Banking On Demography: Population Aging and Financial Integration*

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November 12, 2019

Abstract

This paper argues that an integrated financial sector mitigates negative effects of population aging. We show that U.S. counties with an aging population see an increase in local deposits, reflecting higher saving rates of seniors. Banks use these deposits to increase credit supply. Using detailed data on mortgage lending, we find that banks channel deposits from aging counties towards counties with a younger population. We find no evidence that banks engage in risky lending: they lend less to counties with a high share of sub-prime borrowers or low incomes, and do not lend disproportionately to low-income borrowers. The increase in credit supply has real effects. Counties with a higher market share of aging-exposed banks see an increase in house prices and building permits, as well as in firm formation. Results are robust to controlling for bank and county characteristics through granular fixed effects and an instrumental variable strategy.

JEL classification: E44, G20, G21, J11

Keywords: Demographics, population aging, financial integration, mortgage lending, house prices

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1 Introduction

'America's Biggest Economic Challenge May Be Demographic Decline'
– New York Times, April 2019

Advanced economies are graying. In the U.S., population 65 and up will grow by 18 million over the next decade, increasing its share of the population from 17% today to 21% by 2030. The relentless demographic change threatens living standards: fewer investment opportunities for abundant savings could trap aging economies in an environment of persistently low growth (Adler, Duval, Furceri, Çelik, Koloskova and Poplawski-Ribeiro, 2017). Recent studies confirm that the post-crisis slowdown in growth mainly stems from demographic trends (Fernald, 2016; Fernald and Li, 2019). Faced with threat of secular stagnation, academics and policy makers debate on how to best cope with demographic developments (Berger, Dabla-Norris and Sun, 2019).

This paper argues that an integrated financial sector mitigates negative consequences of population aging by re-allocating capital across markets. Using data on bank deposits at the U.S. county level, we first show that local aging leads to an increase in bank deposits – reflecting that seniors hold more deposits. We then establish that banks use the increase in local deposits to supply credit to *other* counties where they do not raise deposits. Exploiting detailed data on banks' mortgage lending at the county level, we find that integrated banks channel funds from aging counties towards areas with a relatively young population. The increase in loan supply has real effects: building permits increase, and so do house prices and firm formation.

We find no evidence that banks lend to riskier borrowers. While the increase in loan supply leads to higher household debt-to-income ratios, banks lend relatively less to counties with low per capita income or a high share of subprime borrowers. When we differentiate borrowers by income groups, banks do not extend more credit to low-income borrowers, relative to high-income borrowers. Consequently, the share of subprime borrowers declines faster in counties with a stronger increase in credit supply.

Our study begins by investigating the link between local aging and bank deposits. Using the log change in population aged 65 and above from 1997 to 2007 at the county level, we find that an increase in seniors has a positive and strongly significant effect on bank deposits. An increase in elderly population of 10% over a decade leads to an increase in bank deposits of 4.6% over the same time period. The underlying channel is that seniors hold a relatively higher share of their wealth in the form of deposits (Becker, 2007). For banks to be able to channel local deposits to *other* markets, deposits need to increase for banks that operate across counties. We establish that local aging also increases deposits for diversified banks, i.e. banks that lend to multiple counties.

In a second step, we show that the increase in deposits affects bank lending. We define bank *exposure* to aging counties as the deposit-weighted average of the change in aging across counties where banks raise deposits. High exposure implies that banks raise a large share of their deposits in fast-aging counties. Using detailed HMDA data on residential mortgage lending at the bank-county level, we then establish that higher exposure leads to an increase in credit supply. A one standard deviation increase in exposure, corresponding to a synthetic 13% increase in (deposit-weighted) aging, leads to an increase in lending by 7.2%. The increase in lending is stronger in counties with a young population. For counties in the top tercile of the share of population age 20-34 in 1997, lending increases by an additional 1.7%. We include fixed effects at the borrower-county level to control for unobservable characteristics that affect loan demand.

Our estimation faces two key identification challenges. First, we need to ensure that the rise in deposits is due to an increase in local aging, and not due to omitted county or bank variables. We address the issue through fixed effects and an instrumental variable strategy. Our data at the bank-county level allow us to include granular bank fixed effects to control for unobservable bank characteristics, for example risk-taking, that might affect deposits. Coefficients remain significant and similar in magnitude when we account for bank-specific factors, despite a sizeable increase in R^2.

We further exploit plausibly exogenous variation in local aging by instrumenting the change in population 65 and older from 1997 to 2007 with unemployment during the Great Depression. We build on literature that shows a steep decline in fertility during times of economic hardship (Sobotka, Skirbekk and Philipov, 2011). The exclusion restriction is that historical unemployment must not affect the change in bank deposits from 1997 to 2007 through channels other than demographics. We first show that counties with higher unemployment in 1940 experience significantly slower aging over half of a century later. We then estimate two-stage least squares regressions to establish a causal effect of aging on bank deposits. Coefficients in instrumental variable regressions are similar in terms of sign and significance to OLS regressions.

The second challenge to identification is to separate changes in loan supply from loan demand when analyzing bank lending. If banks with high exposure lend to different borrowers than banks with low exposure, any observed change in loan volume reflects both demand and supply effects. Our bank-county level analysis employs county fixed effects to absorb all unobservable county fundamentals (Khwaja and Mian, 2008; Jiménez, Ongena, Peydró and Saurina, 2014). For example, they absorb changes in county employment, migration, or income. The coefficient on exposure is identical without and with county fixed effects, although R^2 increases threefold. This suggests that exposure is orthogonal to observable and unobservable borrower characteristics (Altonji, Elder and Taber, 2005; Oster, 2017).

To further strengthen identification and rule out any direct effect of local aging on bank lending (except through exposure) we exclude counties where banks raise deposits. 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 strongly 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. In other words, we look at lending by above bank to Arlington County only. Excluding deposit-taking counties does not affect coefficients in a statistically or economically meaningful way.[1]

Yet, even after accounting for demand effects, exposed banks could differ from banks with low exposure. For example, the largest or most profitable banks could have the highest exposure to aging counties. While we have no instrument for bank-level exposure, we show that our sample is balanced: high- and low-exposure banks are similar in their observable balance sheet characteristics. When we investigate where banks increase their lending in bank-county regressions, we control for differences across banks by including bank fixed effects. We thus hold all unobservable bank characteristics constant, for example bank size, risk, or capital. In essence, we compare lending by the same bank to the same county at different levels of exposure. Effects remain economically and statistically significant across specifications.

We also investigate whether banks increase their loan supply to risky borrowers. Literature establishes that the pre-crisis credit boom was an important factor contributing to the Great Recession (Mian and Sufi, 2009; Favara and Imbs, 2015). We find that exposed banks supply relatively less credit to low-income counties or counties with a high share of subprime borrowers, two common proxies for borrower risk. Further exploiting HMDA data on borrower income, we find no evidence that banks differentially increase lending to low-income borrowers. These results indicate that banks do not use their additional deposits to supply credit to borrowers that proved particularly risky during the Great

[1] The underlying assumption is that aging in Los Angeles County has no direct effect on mortgage lending in Arlington County, for example through trade. To further rule out linkages through demand for goods, we exclude borrower-counties with a high employment share in tradable industries. Baseline results remain unaffected. We also find that exposed banks decline fewer loans in young counties, further supporting a supply-side explanation.

Recession. Consequently, we find a significant decline in the share of subprime borrowers in counties where exposed banks have larger market shares.

After establishing that local aging leads to an increase in bank deposits and an increase in the supply of residential mortgages, we explore real effects. We show that counties in which exposed banks have a larger market share see an increase in debt-to-income ratios, as well as an increase in house prices and building permits. The positive effect of credit on housing markets also stimulates labor markets: employment increases, especially in the construction and non-tradable sector. We also find an increase in firm formation, reflecting the high sensitivity of young firms to local economic conditions. More firms form in industries that rely on home equity financing. Rising collateral values allow households to borrow against their increase in home equity and start a business.

The paper proceeds as follows. Section 2 provides an overview over related literature and our contribution. Section 3 describes main data sources and variable construction, Section 4 explains empirical strategy and presents results for bank deposits and lending. Section 5 sheds light on the real effects of the increase in loan supply, Section 6 concludes.

2 Literature & Contribution

Our paper speaks to three strands of literature. First, it connects to literature on the macroeconomic effects of population aging. The U.S. economy and other advanced economies are suffering from a secular decline in investment and growth (Fernald, 2014; Cette, Fernald and Mojon, 2016), which sparked a heated debate on causes and consequences (Gordon, 2015; Summers, 2015). One of the main contributors to the slowdown in growth is population aging (Adler, Duval, Furceri, Çelik, Koloskova and Poplawski-Ribeiro, 2017; Fernald, 2016). Maestas, Mullen and Powell (2016) provide state-level evidence for the U.S. that aging leads to lower growth, mainly due to declining labor productivity. Aksoy, Basso, Smith and Grasl (2019) show a negative effect of aging on growth for a sample of OECD countries, Gagnon, Johannsen and Lopez-Salido (2016) provide similar evidence for the U.S. To the best of our knowledge, our paper is the first to empirically investigate the role of the financial sector in mitigating or exacerbating these trends. Our results suggest that better financial integration allows excess savings to be productively used in *other* areas. We thus contribute to the debate on the macroeconomic effects of aging by showing that financial integration is paramount to mitigate the negative relationship between a graying population and growth.

Second, we contribute to literature on banking integration and the current discussion on rising concentration in the banking sector.[2] Recent papers use local shocks, such as natural disasters or gas shale discoveries, to show that banks use internal capital markets to adjust lending (Gilje, Loutskina and Strahan, 2016; Cortés and Strahan, 2017). A related paper is Becker (2007), who uses the fraction of seniors as an instrument to investigate the effects of deposits on firm formation. Our paper analyzes the role of banking integration during secular demographic change and how it affects lending in connected markets. While policy makers worry about adverse effects of rising concentration in the U.S. banking sector, resulting from an ever-growing market share of large banks, we show one important benefit of deeper financial integration: banks re-allocate credit from savings-abundant aging counties to counties with higher growth potential.[3] This channel is likely to grow in relevance in light of rapidly aging population in advanced economies.[4]

Finally, we speak to literature that highlights the role of credit in fueling the pre-crisis housing boom (Mian and Sufi, 2009; Adelino, Schoar and Severino, 2016). Chakraborty, Goldstein and MacKinlay (2018) show that banks shift from commercial into residential real estate lending when local markets experience an increase in real estate values. Favara and Imbs (2015) and Justiniano, Primiceri and Tambalotti (2019) find that an increase in credit supply explains the pre-crisis increase in house prices and household debt. A prominent explanation for the increase in credit supply is the global savings glut hypothesis (Bernanke, 2005). Our paper offers an additional cause of the increase in credit: an aging population and its large pool of savings allow banks to increase credit supply.

3 Data & Variable Definitions

This section explains the construction of our main variables and reports descriptive statistics. For detailed variable definitions and sources, see Appendix B.

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[2] Higher competition improves access to credit for borrowers that rely on soft information, e.g. small firms (Rice and Strahan, 2010; Chava, Oettl, Subramanian and Subramanian, 2013; Berger, Bouwman and Kim, 2017; Liberti and Petersen, 2019), as well as financial inclusion (Celerier and Matray, 2016).

[3] We relate to work on the role of geographically diversified banks in transmitting shocks across different markets (Peek and Rosengren, 1997, 2000; Cetorelli and Goldberg, 2012; Schnabl, 2012; De Haas and Van Lelyveld, 2014; Doerr and Schaz, 2019).

[4] Our work is related to macroeconomic work on capital flows (or lack thereof). Standard models predict that capital-abundant (advanced) countries should invest their savings in capital-scarce (developing) countries (Alfaro, Kalemli-Ozcan and Volosovych, 2014). However, in the data capital does not flow from rich to poor countries (Prasad, Rajan and Arvind, 2007; Gourinchas and Jeanne, 2013), one of the main reasons being weak institutions (Alfaro, Kalemli-Ozcan and Volosovych, 2007; Broner and Ventura, 2010). Our paper shows that, in an advanced economy like the U.S., capital flows from aging slow-growth to young high-growth areas, suggesting that frictions across international borders impede an efficient allocation of capital.

County Data Our main explanatory variable at the county level is the log change in population age 65 and above from 1997 to 2007, Δold_c^{97-07}.[5] We define $share\ young_c$ as the 1997 share of population age 20-34. Detailed population data by age cohort is provided by the National Cancer Institute SEER program. Information on employment in the construction sector, tradable, and non-tradable industries is provided by County Business Patterns (CBP).[6] We also collect 1997 and 2007 data on house prices (source: FHFA), building permits (geoFRED), debt-to-income ratios (FRBNY Consumer Credit Panel, available from 1999), and the share of sub-prime borrowers (geoFRED, available from 1999). Finally, we collect data on employment in firms age zero to one (start-ups) at the county-industry level for 2000 and 2007, provided by the Census Bureau's Quarterly Workforce Indicators (QWI).

As county controls, we include 1997 values of log population (NCI SEER), unemployment rate and labor force participation rate (BLS LAUS), log income per capita (BEA LAPI), as well as employment shares in manufacturing (SIC code 20), wholesale & retail trade (SIC code 50), as well as finance, insurance, and real estate (SIC code 60), provided by CBP.

Bank Data The Federal Deposit Insurance Corporation (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, share of non-interest out of total income, overhead costs (efficiency ratio), non-performing loans, return on assets, total deposits, total liabilities, cash and balances due, and total investment securities. We also collect data on banks' total and residential mortgage lending.

To calculate bank exposure to aging counties, we use data by the FDIC's Summary of Deposits (SOD), which provide yearly information on the geographic distribution of bank deposits. We compute bank exposure as

$$exposure_b = \sum_c \frac{deposits_{b,c}}{deposits_b} \times \Delta old_c^{97-07}, \tag{1}$$

where $deposits_{b,c}$ and $deposits_b$ denote bank b's deposits in county c and bank b's total deposits (both in 1997), and Δold_c^{97-07} is county c's log change in population 65 and older. High $exposure_b$ implies that a large share of bank deposits is held in aging

[5] In the Online Appendix we show that our results remain similar if we use the change in the share of seniors instead of their absolute number.

[6] See Mian and Sufi (2014) and Adelino, Schoar and Severino (2015): two-digit NAICS codes are construction = 23; non-tradable = 44, 45, 72; tradable all other.

counties, while low exposure implies that deposits are held in counties with a low increase in elderly population. An increase in exposure 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 elderly (Δold) of 50% and the other county sees no change in its senior population, exposure equals ($0.5 \times 0.5 + 0.5 \times 0 =$) 0.25. Exposure is constructed using pre-treatment deposit shares, alleviating concerns about banks selectively opening branches in aging counties.

