Large Banks and the Transmission of Financial Shocks

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We explore the role of large banks in propagating economic shocks across the U.S. economy. We show that in 2007 and 2008, large banks operating in U.S. counties most affected by the decline in real estate prices contracted their credit to small businesses in counties that were not affected by falling real estate prices. These exposed banks were also more likely to completely cease operations in unaffected counties. By contrast, healthy banks—those not exposed to real estate price shocks—were more likely to expand operations and even to enter new banking markets, capturing market share in both loans and deposits. On average, the market share gain of healthy banks relative to exposed banks was a standard deviation above the long-run historic average market share growth. This offsetting effect was stronger for counties with a larger presence of exposed banks, and it resulted in changes in market share composition that had lasting effects. However, the net effect was negative and counties with a larger presence of exposed banks experienced slower overall growth in deposits, loans, employment, and number of small business establishments. These effects persist for several years after the initial shock.

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1. Introduction

Large, geographically dispersed banks provide an increasing amount of credit around the world. In the United States, this financial integration has been shown to improve cost and access to credit (e.g., Jayaratne and Strahan, 1996, and Rice and Strahan, 2010). A less understood economic effect of large banks' geographical ubiquity is their role in the economic cycle. Local shocks might affect regional banks, but can be smoothed out by large diversified banks. However, economic shocks in one part of the country may spill over to otherwise unaffected areas through the balance sheets of large banks. We study this effect in the context of the 2007–2009 financial crisis and its aftermath by focusing on small business lending.

The collapse of real estate prices and the subsequent meltdown of sub-prime mortgages raised concerns about the solvency and liquidity of banks, leading to the financial panic that started in late 2007 and reached its peak in the fall of 2008. Although the overall effect was very large, not all geographical areas and not all banks were exposed to the initial decline in real estate prices. We use this variation among large, geographically-dispersed banks to isolate a supply effect. Specifically, we look at the geographically diversified banks' lending and deposit-taking activity in counties that did not experience a significant drop in real estate prices, and compare banks that were and were not exposed to the real estate shocks through their branches located in other counties.

For large companies, the source of bank financing is unlikely to be local. In fact, loans to large companies tend to be syndicated to a group of creditors. Moreover, U.S. firms also may turn to the bond market for financing (e.g., Becker and Ivashina, 2014). Thus, we focus on small business lending using information from the Federal Reserve's data on the Community Reinvestment Act (CRA) corresponding to the 2005–2014 period. The advantage of these data is that they provide information about loan origination to U.S. small business (loans smaller than $1 million in size) at the county level for all except very small banks. The shortfall is that the data do not identify borrowers, and so we cannot directly track an individual firm's ability to smooth credit supply shocks by borrowing from alternative sources. However, because small firms tend to rely on local bank credit, we can use county-level information to assess the economic impact of shocks to banks.

Measuring effects of the 2007–2008 credit supply contraction on small U.S. firms is important in and of itself. Small business represents roughly 98% of all business establishments, 46% of

GDP, and 40% of the employment in the U.S.[1] Small firms are bank dependent. Moreover, estimates of the bank supply contraction for large firms (e.g., Ivashina and Scharfstein, 2010) might understate the effect for the small firms. Indeed, Iyer et al. (2012) use data from Portugal to show that banks exposed to the interbank funding freeze in 2007–2009 cut business lending by more, and only for lending to small firms.

We find that large banks propagate local shocks to otherwise unaffected areas through their balance sheets. Although the gross effect is large, the net effect is muted by expansion in activities of relatively unaffected banks. Large banks that were exposed to the real estate shock through their operations in counties with a large drop in real estate prices substantially contracted their lending from 2006 to 2008, even in counties that did not experience a fall in real estate prices. Over the same period, the lending of large healthy banks stayed the same or even increased. In unaffected counties—those that do not fall into the top quartile of real estate depreciation between June 2006 and December 2007—large banks exposed to the real estate shocks elsewhere cut their lending by 9% from 2006 to 2008, whereas healthy banks increased their lending by 7.7% during the same period. It was not until 2009 (the trough of the widespread economic recession) that healthy banks' lending to small firms started to drop. After 2009, healthy banks' lending stayed the same, and, in some size categories, started to increase, whereas the lending of exposed banks continued to decline through 2010. The results on the extensive margin are very similar: following the collapse in real estate prices, exposed banks were more likely than healthy banks to stop operations and close their branches in counties unaffected by the real estate shock.

We also explore unaffected banks' strategic motives for expansion during the 2006–2008 period and find evidence consistent with opportunistic behavior: not only do healthy banks cut their lending less, they increase it in some counties. In addition, we find some evidence that healthy banks were able to take this opportunity to substantially expand their deposits, mostly by entering new counties. Healthy banks' market share growth, in terms of both loans and deposits, is most pronounced in areas where exposed banks had a larger presence and cut lending and deposits more. Counties with a bigger presence of exposed banks experience more growth in both the loans and deposits of healthy banks, but the growth by healthy banks does not fully make up for the cutbacks

[1] "Small Business GDP: Update 2002-2010," Small Business Administration, January 2012. "Small Firms, Employment and Federal Policy," Congressional Budget Office, March 2012. We are using 100 employees as a threshold.

by exposed banks. Thus, counties with a larger presence of exposed banks experience slower overall growth in both deposits and loans, and these effects persist in the long run. These results have both economic and statistical significance. Whereas deposit market shares generally do not change much, the market share gain of healthy banks relative to exposed banks was a standard deviation above the long-run historic average market share growth. The gain in deposit market shares by healthy banks is similar in magnitude to the effect of deregulation on profitable banks (Jayaratne and Strahan, 1997).

Our core results are constrained to banks with dispersed geographical operations, but the findings are generalizable to small, local banks. Both large and small banks that were initially relatively unaffected by the distant real estate shocks decreased their loan issuance less in the 2006–2008 period than did dispersed banks that were affected by the real estate shock. All results are robust to the exclusion of the top-10 largest banks, to controlling for the turmoil in asset-backed commercial paper (ABCP) markets, and to the exclusion of banks that enter a given county after 2002.

This paper is complementary to research on multinational banks and the role they play in transmitting shocks across borders. This includes Peek and Rosengren (1997, 2000), as well as more recent papers by Chava and Purnanandam (2011), Schnabl (2012), and Cetorelli and Goldberg (2011, 2012a, 2012b). It also relates to the burgeoning literature on the effect of rising asset prices on bank balance sheets (Chakraborty, Goldstein, and MacKinlay 2014; Flannery and Lin 2014) and the effect of banking integration on housing price co-movement across different geographies (Landier, Sraer, and Thesmar (2013)). We also contribute to the recent work on capital flows within financially integrated banks including Berrospide, Black and Keeton (2013) and Cortes and Strahan (2015).

Our paper also relates to the literature that investigates the role of corporate credit supply conditions during the global economic crisis. Our evidence is consistent with the overall severe contraction in credit supply that followed the collapse of real estate prices in the U.S. (e.g. Huang and Stephens (2014) and Greenstone, Mas, and Nguyen (2014)). However, our focus is on the contagion effect through large banks and the competitive forces that counteract this effect through the opportunistic behavior of healthy banks. In addition, while Greenstone, Mas, and Nguyen (2014) focus on the subsample of very small firms, whereas we look at the full CRA sample.

(Given that our results contrast with those in Greenstone, Mas, and Nguyen (2014) we will elaborate on it more once the data and results are presented.)

The outline of the paper is as follows. Section 2 describes the data sources. Section 3 details the identification strategy. Section 4 reports the key empirical results, which demonstrate the propagation of distant shocks through the balance sheets of large banks. Section 5 explores aggregate and long-term effects, and section 6 concludes.

2. Data sources

2.1. The CRA Data

The data on small business loans origination used in our study is collected by the Federal Financial Institutions Examination Council (FFIEC) under the auspices of the Community Reinvestment Act (CRA) enacted by U.S. Congress in 1977. Unlike data collected by FFIEC under the Home Mortgage Disclosure Act (HMDA), which gathers loans and applications for home-related loans, the CRA focuses on small business lending defined as loans not exceeding $1 million. Specifically, the purpose of the CRA is to "encourage insured depository institutions to help meet the credit needs of the communities where they are chartered."[2] To that end, commercial banks and thrifts regulated by the Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation (FDIC), the Federal Reserve System, or, formerly, the Office of Thrift Supervision (OTS), must report annual data on origination and purchases of small loans if they are above a certain size threshold. The assets threshold for reporting institutions increases each year. Notably, prior to 2005, all banks with more than $250 million in assets, or those with less assets but associated with a bank holding company with more than $1 billion in assets, had to file information under the CRA. In 2005 (the beginning of our sample), the size requirement was raised to $1 billion. Since then it has been adjusted slightly each year: in 2007, only institutions with more than $1.033 billion in assets had to file, whereas by 2015, the size threshold rose to $1.221 billion.

We exclude thrifts from our sample so that we may have consistent and consolidated balance sheet and income statement information at the holding company (BHC) level. Our final sample

[2] Information about the CRA's purpose and data submissions can be found in the "Guide to CRA Data Collection and Reporting": http://www.ffiec.gov/cra/guide.htm. Additional information about the details of how institutions file can be found in the "Interagency Q&A": http://www.ffiec.gov/cra/pdf/2010-4903.pdf."

includes 648 banks; these banks account for 72% of all bank deposits in 2006. The fact that only large banks have to file might appear restrictive insofar as small firms are more likely to borrow from smaller banks (e.g., Stein (2002), Berger et al. (2005)). However, as of 2006, CRA filers—banks with more than $1 billion in assets—had on their balance sheets 63% of all small business lending as reported by all banks in their Call Reports. In sum, CRA data covers a large fraction of U.S. banks and a large fraction of bank lending to small firms.

CRA small business loan data is unbiased for filing institutions. As part of their compliance with the CRA, institutions report three types of data. First, institutions must report the aggregate number and amount of loans designated as "community development" lending. Importantly, all filing institutions must also report the aggregate number and amount of *all* small business loans and small farm loans they originated or acquired during the reporting year. The data distinguishes between purchased and originated loans. For the purpose of this study, we only include loan originations. Small business loans—the focus of our study—are loans whose original amounts are $1 million or less and that are either commercial or industrial loans or loans secured by non-farm, non-residential real estate. (Small farm loans are loans with original amounts of $500,000 or less that are either secured by farmland or used to finance agricultural production.)[3]

CRA data are disaggregated by size and geographical location. For both small business and small farm loans, institutions are further required to break out the number of loans and total amount originated into the following categories: (i) loans smaller than $100,000, (ii) loans between $100,000 and $250,000, (iii) loans between $250,000 and $1 million, and (iv) loans issued to very small enterprises with less than $1 million in revenues. Institutions report loans by geographical location called "assessment area." Assessment areas are chosen by the banks but must be larger than a census tract and "consist generally of one or more metropolitan statistical division (MSA/MD) or one or more contiguous political subdivisions, such as counties, cities, or towns."

