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 non-boom 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 non-boom counties and non-shocked banks located therein respond with increased lending.

Keywords: Spillovers, Geographic Networks, Bank Interconnectedness

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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 as well as 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 have exposure to a common regulator (Morrison and White (2013)) or to a common geographic region (Shakya (2020), 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 studying negative spillovers. However, it is plausible that linkages that facilitate negative spillovers also facilitate positive spillovers in the event of a positive shock. An empirical study of positive spillovers between banks is missing in the literature, and I fill this gap by providing the first evidence of positive bank-to-bank spillovers.

For this study, I consider geographic linkages between banks: These are the linkages that are formed between banks when they engage in home lending in the same geographic region (Shakya (2020)). 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 non-shocked banks. Specifically, I show that a non-shocked bank ('subject bank') in a non-boom 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 non-shocked banks then respond by changing their own lending behavior because they are exposed to the same county. Specifically, positive liquidity shocks (shocks to the deposit base here) lead shocked banks to

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

increase lending in non-boom counties (Gilje, Loutskina, and Strahan (2016)). Such behavior can then lead to increases in home prices in non-boom counties (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 non-shocked banks increase their lending in non-boom counties.

This spillover mechanism is distinct from the mechanism that leads shocked banks to increase lending in the first place due to liquidity shock, 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 as mentioned before. Second, the underlying mechanism of spillover is novel, thus adding to the literature that has explored different ways bank-to-bank spillovers occur. While Shakya (2020) is the first to identify geographic linkages between banks considered in this paper, she provides a study of negative spillovers and the underlying mechanism is different; spillovers occur in her study due to investor runs on geographic linkages of 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' from here on) that began in 2003. This positive 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 landowners, who lease their land for fracking, and subsequent deposits in banks. Given the uncertain nature of shale discoveries in different geographic regions and the uncertain nature of viability of the technology, this shock is plausibly an exogenous shock to the liquidity of banks in boom counties (Gilje, Loutskina, and Strahan (2016)).

Given this positive shock on banks exposed to boom counties, I ask how a non-shocked bank that is geographically linked with shocked banks via a non-boom 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 a branch presence in the county. Because banks invest in both physical plant and customer relationships in local markets, and they retain most of the loans they originate there, local markets are important lending markets for banks. Focusing on local banks ensures that I study true lending behavior of banks. Moreover, banks sell most of the loans they originate in non-local 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 banks expand their lending in non-boom counties as a function of their own exposure to well activity in boom counties. Compared with a bank that has an average exposure to well activity, a bank that has a 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 providing evidence of spillovers from shale-shocked to non-shocked banks. For each non-shocked 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 sensitivity of the subject bank to spillovers. Sensitivity of a subject bank is captured by (a) importance of overlapping markets to the linkage banks (higher the importance, the more the shocks of the linkage bank will be felt in the overlapping markets), and (b) the exposure of the subject bank to the overlapping markets (details in section IV).

I find that in a non-boom county, a non-shocked bank increases lending more when its linkages are exposed to greater well activity in boom counties. This result persists even after accounting for subject bank’s own exposure to housing market conditions in its local markets. Compared to a bank that has an average value of *Boom Exposure of Linkages*, a bank that has a standard deviation higher value increases its lending by 11.3 percentage points more. Furthermore, I find that results are being driven by spillovers coming from linkages that have above median asset size amongst shocked banks in a given county, consistent with the intuition that spillovers should be more pronounced coming from larger 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, if occurring via a positive impact on the overlapping market, should affect loans that banks hold on their balance sheet and not the ones that are easily sold off.

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 non-shocked bank each year, I replace its shocked linkages with randomly chosen shocked banks from that year and obtain elasticity of loan growth with respect to *Boom Exposure of Linkages*. Repeating this exercise 1000 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 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 issue in several ways. First, I conduct 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 located within the same county and year. In other words, 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, because it allows comparisons of banks facing the same borrower demands.

Second, I control for a bank's own market exposure in counties other than the one under consideration by taking the weighted average of percent changes in home prices in those markets. Third, there is no evidence of differences in lending in 'good' versus 'bad' markets, which are defined to be markets that observe above and below median percent changes in home prices in the prior year, respectively. Fourth, I show that results persist after excluding 15 best markets, defined to be the ones that observe the highest percent increases in home prices in the prior year.