We use data at the bank-county level on residential mortgage lending in 1997 and 2007, provided by the Home Mortgage Disclosure Act (HMDA).[7] HMDA collects home mortgage application data, covering the vast majority of applications and approved loans in the U.S. The data include application outcome, loan amount, and income for each year.[8] We use 1997 HMDA loan data to construct bank diversification as one minus banks' Herfindahl index across counties:

$$diversification_b^{97} = 1 - \sum_c \left(\frac{loan_{b,c}}{loan_b} \right)^2. \tag{2}$$

High values of diversification imply that banks operate in multiple counties, low values imply that banks operate in few counties or allocate a large share of their loan portfolio to few counties. We define *diversified* as a dummy with value one for banks in the top decile of diversification in 1997. Diversified banks extend around 50% of all HMDA loans in our sample.

As main bank-county level outcome variables, we define the 1997 to 2007 change in deposits and HMDA loans. To account for entry into and exit from counties over the long time period, we standardize the change in deposits and lending by their respective mid-points:

$$\Delta y_{b,c}^{97-07} = \frac{y_{b,c}^{07} - y_{b,c}^{97}}{y_{b,c}^{07} + y_{b,c}^{97}} \times 2,$$

where y denotes either deposits or HMDA loans. This definition bounds growth rates to lie in $[-2, 2]$, where -2 implies that a bank exited a county from 1997 to 2007, and 2

[7] We follow the literature and restrict the sample to conventional or FHA-insured loans, exclude multi-family properties, and keep only originated, approved, and purchased loans. We also drop all observations with missing fips codes or missing borrower income and loans outside of MSAs.

[8] In 2007 mortgage lending averaged around 30% of banks' total lending, and 40% for the largest banks. Additionally, HMDA data represents 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.

that it entered.[9]

Descriptive Statistics Figure 1 provides a map of Δold_c^{97-07} across U.S. counties, where darker areas indicate higher values. There is significant variation in aging across the U.S., as well as within individual states. Most areas see an increase in population 65 and above, with the exception of counties near the Great Plains.

[Figure 1 about here]

Table 1 provides descriptive statistics for our main variables. Panel (a) reports bank balance sheet characteristics from FDIC SDI. Δ denotes changes from 1997-2007, all other variables are as of 1997. In total, our sample includes 2,068 banks. For the average bank, *exposure* increased by 0.09 units, with a significant standard deviation of 0.13. Exposure reflects deposit-weighted aging; a mean of 0.09 implies that the number of seniors increased by 9% in the average county where banks take deposits. Panel (b) reports the 1997 to 2007 change in deposits ($\Delta deposits$) and mortgage lending ($\Delta HMDA$) at the bank-county level. For the average bank-county pair, deposits increased by 16% over the time period (26,518 observations); mortgage lending increased by 120% on average (75,734 observations). The difference in observations reflects that the average bank lends to counties in which it does not raise deposits – a fact we will exploit for identification. Finally, panel (c) reports county level variables for our set of 2,811 counties. Total elderly population (Δold) increased on average by 10% from 1997 to 2007, while the young population remained stable. The mean increase in 10% is close to the mean change in bank *exposure*.

[Tables 1 and 2 about here]

To examine the balancedness of our sample of banks, Table 2 runs multivariate regressions at the bank level, using *exposure* as dependent variable (all variables are normalized). All regressions account for heteroskedasticity through robust standard errors. For our full sample of 2,068 banks, the sample is balanced: no explanatory variable enters the regression significantly at conventional levels. This finding holds for bank holding companies

[9] While the log difference is symmetric about 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 about 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).

with 1997 total assets above 10bn (column 2) and above 50bn (column 3). When we restrict the sample to diversified banks with diversification values above 0.5 and 0.8 in columns (4) to (5), only non-performing loans are a significant explanatory variable of exposure. Results suggest that exposed and non-exposed banks are comparable; we will show that our main findings hold within each sub-sample.[10]

4 Empirical Strategy & Results

This section lays out empirical strategy and reports main results. We first examine how local aging affects bank deposits. In a second step, we analyze how these additional funds change banks' supply of mortgage credit.

4.1 Population Aging & Local Deposits

In a first step, we exploit demographic variation in savings behavior. Figure 2 shows that seniors, defined as population age 65 and older, hold more bank deposits than younger cohorts (Becker, 2007). Based on data from the Survey of Consumer Finances, panel (a) plots average financial assets (left axis) and average deposits (right axis) for different cohorts. Older cohorts have higher levels of financial wealth, as well as deposits. For example, the age cohort of 65+ holds about twice as many deposits as the cohort of 55-64, and more than three times as much as younger cohorts. Not only do elderly hold more deposits, they also have lower debt and are less likely to borrow. In panel (b), younger cohorts have significantly higher debt levels than older cohorts (left axis); for the cohort of 65+ total debt is close to zero. This is reflected in the share of respondents stating that they currently do not borrow money (right axis). While around 5% of younger cohorts state that they did not borrow, almost every third respondent age 65+ reports that he or she did not borrow.

[Figure 2 about here]

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

[10] In unreported regression, we show that aging at the county level has an insignificant effect that is close to zero in magnitude on the probability of a bank opening a branch before our sample period. In other words, we find no evidence that banks open branches in anticipation of future aging, suggesting that there is no selection effect.

funding: as of 1997, the average bank had a ratio of deposits to total liabilities of 84%. A large literature highlights the special role of deposits and how they affect bank lending and risk taking.[11] Building on the fact that older cohorts hold more bank deposits, we investigate the relationship between secular changes in local aging and bank deposits in the following cross-sectional regression equation:

$$\Delta deposits_{b,c}^{97-07} = \beta \ \Delta old_{c}^{97-07} + controls_{b/c} + \theta_b + \epsilon_{b,c}, \tag{3}$$

where $\Delta deposits_{b,c}^{97-07}$ is the change in bank b's deposits in county c from 1997 to 2007; Δold_{c}^{97-07} is the log change in county population age 65 and above from 1997 to 2007. All regressions include bank and county controls as of 1997. Bank controls are log total assets, return on assets, non-performing loans, total deposits over total liabilities, tier-1 capital ratio, non-interest income, overhead costs, and liquidity (defined as cash and gains from securities over total assets). County controls are log population, labor force participation rate, unemployment rate, log income per capita, and employment shares in manufacturing, wholesale and retail trade, as well as finance, insurance, and real estate. Standard errors are clustered on the county (treatment) level to account for correlation among residuals within counties.

In regression equation (3), $\beta > 0$ 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. Since we analyze how banks channel local deposits to other markets, it is necessary that deposits increase also for banks that lend to multiple counties. To this end, we estimate regression (3) separately for concentrated and diversified banks. Diversified banks are banks in the top decile of loan diversification across markets (see equation (2)).

Coefficients in regression equation (3) reflect changes in savings behavior (demand side), but also changes in bank behavior that could affect incentives to deposit funds (supply side, for example changes bank risk). Disaggregated bank-county data allow us to include bank fixed effects (θ_b) that absorb any unobservable bank characteristics. In essence, we compare the effect of aging on deposits of identical banks, as we hold all bank characteristics constant.

[Figure 3 about here]

[11]See, for example, Diamond and Dybvig (1983); Gorton and Pennacchi (1990); Calomiris and Kahn (1991); Diamond and Rajan (2000); Soledad Martinez Peria and Schmukler (2001); Kashyap, Rajan and Stein (2002); Hanson, Shleifer, Stein and Vishny (2015); Arslan, Degerli and Kabaş (2019).

Figure 3 shows a scatter plot of the change in deposits against the change in population 65 and above from 1997 to 2007 on the county level. There is a strong positive relationship, indicating that aging areas see an increase in deposits. To investigate the relationship more rigorously, Table 3 reports regression results for regression equation (3) and shows that aging increases bank deposits. Column (1) shows that local aging has a significant positive effect on deposits of a bank in the same county. Once we add bank fixed effects to control for unobservable bank characteristics in column (2), effect size remains stable. Columns (1)-(2) thus suggest that local aging is associated with a significant and sizeable increase in local deposits, with an elasticity of 0.58. The stability of the coefficient in light of an increase in R^2 of 0.8 suggests that aging is orthogonal to unobservable bank characteristics (Altonji, Elder and Taber, 2005; Oster, 2017).[12]

[Table 3 about here]

We are interested in how banks use local deposits to lend to other counties. This requires that deposits increase for diversified banks that operate in multiple counties. To this end, columns (3) and (4) split the sample into concentrated and diversified banks. Deposits rise significantly for concentrated banks in column (3), and for diversified banks in column (4). Effect size is slightly larger in magnitude for diversified banks. Column (5) interacts Δold with *diversified*. Confirming results in columns (3)-(4), there is a stronger increase in deposits of diversified banks when local economies age. However, the difference is not statistically significant. All in all, Table 3 shows that (diversified) banks see an increase in local deposits when the population ages.

A concern for our estimation is that local aging could be correlated with unobservable county characteristics. For example, aging counties could face dim economic prospects; omitted variables would bias our estimation results. To identify the causal effect of aging on bank deposits, we employ an instrumental variables (IV) strategy that isolates plausibly exogenous variation in local aging based on historical changes in counties' demographic structure. Specifically, we instrument the change in seniors from 1997 to 2007 with log unemployment in 1940. Our argument builds on a large literature that establishes a strong negative effect of economic hardship on fertility rates (Fishback, Haines and Kantor, 2007; Sobotka, Skirbekk and Philipov, 2011; Cherlin, Cumberworth, Morgan and Wimer, 2013).

We use county unemployment in 1940, at the nadir of the Great Depression, as a proxy for fertility rates, which are not available at county level. We argue that counties

[12]The fact that bank exposure is uncorrelated with bank characteristics (Table 2) and that the effect of aging on deposits does not change when we include bank fixed effects suggests that there is no selection effect: banks do not strategically open branches in counties in anticipation of faster aging.

with a more severe depression have fewer seniors 50 years later, i.e. at the beginning of our sample period. In other words, counties with a deeper economic downturn had fewer children between 1930 and 40; and since these children would have been old in 1997 to 2007, a worse depression (and hence lower fertility) is associated with slower aging from 1997 to 2007. For illustration, let us consider a simple example.

Between 1907 and 1942, there are three types of people born: the *early* (indexed by E) are born between 1907 and 1929; the *middle* (indexed by M) are born between 1930 and 31; and the *late* (indexed by L) are born between 1932 and 1942. Absent any major tragedies, E, M, and L live until age 90, after which they leave the economy. In 1997, E's+M's will be age 65 to 90 (i.e. old) and L's will be 55 to 64 (i.e. young). By 2007, a fraction $x < 1$ of E's will have died, i.e. those born between 1907 and 1917, since they reached the age of 90. All L's will now also be old. The total elderly population in 1997 and 2007 is thus given by

$$old_{1997} = E + M, \quad old_{2007} = (1 - x)E + M + L, \quad \Delta old = L - xE.$$

Now suppose that from 1930 onward hardship during the Great Depression depresses fertility rates. Building on work that shows the negative effect of poor economic conditions on fertility, this implies that between 1930 and 1940 there will be fewer births. This is, M and L will be lower, while E remains unaffected. How will this affect Δold? The effect on E does not matter – E's are born before the Great Depression and hence not affected by lower birth rates. Similarly, M's are old in 1997 and 2007 and hence the depression's effect on their size cancels out; however, L's are crucial: the stronger the decline in L, the slower aging in a county from 1997 to 2007.

For two hypothetical counties Adams County (indexed by A) and Brown County (indexed by B), suppose L_A remains constant, while L_B declines to L'_B (because of lower fertility during the Great Depression). Then

$$\Delta old^B - \Delta old^A = L'_B - xE_B - (L_A - xE_A) = L'_B - L_A = L_B - L_A + \Delta L_B = \Delta L_B,$$

where $\Delta L_B = L'_B - L_B < 0$. In other words, the worse the depression, the lower L'_B and hence the slower aging. The intuition is that fewer children are born in a cohort that will make up the new cohort of elderly in 2007, while the effect on the cohort of 1997 is zero (or at least negligible).

Our IV strategy will identify the effect of aging on deposits if it isolates the variation in aging that is uncorrelated with changes in local economic conditions from 1997 to

2007. In other words, unemployment during the Great Depression must not affect the *change* in bank deposits from 1997 to 2007 through any channel other than the *change* in seniors over the same time period. The underlying identifying assumption is hence that the geographic distribution of 1940 unemployment across counties is plausibly exogenous to changes in local economic conditions over half of a century later.

How do we expect omitted variables to bias our OLS regression? Literature argues that aging counties have bleaker economic prospects and lower growth. All else equal, lower growth reduces deposits; the negative correlation between aging and growth leads to a downward bias in our estimation.[13] However, in our data we find no evidence of such a negative relationship: aging is uncorrelated with local income per capita growth or the change in the unemployment rate over the sample period (see Online Appendix). While the absence of evidence is not evidence of absence, we expect the bias in OLS regressions to be modest and IV estimates to be similar in magnitude.

Data on unemployment in 1940 is provided in ICPSR's *Historical, Demographic, Economic, and Social Data: The United States, 1790-1970*, i.e. the historical census at the U.S. county level. We collect 1940 unemployment data for 2,589 counties. During the Great Depression, the unemployment rate increased from around 5% in 1930 to over 20% in the early 1930s and remained elevated at around 15% in 1940. Since the census is decennial, we have no disaggregated information on unemployment in 1935 and hence use 1940 values. Several papers show for historical and current episodes that unemployment, or economic hardship in general, has a negative effect on fertility rates (see Cherlin, Cumberworth, Morgan and Wimer (2013)). We thus use unemployment in 1940 as a proxy for the decline in fertility during the Great Depression.

Our setting requires the following identifying assumption: the depth of the Great depression must not affect bank deposits through omitted variables more than 50 years after the end of the Second World War. To further bolster identification, we control for state-level variation through state fixed effects, exploiting only variation in historical unemployment across counties within the same state for identification.[14] We further include county characteristics as of 1940 to isolate the effect of unemployment. We control for 1940 county population, share of blacks, share of population with no schooling, share of foreign born population, share of rural population, as well as average wages in retail.

[Table 4 about here]

[13] Hence, even if our instrument does not fully purge regressions from these omitted factors, IV regressions provide a conservative estimate.

