

Positive Bank-to-Bank Spillovers

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Abstract

This paper provides the first evidence of positive bank-to-bank spillovers. I show that geographic linkages between banks that engage in home lending in the same geographic region transmit positive shocks from one bank to another. I exploit shocks to the deposit base of banks located in counties experiencing shale oil booms and show that a non-shocked bank in a nonboom county expands lending more if its linkages have greater exposure to shale booms. Results show that the shock exposure of linkages has a positive impact on home prices of nonboom counties, and nonshocked banks located therein respond with increased lending.

I. Introduction

Today's financial system is an intricately connected system in which different types of linkages existing between banks facilitate spillovers and make the actions and financial well-being of banks dependent on one another. Much of the literature suggests that financial spillovers occur through linkages arising due to contractual relationships, such as interbank lending, or due to correlations in asset holdings. However, recent literature suggests that linkages can be formed even when there are no contractual relationships or correlated assets. For example, linkages, and therefore spillovers, are possible between banks if they are exposed to a common regulator (Morrison and White (2013)) or share a geographic region (Shakya (2021), Goel, Song, and Thakor (2014)).¹ This literature that has studied a variety of ways in which bank-to-bank spillovers occur has focused on negative spillovers. However, this raises an important question: Do the linkages that facilitate negative spillovers also facilitate positive spillovers in the event of a positive shock?

Ex ante, the existence of negative spillovers does not necessarily imply similar positive spillovers because a bank's response to positive economic events is not symmetric with its response to negative economic events. For example, the value of a bank's assets, which consist mainly of loans, is generally more sensitive

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¹Please refer to Section II for a discussion of the literature that studies different types of interbank linkages.

to negative events than to positive events, leading to a nonsymmetric response from the bank.² Loans are typically made when it is expected that they will be paid back with a high probability such that a positive event does not improve this probability much and the value of assets does not improve. Therefore, a positive event may not lead to a positive spillover. In fact, positive events may result in loans being refinanced, in which case they result in a negative spillover to the bank if the refinancing occurs with another bank at a lower rate. On the other hand, a negative event will reduce the value of assets if it means that loans are not going to be repaid, leading to a negative spillover. Therefore, it is not clear how likely positive spillovers are, and, if they do occur, how economically significant they are. Moreover, when designing policy efforts to reduce the negative effects of linkages, it is important to be cognizant of their positive effects as well. An empirical study of positive spillovers between banks is missing in the literature, and I fill this gap by providing the first evidence of such spillovers.

For this study, I consider geographic linkages between banks: These are linkages that are formed between banks when they engage in home lending in the same geographic region (Shakya (2021)). Exploiting positive shocks to the deposit base of banks due to their exposure to counties experiencing oil and natural gas shale discoveries (“boom counties”), I show that geographic linkages facilitate transmission of these shocks from shocked to nonshocked banks. Specifically, I show that a nonshocked bank (“subject bank”) in a nonboom county (“housing market”) increases its lending more if banks that are geographically linked with it (“linkages”) have greater exposure to boom counties. In other words, the lending behavior of a bank is affected by financial well-being of *other* banks that are geographically linked with it. Importantly, this spillover effect is economically as significant as the direct effect of boom exposure on lending.

Similar in spirit to Goel, Song, and Thakor (2014), I posit that spillovers occur between geographically linked banks via an impact on the overlapping market: Spillovers occur because a positive shock leads shocked banks to change their lending behavior which improves the housing market conditions of the overlapping county. Geographically linked nonshocked banks then respond by changing their own lending behavior because they are exposed to the same county. Specifically, positive liquidity shocks lead shocked banks to increase lending in nonboom counties (Gilje, Loutskina, and Strahan (2016)). Increases in lending then lead to increases in home prices (Favara and Imbs (2015)). Increases in current home prices imply higher expected future home prices and higher collateral value such that credit exposure in home lending is lower and expected profitability is higher, so nonshocked banks increase lending in nonboom counties.

This spillover mechanism is distinct from the mechanism that leads shocked banks to increase lending in the first place due to liquidity shocks, as I discuss below. Furthermore, it is distinct from the literature that provides implications for the impact of general home prices on lending. While spillovers occur via an impact on home prices, this paper isolates and quantifies the effect, specifically, of spillovers occurring through geographic linkages.

This paper makes two main contributions: First, it provides the first evidence of positive bank-to-bank spillovers. Second, the underlying mechanism of spillover

²I thank the anonymous referee for suggesting this motivation for my paper.

is novel, thus adding to the literature that has explored different ways bank-to-bank spillovers occur. While Shakya (2021) is the first to identify the geographic linkages between banks considered in this paper, she provides a study of negative spillovers, and the underlying mechanism is different; spillovers in her study occur due to investor runs on banks that are geographically linked with shocked banks.

To identify spillovers between banks, I exploit a positive shock on bank liquidity due to unexpected cash windfalls from oil and natural gas “fracking” activities (“well activity”) that began in 2003. This shock was a result of an unanticipated development of a technology that made profitable extraction of vast amounts of oil and natural gas possible. This resulted in large royalty payments to the landowners that lease their land for fracking, and subsequent deposits in banks. Given the uncertain nature of shale discoveries and the viability of the technology, this shock is a plausibly exogenous shock to bank liquidity (Gilje, Loutskina, and Strahan (2016)).

Given this positive shock on banks exposed to boom counties, I ask how a nonshocked bank that is geographically linked with shocked banks via a nonboom county changes its lending behavior. To that end, I construct a geographic network of banks using the Home Mortgage Disclosure Act (HMDA) database, which provides comprehensive data on home lending in the United States and provides information on property location. I say that two banks are linked if both engage in home lending in the same county and if both are local (i.e., both have branch presence in the county). Because banks invest in both physical plant and customer relationships in local markets and retain most of the loans they originate there, local markets are important lending markets for banks. Focusing on local banks ensures that I study the true lending behavior of banks. Moreover, banks sell most of the loans they originate in nonlocal markets such that lending in those markets mostly reflects funding conditions in the securitization market.

I begin my empirical analysis by first showing that shale shock is indeed an economically significant positive shock to banks. I show that shocked banks receive liquidity inflows in the form of greater deposits, and that they expand their lending in nonboom counties. Compared with a bank that has an average exposure to shale well activity, a bank that has a 1-standard-deviation-higher exposure increases lending by 9.5 percentage points more. This result provides the premise for my subsequent study of spillovers between banks, as the spillover mechanism posits that shocks change the lending behavior of shocked banks, thus initiating spillovers. I also find that shocked banks increase lending only in counties where they are local, and not in counties where they are not local, thus making the case for a focus on studying spillovers only from local linkage banks.

I then proceed to provide evidence of spillovers from shale-shocked to nonshocked banks. For each nonshocked subject bank each year, I construct a measure – BOOM_EXPOSURE_OF_LINKAGES – which captures the degree to which its geographic linkages are shocked. I compute BOOM_EXPOSURE_OF_LINKAGES as the weighted average exposure of linkages to well activity in boom counties, where the weights reflect the subject bank’s sensitivity to spillovers. Sensitivity of a subject bank is captured by i) the importance of the overlapping markets to linkage banks (the higher the importance, the more their shocks will be felt in the

overlapping markets), and ii) the exposure of the subject bank to the overlapping markets (details in [Section IV](#)).

I find that in a nonboom county, a nonshocked bank increases lending more if its linkages are exposed to greater well activity in boom counties. This result persists even after accounting for the subject bank's own exposure to housing market conditions. Compared to a bank with an average value of `BOOM_EXPOSURE_OF_LINKAGES`, a bank with a value 1 standard deviation higher increases its lending by 11.3 percentage points more. Furthermore, I find that results are driven by spillovers coming from large shocked banks, consistent with the intuition that spillovers should be more pronounced coming from large banks. Similarly, increases in lending are due to increases in retained loans, as opposed to sold or securitized loans, consistent with the intuition that spillovers should affect loans that are held on bank balance sheets, as opposed to those that are easily sold.

The central identification assumption underlying this study is that spillovers do not occur if there are no linkages. I test the validity of this assumption by studying placebo linkages. For every nonshocked bank each year, I replace its shocked linkages with randomly chosen shocked banks in that year and obtain elasticity of loan growth with respect to `BOOM_EXPOSURE_OF_LINKAGES`. Repeating this exercise 1,000 times, I obtain an empirical distribution of the elasticity coefficient, and this distribution shows that `BOOM_EXPOSURE_OF_LINKAGES` is statistically not different from 0. Therefore, there is no evidence of spillovers through placebo linkages. Moreover, this result shows that the results of this paper are not simply due to factors unobservable to the empiricist.

One endogeneity concern in this study stems from the impact of the subject bank's own market exposure on home lending. I address this concern by conducting a within-market analysis – that is, I include county-year fixed effects in my empirical model such that I focus on within-market variations in `BOOM_EXPOSURE_OF_LINKAGES`, thus comparing banks that are located within the same county and year. Therefore, I compare banks that are exposed to the same market conditions but have different linkages in their network and thus different `BOOM_EXPOSURE_OF_LINKAGES`. Such within-market analysis also addresses concerns of confounding effects from borrower demands. Furthermore, results withstand a host of other tests such as controlling for a bank's own market exposure, comparison of results in counties with good versus bad ex ante market conditions, and exclusion of counties with the best ex ante market conditions.

A related concern of confounding market effect arises from direct spillovers, such as spillovers of supply of deposits from adjacent boom counties. However, results are robust to removing counties that are within 100 miles of boom counties. Yet another concern is the selection of nonshocked banks into counties where shocked banks are present because they expect housing market conditions to improve there. If this entrance is motivated by demands for loans, then results are confounded by demand effects. However, the results are robust to limiting my sample to counties where the subject bank already exists locally when its linkages are first shocked. Results are also robust to excluding large/small markets, large/small subject banks, and large linkage banks, thus accounting for any biases due to the size of the housing markets or the size of the banks.

Next, I study the underlying spillover mechanism. I first provide evidence that spillovers occur via an impact on the overlapping market by showing that non-shocked banks increase lending only in markets where shocked banks exist and not elsewhere. Then I provide direct evidence that boom exposure of linkages leads to increases in home prices in the overlapping markets.

The spillover mechanism also posits that because increases in home prices lead to higher expected future home prices and thus higher collateral value, there is a decline in expected credit exposure in home lending. If this is true, given that markets with bad economies have low borrower credibility, such markets should benefit the most from spillovers. Moreover, given that the spillover effect is *not* a liquidity shock but rather a shock to the expectations of profitability in home lending, banks that are not financially constrained should respond more to spillovers. I find that while banks generally do not increase lending in bad economies as a function of `BOOM_EXPOSURE_OF_LINKAGES`, they do so if they are not financially constrained.

Alternatively, a “liquidity channel” similar to the one in Gilje, Loutskina, and Strahan (2016) – that banks use excess liquidity received from the shale shock to create loans that they were previously unable to – could drive spillovers here. For example, home price increases in the overlapping markets may lead homeowners to sell their homes, resulting in prepayments and an influx of cash, which banks use to create new loans. However, the finding that banks increase lending only in markets where shocked banks exist contradicts this argument; a liquidity channel implies that banks are able to increase lending elsewhere too. Similarly, this channel should benefit financially constrained banks, but I find that it is the banks with financial slack that drive spillovers.

Another hypothesis is that spillovers are due to investors, who in response to rising home prices increase their supply of funds to nonshocked banks, leading those banks to expand lending. In this case, banks dependent on wholesale funds should respond more because wholesale funds are short term and less risky, and it is therefore easy for wholesale investors to quickly increase their funding to banks. However, I do not find any evidence supporting this hypothesis. Similarly, rising home prices could improve the value of under-water loans already held on bank balance sheets, and the resulting improvement in bank health allows banks to lend more. However, comparisons between banks with good and bad health *ex ante* provide no evidence that banks with bad health respond more to spillovers, inconsistent with this hypothesis.

An important question remains: Are these increases in lending rational or profitable? One could argue that nonshocked banks could simply be herding with shocked banks, and their lending behavior is not rational or profitable. However, contrary to this hypothesis, I find that bank return on assets increases and loan charge-offs decrease. Furthermore, there is no evidence that banks take riskier loans. Finally, I highlight the significance of spillovers by providing evidence of economically significant aggregate effects on lending at both bank and county levels.

The rest of the paper is organized as follows: [Section II](#) discusses related literature. [Section III](#) provides background information on shale booms and describes data and sample. [Section IV](#) discusses methods and presents base results as well as

robustness tests. [Section V](#) discusses the spillover mechanism. [Section VI](#) studies the aggregate effects of spillovers, and [Section VII](#) concludes.

II. Literature Review

This paper contributes to the literature that studies interbank connections by providing the first evidence of positive bank-to-bank spillovers and by identifying a novel mechanism of spillover. The literature so far has explored linkages primarily due to contractual relationships and asset correlations, and it has focused on negative spillovers, showing their impact mainly on bank stability (e.g., losses given default, bank failures, default probabilities, etc.).

Examples of linkages due to contractual relationships include those due to interbank lending and those due to credit default swap (CDS) exposures. Of the studies on linkages due to interbank lending, both theoretical papers (e.g., Allen and Gale (2000), Brusco and Castiglionesi (2007), Cifuentes, Ferrucci, and Shin (2005), Rogers and Veraart (2013), Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015), Glasserman and Young (2015)) and empirical papers (e.g., Furfine (2003), Upper and Worms (2004), Amundsen and Arnt (2005), Degryse and Nguyen (2007), Elsinger, Lehar, and Summer (2006), Gai, Haldane, and Kapadia (2011), and Iyer and Peydró (2011)) study negative spillovers. So do papers studying linkages due to CDS exposures (e.g., Markose, Giansante, and Shaghaghi (2012) and Morrison et al. (2017)). Bebchuk and Goldstein (2011) study linkages between interdependent firms and argue that negative spillovers occur via such linkages when banks withdraw funds from firms that are dependent on other firms that cannot obtain financing.

