, that could differ across counties *and* be specific to banks of different sizes In other words, we compare the effect of bank exposure to aging counties on lending and risk taking among banks of near-identical size active in the same county. None of our results are affected by the inclusion of bank size*county fixed effects.

3 Empirical strategy and results

This section lays out the empirical strategy and reports the main results. We first show that local aging increases bank deposits. We then analyze how exposure to aging counties affects banks' credit supply and risk-taking.

3.1 Population aging and local deposits

Figure 2 shows that seniors, defined as the population of age 65 and older, hold more bank deposits than younger cohorts (see also Becker (2007)) – consistent with a lower portfolio share of risky assets for older households (Fagereng et al., 2017). Based on data from the Survey of Consumer Finances, panel (a) plots average financial assets (left axis) and average deposits (right axis) for different age cohorts. Older cohorts have higher levels of financial wealth, as well as deposits. For example, individuals in the age cohort of age 65 and above hold on average about twice as many deposits as those in the cohort of 55-64, and more than three times as much as younger cohorts.[22] Differences in deposit holdings across cohorts imply potentially large effects on bank funding when economies age. Deposits are banks' most important and stable source of funding and a large literature highlights the importance of deposits for bank lending (Gilje et al., 2016).[23]

Building on demographic variation in savings behavior, we investigate the relation between secular changes in local demographics and bank deposits in the following cross-sectional regression at the bank-county level:

$$\Delta deposits_{b,c}^{97-07} = \beta \; \Delta old_c^{97-07} + controls_{b/c}^{97} + \theta_b + \epsilon_{b,c}, \tag{4}$$

where $\Delta deposits_{b,c}^{97-07}$ is the change in bank b's deposits in county c from 1997 to 2007. The explanatory variable Δold_c^{97-07} is the log change in the county population of age 65 and above from 1997 to 2007. County controls as of 1997 include log population, the unemployment rate, log income per capita, the share of blacks, as well as employment shares in manufacturing, retail, and services. Bank controls as of 1997 include the log

[22] Table OA2 in the Online Appendix shows that the positive relation between age and deposits is not explained by differences across cohorts, nor by a large set of individual-level controls such as income, occupation, homeownership or education.

[23] In 1997 the average bank in our sample had a ratio of deposits to total liabilities of 94%. On the importance of deposits, see also Kashyap et al. (2002); Hanson et al. (2015); Arslan et al. (2019).

of total assets, return on assets, nonperforming loans, total deposits over total liabilities, Tier-1 capital ratio, non-interest income, the indicator on bank specialization, and overhead costs. Standard errors are clustered at the bank and county level to account for correlations across observations among the same bank or county.

In Equation 4, $\beta > 0$ indicates that local aging leads to an increase in local bank deposits. The underlying intuition is that the elderly hold more deposits, as shown in Figure 2. Yet, β reflects differences in households' savings behavior and in bank behavior, both of which could affect individuals' incentives to hold deposit. For example changes, banks could decide to offer more attractive rates on deposits. To isolate the effect of aging on deposits, in some specifications we include bank fixed effects (θ_b) that absorb all unobservable bank characteristics. In essence, we compare the effect of aging in different counties on deposits of the same bank, as we hold all bank characteristics constant.

Table 3 reports regression results for Equation 4 and shows that an increase in the number of seniors in a county increases bank deposits.[24] Column (1) includes county controls and shows that aging has a positive effect on bank deposits, significant at the 1% level. Once we add bank controls in column (2), the coefficient is similar in terms of sign, size, and significance. In column (3) we further tighten identification and include bank fixed. Holding all observable and unobservable bank characteristics constant, local aging still is associated with a highly significant increase in deposits. Banks operating in a county with a one standard deviation (sd) larger increase in the number of seniors see a relative increase in local deposits by $(0.15 \times 0.877 =)$ 13.2% (or 11.5% of the average growth in deposits over the sample period).

Including bank controls or bank fixed effects in columns (2) and (3) does not materially change the size or significance of our coefficients relative to column (1), despite increasing the R^2 by more than 30 pp. Our results hence suggest that observable and unobservable bank characteristics are not explaining our findings, reducing potential concerns about self-selection and omitted variable bias (Altonji et al., 2005; Oster, 2019).[25] While we cannot include depositor-county fixed effects in Equation 4, in column (4) we include depositor-state fixed effects to control for confounding factors at the state level.

[24]This finding is in line with results in Becker (2007), who uses the local demographic structure as an instrument for bank deposits.

[25]When we formally test for the presence of bias arising from unobservable bank characteristics (following Oster (2019)), we obtain $\delta = 3.43$ and $\delta = 0.86$ for columns (2) and (3), relative to column (1), so unobservables would need to be 0.86 to 3.43 times as important as observable bank characteristics to render the coefficient insignificant.

Results remain near-identical. Columns (1)–(4) thus suggest that bank deposits increase in aging counties, even after accounting for observable and unobservable bank or state characteristics.

Local aging could be correlated with other county factors that affect deposit growth even after accounting for observable county characteristics or unobservable state-specific shocks. We thus instrument Δ *old*, i.e., the change in the population of age 65 and above from 1997 to 2007, with the change in the population of age 45 to 65 from 1977 to 1987 in the same county. In essence, we use the predetermined component of each counties' age structure − 20 years prior to our sample period − as an instrumental variable for the actual change in the age structure. This approach builds on the assumption that the historical demographic structure is plausibly exogenous to *changes* in contemporaneous confounding factors. For example, it purges Δ *old* from changes in life expectancy, in- or out-migration, or incomes over the sample period.

Table 3, column (5) replicates the specification in column (4), but reports two-stage least squares results, where we predict actual aging with the historical instrument. The coefficient remains similar in terms of sign, size, and significance, suggesting a causal effect of local aging on bank deposits.[26] To further support this interpretation, column (6) additionally controls for the *1997–2007 change* in counties' income per capita, unemployment rate, and house price index. In principle, changes in these variables could explain changes in deposits and be correlated with population aging. Accounting for these factors, column (6) shows that the coefficient on Δ *old* declines only slightly in magnitude and remains significant at the 1% level, which supports the plausible exogeneity of our IV.

This result is confirmed when we formerly test for the sensitivity of the exclusion restriction following Conley et al. (2012). Even if the exclusion restriction would be severely violated – ie the past demographic structure has a large and significant effect on deposit growth during the sample period through channels other than contemporaneous aging – population aging leads to an economically sizeable and statistically significant increase in deposits (see Online Appendix, Figure OA2, for more details). The robustness of our result to relaxations of the exclusion restriction also reflects the strong first stage, with an F-Statistic of over 70.

[26]The coefficient in the IV regression is slightly larger than that in the OLS regressions. This could suggest that the IV overcomes measurement error in the aging variable. Such mis-measurement could arise, if, for example, seniors hold deposits in bank branches outside their residence county. Also note that we lose some observations because of missing demographic data for some counties in earlier years.

Having established a link between local aging and deposits, in a final step we show that banks do not offset the increase in deposits with a reduction in other liabilities. If banks' total liabilities would not increase, the impact of aging on bank lending and risk-taking would be attenuated. In columns (7) and (8) we thus estimate bank-level regressions with the change in banks' total deposits ($\Delta deposits_b$) and liabilities ($\Delta liabilities_b$) as dependent variable and bank exposure, as defined in Equation 1, as main explanatory variable. All regressions include bank-level controls and robust standard errors. We find that exposure has a positive and significant impact on both outcome variables. Moreover, coefficients are close in magnitude, indicating that the overall increase in liabilities is largely driven by the increase in deposits. In what follows, we analyse how the aging-induced increase in deposits affects banks' credit provision and risk-taking.

