Population aging and bank risk-taking

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Abstract

What are the implications of an aging population for financial stability? To examine this question, we exploit geographic variation in aging across U.S. counties. We establish that banks with higher exposure to aging counties increase loan-to-income ratios. Laxer lending standards lead to higher nonperforming loans during downturns, suggesting higher credit risk. Inspecting the mechanism shows that aging drives risk-taking through two contemporaneous channels: deposit inflows due to seniors' propensity to save in deposits; and depressed local investment opportunities due to seniors' lower credit demand. Banks thus look for riskier clients, especially in counties where they operate no branches.

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1 Introduction

The U.S. population of age 65 and above will grow by 18 million (or 33%) over the next decade, and similar developments are taking place in most other advanced economies. This unprecedented rise in the senior population has led to a debate on whether population aging leads to a build-up of risks in the financial sector. High savings rates among seniors might lead to an abundance of savings and depressed returns, thereby potentially encouraging banks to reach for yield (IMF, 2019). Low expected returns and banks' reach for yield, in turn, could give rise to financial instabilities (Brookings, 2019).

This paper provides the first evidence on how an aging population affects bank lending standards. For identification, we exploit the extensive variation in aging that has already occurred across U.S. counties, combined with granular data on bank mortgage loans and deposits. We find that banks more exposed to aging counties relax lending standards as they grant new loans: loan-to-income ratios increase, and in particular in counties where banks operate no branches. Banks with greater exposure also see a sharper rise in nonperforming loans during downturns, implying an increase in credit risk due to population aging. Further analysis suggests that these patterns are shaped by two forces: first, an increase in banks' available funds due to seniors' higher propensity to save in the form of deposits; and second, a contemporaneous aging-induced decrease in the local demand for credit.

To measure banks' presence in aging counties and how it affects lending standards, we define bank exposure as the weighted average change in the number of seniors across counties where banks have branches. Weights are given by deposit shares at the beginning of the sample period. Intuitively, banks with higher exposure have a larger footprint in counties that see a stronger increase in seniors. Our main analysis focuses on the 1997–2007 period and does so for three reasons. First, the period after the financial crisis of 2007/08 is characterized by substantial financial regulatory reforms. These reforms have affected banks' lending decisions and hamper the identification of the respective channels through which population aging affects bank risk-taking. Second, we can exploit the Great Recession as a negative shock to see whether aging-induced risk-taking manifests itself in higher nonperforming loans during a downturn. And third, we avoid the zero lower bound on interest rates (Leahy and Thapar, 2022).

Bank exposure could be correlated with observable or unobservable bank characteristics, posing a threat to identification. We address this challenge in a number of ways. First, we document that high- and low-exposure banks are similar in terms of initial balance sheet characteristics, for example in terms of size, capital ratio, or return on assets. In line with the balancedness in bank co-variates, in regressions we find that including bank controls and bank fixed effects barely affects the magnitude of our estimated coefficients, despite increasing the R^2 substantially. Bank exposure to aging counties is hence likely uncorrelated with observable and unobservable bank characteristics, reducing potential concerns about self-selection and omitted variable bias (Altonji et al., 2005; Oster, 2019).

Second, we develop an instrumental variable approach that exploits the predetermined component of counties' age structure. Specifically, we predict the change in the population of ages 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. We then re-construct exposure, but based on aging predicted from historical trends, and use it as an instrumental variable (IV) for actual bank exposure to aging counties. This approach builds on the assumption that the historical demographic structure is plausibly exogenous to *changes* in contemporaneous confounding factors. Such factors include, for example, changes in life expectancy or economic conditions. To support the plausible exogeneity of our instrument, we show that directly controlling for banks' exposure to contemporaneous changes in county characteristics (e.g. changes in income per capita or the unemployment rate) does not affect our conclusions.

Armed with our measure of bank exposure, we establish that banks more exposed to aging counties relax their lending standards. As the main measure for risk-taking we focus on the loan-to-income (LTI) ratio, which is highly correlated with ex-post default (Fuster et al., 2021). Our results show that a 33 percentage point (pp) increase in bank exposure is associated with a significant rise in LTI ratios by around 22 pp.[1] The effect of exposure on LTI ratios is particularly strong in counties where banks have no branches, which could imply less efficient screening and monitoring (DeYoung et al., 2008; Liberti and Petersen, 2019; Granja et al., 2022). These results are robust to the inclusion of borrower-county fixed effects. Intuitively, these fixed effects enable us to compare two banks with different exposures that lend to the same county, mitigating concerns that risk-taking is driven by changes in borrower-county fundamentals (Khwaja and Mian, 2008; Jiménez et al., 2014).

The relaxation of lending standards among exposed banks suggests an increase in credit risk, with potentially negative consequences for financial stability. To investigate this aspect

[1]Note that 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 unconditional mean and standard deviation of the county-level growth in the number of seniors between 1997 and 2007 equal 12% and 15%, respectively. 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.

in more detail, we show that banks with higher exposure to aging counties see a significantly stronger increase in their share of nonperforming loans during the Great Recession. Importantly, controlling for banks' exposure to the rise in house prices prior to the Great Recession does not affect our estimates. Exposure to aging counties had effects on risk-taking above and beyond banks' exposure to the housing boom. Our findings suggest that the aging-induced relaxation in lending standards negatively affects financial stability during downturns.

Having established a robust association between population aging and bank risk-taking, we investigate the underlying channels that could explain the link. Population aging could affect banks through changes in the supply of and demand for capital. On the one hand, Becker (2007) argues that seniors are more likely to save in the form of deposits, which are a stable and cheap source of funding (Hanson et al., 2015; Carletti et al., 2021). Higher exposure to aging counties could hence lead to deposit inflows and reduce banks' cost of funds, translating into an increase in lending but allowing banks to pursue safer projects with lower returns. On the other hand, an aging population could reduce the local demand for credit and depress returns. Homeownership rates and savings are highest among seniors, and they are less likely to start new companies (Azoulay et al., 2020). An aging-induced decline in the labor force also reduces firms' marginal product of capital, further lowering the demand for capital (Auclert et al., 2021). Aging-exposed banks could hence be confronted with a decline in the demand for credit in counties where they have branches at a time when they experience an increase in available funds. Banks might therefore have to look for new and potentially riskier clients, particularly in counties where they operate no branches.

We first investigate the link between aging and deposits. We find 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 around 25%. Seniors' relatively larger share of wealth held in the form of deposits explains this positive relationship (Becker, 2007). For identification, our regressions absorb 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 observable county characteristics that could explain the rise in deposits. In addition, we show that neither local aging nor bank exposure predict where banks open new branches prior to our sample period. This mitigates the concern that banks strategically opened branches to benefit from future deposit inflows in anticipation of local demographic trends.

We then establish that population aging dampens the local demand for credit. First, we use data from the Survey of Consumer Finances and show that seniors are less likely to borrow or have outstanding debt compared to younger respondents. These correlations hold even after controlling for an extensive set of household-level controls. Second, 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, suggesting that aging leads to a decline in the local demand for mortgages.

The aging-induced deposit inflows and weaker local demand for credit affect the geography of bank lending. Higher exposure leads banks to increase their mortgage lending. The increase in lending is especially large 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. In addition, we find that exposed banks shift their overall portfolio of assets towards asset classes not directly affected by local aging. Specifically, they significantly increase their holdings of securities and trading account assets.

To examine the robustness of our findings, we perform additional tests. We start by investigating how the effect of aging on risk-taking changes along the LTI distribution. We find that the effect is stronger in the right tail of the LTI ratio distribution, suggesting higher risk-taking among already riskier borrower segments. We also show that the risk-taking in no-branch counties is stronger in the right tail of the LTI ratio distribution. In line with the large literature documenting that banks with lower capital ratios engage more in risk-taking, we further find that higher exposure leads to a significantly higher increase in LTI ratios for low-capitalized banks. Next, we consider the share of denied loans as another measure of bank lending standards. Similar to our main results, we find that exposure to aging counties reduces the share of denied loans and that the effect is stronger in no-branch counties.