Examples of papers studying linkages due to asset correlations include Allen, Babus, and Carletti (2012) and Greenwood, Landier, and Thesmar (2015), and they study the negative effect of such linkages on bank stability. Other papers use correlations in stock returns of financial institutions to construct measures of overall connectedness and study the negative impact of connectedness on equity returns or volatility (e.g., Billio et al. (2012), Diebold and Yilmaz (2014)).

Recent literature provides evidence of spillovers via linkages that are not due to contractual relationships or asset correlations. For example, Morrison and White (2013) study interconnections between banks arising due to their exposure to a common regulatory body. They argue that the failure of a bank leads to loss of depositor confidence in the competence of the regulator and thus in other banks regulated by the same regulator. Similarly, Shakya (2021) and Goel, Song, and Thakor (2014) argue that spillovers occur between banks that share a common lending market. However, again, those papers study negative spillovers, while this paper studies positive spillovers.

III. Shale Boom and Data

A. Shale Booms

Natural gas shale booms are surprise events that represent credible positive shocks of considerable economic magnitude to bank liquidity and thus offer appropriate settings for studying bank-to-bank spillovers. As discussed in Gilje (2019)

and Gilje, Loutskina, and Strahan (2016), shale booms began in 2003 after an unanticipated technological innovation, commonly referred to as “horizontal fracking.” Because the viability of this technology and the discovery of shales are highly unpredictable, these booms represent shocks that are exogenous to the characteristics of banks as well as local economies. Furthermore, the economic profitability in the development of shale wells is largely determined by macro-economic factors, such as demands for natural gas, thus strengthening the case for exogeneity of these shocks (Gilje, Loutskina, and Strahan (2016)).

Shale booms also represent shocks of large economic magnitude. Banks receive large sums of deposits as landowners receive payments from oil and gas firms for leasing their land for fracking. In addition to the money received from leasing their land, landowners also receive a large upfront bonus amount at the start of the fracking activity, whether the wells turn out to be productive or not, and a percentage of the value of gas produced as royalty payment over time.³ Because of the economic significance of shale shocks, it is reasonable to expect spillover effects.

I obtain shale well data from Erik Gilje’s website.⁴ This database provides information on the cumulative count of wells that were drilled from 2003 through June 30 of a given year in each county. June 30 corresponds to the date when deposits data for banks are reported. I use deposits data in the construction of my main independent variable `BOOM_EXPOSURE_OF_LINKAGES`, and this reporting convention ensures that both deposits and count of wells are obtained as of the same point in time.

Following Gilje, Loutskina, and Strahan (2016), I focus on Arkansas, Louisiana, North Dakota, Oklahoma, Pennsylvania, Texas, and West Virginia as these states experienced major shale well activity. I define boom counties as the ones that have above median cumulative count of wells in all county-years across these states. This corresponds to any county with more than 11 wells. As of 2017, 227 counties experienced a shale boom and 412 did not. The sample in Gilje, Loutskina, and Strahan (2016) ends in 2010, and the authors use a cutoff of 17 wells to define a boom county. I later show that my results are robust to their definition of a boom county.

B. Data and Sample

I obtain home loan data for states with major shale well activity from the Home Mortgage Disclosure Act (HMDA) database. This database provides a comprehensive coverage of the U.S mortgage market and provides annual data on loan applications (regardless of whether they were approved or not), borrower demographics, lender details, and loan specifics such as loan amount and geographic location of the property. As described in detail in Section IA.1 of the Supplementary

³As an example, Gilje (2019) and Gilje, Loutskina, and Strahan (2016) note that an individual in Eagle Ford Shale who leases out his land at \$10,000/acre would receive an upfront bonus payment of \$6.4 million and a monthly royalty payment equal to 25% of the value of gas produced.

⁴See <http://finance.wharton.upenn.edu/~gilje/>. This database provides information on wells that are associated with horizontal fracking – that is, these wells are associated with the new technology that led to shale oil boom.

Material, I construct a sample of nontrivial loans (>\$50,000) that commercial banks originate from 2003 (start of shale boom) to 2017. I focus on commercial banks and remove all nonbank lenders, because most nonbank lenders fund mortgage lending with securitization (Gilje, Loutskina, and Strahan (2016)) such that their lending behavior is highly affected by funding conditions in the securitization market.

Furthermore, I treat all banks belonging to the same holding company as one bank to ensure that I capture the connectedness of a bank properly. For example, two banks that appear not linked because they operate in different counties may, in fact, be linked via another bank within the same holding company. I aggregate lending at the holding company level and study changes in lending at this level. HMDA also provides information on whether banks sell their loans at the end of the year, and using this information, I classify loans into retained versus sold loans. Table 1 summarizes mortgage growth rate variables, namely percent changes (log changes) in all loans originated, retained loans, and sold loans, at both bank-county-year and bank-year levels.⁵ Similarly, I obtain branch and deposits data from the summary of deposits provided by the Federal Deposit Insurance Corporation (FDIC) and aggregate at the holding company level.

For bank control variables, I obtain data from the call report database (Report of Condition and Income). The control variables include: $\log(\text{TOTAL_ASSETS})$, LIQUIDITY_RATIO ($= \text{LIQUID_ASSETS}/\text{TOTAL_ASSETS}$ as constructed in Acharya and Mora (2015)), $\text{EQUITY}/\text{ASSETS}$, $\text{NET_INCOME}/\text{ASSETS}$, ASSET_QUALITY ($\text{LOAN_CHARGE-OFFS}/\text{TOTAL_ASSETS}$), $\text{MORTGAGE_LOANS}/\text{ASSETS}$, $\text{UNUSED_COMMITMENTS_RATIO}$ ($= \text{UNUSED_COMMITMENTS}/(\text{UNUSED_COMMITMENTS} + \text{TOTAL_ASSETS})$), allowance for loan and lease losses (ALL/ASSETS), and commercial and industrial loans ($\text{C\&I_LOANS}/\text{ASSETS}$).⁶ I construct these variables for each bank RSSD, and for banks belonging to the same holding company, I construct them at the holding company level by taking the size-weighted average of values for each bank. Total assets of the holding company are the sum of assets of all banks belonging to that holding company.

Panel A of Table 1 summarizes these variables. The distributions of bank size ($\log(\text{TOTAL_ASSETS})$) and number of loans originated by banks are skewed due to the presence of some large banks in the sample. However, in my empirical analysis, I show that results continue to hold after excluding banks that are large and small by asset size or loan count.

Furthermore, I include a bank's exposure to percent changes in home prices as a control variable (described in detail later; summarized in Panel A of Table 1). To compute percent changes in home prices, I use the house price index (HPI) (traditional, all-transactions index) provided by the FHFA on their website (<https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx#atvol>). Some of the regressions in this paper that cannot incorporate county-year

⁵As noted in Section IA.1 of the Supplementary Material, the sample constitutes only banks that have filed HMDA in the prior year – that is, banks that were engaged in home lending in the prior year (this avoids any bias on loan growth due to lenders newly entering the business of mortgage lending). However, there are counties where a bank did not originate any loan in the prior year. For observations with 0 prior year lending, I replace 0 by 1 to compute log change in lending.

⁶Liquid assets include cash, federal funds sold and reverse repos, and securities excluding MBS/ABS securities.

TABLE 1
Summary Statistics

Table 1 presents summary statistics for the variables used in the regressions of this paper. Unless otherwise noted, the sample consists of local nonshocked banks in nonboom counties from years 2003 through 2017. The table summarizes variables at bank-county-year, bank-year, and county-year levels as indicated. Counties are local markets for banks (i.e., markets where banks have branch presence). Data on mortgage loans are from Home Mortgage Disclosure Act (HMDA) database; data on branch locations are from the FDIC summary of deposits; and data on shale well activity are from Erik Gilje's website. Sources of other data are noted in detail in the text. Panel A summarizes bank characteristics, and Panel B summarizes market (county) characteristics. Panel C summarizes boom exposure variables. BOOM_EXPOSURE_OF_LINKAGES is constructed at the bank-year level, and captures the exposure of a bank's shocked geographic linkages to well activity in boom counties (described in detail in the text). OWN_BOOM_EXPOSURE is also constructed at the bank-year level and captures a bank's own exposure to well activity in boom counties (described in detail in the text). Panel D summarizes mortgage lending variables. $\Delta \log(\text{LOANS_ORIGINATED})$ is the percent growth in loans originated by a bank from time $t-1$ to t . $\Delta \log(\text{LOANS_ORIGINATED})(\text{Retained Loans})$ and $\Delta \log(\text{LOANS_ORIGINATED})(\text{Sold Loans})$ are defined similarly for loans that are retained in bank portfolios and loans that are sold, respectively.

	<i>N</i>	Mean	SD
<i>Panel A. Bank Characteristics</i>			
<i>All Banks</i>			
(Bank-Year Variation)			
# BRANCHES	6,785	2.69	3.142
# LOANS_ORIGINATED	6,785	183.354	564.343
LAGGED_#LOANS_ORIGINATED	6,785	176.832	676.839
log(TOTAL_ASSETS)	6,785	12.532	1.343
NET_INCOME/ASSETS	6,785	0.009	0.007
CAPITAL/ASSETS	6,785	0.101	0.023
ASSET_QUALITY	6,785	0.004	0.005
MORTGAGES/ASSETS	6,785	0.176	0.101
LIQUIDITY_RATIO	6,785	0.223	0.128
UNUSED_COMMITMENTS_RATIO	6,785	0.093	0.056
ALL/ASSETS	6,785	0.009	0.004
C&I_LOANS/ASSETS	6,785	0.107	0.07
WT_AVG_OF_log(POPULATION)	6,785	11.942	1.42
WT_AVG_OF_log(PERSONAL_INCOME)	6,785	10.481	0.249
WT_AVG_OF_DEBT-TO-INCOME	6,785	1.328	0.692
WT_AVG_OF_PERCENT_FEMALE_POPULATION	6,785	0.507	0.01
WT_AVG_OF_PERCENT_MINORITY_POPULATION	6,785	0.169	0.129
BANK_UNEMPLOYMENT_EXPOSURE	6,785	0.058	0.017
BANK_EXPOSURE_TO_ΔHPI(%)	6,785	0.027	0.036
LAGGED_BANK_EXPOSURE_TO_ΔHPI(%)	6,785	0.027	0.035
BANK_EXPOSURE_TO_ΔHPI(%) (OVERLAPPING MARKETS)	6,082	0.024	0.034
LAGGED_BANK_EXPOSURE_TO_ΔHPI(%) (OVERLAPPING MARKETS)	6,082	0.024	0.034
(Bank-County-Year Variation)			
EXPOSURE_TO_ΔHPI(%)_IN_OTHER_MARKETS	16,539	0.018	0.028
<i>Panel B. Market Characteristics</i>			
<i>All Counties</i>			
(County-Year Variation)			
#Loans Originated	3,349	1158.065	2624.537
Lagged #Loans Originated	3,349	1160.316	2615.758
Median Bank (Nonshocked) Branch Count	3,349	5.431	4.932
Median Bank (Nonshocked) Size	3,349	13.14	1.175
#Shocked Banks	3,349	3.453	4.96
<i>Counties Where #Shocked Banks > 0</i>			
Median Bank (Shocked) Branch Count	2,393	42.761	25.448
Median Bank (Shocked) Size	2,393	17.066	1.996
<i>Panel C. Boom Exposure Variables</i>			
<i>Nonshocked Banks</i>			
(Bank-Year Variation)			
BOOM_EXPOSURE_OF_LINKAGES	6,785	0.773	1.597
BOOM_EXPOSURE_OF_LARGE_LINKAGES	6,785	0.297	0.755
BOOM_EXPOSURE_OF_SMALL_LINKAGES	6,785	0.462	0.887
<i>Shocked and Nonshocked Banks</i>			
OWN_BOOM_EXPOSURE (Local subsample)	9,410	0.466	1.053
OWN_BOOM_EXPOSURE (Non-local subsample)	13,706	0.601	1.359
<i>Panel D. Mortgage Lending Variables</i>			
(Bank-County-Year Variation)			
$\Delta \log(\text{LOANS_ORIGINATED})$	16,539	0.655	2.115
$\Delta \log(\text{LOANS_ORIGINATED})(\text{Retained Loans})$	16,539	0.639	2.141
$\Delta \log(\text{LOANS_ORIGINATED})(\text{Sold Loans})$	16,539	0.337	2.275
Fraction Loans Retained	16,539	0.794	0.293
(Bank-Year Variation)			
$\Delta \log(\text{LOANS_ORIGINATED})$	6,785	0.65	2.064
$\Delta \log(\text{LOANS_ORIGINATED})(\text{Retained Loans})$	6,785	0.642	2.053
$\Delta \log(\text{LOANS_ORIGINATED})(\text{Sold Loans})$	6,785	0.223	1.946

fixed effects include control variables for county market characteristics. These characteristics include $\log(\text{POPULATION})$, $\log(\text{PER_CAPITA_PERSONAL_INCOME})$, $\text{HOUSEHOLD_DEBT-TO-INCOME_RATIO}$, UNEMPLOYMENT_RATE , $\text{PERCENT_FEMALE_POPULATION}$, and $\text{PERCENT_MINORITY_POPULATION}$. I obtain county-level data for population, including female/minority data, from the U.S Census Bureau, per capita personal income data from the Bureau of Economic Analysis, household debt-to-income ratio from the Federal Reserve, and unemployment rate from the U.S Bureau of Labor Statistics.