[14] We also allow differences across states to affect banks heterogeneously by including bank*state fixed effects (unreported).

Table 4 reports results for our two-stage least squares regressions (2SLS). Column (1) reports the first stage at the county level. Our instrument has a strong and highly significant negative effect on Δold, suggesting that there is no weak instrument problem. Higher unemployment in 1940 leads to slower aging from 1997 to 2007. In terms of magnitude, a 1% increase in unemployment leads to a 0.1% slower growth in seniors. Moving a county from the 10^{th} to the 90^{th} percentile in terms of historical unemployment leads to a decline in aging by ($3.78 \times 0.096 =$) 0.36% (one third of the average increase in Δ *old*).

Column (2) reports the reduced form at the bank-county level: our instrument has a negative and significant effect on the change in bank deposits. Columns (3)-(4) replicate columns (1)-(2) in Table 3, but instrument Δold with *log(unemployed 1940)*. Similar to OLS regressions, (instrumented) aging has a positive and highly significant effect on bank deposits. In our preferred specification in column (4), in which we control for bank unobservables through bank fixed effects, coefficients increase in magnitude compared to Table 3 − in line with the argument that counties with high values of Δold suffer from lower growth.[15] In column (4), a 10% increase in (instrumented) elderly from 1997 to 2007 increases bank deposits by 6.3%.

In column (5), we include state fixed effects to control for confounding factors at the state level. While the coefficient of interest declines in magnitude, it remains significant at the 1% level. In column (6) we further include county characteristics as of 1940 to account for differences across counties in 1940. Instrumented aging maintains its statistically and economically significant effect on local bank deposits. Tables 3 and 4 thus show that local aging causally increases local deposits.

4.2 Bank Exposure & Mortgage Lending

After establishing that local aging increases bank deposits, we now turn to banks' asset side. To visually inspect the correlation between bank exposure and loans, Figure 4 provides a binscatter plot of the 1997 to 2007 log change in deposits (panel a) and loans (panel b) at the bank-county level against bank exposure. There is a significant positive relationship, suggesting that banks with a higher share of deposits in aging counties (banks with higher exposure) not only see an increase in deposits, but also in lending. However,

[15] In unreported robustness checks we use a complementary identification strategy and compute the log change in population age 45 to 65 from 1977 to 1987. This age cohort represents the 65 to 85 year old 20 years later and thus mechanically predicts county aging from 1997 to 2007. When we include both instruments in our regression, the Sargan-Hansen test of overidentifying restrictions cannot reject the null and suggests that our instruments are valid.

the positive correlation between exposure and loan growth could be spurious if it reflects unobservable bank or county characteristics.

[Figure 4 about here]

To systematically investigate how exposure to aging counties affects lending, we estimate the following specifications:

$$\Delta HMDA_{b,c}^{97-07} = \beta \ exposure_b + controls_{b/c} + \theta_c + \epsilon_{b,c}, \tag{4}$$

$$\begin{aligned}\Delta HMDA_{b,c}^{97-07} &= \gamma_1 \ exposure_b + \gamma_2 \ county \ characteristic_c \\ &+ \gamma_3 \ exposure_b \times county \ characteristic_c + \theta_b + \theta_c + \epsilon_{b,c},\end{aligned} \tag{5}$$

where $\Delta HMDA_{b,c}^{97-07}$ is the change in bank b's mortgage lending in county c from 1997 to 2007; $exposure_b$ is bank exposure as defined in equation (1). $county \ characteristic_c$ is a characteristic of county c as of 1997, defined below. Bank controls include log total assets, return on assets, non-performing loans, total deposits over total liabilities, tier-1 capital ratio, non-interest income, overhead costs, and liquidity (defined as cash and gains from securities over total assets). County controls include log population, labor force participation rate, unemployment rate, log income per capita, and employment shares in manufacturing, wholesale and retail trade, as well as finance, insurance, and real estate. Standard errors are clustered on the bank (treatment) level to account for correlation of error terms across borrower counties of the same bank. In regression equation (4), we expect $\beta > 0$, i.e. banks with higher exposure use the increase in deposits to increase lending. To identify changes in bank loan supply, we include county fixed effects (θ_c) to control for unobservable county characteristics, for example loan demand. Under the assumption that loan demand in a given county is similar across banks, fixed effects difference out demand forces and allow for a clean identification of loan supply. In essence, we compare two banks that lend to the same county (Khwaja and Mian, 2008; Jiménez, Ongena, Peydró and Saurina, 2014).

Where do banks increase credit supply? To investigate this question, we interact bank exposure with local county characteristics. We first investigate whether banks lend more to 'young markets', i.e. markets with a high share of population age 20-34 in 1997. In general, younger generations have lower financial wealth and are more likely to borrow (see Figure 2). They are also often financially constrained and hence particularly likely to benefit from an increase in credit supply. A reallocation of credit from aging counties towards counties with a young population relaxes credit constraints and improves allocative efficiency − a core function of the banking system.

We also investigate whether banks engage in risky lending by analyzing whether they lend more to low income counties or counties with a high share of subprime borrowers. Interacting bank exposure with county characteristics allows us to include bank fixed effects (θ_b) in addition to county fixed effects. Regression equation (5) saturated with granular fixed effects thus rules out that unobservable bank characteristics explain our findings. However, we are no longer able to separately identify the coefficient on *exposure*.

Table 5 shows that exposed banks increase mortgage lending. Column (1) shows that banks with higher exposure see a significant increase in HMDA loans, conditional on bank and county controls. The economic magnitude is sizeable: A one standard deviation increase in exposure increases banks' supply of mortgages by 7.2% over a decade.[16] Once we account for unobservable county characteristics (for example loan demand) in column (2) through county fixed effects, the coefficient remains almost identical in terms of size, sign, and significance. The stability is remarkable in light on an increase in R^2 by almost 0.3. Columns (1)-(2) suggest that bank exposure is orthogonal to observable and unobservable county characteristics, and that the coefficient captures changes in loan supply (Altonji, Elder and Taber, 2005; Oster, 2017).

[Table 5 about here]

A potential confounding factor is that banks lend where they raise deposits. Since exposure reflects deposit-weighted local aging, local aging could affect bank lending through channels other than exposure. To address this issue, column (3) excludes for each bank all counties in which it raises deposits. In other words, we only look at bank lending to counties that are not part of the construction of *exposure*. 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 strongly correlated with population aging in Los Angeles County. We thus only look at lending by above bank to Arlington County.[17] Coefficients remain similar in terms of sign, size, and significance,

[16] A one standard deviation increase in exposure corresponds to a 13% increase in the (deposit-weighted) average of aging across counties where banks raise deposits. Another way to express magnitudes is by predicting the bank-level change in deposits with exposure, which yields the elasticity of mortgage lending to an aging-induced increase in deposits. We find that HMDA loans increase by 1.5% when deposits increase by 1% due to exposure to aging counties (unreported).

[17] Note that the arising bias is expected to reduce the true effect size: aging counties have lower demand for credit, so if aging confounds exposure, this will reduce the effect we find of exposure on lending.

relative to columns (1)-(2). The stability of our coefficient suggests that bank exposure (and hence aging in counties where banks have branches) has a direct effect on bank lending, irrespective of aging in the borrower county itself.[18] We will use the sample of 'no-deposit counties' as baseline sample for the rest of our paper.

Columns (4) and (5) report results for regression equation (5) and show that banks extend significantly more loans to 'young' counties. Column (4) shows a positive and significant coefficient on the interaction term; for an increase in the share of young by 10%, the average bank sees a 16.7% stronger increase in lending, holding exposure constant. To further strengthen identification and account of unobservable bank characteristics, we include bank fixed effects in column (5). We now compare lending by the same bank to the same county. While we can no longer identify the direct effect of exposure, the coefficient on the interaction term keeps its sign and is significant at the 1% level; it decreases slightly in magnitude. An increase of 10% in the share of young population leads to an additional increase in the supply of residential mortgages by 11.9%. In conclusion, Table 5 shows that banks use the increase in deposits due to demographic change to increase their loan supply. They channel funds from aging counties towards counties with a young population. As the young are generally credit constraint, integrated banks improve the allocation of credit.

4.3 Risky Borrowers & Robustness

Table 5 showed that banks with higher exposure to aging counties increase their supply of residential mortgages. A large and growing literature highlights that the pre-crisis increase in credit, especially to subprime and low-income housholds, contributed to the depth of the Great Recession (Mian and Sufi, 2009; Favara and Imbs, 2015; Chakraborty, Goldstein and MacKinlay, 2018; Justiniano, Primiceri and Tambalotti, 2019). Table 6 investigates in greater detail whether exposed banks engaged in risky lending or lending to low-income households. In column (1) we estimate regression equation (5) and interact bank exposure with dummy *high subprime* that takes on value one if a county is in the top quartile of subprime borrowers as of 1999 (the earliest year for which data is available). Regressions include bank controls and county fixed effects to account for loan demand. We find a negative insignificant coefficient on the interaction term, suggesting that, if anything, banks increased mortgage lending by less to counties with a high share

[18] In robustness checks, we also exclude counties with a high share of employment in tradable industries. This addresses the point that aging in Los Angeles could affect demand for credit in Arlington through demand for tradable goods and services.

of subprime borrowers. Once we add bank fixed effects in column (2), effect size falls to zero. Columns (3)-(4) replace *high subprime* with dummy *low income p.c.* that takes on value one if a county is in the bottom quartile of income per capita as of 1997. Without and with bank fixed effects, we find a negative and significant coefficient on the interaction term. Banks extend fewer loans to low income counties.

[Table 6 about here]

In columns (5)-(7) we make use of our granular data and move to the bank-county-borrower income level. We investigate whether banks extend more loans to low income borrowers. We define *low income borrower* as borrowers with income less than USD 35'000 (in 2000 dollars).[19] Column (5) controls for bank characteristics, column (6) adds county fixed effects, and column (7) bank fixed effects. While low income borrowers experience slower growth in mortgage credit across specifications, the interaction term enters insignificantly and is small in magnitude. Figure 5 plots coefficients on *exposure* when we run regression equation (4) separately for each income group. While effect size increases with higher income groups, none of the differences is statistically significant. In line with columns (1)-(4), this result suggests that banks did not use their additional funds to finance borrowing by low income households. If anything, they supplied (insignificantly) more credit to borrowers with higher income.[20]

Why do we not find any evidence for bank risk taking? One possible explanation is that deposits are a stable and cheap source of funding. Banks thus need not gamble for high returns, but can invest in safe projects and still make a return that exceeds the deposit rate. Literature establishes that depositors are unlikely to switch branches, i.e. deposits are sticky due to switching costs, and that banks extract higher rents (in the form of lower deposit rates) the larger the share of long-term clients. Since the increase in deposits in our setting originates from higher deposit holdings of seniors − who are likely to be with the same branch for several years − banks can offer low deposit rates, further reducing the need to engage in risky endeavors.[21]

[19]The income groups are listed on the vertical axis in Figure 5. Our results do not hinge on whether we define *low income borrower* as borrowers with less than USD 24'000, USD 35'000, or USD 54'000 in income.

[20]In the online appendix, we show that banks deny significantly fewer loan applications in young counties, consistent with an increase in credit supply. We find no differential effect across borrower income groups.

[21]For switching costs and their effects on deposit rates, see Klemperer (1995); Sharpe (1997); Kim, Kliger and Vale (2003); Degryse and Ongena (2008); Hannan and Adams (2011). Kiser (2002) uses survey data to show that households 65 and older are the most likely to be with their first bank ever.

[Figure 5 about here]

Table 7 undertakes further robustness checks based on regression equations (4) and (5). As can be seen from Figure 1, states near the Great Plains see modest to negative change in population 65+ from 1997 to 2007. Column (1) 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. Column (2) strengthens identification by excluding all counties with an above median share of employment in tradable industries (out of total employment). This is to further exclude the possibility that local aging affects bank lending through other channels than bank exposure, namely demand for tradable goods and services. While we lose around half of our observations, the effect of exposure on HMDA lending remains almost identical to baseline results in terms of sign, size, and significance.

Columns (3) and (4) exclude counties in the bottom and 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. Columns (5) and (6) estimate regression equation (5), but interact all bank controls with *share young* (individual coefficients unreported). Column (5) employs bank controls and county fixed effects, column (6) adds bank fixed effects. In horse race specifications, the effect of exposure on lending in young counties remains sizeable and significant. Coefficients are close to their baseline values, reflecting the balancedness in terms of covariates of the bank sample (see Table 2).

[Table 7 about here]

Columns (7)-(10) take another look at bank lending to 'hot' markets. To this end, we take two established measures that capture the ease of increasing the local supply of housing at the MSA level. A large literature has shown that house prices increase faster in inelastic markets, given the same demand shock. If the effect of exposure on lending were only present in inelastic markets, this would suggest that banks fueled the housing bubble. We use a measure of housing supply elasticity from Saiz (2010), as well as the Wharton land use regulation index developed in Gyourko, Saiz and Summers (2008), both normalized to mean zero and standard deviation one. Higher values of elasticity and lower values of the regulation index imply that it is cheaper to expand the stock of housing. We find a negative (positive) significant (insignificant) coefficient on the interaction term of exposure with elasticity (regulation index). Yet, the coefficient on exposure alone remains positive, highly significant, and about 6 times as large in magnitude compared to the interaction effect. This suggests that banks increased credit supply to a large extent irrespective of local housing supply elasticity, further providing evidence that banks did not use the increase in deposits to engage in risky lending in 'bubble markets'. Finally, column (11) uses variation at the intensive margin only, i.e. excludes bank entry and exit across counties. Higher exposure to aging counties leads to a significant increase in lending among counties to which banks lend in 1997 and 2007.

5 Real Effects

The previous sections established that local aging increases bank deposits, and that banks use these deposits to increase mortgage lending. We now investigate whether the increase in the supply of local mortgages has real effects. We run county level regressions of the following form:

$$\Delta y_c^{97-07} = \beta exposure_c + controls_c + \theta_s + \epsilon_c. \tag{6}$$

Δy_c^{97-07} is the log change of different county outcome variables from 1997 to 2007. In our main specifications, we look at county debt-to-income ratios, house prices, and building permits; as well as employment. $exposure_c$ denotes county exposure to aging-exposed banks. We define county exposure analogously to equation (1), but based on the share of HMDA loans instead of deposits. We intend to capture the effect of changes in banks' assets and hence require exposure to reflect banks' importance in local mortgage markets:

$$exposure_c = \sum_b \frac{HMDA_{b,c}}{HMDA_c} \times exposure_b, \tag{7}$$

where $HMDA_{b,c}$ and $HMDA_c$ denote bank b's HMDA loans in county c and county c's total HMDA loans (both as of 1997). High $exposure_c$ implies that a high share of banks active in county c is exposed to aging counties. We normalize $exposure_c$ to mean zero and standard deviation one. All regressions include baseline county controls and use robust standard errors. We weight regressions by initial county population. To tighten identification, we occasionally include state fixed effects (θ_s) and thereby compare the effect of exposure on local economic activity for counties in the same state.