Finally, we also investigate whether laxer lending standards in the form of loan-to-income ratios affect household leverage. The results show that counties in which exposed banks have a larger ex-ante market share also see a stronger increase in household debt-to-income ratios over the sample period. That 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 at the county level.

To the best of our knowledge, this paper is the first to investigate the effects of population aging on lending standards, and to what extent there are spillovers across markets.[2] While this paper's focus is on risk-taking, our paper builds on work that shows how changes in banks' deposit base affect their lending. Becker (2007) uses the local demographic structure as an instrument for changes in bank deposits, but focuses on how the availability of deposits affects local entrepreneurial activity. Gilje et al. (2016) provide evidence that banks exposed to local liquidity inflows from oil and natural gas shale discoveries subsequently increase lending in other counties where they have branches. They find that the effects are especially pronounced for loan types that are subject to more contracting frictions.[3] Our novel results for population aging show that local aging not only leads to deposit inflows, but also reduces the local demand for credit. The combination of both forces explains why banks increase their risk-taking, and why there are spillover effects to no-branch markets.

We also contribute to the literature that explores 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) and periods of low interest rates (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). Credit booms or periods of low interest rates can lead to laxer lending standards and a higher risk of financial crises. However, evidence on the effects of population aging on bank risk-taking is scarce, despite

[2]Recent papers investigate the effects of population aging on various outcomes. Butler and Yi (2021) investigate the effect of an aging population on the U.S. municipal bond market. Kopecky and Taylor (2022) use historical panel data to show that demographic shifts are correlated with asset returns and risk premia. Cravino et al. (2022) show that US population aging accounted for about 20% of the increase in the service share in consumption.

[3]For further papers on the effects of local shocks on bank lending, see Cortés and Strahan (2017); Smolyansky (2019); De Jonghe et al. (2020); Doerr and Schaz (2021) and Rehbein and Ongena (2021), among many others. In addition, Kundu et al. (2022) demonstrate that the geographic concentration of deposits affects how shocks are transmitted across geographies by multi-market banks.

the significant policy attention devoted to this major macroeconomic trend (CGFS, 2018; ECB, 2018; IMF, 2019; OECD, 2019). Our analysis aims to fill this gap in the literature. As advanced economies face an unprecedented increase in the number of seniors over the next decade, the bank 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 and the construction of the main variables. Section 3 explains the empirical strategy and presents our main results on risk-taking and financial stability. Section 4 then investigates the underlying mechanism. Section 5 provides additional tests, and Section 6 concludes.

2 Data and descriptive statistics

This section explains the construction of our main variables and reports descriptive statistics.

Our main analysis focuses on the period from 1997 to 2007, for three 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, particularly mortgage lending, over the post-crisis period, which would make a clean identification of the respective channels through which population aging affects bank risk-taking difficult. 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 analyze whether higher risk-taking in the years leading up to the crisis manifested itself in higher nonperforming loans during the shock episode. That is, we can analyze whether laxer lending standards had an impact on financial stability. And third, we avoid the zero lower bound on interest rates.

2.1 Main variables

Population aging. Our main explanatory variable at the county level is the change in the log of the population of ages 65 and above from 1997 to 2007, denoted by Δold_c. We use the change in the number of seniors (i.e., in the level) rather than the change in the ratio of seniors to the total population (i.e., in the share), because changes in the share could be driven by changes in the numerator or denominator. For example, a decline in the total population of a county would lead to an increase in the share of seniors, even though the number of seniors does not change. In such a case, the relationship between, e.g., deposits or loans and the change in the share of seniors would be driven by the decline in 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.

Bank exposure. To calculate banks' 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 banks' beginning-of-sample exposure as

$$exposure_b = \sum_c \frac{deposits_{b,c}}{deposits_b} \times \Delta old_c, \tag{1}$$

where $deposits_{b,c}$ and $deposits_b$ denote bank b's deposits in county c and its total deposits as of 1997. Δold_c is county c's change in the log of the population of ages 65 and above. High $exposure_b$ implies that a large share of banks' initial deposits is held in aging counties, while low exposure implies that deposits are held in counties with a small increase in the number of seniors. Higher exposure thus corresponds to an increase in deposit-weighted average aging in banks' borrower counties. Exposure is constructed from beginning-of-sample deposit shares, alleviating concerns about banks selectively opening branches in aging counties.

Instrumental variable strategy. Counties that experience a stronger increase in seniors could differ along other dimensions that could matter for deposit growth. We thus predict Δold, i.e., the change in the population of ages 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 county's 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 Δold from changes in life expectancy, in- or out-migration, or incomes over the sample period.

Similar to county aging, bank exposure could be correlated with other (unobservable) factors that affect bank behavior. For example, aging counties could, for whatever reason, face better economic prospects in terms of their unemployment trajectory or income growth. Banks more exposed to aging counties would then also be more exposed to faster growing areas, which poses a threat to our identification strategy. To address this concern beyond the fixed effects strategy (explained below), we construct exposure in Equation (1) based on Δold predicted by the historical demographic structure. In addition, and to test whether exposure to aging counties is correlated with exposure to counties with better growth trajectories, we compute exposure to the changes in local unemployment rates and income per capita, analogous to Equation (1). We obtain a strong first stage, with an F-statistic of almost 60.

LTI ratios, loan and deposit growth. Home Mortgage Disclosure Act data provide detailed information on banks' residential mortgage lending.[4] HMDA covers the vast majority of applications and approved mortgage loans in the U.S. The data include the application outcome (granted or denied), loan amount, and borrower income for each loan. We measure bank risk-taking through the loan-to-income (LTI) ratio, defined as loan volume over applicant income. The LTI ratio is a significant predictor of ex-post default (Fuster et al., 2021) and has been widely used in the literature to measure the riskiness of loans (Dell'Ariccia and Marquez, 2006; Dell'Ariccia et al., 2012; Duchin and Sosyura, 2014). We compute the 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:

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

[4] 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).

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 made loans in 1997 and 2007.

Further, we compute the change in loan amounts and deposits at the bank-county level as

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

where y is either HMDA loans or deposits. For our mortgage analysis, we use 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; Cortés and Strahan, 2017). To account for entry into and exit out of counties over the long time horizon, we standardize the change in variables by their respective mid-points. This definition bounds growth rates to lie in the interval $[-2, 2]$, where -2 implies that a bank exited a county between 1997 and 2007, and 2 that it entered (Davis and Haltiwanger, 1999). 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 and county 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, total residential mortgage loans, the 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. We collect 1997 and 2007 data on banks' total deposits, total liabilities, and total loans and compute the change in the logarithm of each variable.

At the county level, we further collect public information on debt-to-income ratios (Federal Reserve Bank of New York Consumer Credit Panel, available from 1999 onward). We also collect 1997 data on the log of the 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). The CBP also provides information on employment in tradable and nontradable industries. 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.

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.

Survey of Consumer Finances. The Survey of Consumer Finances (SCF) of the Federal Reserve provides detailed information on the allocation of households' financial assets. The SCF is a triennial cross-sectional survey on household assets and demographics. We combine the survey waves from 1998 and 2007 (41,366 observations). We collect information on respondents' total financial assets, deposits, and debt, as well as dummy indicators for whether they borrowed in the past year, had any outstanding debt, or whether they have been turned down for credit, or feared being denied credit in the past 5 years. As control variables, we further use data on the education level, number of children, gender, race, marital status, home ownership, and a dummy for business ownership.

2.2 Descriptive statistics

In the average county, the number of seniors (Δold_c) increased by 12%, with a standard deviation of 15%. These numbers suggest significant variation in population aging across U.S. counties.