[3] Small farm loans and loan purchases are small in magnitude relative to small business loan originations, and including them does not qualitatively change our results. On average, small business loan purchases are 4% of small business loan originations and small farm loans are 8% of small business loans. Because the number of banks that engage in small farm loans or business loan purchases is small, we are not able to confirm that our results hold for just small farm loans or business loan purchases. Our results remain unchanged when adding small farm loans or business loan purchases to business loan originations.

Filing institutions must report CRA lending for geographies where its branches and ATMs are located, as well as "surrounding geographies in which it has originated or purchased a substation portion of its loans."[4] For ease of comparison, we aggregate the data up to the county level.

CRA data complement the small business and farm lending data reported by institutions in Schedule RC-C of the Consolidated Reports of Condition and Income ("Call Report"). The Call Report data are a stock: they report the total number and amount of all small business and small farm loans outstanding. By contrast, the CRA data are a flow: as of the end of each calendar year, the data give insight on the total number and amount of small business loans originated by filing institutions in that year. In contrast to HMDA data or loan data collected through a credit registry in foreign countries, the limitation of CRA data is that they are aggregated by geographical location and by size and do not identify individual borrowers. As mentioned earlier, the data cover only loans smaller than $1 million in origination size issued by relatively large banks.

Data collected under the CRA is used to assign CRA ratings which the FFIEC takes into account when an institution applies to engage in merger and acquisition (M&A) activity or to open a new branch. In the context of our study, one could be concerned that an increase in small lending by relatively healthy banks could be a response to an increase in regulatory and public scrutiny or a desire to pursue M&A more broadly: those banks that can afford it increase lending in counties that were lagging on CRA compliance. The use of a difference in difference approach at the county level gets around these issues.

2.2. Other Data Sources

We use five other main data sources:

Banks' balance sheet data: We obtain quarterly bank and bank-holding accounting data from the Federal Reserve. We use data at the bank holding company (BHC) level (FRB form Y9C), or, if a holding company is not available, we use data at the bank level (Call Report level). Throughout the paper, we use the term "bank" to refer to the consolidated entity.

Deposits: We use annual Summary of Deposit (SOD) data from the FDIC, measured annually as of June 30th, to ascertain the deposits of each bank across its branches in each county. (Commercial banks reported in CRA are a subset of FDIC deposit data.) We aggregate deposits

[4] http://www.ffiec.gov/cra/guide.htm.

data by county to the corresponding bank holding company if the bank holding company exists, and to the corresponding commercial bank if it does not. We also obtain branch-level deposit rate data from RateWatch.

The real estate shock: We obtain county-level real estate price index data from FISERV. FISERV publishes Case-Shiller house price indices using same-house repeated-sales data. Although the data is available at the zip-code level, we use county-level information in correspondence with our data on small business lending.

Local economy: Finally, we use annual county-level demographics data as of 2006 from the Census Bureau and employment data from the County Business Patterns, which are derived from the Census Business Registrar.

3. Empirical design

We want to establish a causal link between bank-level shocks and effect of their propagation on lending and deposit-taking more broadly. To do so, we compare the lending and deposit-taking behavior of banks that were exposed to geographies that suffered severe drops in real estate prices with the behavior of relatively unaffected banks. To identify a supply channel, we examine lending and deposit-taking by these two types of banks within areas that were *not* affected by real estate price shocks.

To illustrate our methodology, consider the case of the following two banks in our sample: PrivateBancorp Inc. and Amcore Financial Corp. PrivateBancorp is a medium-sized regional bank with assets of $3.65B as of June 2006, headquartered in Chicago and primarily operating in the Midwest—Indiana, Illinois, and Michigan. PrivateBancorp had branches in several areas that were severely affected by the real estate crisis, including 13% of its deposits in Oakland and Wayne Counties, MI which experienced real estate declines of 15% and 16%, respectively, from June 2006 to December 2007. Because of the size of its presence in these markets, PrivateBancorp is characterized as "exposed" [to the real estate shock] by our algorithm.

Amcore Financial is also a medium-sized regional bank, with assets of $5.4B as of June 30, 2006. It also serves the Midwest and all of its branches are in Indiana and Wisconsin. However, unlike PrivateBancorp, Amcore did not have branches in counties that experienced a big drop in real estate prices. The worst performing county where Amcore had branches was Vermillion

County, IL, which experienced a 5% decline in real estate prices, and Amcore had less than 5% of its deposits located there. Because of this, Amcore is characterized as "healthy" by our algorithm.

The crux of our identification comes from comparing the deposit-taking and lending activities of exposed banks, such as PrivateBancorp, with healthy banks, such as Amcore, in counties in which they both operate and in which real estate prices did not plummet, such as Cook County, IL and Milwaukee County, WI.

This empirical design requires us to focus on banks that have a broad geographical presence. To measure geographical presence, for each bank, we compute the Herfindahl-Hirschman Index (HHI) of deposits across the counties the bank operates in, as of June 30, 2006. That is, for each bank, we calculate the percent of total deposits that are in each county, and the HHI is the sum of the squared percentages for each bank. Our main sample is constrained to banks in the lowest quartile of the HHI distribution.[5] The banks in this sample represent 65% of all U.S. bank deposits as of 2006.

We define counties affected by the real estate shock as counties in the bottom quartile of the distribution of the change in the Case-Shiller index from 2006:Q2, the quarter in which the real estate market reached its peak, to 2007:Q4, the beginning of the economic recession. Thus, the *affected counties* are counties with a 2006:Q2–2007:Q4 decline in real estate prices in excess of 2.5% (an average decline of 10%). By comparison, the national Case-Shiller index fell by 6.1% during this period. Since banks in our sample have a broad geographical presence, we calculate each bank's deposit-weighted exposure to the affected counties, and then scale this measure by the bank's total deposits as of June 30, 2006. By this measure, banks in the bottom quartile are classified as *exposed* to the real estate shock.[6] We classify banks as *unaffected* or "healthy"

[5] This approach is comparable to Cortes (2013), who defines banks as local if more than two-thirds of their deposits are located in the main MSA or county market where they operate. Our definitions characterize as local all banks that are defined as local by Cortes, and approximately 80% of our local banks are characterized as local by Cortes's definition. Our results are also robust to using the distribution of the number of counties each bank has branches in as a filter.

[6] The results are robust to differing definitions of healthy and exposed based on terciles or quintiles of the distribution. Defining healthy banks as those in the top two quartiles also does not change our results. Measuring the real estate shock from 2006:Q2 to any period from 2007:Q2 to 2008:Q2 does not change our results. Finally, as discussed further in the robustness section, defining healthy and exposed banks based on the number of weak counties the bank has branches in, or the percent of deposits in weak counties, does not change the results.

otherwise. Exposed banks have an average deposit-weighted exposure of -5.7% and healthy banks have an average deposit-weighted exposure of -0.2.[7]

Deposits are an indirect measure of banks' county-level exposure to real estate shocks. In Figure 1, we validate this measure by looking at aggregate metrics that show that banks classified as exposed indeed experience substantial distress. First, as compared to unaffected banks, banks classified as exposed sustain a substantially larger rise in real estate loans past due (as a fraction of total loans) starting in 2007. Second, these exposed banks also show an increase in net charge-offs on real estate loans. Both of these patterns are consistent with high exposure to the real estate shock.

The two lower panels in Figure 1 show evidence for the two mechanisms through which the initial real estate shock led to the contraction in credit supply. The first is capital constraint: although the median Tier 1 capital ratio declined for healthy as well as exposed banks, it sank more, and remained much lower, for exposed banks. Although on paper, even exposed banks had Tier 1 capital ratios higher than the minimum 4% requirement, there was widespread concern that Tier 1 ratios were not representative of banks' true financial health.[8] News outlets reported that this anxiety over banks' financial health led regulators to push banks to raise more capital, making sure that their Tier 1 ratios were much higher than the minimum requirements.[9] The sudden rise in banks' Tier 1 ratios in the last quarter of 2008 and in 2009 is consistent with capital injections.

The second mechanism is increased risk of short-term lending: due to exposed banks' high charge-offs and falling capital ratios, the risk of short-term lending to these banks increased in both the Fed funds and repo markets (e.g., Gorton and Metrick, 2010; Afonso, Kovner, and Schoar, 2011). The last panel of Figure 1 shows that both healthy and exposed banks had trouble rolling over their short term federal funds and repo debt as those markets became stressed in late 2007, but the effect was greater for exposed banks.

[Figure 1]

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[7] Because counties that experienced a larger real estate shock were more likely to be urban and large, by our definitions, the average exposed bank had approximately 47% of its deposits in affected counties, while the average healthy bank only had 13% of its deposits in affected counties.

[8] For example, the *Wall Street Journal* pointed out in April 2008 that Citibank and Merrill Lynch had avoided letting certain write-downs impact their income statements and Tier 1 ratios by classifying them as "comprehensive other income." See "A Way Charges Stay off Bottom Line," *Wall Street Journal*, April 21, 2008.

[9] "Banks Told: Lend More, Save More; Can They Do Both? Regulators Want to See More Capital, Regardless," *Wall Street Journal*, December 26, 2008.

Table 1 presents summary statistics for our sample. The exposed and healthy banks are similar in aggregate loan composition and quality. One caveat is that the size distribution of U.S. banks is highly skewed. As a result, although there are relatively few banks in our sample and they all operate in multiple counties, exposed banks are on average significantly larger than healthy banks. In 2006:Q2, the average exposed bank has 458 branches in 65 counties and assets of $100.8 billion, whereas the average healthy bank has 68 branches in 16 counties and assets of $3.9 billion. Exposed banks also have fewer deposits as a fraction of assets: in 2006, this percentage was 67%, as opposed to 78% for healthy banks. This is also consistent with Figure 1. Excluding the largest 10 banks drops the average assets of exposed banks to $19 billion and narrows the deposits gap by 4 percentage points. As shown in the robustness test, our results remain both economically and statistically significant if we exclude the largest banks. However, due to the distribution of bank size, trying to closely match banks by size substantially reduces the economic relevance of the sample.