Table 8 shows that higher county exposure leads to an increase in debt-to-income ratios, as well as an increase in house prices and building permits. Column (1) reports a positive coefficient on county exposure, suggesting that counties with higher exposure to aging-exposed banks see an increase in their debt-to-income ratio, significant at the 5% level. Once we include state fixed effects in column (2), the coefficient doubles in magnitude and becomes significant at the 1% level. The increase in the supply of mortgages hence translates into an overall increase in household debt, relative to income. Columns (3)-(4) repeat the exercise, but use the log change in the county house price index as dependent variable; columns (5)-(6) use the log change in building permits. County exposure has a strong and significant positive effect on house prices as well as permits. Columns (1)-(6) in Table 8 suggests that the increase in the supply of mortgages leads to an increase in household debt, as well as construction activity and house prices. Finally, columns (7)-(8) use the change in the share of subprime borrowers as dependent variable. In line with results in Table 6 on bank lending to risky borrowers, we find that counties with higher exposure see a significant decline in the share of subprime borrowers.

[Table 8 about here]

Does the increase in credit supply and stimulated housing markets affect employment? To this end, Table 9 uses the 1997 to 2007 log change in employment as dependent variable. Column (1) reports a positive and significant effect of county exposure on total employment. For a one standard deviation increase in exposure, employment increases by 6.3% over a decade. Columns (2)-(4) split total employment into construction, non-tradable, and tradable industries. Reflecting higher activity in local housing markets, the effect of county exposure on employment is strongest in the construction sector. However, we also find positive effects on employment in non-tradable sectors, as well as a weaker effect on tradable sectors. The latter could reflect local spillover effects from the real estate sector (Stroebel and Vavra, 2019). Column (5) uses the log change in employment among firms age 0-1 (start-ups), which are particularly sensitive to changes in local economic conditions. We find a positive significant effect of exposure on start-up employment that exceeds the effect for total employment.

[Table 9 about here]

Finally, columns (6)-(8) investigate the collateral channel (Chaney, Sraer and Thesmar, 2012) at the county-industry level, where industry refers to the respective 2-digit

Naics code. The collateral channel suggests that rising local real estate prices relax collateral constraints, since real estate often serves as collateral. Young firms are opaque and inherently risky, and especially dependent on home equity as collateral to secure loans (Steijvers and Voordeckers, 2009). Consequently, we expect firm formation to be more sensitive to county exposure in industries where more young firms use home equity financing, since these benefit disproportionately from the increase in house prices. Using the 2007 Survey of Business Owners (SBO) we define *home equity (%)* as the industry share of young firms that use home equity to start or expand their business. For the average industry, 8.7% of firms report using home equity financing, with a maximum of 13.6%.[22] We then interact county exposure with *home equity*. The positive but imprecisely estimated coefficient on the interaction term in column (6) suggests that industries that rely more on home equity financing expand faster in high-exposure counties – likely because they benefit from rising local house prices due to the increase in credit supply. Columns (7) and (8) add industry and county fixed effects to tighten identification and control for unobservable changes at the industry and county level. The coefficient on the interaction term remains positive and becomes significant at the 5% level. In terms of magnitude, it remains stable across specifications, despite an increase in R^2 by an order of (0.240/0.035 =) 7.

Tables 8 and 9 suggest that the increase in credit supply stimulates local housing markets and employment. However, our results (and especially their magnitudes) have to be taken with a grain of salt. While our bank-county level analyses allow for identification through granular fixed effects and an IV strategy, as well as specifications in which we address alternative explanations, our options on the county level are limited. County exposure as defined in equation (7) reflects the importance of banks that hold a high share of their deposits in aging counties; yet, it could be correlated with observable and unobservable county characteristics. Depending on the correlation of these factors with exposure, our coefficients could be biased even after inclusion of county controls and state fixed effects. In brief: while an increase in local house prices and construction activity in response to an increase in mortgage *supply* seems sensible, we want to caution against taking our county-level estimates and especially their effect size at face value.

[22]We focus on firms formed between 1990 and 1999 that require less than USD 100'000 to start a business. For each industry i we then compute the average fraction of young firms f that reports using home equity financing to start or expand their business as: $home\ equity_i = \frac{\sum_{f=1}^{F_i} \mathbb{1}(uses\ home\ equity_f)}{\sum_{f=1}^{F_i} 1}$ (see Doerr (2019)). The two-digit Naics industries with the highest home equity share are accommodation and food services (72) and manufacturing (23), those with the lowest mining (21) and management of companies (55).

6 Conclusion

Our results suggest that an integrated financial sector mitigates negative effects of population aging. Banks benefit from higher deposits in counties with an aging population and use the increase in funds to supply more credit to other markets. The increase in credit supply has real effects. Counties with a higher market share of aging-exposed banks see an increase in house prices and building permits; they also experience an increase in firm formation.

While policy implications are hard to assess fully, especially in light of the recent debate on rising concentration in the banking sector, this paper highlights a clear benefit of banking integration: by reallocating funds from aging regions with abundant savings towards counties with a young and credit-constrained population, banks increase allocative efficiency. This channel is likely to grow in importance as advanced economies age.

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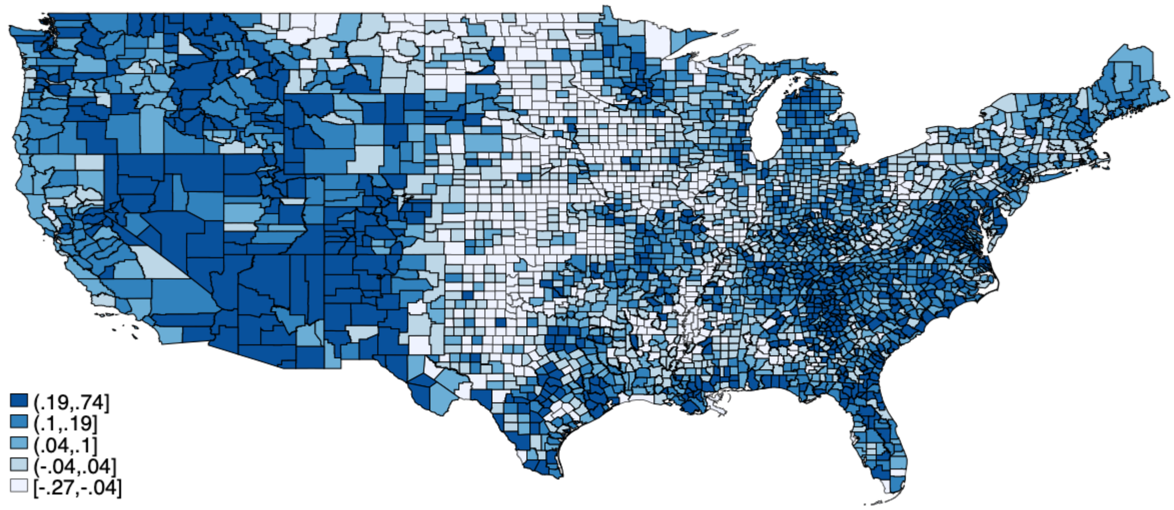
A Figures & Tables

A.1 Figures

Figure 1: **Population aging: Geographic variation**

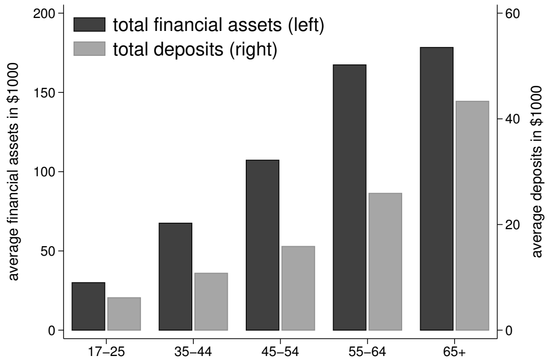


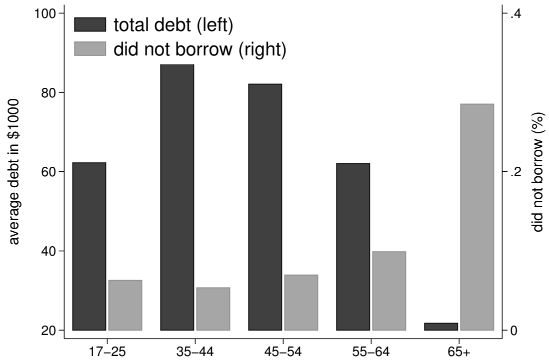
Note: This Figure shows a map of U.S. counties and their log change in population age 65 and above from 1997 to 2007. Darker areas indicate higher values of $\Delta aging$, lighter areas lower values.

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

(a) Assets and deposits

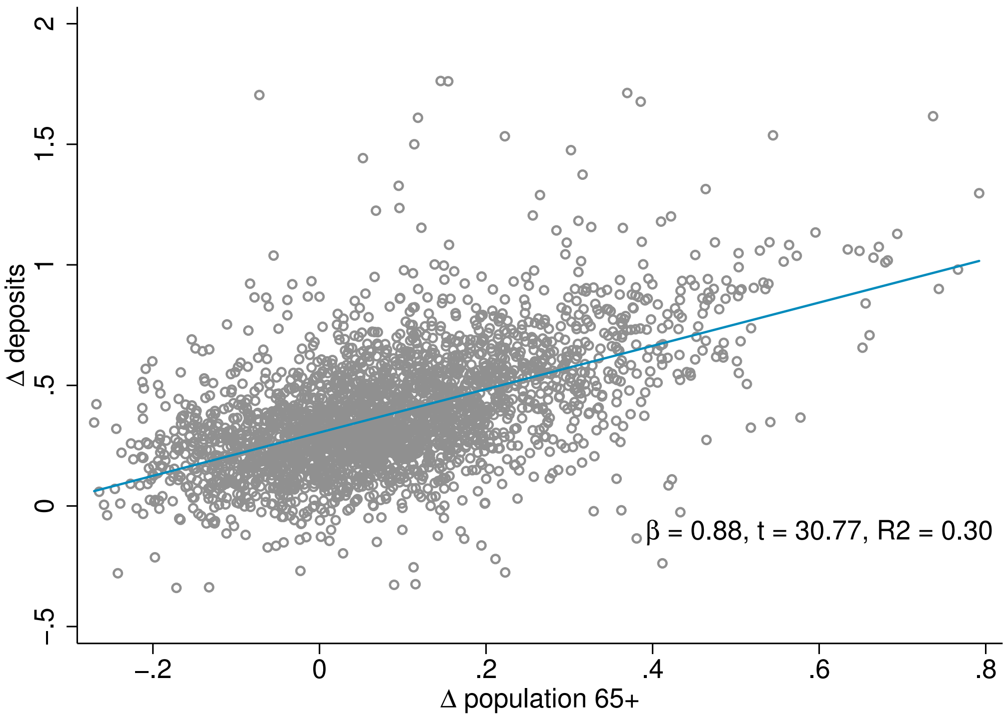
(b) Debt and borrowing





Note: This Figure uses data from the Survey of Consumer Finances (1995-2007). Panel (a) plots total financial assets in $1000 on the left axis and total deposits in $1000 on the right axis for the average household in each age bin. Panel (b) plots total debt in $1000 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 lower debt and are less likely to borrow.

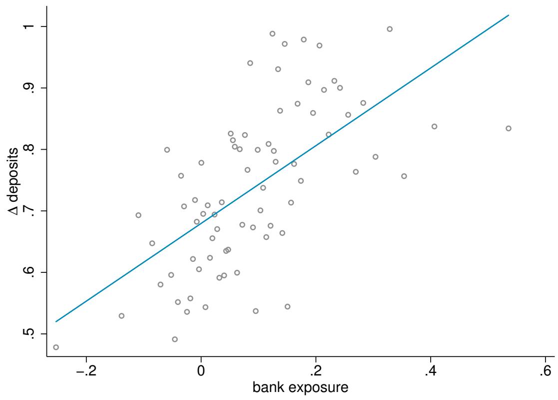
Figure 3: **Population aging and deposit growth (county)**



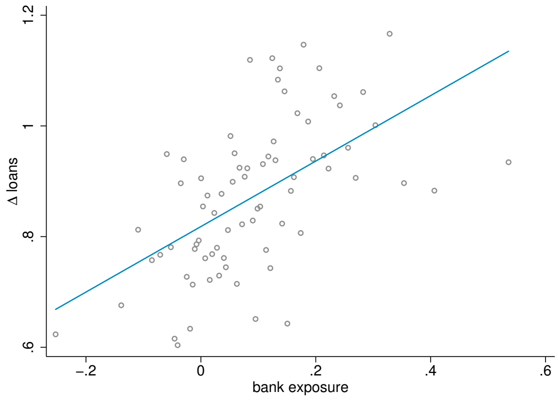
Note: This Figure provides a scatter plot on the county level of the log change in deposits on the y-axis against the log change in population age 65 and above on the x-axis (both from 1997 to 2007). The blue line denotes the linear fit. Coefficients, t-value, and R^2 result from a regression of $\Delta deposits_c = \Delta aging_c + \epsilon_c$ with robust standard errors ($n = 2,801$). There is a strong positive relationship between aging at the county level and changes in local deposits.