Table 1 provides descriptive statistics for the main variables. In total, our sample includes 1,843 banks for which we have data on loans and deposits over the sample period. Panel (a) summarizes bank *exposure* and other balance sheet characteristics from the SDI. For the average bank, exposure equals 0.10, with a standard deviation of 0.11. As exposure reflects deposit-weighted aging, a mean of 0.10 implies that the number of seniors increased by 10% in the average county where a bank takes deposits.

Panel (b) reports summary statistics at the bank-county level. 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. For example, LTI ratios increased by more than 20 pp at the 90^{th} percentile. The share of denied loans increased by 7 pp on average. 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).[5] Along the intensive margin (disregarding bank entry and exit across counties), lending increased by 84% (17,643 observations). Finally, panel (c) reports summary statistics for county-level variables for the set of 2,163 counties.

Balancedness. To examine the balancedness in beginning-of-sample covariates among 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 and engage less in mortgage lending (the differences are significant at the 10% level). They are statistically similar in terms of the share of nonperforming loans, return on assets, capital ratio, ratio of deposits to liabilities, or efficiency ratio (reflecting overhead costs). There is also no significant difference in the share of C&I loans or the share of loans extended to no-branch counties.

A potential concern for identification is that banks strategically opened branches to benefit from future deposit inflows in anticipation of demographic trends. In the Online Appendix, we show that neither local aging nor bank exposure predicts in which counties banks open new branches prior to 1997. Specifically, we regress different measures that indicate whether banks opened branches on population aging or bank exposure and find no systematic relationship. These results mitigate concerns about such selection effects.

[5] The difference in the number of observations reflects that the average bank lends to counties in which it does not raise deposits.

3 Population aging and bank risk-taking

The unprecedented rise in the senior population has led to a debate on whether population aging leads to a build-up of risks in the financial sector. High savings rates among seniors might lead to an abundance of savings and depressed returns, thereby potentially encouraging banks to reach for yield and engage in risk-taking (IMF, 2019). Higher risk-taking by financial institutions in turn could give rise to financial instabilities (Brookings, 2019). In this section, we first analyze the effect of population aging on banks' loan-to-income ratios and non-performing loans. In the next section, we explore the underlying mechanism that drives the link between population aging and risk-taking.

3.1 Population aging and lending standards

To investigate the effects of an aging population on bank risk-taking, we estimate the following regression at the bank-county level:

$$\Delta LTI_{b,c} = \beta\ \Delta\ exposure_b + controls_{b/c} + \theta_c + \epsilon_{b,c}, \tag{4}$$

where $\Delta LTI_{b,c}$ is the change in bank b's average LTI ratio in mortgage lending in county c over the sample period. Variable $exposure_b$ is bank exposure to aging counties at the beginning of the sample, as defined in Equation (1). 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. We also control for the share of residential mortgages out of total assets, to preclude that our estimated coefficients are driven by exposure to the mortgage market, and to account for the riskiness of the overall bank portfolio. All controls are as of the beginning of the sample period. County controls include the change in the log of the total population, as well as the unemployment rate, log income per capita, the share of blacks, the log of the population, and the employment shares in manufacturing, retail, and services, also all at the beginning of the sample period. Standard errors are clustered at the bank and county level.

Equation (4) faces the common identification challenge to account for differences in the underlying characteristics of banks' borrowers. If more exposed banks lend to counties with different characteristics than less exposed banks, any observed change in LTI ratios 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, these fixed effects difference out demand forces and allow for identification of supply effects. Intuitively, these fixed effects enable us to compare two banks with different exposure that lend to the same county (Khwaja and Mian, 2008; Jiménez et al., 2014).

Table 3, panel (a) reports the regression results for Equation (4) and shows that higher exposure to aging counties leads to higher LTI ratios. Column (1) shows that exposure has a positive effect on bank risk-taking, significant at the 1% level. When we add bank controls in column (2), the coefficient of exposure remains similar in terms of sign, size, and significance. In line with results in Table 2, this finding suggests that exposure is not systematically correlated with other observable bank characteristics. Column (3) accounts for observable differences across borrower-counties by adding county controls, and column (4) further tightens identification by including borrower-county fixed effects. Holding all observable and unobservable county characteristics constant, exposure to aging counties is still associated with a highly significant increase in LTI ratios. The magnitude of the coefficient remains similar to column (2). Banks with one standard deviation (sd) higher exposure see a relative increase in their LTI ratio by $(0.11 \times 0.41 =)$ 4.5 pp.

Including bank controls, county controls, or county fixed effects in columns (2)–(4) does not materially change the size or significance of our coefficients relative to column (1), despite a substantial increase in the R^2. Our results hence suggest that the correlation between bank exposure and observable bank or unobservable county characteristics is low, reducing potential concerns about self-selection and omitted variable bias (Altonji et al., 2005; Oster, 2019).

To support the argument that exposure to aging counties causes an increase in risk-taking, column (5) replicates the specification in column (4), but instruments bank exposure with exposure constructed from the historical age structure (see Section 2). Supporting the notion that bank exposure is likely orthogonal to several bank and county characteristics, the coefficient on exposure remains positive and significant at the 1% level.[6] These findings suggest a causal effect of bank exposure on LTI ratios.

Providing further support for a causal link from exposure to risk-taking, column (6) additionally controls for banks' exposure to the *changes* in counties' income per capita and

[6] The first-stage F-statistic equals 54.43. The coefficient in the IV regression is larger than that in the OLS regressions, which could suggest that the IV overcomes measurement error in the exposure variable. Such mismeasurement could arise if, for example, seniors hold deposits in bank branches outside their residence county (which happens when e.g. 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).

unemployment rate. As discussed above, to the extent that aging counties might systematically differ in their economic prospects and growth trajectories, these exposure variables could explain changes in risk-taking and be correlated with exposure to aging counties. Accounting for these factors, column (6) shows that the coefficient on *exposure* declines only slightly in magnitude, but remains significant at the 1% level, which supports the plausible exogeneity of our IV.

The increase in risk-taking among exposed banks could be correlated with banks' overall credit growth or expansion into new markets. Indeed, the literature on credit booms has identified a negative effect of rapid credit growth on lending standards (Dell'Ariccia and Marquez, 2006; Dell'Ariccia et al., 2012). We investigate these possibilities in panel (b). Column (1) controls for loan growth in each bank-county cell. It shows that the estimated coefficient remains highly significant and declines only modestly in value compared to the baseline estimate in panel (a), column (5). In a similar spirit, column (2) shows that greater risk-taking by exposed banks is also present in counties where banks had a branch presence in 1997 and 2007, i.e., where there was no branch expansion. These findings suggest that risk-taking is not driven by banks' market expansion.

Previous work has further shown that a greater borrower distance to the nearest branch requires banks to rely more on hard information (DeYoung et al., 2008). A greater distance can hence result in less efficient screening and monitoring of borrowers, leading to the build-up of risks (Granja et al., 2022). These considerations suggest that an increase in LTI ratios in counties where banks have no physical presence could lead to greater increases in credit risk. We hence investigate whether the effect of exposure on risk-taking depends on banks' initial branch network.

In column (3), we first interact exposure with the dummy *no branch*, which takes on a value of one in counties where banks had no branch at the beginning of the sample period. Results show that banks increase their LTI ratios significantly more in counties where they have no branch. Column (4) confirms this finding once we add bank fixed effects to control for any unobservable bank-level characteristics. By opening new branches, banks can mitigate informational frictions in the lending process. Consistent with this interpretation, columns (5) and (6) show that the coefficient on the interaction term *exposure* $\times$ *no branch* increases in size when the dummy *no branch* takes on a value of one in counties where banks had no branches in 1997 *and* opened no branches until 2007.