A related concern of confounding market effect arises from direct spillovers from adjacent boom counties. For example, non-shocked banks in non-boom counties could increase lending due to spillovers of supply of deposits from adjacent boom counties. I show that results are robust to removing counties that are within 100 miles of boom counties. Yet another concern is selection of non-shocked banks into counties where shocked banks are present. Banks may enter these markets if they expect better housing market conditions due to the lending behavior of shocked banks. If this entrance is motivated by the need to fund loans, then results are confounded by demand effects.

To address this concern, for each bank, I limit my sample to counties where the bank already exists locally when its linkages are first shocked. I find that results remain.

I conduct a host of other robustness tests. I find that results are robust to excluding large/small markets, large/small subject banks, as well as large linkage banks, thus accounting for any biases due to the size of the housing markets and the size of the banks. Additionally, I consider an alternate construction of *Boom Exposure of Linkages*, which captures the exposure of linkages to *growth* in well activity from the start of the boom – and I find that results continue to hold.

Next, I study the underlying mechanism of spillover. I first provide evidence that spillovers occur via an impact on the overlapping market. If this is true, non-shocked banks should increase lending only in markets where shocked banks exist and not elsewhere. I find that this is indeed the case. Furthermore, I provide direct evidence that boom exposure of linkages has a positive impact on the home prices of overlapping markets. I show that the weighted average exposure of the subject bank to percent changes in home prices in overlapping markets increases as its linkages have greater exposure to well activity in boom counties.

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 borrowers in markets with bad economy have low credit credibility, such markets should benefit the most from spillover effects. 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, in general, 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, one could argue that the same mechanism that causes shocked banks to increase lending in non-boom counties also causes non-shocked banks to increase lending. Gilje, Loutskina, and Strahan (2016) argue that a liquidity shock allows banks to originate loans that they were previously unable to originate due to contracting frictions. In the context of this paper, one could argue that home price increases due to the lending behavior of shocked banks lead homeowners to sell their homes, resulting in prepayments, and, thus, an influx of cash for banks ("liquidity channel"). However, the results of this paper contradict this argument. First, banks increase lending only in markets where shocked banks exist. If "liquidity" channel was at work, banks should be able to increase lending elsewhere too. Second, this channel should benefit financially constrained banks. On the contrary, I find that spillovers are driven by banks that are not financially constrained.

Another alternate hypothesis for spillover mechanism is that spillovers are due to investors who provide funds to banks. Increases in home prices due to the lending behavior of shocked banks could encourage investors to increase their supply of funds to non-shocked banks in the same market, thus leading those banks to expand lending. If this mechanism were at work, banks dependent on wholesale funds should respond more, because it is easy for wholesale investors to quickly increase their supply of funds to banks, given short-term and less risky nature of wholesale funds. However, I do not find any evidence supporting this hypothesis.

Finally, I study aggregate effects of spillovers at bank and county levels. If spillovers simply lead banks to reallocate their supply of loans from one county to another where shocked banks are present, one may not observe aggregate increase in lending at the bank level. Similarly, if non-shocked banks in a non-boom county are simply competing loans away from one another, there may not be an aggregate increase in lending at the county level. However, I find that there is an economically significant increase in aggregate 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 used in this paper. Section IV discusses methods and presents base results; Section V presents robustness tests; and section VI discusses the spillover mechanism. Section VII studies aggregate effects of spillovers on bank and county levels, and section VIII 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 has explored linkages primarily due to contractual relationships and asset correlations, and it has focused on negative spillovers, showing the impact of interconnectedness 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), Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015), Rogers and Veraart (2013), Cifuentes, Ferrucci, and Shin (2005), 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), Iyer and Peydró (2011) etc.) 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 any 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 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 Yılmaz (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 on the competence of the regulator and thus on other banks regulated by the same regulator. Similarly, Shakya (2020), and Goel, Song, and Thakor (2014) argue that spillovers occur between banks that share a common lending market. However, again, these papers study negative spillovers, while this paper studies positive spillovers.

III. Shale Boom and Data

III.1. Shale Booms

Natural gas shale booms are surprise events that represent shocks of considerable economic magnitude to bank liquidity. Based on Gilje (2019) and Gilje, Loutskina, and Strahan (2016), I provide a brief description of these events and discuss their exogenous nature.