I will be referring to all independent banks and groups of banks belonging to the same holding company as “banks” from here on. My final sample consists of nonshocked banks in nonboom counties, where the banks are local, from years 2003 through 2017. This sample consists of 16,539 bank-county-year observations with 1,062 unique banks and 411 unique counties.

Panel A of [Table 1](#) shows that banks in my sample have on average 3 branches and originate 183 loans. Within a county-year, Panel B shows that new loans average 1158 and the median bank has 5 branches on average.⁷ Similarly, within a county-year, there are 4 shocked banks on average. In a subsample of counties where shocked banks are locally present, the median shocked bank has on average 43 branches.⁸ Therefore, shocked banks generally operate in more counties, and as the size distribution of shocked banks shows, they are also larger. Additionally, the distribution is skewed; however, I show later that my results persist after excluding linkages that are very large. The distribution of loan count at the county-year level is also skewed; however, I find that results are robust to excluding the smallest and the largest counties by loan count each year.

An important observation in Panel D of [Table 1](#) is that each year, banks on average retain 79.4% of loans they originate in a local county and sell the rest. Furthermore, in unreported tables, I find that banks sell a larger fraction of loans (46%) in nonlocal markets. These numbers underscore the importance of focusing on local markets to study home lending. They are consistent with the intuition that because branches provide closer access to borrower information, banks have an information advantage in local markets and can retain more loans in these markets. Therefore, a bank’s true lending behavior is reflected more in local markets, compared to nonlocal markets, where they sell a large fraction of loans such that their lending behavior there is influenced by funding conditions in the securitization market. As mentioned before, this observation also serves as a premise for defining banks to be linked only if they overlap in their local markets.

IV. Methods and Results

A. Shale Well Shock and Mortgage Lending

I begin my analysis by showing that shale shock is indeed a positive shock to banks and that it is significant enough to change the lending behavior of banks. In Section IA.2 of the Supplementary Material, I show that the shock leads to liquidity

⁷The median bank is the bank having the median number of branches in a given county-year.

⁸Here, the median bank is the bank having the median number of branches in a given county-year.

inflows in banks in the form of greater deposits.⁹ Banks receive greater deposits because land owners in boom counties receive cash windfalls, which they deposit at banks or use to pay back outstanding loans (Gilje, Loutskina, and Strahan (2016)). Compared to a nonshocked bank, deposits at a shocked bank with an average share of deposits in boom counties grow from 2002 to t at a 1.4 percentage points faster rate.

Next, I show that the shale shock leads banks to change their lending behavior. I show that banks increase their lending in nonboom counties more if they have greater exposure to well activity in boom counties. I consider bank lending only in nonboom counties in order to avoid the direct market effect of counties experiencing shale booms. This result provides the premise for the study of subsequent spillover effects, as the spillover mechanism posits that shocks lead to changes in bank lending behavior which then initiates spillovers.

For each bank, I compute OWN_BOOM_EXPOSURE, which captures a bank's exposure to well activity using the weighted average of log of cumulative count of wells in local boom counties. The weights are the shares of deposits that the bank holds in each county each year. This study includes both shocked and nonshocked banks, and for nonshocked banks, this variable takes the value 0. As mentioned before, boom counties are the ones that have above median cumulative counts of wells in all county-years. Focusing on local boom markets ensures that the bank has close access to depositors with cash windfalls. Furthermore, because the bank is local, the market is important for the bank – it is invested in both physical plant and customer relationships such that it responds to well activity in that market. Panel C of Table 1 summarizes OWN_BOOM_EXPOSURE and presents its distribution in subsamples of local and nonlocal markets separately.

Given that contemporaneous shares of deposits could be affected by new deposits from the shock itself, in unreported tables, I construct OWN_BOOM_EXPOSURE using lagged deposit shares to capture a bank's exposure to well activity and obtain similar results. To be consistent with the construction of BOOM_EXPOSURE_OF_LINKAGES in the next section, which uses contemporaneous deposit shares, I present results for OWN_BOOM_EXPOSURE which also uses contemporaneous deposit shares. Furthermore, in unreported tables, I find that results are similar if I use shares of deposits in boom counties as a measure for a bank's shock exposure as in Gilje, Loutskina, and Strahan (2016). Results are also robust to using lagged shares of deposits.

Using the following model, I study how a bank changes its lending in year t from prior year $t-1$ in a nonboom county, as a function of OWN_BOOM_EXPOSURE:

$$(1) \quad \Delta \log(\text{MORTGAGE_LENDING}_{i,c})_t = \alpha + \beta \text{OWN_BOOM_EXPOSURE}_{i,t} \\ + \text{BANK_CONTROLS}_{i,t-1} \\ + \text{COUNTY} \times \text{YEAR} \cdot E + \varepsilon_{i,c,t}$$

In this model, the unit of analysis is for a bank in a nonboom county each year. $\Delta \log(\text{MORTGAGE_LENDING}_{i,c})_t$ is the percent growth in mortgage

⁹I thank the anonymous referee for suggesting this test.

lending of bank i in county c in year t . County c is local for bank i . OWN_BOOM_EXPOSURE $_{i,t}$ is as described earlier. Bank control variables are constructed as of the prior year-end, and I winsorize all variables at 1%. I also include county-year fixed effects in all regressions and cluster standard errors by bank. The coefficient of interest here is β . If banks increase lending as a function of their boom exposure, I expect $\beta > 0$.

Table 2 presents the results. This table shows how banks change their lending in nonboom counties as a function of their own boom exposure. Columns 1 and 2 study changes in lending in local markets, whereas columns 3 and 4 study changes in lending in nonlocal markets.

Column 1 of Table 2 shows that banks increase lending in local nonboom counties if they are exposed to a greater degree of shale well activity. I account for any confounding effect of local housing market conditions by conducting a within-market analysis using county-year fixed effects, thereby comparing banks that are exposed to the same market conditions. In column 2, I further account for the confounding effect of housing market conditions in *other* local markets of

TABLE 2
Own Boom Exposure

Table 2 reports regressions of a bank's percent growth in home lending in a given county and year on the bank's OWN_BOOM_EXPOSURE. OWN_BOOM_EXPOSURE captures a bank's exposure to well activity in boom counties (described in detail in the text). A boom county is a county that has above median count of cumulative wells in all county-years. The sample in this regression includes both shocked and nonshocked banks in nonboom counties from 2003 to 2017. Columns 1 and 2 study percent growth in mortgage originations in local counties. Columns 3 and 4 study percent growth in mortgage originations in nonlocal counties. All regressions include county-year fixed effects. Standard errors are clustered by bank, and t -statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	$\Delta \log(\text{LOANS_ORIGINATED})$			
	Local		Non-Local	
	1	2	3	4
OWN_BOOM_EXPOSURE	0.0816** (2.409)	0.0833** (2.435)	-0.0213 (-0.855)	0.0128 (0.511)
EXPOSURE_TO_ΔHPI(%)_IN_OTHER_MARKETS		-0.993 (-0.571)		-10.99*** (-5.734)
log(TOTAL_ASSETS)	-0.0225 (-0.799)	-0.0201 (-0.675)	-0.170*** (-7.536)	-0.158*** (-7.472)
NET_INCOME/ASSETS	-18.85*** (-3.254)	-18.79*** (-3.238)	-17.70*** (-2.888)	-19.41*** (-3.113)
CAPITAL/ASSETS	5.532*** (3.610)	5.508*** (3.578)	2.670* (1.762)	2.422 (1.571)
ASSET_QUALITY	12.46 (1.509)	12.23 (1.465)	-6.766 (-0.698)	-9.149 (-0.912)
MORTGAGES/ASSETS	-0.844** (-2.446)	-0.857** (-2.449)	-0.924** (-2.114)	-1.325*** (-3.296)
LIQUIDITY_RATIO	-0.318 (-1.221)	-0.322 (-1.229)	-1.366*** (-3.492)	-1.198*** (-3.216)
UNUSED_COMMITMENTS_RATIO	0.690 (0.599)	0.696 (0.604)	0.246 (0.371)	0.273 (0.422)
ALL/ASSETS	7.830 (0.598)	7.539 (0.581)	-11.76 (-0.958)	-14.50 (-1.206)
C&I_LOANS/ASSETS	-0.475 (-0.836)	-0.471 (-0.832)	-0.0950 (-0.164)	-0.198 (-0.338)
Constant	0.641 (1.561)	0.633 (1.534)	5.687*** (14.873)	5.867*** (15.942)
County-year fixed effects	Yes	Yes	Yes	Yes
No. of obs.	34,142	34,142	132,205	132,205
Adjusted R^2	0.107	0.107	0.064	0.071

a bank by including a control for contemporaneous weighted average exposure of the bank to percent changes in home prices in counties other than the one under consideration (EXPOSURE_TO_ΔHPI(%)_IN_OTHER_MARKETS). The weights are the bank's shares of deposits in each county each year. I find that results do not change. In fact, the magnitude of OWN_BOOM_EXPOSURE increases slightly.

To understand the economic significance of the impact of OWN_BOOM_EXPOSURE, consider a bank with an average value for this variable (= 0.466), and a bank with a value 1 standard deviation higher (= 0.466 + 1.053 = 1.519). Column 2 of Table 2 implies that the latter bank increases its lending by 9.5 percentage points more than the former bank (= $e^{(1.519 \times 0.0833)} - e^{(0.466 \times 0.0833)}$).

I conduct similar tests for nonlocal markets and present results in columns 3 and 4 of Table 2. There is no evidence that banks change lending in nonlocal markets. OWN_BOOM_EXPOSURE is statistically insignificant in both columns. Moreover, it is negative in column 3. While it is positive in column 4, it is economically very small. These results are consistent with the idea that banks have an information advantage in local markets that allows them to increase lending in these markets, as opposed to nonlocal markets (Gilje, Loutskina, and Strahan (2016)).

Therefore, the shale shock is indeed a positive shock to banks, and it causes banks to increase lending in nonboom markets. That shocked banks increase lending only in local markets makes a further case for focusing on spillovers from local linkages only in the next sections.

B. Spillover Effect

1. Construction of Boom Exposure of Linkages

In this subsection, I describe how I construct my main independent variable – BOOM_EXPOSURE_OF_LINKAGES. As defined before, two banks are geographically linked if they are local and engage in mortgage lending in the same market (county). I construct this variable for each nonshocked bank in each year as the weighted average exposure of its shocked linkage banks to the log of cumulative count of wells in their local boom markets. The weights reflect the sensitivity of the nonshocked bank to spillovers from its linkages as described below.

Consider the computation of BOOM_EXPOSURE_OF_LINKAGES for a nonshocked bank X in year t . Let M be the set of all local markets for X . Linkage banks for X are all shocked banks that are local in any $m \in M$. Let $w_{m,t}^i$ be the fraction of deposits that bank i holds in county m in year t . I follow the following 3-step process:

Step 1. Compute each linkage bank's exposure to well activity.

In step 1, I identify all shocked linkage banks of X . Then for each shocked linkage bank, I compute its exposure to well activity in local boom counties by taking the weighted average of the natural logarithm of cumulative count of wells in those counties. The weight used is the bank's share of deposits in each market. So for a linkage bank Y , its exposure to well activity in boom counties is

$$(2) \text{ Boom Exposure of } Y \text{ in year } t = \text{BOOM_EXP}_t^Y = \sum_c w_{c,t}^Y \log(C_WELLS_{c,t}),$$

where $C_WELLS_{c,t}$ is the cumulative count of wells in county c in year t since the beginning of shale boom (i.e., 2003). Note $w_{c,t}^Y > 0$ only in local markets of Y , so the expression in 2 takes the weighted average of well activity only in local markets of Y .

Step 2. Weigh each linkage bank's boom exposure by the subject bank's sensitivity to it.

Because banks may overlap in more than one market, the next step entails giving more weight to markets where X is more sensitive to spillovers from shocked banks. I do so by weighing each linkage bank's boom exposure by i) the importance of the overlapping market to the linkage bank, and ii) the importance of the overlapping market to X . I capture the importance of a market to a bank by the fraction of deposits that the bank holds in that market. The effect of a shocked bank's boom exposure should be felt more in markets that are important to that bank. Therefore, assigning a weight for the importance of the market to the shocked bank ensures that I give more weight to areas where X is more likely to experience spillovers. Assigning a weight for the importance of the market to X captures X 's exposure to the linkage bank via that market. So for a shocked bank Y that is linked with X via county a , I capture X 's sensitivity to Y 's shock as follows:

$$(3) \text{ Weighted boom exposure of } Y \text{ in county } a \text{ in year } t = w_{a,t}^X w_{a,t}^Y \text{ BOOM_EXP}_t^Y$$

If X overlaps with Y in counties a and b , I sum up the weights for each of these counties:

$$(4) \text{ Weighted boom exposure of } Y \text{ in counties } a \text{ and } b \text{ in year } t = \left(w_{a,t}^X w_{a,t}^Y + w_{b,t}^X w_{b,t}^Y \right) \text{ BOOM_EXP}_t^Y.$$

Extended to all overlapping counties m , weighted boom exposure of linkage bank Y is then

$$(5) \text{ Weighted boom exposure of } Y \text{ in year } t = \left(\sum_{m \in M} w_{m,t}^X w_{m,t}^Y \right) \text{ BOOM_EXP}_t^Y.$$

Again, for bank i in county m , $w_{m,t}^i > 0$ only if it has a branch in m , so in equation (5), $w_{m,t}^X w_{m,t}^Y > 0$ only if both X and Y are local in m – that is, if X and Y are geographically linked.