3.2 Exposure, lending, and risk-taking

Banks operating in aging counties are subject to two opposing forces. On the one hand, population aging leads to an increase in banks' available funding in the form of deposits, as shown in Section 3.1. Easing funding conditions could in turn spur bank lending. On the other hand, an aging population could reduce the demand for credit. Seniors usually own their property and have high savings, so they have less need to borrow. In addition, seniors are also significantly less likely to start new companies (Azoulay et al., 2020), further dampening the demand for credit. Finally, aging leads to a decline in the labor force participation rate. As firms' marginal product of capital increases in the amount of available labor, a fall in the supply of labor reduces firms' demand for capital (Auclert et al., 2021).[27]

Figure 2, panel (b) confirms that younger cohorts have significantly higher debt levels than older cohorts (left axis); for the cohort of age 65 and above total debt is close to zero. The share of respondents stating that they 'currently do not borrow' (right axis) reflects this. While around 5% of younger cohorts state that they did not borrow, almost every third respondent of age 65 and above reports that he or she did not borrow. To formally investigate whether an increase in seniors affects the demand for credit, we decompose mortgage loan growth in each bank-county cell into supply and demand factors, following

[27]Several studies argue that aging contributes to slower growth and reduces investment opportunities (Fernald and Li, 2019). Maestas et al. (2016) and Gagnon et al. (2016) provide state-level evidence for the U.S. that aging leads to lower growth, mainly due to declining labor productivity. Aksoy et al. (2019) show a negative effect of aging on growth for a sample of OECD countries.

Amiti and Weinstein (2018). We then aggregate demand factors to the county level, where we weight demand factors with the respective initial bank-county loan shares, and investigate how they are affected by local aging.

Table 4 provides evidence that higher growth among seniors has a significant and economically sizeable negative effect on the credit demand factor in column (1). Adding county-level controls in column (2) confirms this finding, and so does an instrumental variable regression in column (3). As above we instrument the change in the population of age 65 and above from 1997 to 2007 with the change in the population of age 45 to 65 from 1977 to 1987 in the same county. Exploiting the predetermined component of each counties' age structure shows that the local demand for credit declines as the number of seniors increases. When we further control for changes in contemporary county characteristics in column (4), results remain qualitatively unaffected.

Taken together, these patterns suggest that exposed banks could be forced to look for new investment projects precisely at a time when they experience an increase in available funds. In what follows, we first investigate how exposure to aging counties – and the associated increase in available funds – affects bank lending, both locally and in markets where they operate no branches. We then analyse the effects on lending standards.

Bank lending. To investigate the effect of bank exposure to aging counties on lending we estimate bank-county level regressions of the following form:

$$\Delta HMDA_{b,c}^{97-07} = \beta \; exposure_{b}^{97} + controls_{b/c}^{97} + \theta_c + \epsilon_{b,c}, \tag{5}$$

where $\Delta HMDA_{b,c}^{97-07}$ is the change in bank b's mortgage lending in county c from 1997 to 2007. Variable $exposure_b$ is bank exposure to aging counties in 1997, as defined in Equation 1 and constructed from changes in the senior population predicted with historical demographic changes. Bank controls include log total assets, return on assets, nonperforming loans, total deposits over total liabilities, Tier-1 capital ratio, non-interest income, the indicator on bank specialization, and overhead costs, all as of 1997. County controls include log population, unemployment rate, log income per capita, the share of blacks, as well as employment shares in manufacturing, retail, and services, also all as of 1997. Standard errors are clustered at the bank and county level.

The key identification challenge is to isolate changes in loan supply. If more-exposed banks lend to counties with different characteristics than less-exposed banks, any observed differential change in loan volume reflects both county (demand) and bank (supply) factors. To address this challenge, we include granular borrower-county fixed effects (θ_c) that absorb any unobservable county characteristics, for example changes in consumption, employment, or loan demand. Under the assumption that loan demand in a county is similar across banks, fixed effects difference out demand forces and allow for an identification of supply effects. With county fixed effects, we compare two banks with different exposure that lend to the same county (Khwaja and Mian, 2008; Jiménez et al., 2014).

Table 5 shows that more-exposed banks have higher loan growth over the sample period. In column (1) we regress the change in loans on exposure and bank controls. The coefficient of interest is positive and significant at the 1% level. Column (2) shows that this positive relation remains when we include county controls. Once we further account for unobservable county characteristics in column (3) through county fixed effects, the coefficient remains almost identical in terms of size, sign, and significance to that in column (2). The economic magnitude is sizeable: a one standard deviation increase in exposure is associated with an increase in bank lending by ($0.11 \times 0.990 =$) 10.9% (10.6% of the average growth in HMDA loans). The stability of the coefficient across specifications and the increase in R^2 by over 15 pp suggests that bank exposure is orthogonal to unobservable county characteristics (Altonji et al., 2005; Oster, 2019).[28] These results suggest that the coefficient on exposure likely reflects changes in loan supply and is unrelated to potentially confounding demand factors.

Yet, as argued above (and shown in Table 4), a rise in the number of seniors dampens the local demand for credit. The increase in available funds and decline in the local demand for credit could force exposed banks to lend to counties where they raise no deposits, i.e., where they have no branches and are not directly exposed to the aging-induced decline in credit demand. To investigate this possibility, columns (4) and (5) interact exposure with the dummy *no branch* that takes on a value of one in counties where a bank operates no branches. In column (4) we find that more-exposed banks' loan growth is significantly higher in counties where they have no branch. In terms of magnitude, the increase in lending is over 50% stronger in no-branch counties. Once we add bank fixed effects in column (5) to control for any unobservable bank-level characteristics, the interaction term increases in magnitude and remains significant at the 5% level. The results in Table 5 thus suggest that banks' exposure to aging counties leads to a significant

[28]Formally testing for the presence of bias arising from unobservable bank characteristics, we obtain $\delta = 0.76$, so unobservables would need to be 0.76 times as important as observable county characteristics to render the coefficient insignificant.

and economically sizeable increase in credit, especially in counties where banks raise no deposits.

So far, we have focused on banks' (on-balance sheet) mortgage lending. Does exposure also increase banks' aggregate lending? Column (6) shows results from a bank-level regression of the log change in banks' total loans on bank exposure and controls. Exposed banks see significantly higher growth also in their total lending. This suggest that the aging-induced increase in mortgage credit does not crowd out other forms of lending. Instead, banks' loan volume increases overall, consistent with an overall increase in banks' funding.

Risk-taking. Higher exposure and the associated increase in credit could lead to an increase in banks' risk-taking.[29] To systematically investigate this relation, we estimate Equation 5 with the change in banks' loan-to-income ratio in each borrower county as dependent variable. In each regression, we include baseline bank controls and county fixed effects, thereby absorbing any unobservable county characteristics.

Table 6, panel (a), shows that exposed banks increase their LTI ratios. Column (1) reports a positive coefficient on exposure that is significant at the 1% level. Banks with a one standard deviation higher exposure increase their average LTI ratio by an additional ($0.11 \times 0.694 =$) 7.6 pp. Columns (2) and (3) show that the increase in LTI ratios is not uniform along the distribution: banks with a one standard deviation higher exposure increase the LTI ratio by 6.9 pp vs. 8.8 pp at the 25^{th} and 75^{th} percentile. In other words, while more-exposed banks increased LTI ratios by more than less-exposed banks, they did so particularly among borrowers that already had high LTI ratios.[30] Below, we obtain similar findings for the share of denied loans.

A large literature shows that banks with lower capital ratios engage more in risk-taking when their funding conditions ease (Altunbas et al., 2014; Jiménez et al., 2014), as cheaper access to funds relaxes banks' capital constraints arising from moral hazard problems (Adrian and Shin, 2010). Column (4) thus interacts exposure with banks' Tier-1 capital ratio. It shows that higher exposure leads to a significantly smaller increase in

[29]Previous literature provides evidence that an increase in banks' credit supply is often associated with laxer lending standards. See, for example, Berger and Udell (2004); Dell'Ariccia and Marquez (2006); Mendoza and Terrones (2008); Dell'Ariccia et al. (2012), and Dell'Ariccia et al. (2012).