Taken together, Table 3 shows that banks with higher exposure to aging counties increase their LTI ratios, especially in counties where they have no branches. These findings suggest an increase in credit risk, which we will investigate in the next section.

3.2 Do laxer lending standards result in higher credit risk and losses?

Does the aging-induced decline in lending standards lead to an increase in credit risk? Relatedly, are there consequences for the performance of exposed banks during a negative shock, and hence for financial stability more broadly?

Evidence from the Great Recessions suggests so: Figure 1, 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 extent for high-exposure banks, relative to low-exposure banks. The difference between the series peaks in 2010 and only reverts to similar levels by 2015. Figure 1 thus suggests that high exposure banks fared worse during the Great Recession, relative to low exposure banks. However, there was no discernible difference in pre-trends, i.e., greater risk-taking did manifest itself in higher NPL ratios only once the economy entered a downturn.

To investigate the effects of exposure on nonperforming loans in more detail, we estimate bank-level regressions of the following form:

$$\Delta y_b = \beta \; exposure_b + \delta \; exposure \; to \; \Delta hpi_b^{97-07} + controls_b + \epsilon_b, \tag{5}$$

where y_b is the 2007 to 2010 change in the ratio of nonperforming residential mortgage loans (1–4 family homes) to total assets or the ratio of overall nonperforming loans to total assets. Exposure denotes bank exposure to aging counties, predicted by the historical demographic structure. Bank controls include the log 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, the share of residential mortgages out of total assets, and overhead costs, all as of 1997. To ensure that our findings do not reflect that exposed banks are also more exposed to the pre-crisis housing boom, we construct banks' exposure to the change in county-level house price indices ('hpi') from 1997 to 2007 ($exposure \; to \; \Delta hpi_b$) analogously to Equation (1). In bank-level regressions, we can no longer control for possible confounding factors at the county level, so it is important to keep in mind that the coefficient β could at least in part reflect unobservable demand factors.

Column (1) of Table 4 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 the 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 around 12% stronger growth in nonperforming loans during the Great Recession (around one-sixth 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 conclusion, results in Table 3 suggest that banks exposed to aging counties increase their loan-to-income ratios, likely taking on credit risk. The effects are more pronounced in counties where banks have no physical presence – implying geographic spillover effects of population aging on financial stability. Table 4 shows that the aging-induced increase in risk-taking before the Great Recession led to a sharper increase in nonperforming loans during the crisis. Exposure to aging counties could therefore have exacerbated the negative effects of the Great Financial Crisis on bank health and financial stability – irrespective of banks' exposure to the housing boom.

In what follows, we explore the underlying mechanisms that drive the link between population aging and bank risk-taking.

4 Inspecting the mechanism: deposits and local loan demand

As we show in this section, banks operating in aging counties are subject to two opposing forces that affect their risk-taking behaviour. First, population aging leads to an increase in banks' available funding in the form of deposits. Second, an aging population reduces the local demand for credit.

4.1 Aging and deposits

Seniors have a higher propensity to hold deposits (Becker, 2007), consistent with a lower portfolio share of risky assets among older households (Fagereng et al., 2017). Panel (a) of Figure 2 plots average financial assets (left axis) and average deposits (right axis) for different age cohorts. Seniors, defined as the population of age 65 and above, hold on average about twice as much deposits as those in the cohort of 55-64, and more than three times as much as younger cohorts. The Online Appendix shows that the positive relationship between age and deposits is not explained by cohort fixed effects, nor by a large set of individual-level controls such as income, occupation, homeownership, or education.

Such differences in deposit holdings across age cohorts imply potentially large effects on banks' funding conditions when economies age, as deposits are a safe and cheap source of funding (Kashyap et al., 2002; Hanson et al., 2015; Carletti et al., 2021). Moreover, deposits by customers that have a longer relationship with a bank have been shown to be more stable (Iyer and Puri, 2012; Iyer et al., 2016) – which is the case for senior citizens.[7] Deposit inflows due to exposure to aging counties could hence be an important factor in explaining banks' risk-taking behavior.

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

$$\Delta deposits_{b,c} = \beta \ \Delta old_c + controls_{b/c} + \theta_b + \epsilon_{b,c}, \tag{6}$$

where $\Delta deposits_{b,c}$ is the change in bank b's deposits in county c over the sample period. The explanatory variable Δold_c is the change in the log county population of ages 65 and above. Due to a possible correlation between local aging and other county-level factors, we instrument Δold_c with the historical demographic structure, as explained in Section 2. County controls include the unemployment rate, log income per capita, the share of blacks, the log of the population, the change in the total population as well as employment shares in manufacturing, retail, and services, all at the beginning of the sample period. Bank controls include the log of total assets, return on assets, nonperforming loans, total deposits over total

[7]According to the Survey of Consumer Finances, respondents of age 65 and above are almost twice as likely than younger cohorts to state that they chose their financial institution because they "banked there a long time".

liabilities, Tier-1 capital ratio, non-interest income, the indicator on bank specialization, the share of residential mortgages out of total assets, and overhead costs, all at the beginning of the sample period. Standard errors are clustered at the bank and county level.

In Equation (6), a coefficient $\beta > 0$ would indicate 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, 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 5 shows that an increase in the number of seniors in a county increases bank deposits. 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. While we cannot include depositor-county fixed effects in Equation (6), in column (3) we include depositor-state fixed effects to control for confounding factors at the state level. The coefficient on Δ *old* declines in magnitude, but remains positive and significant at the 1% level.

In column (4), we further tighten identification and include bank fixed effects. 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 ($0.15 \times 0.640 =$) 9.6% (or around 8.4% of the average growth in deposits over the sample period). These results suggest a causal effect of local aging on bank deposits. To further support this interpretation, column (5) additionally controls for the *1997–2007 change* in counties' income per capita and unemployment rate (note that regressions already account for the change in the total population). In principle, differences in economic prospects could affect deposits and be correlated with population aging. Accounting for these factors, column (5) shows that the coefficient on Δold remains positive and significant at the 5% level.

4.2 The local demand for credit

Beyond the positive effect on deposits, an aging population could reduce the local 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. Further, an increase in the number of seniors 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).[8] Consistent with lower demand for credit by seniors, Figure 2, panel (b) shows that older cohorts have significantly lower debt levels than younger 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) also reflects this: While around 5% of younger cohorts state that they did not borrow, almost

[8]Several studies argue that aging contributes to slower growth and reduces investment opportunities (Fernald and Li, 2019). Maestas et al. (2023) and Gagnon et al. (2021) 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.

every third respondent of age 65 and above reports that he or she did not borrow.

We confirm these differences in borrowing behavior with respondent (i)-level data from the SCF. We estimate the following regression:

$$y_i = \beta \; respondent \; age \; 65_i + controls_i + \tau_t + \epsilon_i.$$

The independent variable *respondent age* 65_i is a dummy with a value of one if the respondent is of age 65 and above, and zero otherwise. Table 6 shows results. In columns (1)–(2), the dependent variable is a dummy that takes on a value of one if a respondent indicated that he/she has not borrowed over the past year. Column (1) shows that seniors are 20.9% more likely not to have borrowed, compared to younger respondents. Adding an extensive set of household-level controls (the log of total financial wealth, the education level, number of kids, gender, race, marital status, home ownership, and a dummy for business ownership), as well as survey wave fixed effects, narrows the gap only slightly in column (2). We obtain similar results when we use a dummy that takes on a value of one if a respondent indicated that he/she has no outstanding household debt in columns (3)–(4). For example, column (4) suggests that seniors are around 36% less likely to have any debt, compared to younger respondents. In principle, infrequent borrowing and no outstanding debt could also result from supply factors, e.g. age-specific discrimination by financial institutions that leads to higher denial rates. To investigate this explanation, columns (5)–(6) use a dummy for whether a respondent indicated that he/she has been turned down for credit or feared being denied credit in the past 5 years. Results show that seniors are significantly less likely to have been turned down for credit, which is consistent with the argument that seniors' demand for credit is lower than that of younger respondents.