Figure 4: **Bank exposure to aging counties**

(a) Bank deposit growth

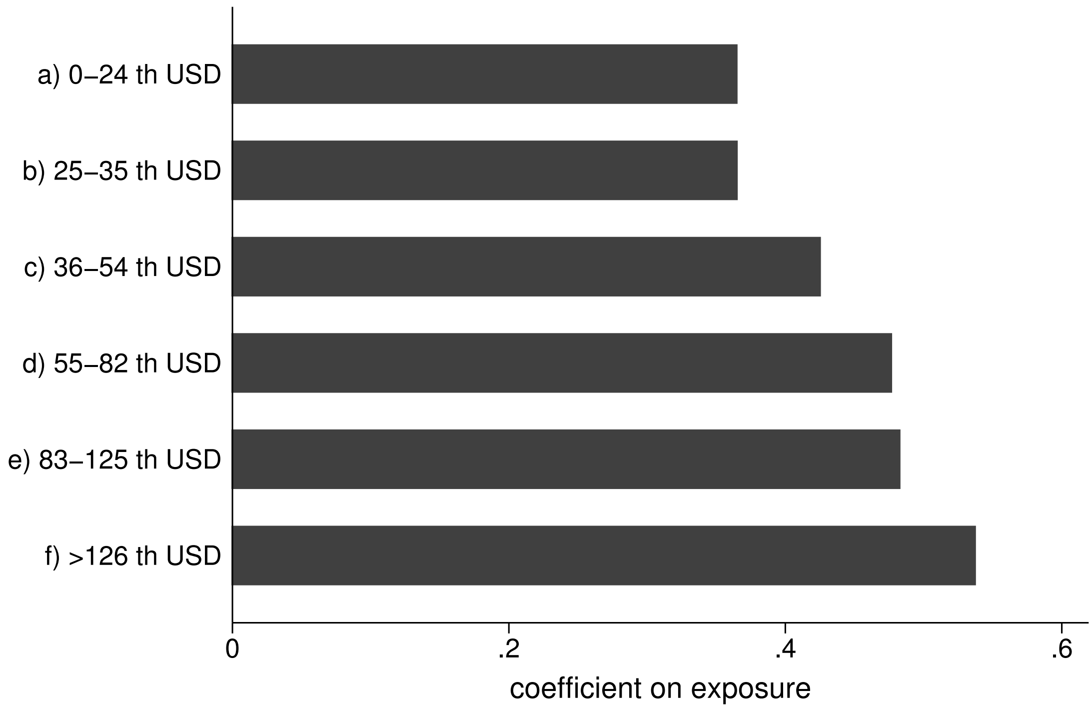


(b) Bank loan growth



Note: This Figure shows binscatter plots at the bank level of the log change in total deposits in panel (a) and the change in total lending in panel (b) on the y-axis (both from 1997 to 2007), against bank exposure (as defined in equation (1)) on the x-axis. There is a strong positive relationship between bank exposure to aging counties and changes in bank deposits and loans.

Figure 5: **Bank exposure and loans: By borrower income**



Note: This Figure plots coefficients on exposure in regression equation (4) at the bank-county level for different classes of borrower income. Regressions include county fixed effects and bank controls, standard errors are clustered on the bank level. All coefficients are significant at the 1% level, but not statistically different from each other (unreported).

A.2 Tables

Table 1: **Descriptive statistics**

	mean	sd	min	max	count
Panel (a): Bank level					
Δ loans	0.87	0.62	-0.89	4.00	2068
Δ mortgages	0.61	0.74	-3.14	4.74	2068
exposure	0.09	0.13	-0.34	0.67	2068
log(assets)	12.02	1.25	9.98	19.62	2068
non-performing loans (%)	0.17	0.43	-1.17	3.15	2068
ROA (%)	0.01	0.01	-0.03	0.05	2068
deposits (%)	0.94	0.08	0.37	1.00	2068
liquidity (%)	0.05	0.03	0.00	0.24	2068
tier 1 capital (%)	0.18	0.10	0.08	0.90	2068
non-interest income (%)	0.82	0.90	0.01	7.34	2068
efficiency (%)	0.62	0.14	0.27	1.78	2068
diversification	0.36	0.28	0.00	0.99	2068
Panel (b): Bank-county level					
Δ deposits	0.16	1.69	-2.00	2.00	26518
Δ HMDA	1.20	1.37	-2.00	2.00	75734
Panel (c): County level					
Δ old	0.10	0.15	-1.15	1.01	2811
Δ young	-0.04	0.14	-1.09	0.80	2811
Δ HPI	0.46	0.19	0.07	1.18	2055
Δ debt-to-income	0.69	0.56	-2.31	3.46	2810
Δ employment	0.07	0.21	-0.76	1.05	2811
Δ emp construction	0.18	0.45	-1.79	2.11	2811
Δ emp non-tradable	0.09	0.22	-1.10	1.05	2811
Δ emp tradable	0.06	0.25	-1.02	1.27	2811
share old	0.15	0.04	0.02	0.35	2811
share young	0.19	0.04	0.10	0.47	2811
log population	10.40	1.27	6.78	16.04	2811
share black	0.10	0.15	0.00	0.87	2811
share old	0.15	0.04	0.02	0.35	2811
unemployment rate	0.06	0.03	0.01	0.33	2811
participation rate	0.94	0.03	0.67	0.99	2811
log income per capita	9.93	0.20	9.07	11.15	2811
exposure (county)	-0.00	1.00	-3.09	3.34	816

Note: This Table shows descriptive statistics (mean, standard deviation, minimum, maximum, and number of observations) for main variables at the bank, bank-county, and county level. All variables as of 1997, Δ denotes 1997 to 2007 changes. For variable definitions see Section 3 and Appendix B.

Table 2: **Multivariate descriptive statistics: Bank exposure**

VARIABLES	(1) exposure	(2) assets $\geq 10bn$ exposure	(3) assets $\geq 50bn$ exposure	(4) div ≥ 0.5 exposure	(5) div ≥ 0.8 exposure
log(assets)	-0.052	-0.010	-0.042	0.021	0.024
	(0.036)	(0.048)	(0.082)	(0.036)	(0.057)
non performing loans (%)	-0.014	-0.002	-0.004	-0.072*	-0.084*
	(0.050)	(0.058)	(0.065)	(0.038)	(0.044)
ROA (%)	0.028	0.021	0.009	-0.028	-0.033
	(0.065)	(0.079)	(0.104)	(0.055)	(0.069)
deposits (%)	-0.066	-0.075	-0.114	-0.000	-0.016
	(0.044)	(0.054)	(0.087)	(0.043)	(0.057)
liquidity (%)	0.011	-0.030	-0.036	0.074	0.116
	(0.092)	(0.124)	(0.141)	(0.091)	(0.124)
tier 1 capital (%)	-0.046	-0.036	-0.030	-0.032	-0.024
	(0.061)	(0.070)	(0.078)	(0.054)	(0.056)
non-interest income (%)	-0.013	-0.017	-0.022	-0.032	-0.047
	(0.051)	(0.058)	(0.071)	(0.046)	(0.051)
efficiency (%)	-0.025	-0.031	-0.038	-0.023	-0.022
	(0.029)	(0.033)	(0.042)	(0.026)	(0.029)
Observations	2,068	154	47	686	144
R-squared	0.044	0.074	0.112	0.102	0.173

Note: This Table shows results for multivariate regressions of the form $exposure_b = controls_b + \epsilon_b$ at the bank level, where *exposure* is defined in equation (1). Standard errors are robust. *assets* refers to total bank holding company assets, *div* is bank diversification as defined in equation (2). Across specifications, the sample is balanced; except for non-performing loans, no bank balance sheet item has significant explanatory power for exposure. For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

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

VARIABLES	(1) Δ deposits	(2) Δ deposits	(3) conc. Δ deposits	(4) div. Δ deposits	(5) Δ deposits
Δ old	0.628***	0.599***	0.525***	0.644***	0.547***
	(0.063)	(0.047)	(0.077)	(0.056)	(0.070)
Δ old $\times$ diversified					0.080
					(0.083)
Observations	21,039	21,039	9,312	11,727	21,039
R-squared	0.030	0.828	0.849	0.814	0.828
County Controls	✓	✓	✓	✓	✓
Bank Controls	✓	-	-	-	-
Bank FE	-	✓	✓	✓	✓

Note: This Table shows results for regression equation (3). All regressions include bank and county controls, standard errors are clustered on the county level. Faster aging at the county level (Δold) leads to an increase in bank deposits; this finding holds for diversified banks, i.e. banks that operate in multiple counties (*diversification* is defined in equation (2)). For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: **Population aging and local deposits: 2SLS**

VARIABLES	(1) first stage Δ old	(2) red. form Δ deposits	(3) 2SLS Δ deposits	(4) 2SLS Δ deposits	(5) 2SLS Δ deposits	(6) 2SLS Δ deposits
log(unemployed 1940)	-0.096***	-0.045***				
	(0.004)	(0.012)				
Δ old			0.494***	0.628***	0.413***	0.469***
			(0.128)	(0.104)	(0.100)	(0.162)
Observations	2,589	20,752	20,752	20,752	20,752	20,752
R-squared	0.344	0.027	0.030	0.050	0.035	0.036
County Controls	✓	✓	✓	✓	✓	✓
Bank Controls	-	✓	✓	-	-	-
Bank FE	-	-	-	✓	✓	✓
State FE	-	-	-	-	✓	✓
County Controls 1940	-	-	-	-	-	✓
F-statistic			236.5	221	256.1	121.6

Note: This Table shows results for instrumental variable (IV) regressions in regression equation (3), where we instrument Δold with log 1940 unemployed at the county level. Column (1) reports the first stage at the county level with robust standard errors and county controls. Columns (2)-(7) estimate regression equation (3), all regressions include bank and county controls, standard errors are clustered on the county level. Column (2) reports the reduced form, column (3)-(7) two-stage least squares (2SLS) regressions. F-statistics refer to the Anderson-Rubin test statistic. Faster aging at the county level (Δold) leads to an increase in bank deposits in 2SLS regressions. For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: **Bank exposure and loans**

	(1)	(2)	(3)	(4)	(5)
			no deposits	no deposits	no deposits
VARIABLES	Δ HMDA	Δ HMDA	Δ HMDA	Δ HMDA	Δ HMDA
exposure	0.552***	0.525***	0.544***	0.193	
	(0.161)	(0.156)	(0.160)	(0.139)	
exposure × share young				1.673**	1.189***
				(0.768)	(0.316)
Observations	75,734	75,734	69,725	69,725	69,725
R-squared	0.298	0.589	0.591	0.592	0.709
Bank Controls	✓	✓	✓	✓	-
County Controls	✓	-	-	-	-
County FE	-	✓	✓	✓	✓
Bank FE	-	-	-	-	✓

Note: This Table shows results for regression equations (4) and (5). All regressions include bank and county controls, standard errors are clustered on the bank level. *exposure* is defined in equation (1), *share young county* is the county share of population age 20-34 in 1997. Columns (3)-(5) exclude all counties in which banks raise deposits, i.e. only look at lending by banks to counties where they have no deposits. Higher bank exposure leads to an increase in bank lending, especially to young counties. For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: **Bank risk taking**

VARIABLES	(1) Δ HMDA	(2) Δ HMDA	(3) Δ HMDA	(4) Δ HMDA	(5) Δ HMDA	(6) Δ HMDA	(7) Δ HMDA
exposure	0.564***		0.604***		0.483***	0.457***	
	(0.160)		(0.172)		(0.147)	(0.138)	
exposure × high subprime	-0.074	-0.001					
	(0.054)	(0.037)					
exposure × low income p.c.			-0.208**	-0.128*			
			(0.084)	(0.077)			
low income borrower					-0.309***	-0.288***	-0.300***
					(0.056)	(0.051)	(0.048)
exposure × low income borrower					-0.026	-0.027	0.012
					(0.082)	(0.075)	(0.068)
Observations	69,955	69,725	69,955	69,725	232,370	232,370	232,268
R-squared	0.591	0.708	0.593	0.709	0.245	0.499	0.596
Bank Controls	✓	-	✓	-	✓	✓	-
County FE	✓	✓	✓	✓	-	✓	✓
Bank FE	-	✓	-	✓	-	-	✓

Note: This Table shows results for regression equation (5). All regressions include bank and county controls, standard errors are clustered on the bank level. *exposure* is defined in equation (1), *high subprime* and *low income p.c.* are dummies with value one if a county is in the top (bottom) tercile of the share of subprime borrowers (per capita income) as of 1997. Column (5)-(7) are at the bank-county-borrower income level. *low income borrower* are borrowers with income less than USD 35'000 (in 2000 dollars). Banks do not lend more to low income counties or counties with a higher share of subprime borrowers, nor do they lend relatively more to low-income borrowers. For variable definitions, see Section 3 and Appendix B. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: **Further robustness checks**

VARIABLES	(1) no plains Δ HMDA	(2) high NT Δ HMDA	(3) no low Δ old Δ HMDA	(4) no high Δ old Δ HMDA	(5) horse race Δ HMDA	(6) horse race Δ HMDA	(7) MSA Δ HMDA	(8) MSA Δ HMDA	(9) MSA Δ HMDA	(10) MSA Δ HMDA	(11) int. margin Δ HMDA
exposure	0.530***	0.536***	0.544***	0.544***	0.251**		0.610***		0.610***		0.613**
	(0.157)	(0.166)	(0.160)	(0.161)	(0.123)		(0.181)		(0.181)		(0.307)
exposure × share young					1.399**	0.818**					
					(0.596)	(0.413)					
exposure × elasticity							-0.089**	-0.078**			
							(0.036)	(0.035)			
exposure × regulation index									0.063	0.048	
									(0.039)	(0.038)	
Observations	57,394	35,422	52,802	52,067	69,955	69,725	55,117	54,805	55,117	54,805	16,596
R-squared	0.600	0.567	0.583	0.592	0.593	0.710	0.554	0.702	0.553	0.702	0.374
Bank Controls	✓	✓	✓	✓	✓	-	✓	-	✓	-	✓
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bank FE	-	-	-	-	-	✓	-	✓	-	✓	-
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Note: This Table shows results for regression equations (4) and (5). All regressions include bank and county controls, standard errors are clustered at the bank level. *exposure* is defined in equation (1), *share young* denotes the share of county population age 20-34 in 1997. *no plains* excludes all states in the lower quartile of Δold. Column (2) excludes all counties with an above median share of employment in tradable industries (out of total employment). Columns (3) and (4) exclude counties in the bottom and top quartile of Δold. Columns (5) and (6) estimate regression equation (5), but interact all bank controls with *share young* (individual coefficients unreported). Columns (7)-(10) interact *exposure* with two established measures that capture the ease of increasing the local stock of housing at the MSA level. Higher values of elasticity and lower values of the regulation index imply that it is cheaper to expand the stock of housing. For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: **County exposure, debt, and the housing market**

VARIABLES	(1) Δ debt-to-inc	(2) Δ debt-to-inc	(3) Δ HPI (log diff)	(4) Δ HPI (log diff)	(5) Δ permits	(6) Δ permits	(7) Δ subprime	(8) Δ subprime
exposure (county)	0.048**	0.091***	0.077***	0.077***	0.090**	0.093*	-0.009***	-0.008***
	(0.019)	(0.027)	(0.016)	(0.014)	(0.038)	(0.053)	(0.001)	(0.002)
Observations	816	816	804	804	812	812	816	816
R-squared	0.186	0.431	0.503	0.884	0.289	0.513	0.308	0.593
County Controls	✓	✓	✓	✓	✓	✓	✓	✓
State FE	-	✓	-	✓	-	✓	-	✓