[30]As we show in panel (b) of Table 7, the difference in impact is even more pronounced for LTI ratios at the 10^{th} and 90^{th} percentile.

LTI ratios for well-capitalized banks.[31]

In Table 5 we have found that exposed banks lend more especially in counties where they have no branch. This raises concerns that banks might take on riskier clients in counties where they have no physical presence, because a greater borrower distance to the nearest branch requires banks to rely more on hard information (DeYoung et al., 2008) and can result in a less efficient screening and monitoring of borrowers (Granja et al., 2018). In column (5) we thus interact exposure with the dummy *no branch* and find that banks increase their LTI ratios by more in counties where they have no branch. Column (6) confirms this finding once we add bank fixed effects to control for any unobservable bank-level characteristics.[32] As we further show below in Table 7, the increase in exposed banks' LTI ratios in counties where they have no branch is especially pronounced in the right tail of the LTI ratio distribution.

Finally, more competitive markets have been shown to be associated with increased risk-taking (Marquez, 2002; Ruckes, 2004; Martinez-Miera and Repullo, 2010). To this end, in column (7) we investigate the role of local competition, measured by the Herfindahl index of deposit concentration. We define high-competition areas as those with values of the Herfindahl index in the bottom tercile of concentration; low-competition areas lie in the top tercile. In column (7) we find a positive coefficient on the interaction term of exposure and competition, significant at the 10% level (the coefficients on exposure and the dummy *high competition* are absorbed by county and bank fixed effects). Exposed banks increase their LTI ratio by more in competitive than in less-competitive counties.

In conclusion, results in Table 6, panel (a), suggest that exposed banks use the increase in deposits due to demographic change not only to increase lending, but also to relax lending standards. These effects are more pronounced for banks with lower capital ratios and in counties where they have no physical presence.

Credit risk and nonperforming loans during a shock. So far, we have shown that banks with higher exposure to aging counties increase their lending and risk-taking, which suggests an increase in credit risk. Did the increase in credit risk have consequences

[31]The interaction term is insignificant for LTI ratios at the 10^{th} percentile, but significant at the 1% level at the 90^{th} percentile, suggesting that higher capital ratios reduce risk-taking especially in the riskier segments (unreported).

[32]Note that including bank fixed effects does not affect the magnitude of our coefficients of interest, despite increasing the R^2 substantially. These suggest that exposure to aging counties aging is uncorrelated with observable and unobservable bank characteristics (Altonji et al., 2005; Oster, 2019).

for the performance of exposed banks during an episode of a negative shock, and hence for financial stability? Evidence from the Great Recessions suggests so: Figure 3, panel (a) shows the evolution of the ratio of nonperforming 1–4 family residential loans to assets from 2000 to 2015 for banks in the bottom (black dashed line) and top tercile (blue solid line) of the *exposure* distribution. Panel (b) depicts the same plot for overall nonperforming loans as a share of assets. Up until 2007, the series for high- and low-exposure banks are indistinguishable. After 2007 NPLs increase to a larger extend for high-exposure banks, relative to low-exposure banks. The difference across series peaks in 2010 and only reverts to similar levels by 2015. Figure 3 thus suggests that high exposure banks fared worse during the Great Recession, relative to low exposure banks, even if there was no discernible difference in pre-trends.

We investigate these patterns in more detail in panel (b) of Table 6. We estimate bank-level regressions with the 2007 to 2010 change of the following variables as dependent variables: the ratio of nonperforming residential mortgages loans (1–4 family homes) to total assets, the ratio of overall nonperforming loans to total assets, and the ratio of total loans over pre-crisis total assets. To ensure that our findings do not reflect that more-exposed banks are also more-exposed to the pre-crisis housing boom, we construct banks' exposure to the change in county-level house prices from 1997 to 2007 analogously to Equation 1. In bank-level regressions we can no longer control for possibly confounding factors at the county level, so it is important to keep in mind that the estimates could at least in part reflect demand factors.

Column (1) shows that exposed banks see a significant increase in their NPL ratio on residential mortgage loans. Controlling for banks' exposure to the housing boom in column (2) does not affect the coefficient on exposure in any statistically or economically meaningful way. Columns (3) and (4) repeat the exercise, but use the change in banks' total NPL ratio as dependent variable. Similar to columns (1) and (2), there is a strong positive and highly significant relationship: exposed banks see a stronger rise in nonperforming loans. In column (4), a one standard deviation increase in exposure is associated with a 12.7% stronger growth in non-performing loans during the Great Recession (17.6% of the average growth in NPLs). While columns (1) and (2) directly follow from our main finding − exposed banks increase their provision of mortgage loans and increase their LTIs − findings in columns (3) and (4) suggest that risk-taking in mortgage lending had repercussions on overall bank performance during the crisis. In line with this argument, columns (5) and (6) show that more-exposed banks see a significantly stronger decline in total loans during the crisis, relative to less-exposed banks.

Results in Table 6 thus suggest that banks that are more-exposed to aging counties increase their credit supply, but relax lending standards. The increase in risk-taking before the Great Recession likely led to a sharper increase in nonperforming loans during the crisis. Exposure to aging counties could therefore have exacerbated the negative effects of the recession on bank health – irrespective of banks' exposure to the housing boom.

4 Additional tests

Table 7, panel (a), performs further analyses based on Equation 5. Column (1) excludes for each bank all counties in which it raises deposits, addressing the concern that, since exposure reflects deposit-weighted local aging, aging could affect bank lending in the same county through channels other than exposure.[33] We thus only analyze bank lending to counties that are not part of the construction of *exposure*.[34] The coefficient on exposure remains similar in terms of sign and significance to the baseline specification. It slightly increases in magnitude, which suggests that unobservable county characteristics are, if anything, negatively correlated with exposure and loan growth – in line with the notion that seniors have lower demand for credit.

To further rule out spillovers through the real economy, we also exclude counties with a high share of employment in tradable industries in column (2). This addresses the point that aging in one county could affect demand for credit in another county through changes in demand for tradable goods and services. Excluding counties with a high share of employment in the tradable sector leads to a decline in sample size. Yet, the coefficient on exposure remains significant and similar in magnitude to column (1). We obtain near-identical results in column (3) when we exclude counties in the top quartile of the Social Connectedness Index, further suggesting that spillovers through the real economy do not

[33]The underlying assumption is that deposits raised by banks in a given county are raised from residents of that county. Amel et al. (2008) show that between 1992 and 2004 the median distance between a depositor and its bank is three miles and remained constant over time.

[34]For example, suppose a bank raises deposits in Los Angeles County (CA), and lends to Los Angeles County and Arlington County (VA). Equation 1 implies that exposure is then correlated with population aging in Los Angeles County. To remove the potentially confounding effect of aging on lending, we only look at lending by above bank to Arlington County. Note that the arising bias is expected to lead to a downward bias: aging counties have lower demand for credit, so if aging confounds exposure, it will attenuate the estimated effect of exposure on lending.

explain the results.[35]

As can be seen from Figure 1, counties in the Great Plains see only a modest to negative change in population age 65 and above from 1997 to 2007. Column (4) thus excludes all states in the lower quartile of Δold, which overlap to a large extent with the Great Plains area, and shows that coefficients remain close to baseline values. Columns (5) excludes counties in the top quartile of Δold. The coefficient on exposure remains close to baseline values. These results suggest that the positive effect of bank exposure on lending is not driven by individual counties with abnormally fast or slow aging. Column (6) further restricts the sample to counties in areas with a low local housing supply elasticity, i.e. areas which have been shown to have experienced a slower decline in house prices during the boom; the coefficient on exposure remains positive and significant. Column (7) uses variation at the intensive margin only, i.e. excludes bank entry and exit across counties. Higher exposure to aging counties also leads to a significant increase in lending among counties to which banks lend in 1997 and 2007. The decline in coefficient size in column (7) relative to our baseline findings is in line with the fact that banks extend more loans to counties where they operate no branches in 1997 – in other words, more-exposed banks enter new markets.