To provide further evidence that an increase in the number of seniors reduces the *local* demand for credit, we decompose mortgage loan growth in each bank-county cell into supply and demand factors, following Amiti and Weinstein (2018). To do so, we start from the following equation: $\Delta HMDA = \alpha_c + \beta_b + \varepsilon_{c,b}$, where the dependent variable is the growth in the amount of all mortgages originated by bank b in county c. The borrower-county demand channel is captured by α_c, while β_b denotes the bank supply channel. As described in Amiti and Weinstein (2018), this equation implies an adding up constraint that makes it possible to recover α_c, and β_b through a weighted least squares regressions, with weights given by the beginning-of-period share of total loans of bank b originated in county c over total loans originated in county c. For our regressions, we aggregate demand factors to the county level and investigate how they are affected by local aging.

Table 7 shows that higher growth in the number of seniors has a significant and economically sizeable negative effect on the credit demand factor. Column (1) shows that an increase in the number of seniors leads to a significant decline in the demand for mortgages. Adding a battery of county-level controls in column (2) confirms this finding. In column (3), we use the instrumental strategy that we explain in Section 2 and confirm 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.

4.3 The geography of lending and banks' asset allocation

Taken together, the analysis in this section suggests that banks operating branches in aging counties are subject to deposit inflows, but at the same time face lower demand and fewer investment opportunities in these counties. These two forces could force banks to look for new clients, in particular in counties where they operate no branches. To investigate the effects of population aging on bank lending across markets, we estimate Equation (4) with the change in banks' mortgage lending in each borrower county as the dependent variable.

Table 8 shows that more exposed banks have higher loan growth over the sample period. In column (1), we regress the change in mortgage loan amounts 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 account for unobservable county characteristics through county fixed effects. The economic magnitude is sizeable: a one standard deviation increase in exposure is associated with an increase in bank lending by $(0.11 \times 1.377 =)$ 15.1%.

How does banks' exposure to aging counties shape the geography of their lending? If aging lowers the local demand for credit while increasing deposit inflows, banks may channel their loan supply to counties where they have no branches and are not directly exposed to the aging-induced decline in credit demand. To investigate this possibility, columns (3) and (4) interact exposure with the dummy *no branch* that takes on a value of one in counties where a bank operates no branches. In column (3), 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 almost 50% stronger in no-branch counties. Once we add bank fixed effects in column (4) to control for any unobservable bank-level characteristics, the interaction term remains similar in magnitude and significance. These results suggest that banks' exposure to aging counties leads to a significant and economically sizeable increase in credit, especially in counties where banks have no branches – in line with the findings for loan-to-income ratios, which suggested that banks relax lending standards by more in counties where they have no branches.

In face of lower demand for credit locally, banks not only can adjust their mortgage footprint geographically, but also shift their portfolio into other asset classes. To this end, we estimate bank-level regressions with bank exposure and bank-level control variables as independent variables. Columns (5) and (6) first use the change in the log of banks' total residential real estate loans as well as total loans and leases as dependent variables. Consistent with the HMDA results, more exposed banks see significantly higher growth in total residential real estate lending in column (5). However, growth in total loans increases by more, suggesting that banks shift their portfolio towards loan types that are less affected by the aging-induced decline in the local demand for credit.

Columns (7), (8), and (9) further look at growth in non-loan assets, i.e., in securities (SC), cash balances (CB), and trading account assets (TAA). Returns on these assets are unlikely to be correlated with changes in banks' local demand for credit. Results show that exposure has a significant positive effect on all three asset classes, with larger effects on securities and trading account assets. Taken together, these results suggest that banks exposed to aging counties use their funds to increase lending in counties not directly affected by lower loan demand, but also shift into asset classes other than mortgage loans.

5 Additional tests and robustness

Table 9 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. We find that the impact of exposure is stronger in the right tail of the LTI ratio distribution. Columns (3)–(4) further show that banks increase their LTI ratios by more in counties where they have no branch − and again especially in the right tail of the LTI ratio distribution. 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 (5) thus interacts exposure with banks' Tier-1 capital ratio. It shows that higher exposure leads to a significantly smaller increase in LTI ratios for well-capitalized banks.

Columns (6)–(8) use the share of loans denied as the dependent variable. Column (6) shows that more-exposed banks also denied significantly fewer loans, and column (7) shows that this is more pronounced among weakly capitalized banks. Column (8) 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 Table 9 complement our main finding that exposure to aging counties increases banks' risk-taking: banks with higher exposure increase risk-taking, especially among borrowers with higher LTI ratios, and they deny fewer loans.

The Online Appendix provides further details on our instrumental variable strategy. 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. We further show that controlling for changes in the prime working-age population or young population, either directly or via banks' exposure does not affect our results . 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. 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.

6 Conclusion

Exploiting geographic variation in the change in seniors across the U.S., we establish that banks more exposed to aging counties increase their loan-to-income ratios by more and experience a sharper rise in nonperforming loans during the Great Recession. Inspecting the mechanism, we find that an aging-induced inflow of deposits, together with a decline in the local demand for credit, explains the link between population aging and bank risk-taking.

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, and through geographic spillovers do so even in regions and countries that are not directly affected by an aging population. As advanced economies face an unprecedented increase in the number of seniors over the next decade, this is a worrying finding. However, the fact that risk-taking is more pronounced for banks with lower capital ratios could mean that prudent capital regulation limits the negative consequences of population aging for financial stability.

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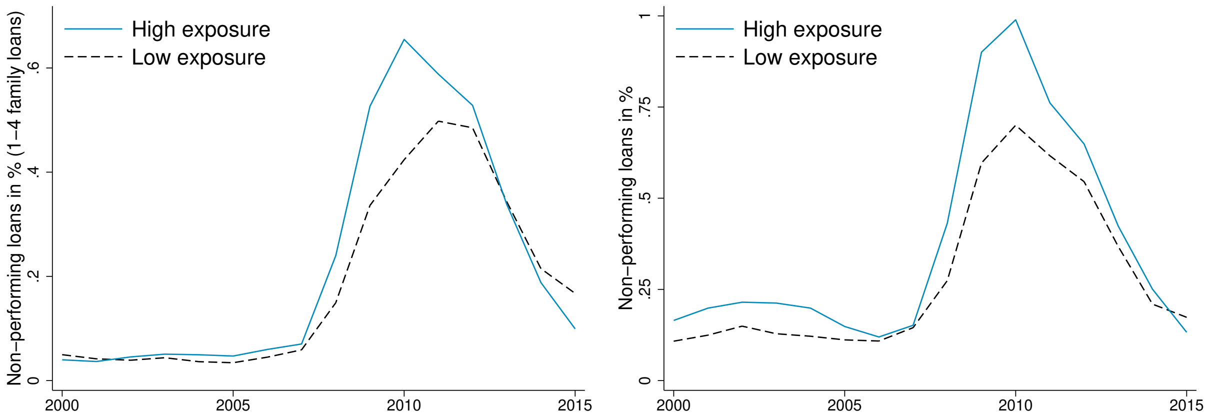
Figures and tables

Figure 1: **Nonperforming loans during the Great Recession**

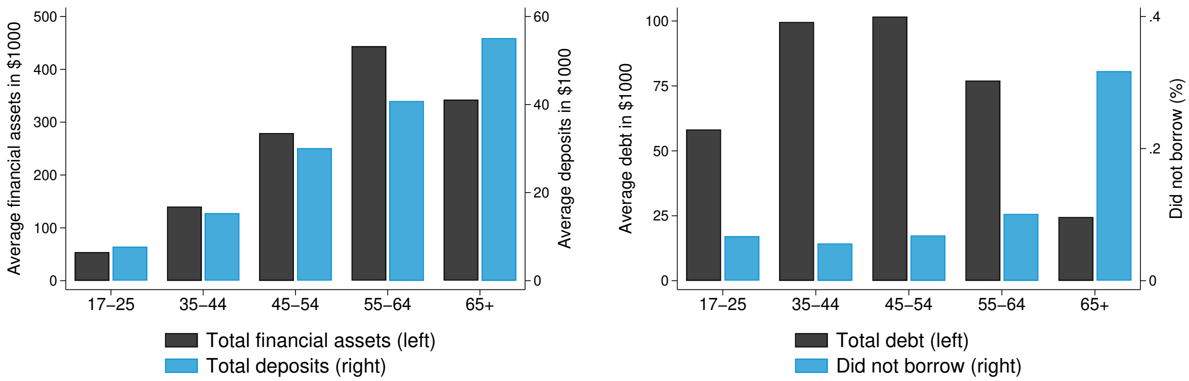
(a) Nonperforming 1-4 family loans (b) Nonperforming loans



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.