Step 3. Sum up weighted boom exposures of all linkages.

Finally, I consider all shocked linkages of X and sum up their weighted boom exposures computed in step 2. The final expression for BOOM_EXPOSURE_OF_LINKAGES for X is the following:

$$(6) \quad \text{BOOM_EXPOSURE_OF_LINKAGES for } X \text{ in year } t \\ = \sum_i \sum_{m \in M} w_{m,t}^X w_{m,t}^i \text{ BOOM_EXP}_t^i.$$

where i is a shocked bank that is geographically linked with X in year t .

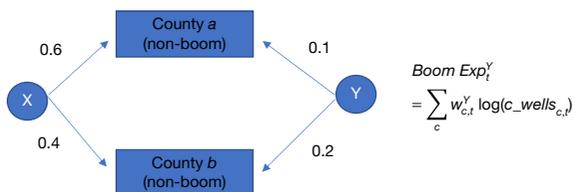
By constructing BOOM_EXPOSURE_OF_LINKAGES at the bank level and studying how banks change their lending in each county as a function of this variable, I implicitly account for the possibility that banks may also learn from the lending behavior of shocked banks and subsequent increases in home prices in one nonboom county and expect similar increases in home prices in other nonboom counties if shocked banks exist in those counties as well.

Figure 1 illustrates the construction of BOOM_EXPOSURE_OF_LINKAGES in a hypothetical network of two banks. *X* is a nonshocked bank, local in counties *a* and *b*, both of which are nonboom counties. *Y* is shocked via other local boom counties (not shown). It is also local in *a* and *b*. Solid arrows represent lending in a market, and the numbers along the arrows represent a bank’s shares of deposits in the markets. Here, bank *X* is the subject bank – the one that is on the receiving end of spillovers and the one whose lending behavior I study – and *Y* is *X*’s linkage bank.

As described in detail in Section IA.3 of the Supplementary Material, $BOOM_EXP_t^Y$ is *Y*’s exposure to well activity in year *t*, and after assigning weights that capture *X*’s sensitivity to spillovers from *Y* via counties *a* and *b*, $BOOM_EXPOSURE_OF_LINKAGES$ for *X* is given by $(0.6 \times 0.1 + 0.4 \times 0.2) BOOM_EXP_t^Y$ (see Part (i) of Figure 1). Part (ii) of Figure 1 extends this network to a network consisting of an additional shocked bank *Z*, which is also local in counties *a* and *b*. $BOOM_EXPOSURE_OF_LINKAGES$ for *X* is then the

FIGURE 1
Illustration of Measure Construction

Figure 1 presents an illustration of the construction of BOOM_EXPOSURE_OF_LINKAGES. It shows a stylized network of two hypothetical banks – a nonshocked bank *X* and a shocked bank *Y* – in counties (markets) *a* and *b* that are both nonboom counties. A boom county is a county that has above median count of cumulative wells (C_WELLS) in all county-years. Solid arrows indicate home lending in a county. Both *X* and *Y* are local in *a* and *b*, and the numbers against the arrows are the shares of deposits that they hold in the corresponding county. $BOOM_EXP_t^Y$ is bank *Y*’s weighted exposure to the natural logarithm of cumulative count of wells in boom counties, where weights are deposit shares that *Y* holds in each boom county. Part (i) discusses the construction of $BOOM_EXPOSURE_OF_LINKAGES$ for *X* in this hypothetical network. Part (ii) extends the network to a network that includes an additional shocked bank *Z*, and discusses the construction of $BOOM_EXPOSURE_OF_LINKAGES$ for *X*. Bank *Z* is also local and engages in home lending in both markets *a* and *b*. This network can be extended to *n* banks, and $BOOM_EXPOSURE_OF_LINKAGES$ for *X* can be computed similarly.



$$Boom\ Exp_t^Y = \sum_c w_{c,t}^Y \log(c_wells_{c,t})$$

- (i) In a world of banks *X* and *Y*:

Y’s boom exposure, $Boom\ Exp_t^Y = \sum_c w_{c,t}^Y \log(c_wells_{c,t})$

$BOOM_EXPOSURE_OF_LINKAGES$ for *X*: $(0.6 \cdot 0.1 + 0.4 \cdot 0.2) Boom\ Exp_t^Y$

- (ii) In a world of banks *X*, *Y*, and *Z*, where *Z* is local and engages in home lending in counties *a* and *b*:

$BOOM_EXPOSURE_OF_LINKAGES$ for *X*:

$$(0.6 \cdot 0.1 + 0.4 \cdot 0.2) Boom\ Exp_t^Y + (0.6 \cdot w_a^Z + 0.4 \cdot w_b^Z) Boom\ Exp_t^Z$$

where w_m^Z = fraction of deposits that bank *Z* holds in county *m*

weighted average of boom exposures of Y and Z , given by $(0.6 \times 0.1 + 0.4 \times 0.2) \text{BOOM_EXP}_t^Y + (0.6 \times w_a^Z + 0.4 \times w_b^Z) \text{BOOM_EXP}_t^Z$, where w_m^Z is bank Z 's share of deposits in county m . This network can be extended to n banks, and $\text{BOOM_EXPOSURE_OF_LINKAGES}$ for X can be computed similarly.

Panel C of [Table 1](#) summarizes $\text{BOOM_EXPOSURE_OF_LINKAGES}$ for the sample. It shows that this variable has a mean of 0.773 and a standard deviation of 1.597.

2. Boom Exposure of Linkages and Mortgage Lending

In this subsection, I study how a nonshocked bank in a nonboom county changes its lending as a function of the shock exposure of linkage banks. The model I use is similar in spirit to the model used in [Giroud and Mueller \(2019\)](#) in a different context. I estimate the following:

$$(7) \quad \Delta \log(\text{MORTGAGE_LENDING}_{i,c,t}) \\ = \alpha + \beta \text{BOOM_EXPOSURE_OF_LINKAGES}_{i,t} \\ + \text{BANK_CONTROLS}_{i,t-1} + \text{COUNTY} \times \text{YEAR} F \cdot E + \varepsilon_{i,c,t}$$

Here, $\Delta \log(\text{MORTGAGE_LENDING}_{i,c,t})$ is the percent growth in mortgage lending of a nonshocked bank i in a nonboom county c at time t . $\text{BOOM_EXPOSURE_OF_LINKAGES}_{i,t}$ is as described before. Because $\text{BOOM_EXPOSURE_OF_LINKAGES}_{i,t}$ is constructed at the bank level each year, this variable does not vary across counties in each bank-year. Therefore, I cluster standard errors at the bank level. I also include county-year fixed effects to control for housing market conditions and borrower demand effects. All bank control variables are constructed as of the prior year. The coefficient of interest here is β , and any spillover effect implies that $\beta > 0$.

[Table 3](#) presents regression results for model 7. Column 1 studies growth in lending of a nonshocked bank in a nonboom county as a function of $\text{BOOM_EXPOSURE_OF_LINKAGES}$. Results show that a bank increases mortgage lending as its linkages are exposed to greater well activity in boom counties. To understand the magnitude of this result, consider a bank with an average value of $\text{BOOM_EXPOSURE_OF_LINKAGES}$ ($= 0.773$) and a bank with a value 1 standard deviation higher ($= 0.773 + 1.597 = 2.37$). Column 1 implies that the latter bank increases its lending by 10.9 percentage points more than the former bank ($= e^{(2.37 \times 0.0621)} - e^{(0.773 \times 0.0621)}$).

In column 2 of [Table 3](#), I address the possibility that the increase in lending could be confounded by the subject bank's own market exposure. As mentioned before, I include county-year fixed effects and conduct a within-market analysis such that I compare banks that are exposed to the same market conditions. To account for any market effect from *other* local markets of the bank, I include $\text{EXPOSURE_TO_}\Delta\text{HPI}(\%) \text{ IN_OTHER_MARKETS}$ as a control variable in column 2. As before, $\text{EXPOSURE_TO_}\Delta\text{HPI}(\%) \text{ IN_OTHER_MARKETS}$ is a bank's weighted average exposure to percent changes in home prices in local markets other than the one under consideration, and the weights used are the bank's contemporaneous shares of deposits in each market. Results persist, and, in fact, the coefficient of $\text{BOOM_EXPOSURE_OF_LINKAGES}$ increases slightly.

TABLE 3
Boom Exposure of Linkages

Table 3 reports regressions of a bank's percent growth in home lending in a given county and year on the bank's BOOM_EXPOSURE_OF_LINKAGES. BOOM_EXPOSURE_OF_LINKAGES captures the exposure of a bank's shocked geographic linkages to well activity in boom counties (described in detail in the text). The sample in this regression includes nonshocked banks in nonboom counties from 2003 to 2017. Column 1 presents results for the regression that does not include EXPOSURE_TO_AHPI(%)_IN_OTHER_MARKETS, while column 2 presents results for the regression that includes it. EXPOSURE_TO_AHPI(%)_IN_OTHER_MARKETS captures a bank's own exposure to percent changes in home prices in counties other than the one under consideration. Column 3 breaks BOOM_EXPOSURE_OF_LINKAGES into two parts: BOOM_EXPOSURE_OF_LARGE_LINKAGES that captures boom exposure of linkages that have above median asset size among shocked banks in a given county, and BOOM_EXPOSURE_OF_SMALL_LINKAGES that captures boom exposure of linkages that have below median asset size. All regressions include county-year fixed effects. Standard errors are clustered by bank, and *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	$\Delta \log(\text{LOANS_ORIGINATED})$		
	1	2	3
BOOM_EXPOSURE_OF_LINKAGES	0.0621** (2.003)	0.0642** (2.075)	
EXPOSURE_TO_AHPI(%)_IN_OTHER_MARKETS		2.145 (1.571)	1.982 (1.454)
BOOM_EXPOSURE_OF_LARGE_LINKAGES			0.240*** (2.646)
BOOM_EXPOSURE_OF_SMALL_LINKAGES			-0.0779 (-0.978)
$\log(\text{TOTAL_ASSETS})$	-0.0310 (-0.946)	-0.0372 (-1.136)	-0.0372 (-1.138)
NET_INCOME/ASSETS	-39.71*** (-6.454)	-39.88*** (-6.465)	-39.70*** (-6.432)
CAPITAL/ASSETS	9.334*** (4.115)	9.422*** (4.138)	9.275*** (4.047)
ASSET_QUALITY	-24.24*** (-3.488)	-23.92*** (-3.439)	-23.49*** (-3.379)
MORTGAGES/ASSETS	-0.984** (-2.159)	-0.971** (-2.130)	-0.940** (-2.059)
LIQUIDITY_RATIO	-0.731** (-2.139)	-0.710** (-2.078)	-0.699** (-2.049)
UNUSED_COMMITMENTS_RATIO	-0.281 (-0.423)	-0.296 (-0.443)	-0.304 (-0.456)
ALL/ASSETS	-11.70 (-1.157)	-11.95 (-1.181)	-12.24 (-1.211)
C&L_LOANS/ASSETS	0.286 (0.592)	0.302 (0.625)	0.293 (0.603)
Constant	1.023** (2.232)	1.054** (2.306)	1.074** (2.354)
County-year fixed effects	Yes	Yes	Yes
No. of obs.	16,539	16,539	16,539
Adjusted R^2	0.066	0.066	0.067

Specifically, a bank with BOOM_EXPOSURE_OF_LINKAGES at a value 1 standard deviation higher than the mean increases its lending by 11.3 percentage points more than a bank with BOOM_EXPOSURE_OF_LINKAGES at the mean.

In column 3 of Table 3, I break BOOM_EXPOSURE_OF_LINKAGES into two parts – one capturing boom exposure of *Large Linkages* and the other capturing boom exposure of *Small Linkages* (summarized in Table 1). I define a bank to be small if it has below median size among shocked banks in each overlapping market and large if it has above median size.¹⁰ Spillovers, if they exist, should

¹⁰For counties where only one shocked bank is present, I label this bank large such that it appears in the construction of BOOM_EXPOSURE_OF_LARGE_LINKAGES. Results are similar (in unreported

be stronger coming from large linkages. Column 3 shows that the results are indeed driven by boom exposure of large linkages. Compared to a bank with `BOOM_EXPOSURE_OF_LARGE_LINKAGES` at the mean ($= 0.297$), a bank with a value 1 standard deviation higher ($= 0.297 + 0.755 = 1.052$) increases its lending by 21.3 percentage points more. On the other hand, `BOOM_EXPOSURE_OF_SMALL_LINKAGES` is statistically insignificant and negative, indicating no spillovers from small linkages.

C. Retained Versus Sold Loans

Next, I study whether spillover effects on mortgage lending are different for retained versus sold loans. Banks hold certain loans in their portfolio due to contracting frictions, such as asymmetric information between banks and investors that make it difficult to sell them (Gilje, Loutskina, and Strahan (2016)). If spillover effects improve expected future home prices and thus reduce credit exposure in mortgage lending, banks should increase lending of loans that they hold on their balance sheets as opposed to loans that can be easily sold off. Therefore, in this section, I break growth in lending into growth in retained loans and growth in sold loans.