[TABLE 1]

Ultimately, we need the clienteles of the banks in our sample to be comparable within the dimensions that we are looking at: lending to small firms and deposits taking. Note that a borrower fixed effect approach—an approach typically used to identify effects of credit supply in countries with a centralized credit registry—does something very similar: it assumes banks to be comparable because they lend to the same borrower, and not because banks characteristics on aggregate look the same. The underlying assumption in such an approach is that different banks lend to the same borrower for the same purpose and/or with the same collateral. In our sample, deposits are covered by Federal Deposit Insurance and, in that sense, are comparable. We will also examine deposit pricing to confirm this comparability. Our loan data is from CRA compliance, which was enacted by U.S. Congress "to encourage depository institutions to help meet the credit needs of the communities in which they operate;" as such, this is a subset of local bank loans that are believed to be comparable from a policy prospective.[10] This means that a firm's employment is local, but it does not necessarily mean that the demand for the products is local. The concern is that PrivateBancorp and Amcore Financial, from our earlier example, both lend to small firms in Cook and Milwaukee counties, but PrivateBancorp lends to exporting firms (i.e., firms with out-of-

[10] http://www.ffiec.gov/cra/history.htm.

county demand) and these firms, in turn, might be affected by the out-of-county shock through a drop in demand. To address this possibility, we look at the trends in lending growth leading up to the real estate shock. (See Figure 2.)

If exposed banks are indeed lending to exporting firms, we would expect not only a differential collapse in lending following the real estate shock, but a differential rise in lending leading up to the shock. In other words, the positive correlation with activities in counties with the real estate boom should arise throughout the cycle and not just in the downturn. Figure 2 suggest that this is not the case: the lending patterns from 1996 to 2006 are very similar for both groups, especially in the $250,000 to $1 million category, which comprises the majority of the value of small business lending done by the banks. We test for trends (displayed beneath the figure) in the pre-crisis period of the figure by regressing the amount of each bank's small business lending (scaled by the 2006 level) on our indicator for healthy banks, a time trend, and the interaction of the two, using county fixed effects. The results show that there is no differential time trend between the two groups (the interaction is not statistically significant) and the indicator for a healthy bank is not significant in the period prior to the crisis.[11]

[FIGURE 2]

There are other alternative explanations, which we discuss when presenting the results.

4. Results

4.1. Intensive margin

We begin the analysis with the intensive margin. Table 2 presents the basic results: there are marked differences in lending and deposit-taking behavior of banks exposed to real estate shock and banks that are unaffected by the shock. In fact, these healthy banks tended to increase their lending while exposed banks cut their lending (recall that we are looking at the counties that did not experience a decline in real estate price). For example, on average, exposed banks extended 15% fewer loans per county in 2008 than in 2006, whereas unaffected banks increased the number of loans they extended by 1.6%. Similarly, exposed banks cut their total lending by 9%, whereas unaffected banks increased their lending by approximately 8%. This pattern is consistent across all loan size categories—unaffected banks either cut lending much less than exposed banks, or

[11] We also find no difference in pre-trends when using the yearly percent change, the dependent variable we use in the rest of the analysis.

they increased lending. Interestingly, the only category in which both types of banks cut their loan originations was lending to firms with revenues of less than $1 million. Healthy banks cut the number of loans to these firms by 10%, and the loan amount by 4%; exposed firms cut even more, slashing their number of loans to these businesses by 23% and the loan amount by 14%.

[TABLE 2]

The deposits analysis indicates that—despite deposit insurance—on average, county deposits for exposed banks shrank by 10% between 2006 and 2008, whereas they grew by 10% for healthy banks. The distribution is non-normal, but the medians also suggest a similar story: the median percent change in deposits was 3.8% for exposed banks and 7.7% for healthy banks. Both healthy and exposed banks seem to have expanded the number of their branches during the 2006 to 2008 period, but healthy banks grew more, opening on average 6.5% new branches in a county, whereas exposed banks only opened 2% more branches in each county.

4.1.1. Intensive margin: Lending activity 2006–2008

In Table 3 we look more formally at lending within counties that are unaffected by the direct real estate shock. We estimate regressions of the form:

$$\Delta L_{il} = \alpha + \beta G_i + \gamma X_i + \delta_l + \varepsilon_{il} . \qquad (1)$$

ΔL_{il} is the change in the logarithm of the amount of small business loans extended by bank i in county l between 2006 and 2008, in millions.[12] G_i, our main variable of interest, is an indicator variable that is equal to 1 for banks classified as healthy and 0 for banks exposed to the real estate shock. β, the coefficient of interest, can be interpreted as the difference in the percent change in lending from 2006 to 2008 between exposed and healthy banks.[13] X_i is the set of bank-level control variables. δ_l are county fixed effects. By including county fixed effects, we make sure that we are identifying the impact of being a healthy or an exposed bank on lending within each county.

In specification (1), we find that, controlling for the lending volume, healthy banks increased their lending more than weak banks. Specification (2) adds county fixed effects (δ_l) and

[12] The results are robust to using the change in lending rather than the percent change in lending. The loans and deposits data are winsorized at the 0.5% level.

[13] For a difference in logarithms to be interpreted as a percent change, the actual percent change needs to be small because the interpretation relies on the approximation log(1+x)≈x, for x near 0. If the percent change is large, as it is in some of our observations, the approximation no longer holds. However, our results are robust to using the actual percent change in lending as the dependent variable.

specification (3) also controls for the log of assets to account for the size of the bank. Further, to control for differences in bank strategy, in specification (4) we control for deposits as a fraction of assets, insured deposits as a fraction of total deposits, loans as a fraction of assets, and real estate loans as a fraction of assets. Specification (5) adds controls for the amount of loans that are past due as a fraction of total loans, the amount of net charge-offs (charge-offs minus recoveries) as a fraction of total loans, Tier 1 ratio, and the amount of asset-backed securities as a fraction of total assets. All bank variables are measured as of June 30, 2006. Specifications (4) and (5) show that our results are not driven by differences in strategy or differences in exposure to real estate or to the securitization market. The control variables generally have the signs that would be expected. The log of the loan originations as of 2006, which is a measure of the bank's activity in the county, is negative and significant, suggesting that banks with more market power cut lending more. The log of assets becomes significant once we control for other bank balance sheet variables.[14] Banks with more deposits over assets cut lending less, probably because the healthy dispersed banks are on average smaller and so have higher deposits as a fraction of assets. Standard errors in all specifications are clustered at the bank level. Clustering at both the bank and county levels does not change the standard errors or the significance of the coefficients. In unreported results, we show that, as Table II suggests, these effects persist across all loan sizes, but are concentrated among loans to firms with revenues of more than $1 million.

The central takeaway is that the difference in lending between healthy and exposed banks is economically and statistically significant, and robust across specifications. On average, the difference in lending between healthy and exposed banks is about 25.2 percentage points per county. This corresponds to an 8.4-percentage-point difference in the weighted average real estate price decline for affected versus unaffected banks. These results are similar to those of Huang and Stephens (2014), who find that a bank's exposure to a 1% decrease in real estate prices reduces new small business lending by approximately 3–4%. The large economic magnitude of the decline in lending is also consistent with the results for the same period in Ivashina and Scharfstein (2010).

[14] This is potentially due to non-linearities in the relationship between bank performance and assets. As mentioned earlier, exposed banks, which performed worse, tend to be larger. But some of the largest exposed banks actually performed better than smaller banks, a result which is potentially explained by government policies such as TARP, which were primarily targeted at large banks. As we discuss below, our results are unchanged when we run them on a constrained sample that removes the largest banks. When we do so, assets impact the change in the amount of loans in a statistically significant way.

[TABLE 3]

Specifications (6) through (10) of Table 3 offer a range of robustness tests. Specification (6) shows that the results are robust to exclusion of the ten largest banks. Another related concern is that exposed and healthy banks may have different expansionary policies. For example, it could be the case that exposed banks only entered many of the counties we examine in the early to mid-2000s, during the real estate boom and expansionary monetary policy of the period. If these banks over-expanded and decided to scale back, then it would be natural that from 2006 to 2008, they decreased lending in many of the counties that they had just recently entered. In other words, these might be non-core counties for the bank's business, and as such it might make sense to cut the credit in such counties even if there were no changes in demand for credit. Although this still represents a contraction in credit that is propagated into otherwise healthy geographical areas by large dispersed banks, it is a different channel, and it might have different implications for borrowers. To alleviate this concern, in specification (7), we re-estimate our main results using only counties where a bank had branches before 2002. In addition we use only these counties when creating the dispersed and exposed variables. Again, it is still the case that, even when controlling for various balance sheet variables, exposed banks reduce their lending more than healthy banks. Furthermore, the results remain the same if we exclude observations corresponding to bank mergers and acquisitions and failures, as presented in specification (8).

Next, we perform robustness checks to determine that our results are not driven by the precise definition of dispersed and exposed banks. In specification (9), we look at the sample of banks in the top quartile of the distribution for the number counties the bank has branches in and define "exposed" as the top quartile of the distribution for the number of affected counties the bank has branches in. Our last robustness result compares exposed banks with local banks. For methodological reasons, our main control sample is constrained to banks with a large geographical footprint. However, banks with a large geographical presence may respond to shocks elsewhere (shocks that are different from, but contemporaneous to, the decline in real estate markets), not just in the counties we analyze. In that sense, looking at the small banks as a control group provides an insightful observation. Since these banks are, by definition, local, their lending only reflects local conditions. Table 3, specification (10) reports results for this last robustness test; the coefficient of interest remains statistically significant at 10%.

Similar to the parallel trends test for evolution of credit reported in Figure 2, we run placebo tests (unreported) in which we use differences in lending during the pre-crisis period (e.g., the percent change in lending from 2003 to 2005) as the dependent variable. In these regressions, the healthy bank indicator G_i is not statistically significant, confirming that the difference in lending between healthy and exposed banks arises solely in the pre-crisis period.

Furthermore, it is possible that other events that arose during the early stages of the financial crisis—rather than real estate shock—drive our results. One alternative explanation is that the larger banks that were exposed to the real estate shock had larger commitments to off-balance-sheet asset-backed commercial paper (ABCP) vehicles. When the ABCP market froze in late 2007, banks that had existing commitments to these vehicles had to provide liquidity and/or credit to them. As explained in the methodology section, this would have implications for the specific type of channel at work, although we would still be identifying a supply channel. In addition, controlling for the amount of ABCP liquidity and credit commitments as a fraction of assets does not change our results.[15]

Finally, in unreported results, we perform our analysis on a propensity-score-matched sample of banks. After matching on the bank-level observables we control for in our analysis, and only keeping matches that lie on the support of the propensity score distribution, we obtain a sample of 57 exposed and 40 healthy banks. The results of this section, and most of the subsequent sections, are robust to using this subsample. We do not focus on this subsample due to the small number of observations and subsequent lack of power and economic relevance.