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.

Table 1: **Descriptive statistics**

	mean	sd	min	max	count
Panel (a): Bank level					
exposure	0.10	0.11	-0.12	0.55	1843
log(assets)	12.06	1.27	10.14	19.62	1843
non-performing loans (%)	1.69	4.20	-11.82	30.77	1843
return on assets (%)	1.16	0.56	-2.85	4.05	1843
deposits (%)	94.10	7.64	37.43	99.95	1843
tier 1 capital ratio (%)	17.87	9.53	7.69	84.74	1843
non-interest income (%)	79.96	81.75	1.90	617.53	1843
efficiency ratio	61.47	14.14	27.27	174.52	1843
share mortgages (%)	29.90	19.55	0.32	90.09	1843
Δ deposits	0.75	0.53	-0.41	3.21	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 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 (p90)	0.20	1.32	-4.64	6.18	20979
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 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	0.12	0.15	-0.34	1.01	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

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.

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 (%)	1.55	(0.38)	1.83	(0.45)	-0.28
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
efficiency (%)	61.67	(14.08)	61.28	(14.21)	0.39
share CI loans (%)	11.96	(12.08)	13.85	(11.31)	-1.89
share mortgages (%)	31.60	(19.61)	28.20	(19.34)	3.40*
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.

Table 3: **Population aging and lending standards**

Panel (a): Exposure to aging counties and LTI ratios

	(1)	(2)	(3)	(4)	(5)	(6)
					IV	IV
VARIABLES	Δ LTI	Δ LTI	Δ LTI	Δ LTI	Δ LTI	Δ LTI
exposure	0.443***	0.435***	0.446***	0.406***	0.678***	0.599***
	(0.068)	(0.071)	(0.073)	(0.076)	(0.091)	(0.091)
Observations	20,500	20,500	20,500	20,500	20,500	20,500
R-squared	0.002	0.060	0.066	0.110		
Bank Controls	-	✓	✓	✓	✓	Δ
County Controls	-	-	✓	-	-	-
County FE	-	-	-	✓	✓	✓
Bank FE	-	-	-	-	-	-

Panel (b): Branch networks

	(1)	(2)	(3)	(4)	(5)	(6)
	credit booms	stable BN			97 and 07	97 and 07
	IV	IV	IV	IV	IV	IV
VARIABLES	Δ LTI	Δ LTI	Δ LTI	Δ LTI	Δ LTI	Δ LTI
exposure	0.529***	0.766***	0.226*		0.144	
	(0.089)	(0.097)	(0.131)		(0.122)	
no branch			-0.115***	-0.180***	-0.131***	-0.162***
			(0.019)	(0.019)	(0.019)	(0.019)
exposure × no branch			0.484***	0.569***	0.735***	0.657***
			(0.165)	(0.168)	(0.152)	(0.160)
Observations	20,500	18,035	20,500	20,108	20,500	20,108
Bank Controls	✓	✓	✓	-	✓	-
County Controls	-	-	-	-	-	-
County FE	✓	✓	✓	✓	✓	✓
Bank FE	-	-	-	✓	-	✓

Note: Panel (a) shows results for Equation 4 at the bank-county level. The dependent variable is the change in the average loan-to-income (LTI) ratio. *exposure* denotes bank exposure to aging counties (as defined in Equation 1). Column (6) in panel (a) includes bank exposure to the 1997 to 2007 change in income per capita and the unemployment rate as additional bank-level controls. Column (1) in panel (b) controls for credit growth in each bank-county cell; column (2) restricts the sample to bank-county cells in which banks had branches in 1997 and 2007. *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, and zero otherwise in columns (3) and (4). In columns (5) and (6), the dummy takes on a value of one in bank-county pairs in which a bank does not operate branches in 1997 and 2007. Standard errors are clustered at the bank and county level. The Anderson-Rubin F-Statistic equals 54.43. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: **Nonperforming loans during the Great Recession**

VARIABLES	(1) Δ NPL (mort)	(2) Δ NPL (mort)	(3) Δ NPL	(4) Δ NPL
exposure	0.865***	0.852***	1.136***	1.123***
	(0.300)	(0.295)	(0.322)	(0.316)
exposure to Δ hpi 1997-07		0.276***		0.275***
		(0.087)		(0.083)
Observations	1,661	1,661	1,661	1,661
R-squared	0.081	0.091	0.102	0.109
Bank Controls	✓	✓	✓	✓

Note: This table shows results for regressions at the bank level. The dependent variable is the 2007 to 2010 change in the share of nonperforming residential mortgage loans (columns (1) and (2)); the 2007 to 2010 change in the share of nonperforming loans (columns (3) and (4)). *exposure* denotes bank exposure to aging counties (as defined in Equation 1), constructed from the predicted change in seniors. *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. The Anderson-Rubin F-Statistic equals 8.34. Standard errors are robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: **Population aging and local deposits**

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Δ deposits	Δ deposits	Δ deposits	Δ deposits	Δ deposits
Δ old	0.793***	0.759***	0.563***	0.640***	0.471**
	(0.294)	(0.279)	(0.195)	(0.203)	(0.203)
Observations	12,947	12,947	12,947	12,942	12,244
County Controls	✓	✓	✓	✓	Δ
Bank Controls	-	✓	✓	-	-
State FE	-	-	✓	✓	✓
Bank FE	-	-	-	✓	✓

Note: This table shows results for Equation 6 at the bank-county level in columns (1)–(5). The dependent variable is the change in deposits. Δold denotes the change in the log of the county population of ages 65 and above, predicted with the change in the population of age 45 to 65 from 1977 to 1987 in each county. Column (5) includes the 1997 to 2007 change in income per capita and the unemployment rate as additional county-level controls. Standard errors are clustered at the bank and county level. The Anderson-Rubin F-Statistic equals 16.38. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: **Seniors are less likely to borrow**

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	never borrow	never borrow	has any debt	has any debt	turned down	turned down
respondent age 65+	0.209***	0.188***	-0.422***	-0.358***	-0.251***	-0.158***
	(0.003)	(0.006)	(0.004)	(0.008)	(0.005)	(0.005)
Observations	41,366	41,366	41,366	41,366	41,366	41,366
R-squared	0.080	0.101	0.176	0.247	0.058	0.178
Survey wave FE	-	✓	-	✓	-	✓
Controls	-	✓	-	✓	-	✓