Note: This Table shows results for regression equation (6) at the county level. *exposure (county)* is defined in equation (7). All regressions include county controls, standard errors are robust. Exposed counties see an increase in debt-to-income ratios, house prices, and building permits. For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: **County exposure and employment**

VARIABLES	(1) Δ emp	(2) Δ emp const	(3) Δ emp NT	(4) Δ emp T	(5) Δ start-up	(6) Δ start-up	(7) Δ start-up	(8) Δ start-up
exposure (county)	0.063***	0.095***	0.077***	0.055***	0.087***	-0.015	-0.021	
	(0.006)	(0.010)	(0.007)	(0.006)	(0.014)	(0.086)	(0.068)	
home equity (%)						-0.528		
						(0.850)		
exposure × home equity (%)						1.280	1.307**	1.312**
						(0.847)	(0.657)	(0.658)
Observations	816	816	816	816	608	9,285	9,285	9,285
R-squared	0.413	0.354	0.343	0.363	0.331	0.035	0.169	0.240
County Controls	✓	✓	✓	✓	✓	✓	✓	-
Industry FE	-	-	-	-	-	-	✓	✓
County FE	-	-	-	-	-	-	-	✓

Note: This Table shows results for regression equation (6) at the county level in columns (1)-(5). *exposure (county)* is defined in equation (7). All regressions include county controls, standard errors are robust. Δ *emp const*, Δ *emp NT*, and Δ *emp T* refer to employment in the construction sector, non-tradable, and tradable industries. Δ *start-up* is employment among firms age 0-1. Columns (6)-(8) are on the county-industry level. *home equity* denotes the industry share of young firms that use home equity to start or expand their business (source SBO). For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

B Variable Definitions

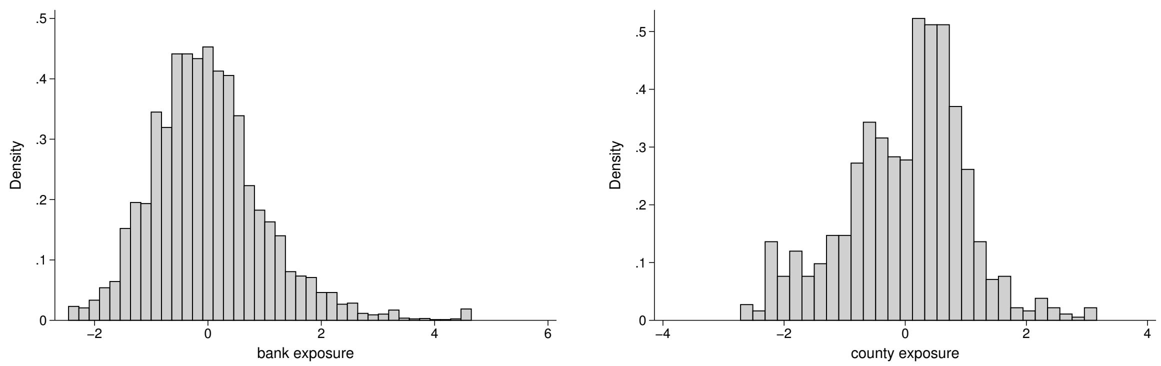
Variable name	Description	Source
Bank level		
exposure	bank exposure to aging counties (deposit-weighted)	FDIC SOD
log(assets)	log total assets	FDIC SDI
non-performing loans (%)	share of NPL over total loans	FDIC SDI
ROA (%)	return on assets	FDIC SDI
deposits (%)	total deposits over total liabilities	FDIC SDI
liquidity (%)	cash and gains from securities over total assets	FDIC SDI
tier 1 capital (%)	tier 1 capital ratio	FDIC SDI
non-interest income (%)	non-interest income over average assets	FDIC SDI
diversification	bank diversification (HMDA-based)	HMDA
Bank-county level		
Δ deposits	Change in bank deposits	FDIC SOD
Δ HMDA	Change in bank HMDA loans	HMDA
County level		
Δ old	change in population 65+	NCI SEER
log(unemployed 1940)	log total unemployed 1940	ICPSR
Δ HPI	change in house price index	FHFA
Δ debt-to-income	change in debt-to-income ratio	FRBNY
Δ employment	change in total employment	CBP
Δ emp construction	change in employment (construction sector)	CBP
Δ emp non-tradable	change in employment (non-tradable industries)	CBP
Δ emp tradable	change in employment (tradable industries)	CBP
Δ start-ups	change in employment (firms age 0-1)	QWI
Δ permits	change in building permits	geoFRED
log population	log total population	NCI Seer
unemployment rate	unemployment rate	BLS LAUS
participation rate	labor force participation rate	BLS LAUS
log income per capita	log income per capita	BEA LAPI
sub-prime borrowers	share of sub-prime borrowers	geoFRED
share young	share of population age 25-34	NCI SEER
exposure (county)	county exposure to bank exposure	HMDA
Other variables		
home equity	industry share of firms using home equity	SBO
elasticity	MSA housing supply elasticity	Saiz (2010)
regulation	MSA land use regulation index	Gyourko et al. (2008)
low income borrower	borrower with income $<$ \$ 35,000	HMDA

Note: This Table shows variable definitions. Changes (Δ) are from 1997 to 2007, all other variables are as of 1997. For details see Section 3 and text.

Online Appendix

Figure OA1: **Bank and county exposure: Distribution**

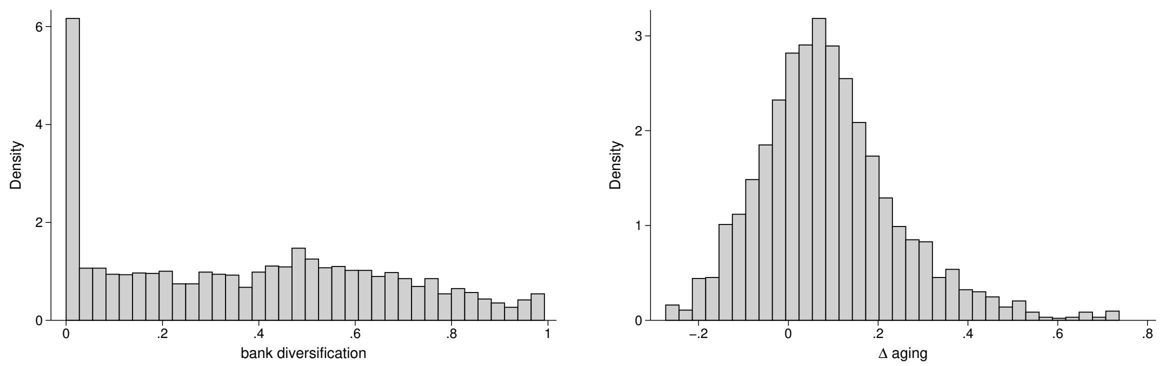
(a) Bank exposure (b) County exposure



Note: Distribution of bank and county exposure (both normalized).

Figure OA2: **Bank diversification and county aging: Distribution**

(a) Bank diversification (b) County aging

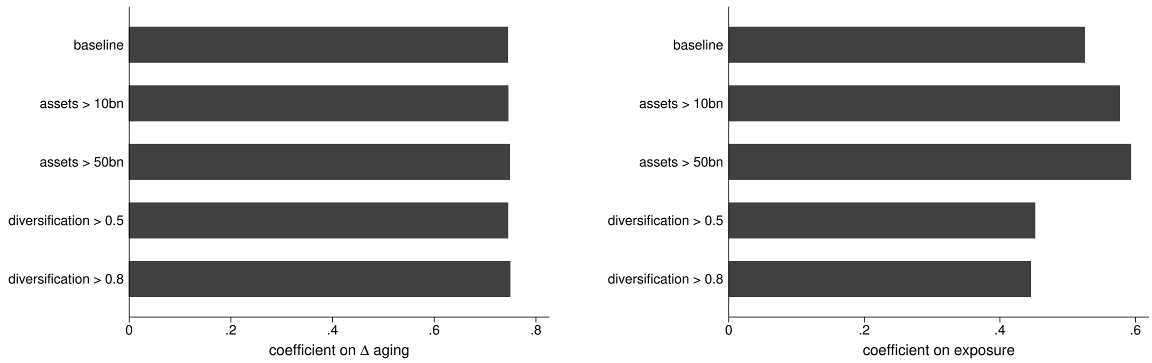


Note: Distribution of bank diversification as of 1997 and county aging 1997-2007.

Figure OA3: **Coefficients in sub-samples**

(a) Deposits: Δ old

(b) Loans: Bank exposure

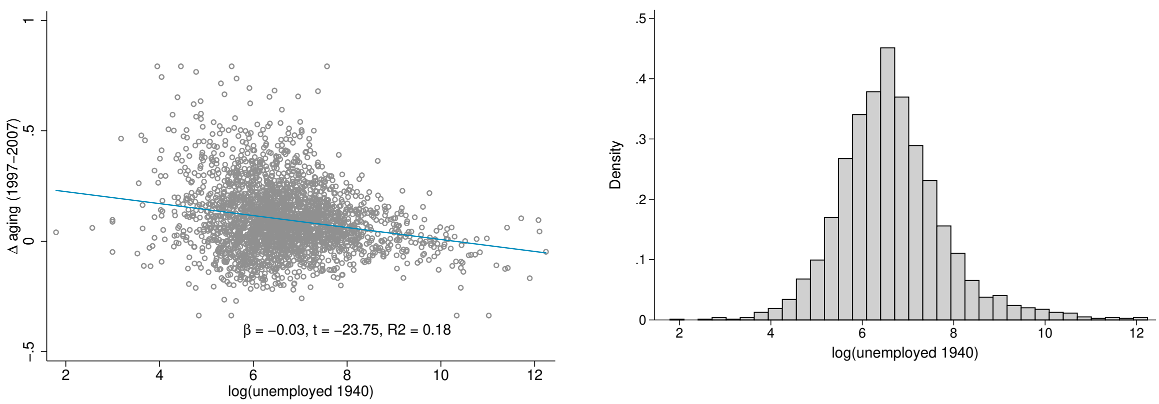


Note: Coefficients for sub-samples of banks (for sub-samples, see Table 2). Panel (a) reports coefficients on Δold in regression equation (3), panel (b) on *exposure* in in regression equation (4). All coefficients are significant at the 1% level. As shown in Table 2, bank characteristics are balanced across samples.

Figure OA4: **IV and the Great Depression**

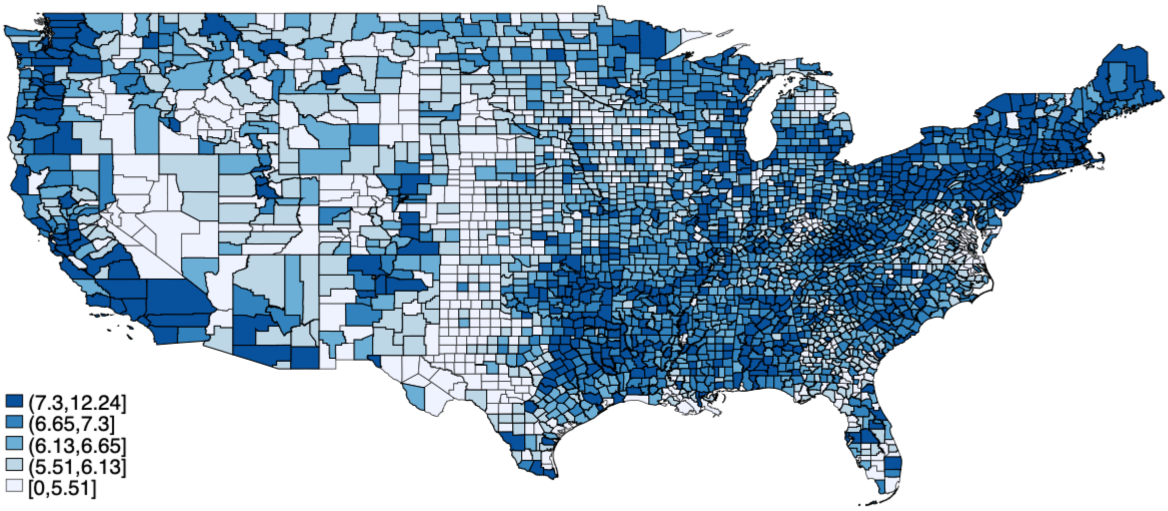
(a) Aging IV

(b) Unemployment 1940



Note: Panel A shows a scatter plot of change in population 65 and above from 1997 to 2007 on the y-axis against log unemployment in 1940 on the x-axis. Panel B show the distribution of log unemployment in 1940.

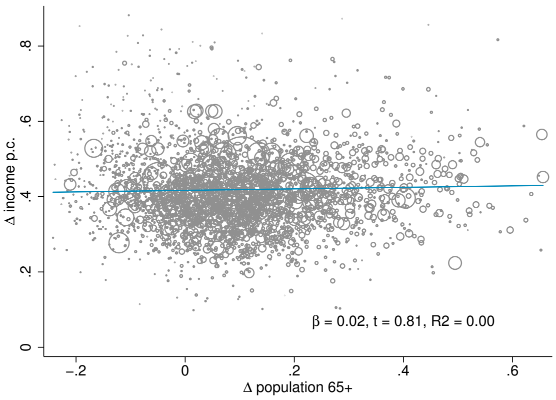
Figure OA5: **Unemployment 1940: Geographic variation**



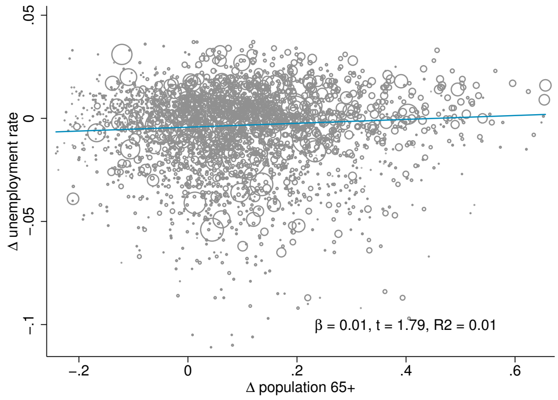
Note: This Figure shows a map of U.S. counties and their (log) total unemployment in 1940. Darker areas indicate higher values of unemployment, lighter areas lower values.