Columns 1 and 2 in Table 4 present results for retained loans, while columns 3 and 4 present results for sold loans. Results show that the growth in lending is driven by increases in retained loans. The magnitude of the coefficient of `BOOM_EXPOSURE_OF_LINKAGES` in column 1 is similar to that in the base

TABLE 4
Retained Versus Sold Loans

Table 4 reports regressions of a bank's percent growth in home lending in a given county and year on the bank's `BOOM_EXPOSURE_OF_LINKAGES`. `BOOM_EXPOSURE_OF_LINKAGES` captures the exposure of a bank's shocked geographic linkages to well activity in boom counties (described in detail in the text). The sample in this regression includes nonshocked banks in nonboom counties from 2003 to 2017. Columns 1–2 present results for retained loans, while columns 3–4 present results for sold loans. Columns 2 and 4 break `BOOM_EXPOSURE_OF_LINKAGES` into two parts: `BOOM_EXPOSURE_OF_LARGE_LINKAGES` that captures boom exposure of linkages that have above median asset size among shocked banks in a given county, and `BOOM_EXPOSURE_OF_SMALL_LINKAGES` that captures boom exposure of linkages that have below median asset size. All regressions include county-year fixed effects and bank control variables. Standard errors are clustered by bank, and *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	$\Delta \log(\text{LOANS_ORIGINATED})$			
	Retained Loans		Sold Loans	
	1	2	3	4
<code>BOOM_EXPOSURE_OF_LINKAGES</code>	0.0614** (1.981)		0.0197 (0.802)	
<code>BOOM_EXPOSURE_OF_LARGE_LINKAGES</code>		0.187** (2.038)		-0.0181 (-0.227)
<code>BOOM_EXPOSURE_OF_SMALL_LINKAGES</code>		-0.0385 (-0.488)		0.0522 (0.611)
<code>EXPOSURE_TO_AHPI(%)_IN_OTHER_MARKETS</code>	1.737 (1.300)	1.621 (1.214)	2.899** (1.982)	2.931** (1.994)
County-year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
No. of obs.	16,539	16,539	16,539	16,539
Adjusted R^2	0.059	0.059	0.023	0.023

tables) if I label this bank as small such that it appears in the construction of `BOOM_EXPOSURE_OF_SMALL_LINKAGES` instead.

regressions of Table 3. Furthermore, spillovers from large banks drive the results (column 2). In contrast, results in columns 3 and 4 for sold loans are statistically and economically insignificant. That BOOM_EXPOSURE_OF_LINKAGES affects loans that banks retain also indicates that spillovers have an important on-balance-sheet impact on banks.

D. Placebo Test

The underlying identification assumption in model 7 is that there will be no spillovers if shocked banks are not geographically linked with nonshocked banks. In this subsection, I test the validity of this assumption by considering placebo linkages and testing whether there are any spillovers via these false linkages. If the identification assumption holds, I expect no spillovers. Any spillover effect would be indicative of unobservable factors driving the results in this paper.

For each nonshocked bank in each nonboom county and year, I replace all shocked linkage banks with randomly chosen banks from the universe of all other shocked banks in that year.¹¹ Because these placebo linkages do not exist in the county under consideration, I replace the weights used in the construction of BOOM_EXPOSURE_OF_LINKAGES to capture the importance of the market to the linkage bank with random weights. These random weights are chosen from the distribution of branch exposures in my sample, excluding the ones in the county-year under consideration. For the weight that captures the importance of the market to the subject bank, I keep the bank's true branch exposure. Then I construct BOOM_EXPOSURE_OF_LINKAGES following the same method as before but using placebo linkages and random weights of market importance to linkage banks. I then estimate model 7 and store the coefficient of BOOM_EXPOSURE_OF_LINKAGES. I repeat this process 1,000 times and obtain an empirical distribution of this coefficient.

Figure 2 presents the histogram of this distribution. The mean coefficient is 0.043. In the figure, I also present different percentiles of the empirical distribution of the coefficient, and these percentiles form the bootstrap confidence intervals. As the distribution shows, the 90% confidence interval for the coefficient is $[-0.008, 0.093]$. Note that 0 lies within this confidence interval. Therefore, the mean coefficient is not statistically different from 0. In other words, there is no evidence that spillovers occur via placebo linkages. Furthermore, given this result, it is unlikely that the spillovers documented in this paper are simply due to unobservable factors.

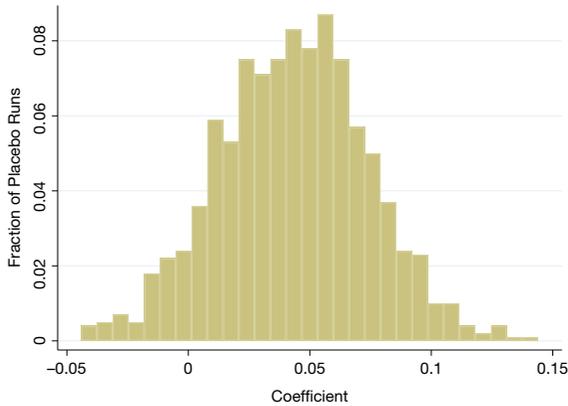
E. Robustness Tests

The results of this paper persist in a host of robustness tests reported in Section IA.4 of the Supplementary Material. First, I show that the results are not simply due to the confounding effect of direct deposit spillovers from neighboring boom counties. Results hold when I drop all counties that are within 100 miles of a

¹¹These random shocked banks could still be linked with the subject bank via other counties. However, this choice biases against finding results of no spillovers via placebo linkages. In unreported tables, I find that choosing random banks from a sample of shocked banks that do not overlap with the subject bank in any other county (local or non-local) does not change the results of the placebo test.

FIGURE 2
Placebo Test

Figure 2 presents the histogram of the distribution of the elasticity of a bank's percent growth in mortgage originations in a given county and year with respect to `BOOM_EXPOSURE_OF_LINKAGES` in an exercise of 1,000 placebo runs of model 7. Each placebo run replaces shocked geographic linkages of a bank in a given county and year with randomly chosen banks from the universe of shocked banks in that year. It also replaces the weight corresponding to the importance of an overlapping market to the linkage bank with randomly chosen weight from the distribution of branch exposures in the sample. (See Section IV for details.) Below the histogram, I present different percentiles of the empirical distribution of the elasticity coefficient. These percentiles form the bootstrap confidence intervals for the elasticity coefficient.



Distribution of Placebo Run Coefficient

Min	1%	5%	10%	25%	50%	75%	90%	95%	99%	Max
-0.044	-0.03	-0.008	0.004	0.023	0.044	0.064	0.081	0.093	0.115	0.144

boom county (column 1 of Supplementary Table IA.2).¹² Second, banks may select into counties where shocked banks are present if they expect market conditions to improve there. If this selection is motivated by demands for loans, then my results are confounded by demand effects. Results persist when I study the lending behavior of nonshocked banks only in counties where they were already local when their linkages were first shocked (column 2 of Supplementary Table IA.2).

Third, I address concerns about confounding effects from a bank's own market exposure. Column 3 of Supplementary Table IA.2 shows that spillovers in counties with good ex ante housing market conditions – those that observed above median changes in home prices in the prior year – are indistinguishable from those in counties with bad ex ante market conditions – those that observed below median changes in home prices in the prior year. Furthermore, results are robust to excluding the 15 markets with the best ex ante market conditions in each year (column 4 of Supplementary Table IA.2).

Fourth, I show that my results are robust to market and bank size effects. Column 5 of Supplementary Table IA.2 and column 1 of Supplementary Table IA.4

¹²I also run all regressions presented so far as well as regressions to be discussed in later sections excluding counties that are within 100 miles of boom counties. Excluding these counties drops the count of observations from 16,539 to 8,684. However, the majority of results persist, and in the few tests for which results are somewhat different, the key interpretation of the results does not change. These results are available upon request.

show that results are robust to removing the 15 largest and the 15 smallest counties by prior year loan count. Supplementary Table IA.3 shows that spillovers experienced by small versus large banks are indistinguishable, and that results are robust to excluding large/small subject banks and large linkage banks. I further address any issues of statistical noise from small observation counts by removing observations based on fewer than 15 loans (column 2 of Supplementary Table IA.4) and by removing the 15 smallest banks by prior year loan count (column 3 of Supplementary Table IA.4).

Finally, my results are robust to an alternate independent variable that captures linkage exposure to percent *growth* in the number of shale wells (Supplementary Table IA.5).

V. Spillover Mechanism

In this section, I study the underlying mechanism of spillovers. The mechanism I study posits that spillovers occur via an impact on the housing market where shocked and nonshocked banks overlap. Spillovers occur because positive shocks lead banks to change their lending behavior, which has a positive impact on the home prices of the overlapping market. Nonshocked banks respond to such improvements in the housing market by expanding their lending. Banks expand lending because higher current home prices imply higher expected future home prices and higher collateral value, and therefore lower credit exposure and higher expected profitability in lending.

The proposed mechanism leads to three testable hypotheses: i) Spillovers occur only in markets overlapping between shocked and nonshocked banks; ii) `BOOM_EXPOSURE_OF_LINKAGES` has a positive impact on the home prices of the overlapping markets; and iii) Spillovers are stronger in areas where borrower credibility is low and for banks that have more exposure to areas of low borrower credibility. I test each of these hypotheses in the following subsections.

A. Spillovers via the Overlapping Market

I begin by providing evidence that spillovers occur via an impact on markets where shocked and nonshocked banks overlap. The sample in this paper includes all nonboom counties where nonshocked banks exist locally. While some counties have locally present shocked banks, others do not. If spillovers occur via an impact on the overlapping market, then one should expect results only in markets where a shocked bank is present. To test this, I break my sample into two subsamples: one that includes observations for markets where a shocked bank exists locally, and one that includes observations for markets where a shocked bank does not exist locally.

Table 5 presents the results. Columns 1–3 present results for markets where a shocked bank is present. Column 1 studies all loans, column 2 studies retained loans, whereas column 3 studies sold loans. Results provide evidence of spillovers in these markets. Column 1 shows that `BOOM_EXPOSURE_OF_LINKAGES` is statistically significant, and the magnitude is slightly higher than the one in the base regression in column 2 of Table 3. The next two columns show that the increases in lending are driven by increases in retained loans, consistent with prior results.

TABLE 5
Spillovers via the Overlapping Market

Table 5 studies spillovers in counties with locally present shocked banks versus counties with no locally present shocked banks. It reports regressions of a bank's percent growth in home lending in a given county and year on the bank's BOOM_EXPOSURE_OF_LINKAGES. BOOM_EXPOSURE_OF_LINKAGES captures the exposure of a bank's shocked geographic linkages to well activity in boom counties (described in detail in the text). The sample in this regression includes nonshocked banks in nonboom counties from 2003 to 2017. Columns 1–3 present results for counties where a shocked bank exists locally. Columns 4–6 present results for counties where a shocked bank does not exist locally. Columns 1 and 4 present results for all loans; columns 2 and 5 present results for retained loans; columns 3 and 6 present results for sold loans. All regressions include county-year fixed effects and bank control variables. Standard errors are clustered by bank, and *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	$\Delta \log(\text{LOANS_ORIGINATED})$					
	Shocked Bank Present			Shocked Bank Not Present		
	All Loans	Retained Loans	Sold Loans	All Loans	Retained Loans	Sold Loans
	1	2	3	4	5	6
BOOM_EXPOSURE_OF_LINKAGES	0.0689** (2.210)	0.0649** (2.070)	0.0212 (0.878)	-0.210 (-1.353)	-0.210 (-1.447)	0.0940 (0.533)
EXPOSURE_TO_ΔHPI (%)_IN_OTHER_MARKETS	2.615* (1.879)	2.383* (1.731)	2.059 (1.506)	0.311 (0.093)	-0.834 (-0.251)	6.616 (1.364)
County-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	12,819	12,819	12,819	3,720	3,720	3,720
Adjusted R^2	0.056	0.050	0.016	0.112	0.102	0.028

Columns 4–6 of Table 5 present results for lending in markets where shocked banks do not exist locally. These three columns study all loans, retained loans, and sold loans, respectively. There is no evidence of spillovers in this subsample. The elasticity coefficient of BOOM_EXPOSURE_OF_LINKAGES is statistically insignificant in all three columns. While the smaller subsample size may contribute to the statistically insignificant result, it is important to note that in columns 4 and 5, this coefficient is negative, inconsistent with a spillover effect that implies a positive coefficient.

B. Spillovers and Home Prices

Next, I provide more direct evidence of the impact of boom exposure of linkages on markets where shocked and nonshocked banks overlap: I show that the boom exposure of linkages leads to an increase in a bank's exposure to home price changes in the overlapping markets.

For each bank in each year, I construct a variable BANK_EXPOSURE_TO_ΔHPI(%) (OVERLAPPING MARKETS), which is the weighted average of percent changes in home prices in all local markets where the bank overlaps with shocked banks.¹³ The weights used are the bank's shares of deposits in those markets. Then I study how BANK_EXPOSURE_TO_ΔHPI(%) (OVERLAPPING MARKETS) changes as a function of BOOM_EXPOSURE_OF_LINKAGES.

¹³In unreported tables, I find that results are similar if I define BANK_EXPOSURE_TO_ΔHPI(%) to include all local markets of the subject bank, irrespective of whether these markets overlap with shocked banks or not.