Note: This table shows results for the following regression $y_i = \beta$ $respondent\ age\ 65_i + controls_i + \tau_t + \epsilon_i$, where the age group 17-64 is the omitted category. The dependent variable in columns (1)–(2) is a dummy variable that takes on a value of one if a respondent indicated that he/she has not borrower over the past year. The dependent variable in columns (3)–(4) is a dummy variable that takes on a value of one if a respondent indicated that he/she has no outstanding household debt. The dependent variable in columns (5)–(6) is a dummy variable that takes on a value of one if a respondent indicated that he/she has been turned down for credit or feared being denied credit in the past 5 years. Columns (2), (4), and (6) add an extensive set of household-level controls: the log of total financial wealth, the education level, number of kids, gender, race, marriage status, home ownership, and a dummy for business ownership. Source: Survey of Consumer Finances 1998 and 2007. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: **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	-0.563***	-0.733**	-0.796**	-0.968***
	(0.206)	(0.318)	(0.357)	(0.252)
Observations	754	754	754	745
R-squared	0.008	0.203		
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 ages 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 and the unemployment rate as additional county-level controls. Standard errors are robust. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: **Bank exposure and lending**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					bank	bank	bank	bank	bank
VARIABLES	Δ hmda	Δ hmda	Δ hmda	Δ hmda	Δ RE	Δ loans	Δ SC	Δ CB	Δ TAA
exposure	1.728***	1.377***	0.720***		0.437**	0.612***	0.788***	0.508***	0.652**
	(0.095)	(0.094)	(0.186)		(0.178)	(0.159)	(0.262)	(0.170)	(0.300)
no branch			0.851***	0.651***					
			(0.023)	(0.024)					
exposure × no branch			0.654***	0.518***					
			(0.162)	(0.184)					
Observations	51,727	51,727	51,727	51,659	1,750	1,750	1,750	1,750	1,750
Bank Controls	✓	✓	✓	-	✓	✓	✓	✓	✓
County FE	-	✓	✓	✓	-	-	-	-	-
Bank FE	-	-	-	✓	-	-	-	-	-

Note: This table shows results for regressions at the bank-county level in columns (1)–(4) and at the bank level in columns (5)–(9). The dependent variable is the change in bank-county HMDA loans that are not sold by the end of the year in columns (1)–(4). It is the change in total residential mortgage loans and total loans in columns (5) and (6). Columns (7), (8), and (9) use the change in securities (SC), cash balances (CB), and trading account assets (TAA) as dependent variables. *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. Standard errors are clustered at the bank and county level in columns (1)–(4). Columns (5)–(9) use robust standard errors. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 9: **Robustness tests**

VARIABLES	(1) Δ LTI (p10)	(2) Δ LTI (p90)	(3) Δ LTI (p10)	(4) Δ LTI (p90)	(5) Δ LTI	(6) Δ denied	(7) Δ denied	(8) Δ denied
exposure	0.246***	1.014***			1.392***	-0.185***	-0.711***	
	(0.089)	(0.143)			(0.151)	(0.022)	(0.038)	
no branch			-0.247***	-0.129***				0.027***
			(0.018)	(0.032)				(0.005)
exposure × no branch			0.058	1.048***				-0.077**
			(0.149)	(0.266)				(0.036)
exposure × Tier-1 capital ratio					-3.449***		2.542***	
					(0.605)		(0.154)	
Observations	20,500	20,500	20,108	20,108	20,500	20,500	20,500	20,108
Bank Controls	✓	✓	-	-	✓	✓	✓	-
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank FE	-	-	✓	✓	-	-	-	✓

Note: This table shows results for Equation 4 at the bank-county level. The dependent variable is the change in the loan-to-income (LTI) ratio at different percentiles in columns (1)–(5); and the change in the share of loans denied in columns (6)–(8). *exposure* denotes bank exposure to aging counties (as defined in Equation 1). The variable *no branch* is a dummy with a value of one for bank-county pairs in which a bank does not operate branches in 1997; *Tier-1 capital* denotes banks' Tier-1 capital ratio (as of 1997); Columns (3), (4), and (8) include bank and county fixed effects. The remaining columns include bank controls and county fixed effects. Standard errors are clustered at the bank and county level. *** p<0.01, ** p<0.05, * p<0.1.

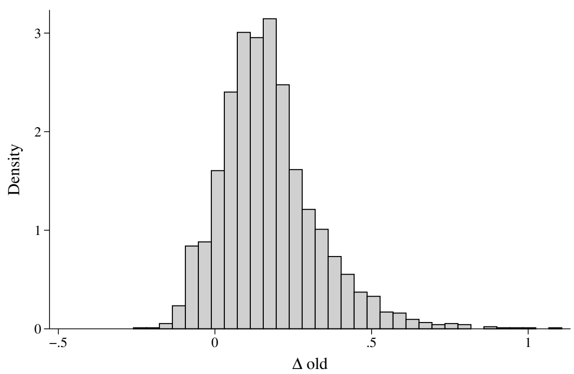
A Online Appendix

Table OA1: Variable Definitions

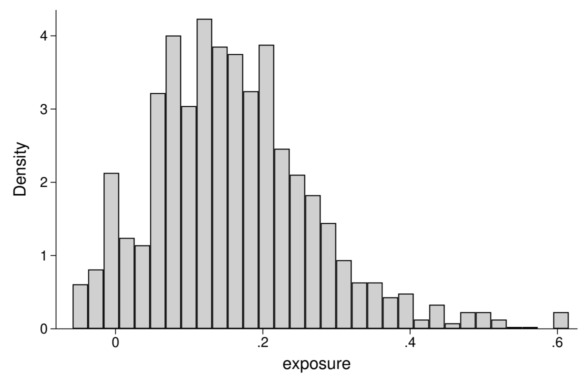
Variable name	**Description**	**Source**
Bank level		
exposure	bank exposure to aging counties (deposit-weighted)	FDIC SOD, NCI SEER
Δ deposits	change in total deposits	FDIC SDI
Δ loans	change in total bank loans	FDIC SDI
Δ mortgages	change in total residential mortgage loans	FDIC SDI
log(assets)	log 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(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

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

(a) County aging



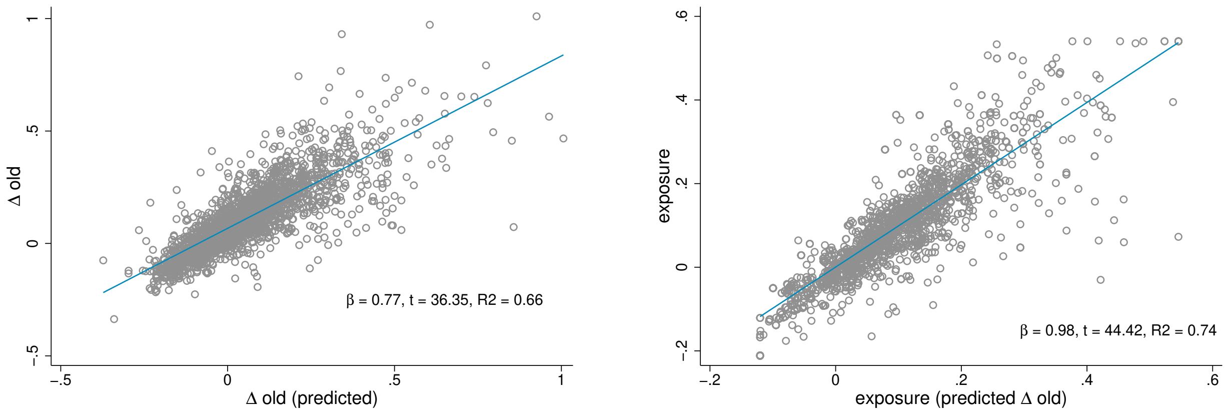
(b) Bank exposure



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).