Shale booms started in 2003 after an unanticipated technological innovation, commonly referred to as "horizontal fracking." Because the viability of this technology and the discovery of natural gas shales in different geographic regions are highly unpredictable, these booms represent shocks that are exogenous to the characteristics of local economies as well as bank characteristics. Furthermore, the economic profitability in the development of shale wells is largely determined by macroeconomic factors such as demands for natural gas, thus strengthening the case for exogeneity of these shocks (Gilje, Loutskina, and Strahan (2016)). Therefore, shale booms represent credible positive shocks to banks and thus offer appropriate settings for the study of spillovers from shale-shocked to non-shocked banks.

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 out 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. As 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. Because of such economic significance of shale shocks, it is reasonable to expect spillover effects, thus making these boom events appropriate settings for this study.

I obtain shale well data from Erik Gilje's website.[2] This database provides information on the cumulative count of wells that were drilled from 2003 through June 30 of a given year in a given 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 as of the same point in time. And the wells that the database counts are the ones that are associated with "horizontal fracking" – that is, these wells are associated with the new technology that led to shale oil boom.

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-year observation with more than 11 shale wells. As of 2017, 227 counties across these states experienced 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 shale wells to define a boom county. In my empirical analysis, I find that my results are robust to their definition of a boom county.

[2] See http://finance.wharton.upenn.edu/~gilje/

III.2 Data and Sample

I obtain detailed home loan data from the Home Mortgage Disclosure Act (HMDA) database. Congress enacted HMDA in 1975 to improve public reporting of mortgage loans, and U.S. financial institutions are required to report HMDA data to their regulators if they meet certain criteria, such as a threshold for asset size and whether the institution has a home office or branch in a Metropolitan Statistical Area (MSA).[3,4] This is an annual database containing information on loan applications (regardless of whether or not they were approved), borrower demographics, lender details, and loan specifics such as loan amount and geographic location of the property.

This database provides a comprehensive coverage of the mortgage market. For example, Avery et al. (2010) note that in 2008, commercial banks filing HMDA carried 93% of the total mortgage dollars outstanding on commercial bank portfolios at the time. Although lenders with offices only in non-metropolitan areas are exempt from filing HMDA, as Dell'Ariccia, Igan, and Laeven (2012) note, 83.2% of the population in 2006 lived in metropolitan areas. Therefore, the data in HMDA are well representative of the residential mortgage lending activity in the U.S.

I obtain lender information from HMDA Lender file, constructed by Robert Avery at Federal Housing Finance Agency (FHFA).[5] This file gives information on the type of the lender, such as whether it is a commercial bank or an independent mortgage bank. It also matches every lender who has filed a HMDA report on and after 1993 with the identification code (RSSD) used by the Federal Reserve. If a HMDA lender is a commercial bank, it provides RSSD for the bank. If the lender is a subsidiary of a bank, it matches the lender to the bank, and if it is a subsidiary of a bank holding company, it matches the lender to the lead bank in the holding company. If the lender is merged into another institution, the lender is matched with the acquiring institution.

Combining loan data from HMDA loan files with lender information from HMDA lender file, I construct a sample of non-trivial loans (loans greater than $50,000 in size) that commercial banks originate during the calendar years 2003 (the year of the start of shale boom) through 2017.

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[3] This law was enacted to ensure that lenders were serving the housing needs of their communities in an indiscriminatory way.

[4] Any depository institution that has a home office or branch in an MSA is required to file HMDA if it has made a home purchase loan on a one to four unit dwelling or has refinanced a home purchase loan, and has assets above an annually adjusted threshold. Every December, the Consumer Financial Protection Bureau announces the threshold for the following year. For example, in 2007, this threshold was $36 million. Any non-depository institution (e.g., a mortgage company that does not accept deposits but raises funds for lending by borrowing from banks or capital markets) is required to file if at least 10% of its loan portfolio is composed of home purchase loans, and if it holds assets exceeding $10 million. See Dell'Ariccia, Igan, and Laeven (2012).

[5] This file is available at Neil Bhutta's webpage: https://sites.google.com/site/neilbhutta/data

I focus on commercial banks and remove all non-bank lenders, because most non-bank 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. And as mentioned before, I focus on states with major shale activity, so I filter for loans originated in Arkansas, Louisiana, North Dakota, Oklahoma, Pennsylvania, Texas, and West Virginia.