Because the dependent variable varies by bank-year, the unit of analysis here is for a given bank in a given year. I estimate the following model:

$$\begin{aligned}
 (8) \text{ BANK_EXPOSURE_TO_}\Delta\text{HPI}(\%)(\text{Overlapping Markets})_{i,t} \\
 &= \alpha + \beta \text{ BOOM_EXPOSURE_OF_LINKAGES}_{i,t} \\
 &+ \text{BANK_CONTROLS}_{i,t-1} + \text{AVERAGE_MARKET_CONTROLS}_{i,t} \\
 &+ \text{BANK } F.E + \text{YEAR } F.E + \varepsilon_{i,t},
 \end{aligned}$$

where $\text{BANK_EXPOSURE_TO_}\Delta\text{HPI}(\%)(\text{OVERLAPPING_MARKETS})_{i,t}$ is constructed as described above for each nonshocked bank i in year t , and $\text{BOOM_EXPOSURE_OF_LINKAGES}_{i,t}$ is constructed as before.

Given that this model is constructed at the bank-year level, unlike the previous model, there is no way to fully absorb county market characteristics. Therefore, identification is less compelling in this model. However, I account for market characteristics as best as I can by including control variables for contemporaneous average market characteristics of the overlapping counties. For every bank each year, I consider a market characteristic of each overlapping market, and take the weighted average, where weights are the shares of deposits that the bank holds in each market. These market characteristics include $\log(\text{POPULATION})$, $\log(\text{PER_CAPITA_PERSONAL_INCOME})$, $\text{HOUSEHOLD_DEBT-TO-INCOME_RATIO}$, UNEMPLOYMENT_RATE , $\text{PERCENT_FEMALE_POPULATION}$, and $\text{PERCENT_MINORITY_POPULATION}$. Furthermore, I include lagged bank control variables, bank and year fixed effects, and cluster standard errors by bank. The spillover mechanism implies that $\beta > 0$.

Table 6 presents the results.¹⁴ Column 1 shows that as linkages have exposure to greater shale well activity, a subject bank's exposure to home price changes in the overlapping markets increases. To understand the magnitude of this result, consider a bank with an average value of $\text{BOOM_EXPOSURE_OF_LINKAGES}$ ($= 0.773$) and a bank with a value 1 standard deviation higher ($= 0.773 + 1.597 = 2.37$). Column 1 implies that while the former bank's weighted average exposure to percent changes in home prices is 0.30% ($= 0.773 \times 0.00392$), the latter bank's exposure is 0.93% ($= 2.37 \times 0.00392$). In other words, the latter bank observes a 0.63 percentage point more increase in home prices. This value corresponds to 26.1% of the mean value of $\text{BANK_EXPOSURE_TO_}\Delta\text{HPI}(\%)(\text{OVERLAPPING_MARKETS})$ ($= 2.4\%$). Therefore, there is an economically significant impact of $\text{BOOM_EXPOSURE_OF_LINKAGES}$ on home prices of the overlapping markets.

¹⁴The number of observations in this table is different than the bank-year observations in the summary statistics of Table 1. This is because the bank characteristics summarized in Table 1 are for the main sample of nonshocked banks in non-boom counties used in the base regressions of model 7. There are singleton observations that are dropped in the base regressions. The bank characteristics summarized are for the banks that remain after the singleton observations are dropped. In Table 6, I use all bank-year observations, including those that are dropped in the base regressions. However, note that any singletons in the bank-year level regression of model 8 are dropped, resulting in the differences in the number of observations here versus Table 1. In unreported tables, I rerun tests of Table 6 for only those bank-year observations that are included in the sample used in the base regressions and find similar results.

TABLE 6
Boom Exposure of Linkages and Home Prices

Table 6 reports regressions (at the bank-year level) of a bank's exposure to percent changes in home prices in markets overlapping with shocked banks ($BANK_EXPOSURE_TO_ΔHPI(\%)(OVERLAPPING_MARKETS)$) on the bank's $BOOM_EXPOSURE_OF_LINKAGES$. $BOOM_EXPOSURE_OF_LINKAGES$ captures the exposure of a bank's shocked geographic linkages to well activity in boom counties (described in detail in the text). The sample in this regression includes nonshocked banks from 2003 to 2017. $BANK_EXPOSURE_TO_ΔHPI(\%)(OVERLAPPING_MARKETS)$ is computed for each bank in each year as the weighted average of percent changes in home prices in the bank's local markets (counties) overlapping with shocked banks. The weights are the fractions of deposits that the bank holds in each county. Columns 3 and 4 break $BOOM_EXPOSURE_OF_LINKAGES$ into two parts: $BOOM_EXPOSURE_OF_LARGE_LINKAGES$ that captures boom exposure of linkages that have above median asset size among shocked banks in a given county, and $BOOM_EXPOSURE_OF_SMALL_LINKAGES$ that captures boom exposure of linkages that have below median asset size. All regressions include bank and year fixed effects. Standard errors are clustered by bank, and *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	BANK_EXPOSURE_TO_ΔHPI(%) (Overlapping Markets)			
	1	2	3	4
BOOM_EXPOSURE_OF_LINKAGES	0.00392*** (8.196)	0.00338*** (8.574)		
BOOM_EXPOSURE_OF_LARGE_LINKAGES			0.00727*** (8.191)	0.00600*** (7.457)
BOOM_EXPOSURE_OF_SMALL_LINKAGES			0.00194** (2.050)	0.00182** (2.285)
LAGGED_BANK_EXPOSURE_TO_ΔHPI(%) (OVERLAPPING MARKETS)		0.215*** (6.661)		0.211*** (6.492)
Bank control variables	Yes	Yes	Yes	Yes
Average market control variables	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
No. of obs.	6032	6032	6032	6032
Adjusted R ²	0.624	0.641	0.625	0.642

While I control for housing market conditions of the overlapping markets, one could still argue that the positive elasticity coefficient of $BOOM_EXPOSURE_OF_LINKAGES$ in column 1 of Table 6 could be confounded by market effects. In order to address this concern further, in column 2, I include an additional control variable for lagged exposure to home price changes in overlapping markets ($LAGGED_BANK_EXPOSURE_TO_ΔHPI(\%)(OVERLAPPING_MARKETS)$). If the result in column 1 is due to market effects, then this control variable should explain away the effect of $BOOM_EXPOSURE_OF_LINKAGES$. However, including this control variable does not change the result – the magnitude of $BOOM_EXPOSURE_OF_LINKAGES$ declines only slightly, while remaining statistically significant.

In column 3 of Table 6, I break $BOOM_EXPOSURE_OF_LINKAGES$ into two parts – $BOOM_EXPOSURE_OF_LARGE_LINKAGES$ and $BOOM_EXPOSURE_OF_SMALL_LINKAGES$. While both are statistically significant, the effect of $BOOM_EXPOSURE_OF_LARGE_LINKAGES$ is economically larger. For a standard deviation increase in boom exposure of large linkages from the mean, a subject bank observes a 0.55 percentage point higher increase in home prices. On the other hand, for a similar increase in boom exposure of small linkages from the mean, the subject bank observes only a 0.17 percentage point increase in home prices. Again, this is consistent with the intuition that spillovers, if present, should be stronger coming from large banks. Column 4 conducts a similar test, now controlling for the subject bank's lagged exposure to percent changes in home

prices in overlapping markets. The coefficients decline in magnitude only slightly and they remain statistically significant.

C. Borrower Credibility and Bank Financial Slack

According to the proposed spillover mechanism, increases in home prices lead to higher expected future home prices and higher collateral value, which in turn implies lower credit exposure in home lending. This implies that markets where borrower credibility is low should benefit the most from increases in home prices. Because borrower credibility is low in markets with bad economic conditions, these economies should benefit the most. Moreover, while boom exposure is a shock to bank liquidity for shocked banks, the spillover effect is *not* a shock to bank liquidity for nonshocked banks. Instead, the spillover effect leads to expectations of higher future home prices and thus encourages banks to lend more. Therefore, I expect banks that are not financially constrained or have greater financial slack to respond more to spillovers.

To capture the economy of a market, I use county-level unemployment rates. In column 1 of [Table 7](#), I interact `BOOM_EXPOSURE_OF_LINKAGES` with `BORROWER_CREDIBILITY`, where `BORROWER_CREDIBILITY` is contemporaneous unemployment rate of the county in question. In column 2, I interact `BOOM_EXPOSURE_OF_LINKAGES` with `HIGH_CAPITAL/ASSETS`, which identifies banks that have above median capital-to-assets ratio in a given year and thus have greater financial slack. I find that the interaction term in column 1 is statistically insignificant, so banks generally do not increase lending in bad economies as a function of boom exposure of linkages.¹⁵ On the other hand, the interaction in column 2 is statistically significant, implying that banks with greater financial slack increase lending as a function of boom exposure of linkages.

Speaking in economic terms, if a bank has high financial slack, it increases its lending by 22 percentage points more if it has `BOOM_EXPOSURE_OF_LINKAGES` at a value 1 standard deviation higher than the mean than if it has a value at the mean. On the other hand, the effect of `BOOM_EXPOSURE_OF_LINKAGES` is statistically insignificant for banks with low financial slack.

In column 3 of [Table 7](#), I ask whether banks with high financial slack increase their lending in bad economies more in response to greater boom exposure of linkages. I include a triple interaction between `BOOM_EXPOSURE_OF_LINKAGES`, `BORROWER_CREDIBILITY`, and `HIGH_CAPITAL/ASSETS`, where `BORROWER_CREDIBILITY` is `UNEMPLOYMENT_RATE`. As results show, the triple interaction term is positive and statistically significant, implying that in response to higher `BOOM_EXPOSURE_OF_LINKAGES`, banks with high financial slack increase lending more in areas with higher unemployment rate (i.e., areas where borrower credibility is low). This is consistent with the spillover mechanism that suggests that spillovers lead to lower credit exposure in home lending, such that spillovers are felt more in areas with low borrower credibility.

¹⁵Note that I drop the explanatory variable `UNEMPLOYMENT_RATE` in this specification in order to include country-year fixed effects that are collinear with this variable.

TABLE 7
 Boom Exposure of Linkages, Financial Slack, and Borrower Credibility

Table 7 studies the interaction between boom exposure of linkages, financial slack, and borrower credibility, where borrower credibility is unemployment rate or bank unemployment exposure. It reports regressions of a bank's percent growth in home lending in a given county and year on the bank's BOOM_EXPOSURE_OF_LINKAGES. BOOM_EXPOSURE_OF_LINKAGES captures the exposure of a bank's shocked geographic linkages to well activity in boom counties (described in detail in the text). The sample in this regression includes nonshocked banks in nonboom counties from 2003 to 2017. Column 1 includes an interaction between BOOM_EXPOSURE_OF_LINKAGES and UNEMPLOYMENT_RATE. Column 2 includes an interaction between BOOM_EXPOSURE_OF_LINKAGES and HIGH_CAPITAL/ASSETS, which takes the value 1 for banks that have above median capital-to-assets ratio in a given year. Column 3 includes a triple interaction between BOOM_EXPOSURE_OF_LINKAGES, UNEMPLOYMENT_RATE, and HIGH_CAPITAL/ASSETS. Column 4 includes an interaction between BOOM_EXPOSURE_OF_LINKAGES and BANK_UNEMPLOYMENT_EXP, which is the weighted average of unemployment rates in the subject banks' local counties. The weights are the shares of deposits that the bank holds in each county. Column 5 includes a triple interaction between BOOM_EXPOSURE_OF_LINKAGES, BANK_UNEMPLOYMENT_EXP, and HIGH_CAPITAL/ASSETS. All regressions include county-year fixed effects and bank control variables. Standard errors are clustered by bank, and *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Δlog(LOANS_ORIGINALD)				
	UNEMPLOYMENT_RATE			BANK_UNEMPLOYMENT_EXP	
	1	2	3	4	5
BOOM_EXPOSURE_OF_LINKAGES	0.114 (0.806)	0.0311 (0.887)	0.285* (1.827)	0.0745 (0.517)	0.214 (1.369)
BOOM_EXPOSURE_OF_LINKAGES × BORROWER_CREDIBILITY	-0.727 (-0.290)		-4.736* (-1.740)	0.0569 (0.023)	-3.348 (-1.229)
BOOM_EXPOSURE_OF_LINKAGES × HIGH_CAPITAL/ASSETS		0.0838** (2.382)	-0.268* (-1.844)		-0.215 (-1.367)
BOOM_EXPOSURE_OF_LINKAGES × BORROWER_CREDIBILITY × HIGH_CAPITAL/ASSETS			6.561** (2.511)		5.490** (1.968)
HIGH_CAPITAL/ASSETS × BORROWER_CREDIBILITY			-0.206 (-0.065)		0.246 (0.064)
HIGH_CAPITAL/ASSETS	0.221*** (3.065)	0.171** (2.216)	0.174 (0.899)	0.218*** (3.022)	0.146 (0.638)
BORROWER_CREDIBILITY				7.085* (1.864)	7.167* (1.870)
EXPOSURE_TO_AHPI(%)_ IN_OTHER_MARKETS	1.820 (1.332)	1.767 (1.288)	1.799 (1.319)	1.870 (1.369)	1.850 (1.355)
County-year fixed effects	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes
No. of obs.	16,539	16,539	16,539	16,539	16,539
Adjusted R ²	0.060	0.061	0.062	0.061	0.062

Because spillovers do not affect bank liquidity but rather improve housing market conditions making home lending more attractive, only banks with financial slack respond with increased lending.

Additionally, the finding that the interaction term in column 1 of Table 7 is not statistically significant, but the triple interaction term in column 3 is, suggests that the results are due to banks with financial slack and not due to general housing market conditions of the county in question. In other words, these results are bank effects as opposed to market effects.