4.1.2. Intensive margin: Branches and Deposits, 2006–2008

Next, we examine whether healthy banks are also more likely to increase the number of branches they operate in a county. To do so, first, we extend the univariate analysis of Table 2 by regressing the percent change in the number of branches from 2006 to 2008 on our Healthy Bank indicator G_i and on our set of controls. This is the first specification of Table 4. (The estimated regression is the same as (1) of Table 3, but has a different dependent variable.) The coefficient on G_i is positive and significant, suggesting that healthy banks that had branches in a given county in

[15] We also tried controlling for the difference in ABCP liquidity and credit exposure from 2006 to 2008, which should be a measure of how much liquidity and credit support banks had to provide during that period. Again, our results remain unchanged.

2006 were more likely to expand their number of branches from 2006 to 2008 than similar exposed banks. Most banks did not expand the number of branches in a county (the median change in the number of branches is 0). To ensure that a few outliers do not drive our results, in specification (2) we replace the dependent variable with an indicator variable that is equal to 1 if the number of branches increased, -1 if it decreased, and 0 if it stayed the same. We run this regression using an ordered probit model; as such, the specification controls for county covariates rather than county fixed effects. The reported coefficients are the marginal effects of each independent variable on the probability of bank-branch expansion, evaluated at the mean of the variable's distribution. Standard errors are clustered at the bank level, but clustering at both the bank and county levels produces similar results. Our results remain strong and highly statistically significant—healthy banks are much more likely to expand their number of branches in the counties they are already in. These results are robust to exclusion of observations corresponding to merger and acquisition activity.

[TABLE 4]

Next, we consider whether healthy banks are more likely to expand deposits than similar exposed banks. In specification (3), the healthy bank indicator is positive and significant at the 10% level, implying that healthy banks increase their deposits by 7 percentage points more than exposed banks. In comparison to the effect on lending, this might seem small. But deposits—especially retail deposits—tend to be very sticky, and capturing new deposits may be harder than capturing new borrowers. Furthermore, in specification (4), we use deposits per branch as the dependent variable. There is no difference between healthy and exposed banks in terms of the growth of deposits per branch, which suggests that the growth of the deposit base is achieved through new branches. Importantly, specifications (3) and (4) only consider banks that still operate in the county. In specification (5), we add to the sample banks that completely exit the county (i.e., percent change in their deposits is -100%). The coefficient of G_i is positive and statistically significant at the 1% level. So, once we account for banks that exit a county, healthy banks are clearly able to increase their deposits more than exposed banks. (The problem with this analysis, which we address next, is that the coefficient of 110% is inflated by comparisons to banks that exit.)

In specifications (6), we consider the change in market share as the dependent variable.[16] We regress the change in deposit market share from 2006 to 2008 on our set of controls and the healthy bank indicator, G_i. Our definition of market share is holistic and captures both entries and exits. G_i is positive and significant at the 1% level, which suggests that, relative to exposed banks in the same county, healthy banks increase their market share of deposits in the county. The estimate suggests that the increase in deposit market share is 2.5 percentage points higher for healthy banks than for exposed banks. This magnitude is economically significant within the historical context. Using deposit data from 1994 to 2006, we estimate that during this time period, the average market share change over any two year period is a decrease of 0.06 percentage points (after de-meaning by year and by county, consistent with our regressions).[17] The standard deviation is approximately 2 percentage points. Thus, a difference of 2.5 percentage points is bigger than the historical difference between a bank with average growth in deposits market share and a bank with one-standard-deviation higher growth in deposits market share. Also, Strahan (2002) finds that post-geographical deregulation, small banks in aggregate lost 2% of their deposits share as a result of increased competition. This implies that the increase in the market share for the average healthy bank, relative to an exposed bank, is comparable to the impact of geographical deregulation on all small banks.

An interesting point to note about the increases in deposits captured by healthy banks is that they do not stem from higher interest rates on deposits. Using branch-level deposit rate data from RateWatch, we re-estimate specification (3) of Table 4 using the change in deposit rates from 2006 to 2008 as the dependent variable.[18] The results are presented in Table 5. Column (1) uses the change in the money market rate; column (2) uses the change in the rate on 12-month Certificates of Deposit (CDs), and column (3) uses the change in the rate on 5-year CDs. All rates correspond to the deposit rate on an account with a balance of $10,000 as these are the accounts for which RateWatch has the most data, but the results are robust to using other types of deposit accounts

[16] For ease of interpretation, we use the change in market shares rather than the percent change. We also do not control for loans or deposits as of 2006 because that would limit our sample to those bank-county pairs in which the bank had branches in 2006.
[17] We consider a change over two years so as to be comparable with our main analysis for the two-year period of 2006–2008.
[18] For each bank, we obtain the mean change in deposit rates at the county level (across all branches in that county) and use this as the dependent variable. Using the median as the dependent variable does not change our results.

and other deposit balances. In all cases, there is no statistically significant difference between the rates that healthy and exposed banks offer.

[TABLE 5]

Since banks do not seem to adjust their deposit pricing in order to attract deposits, it is likely that depositors avoid exposed banks and instead flock to healthy banks simply because of the fact that the latter are healthy. This is especially true of higher-net-worth individuals and of firms, which are more likely to be informed about the balance sheet health of the banks that house their cash deposits. A similar lack of confidence in banks affected by the real estate shock and burgeoning financial crisis caused the FDIC to extend unlimited deposit insurance to all banks in October of 2008. There is also some weak evidence that healthy banks used advertising to attract depositors, perhaps by signaling their own high quality. Between June 2006 and June 2008, healthy banks spent more on advertising expenses as a percentage of total assets than exposed banks, although the difference is not statistically significant.

4.2. Extensive margin: County exit and entry, 2006–2008

In Table 6, Panel A, we examine whether banks exposed to the real estate shock are more likely to exit a county than unaffected banks. The dependent variable is an indicator equal to 1 if a bank that had branches in the country as of June 2006 no longer has branches in that county as of June 2008, and 0 otherwise. As before, the central explanatory variable is *Healthy bank*. Specification (1) is estimated using OLS with county fixed effects. Specifications (2) and (3) are estimated using probit. Because probit produces inconsistent estimates when using fixed effects, we instead include county-level controls. These covariates include the change in real estate prices from June 2002 to June 2006 and the change in real estate prices from June 2006 to December 2007; the debt-to-income ratio, the total population, total number of households, household median income, housing density, percent of households below the poverty line, the unemployment rate, and the percentages of households working in finance, construction and real estate, all as of 2006.[19] All coefficients are reported as marginal effects at the mean of the distribution except for the coefficient of interest, the *Healthy bank* indicator, which is a binary variable. Reported standard errors are clustered at

[19] The debt-to-income data is obtained from the Mian and Sufi (2010) dataset available on Amir Sufi's website.

the bank level; clustering at both the bank and county level or just at the county level produces similar results.

Either estimation approach suggests that healthy, unaffected banks are less likely to exit counties that did not experience a real estate decline. For example, specification (2) of Panel A suggests that healthy banks are 4 percentage points less likely to exit a county relative to an exposed bank in the same county (compared to the unconditional mean of 10%). Specification (3) of Panel A drops observations that correspond to exit due to bank failures and M&A. The coefficient on G_i is much smaller in magnitude because M&A activity accounts for a large portion of exits. That said, the coefficient is still statistically significant, which implies that exposed banks are more likely to exit a county even if they do not fail and do not undergo M&A activity. [20]

[TABLE 6]

In Table 6, Panel B, we look at whether healthy banks are more likely to enter counties where they did not have branches before 2006. For this analysis, each observation corresponds to a bank-county pair where the bank did not have any branches in the county in 2006, but did have branches in an adjacent county. The dependent variable is an indicator equal to 1 if the bank entered the county in 2007 or 2008, and 0 otherwise. We use probit regression and control for county covariates. As before, the coefficients presented are marginal effects. The coefficient on G_i is positive and significant, suggesting that healthy banks were 4.3 percentage points more likely to expand into new counties than exposed banks.

Specifications (2)–(4) further test whether healthy banks were relatively more likely than exposed banks to expand into counties that are traditionally difficult to enter. In specification (2), we measure the difficulty of entry into a county by the number of banks that had entered that county in the previous 10 years. The explanatory variable of interest is the negative of the log of the number of banks that entered the county from 1996 to 2005; a larger value implies that the county is harder to enter. The coefficient on this variable is negative and significant, while the coefficient on its interaction with G_i is positive and significant, implying that exposed banks are less likely to expand into hard to enter counties, and healthy banks are relatively more likely to.[21]

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[20] The results are robust to using a fixed-effects logit.

[21] All coefficients, including the interactions, are reported as marginal effects at the means of the relevant variables using the Stata command *margins*.

Another measure for the difficulty of expanding into a county is the HHI of deposits in that county, a measure we use in specification (3). More concentrated markets should be harder to enter because a few banks control most of the market share in those markets and so consumers probably have longer relationships with one of these banks. The table supports this hypothesis. The coefficient on the Deposits HHI variable is negative and significant, whereas the coefficient on the interaction between the HHI and G_i is positive and significant. Again, exposed banks are less likely to enter into concentrated markets, whereas healthy banks are relatively more likely to.

A final measure of difficulty of entry is an index compiled by Rice and Strahan (2010). This is a state-level index that measures the barriers to cross-state entry that a state imposes on its banking markets. The index uses the values 0 to 4, which correspond to how many of the following restrictions a state imposes: a minimum age of 3 for institutions of out-of-state acquirers; a ban on de novo branching; a ban on acquisition of individual branches by out-of-state institutions; a deposit cap of 30% for each institution. In specification (4), we use this variable as a proxy for difficulty of entry and restrict the observation to the set of out-of-state counties that each bank can expand into. As expected, the coefficient on this variable is negative and significant, but the interaction with G_i is positive and significant. Exposed banks are less likely to enter counties in states with restrictions, but healthy banks are relatively more like to do so. Note that, in specifications (3) and (4), the coefficient on G_i is positive, but no longer significant. This implies that healthy banks do not generally expand more, but only expand relatively more into counties into which they otherwise have trouble entering, with difficulty of entry measured by each county's competitive or regulatory environment.

4.3. Opportunistic motives

The results in Panel B of Table 6 point to opportunistic motives for bank expansion into counties that were not affected by direct real estate shocks. Another way that healthy banks could have taken advantage of their strong balance sheets was to expand deposits and lending in markets where they already had a presence. As exposed banks cut new lending, healthy banks could have captured their market shares. Table 7 presents evidence to support this hypothesis. In Panel A, the dependent variable is the percent change in lending; in Panel B, it is the percent change in deposits. In both panels, the first 3 regressions are run only on the healthy banks and the next 3 only on the exposed banks. All regressions are estimated with bank fixed effects and standard errors clustered by bank. Because we use bank fixed effects, the results can be interpreted as within-bank analysis.