Figure OA6: **Aging and local economic conditions**

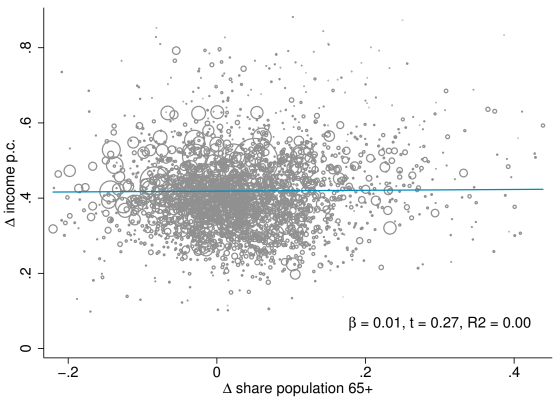
(a) Income per capita



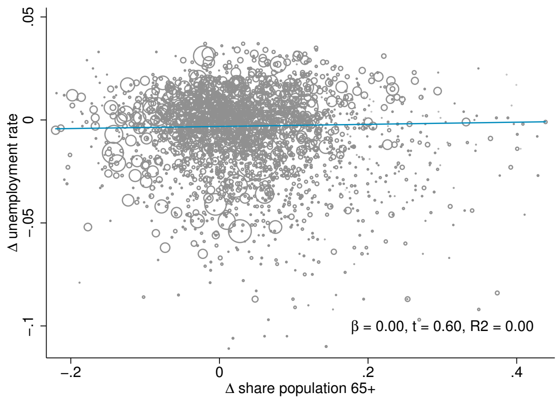
(b) Unemployment rate



(c) Income per capita



(d) Unemployment rate



Note: This Figure provides a scatter plot on the county level of the change in log income per capita or unemployment rate from 1997 to 2007 on the y-axis. The x-axis uses the log change from 1997 to 2007 in absolute population age 65 and above (panels a and b) and in the share of population age 65 and above (panels c and d). Blue lines denote the linear fit. Coefficients, t-value, and R^2 result from a regression of $\Delta y_c = \Delta old_c$ with robust standard errors ($n = 3,023$). There is no relationship between aging at the county level and local economic conditions.

Table OA1: **Robustness: Aggregate county deposits and aggregate bank lending**

VARIABLES	(1) county Δ deposits	(2) bank Δ deposits	(3) bank Δ loans	(4) bank Δ mortgages	(5) county Δ subprime	(6) county Δ HPI	(7) county Δ permits
Δ aging	0.989***						
	(0.105)						
exposure		0.222***	0.257***	0.299***			
		(0.063)	(0.083)	(0.101)			
exposure (county)					-0.741***	0.111***	-0.061
					(0.087)	(0.014)	(0.059)
housing supply elasticity						-0.077***	0.022
						(0.007)	(0.022)
exposure (county) × elasticity						-0.030***	0.062***
						(0.005)	(0.022)
Observations	1,322	2,068	2,068	2,068	817	733	740
R-squared	0.460	0.446	0.460	0.567	0.200	0.512	0.126
County Controls	✓	-	-	-	✓	✓	✓
Bank Controls	-	✓	✓	✓	-	-	-

Note: This Table shows regressions at the aggregate county level and bank holding company level. Column (1) shows that aging counties see an increase in total deposits. Higher bank exposure leads to an increase in total bank deposits in column (2); in total bank lending in column (3), and in mortgage lending in column (4) . Column (5) shows that counties in which exposed banks have a larger market share see a significant decline in the share of subprime borrowers. Column (6) and (7) show that, while house prices rise faster in MSAs with low housing supply elasticity, there is none the less an increase in building permits in these areas. This is, the increase in credit fuels construction activity. For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

Table OA2: **Robustness: Share of denied loans**

VARIABLES	(1) Δ denied	(2) Δ denied	(3) no deposits Δ denied	(4) no deposits Δ denied	(5) no deposits Δ denied
exposure	0.036	0.035	0.041	0.057	
	(0.000)	(0.073)	(0.078)	(0.078)	
exposure × young county				-0.025***	-0.023**
				(0.009)	(0.010)
Observations	21,007	21,007	16,106	16,106	16,106
R-squared	0.040	0.166	0.188	0.189	0.311
Bank Controls	✓	✓	✓	✓	-
County Controls	✓	-	-	-	-
County FE	-	✓	✓	✓	✓
Bank FE	-	-	-	-	✓
Cluster	Bank	Bank	Bank	Bank	Bank

Note: This Table shows results for regression equations (4) and (5), but uses the 1997-2007 change in the fraction of denied loans as dependent variable. We define the share of denied loans as the fraction of denied loans out of originated and approved loans (intensive margin only). All regressions include bank and county controls, standard errors are clustered at the bank level. *exposure* is defined in equation (1), *young county* is a dummy with value one if a county is in the top tercile of share of population age 20-34 in 1997. Columns (5)-(7) exclude all counties in which banks raise deposits, i.e. only look at denied loans by banks to counties where they have no deposits. Higher bank exposure leads to a decline in denied loans in young counties. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table OA3: **Robustness: Do banks open new branches?**

VARIABLES	(1) Δ branches	(2) Δ branches	(3) Δ branches	(4) P(open)	(5) P(open)	(6) P(open)	(7) small br. Δ deposits	(8) small br. Δ deposits	(9) small br. Δ deposits
Δ aging	0.374***	0.275***		0.224***	0.198***		0.543***	0.451***	
	(0.039)	(0.052)		(0.021)	(0.030)		(0.080)	(0.132)	
Δ aging × diversified		0.153**	0.253***		0.041	0.097**		0.139	0.319**
		(0.072)	(0.079)		(0.034)	(0.038)		(0.147)	(0.151)
Observations	20,732	20,732	20,732	20,732	20,732	20,732	14,974	14,974	14,783
R-squared	0.686	0.686	0.721	0.606	0.606	0.679	0.691	0.691	0.756
County Controls	✓	✓	-	✓	✓	-	✓	✓	-
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
County FE	-	-	✓	-	-	✓	-	-	✓
Cluster	County	County	County	County	County	County	County	County	County

Note: This Table shows results for regression equation (3), but uses the 1997-2007 log change in number of bank branches (columns (1)-(3)) or the probability of opening at least one new branches (columns (4)-(6)) at the bank-county level as dependent variable. Columns (7)-(9) use the change in deposits as dependent variable, but exclude all branches that cover more than 10% of total bank deposits (in 1997 or 2007) and belong to banks with more than one branch (so it only looks at the change in deposits of small branches). Data are provided by FDIC SOD. Standard errors are clustered at the county level. Faster aging at the county level (Δold) leads to an increase in bank branches and deposits in small branches; this finding holds for diversified banks, i.e. banks that operate in multiple counties (*diversification* is defined in equation (2)). *** p<0.01, ** p<0.05, * p<0.1.

Aging: Absolute vs. share

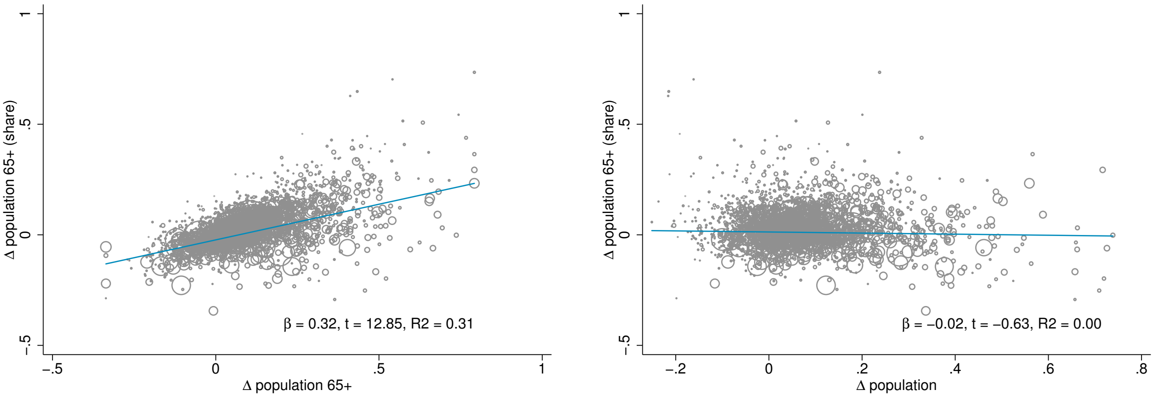
We use the log change in total population age 65 and above as main explanatory, based on the fact that the average senior holds more deposits than younger generations. Hence an increase in the *absolute* number of elderly leads to an increase in the *absolute* value of deposits. The *share* of seniors could vary due to changes in the denominator (e.g. slow population growth or out-migration), even if the absolute number of seniors stays constant. Consequently, a change in the share of seniors induced by a change in total population would *not* generate an increase in total deposits, but a decline.

Nonetheless, we investigate the distinction between change in total seniors and the change in their share in more detail. To this end, we define the log change from 1997 to 2007 as: $\Delta\frac{pop\ 65+}{total\ pop} = \Delta(pop\ 65+) - \Delta(total\ pop)$. Figure OA7 provides a scatter plot of $\Delta\frac{pop\ 65+}{total\ pop}$ against its two components, $\Delta(pop\ 65+)$ in panel (a) and $\Delta(total\ pop)$ in panel (b). The majority of the variation in the share of seniors is driven by the change in their absolute number; the change in population itself has no economically or statistically significant effect.

The correlation between $\Delta\frac{pop\ 65+}{total\ pop}$ and $\Delta(pop\ 65+)$ is 0.59, and -0.05 for $\Delta(total\ pop)$. When we perform a Shorrocks-Shapely decomposition of the R^2 in regression $\Delta\frac{pop\ 65+}{total\ pop}_c = \delta_1\ \Delta(pop\ 65+)_c + \delta_2\ \Delta(total\ pop)_c + \epsilon_c$ (which equals 1 by construction), we find that the component of R^2 related to $\Delta(pop\ 65+)$ equals 67% and is significantly higher than the component related to $\Delta(total\ pop)$ (33%). Consequently, when we estimate regression equation (3), but use the log change in the *share* of seniors, we obtain similar results to using the log change in *total* seniors (see Table OA4).

Figure OA7: **Population aging: Decomposition**

(a) Population 65 and above | (b) Total population



Note: This Figure provides a scatter plot on the county level of the log change in the share of population 65+ over total population from 1997 to 2007 on the y-axis. The x-axis uses the log change in absolute population age 65 and above (panel a) and in total population (panels b). Blue lines denote the linear fit. Coefficients, t-value, and R^2 result from a regression of $\Delta \frac{pop\ 65+}{total\ pop} = \Delta x_c$ with robust standard errors ($n = 2,334$).

Table OA4: **Population aging (share) and local deposits**

	(1)	(2)	(3)
		conc.	div.
VARIABLES	Δ deposits	Δ deposits	Δ deposits
Δ aging	0.340***	0.135	0.468***
	(0.087)	(0.142)	(0.102)
Observations	20,836	9,232	11,604
R-squared	0.827	0.848	0.812
County Controls	✓	✓	✓
Bank FE	✓	✓	✓

Note: This Table shows results for regression equations (3), but uses the log change in the *share* of seniors. Standard errors are clustered at the county level. For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

C IV: The Great Depression

C.1 A simple example

What's the idea? There is ample evidence that economic hardship reduces fertility. What we exploit here is the depth of the Great Depression and its effect on fertility. In simple terms, counties with a worse depression had fewer children between 1930 and 40; and since these children would have been old in 1997 to 2007, a worse depression (and hence lower fertility) is associated with slower aging from 1997 to 2007.

As an example, let us consider two counties: Adams County (indexed by A) and Brown County (indexed by B). Between 1907 and 1942, there are three types of people born:

- The early (indexed by E) are born between 1907 and 1929
- The middle (indexed by M) are born between 1930 and 31
- The late (indexed by L) are born between 1932 and 1942

Absent any major tragedies, E, M, and L live until age 90, after which they leave the economy.

In 1997, E's+M's will be age 65 to 90 (i.e. old) and L's will be 55 to 64 (i.e. young). By 2007, a fraction $x < 1$ of E's will have died, i.e. those born between 1907 and 1917, since they reached the age of 90. All L's will now also be old. This is, the total old population is

- $old_{1997} = E + M$
- $old_{2007} = (1 - x)E + M + L$
- $\Delta old = L - xE$

In 1930 the Great Depression hits and depresses fertility rates. What that means is that between 1930 and 1940, there will be fewer births. This is, $MandL$ will be lower, while E remains unaffected. How will this affect aging Δold?

- E does not matter - they are born before the Great Depression and hence not affected by lower birth rates
- M does not matter - they are old in 1997 and 2007 and hence the depression's effect on their size cancels out

- L does matter: the stronger the decline in L, the slower aging in a county!

Suppose L_A remains constant, while L_B declines to L'_B (because of lower fertility during the Great Depression). Then

$$\Delta old^B - \Delta old^A = L'_B - xE_B - (L_A - xE_A) = L'_B - L_A = L_B - L_A + \Delta L_B = \Delta L_B$$

,

where $\Delta L_B = L'_B - L_B < 0$. In other words, the worse the depression, the lower L'_B and hence the slower aging. The intuition is that fewer children are born in that will make up the new cohort of elderly in 2007, while the effect on the cohort of 1997 is zero (or at least negligible).

One possible concern about using the Great Depression would be that the counties that were hit hard during the depression, might be still suffering from it between 1997-2007 (of course this is unlikely). Maybe we can device some small checks that this is not the case. For instance

- We can show that unemployment rate in 1940 is not correlated with unemployment rate in 2000 (or for other years).
- We can show that unemployment rate in 1940 is not correlated with aging between 1987-1997, as we hypothesized. Similar to a placebo test.