For any given year, I limit my sample to lenders that filed HMDA in the prior year – that is, a lender in my sample originates at least one loan in the previous year.[6] This filter avoids any bias on loan growth due to lenders newly entering the business of mortgage lending. I keep conventional (loans not insured by government agencies) and Federal Housing Administration (FHA) loans, and drop loans guaranteed by Veteran's Affairs (VA) and Farmers Home Administration (FmHA).[7] HMDA also provides information on whether loans are sold as of the calendar year end, and because loans that are originated to be sold are immediately sold within few months, I classify loans that are not sold within the given calendar year as loans that banks retain on their balance sheet (Rosen (2011), Berrospide, Black, and Keeton (2016), Duchin and Sosyura (2014), Gilje, Loutskina, and Strahan (2016)).

Next, using bank RSSD ID for each HMDA lender from the lender file, I match the lender to the highest bank holding company in the year of observation, and treat all banks belonging to the same bank holding company as one bank. This ensures that I capture 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 bank holding company. Working at the bank holding company level avoids such issue. I aggregate lending by banks at the bank holding company level and study changes in lending at this level.

To construct bank control variables, I obtain data from the call report database (Report of Condition and Income), which provides detailed information on a bank's income statement, and on-balance sheet and off-balance sheet items. All financial institutions regulated by the Federal Reserve Bank, Federal Deposit Insurance Corporation (FDIC), and the Office of the Comptroller of the Currency (OCC) are required, on a quarterly basis, to file these reports. These reports are publicly available through the Federal Reserve Bank of Chicago.

[6] The total number of loans drops by 9.4% after filtering for lenders that originate at least one loan in the prior year.
[7] Filtering out VA and FmHA loans drops an additional 1.4% of loans.

The control variables that I construct from this database include: log(total assets), liquidity ratio (= liquid assets/total assets as constructed in Acharya and Mora (2015)), equity/assets, net income/assets, asset quality (loan charge-offs/total assets), mortgage loans/assets, unused commitments ratio (= unused commitments / (unused commitments + total assets)), allowance for loan and lease losses (ALL)/assets, and commercial and industrial loans (C&I loans)/assets.[8] I construct these variables for each bank RSSD, and for banks belonging to the same bank holding company, I construct them at the holding company level by taking size weighted average of values for each bank. Total assets at holding company level is the sum of assets for all banks belonging to that holding company.

Furthermore, I include a bank's exposure to housing market conditions in local counties as a control variable in my model. I construct this variable by taking the weighted average of percent changes in home prices, as described in detail later. To compute percent changes in home prices, I use the house price index (HPI) (traditional, all-transactions index) provided by the FHFA in their website.[9] Some of the regressions in this paper that cannot incorporate county-year fixed effects include control variables for county market characteristics. These characteristics include log(population), log(per capita personal income), household debt-to-income ratio, unemployment rate, percent female population, and 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.

For each bank RSSD each year, I also obtain data on branch location and deposit amounts as of June 30 of a given year from the Summary of Deposits provided by the Federal Deposit Insurance Corporation (FDIC). For banks belonging to the same holding company, I sum up deposits at the holding company level. I use this information on branch deposits to construct geographic linkages and to capture a bank's exposure to boom counties, as will be described later.

I will be referring to all independent banks and groups of banks belonging to the same highest holding company as "banks" from here on. My final sample consists of non-shocked banks in non-boom counties, where the banks are local, from years 2003 through 2017. This sample

[8] Liquid assets include cash, federal funds sold and reverse repos, and securities excluding MBS/ABS securities.
[9] HPI Index data are available at https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx#atvol.

consists of a total of 16,539 bank-county-year observations. There are 1062 unique banks and 411 unique counties. I describe this sample in detail in the next subsection.

III.3 Summary Statistics

Table 1 presents summary statistics for the sample. In Panel A, I present descriptive statistics for bank characteristics. This panel shows that banks, on average, have 3 branches and originate 183 loans. This panel also summarizes other bank characteristics that I control for in my regressions. Also summarized are a bank's average exposure to contemporaneous and lagged percent changes in home prices in all of its local markets, markets where shocked banks are present, and all markets excluding the one under consideration – which I use in different specifications of my model. One observation to note in this panel is the distribution of bank size (log(total assets)) and that of the number of loans originated by banks. This distribution is skewed due to the presence of some large banks in my sample. However, in my empirical analysis, I conduct several robustness tests to show that my results continue to hold after excluding banks that are large and small – by asset size and loan count.