In both Panels A and B, we focus on three main independent variables. The first is aggregate percent change in lending (deposits) by other banks in the county from 2006 to 2008. The results indicate that the growth of lending and deposits of healthy banks are negatively related to the growth of other banks in the same counties, while there is no relation for exposed banks. This implies that healthy banks increase deposits and loans more in counties where other banks increase them less. In the context of the healthy and exposed banks, this suggests that as exposed banks cut lending, healthy banks step in. Note that although the result on deposits may be partially a mechanical effect of depositors switching from exposed to healthy banks, that doesn't take into account the secular trend in deposit growth rates. In addition, the result for loans is less likely to be purely mechanical. For example, if decreased demand for loans were partially driving our results, one would expect a small and positive magnitude on the coefficient on the variable of interest.

[TABLE 7]

In specifications (2) and (5), we further show that healthy banks increase lending and deposits more in counties with more exposed banks. We measure a county's exposure to the real estate shock through the exposure of banks with branches in the county. Specifically, we use the deposit-weighted average, across banks, of the exposure to the real estate drop and define the indicator variable *Exposed county* to be equal to 1 if this measure is in the upper quartile of exposure, and 0 otherwise. As the table shows, healthy banks increase deposits more in unaffected counties with a bigger presence of exposed banks. (Although on average, healthy banks do not have higher loan growth in these counties from 2006 to 2008, higher loan growth does arise in the long run, as we show below.)

Finally, in specifications (3) and (6), we examine whether healthy and exposed banks vary their loan and deposit growth based on the deposit concentration of each county, as measured by the deposit HHI. Exposed banks seem to cut their lending less in concentrated markets; this is to be expected because their rents from lending are probably higher in concentrated markets. There is no effect on deposits. Interestingly, healthy banks do not seem to increase lending or deposits more in concentrated markets, probably because they opportunistically increase growth more in areas where their market share is low. We have already shown in Table 6, however, that healthy banks do use this opportunity to enter concentrated markets where they did not already have branches. In unreported results, we also document that healthy banks are more likely to increase deposits and loans in markets they entered during the previous five years, while exposed banks do not discriminate between those and other counties.

As in the previous section, there is no evidence that the increased deposits are due to opportunistically higher deposit rates by healthy banks. On the other hand, there is some weak evidence that exposed banks increase their deposit rates more in counties with higher deposit outflows, in exposed counties, and in more concentrated counties. These results are presented in the Appendix.

5. Persistence and economic impact of the effects

We have shown that healthy banks outpace exposed banks in both the intensive margin of increasing deposits and loans and the extensive margin of entry and exit. They also opportunistically expand in areas that did not experience a real estate decline but that have a high concentration of banks exposed to the real estate shock. In this section, we show that the changes in market structure we document persisted in the long-term and did not subside after the period of turmoil from 2006 to 2008. Although isolating the long-term impact of the real estate shock is hard due to general turmoil in the financial markets as well as policy interventions, this fact should make it more difficult for us to find persistent changes in the market structure.

Table 8 examines the long-term effects of the discrepancies between exposed and healthy banks: the dependent variable is the change from 2006 to 2014 in the variable of interest. In specifications (1) and (2), the dependent variables are the percent change in deposits and in small business originations, respectively. The coefficient on G_i is positive and significant in both regressions, suggesting that the percent change in deposits and lending from 2006 to 2014 is higher for healthy banks than for exposed banks. In specifications (3) and (4), the dependent variables are the change in the market share of deposits and small business loans. In both cases, healthy banks increase their market shares more than exposed banks and the difference is both statistically and economically significant. The change in market shares from 2006 to 2014 is 4.6 percentage points higher for healthy banks in deposits and 8.8 percentage points higher in lending.

[TABLE 8]

In the previous tables, we measured the differences between healthy and exposed banks within the same county. Next, we examine the overall effect on the county in specifications (1)–(4) of Panel A of Table 9. The dependent variables in specifications (1)–(4) are calculated as aggregates across all healthy banks in a county. The main independent variable of interest is *Exposed county*, the indicator variable for whether a county is exposed to the real estate shock through the presence of branches of affected banks. Consistent with our conclusions in the preceding sections, the total percent change in both deposits and loans of healthy banks increases more in counties with a larger presence of exposed banks, and the overall market share of healthy banks also increases more in these counties. In specifications (5)–(6), the dependent variables are total deposit and loan growth across all banks in the county. The results indicate that although healthy banks increase lending and deposits more in areas that have been further exposed to the shock, they do not fully make up for the impact of the shock. Counties more exposed to the shock had deposits growth of 2.5 percentage points less, and loan growth of 9 percentage points less, than similar counties that were not exposed to the shock. Specification (7) tests whether the fact that a county is more exposed to the real estate shock changes its bank concentration, as measured by the deposit HHI. Although the effect is negative, it is not significant. Since we have shown that healthy banks are more likely to enter new and concentrated markets, one might expect the deposit HHI to decrease more in the long run as new entrants grow their market shares.

[TABLE 9]

Panel B of Table 9 replicates Panel A, but uses the change from 2006 to 2014 for all dependent variables. The results are very similar to those of Panel A. Notably, it appears that in the long run, the deposit concentration in exposed counties decreases, as healthy banks enter new, concentrated markets and begin to grow their market shares.

As with the results in previous tables, although the coefficients in this table appear to be small in magnitude, they are economically significant in the historic context. For example, specification (3) of Panel B shows that between 2006 and 2014 healthy banks in exposed counties grew their aggregate market share by 8.2 percentage points more than in other counties. By comparison, Jayaratne and Strahan (1997) find that high-profit banks increase their market shares by 6.7 percentage points in the 6 years following geographic deregulation, relative to a comparable 6 years pre-deregulation. Similarly, Strahan (2002) shows that HHI decreases by 76 points in the post-deregulation period, which is consistent with the results of specifications (7) of Panels A and B.

Finally, we examine whether these differences in deposit-taking and lending have an effect on the real economy. Using data from the County Business Patterns (CBP), derived from the Census Business Registrar, we examine how county employment and number of establishments differs between counties with a large presence of exposed banks and counties without this presence.[22] In essence, we rerun the analysis of Table 9 using changes in employment and number of firms as the dependent variables. Because the recession did not start until the end of 2007 and changes in firm employment lagged the changes in small business lending, increasing through 2007 and early 2008, we use the period from 2007–2009 instead of 2006–2008 in our analysis.

In specification (1) of Panel A of table 10, we use the percent change in employment as the dependent variable. Specification (2) uses the percent change in total number of establishments. Specifications (3)–(5) use the percent change in establishments with 1–19 workers, 20–49 workers, and more than 50 workers, respectively. The first specification shows that there is a statistically significant difference in the change in county employment between exposed and unexposed counties. On average, the drop in employment is 1.5 percentage points less for exposed counties than unexposed counties. Considering that the total drop in employment from 2007 to 2009 was 7%, this is an economically significant difference. The second specifications shows a similar difference in the number of establishments, with exposed counties at a 1-percentage-point higher drop in number of establishments during the time period. The last three columns of the table show that this drop in the number of establishments mainly comes from smaller firms with fewer than 50 employees, as there is no difference between exposed counties and non-exposed counties in terms of the number of establishments for firms with more than 50 employees. This is intuitive since our exposed county variable captures the drop in the existence of banks that cut small business lending and this type of funding is probably less important for larger firms.

[TABLE 10]

[22] Unfortunately, the CBP has data for county employment and number of establishments split by firm size, but not employment split by firm size.

Panel B of Table 10 repeats the analysis for the 2007 to 2013 time period.[23] The results show that due to the existence of exposed banks, exposed counties experience a higher drop in the number of small businesses, which lasts through 2013. This effect seems to only be persistent for the smallest firms, those with less than 20 employees. Firms with more than 20 employees seem to recover much faster after 2010.

Our results contrast with those of Greenstone, Mas, and Nguyen (2014) who find that while the decrease in small business lending has a statistically significant impact on employment, the effect is not economically meaningful. One reason for this difference comes from the fact that Greenstone, Mas, and Nguyen use a subsample of small business lending data from the CRA: lending to firms with less than $1 million in revenues. This subsample comprises 45% of all small business lending originated in 2005 (and 48% of the number of loans originated). In terms of employment, to match this data to the U.S. Census Longitudinal Business Database (LBD), Greenstone, Mas, and Nguyen consider firms with less than $1 million in revenues to be equivalent to firms with fewer than 20 employees.[24] Firms with fewer than 20 employees represent about 18% of all employment. The Small Business Administration (SBA) generally classifies as "small" firms with less than 500 employees (the average small firm in the SBA sample has annual revenues of $14 million), and firms with fewer than 500 employees represent about 55% of all employment. Thus, although the result for the subsample of very small firms is interesting, this makes an argument for looking at the full CRA sample, especially if one is interested in broader economic implications.

6. Final remarks

The years 2008–2010 were hard times. In the United States, unemployment rose to the highest levels in thirty years, and GDP per capita fell by 3% in a single year. While these adverse outcomes were widely felt across the economy, their causes were more localized. This paper studies propagation of these local shocks into the broader economy.

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[23] The latest CBP data is as of the end of 2013 so we cannot examine the period ending in 2014 as we do in our other tables.

[24] It is possible that some firms with fewer than 20 employees receive small business loans but have more than $1 million in revenues. If that is the case, the effect of the decline in lending supply on their employment would not be captured when only considering loan supply for loans to firms of less than $1 million in revenues.

We find that banks exposed to a real estate shock in their portfolio reduced their lending in local markets that had not experienced sharp declines in real estate prices, as compared to less exposed banks' lending in the same markets. These results are both statistically and economically significant. Further, we find that exposed banks were more likely to exit by closing all branches in markets that had not experienced real estate price declines, as compared to healthy, less-exposed banks. We also show that healthy banks used their stronger balance sheets to enter new markets and to opportunistically gain market shares in both deposits and small business lending in markets that were hit harder by the presence of exposed banks. These gains in market shares remain in the long run and are comparable in magnitude to changes resulting from the geographic deregulation of U.S. banking sector.

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Figure 1
The Effect of the Real Estate Shock on Healthy and Exposed Banks

This figure shows the effect of the real estate shock on various characteristics of healthy and exposed banks over time.