C.2 IV: log unemployment 1940

Table OA5: **Population aging and Great Depression: First stage**

VARIABLES	(1) Δ aging	(2) Δ aging	(3) Δ aging	(4) Δ aging	(5) pop-wt Δ aging
log total unemployed (1940)	-0.095***	-0.096***	-0.077***	-0.068***	-0.068***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	2,587	2,587	2,587	2,587	2,587
R-squared	0.287	0.345	0.442	0.579	0.581
County Controls	-	✓	✓	✓	✓
County Controls 1940	-	-	✓	✓	✓
State FE	-	-	-	✓	✓

Note: This Table shows results for instrumental variable (IV) regressions in regression equation (3), where we instrument Δold with log World War II deaths at the county level. Column (1) reports the first stage at the county level with robust standard errors and county controls. Columns (2)-(7) estimate regression equation (3), all regressions include bank and county controls, standard errors are clustered on the county level. Column (2) reports the reduced form, column (3)-(7) two-stage least squares (2SLS) regressions. F-statistics refer to the Anderson-Rubin test statistic. Faster aging at the county level (Δold) leads to an increase in bank deposits in 2SLS regressions. For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

Table OA6: **Population aging and local branches: 2SLS**

VARIABLES	(1) Δ branches (int)	(2) Δ branches (int)	(3) conc Δ branches (int)	(4) div Δ branches (int)	(5) 2SLS Δ branches (int)	(6) 2SLS conc Δ branches (int)	(7) 2SLS div Δ branches (int)
Δ aging	0.454***	0.549***	0.229**	0.705***	0.763***	0.005	1.125***
	(0.048)	(0.066)	(0.090)	(0.080)	(0.127)	(0.151)	(0.160)
Observations	6,503	6,132	3,017	3,115	6,132	3,017	3,115
R-squared	0.115	0.366	0.447	0.302	0.129	0.098	0.144
County Controls	✓	✓	✓	✓	✓	✓	✓
Bank FE	-	✓	✓	✓	✓	✓	✓

VARIABLES	(1) 1: enter county	(2) 1: enter county	(3) conc 1: enter county	(4) div 1: enter county	(5) 2SLS 1: enter county	(6) 2SLS conc 1: enter county	(7) 2SLS div 1: enter county
Δ aging	0.201***	0.166***	0.186***	0.163***	0.118**	0.081	0.147***
	(0.020)	(0.023)	(0.042)	(0.026)	(0.049)	(0.082)	(0.056)
Observations	20,752	20,752	9,213	11,539	20,752	9,213	11,539
R-squared	0.008	0.446	0.456	0.441	0.012	0.011	0.017
County Controls	✓	✓	✓	✓	✓	✓	✓
Bank FE	-	✓	✓	✓	✓	✓	✓

VARIABLES	(1) Δ branches (ext)	(2) Δ branches (ext)	(3) conc Δ branches (ext)	(4) div Δ branches (ext)	(5) 2SLS Δ branches (ext)	(6) 2SLS conc Δ branches (ext)	(7) 2SLS div Δ branches (ext)
Δ aging	0.602***	0.557***	0.474***	0.613***	0.587***	0.308*	0.735***
	(0.064)	(0.051)	(0.086)	(0.060)	(0.111)	(0.174)	(0.129)
Observations	20,752	20,752	9,213	11,539	20,752	9,213	11,539
R-squared	0.007	0.787	0.804	0.775	0.038	0.029	0.046
County Controls	✓	✓	✓	✓	✓	✓	✓
Bank FE	-	✓	✓	✓	✓	✓	✓

Note: This Table shows results for instrumental variable (IV) regressions in regression equation (3), where we instrument Δold with log World War II deaths at the county level. Column (1) reports the first stage at the county level with robust standard errors and county controls. Columns (2)-(7) estimate regression equation (3), all regressions include bank and county controls, standard errors are clustered on the county level. Column (2) reports the reduced form, column (3)-(7) two-stage least squares (2SLS) regressions. F-statistics refer to the Anderson-Rubin test statistic. Faster aging at the county level (Δold) leads to an increase in bank deposits in 2SLS regressions. For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

Table OA7: **Population aging and local deposits: 2SLS**

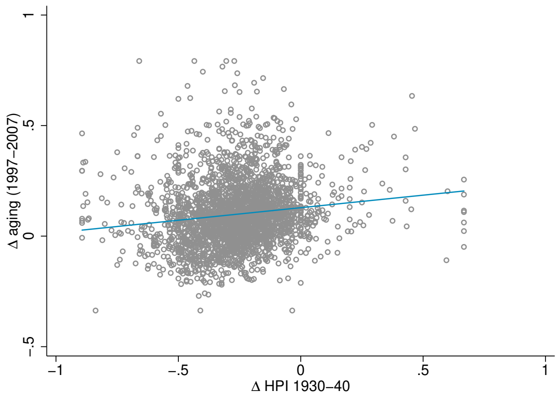
VARIABLES	(1) first stage Δ old	(2) red. form Δ deposits	(3) 2SLS Δ deposits	(4) 2SLS Δ deposits	(5) 2SLS Δ deposits	(6) 2SLS Δ deposits
log(unemployed 1940)	-0.096***	-0.045***				
	(0.004)	(0.012)				
Δ old			0.494***	0.628***	0.413***	0.469***
			(0.128)	(0.104)	(0.100)	(0.162)
Observations	2,589	20,752	20,752	20,752	20,752	20,752
R-squared	0.344	0.027	0.030	0.050	0.035	0.036
County Controls	✓	✓	✓	✓	✓	✓
Bank Controls	-	✓	✓	-	-	-
Bank FE	-	-	-	✓	✓	✓
State FE	-	-	-	-	✓	✓
County Controls 1940	-	-	-	-	-	✓
F-statistic			236.5	221	256.1	121.6

Note: This Table shows results for instrumental variable (IV) regressions in regression equation (3), where we instrument Δold with log World War II deaths at the county level. Column (1) reports the first stage at the county level with robust standard errors and county controls. Columns (2)-(7) estimate regression equation (3), all regressions include bank and county controls, standard errors are clustered on the county level. Column (2) reports the reduced form, column (3)-(7) two-stage least squares (2SLS) regressions. F-statistics refer to the Anderson-Rubin test statistic. Faster aging at the county level (Δold) leads to an increase in bank deposits in 2SLS regressions. For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

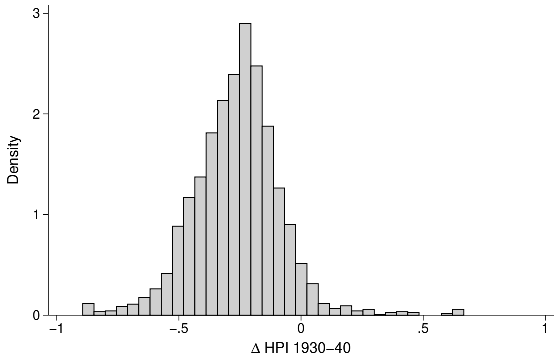
C.3 IV: Δ HPI 1930-40

Figure OA8: **IV and the Great Depression**

(a) Aging IV

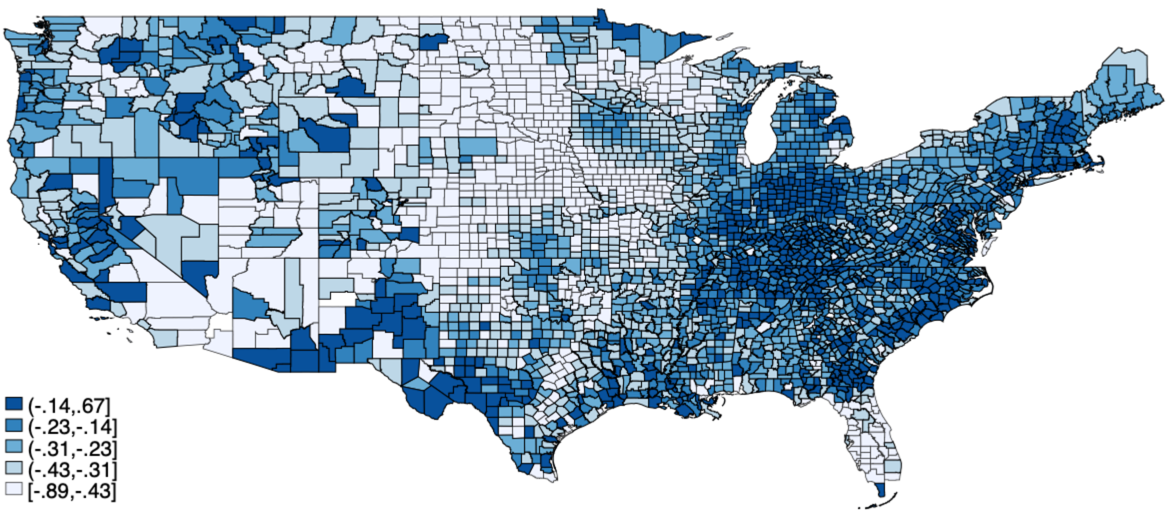


(b) Δ HPI 1930-40



Note: Panel A shows a scatter plot of change in population 65 and above from 1997 to 2007 on the y-axis against Δ HPI 1930-40 on the x-axis. Panel B show the distribution of Δ HPI 1930-40.

Figure OA9: **Δ HPI 1930-40: Geographic variation**



Note: This Figure shows a map of U.S. counties and their Δ HPI 1930-40. Darker areas indicate higher values of Δ HPI 1930-40, lighter areas lower values.

Table OA8: **Population aging and Great Depression: First stage**

	(1)	(2)	(3)	(4)	(5)
					pop-wt
VARIABLES	Δ aging	Δ aging	Δ aging	Δ aging	Δ aging
Δ HPI 1930-40	0.114***	0.107***	0.086***	0.040**	0.070***
	(0.018)	(0.018)	(0.015)	(0.016)	(0.022)
Observations	2,585	2,585	2,585	2,585	2,585
R-squared	0.019	0.126	0.568	0.648	0.659
County Controls	-	✓	✓	✓	✓
County Controls 1940	-	-	✓	✓	✓
State FE	-	-	-	✓	✓

Note: This Table shows results for instrumental variable (IV) regressions in regression equation (3), where we instrument Δold with log World War II deaths at the county level. Column (1) reports the first stage at the county level with robust standard errors and county controls. Columns (2)-(7) estimate regression equation (3), all regressions include bank and county controls, standard errors are clustered on the county level. Column (2) reports the reduced form, column (3)-(7) two-stage least squares (2SLS) regressions. F-statistics refer to the Anderson-Rubin test statistic. Faster aging at the county level (Δold) leads to an increase in bank deposits in 2SLS regressions. For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

Table OA9: **Population aging and local branches: 2SLS**

VARIABLES	(1) Δ branches (int)	(2) Δ branches (int)	(3) conc Δ branches (int)	(4) div Δ branches (int)	(5) 2SLS Δ branches (int)	(6) 2SLS conc Δ branches (int)	(7) 2SLS div Δ branches (int)
Δ aging	0.351***	0.398***	0.360***	0.462***	-0.213	1.227	-0.177
	(0.068)	(0.089)	(0.128)	(0.109)	(0.513)	(1.576)	(0.636)
Observations	6,480	6,108	3,001	3,107	6,108	3,001	3,107
R-squared	0.117	0.370	0.450	0.310	0.122	0.079	0.151
County Controls	✓	✓	✓	✓	✓	✓	✓
Bank FE	-	✓	✓	✓	✓	✓	✓

VARIABLES	(1) 1: enter county	(2) 1: enter county	(3) conc 1: enter county	(4) div 1: enter county	(5) 2SLS 1: enter county	(6) 2SLS conc 1: enter county	(7) 2SLS div 1: enter county
Δ aging	0.262***	0.200***	0.208***	0.201***	0.535**	0.532	0.590**
	(0.029)	(0.030)	(0.057)	(0.033)	(0.236)	(0.519)	(0.270)
Observations	20,649	20,649	9,157	11,492	20,649	9,157	11,492
R-squared	0.009	0.447	0.457	0.442	0.006	0.008	0.007
County Controls	✓	✓	✓	✓	✓	✓	✓
Bank FE	-	✓	✓	✓	✓	✓	✓

VARIABLES	(1) Δ branches (ext)	(2) Δ branches (ext)	(3) conc Δ branches (ext)	(4) div Δ branches (ext)	(5) 2SLS Δ branches (ext)	(6) 2SLS conc Δ branches (ext)	(7) 2SLS div Δ branches (ext)
Δ aging	0.882***	0.601***	0.556***	0.648***	1.280***	1.798*	1.349**
	(0.092)	(0.065)	(0.112)	(0.078)	(0.482)	(1.059)	(0.571)
Observations	20,649	20,649	9,157	11,492	20,649	9,157	11,492
R-squared	0.009	0.787	0.805	0.776	0.034	0.013	0.043
County Controls	✓	✓	✓	✓	✓	✓	✓
Bank FE	-	✓	✓	✓	✓	✓	✓

Note: This Table shows results for instrumental variable (IV) regressions in regression equation (3), where we instrument Δold with log World War II deaths at the county level. Column (1) reports the first stage at the county level with robust standard errors and county controls. Columns (2)-(7) estimate regression equation (3), all regressions include bank and county controls, standard errors are clustered on the county level. Column (2) reports the reduced form, column (3)-(7) two-stage least squares (2SLS) regressions. F-statistics refer to the Anderson-Rubin test statistic. Faster aging at the county level (Δold) leads to an increase in bank deposits in 2SLS regressions. For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.

Table OA10: **Population aging and local deposits: 2SLS**

VARIABLES	(1) first stage Δ aging	(2) red. form Δ deposits	(3) red. form Δ deposits	(4) 2SLS Δ deposits	(5) 2SLS Δ deposits	(6) conc 2SLS Δ deposits	(7) div 2SLS Δ deposits	(8) 2SLS Δ deposits	(9) 2SLS Δ deposits
Δ HPI 1930-40	0.107***	0.088**	0.114***						
	(0.018)	(0.038)	(0.038)						
Δ aging				-1.330	1.297**	1.548*	1.377*	1.418***	1.131
				(0.995)	(0.604)	(0.835)	(0.763)	(0.496)	(0.788)
Observations	2,587	20,649	20,649	20,649	20,649	9,157	11,492	20,649	20,649
R-squared	0.126	0.826	0.827	0.001	0.036	0.011	0.045	0.043	0.033
County Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bank FE	-	✓	✓	-	✓	✓	✓	✓	✓
County Controls 1940	-	-	✓	-	-	-	-	✓	✓
State FE	-	-	-	-	-	-	-	-	✓
F-statistic				11.02	8.670	8.860	7.290	17.30	5.510

Note: This Table shows results for instrumental variable (IV) regressions in regression equation (3), where we instrument Δold with log 1940 unemployed at the county level. Column (1) reports the first stage at the county level with robust standard errors and county controls. Columns (2)-(7) estimate regression equation (3), all regressions include bank and county controls, standard errors are clustered on the county level. Column (2) reports the reduced form, column (3)-(7) two-stage least squares (2SLS) regressions. F-statistics refer to the Anderson-Rubin test statistic. Faster aging at the county level (Δold) leads to an increase in bank deposits in 2SLS regressions. For variable definitions, see Section 3 and Appendix B. *** p<0.01, ** p<0.05, * p<0.1.