Columns (8)–(9) further confirm the main finding for the full samples of mortgage loans (i.e., including those that were sold in the respective calendar year); as well as for mortgages above the jumbo-loan threshold. Since these loans are information sensitive, they are difficult to securitize and mostly kept on-balance sheet (Cortés and Strahan, 2017). The variable *exposure* has a positive and highly significant effect in both columns.

Panel (b) investigates bank risk-taking in more depth. We first investigate the LTI ratio distribution in columns (1) and (2) by looking at the 10^{th} and 90^{th} percentile separately. Results confirm our findings in Table 6: the impact of exposure is stronger on the right tail of the LTI ratio distribution. Columns (3)–(6) further show that banks increase their LTI ratios by more in counties where they have no branch − and especially in the right tail of the LTI ratio distribution. Column (7) shows that more-exposed banks also denied significantly fewer loans, and column (8) shows that this is more pronounced among weakly capitalized banks. Column (9) reveals that – similar to findings for the LTI ratio – exposed banks deny fewer loans in counties where they operate no branches. Taken together, results in panel (b) complement our main finding that exposure to aging

[35]For details, see Bailey et al. (2018). Note that the index is as of 2020, yet literature shows that connectedness is highly persistent (Rehbein and Rother, 2020).

counties increases banks' risk-taking: banks with higher exposure increase risk-taking specially among borrowers with higher LTI ratios, and they deny fewer loans.

Online appendix. In the Online Appendix, we provide further details on our instrumental variable strategy. We report the results of our first stage regression and examine the validity of the instrument if the exclusion restriction would be violated (see Figure OA2). We also establish that neither local aging nor bank exposure systematically predict in which counties banks open new branches prior to 1997, ameliorating concerns about banks' strategically opening branches to benefit from the aging-induced rise in savings (see Table OA3).

We further show that controlling for local population growth or banks' exposure to overall population growth in borrower counties does not affect our results; and neither does controlling for changes in the prime working age population or young population, either directly or via banks' exposure (see Table OA4). Further, including bank size*county fixed effects, taking into account potential differences in demand factors across banks of different sizes, does not materially affect our estimates (see Table OA5). These results suggest that the estimated coefficients on aging do not spuriously reflect a correlation between the growth in the senior population and population growth in other demographic groups.

Finally, we find that counties in which exposed banks have a larger market share see a stronger increase in household debt-to-income ratios (see Figure OA3). The increase in risk-taking and *loan*-to-income ratios at the bank level is mirrored in an increase of households' *debt*-to-income ratios.

5 Conclusion

Exploiting geographic variation in the change in seniors across the U.S., we first show that county-level population aging leads to an increase in local bank deposits, reflecting higher savings rates of seniors. We then establish that banks exposed to aging counties increase their lending, especially in counties where they raise no deposits. They also increase loan-to-income ratios by more, deny fewer loans, and experience a sharper rise in nonperforming loans during the Great Recession. In other words, banks exposed to aging counties relax their lending standards.

These findings help shed light on how a major macroeconomic trend – population aging – affects the financial sector through changes in the supply of and demand for capital. Our novel results have implications for policy: Population aging could lead to financial instability, a worrying finding in light of the fact that advanced economies face an unprecedented increase in the number of seniors over the next decade. The fact that risk-taking is more pronounced for banks with lower capital ratios could mean that prudent capital regulation could limit the negative consequences of population aging for financial stability.

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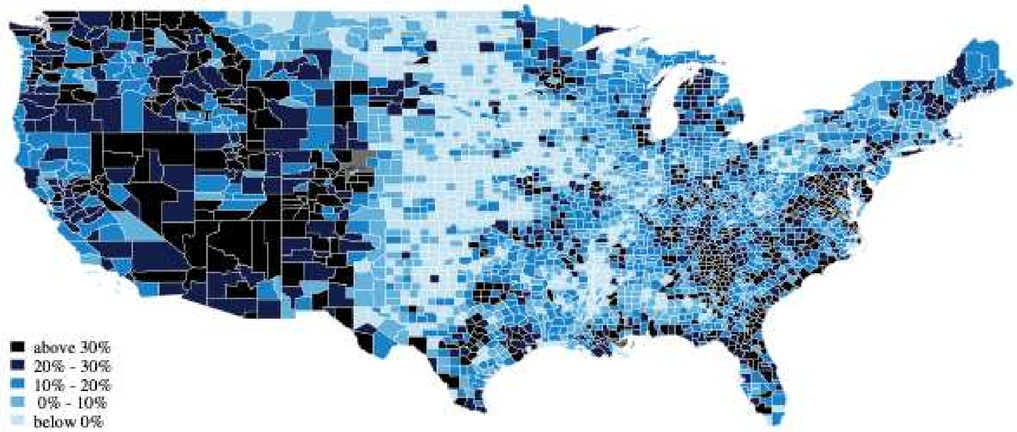
Figures and tables

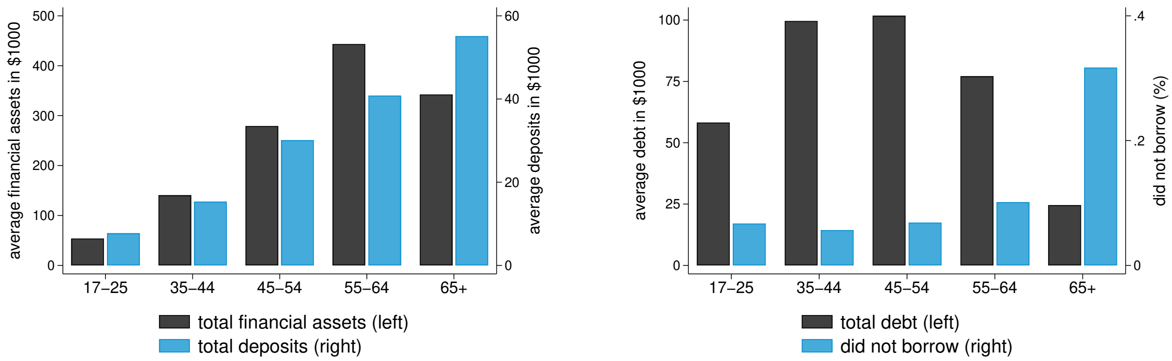
Figure 1: **Population aging – geographic variation**



Note: This figure shows a map of U.S. counties and their log change in the population of age 65 and above from 1997 to 2007. Darker colors indicate higher values of Δ *old*, lighter colors lower values. No data is available for counties in gray.