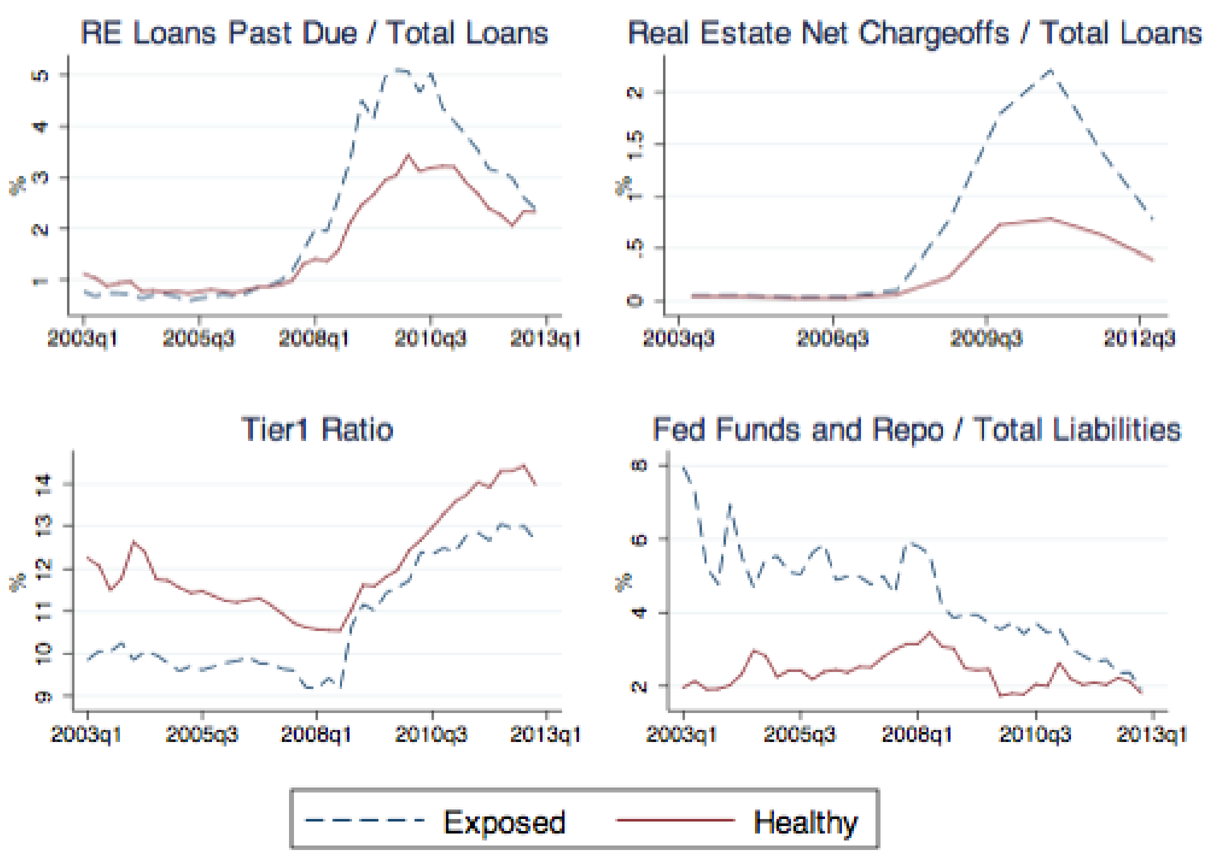
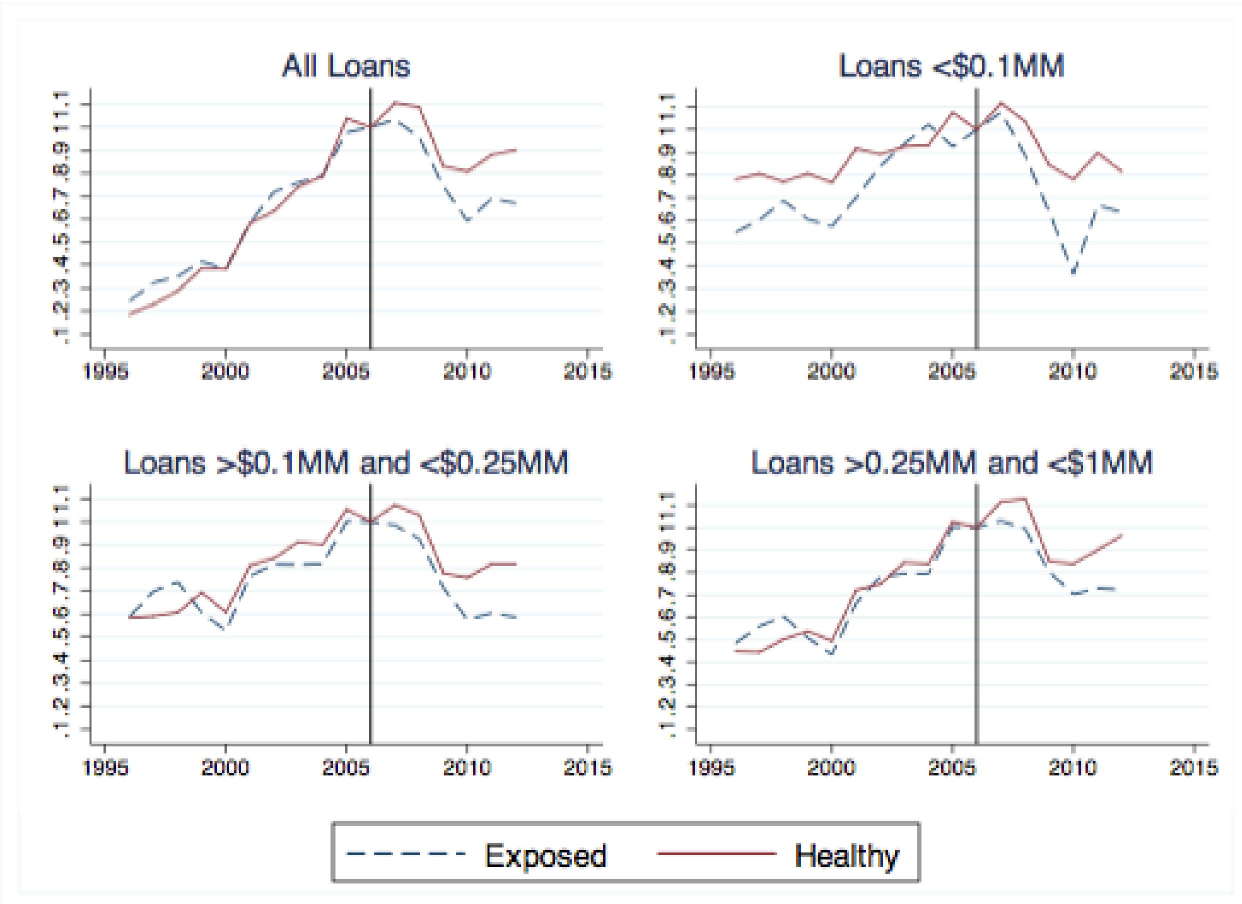


Figure 2
Loan Volume, 1996-2012

This figure shows the evolution of lending to small firms by loan size. The data are from CRA. Loan volume is indexed to 2006 levels. The figure reports an equal weighted average across counties that did not experience a drop in real estate prices, focusing on the difference between exposed and healthy dispersed banks.



Test of trends in lending by exposed and healthy banks prior to 2006 (top left panel):

$$L_{ilt} = \alpha + \beta G_i + \gamma t + \zeta\, t \text{ x } G_t + \delta_l + \varepsilon_{il}$$

Healthy bank (G_i)	-0.296
	(0.207)
Linear time trend (t)	0.073***
	(0.022)
Interaction (t x G_t)	0.027
	(0.022)
Fixed effect: County (δ_l)	Yes
Observations	37559
R^2	0.156

Table 1
Bank Characteristics

This table compares banks exposed to the real estate shock and banks that were unaffected by the real estate shock as of June 30, 2006. The first 3 columns correspond to the full sample. The fourth and fifth columns exclude banks in the top 10 by size. There are no healthy banks in the top 10 banks by size. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Exposed banks (Obs.= 79)	Healthy banks (Obs. =195)	Diff.		Exposed excluding top10 (Obs.= 69)	Diff.	
Assets ($billion)	100.77	3.85	96.92	***	19.420	15.567	***
Number of branches	458.23	67.52	390.71	***	183.61	116.08	***
Number of counties	64.77	16.01	48.77	***	34.855	18.850	***
Deposits/Total assets	0.673	0.780	-0.107	***	0.714	-0.076	***
Loans/Total assets	0.647	0.682	-0.034	**	0.661	-0.020	
Real estate loans/Loans	0.714	0.747	-0.032		0.733	-0.013	
C&I loan /Loans	0.181	0.150	0.031	**	0.178	0.028	**
Past due/Loans	0.015	0.013	0.002		0.014	0.001	
Net charge-offs/Loans	0.001	0.001	0.000	*	0.001	0.000	
MBS/Assets	0.098	0.083	0.016		0.098	0.015	
Contingent claims/Total assets	0.001	0.000	0.001		0.001	0.001	
Tier 1 capital ratio	0.107	0.119	-0.012	**	0.110	-0.008	

Table 2
Change in Lending and Deposits: Exposed Banks vs. Healthy Banks

This table compares the evolution of deposits and loans from 2006 to 2008 for exposed and healthy banks in our sample. The analysis is constrained to counties that did not experience a collapse in real estate prices. Each observation corresponds to a bank-county pair. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Counties unaffected by the direct real estate shock					
	Exposed banks		Healthy banks			
Variable:	Mean	Obs.	Mean	Obs.	Diff.	
Number of loans to small enterprise, 2006 (1,000s)	0.215	2,027	0.141	1,587	0.074	***
Amount of loans to small enterprise, 2006 ($million)	23.461	2,027	18.757	1,587	4.704	**
Percent change between 2006 and 2008:						
Number of small business loans	-0.152	2,027	0.016	1,587	-0.168	***
Number of loans that are <100K	-0.198	2,027	-0.008	1,587	-0.190	***
Number of loans that are >100K and <250K	-0.111	2,027	0.027	1,587	-0.139	***
Number of loans that are >250K and <1M	-0.052	2,027	0.111	1,587	-0.163	***
Number of loans to firms with <$1M revenue	-0.232	2,027	-0.101	1,587	-0.131	***
Number of loans to firms with >$1M revenue	-0.104	2,027	0.219	1,587	-0.323	***
Amount of small business loans	-0.090	2,027	0.077	1,587	-0.167	***
Amount of loans that are <100K	-0.146	2,027	0.006	1,587	-0.152	***
Amount of loans that are >100K and <250K	-0.074	2,027	0.026	1,587	-0.100	***
Amount of loans that are >250K and <1M	-0.038	2,027	0.105	1,587	-0.143	***
Amount of loans to firms with <$1M revenue	-0.136	2,027	-0.040	1,587	-0.096	***
Amount of loans to firms with >$1M revenue	-0.040	2,027	0.181	1,587	-0.221	***
Number of branches	0.019	1,951	0.065	1,557	-0.046	***
Deposits/Assets	0.002	1,951	0.008	1,557	-0.006	***
Deposits	-0.095	1,951	0.101	1,557	-0.196	***