To understand the economic significance of the results in column 3 of Table 7, consider a bank with high financial slack (i.e., HIGH_CAPITAL/ASSETS = 1). In markets with an average unemployment rate, a standard deviation increase in BOOM_EXPOSURE_OF_LINKAGES from the mean leads the bank to increase its lending by 24.7 percentage points more. In markets with a 1-standard-deviation-higher unemployment rate, the bank's response is higher. A similar increase in BOOM_EXPOSURE_OF_LINKAGES leads the bank to increase lending by 32.8

percentage points more.¹⁶ So the difference in the response of this bank in these two markets is 8.1 (= 32.8–24.7) percentage points. Now, consider a bank with low financial slack (i.e., HIGH_CAPITAL/ASSETS = 0). In markets with an average unemployment rate, a standard deviation increase in BOOM_EXPOSURE_OF_LINKAGES from the mean leads this bank to increase lending by only 0.1 percentage points more, while in a market with a 1-standard-deviation-higher unemployment rate, a similar increase in BOOM_EXPOSURE_OF_LINKAGES actually results in the bank decreasing lending by 11.8 percentage points more.¹⁷ As per column 3 of Table 7, such a response from a bank with high financial slack is statistically different from that of a bank with low financial slack.

Next, if the proposed mechanism is true, one can also expect banks operating more in bad economies to respond more to spillovers. I test this hypothesis in columns 4 and 5 of Table 7. For each bank, each year, I construct BANK_UNEMPLOYMENT_EXP, which is the weighted average of unemployment rates in the bank's local markets. The weights are the shares of deposits that the bank holds in each market. In column 4, I include an interaction between BOOM_EXPOSURE_OF_LINKAGES and BORROWER_CREDIBILITY, where BORROWER_CREDIBILITY is BANK_UNEMPLOYMENT_EXP. I find that this interaction term is statistically insignificant. Therefore, banks that operate more in bad economies generally do not increase lending as a function of boom exposure of linkages. However, in column 5, I consider a triple interaction between BOOM_EXPOSURE_OF_LINKAGES, BORROWER_CREDIBILITY, and HIGH_CAPITAL/ASSETS, where BORROWER_CREDIBILITY is BANK_UNEMPLOYMENT_EXP. This term is statistically significant – that is, banks that operate more in bad economies increase lending more as a function of shock exposure of linkages, if they are not financially constrained.

These results are also economically significant. To understand the economic significance, consider a bank with high financial slack (HIGH_CAPITAL/ASSETS = 1). In response to a standard deviation increase in BOOM_EXPOSURE_OF_LINKAGES from the mean, the bank increases its lending by 23.9 percentage points more if it has an average value for BANK_UNEMPLOYMENT_EXP. It increases lending by 32.9 percentage points more if it has a value 1 standard deviation higher than the average for BANK_UNEMPLOYMENT_EXP. So the difference in these responses if the bank has average BANK_UNEMPLOYMENT_EXP versus if it has a standard deviation

¹⁶This number is computed as follows: In a market with average unemployment rate (=0.06), the difference in lending for a standard deviation increase in BOOM_EXPOSURE_OF_LINKAGES is $e^{(2.37(0.285-4.736 \times 0.06-0.268+6.561 \times 0.06))} - e^{(0.773(0.285-4.736 \times 0.06-0.268+6.561 \times 0.06))}=24.7$. Note that mean of BOOM_EXPOSURE_OF_LINKAGES is 0.773, and mean + 1sd of BOOM_EXPOSURE_OF_LINKAGES is 2.37. In a market with mean + 1sd unemployment rate (= 0.06 + 0.018 = 0.078), the difference in lending for a standard deviation increase in BOOM_EXPOSURE_OF_LINKAGES is computed similarly to yield 32.8. So the difference in the percentage points of these responses is 32.8–24.7 = 8.1.

¹⁷This number is computed as follows: In a market with average unemployment rate (=0.06), the difference in lending for a standard deviation increase in BOOM_EXPOSURE_OF_LINKAGES is $e^{(2.37(0.285-4.736 \times 0.06))} - e^{(0.773(0.285-4.736 \times 0.06))}=0.1$. In a market with mean + 1sd unemployment rate (=0.06 + 0.018 = 0.078), the difference in lending for a standard deviation increase in BOOM_EXPOSURE_OF_LINKAGES is computed similarly to yield –11.8.

higher than average `BANK_UNEMPLOYMENT_EXP` is 9 (= 32.9–23.9) percentage points. Instead, if the bank has low financial slack (`HIGH_CAPITAL/ASSETS` = 0), a similar difference in the responses to a similar increase in `BOOM_EXPOSURE_OF_LINKAGES` is –8.9 percentage points.

Therefore, as linkages experience larger positive shocks, banks with financial slack increase lending more in areas where borrower credibility is low. Similarly, if banks with financial slack operate more in areas with low borrower credibility, they increase lending more. These results are consistent with spillovers leading to improvements in credit exposure in home lending.

D. Alternate Mechanisms

These results withstand several tests of alternate hypotheses for the spillover mechanism as discussed in Section IA.5 of the Supplementary Material. First, I argue that a “liquidity channel” similar to the one in Gilje, Loutskina, and Strahan (2016) – that banks use the liquidity received from the shock to create loans that were previously difficult to create – does not cause spillovers here. It is possible that home price increases in the overlapping markets lead homeowners to sell their homes, resulting in prepayments and thus an influx of liquidity for nonshocked banks, who then use it to create new loans. However, because banks increase lending only in markets where shocked banks exist, and there is no obvious reason why they would not use the new liquidity to create loans in markets where shocked banks do not exist, it is unlikely that the liquidity channel is driving spillovers. Moreover, this channel implies that financially constrained banks increase lending more, but results show that spillovers are driven by banks with financial slack.

Second, one could argue that spillovers are due to investors who in response to home price increases in the overlapping markets increase their funds to banks, who then expand lending. To address this hypothesis, I study the behavior of banks dependent on wholesale funds in Section IA.5.2 of the Supplementary Material. Because wholesale funds are short term and less risky, it is easy for wholesale fund investors to quickly adjust their funds to banks so that banks dependent on wholesale funds should respond more to spillovers. However, I do not find any evidence supporting this mechanism.

Third, rising home prices in the overlapping markets could improve the value of under-water loans in depressed areas held on bank balance sheets, and the resulting improvement in bank health could allow banks to lend more.¹⁸ However, the finding that the better capitalized banks drive the results is inconsistent with this hypothesis. In Section IA.5.3 of the Supplementary Material, I also compare the behavior of banks exposed to greater versus smaller home price declines in the prior year. This hypothesis implies that the former banks respond more to spillovers given that their health would improve more when home prices increase in the current year. However, I do not find any evidence that this is the case. Similarly, there is no evidence that banks with bad asset quality (captured by loan charge-offs) *ex ante* respond more to spillovers, again inconsistent with the hypothesis.

¹⁸I thank the anonymous referee for suggesting this alternate explanation for spillovers.

E. Rational Lending

Results have so far shown that spillovers occur from one bank to another and that they occur via an impact on the overlapping housing market. However, an important question remains: Do these spillovers lead to rational or profitable increases in home lending? One explanation that would be consistent with the results is that shocked banks lend more in nonboom counties not because it was profitable, but simply because they had a liquidity inflow that needed to be invested, and nonshocked banks simply copied this behavior.¹⁹ While the results in Gilje, Loutskina, and Strahan (2016) suggest rational lending by shocked banks, it is still possible that nonshocked banks are simply exhibiting herding behavior and engaging in unprofitable lending.

Ruling this alternate hypothesis out is challenging given that it is difficult to track the performance of individual loans and the resulting impact on lenders (Gilje, Loutskina, and Strahan (2016)).²⁰ However, I address this hypothesis by studying the impact of spillovers on overall ex post bank-level profitability and loan performance, based on data available in call reports, and by studying the impact of spillovers on contemporaneous riskiness of loans originated, based on information available in the HMDA loan database. If the alternate hypothesis is driving the results, then nonshocked banks should experience lower profitability and higher losses after originating loans. Similarly, one could also expect irrational lending to result in banks originating riskier loans.

I consider three main dependent variables. First, following Gilje, Loutskina, and Strahan (2016), I compute for each bank in each year, a variable $NET_INCOME_{t+1}/ASSETS_t$, which is the return on assets computed as the ratio of net income in year $t+1$ to total assets in year t . Second, I compute $ASSET_QUALITY_{t+1}$, which is the ratio of loan charge-offs in year $t+1$ to total loans in year t . Finally, I compute contemporaneous $LOAN_TO_INCOME_t$ ratio, which is the mean of loan amount to applicant income ratio for all loans created by a bank each year. Given that these variables vary by bank-year, the unit of analysis here is for a given bank in a given year. I estimate the following model:

$$(9) \quad \begin{aligned} BANK_PERFORMANCE_{i,t+1}/RISK_{i,t} = & \alpha \\ & + \beta BOOM_EXPOSURE_OF_LINKAGES_{i,t} \\ & + BANK_CONTROLS_{i,t-1} + BANK\ F.E + YEAR\ F.E + \varepsilon_{i,t}, \end{aligned}$$

where $BANK_PERFORMANCE_{i,t+1}/RISK_{i,t}$ is one of the dependent variables described above and $BOOM_EXPOSURE_OF_LINKAGES_{i,t}$ is constructed as before. I also include lagged bank control variables, bank and year fixed effects, and cluster standard errors by bank.²¹

¹⁹I thank the anonymous referee for pointing this out.

²⁰For example, some loans may have credit protection or they may be securitized, so if loans go bad, the originating lender may not be affected or losses may be shared with other investors (Gilje, Loutskina, and Strahan (2016)).

²¹Results of the regression of model 9 are robust to including average market characteristics similar to the ones in model 8 (in unreported tables).

TABLE 8
Rational Lending

Table 8 reports regressions (at the bank-year level) of bank performance and risk on the bank's BOOM_EXPOSURE_OF_LINKAGES. BOOM_EXPOSURE_OF_LINKAGES captures the exposure of a bank's shocked geographic linkages to well activity in boom counties (described in detail in the text). The sample in this regression includes nonshocked banks from 2003 to 2017. Column 1 uses RETURN_ON_ASSETS, computed as the ratio of NET_INCOME at $t + 1$ to ASSETS at t , as a measure of bank performance. Column 2 uses ASSET_QUALITY, computed as the ratio of charge-offs on loan and lease losses at $t + 1$ to total loan value at t , as a measure of bank performance. Column 3 uses contemporaneous LOAN-TO-INCOME ratio as a measure of bank risk. All regressions include bank and year fixed effects. Standard errors are clustered by bank, and t -statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	NET_INCOME _{<i>t</i>+1} /ASSETS _{<i>t</i>}	ASSET_QUALITY _{<i>t</i>+1}	LOAN-TO-INCOME _{<i>t</i>}
	1	2	3
BOOM_EXPOSURE_OF_LINKAGES	0.000389** (2.548)	-0.000381*** (-2.590)	0.00518 (0.472)
log(TOTAL_ASSETS)	-0.00288*** (-3.295)	0.00398*** (6.543)	0.114*** (3.468)
NET_INCOME/ASSETS	0.269*** (7.333)	-0.0645** (-2.240)	-2.032 (-1.257)
CAPITAL/ASSETS	-0.0393*** (-3.125)	0.00940 (1.071)	0.483 (0.844)
ASSET_QUALITY	0.0199 (0.547)	0.0424 (1.457)	3.623* (1.860)
MORTGAGES/ASSETS	0.0112** (2.407)	-0.00859** (-2.425)	0.384* (1.807)
LIQUIDITY_RATIO	0.000612 (0.311)	-0.00183 (-1.103)	-0.242* (-1.777)
UNUSED_COMMITMENTS_RATIO	0.00365 (0.524)	-0.000393 (-0.074)	-0.601* (-1.727)
ALL/ASSETS	-0.0916 (-1.194)	0.307*** (4.457)	-7.201** (-2.152)
C&I_LOANS/ASSETS	0.00385 (0.865)	0.000630 (0.193)	0.277 (1.102)
Constant	0.0447*** (3.904)	-0.0464*** (-5.838)	0.449 (1.080)
Bank fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
No. of obs.	6539	6539	6679
Adjusted R ²	0.477	0.360	0.380

In column 1 of Table 8, I regress $\text{NET_INCOME}_{t+1}/\text{ASSETS}_t$ on BOOM_EXPOSURE_OF_LINKAGES and find no evidence of irrational lending by banks. In fact, spillovers lead to a statistically and economically significant increase in the overall return on assets of a bank. Specifically, a standard deviation increase in BOOM_EXPOSURE_OF_LINKAGES leads to a 0.06% increase in the return on assets the following year. This increase is 6.5% of the mean return on assets (= 0.96%) for the sample.

Similarly, in column 2 of Table 8, there is no evidence of irrational lending by banks. Instead, I find that loan performance improves the following year. Specifically, the loan charge-offs ratio decreases by 0.06%, and this decrease is 13.5% of the mean loan charge-offs ratio (= 0.45%) for the sample. Finally, in column 3, I do not find any evidence that banks originate riskier loans. The effect of spillovers on bank risk is statistically as well as economically insignificant. Therefore, results do not show that spillovers are due to irrational lending by nonshocked banks.²²

²²The differences in the number of observations in the bank-year regressions of Tables 6, 8, and 9 are due to the differences in the number of observations for which the dependent variables have nonmissing values.