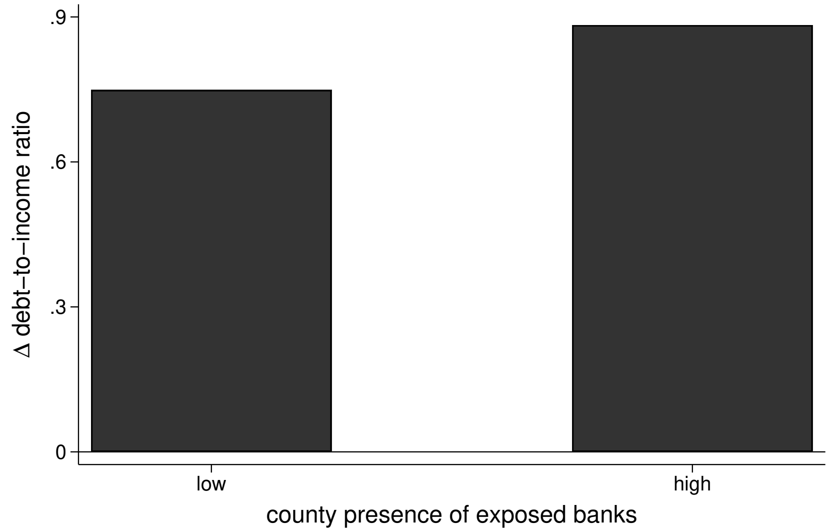
Figure OA2: **Instrumental variable strategy**

(a) First stage – aging (b) First stage – exposure



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) plots banks' actual and predicted exposure, where predicted exposure uses Δold $(predicted)$.

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**

	(1)	(2)	(3)	(4)
VARIABLES	log(deposits)	log(deposits)	log(deposits)	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 $log(deposits)_i = age\ group_i + controls_i + \tau_t + \epsilon_i$, where the age group 17-34 is the omitted category. Column (3) adds an extensive set of household-level controls: 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?**

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Δ branches	open br	entry	Δ branches	open br	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. 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 (6) 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, permanent branch sample, and denied loans**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					97 and 07	97 and 07		
VARIABLES	Δ hmda	Δ hmda	Δ LTI (avg)	Δ LTI (avg)	Δ LTI (avg)	Δ LTI (avg)	Δ denied	Δ denied
exposure	1.121***		0.849***		0.132		-0.232***	
	(0.077)		(0.096)		(0.115)		(0.025)	
no branch		0.634***		-0.211***	-0.138***	-0.162***		0.027***
		(0.026)		(0.023)	(0.019)	(0.019)		(0.005)
exposure × no branch		0.512**		0.670***	0.756***	0.657***		-0.073*
		(0.202)		(0.191)	(0.153)	(0.160)		(0.044)
Observations	49,781	49,633	19,140	18,644	20,500	20,108	19,140	18,644
Bank Controls	✓	-	✓	-	✓	-	✓	-
Bank size*County FE	✓	✓	✓	✓	✓	✓	✓	✓
Bank FE	-	✓	-	✓	-	✓	-	✓

Note: This table shows results for regressions at the bank-county level. The dependent variable is the change in bank-county HMDA loans in columns (1)–(2); the change in the LTI ratio in columns (3)–(6); and the change in the share of denied loans in columns (7)–(8). *exposure* denotes bank exposure to aging counties (as defined in Equation 1). In columns (3)–(4), *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. In columns (5)–(6), *no branch* is a dummy with a value of one for bank-county pairs in which a bank had no branches in 1997 *and* did not open any branches during the sample period, 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.

Amiti-Weinstein Decomposition

To provide evidence on the negative influence of aging on local mortgage loan demand, we use the method developed by Amiti and Weinstein (2018). To understand the intuition behind this method, consider the following fixed effects model

$$\Delta L_{cbt} = \alpha_{ct} + \beta_{bt} + \epsilon_{cbt}, \tag{OA1}$$

where the growth in loans of borrower c (a county in our case) obtained from a lender b at time t is regressed on borrower-time (α_{ct}) and lender-time (β_{bt}) fixed effects. α_{ct} captures the component in loan variation explained by borrower-level variation and β_{bt} captures the component explained by lender-level variation. Amiti and Weinstein (2018) illustrate that the empirical counterparts of α_{ct} and β_{bt} provide estimates for loan demand and loan supply channels, respectively, if appropriately weighted.

Amiti and Weinstein (2018) develop their method by modifying the model in OA1 in two ways. The first modification ensures that the estimated borrower and lender shocks aggregate up to exactly match total loan growth in the economy. They show that this adding up constraint is satisfied when one uses lagged loan amounts as weights. The second modification establishes that the method incorporates both the formation and termination of lending relationships. This modification is done by changing the normalization by dropping the first borrower and lender from the estimation.

Formally, these modifications enable Amiti and Weinstein (2018) to obtain lender- and borrower-level shocks by solving the following system of $B + C$ equations up to a numeraire:

$$D^B_{bt} = \frac{\sum_f L_{cbt} - \sum_f L_{cb,t-1}}{\sum_c L_{cb,t-1}} = \hat{c}_t + \hat{\ddot{\beta}}_{bt} + \sum_c \phi_{cb,t-1}\hat{\ddot{\alpha}}_{ct} \tag{OA2}$$

$$D^C_{ct} = \frac{\sum_b L_{cbt} - \sum_b L_{cb,t-1}}{\sum_b L_{cb,t-1}} = \hat{c}_t + \hat{\ddot{\alpha}}_{ct} + \sum_b \theta_{cb,t-1}\hat{\ddot{\beta}}_{bt} \tag{OA3}$$

where D represents the growth of bank's total lending, or firm's total borrowing, and $\hat{c}_t$ is a time fixed effect. $\phi_{cb,t-1} \equiv \frac{L_{cb,t-1}}{\sum_c L_{cb,t-1}}$ and $\theta_{cb,t-1} \equiv \frac{L_{cb,t-1}}{\sum_b L_{cb,t-1}}$ show the weight of each loan for the banks and counties, respectively. $\hat{\ddot{\beta}}_{bt}$ and $\hat{\ddot{\alpha}}_{ct}$ are modified forms of $\hat{\beta}_{bt}$ and $\hat{\alpha}_{ct}$ in OA1, where $\hat{\ddot{\beta}}_{bt} \equiv \beta_{bt} - \beta_{1t}$ and $\hat{\ddot{\alpha}}_{ct} \equiv \alpha_{ct} - \alpha_{1t}$. Note that β_{1t} and α_{1t} are the fixed effects of the first lender and borrower, which are dropped from the estimation for normalization purposes. In these equations, $\ddot{\beta}_{bt}$ captures the lender supply shocks and $\ddot{\alpha}_{ct}$ the borrower demand shocks. In words, this method explains a lender's aggregate loan growth by lender-specific loan supply factors and a weighted average of changes in loan demand of its borrowers. Similarly, a borrower's aggregate loan growth is driven by its loan demand and a weighted average of loan supply factors of all its lenders.

After obtaining α_{ct} and β_{bt}, we can decompose the aggregate loan growth D_t into three components.

$$D_t = (\bar{A}_t + \bar{B}_t) + \mathbf{W^B_{t-1}\Phi_{t-1}\dot{A}_t} + \mathbf{W^B_{t-1}\dot{B}_t} \tag{OA4}$$

The first component, $(\bar{A}_t + \bar{B}_t)$, shows the common shocks on aggregate lending and measures what happens to the lending of the median borrower-lender pair. The second components are vectors, $\mathbf{\dot{A}_t}$ and $\mathbf{\dot{B}_t}$, that stack borrower- and lender-level shocks, α_{ct} and β_{bt}. These vectors show the granular shocks a là Gabaix (2011) and are expressed as deviations from

$\bar{A}_t$ and $\bar{B}_t$. These vectors measure the importance of granular shocks on aggregate lending. $\mathbf{\Phi_{t-1}}$ is a weighting matrix and $\mathbf{W^B_{t-1}}$ is the share of lender l's loan volume out of total lending by all lenders in year t.