Figure 2: **Assets and debt by age group**

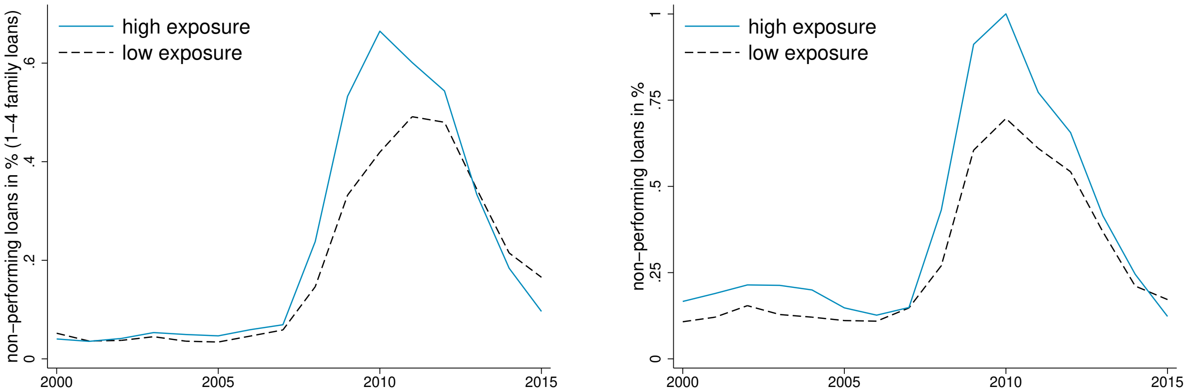
(a) Assets and deposits (b) Debt and borrowing



Note: This figure uses data from the Survey of Consumer Finances (1995-2007). Panel (a) plots total financial assets in $1,000 on the left axis and total deposits in $1,000 on the right axis for the average household in each age bin. Panel (b) plots total debt in $1,000 on the left axis and the fraction of respondents answering *yes* to the question of whether they borrowed money on the right axis for each age bin. Older households are wealthier and hold more deposits; they also have less debt and are less likely to borrow.

Figure 3: **Nonperforming loans during the Great Recessions**

(a) Nonperforming 1-4 family loans (b) Nonperforming loans



Note: This figure shows the evolution of nonperforming 1-4 family residential loans (over total assets) in panel (a) and of total nonperforming loans (over total assets) in panel (b). We split the sample into banks that lie in the top (high exposure, blue solid line) and bottom (low exposure, black dashed line) tercile of the distribution of bank exposure (as defined in Equation 1). Each series presents the average across all banks in the respective tercile. Banks with high exposure see a stronger increase in nonperforming loans from 2007 to 2010, relative to banks with low exposure. There are no differential pre-trends in the period before 2007.

Table 1: **Descriptive statistics**

	mean	sd	min	max	count
Panel (a): Bank level					
exposure	0.16	0.11	-0.06	0.62	1843
log(assets)	12.06	1.27	10.14	19.62	1843
non-performing loans (%)	0.17	0.42	-1.18	3.08	1843
return on assets (%)	0.01	0.01	-0.03	0.04	1843
deposits (%)	0.94	0.08	0.37	1.00	1843
tier 1 capital ratio (%)	0.18	0.10	0.08	0.85	1843
non-interest income (%)	0.01	0.01	0.00	0.06	1843
efficiency (%)	0.61	0.14	0.27	1.75	1843
Δ deposits	0.75	0.53	-0.41	3.21	1843
Δ liabilities	0.79	0.54	-0.38	3.22	1843
Δ loans	0.89	0.59	-0.70	3.46	1843
Δ NPL 2007-2010	0.72	1.17	-2.58	6.47	1664
Δ NPL 2007-2010 (1-4 family)	0.51	0.99	-1.98	5.55	1664
Panel (b): Bank-county level					
Δ deposits	1.14	1.05	-2.00	2.00	13086
Δ hmda	1.03	1.45	-2.00	2.00	53197
Δ hmda (intensive)	0.84	1.76	-4.01	6.37	17643
Δ loan-to-income (mean)	-0.04	0.85	-2.94	3.28	20979
Δ loan-to-income (p10)	-0.25	0.80	-3.17	2.83	20979
Δ loan-to-income (p25)	-0.19	0.81	-2.95	2.73	20979
Δ loan-to-income (p75)	0.05	1.04	-3.37	3.79	20979
Δ loan-to-income (p90)	0.20	1.32	-4.64	6.18	20979
Δ denied	0.07	0.23	-0.60	0.83	20979
no branch dummy	0.91	0.29	0.00	1.00	53197
Panel (c): County level					
Δ old	0.18	0.15	-0.26	1.11	2163
log(population)	10.75	1.18	7.82	16.04	2163
share black	0.09	0.14	0.00	0.85	2163
unemployment rate	0.05	0.03	0.01	0.28	2163
log(income p.c.)	9.96	0.20	9.07	11.15	2163
employment share manufacturing	0.23	0.14	0.00	0.84	2163
employment share retail trade	0.24	0.06	0.02	0.57	2163
employment share services	0.30	0.09	0.06	0.99	2163

Note: This table shows descriptive statistics (mean, standard deviation, minimum, maximum, and number of observations) for the main variables at the bank, bank-county, and county level. All variables in levels are as of 1997, a 'Δ' denotes 1997 to 2007 changes, unless indicated otherwise. For variable definitions, see Section 2.

Table 2: **Balancedness**

	low exposure		**high exposure**		**mean diff.**
	mean	sd	mean	sd	
log(assets)	12.11	(1.26)	12.01	(1.26)	0.10*
non-performing loans (%)	0.16	(0.04)	0.18	(0.04)	-0.02
return on assets (%)	1.10	(0.55)	1.22	(0.57)	-0.12
deposits (%)	93.99	(7.41)	94.18	(7.94)	-0.19
tier 1 capital ratio (%)	18.80	(10.66)	16.97	(8.42)	1.83
non-interest income (%)	0.70	(0.82)	0.89	(0.80)	-0.19**
efficiency (%)	61.67	(14.08)	61.28	(14.21)	0.39
share CI loans (%)	11.96	(12.08)	13.85	(11.31)	-1.89
no branch (% of counties)	77.04	(42.08)	80.24	(39.84)	-3.20
Observations	922		921		1843

Note: This table shows results for a balancedness test of 1997 bank covariates. Banks with low (high) exposure are defined as banks with exposure below (above) the median of the distribution of exposure (as defined in Equation 1). *mean* denotes the mean and *sd* the standard deviation, *mean diff.* denotes the differences in means. We test for the statistical significance of the difference in means by regressing the exposure dummy on control variables in a logistic regression. For variable definitions, see Section 2.

Table 3: **Population aging and local deposits**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					IV	IV	Bank	Bank
VARIABLES	Δ deposits	Δ deposits	Δ deposits	Δ deposits	Δ deposits	Δ deposits	Δ deposits	Δ liabilities
Δ old	1.032***	1.028***	0.877***	0.828***	0.855***	0.746***		
	(0.103)	(0.111)	(0.106)	(0.103)	(0.127)	(0.122)		
exposure							0.712***	0.693***
							(0.128)	(0.131)
Observations	13,086	13,086	13,086	13,086	12,942	12,244	1,843	1,843
R-squared	0.047	0.100	0.350	0.388			0.173	0.155
County Controls	✓	✓	✓	✓	✓	Δ	-	-
Bank Controls	-	✓	-	-	-	-	✓	✓
Bank FE	-	-	✓	✓	✓	✓	-	-
State FE	-	-	-	✓	✓	✓	-	-

Note: This table shows results for Equation 4 at the bank-county level in columns (1)–(6). The dependent variable is the change in deposits. Δold denotes the log change in the county population of age 65 and above. Columns (5) and (6) are 2SLS regressions that instrument Δ *old* with the change in the population of age 45 to 65 from 1977 to 1987 in each county. Column (6) includes the 1997 to 2007 change in income per capita, the unemployment rate, and house price index as additional county-level controls. Columns (7)–(8) report regressions at the bank level ($\Delta y_b = \beta \ exposure_b + controls_b + \varepsilon_b$) and use the change in total deposits and total liabilities as dependent variables. *exposure* measures banks' exposure to aging counties (as defined in Equation 1). For fixed effects and controls, see table footer. Standard errors are clustered at the bank and county level in columns (1)–(6). Columns (7)–(8) use robust standard errors. For variable definitions, see Section 2. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: **Population aging and the demand for credit**

	(1)	(2)	(3)	(4)
			IV	IV
VARIABLES	Δ loan demand (AW)	Δ loan demand (AW)	Δ loan demand (AW)	Δ loan demand (AW)
Δ old	-0.590***	-0.672**	-0.781**	-0.961***
	(0.197)	(0.297)	(0.350)	(0.251)
Observations	754	754	754	745
R-squared	0.009	0.201		
County Controls	-	✓	✓	Δ