VI. Aggregate Effects

In this section, I provide evidence of the impact of spillovers on an aggregate bank level. It is possible that a bank may be reallocating lending from one market to another, where shocked banks are present, in order to take advantage of the improved housing market conditions. If so, there may be no aggregate increase in lending at the bank level. While reallocation of lending is interesting in its own right, I find that spillovers do not just lead banks to reallocate loans from one area to another, but rather they have an economically significant impact at the bank level.

To that end, I construct loan growth at the bank-year level by taking the weighted average of loan growth (log change in mortgage lending) in all local nonboom markets of a bank. The weights are the shares of deposits that the bank holds in each market. Then I study how BOOM_EXPOSURE_OF_LINKAGES affects loan growth at the bank-year level. The unit of analysis in this study is for a given bank in a given year. I estimate the following model:

$$(10) \quad \Delta \log(\text{MORTGAGE_LENDING}_{i,t}) = \\ \alpha + \beta \text{BOOM_EXPOSURE_OF_LINKAGES}_{i,t} \\ + \text{BANK_CONTROLS}_{i,t-1} + \text{AVERAGE_MARKET_CONTROLS}_{i,t} \\ + \text{BANK } F.E + \text{YEAR } F.E + \varepsilon_{i,t},$$

where $\Delta \log(\text{MORTGAGE_LENDING}_{i,t})$ is constructed as described above for each nonshocked bank i in year t , and $\text{BOOM_EXPOSURE_OF_LINKAGES}_{i,t}$ is constructed as before. Similar to model 8, I include control variables for contemporaneous weighted average market characteristics of the subject bank's local markets. These variables consider all local markets of the bank, as opposed to just those overlapping between shocked and nonshocked banks as in model 8. I also include lagged bank control variables, bank and year fixed effects, and cluster standard errors by bank.

Table 9 presents the results.²³ Column 1 presents results for all loans; column 2 presents results for retained loans; and column 3 presents results for sold loans. As column 1 shows, there is an increase in lending at the bank level due to BOOM_EXPOSURE_OF_LINKAGES. A bank with BOOM_EXPOSURE_OF_LINKAGES at a value 1 standard deviation higher than the mean increases its lending by 15.9 percentage points more than a bank with BOOM_EXPOSURE_OF_LINKAGES at the mean. Columns 2 and 3 show that these results are driven by growth of retained loans, consistent with prior results. Therefore, spillovers have a significant on-balance sheet impact at the bank level.

In Section IA.6 of the Supplementary Material, I also provide evidence of the impact of spillovers on an aggregate county level. Banks with higher

²³For reasons similar to those described in 14, the number of observations in this table is different than the ones in the summary statistics of Table 1. Just as in 14, I rerun the tests of Table 9 for only those bank-year observations that are included in the sample in the base regressions and find similar results (in unreported tables).

TABLE 9
Bank Aggregates

Table 9 reports regressions at the aggregate bank-year level. It presents regressions of a bank's percent growth in home lending at bank-year level on the bank's BOOM_EXPOSURE_OF_LINKAGES. BOOM_EXPOSURE_OF_LINKAGES captures the exposure of a bank's shocked geographic linkages to well activity in boom counties (described in detail in the text). The sample in this regression includes nonshocked banks from 2003 to 2017. Column 1 presents results for all loans; column 2 presents results for retained loans; and column 3 presents results for sold loans. All regressions include bank and year fixed effects. Standard errors are clustered by bank, and *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	$\Delta \log(\text{LOANS_ORIGINATED})$		
	All Loans 1	Retained Loans 2	Sold Loans 3
BOOM_EXPOSURE_OF_LINKAGES	0.0870** (2.157)	0.110*** (2.748)	0.0198 (0.643)
log(TOTAL_ASSETS)	-0.793*** (-4.074)	-0.812*** (-4.221)	-0.0741 (-0.498)
NET_INCOME/ASSETS	-32.65*** (-4.080)	-28.35*** (-3.578)	-15.55** (-2.322)
CAPITAL/ASSETS	13.13*** (4.434)	11.40*** (3.938)	4.410* (1.827)
ASSET_QUALITY	-27.28*** (-3.651)	-22.55*** (-3.065)	-19.74*** (-2.885)
MORTGAGES/ASSETS	-4.322*** (-4.293)	-4.613*** (-4.785)	-0.315 (-0.384)
LIQUIDITY_RATIO	0.738 (1.434)	0.995* (1.962)	-0.693* (-1.681)
UNUSED_COMMITMENTS_RATIO	0.750 (0.554)	0.413 (0.305)	0.435 (0.403)
ALL/ASSETS	-32.98** (-2.333)	-28.49** (-2.025)	-13.76 (-1.182)
C&I_LOANS/ASSETS	-0.410 (-0.397)	0.153 (0.144)	-1.540* (-1.840)
WT_AVG_OF_log(POPULATION)	-0.511*** (-4.007)	-0.465*** (-3.552)	-0.109 (-1.273)
WT_AVG_OF_log(PERSONAL_INCOME)	0.823 (1.483)	0.656 (1.193)	0.884* (1.774)
WT_AVG_OF_DEBT-TO-INCOME	0.0810 (0.580)	0.100 (0.724)	0.0427 (0.399)
BANK_UNEMPLOYMENT_EXPOSURE	10.66** (2.311)	9.218** (2.063)	5.749 (1.447)
WT_AVG_OF_PERCENT_FEMALE_POPULATION	13.41 (0.978)	8.090 (0.606)	14.18 (1.178)
WT_AVG_OF_PERCENT_MINORITY_POPULATION	1.501 (0.669)	1.093 (0.493)	2.524* (1.756)
LAGGED_BANK_EXPOSURE_TO_ΔHPI(%)	0.124 (0.099)	0.947 (0.756)	-2.370* (-1.894)
Constant	0.0860 (0.009)	4.359 (0.464)	-14.55* (-1.733)
Bank fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
No. of obs.	6726	6726	6726
Adjusted R^2	0.113	0.098	-0.015

BOOM_EXPOSURE_OF_LINKAGES could simply outcompete loans away from banks with lower BOOM_EXPOSURE_OF_LINKAGES such that there is no net increase in lending at the county level. Using the size-weighted average of loan growth and the size-weighted average of BOOM_EXPOSURE_OF_LINKAGES for nonshocked banks in nonboom counties, I show that spillovers have an economically significant impact at the county level as well.

VII. Conclusions

In this paper, I provide the first evidence of positive bank-to-bank spillovers. I show that geographic linkages that form between banks when they engage in home lending in the same geographic region facilitate positive spillovers between banks. I consider a positive shock to the liquidity of banks that are exposed to counties experiencing shale oil booms and show that nonshocked banks that are geographically linked with shocked banks experience spillovers; they increase lending more if their linkages are exposed to greater well activity in boom counties.

For each nonshocked bank in each year, I construct a variable, BOOM_EXPOSURE_OF_LINKAGES, which captures the exposure of its linkage banks to well activity in boom counties. I find that a bank with a value 1 standard deviation higher than the mean for BOOM_EXPOSURE_OF_LINKAGES increases its lending by 11.3 percentage points more than a bank with this variable at the mean. Such positive spillovers occur via an impact on the markets overlapping between shocked and nonshocked banks. Specifically, BOOM_EXPOSURE_OF_LINKAGES has a positive impact on home prices in the overlapping markets. Because higher current home prices imply higher expected future home prices and higher collateral value, credit exposure in home lending is lower and expected profitability is higher, leading banks to increase lending.

This study is important for two reasons. First, it provides the first evidence of positive bank-to-bank spillovers. Second, the underlying mechanism of spillover is novel, so this paper adds to the literature by identifying a new mechanism of transmission of shocks between banks.

Supplementary Material

To view supplementary material for this article, please visit <http://doi.org/10.1017/S0022109022000667>.

References

- Acemoglu, D.; A. Ozdaglar; and A. Tahbaz-Salehi. "Systemic Risk and Stability in Financial Networks." *American Economic Review*, 105 (2015), 564–608.
- Acharya, V. V., and N. Mora. "A Crisis of Banks as Liquidity Providers." *Journal of Finance*, 70 (2015), 1–43.
- Allen, F.; A. Babus; and E. Carletti. "Asset Commonality, Debt Maturity and Systemic Risk." *Journal of Financial Economics*, 104 (2012), 519–534.
- Allen, F., and D. Gale. "Financial Contagion." *Journal of Political Economy*, 108 (2000), 1–33.
- Amundsen, E., and H. Arnt. "Contagion Risk in the Danish Interbank Market." Working Paper No. 29, Danmarks Nationalbank (2005).
- Avery, R. B.; N. Bhutta; K. P. Brevoort; G. B. Canner; and C. N. Gibbs. "The 2008 HMDA Data : The Mortgage Market During a Turbulent Year." *Federal Reserve Bulletin*, 96 (2010), 0–0.
- Bebchuk, L. A., and I. Goldstein. "Self-Fulfilling Credit Market Freezes." *Review of Financial Studies*, 24 (2011), 3519–3555.
- Berrospide, J.; L. K. Black; and W. R. Keeton. "The Cross-Market Spillover of Economic Shocks Through Multi-Market Banks." *Journal of Money, Credit and Banking*, 48 (2016), 957–988.
- Billio, M.; M. Getmansky; A. W. Lo; and L. Pelizzon. "Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors." *Journal of Financial Economics*, 104 (2012), 535–559.

- Brusco, S., and F. Castiglionesi. "Liquidity Coinsurance, Moral Hazard, and Financial Contagion." *Journal of Finance*, 62 (2007), 2275–2302.
- Cifuentes, R.; G. Ferrucci; and H. S. Shin. "Liquidity Risk and Contagion." *Journal of the European Economic Association*, 3 (2005), 556–566.
- Dagher, J., and K. Kazimov. "Banks Liability Structure and Mortgage Lending During the Financial Crisis." *Journal of Financial Economics*, 116 (2015), 565–582.
- Degryse, H., and G. Nguyen. "Interbank Exposures: an Empirical Examination of Systemic Risk in The Belgian Banking System." *International Journal of Central Banking*, 3 (2007), 123–171.
- Dell’Ariccia, G.; D. Igan; and L. Laeven. "Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market." *Journal of Money, Credit and Banking*, 44 (2012), 367–384.
- Diebold, F. X., and K. Yilmaz. "On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms." *Journal of Econometrics*, 182 (2014), 119–134.
- Duchin, R., and D. Sosyura. "Safer Ratios, Riskier Portfolios: Banks’ Response to Government Aid." *Journal of Financial Economics*, 113 (2014), 1–28.
- Elsinger, H.; A. Lehar; and M. Summer. "Risk Assessment for Banking Systems." *Management Science*, 52 (2006), 1301–1314.
- Favara, G., and J. M. Imbs. "Credit Supply and the Price of Housing." *American Economic Review*, 105 (2015), 958–992.
- Furfine, C. "Interbank Exposures: Quantifying the Risk of Contagion." *Journal of Money, Credit, and Banking*, 35 (2003), 111–128.
- Gai, P.; A. Haldane; and S. Kapadia. "Complexity, Concentration and Contagion." *Journal of Monetary Economics*, 58 (2011), 453–470.
- Gilje, E. P. "Does Local Access to Finance Matter? Evidence from U.S. Oil and Natural Gas Shale Booms." *Management Science*, 65 (2019), 1–18.
- Gilje, E. P.; E. Loutschina; and P. E. Strahan. "Exporting Liquidity: Branch Banking and Financial Integration." *Journal of Finance*, 71 (2016), 1159–1184.
- Giroud, X., and H. M. Mueller. "Firms’ Internal Networks and Local Economic Shocks." *American Economic Review*, 109 (2019), 3617–3649.
- Glasserman, P., and H. P. Young. "How Likely is Contagion in Financial Networks?" *Journal of Banking & Finance*, 50 (2015), 383–399.
- Goel, A. M.; F. Song; and A. V. Thakor. "Correlated Leverage and Its Ramifications." *Journal of Financial Intermediation*, 23 (2014), 471–503.
- Greenwood, R.; A. Landier; and D. Thesmar. "Vulnerable Banks." *Journal of Financial Economics*, 115 (2015), 471–485.
- Iyer, R., and J. L. Peydró. "Interbank Contagion at Work: Evidence from a Natural Experiment." *Review of Financial Studies*, 24 (2011), 1337–1377.
- Markose, S.; S. Giansante; and A. R. Shaghghi. "'Too Interconnected to Fail' Financial Network of US CDS Market: Topological Fragility and Systemic Risk." *Journal of Economic Behavior & Organization*, 83 (2012), 627–646.
- Morrison, A. D.; M. Vasios; M. I. Wilson; and F. Zikes. "Identifying Contagion in a Banking Network." FEDS Working Paper No. 2017–082 (2017).
- Morrison, A. D., and L. White. "Reputational Contagion and Optimal Regulatory Forbearance." *Journal of Financial Economics*, 110 (2013), 642–658.
- Rogers, L. C. G., and L. M. Veraart. "Faliure and Rescue in an Interbank Network." *Management Science*, 59 (2013), 882–898.
- Rosen, R. J. "The Impact of the Originate-to-Distribute Model on Banks Before and During the Financial Crisis." Working Paper, Federal Reserve Bank of Chicago (2011).
- Shakya, S. "Geographic Networks and Spillovers Between Banks." Working Paper, Arizona State University (2021).
- Upper, C., and A. Worms. "Estimating Bilateral Exposures in the German Interbank Market: Is There a Danger of Contagion?" *European Economic Review*, 48 (2004), 827–849.