Table 3
Change in Lending, 2008 vs. 2006

The analysis is constrained to counties that did not experience a collapse in real estate prices. The variable of interest is *Healthy bank*, equal to 1 if a bank was not exposed to the collapse in real estate prices across the counties in which it operates. Specifications (1)–(5) correspond to the main result (with increasing number of controls). Specifications (6)–(10), examine robustness of the results. The sample used in specification (6) excludes the ten biggest banks. In specification (7), we discard observations where a given bank had entered after 2002 (i.e., new or non-traditional markets). In specification (8), we remove observations corresponding to mergers and acquisitions and bank failures. In specification (9), we change the definition of the variables; specifically, "large" banks are defined as those in the top quartile of the distribution of the number of counties each bank operates in and "exposed" as the top quartile of the distribution of the number of weak counties each bank operates in. In specification (10), we change our control group from healthy geographically dispersed banks to local banks. Because the analysis is constrained to counties that did not experienced contraction in real estate prices, local banks were also not exposed to the real estate shock. Standard errors (reported in brackets) are clustered at the bank level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively

Dependent variable:	%Δ Loan amount									
	Main result					Robustness				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Healthy bank (G_i)	0.149***	0.162***	0.218**	0.237***	0.252***	0.248***	0.154**	0.141**	0.161***	0.174*
	(0.049)	(0.046)	(0.087)	(0.079)	(0.076)	(0.089)	(0.067)	(0.055)	(0.060)	(0.103)
Log(SBL loans in county), 2006	-0.063***	-0.091***	-0.092***	-0.100***	-0.103***	-0.106***	-0.108***	-0.089***	-0.100***	-0.109***
	(0.013)	(0.021)	(0.021)	(0.019)	(0.018)	(0.024)	(0.018)	(0.015)	(0.021)	(0.026)
Log(Assets), 2006	--	--	0.016	0.061***	0.081***	0.072**	0.048**	0.058***	0.084***	0.100***
			(0.015)	(0.023)	(0.024)	(0.031)	(0.022)	(0.016)	(0.026)	(0.033)
Deposits/Assets, 2006	--	--	--	0.749***	0.926***	0.825**	1.051***	0.938***	1.123***	1.162***
				(0.263)	(0.273)	(0.384)	(0.297)	(0.239)	(0.267)	(0.328)
Insured deposits/Deposits, 2006	--	--	--	-0.234	-0.458**	-0.338	-0.386	-0.387**	-0.275	-0.392
				(0.184)	(0.202)	(0.306)	(0.251)	(0.182)	(0.198)	(0.265)
Loans/Assets, 2006	--	--	--	0.099	0.227	0.540	-0.089	-0.049	0.047	0.257
				(0.254)	(0.246)	(0.329)	(0.330)	(0.221)	(0.248)	(0.334)
Real estate loans/Total loans, 2006	--	--	--	0.126	0.278	0.204	0.176	0.277	0.402*	0.484
				(0.180)	(0.208)	(0.247)	(0.269)	(0.218)	(0.237)	(0.318)
Net charge-offs/Total loans, 2006	--	--	--	--	17.385	11.212	29.083	22.155	17.533	4.966
					(16.865)	(22.548)	(21.170)	(16.656)	(18.096)	(21.099)
Past due loans/Total loans, 2006	--	--	--	--	-0.083	-3.758	2.302	-0.365	-1.497	2.408
					(2.952)	(3.903)	(2.875)	(2.953)	(2.900)	(3.820)
Tier 1 ratio, 2006	--	--	--	--	1.816**	2.090**	0.670	1.723**	2.450***	2.299**
					(0.908)	(0.967)	(1.079)	(0.762)	(0.795)	(1.120)
ABS/Assets, 2006	--	--	--	--	2.586	3.409	3.371	1.470	1.632	1.331
					(2.029)	(2.284)	(2.596)	(1.707)	(2.132)	(2.235)
Fixed effect: County (δ_l)	--	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3499	3499	3499	3207	3207	2099	2188	3041	3285	2426
R^2	0.062	0.267	0.270	0.300	0.310	0.403	0.371	0.302	0.286	0.335

Table 4
Deposits and Branches

This table examines whether healthy banks are more likely to expand their number of branches and enter new counties. Specifications (1)–(2) focus on the change in the number of branches in counties where the bank already has branches. In specification (2), the dependent variable is equal to 1 if the number of branches increased, 0 if it stayed the same, and -1 if it decreased, and an ordered probit is estimated. Specification (5) includes observations corresponding to a bank's exit from a county. Specification (6) includes observations corresponding to both exit from and entry into a county. Standard errors (reported in brackets) are clustered at the bank level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	%Δ Branches (1)	%Δ Branches (Ordinal) (2)	%Δ Deposits (3)	%Δ Deposits (per branch) (4)	%Δ Deposits (including exit) (5)	Δ Market share of deposits (6)
Healthy bank (G_i)	0.059**	0.223*	0.076*	-0.061	1.199***	0.025***
	(0.027)	(0.122)	(0.042)	(0.082)	(0.414)	(0.009)
Log(Assets), 2006	0.001	-0.052	0.033**	0.060**	0.518***	0.004**
	(0.007)	(0.039)	(0.014)	(0.027)	(0.099)	(0.002)
Deposits/Assets, 2006	-0.098	-0.689	0.082	0.551	1.311	-0.016
	(0.105)	(0.590)	(0.213)	(0.438)	(2.026)	(0.021)
Insured deposits/Deposits, 2006	-0.043	-0.838**	-0.127	-0.300	-0.213	-0.003
	(0.074)	(0.379)	(0.149)	(0.261)	(0.921)	(0.014)
Loans/Assets, 2006	0.152*	0.684*	0.380**	0.182	1.736	0.016
	(0.079)	(0.405)	(0.166)	(0.364)	(1.451)	(0.016)
Real estate loans/Total loans, 2006	-0.017	0.379	-0.098	-0.199	-0.646	-0.001
	(0.046)	(0.258)	(0.134)	(0.272)	(0.745)	(0.013)
Net Charge-offs/Total loans, 2006	6.499	59.383*	-3.160	-9.182	-108.982	-0.824
	(6.132)	(30.892)	(17.950)	(33.122)	(114.520)	(1.795)
Past due loans/Total loans, 2006	-0.407	2.907	-3.524*	-6.155*	8.550	0.097
	(0.953)	(4.484)	(1.994)	(3.660)	(15.082)	(0.229)
Tier 1 ratio, 2006	-0.075	0.945	0.687	2.625	12.241**	0.041
	(0.262)	(1.402)	(0.823)	(1.746)	(4.848)	(0.051)
ABS/Assets, 2006	0.426	-0.243	1.892	4.131	16.471***	0.428**
	(0.358)	(2.446)	(1.534)	(3.770)	(5.667)	(0.189)
Log(Deposits), 2006	-0.014***	-0.010	-0.131***	-0.336***	-0.222***	--
	(0.004)	(0.029)	(0.013)	(0.051)	(0.048)	
Log(Num Branches), 2006	-0.003***	-0.025***	--	--	--	--
	(0.001)	(0.007)				
Fixed effect: County (δ_l)	Yes	--	Yes	Yes	Yes	Yes
County controls	--	Yes	--	--	--	--
Observations	3209	3184	3208	3208	3747	5353
R^2	0.270	0.058	0.335	0.313	0.278	0.232

Table 5

Change in Deposit Rates, 2008 vs. 2006

This table compares the change in deposit rates from 2006 to 2008 for healthy banks and for exposed banks. In specification (1) the dependent variable is the change in the deposit rate for a money market account with a balance of $10,000. In specifications (2) and (3), the dependent variables are the changes in the deposit rates for a CD with a $10,000 balance and maturity of one year and five years, respectively. Standard errors (reported in brackets) are clustered at the bank level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively

Dependent variable:	Money market	12-month CD	5-year CD
	(1)	(2)	(3)
Healthy bank (G_i)	-0.071	0.011	-0.251
	(0.124)	(0.097)	(0.196)
Log(Deposits in County), 2006	0.002	0.005	0.037***
	(0.007)	(0.007)	(0.012)
Log(Assets), 2006	-0.069**	-0.090***	-0.014
	(0.030)	(0.024)	(0.041)
Deposits/Assets, 2006	-0.766*	-0.090	0.216
	(0.404)	(0.405)	(0.499)
Insured deposits/Deposits, 2006	-0.045	-0.066	1.394**
	(0.316)	(0.308)	(0.704)
Loans/Assets, 2006	0.751**	-0.118	0.192
	(0.297)	(0.311)	(0.465)
Real estate loans/Total loans, 2006	0.052	0.266	-0.711*
	(0.240)	(0.239)	(0.411)
Net charge-offs/Total loans, 2006	12.000	52.952	-8.994
	(26.320)	(34.696)	(69.281)
Past due loans/Total loans, 2006	-1.473	-5.008	1.505
	(3.591)	(3.102)	(6.158)
Tier 1 ratio, 2006	1.456	0.038	-3.358*
	(1.203)	(0.819)	(1.908)
ABS/Assets, 2006	6.638	6.811**	6.989**
Fixed effect: County (δ_l)	Yes	Yes	Yes
Observations	1361	1393	1314
R^2	0.758	0.702	0.405

Table 6
Extensive Margin

In Panel A, the dependent variable is an indicator equal to 1 if a bank that had branches in the country as of June 2006 but no longer has branches in that county as of June 2008, and 0 otherwise. Specification (3) excludes observations corresponding to exit due to bank failure and M&A activity. In Panel B, the dependent variable is equal to 1 if the bank entered the county between June 2006 and June 2008, and a probit is estimated. In all specifications, the coefficients reported are marginal effects. Standard errors (reported in brackets) are clustered at the bank level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Exit

	OLS (1)	Probit (2)	Probit (3)
Healthy bank (G_i)	-0.208***	-0.036***	-0.003**
	(0.073)	(0.011)	(0.001)
Change in real estate prices 2002Q2–2006Q2	--	-0.003	0.008
		(0.043)	(0.009)
Change in real estate prices 2006Q2–2007Q4	--	-0.003	-0.004
		(0.015)	(0.004)
Debt to Income Ratio, as of 2006	--	-0.008	-0.001
		(0.006)	(0.001)
Number of households (million)	--	-0.036	-0.051
		(0.124)	(0.057)
Total population (million)	--	0.014	0.020
		(0.046)	(0.022)
Median household income ($ thousand)	--	0.136	-0.004
		(0.360)	(0.058)
Number of houses per square mile	--	2.740	-0.207
		(2.909)	(0.898)
Fraction of population below the poverty line	--	0.009	-0.022
		(0.073)	(0.026)
Fraction of labor force unemployed	--	-0.013	0.056
		(0.158)	(0.050)
Fraction of labor employed in real estate	--	0.026	-0.049
		(0.097)	(0.037)
Fraction of labor employed in finance	--	0.145	0.006
		(0.096)	(0.016)
Fraction of labor employed in construction	--	-0.711	0.090
		(0.486)	(0.097)
Fixed effect: County	Yes	--	--
Observations	3,897	3828	3494
R^2	0.290	0.165	0.218