Note: This table shows results for regressions at the county level. The dependent variable is the demand factor of a decomposition of HMDA loan growth (1997-2007) following Amiti and Weinstein (2018). The dependent variable is standardized to a mean of zero and standard deviation one. Δ *old* denotes the change in the county population of age 65 and above. Column (3) instruments Δ *old* with the change in the population of age 45 to 65 from 1977 to 1987. Column (4) includes the 1997 to 2007 change in income per capita, the unemployment rate, and house price index as additional county-level controls. Standard errors are robust. For variable definitions, see Section 2. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: **Bank exposure and lending**

	(1)	(2)	(3)	(4)	(5)	(6)
						bank
VARIABLES	Δ hmda	Δ hmda	Δ hmda	Δ hmda	Δ hmda	Δ loans
exposure	1.244***	1.106***	0.990***	0.729***		0.722***
	(0.071)	(0.070)	(0.070)	(0.169)		(0.146)
no branch				0.856***	0.634***	
				(0.033)	(0.033)	
exposure × no branch				0.375**	0.410**	
				(0.181)	(0.180)	
Observations	51,727	51,727	51,727	51,727	51,659	1,843
R-squared	0.051	0.074	0.207	0.238	0.513	0.130
Bank Controls	✓	✓	✓	✓	-	✓
County Controls	-	✓	-	-	-	-
County FE	-	-	✓	✓	✓	-
Bank FE	-	-	-	-	✓	-

Note: This table shows results for Equation 5 at the bank-county level in columns (1)–(5) and at the bank level in column (6). The dependent variable is the change in bank-county HMDA loans that are not sold by the end of the year in columns (1)–(5); and the change in total loans in column (6). *exposure* denotes bank exposure to aging counties (as defined in Equation 1). *no branch* is a dummy with a value of one for bank-county pairs in which a bank does not operate branches in 1997, and zero otherwise. For fixed effects and controls, see table footer. Standard errors are clustered at the bank and county level in columns (1)–(5). Column (6) uses robust standard errors. For variable definitions, see Section 2. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: **Risk-taking**

(a): **Loan-to-income ratios**

VARIABLES	(1) LTI (avg)	(2) LTI (p25)	(3) LTI (p75)	(4) LTI (avg)	(5) LTI (avg)	(6) LTI (avg)	(7) LTI (avg)
exposure	0.694***	0.625***	0.804***	1.440***	0.365***		
	(0.083)	(0.080)	(0.101)	(0.142)	(0.119)		
exposure × Tier-1 capital ratio				-3.856***			
				(0.607)			
no branch					-0.147***	-0.213***	
					(0.027)	(0.028)	
exposure × no branch					0.416***	0.520***	
					(0.148)	(0.152)	
exposure × high competition							0.337*
							(0.172)
Observations	20,979	20,979	20,979	20,979	20,979	20,588	20,578
R-squared	0.113	0.101	0.117	0.116	0.115	0.373	0.370
Bank Controls	✓	✓	✓	✓	✓	-	-
County FE	✓	✓	✓	✓	✓	✓	✓
Bank FE	-	-	-	-	-	✓	✓

(b): **The Great Recession**

VARIABLES	(1) Δ NPL (mort)	(2) Δ NPL (mort)	(3) Δ NPL	(4) Δ NPL	(5) Δ loans/asset	(6) Δ loans/asset
exposure	0.896***	0.869***	1.183***	1.157***	-0.115*	-0.116*
	(0.291)	(0.286)	(0.312)	(0.307)	(0.062)	(0.061)
exposure to Δ hpi 1997-07		0.271***		0.269***		0.010
		(0.087)		(0.083)		(0.017)
Observations	1,661	1,661	1,661	1,661	1,661	1,661
R-squared	0.082	0.092	0.103	0.110	0.045	0.045
Bank Controls	✓	✓	✓	✓	✓	✓

Note: Panel (a) shows results for Equation 5 at the bank-county level. The dependent variable is the change in the average loan-to-income (LTI) ratio in columns (1) and (4)–(7); columns (2) and (3) use the change in the LTI ratios at the 25^{th} and 75^{th} percentile. *exposure* denotes bank exposure to aging counties (as defined in Equation 1). *Tier-1 capital* denotes banks' Tier-1 capital ratio (as of 1997); *no branch* is a dummy that takes on a value of one in bank-county pairs in which a bank does not operate branches in 1997. *high competition* denotes counties in the top tercile of the distribution of the county HHI (based on deposit shares, as of 1997). For fixed effects and controls, see table footer. Standard errors are clustered at the bank and county level. Panel (b) shows results for regressions at the bank level. The dependent variable is the 2007 to 2010 change in the share of nonperforming residential mortgages loans (columns (1) and (2)); the 2007 to 2010 change in the share of nonperforming loans (columns (3) and (4)); and the 2007 to 2010 change in total lending, standardized by pre-crisis assets (columns (5) and (6)). *exposure to Δ hpi 1997-07* denotes deposit-weighted bank exposure to the increase in county-level house prices from 1997 to 2007. Each regression includes bank controls as of 1997. Standard errors are robust. For variable definitions, see Section 2. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: **Robustness tests**

(a): **Bank lending**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	no branch	low NT	low SCI	no plains	no high Δ old	low elasticity	int. margin	off BS	jumbo
VARIABLES	Δ hmda	Δ hmda	Δ hmda	Δ hmda	Δ hmda	Δ hmda	Δ hmda	Δ hmda	Δ hmda
exposure	1.123***	1.212***	1.205***	0.823***	0.864***	1.064***	1.466***	1.039***	1.836***
	(0.072)	(0.086)	(0.079)	(0.076)	(0.073)	(0.075)	(0.164)	(0.060)	(0.104)
Observations	48,408	33,694	37,731	42,434	47,455	42,598	17,643	65,720	23,442
R-squared	0.208	0.210	0.172	0.211	0.207	0.210	0.172	0.230	0.213
Bank Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

(b): **Risk-taking**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	LTI (p10)	LTI (p90)	LTI (p10)	LTI (p25)	LTI (p75)	LTI (p90)	% denied	% denied	% denied
exposure	0.339***	0.989***					-0.195***	-0.704***	
	(0.080)	(0.129)					(0.020)	(0.034)	
exposure × Tier-1 capital ratio								2.630***	
								(0.138)	
no branch			-0.250***	-0.249***	-0.181***	-0.190***			0.034***
			(0.026)	(0.027)	(0.035)	(0.046)			(0.006)
exposure × no branch			0.048	0.336**	0.709***	1.021***			-0.089**
			(0.145)	(0.147)	(0.189)	(0.258)			(0.035)
Observations	20,979	20,979	20,588	20,588	20,588	20,588	20,979	20,979	20,588
R-squared	0.093	0.105	0.300	0.328	0.377	0.346	0.160	0.176	0.464
Bank Controls	✓	✓	-	-	-	-	✓	✓	-
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bank FE	-	-	✓	✓	✓	✓	-	-	✓

Note: Panel (a) shows results for Equation 5 at the bank-county level. The dependent variable is the change in HMDA loans that are not sold by the end of the year (i.e., retained on balance sheet) in columns (1)–(6). *exposure* denotes bank exposure to aging counties (as defined in Equation 1). Column (1) excludes all counties in which a bank operates a branch in 1997; column (2) excludes counties with high share of employment in tradable industries; column (3) excludes counties within the top quartile of the Social Connectedness Index. Column (4) excludes all states located in the Great Plains. Columns (5) excludes counties in the top quartile of Δold. Column (6) restricts the sample to counties in MSAs with a low housing supply elasticity. Column (7) focuses on lending along the intensive margin. Column (8) uses the change in total bank-county HMDA loans, including those that were sold at the end of the year, as dependent variable. Column (9) uses the change in total bank-county HMDA loans that exceed the conforming loan limit ('jumbo loans') as dependent variable. Standard errors are clustered at the bank and county level. Each regression includes bank controls and county fixed effects. Panel (b) shows results for Equation 5 at the bank-county level. The dependent variable is the change in the loan-to-income (LTI) ratio at different percentiles in columns (1)–(6); and the change in the share of loans denied in columns (7)–(9). *Tier-1 capital* denotes banks' Tier-1 capital ratio (as of 1997); *no branch* is a dummy with a value of one for bank-county pairs in which a bank does not operate branches in 1997. Columns (1), (2), and (8) include bank controls and county fixed effects. The remaining columns include bank and county fixed effects. Standard errors are clustered at the bank and county level. For variable definitions, see Section 2. *** p<0.01, ** p<0.05, * p<0.1.

A Online Appendix

Table OA1: Variable Definitions

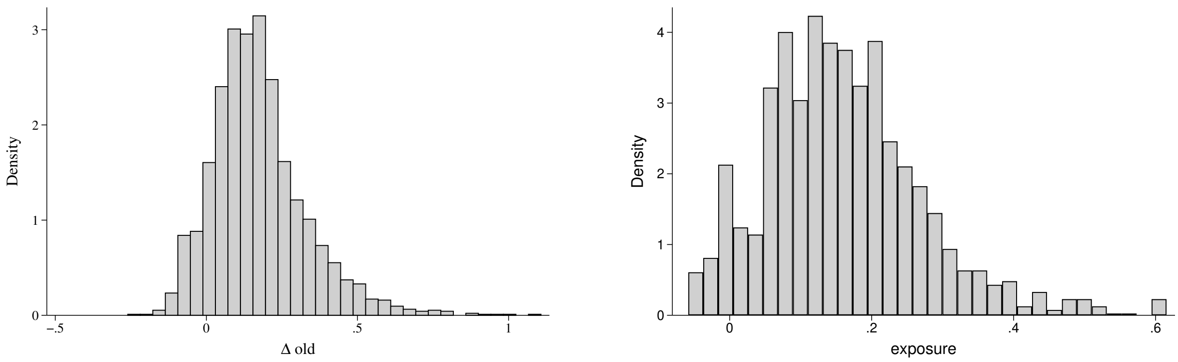
Variable name	Description	Source
Bank level		
exposure	bank exposure to aging counties (deposit-weighted)	FDIC SOD, NCI SEER
Δ deposits	change in total deposits	FDIC SDI
Δ loans	change in total bank loans	FDIC SDI
Δ mortgages	change in total residential mortgage loans	FDIC SDI
log(assets)	log total assets	FDIC SDI
non-performing loans (%)	share of NPL over total loans	FDIC SDI
ROA (%)	return on assets	FDIC SDI
deposits (%)	total deposits over total liabilities	FDIC SDI
tier 1 capital (%)	tier 1 capital ratio	FDIC SDI
non-interest income (%)	non-interest income over average assets	FDIC SDI
Δ NPL (mort)	change in net charge-offs on mortgage loans 2007-10	FDIC SDI
Δ NPL	change in net charge-offs on all loans 2007-10	FDIC SDI
Δ loans/asset	change in loans over pre-crisis assets 2007-10	FDIC SDI
Bank-county level		
Δ deposits	Change in deposits	FDIC SOD
Δ HMDA	Change in mortgage loans	HMDA
Δ LTI (mean)	Change in average loan-to-income ratio	HMDA
Δ LTI (pX)	Change in X-percentile loan-to-income ratio	HMDA
Δ denied	Change in share of denied mortgage loans	HMDA
County level		
Δ old	change in population 65+	NCI SEER
log(unemployed 1940)	log total unemployed 1940	ICPSR
log(population)	log total population	NCI Seer
unemployment rate	unemployment rate	BLS LAUS
participation rate	labor force participation rate	BLS LAUS
log(income p.c.)	log income per capita	BEA LAPI
employment share manufacturing	employment share of manufacturing sector (SIC 20)	CBP
employment share retail trade	employment share of retail trade sector (SIC 50)	CBP
employment share services	employment share services sector (SIC 70)	CBP
Δ debt-to-inc	Change in debt-to-income ratio	FRBNY
presence of exposed banks	loan-weighted average across bank exposure of banks active in county	HMDA, FDIC SOD, NCI SEER
Other variables		
elasticity	MSA housing supply elasticity	Saiz (2010)

Note: This table reports variable definitions and sources. Changes (Δ) are from 1997 to 2007, all other variables are as of 1997 (unless indicated otherwise). For details see Section 2.

Figure OA1: **County aging and bank exposure – Distribution**

(a) County aging

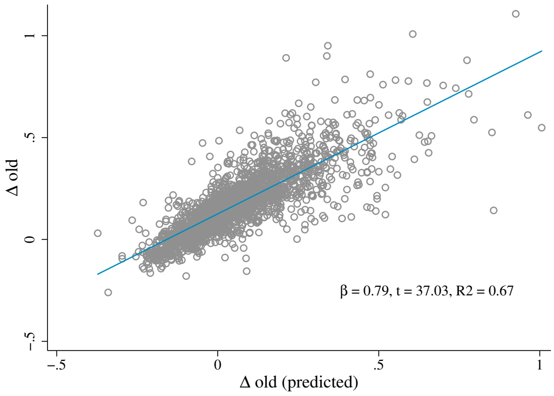
(b) Bank exposure



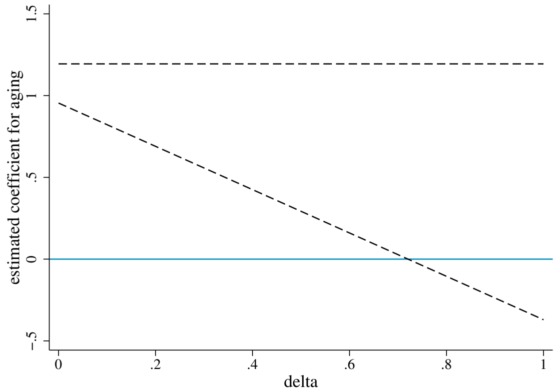
Note: This figures shows the distributions of the county-level log change in the population of age 65 and above from 1997 to 2007 in panel (a) and bank exposure as defined in Equation 1 in panel (b).