Panel B: Entry

	(1)	(2)	(3)	(4)
Healthy bank (G_i)	0.047***	0.100***	0.022	0.026
	(0.014)	(0.034)	(0.019)	(0.029)
– Log (Number of new banks, 1996–2005)	--	-0.044***	--	--
		(0.014)		
Healthy bank x –Log (Number of new banks)	--	0.023*	--	--
		(0.012)		
Deposits HHI (2006)	--	--	-0.013*	--
			(0.007)	
Healthy bank x Deposits HHI	--	--	0.013*	--
			(0.008)	
Rice and Strahan (2010) index	--	--	--	-0.015**
				(0.006)
Healthy bank x Rice-Strahan index	--	--	--	0.012*
				(0.006)
County level controls (as in Panel A)	Yes	Yes	Yes	Yes
Observations	6484	6484	6484	1421
R^2	0.082	0.091	0.086	0.187

Table 7
Opportunistic Behavior

This table tests whether healthy banks opportunistically increased their deposits and loans in certain counties. The regressions are estimated using OLS with bank fixed effects. Standard errors (reported in brackets) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Loans

Dependent variable:	%Δ Loan amount					
	Healthy Banks			Exposed Banks		
	(1)	(2)	(3)	(4)	(5)	(6)
%Δ Total loans	-0.034*	--	--	-0.014	--	--
	(0.020)			(0.020)		
Exposed county	--	0.003	--	--	0.020	--
		(0.036)			(0.035)	
Deposits HHI	--	--	0.001	--	--	0.020**
			(0.014)			(0.010)
Fixed effect: County (δ_l)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1505	1542	1542	1875	1905	1905
R^2	0.383	0.378	0.334	0.270	0.270	0.229

Panel B: Deposits

Dependent variable:	%Δ Deposits					
	Healthy Banks			Exposed Banks		
	(1)	(2)	(3)	(4)	(5)	(6)
%Δ Total deposits	-0.504***	--	--	-0.111	--	--
	(0.160)			(0.086)		
Exposed county	--	0.104**	--	--	-0.058*	--
		(0.045)			(0.033)	
Deposits HHI	--	--	-0.017	--	--	-0.007
			(0.016)			(0.012)
Fixed effect: County (δ_l)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1631	1649	1649	2009	2049	2049
R^2	0.391	0.288	0.286	0.235	0.394	0.393

Table 8
Long-Term Effects

This table tests whether the differences in gains in loans and deposits between healthy and exposed banks persist in the long term. In all specifications, the dependent variable is defined as the change from 2006 to 2014. Standard errors (reported in brackets) are clustered at the bank level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	%Δ Deposits	%Δ Loans	Δ Market share (deposits)	Δ Market share (loans)
	(1)	(2)	(3)	(4)
Healthy bank (G_i)	0.242***	0.101*	0.046***	0.088***
	(0.082)	(0.059)	(0.006)	(0.014)
Log(Assets), 2006	0.168***	0.047***	0.010***	0.023***
	(0.036)	(0.017)	(0.002)	(0.004)
Deposits / Assets, 2006	0.812	1.386***	0.060**	0.180***
	(0.517)	(0.290)	(0.024)	(0.049)
Insured Deposits / Deposits, 2006	-1.942***	-1.474***	-0.043**	-0.114***
	(0.396)	(0.218)	(0.018)	(0.039)
Loans / Assets, 2006	0.846**	-0.461**	-0.014	-0.017
	(0.420)	(0.232)	(0.017)	(0.036)
Real Estate Loans / Loans, 2006	-0.251	-0.164	-0.027**	-0.099***
	(0.192)	(0.136)	(0.012)	(0.027)
Net Charge offs / Loans, 2006	-34.883	1.108	-2.762*	-8.356**
	(35.293)	(21.318)	(1.598)	(3.741)
Past Due / Loans, 2006	0.746	-11.383***	0.651***	0.899*
	(6.105)	(3.136)	(0.210)	(0.516)
Tier 1 ratio, 2006	8.013***	3.328***	0.161***	0.556***
	(2.160)	(0.984)	(0.061)	(0.164)
ABS / Assets, 2006	9.322***	1.440	0.746***	-0.021
	(2.680)	(1.884)	(0.227)	(0.311)
Log(Deposits in County), 2006	-0.231***	--	--	--
	(0.030)			
Log(SBL Loans in County), 2006	--	-0.273***	--	--
		(0.022)		
Fixed effect: County (δ_l)	Yes	Yes	Yes	Yes
Observations	2425	2425	3448	3448
R^2	0.358	0.454	0.346	0.313

Table 9
Aggregate Effect

This table examines the aggregate effect at the county level. County exposure is measured as the deposit-weighted average, across banks, of the real estate exposure of banks in each county. The main variable of interest, *Exposed County*, is equal to 1 if the county lies in the top quartile of this distribution. In Panel A, all dependent variables are changes from 2006 to 2008. In Panel B, the dependent variables are changes from 2006 to 2014. All specifications include county controls. The analysis is constrained to counties that did not experience a real estate drop. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: 2006 to 2008

Dependent variable:	%Δ Healthy deposits	%Δ Healthy loans	Δ Healthy market share (deposits)	Δ Healthy market share (loans)	%Δ Deposits	%Δ Loans	Δ Deposit HHI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposed county	0.029***	0.098*	0.034***	0.068***	-0.025*	-0.090*	-68.787
	(0.011)	(0.059)	(0.009)	(0.017)	(0.014)	(0.054)	(47.740)
County level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	715	715	704	704	716	716	716
R^2	0.129	0.034	0.058	0.054	0.168	0.027	0.128

Panel B: 2006 to 2014

Dependent variable:	%Δ Healthy deposits	%Δ Healthy loans	Δ Healthy market share (deposits)	Δ Healthy market share (loans)	%Δ Deposits	%Δ Loans	Δ Deposit HHI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exposed county	0.041**	0.149*	0.082***	0.099***	-0.067***	-0.273***	-158.327**
	(0.017)	(0.088)	(0.016)	(0.030)	(0.025)	(0.096)	(69.711)
County level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	689	689	680	680	699	699	699
R^2	0.224	0.117	0.090	0.050	0.202	0.087	0.111

Table 10
Impact on Real Economy

This table examines the effect at the county level on the real economy. County exposure is measured as the deposit-weighted average, across banks, of the real estate exposure of banks in each county. The main variable of interest, *Exposed County*, is equal to 1 if the county lies in the top quartile of this distribution. In Panel A, all dependent variables are changes from 2007 to 2009. In Panel B, the dependent variables are changes from 2007 to 2013. All specifications include county controls. The analysis is constrained to counties that did not experience a real estate drop. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: 2007 to 2009

Dependent variable:	%Δ Employment	%Δ Num of Establishments	%Δ Num of Establishments, 1-19 employees	%Δ Num of Establishments, 20-49 employees	%Δ Num of Establishments, 50+ employees
	(1)	(2)	(3)	(4)	(7)
Exposed county	-0.015**	-0.009**	-0.008**	-0.021*	-0.003
	(0.007)	(0.004)	(0.004)	(0.011)	(0.014)
County level controls	Yes	Yes	Yes	Yes	Yes
Observations	716	716	716	716	716
R^2	0.136	0.149	0.119	0.117	0.033

Panel B: 2007 to 2013

Dependent variable:	%Δ Employment	%Δ Num of Establishments	%Δ Num of Establishments, 1-19 employees	%Δ Num of Establishments, 20-49 employees	%Δ Num of Establishments, 50+ employees
	(1)	(2)	(3)	(4)	(7)
Exposed county	-0.002	-0.012**	-0.014**	-0.005	0.021
	(0.010)	(0.006)	(0.006)	(0.015)	(0.018)
County level controls	Yes	Yes	Yes	Yes	Yes
Observations	716	716	716	716	716
R^2	0.158	0.274	0.265	0.078	0.094

Appendix

Table A1

Opportunistic Pricing Behavior

This table tests whether healthy banks opportunistically increased their deposit rates in order to attract deposits. The regressions are estimated using OLS with bank fixed effects. Standard errors (reported in brackets) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: 12 Month CD

Dependent variable:	%Δ Deposit Rates					
	Healthy Banks			Exposed Banks		
	(1)	(2)	(3)	(4)	(5)	(6)
%Δ Total loans	0.037			0.032		
	(0.087)			(0.046)		
Exposed county		-0.014			0.045	
		(0.029)			(0.070)	
Deposits HHI			0.003			0.024*
			(0.012)			(0.012)
Fixed effect: County (δ_l)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	595	595	595	679	679	679
R^2	0.940	0.940	0.940	0.457	0.458	0.457

Panel B: 5 Year CD

Dependent variable:	%Δ Deposit Rates					
	Healthy Banks			Exposed Banks		
	(1)	(2)	(3)	(4)	(5)	(6)
%Δ Total loans	-0.136			-0.141***		
	(0.133)			(0.052)		
Exposed county		0.012			0.140**	
		(0.035)			(0.057)	
Deposits HHI			0.012			-0.018
			(0.016)			(0.012)
Fixed effect: County (δ_l)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	549	549	549	676	676	676
R^2	0.879	0.879	0.878	0.630	0.631	0.628

Table A2

Opportunistic Behavior: Long Term

This table tests whether healthy banks opportunistically increased their deposits and loans in the long term. The regressions are estimated using OLS with bank fixed effects. All dependent variables are defined as changes from 2006 to 2012. Standard errors (reported in brackets) ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: %Δ Loans

Dependent variable:	%Δ Loan amount					
	Healthy Banks			Exposed Banks		
	(1)	(2)	(3)	(4)	(5)	(6)
%Δ Total loans	-0.163***			-0.153**		
	(0.041)			(0.064)		
Exposed county		0.090**			0.047	
		(0.043)			(0.044)	
Deposits HHI			-0.007			0.030**
			(0.022)			(0.012)
Fixed effect: County (δ_l)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1209	1264	1264	1378	1416	1416
R^2	0.484	0.468	0.406	0.463	0.457	0.367

Panel B: %Δ Deposits

Dependent variable:	%Δ Deposits					
	Healthy Banks			Exposed Banks		
	(1)	(2)	(3)	(4)	(5)	(6)
%Δ Total deposits	-1.495*			-0.688*		
	(0.862)			(0.374)		
Exposed county		0.129**			-0.030	
		(0.057)			(0.069)	
Deposits HHI			-0.020			-0.009
			(0.031)			(0.021)
Fixed effect: County (δ_l)	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1417	1433	1433	1684	1711	1711
R^2	0.471	0.393	0.353	0.552	0.524	0.513