Figure OA2: **Instrumental variable strategy**

(a) First stage

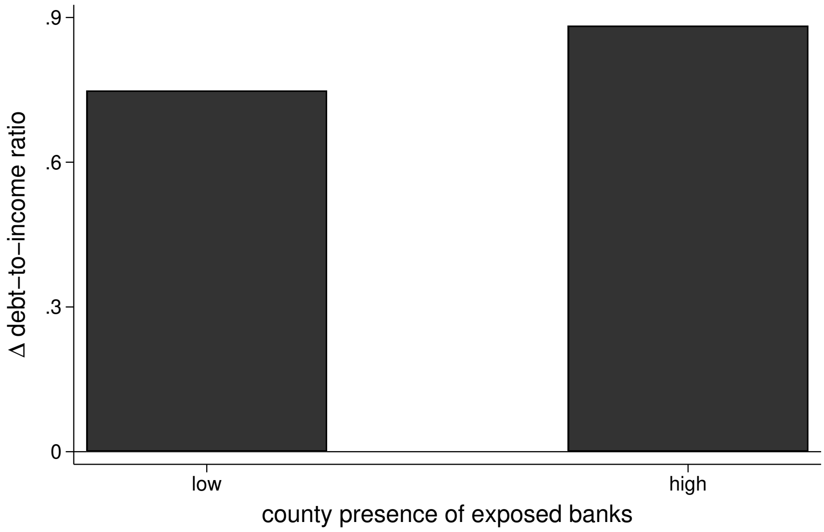


(b) Sensitivity to exclusion restriction



Note: Panel (a) plots counties' actual and predicted change in seniors. Δold denotes the change in county population age 65 and above, and Δold (*predicted*) denotes the change in county population of age 45 to 65 from 1977 to 1987. Panel (b) shows how large the exclusion restriction violation would need to be in order to invalidate the reduced form results for bank deposits. The panel uses the 'union of confidence intervals' approach by Conley et al. (2012). The dashed lines plot the union of 90% confidence intervals, the parameter δ varies the possible values of γ (the size of the exclusion restriction violation) such that $\gamma \in [-2\delta, 2\delta]$.
The panel suggests that aging has a significant effect on deposit growth even if the exclusion restriction is violated. The underlying regression is $\Delta deposits = \beta \Delta old + \gamma IV + \varepsilon$, with the prior that $\gamma > 0$ (ie, past aging has, if anything, a positive effect on today's deposit growth). A value of $\gamma = 0$ (on the interval of $[0, \delta]$), ie a valid exclusion restriction and no effect of the instrument on deposit growth except through the change in seniors, yields a parameter of $\beta = 1.076$ and a 90% confidence band of $[0.953, 1.200]$. As we relax the exclusion restriction, the effect of aging on deposits remains significant and positive. For example, for a value of $\gamma = 0.4$ (ie, an effect of a one unit change in the instrument on deposit growth of 40% that is operating through channels other than contemporaneous aging) the corresponding 90% confidence set for β is approximately [0.500,1.200]. In other words, a one unit increase in aging leads to an increase in deposits of on average 85% (and at least 50%, in terms of 90% confidence bands) even if the exclusion restriction is severely violated – that is, even if the past demographic structure has a large and significant effect on deposit growth during our sample period through channels other than contemporaneous aging.

Figure OA3: **Change in county-level debt-to-income ratios**



Note: This figure shows the average change in the county-level debt-to-income ratio from 1997 to 2007. We split the sample into counties that lie in the top, middle, and bottom tercile of local presence of exposed banks. *presence* is computed as the average exposure of banks active in a county, weighted by each banks local HMDA loan volume ($presence_c = \sum_b \frac{l_{b,c}}{l_c} \times exposure_b$, where $l_{b,c}$ and l_c denote bank b's HMDA loans in county c and county c's total HMDA loans (both as of 1997)). Counties with higher values of *presence* have a higher share of loans extended by high-exposure banks.

Table OA2: **The relation between age and deposits**

VARIABLES	(1) log(deposits)	(2) log(deposits)	(3) log(deposits)	(4) log(deposits)
age group 35-64	0.848***	0.842***	0.320***	-0.209***
	(0.022)	(0.022)	(0.024)	(0.017)
age group 65+	1.658***	1.656***	1.312***	0.258***
	(0.026)	(0.026)	(0.042)	(0.030)
log(financial wealth)				0.641***
				(0.003)
Observations	58,078	58,078	58,078	58,078
R-squared	0.065	0.066	0.308	0.630
Survey wave FE	-	✓	✓	✓
Controls	-	-	✓	✓

Note: This table shows results for the following regression $log(deposits)_i = agegroup_i + controls_i + \tau_t + \epsilon_{i,}$, where the age group 17-34 is the omitted category Column (3) adds an extensive set of household-level controls: age, education level, number of kids, occupation, gender, race, marriage status, home ownership, and a dummy for business ownership. Column (4) further controls for the log of respondents' overall financial wealth. Source: Survey of Consumer Finances 1992, 1998, and 2007. *** p<0.01, ** p<0.05, * p<0.1.

Table OA3: **Did banks open branches between 1994 and 1997?**

VARIABLES	(1) Δ branches	(2) open br	(3) entry	(4) Δ branches	(5) open br	(6) entry
Δ old	-1.002	0.125*	0.096			
	(0.677)	(0.074)	(0.082)			
exposure				1.192	0.206	0.287*
				(1.358)	(0.126)	(0.153)
Observations	16,977	16,977	16,977	17,026	17,026	17,026
R-squared	0.173	0.390	0.387	0.115	0.199	0.158
County Controls	✓	✓	✓	-	-	-
Bank FE	✓	✓	✓	-	-	-
Bank Controls	-	-	-	✓	✓	✓
County FE	-	-	-	✓	✓	✓

Note: This table shows results for regressions at the bank-county level (see Equation 5). The dependent variables are the change in the number of branches (columns (1) and (4)), a dummy with value one if a bank opened a branch in a county (columns (2) and (5)), and a dummy with value one if a bank entered a county (columns (3) and (6)). Δold denotes the log change in county population age 65 and above. *exposure* denotes bank exposure to aging counties (see Equation 1). Standard errors are clustered at the bank and county level. For variable definitions, see Section 2. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table OA4: **Growth and exposure – other demographic groups**

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Δ deposits	Δ deposits	Δ deposits	Δ hmda	Δ hmda	Δ hmda
Δ old	0.762***	0.857***	0.670***			
	(0.108)	(0.116)	(0.139)			
exposure				1.694***	1.681***	1.778***
				(0.111)	(0.113)	(0.112)
Observations	13,086	13,086	13,086	47,004	47,004	47,004
R-squared	0.350	0.350	0.351	0.209	0.209	0.209
County Controls	✓	✓	✓	-	-	-
Bank Controls	-	-	-	✓	✓	✓
Bank FE	✓	✓	✓	-	-	-
County FE	-	-	-	✓	✓	✓
Δ pop	✓	✓	✓	✓	✓	✓
Δ young	-	✓	✓	-	✓	✓
Δ prime age	-	-	✓	-	-	✓

Note: This table shows results at the bank-county level for regression equation (4) with the change in deposits as dependent variable in columns (1)–(3); and for regression equation (3) with the change in HMDA loans as dependent variable in columns (4)–(6). *old* denotes the population 65 and above. Each column in columns (1)–(3) controls for population growth in a different cohort (*pop*, *young*, *prime working age*, corresponding to the total population, population age 29 and younger, and population age 25-44, respectively). Each column in columns (4)–(6) controls for bank exposure to each of these groups. The different exposure measure are constructed as defined in Equation 1. For variable definitions, see Section 2. *** p<0.01, ** p<0.05, * p<0.1.

Table OA5: **Bank size*county fixed effects: lending and risk-taking**

VARIABLES	(1) Δ hmda	(2) Δ hmda	(3) Δ LTI (avg)	(4) Δ LTI (avg)	(5) Δ denied	(6) Δ denied
exposure	1.083***		0.890***		-0.245***	
	(0.075)		(0.093)		(0.025)	
no branch		0.618***		-0.257***		0.033***
		(0.036)		(0.033)		(0.008)
exposure × no branch		0.394**		0.679***		-0.081*
		(0.198)		(0.186)		(0.043)
Observations	49,781	49,633	19,140	18,644	19,140	18,644
R-squared	0.262	0.544	0.198	0.415	0.218	0.492
Bank Controls	✓	✓	✓	✓	✓	✓
Bank size*County FE	✓	✓	✓	✓	✓	✓
Bank FE	-	✓	-	✓	-	✓

Note: This table shows results for Equation 5 at the bank-county level. The dependent variable is the change in bank-county HMDA loans that are not sold by the end of the year in columns (1)–(2); the change in the LTI ratio in columns (3)–(4); and the change in the share of denied loans in columns (5)–(6). *exposure* denotes bank exposure to aging counties (as defined in Equation 1). *no branch* is a dummy with a value of one for bank-county pairs in which a bank does not operate branches in 1997, and zero otherwise. For fixed effects and controls, see table footer. Standard errors are clustered at the bank and county level. For variable definitions, see Section 2. *** p<0.01, ** p<0.05, * p<0.1.