Panel B summarizes market (county) characteristics. The median bank in a given county-year has on average 5 branches.[10] Similarly, in each county-year, there are on average 4 banks that are shocked. For a subsample of counties where shocked banks are locally present in a given year, I present the distribution of shocked bank characteristics. These shocked banks constitute the linkage banks in my sample. The median shocked bank has on average 43 branches. Comparing the average size of the median shocked banks in this subsample and that of the median non-shocked banks in all counties, the shocked banks are generally larger in size and operate in greater number of counties.[11] There is also a greater variation in the size of shocked banks, owing to the presence of some large multimarket shocked banks. Later in my empirical analysis, I address concerns of skewness in the distribution of the size of shocked banks and show that my results continue to hold after excluding linkages that are very large by asset size.

Panel B also shows that there are, on average, 1158 new mortgage originations in a county-year observation, and the distribution of this loan count is also skewed. To address concerns of biases due to county size by loan count, I will later show that my results are robust to excluding

[10] Median bank is the bank having median number of branches in a given county-year.
[11] Here, median bank is the bank having median size in a given county-year.

the smallest and largest counties by loan count each year. This panel also summarizes other market characteristics that I use as control variables in some of my regressions.

In panel C, I summarize boom exposure variables. *Boom Exposure of Linkages* is the main independent variable of interest. I construct this variable for each bank in each year, and it captures the average exposure of its geographic linkages in all of its local markets to the log of cumulative count of wells in shale boom counties. The construction of this variable is described in detail in the next section. It takes an average value of 0.773 and has a standard deviation of 1.597. In my empirical analysis, I also break this variable into parts representing boom exposure of large versus small linkages in a given county-year, and panel C summarizes these variables as well.

Own Boom Exposure captures a bank's own average exposure to log of cumulative count of wells in shale boom counties. This variable is also constructed at the bank-year level and described in detail in the next section. I present the distribution of this variable in subsamples of local markets and non-local markets separately, and the distribution includes both shocked and non-shocked banks as will be discussed later. When I study county level aggregate effects of spillovers, I consider *County Boom Exposure of Linkages,* which is a size weighted average measure of *Boom Exposure of Linkages* of banks in a given county-year. Panel C summarizes this variable as well, and its construction is discussed in detail section VII.

Panel D summarizes variables related to mortgage lending. This panel presents the main dependent variables, namely percent changes (log changes) in all loans originated, retained, and sold. While the sample only constitutes banks that have filed HMDA in the prior year – meaning banks that were engaged in home lending in the prior year – there are counties where a bank did not originate any loan in the prior year, and the computation of loan growth variable includes these observations.[12] For studies of aggregate effects at bank and county levels, I construct loan growth variables at bank-year and county-year levels. Panel D summarizers these variables as well.

Panel D also summarizes the fraction of loans in local markets that banks retain. 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 in non-local markets. On average, they sell 46% of the loans they originate in a non-local county each year.

These numbers underscore the importance of focusing on local markets to study home lending in this paper. They are consistent with the intuition that because branches provide closer

[12] For bank-county-year observations with 0 prior year lending, I replace 0 by 1 to compute log change in lending.

access to borrower information, banks have an information advantage in local markets and are able to retain more loans they create in these markets. Therefore, a bank's true lending behavior is reflected more in local markets, where they retain majority of loans, compared to non-local markets, where they sell a large fraction of their loans such that their lending behavior is influenced by funding conditions in the securitization market. And 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

IV.1. Shale Well Shock and Mortgage Lending

I begin my empirical 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. I show that banks increase their lending in non-boom counties more if they have greater exposure to well activity in boom counties. I consider bank lending only in non-boom counties in order to avoid the direct market effect of counties experiencing shale booms. This result also 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 non-shocked banks, and for banks that are not shocked, this variable takes the value 0. As mentioned before, boom counties are the ones that have above median cumulative count of wells in all county-years in my sample. And 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.

Given that contemporaneous shares of deposits could be affected by new deposits from the shock itself, in unreported tables, I also construct *Own Boom Exposure* using lagged deposit shares to capture a bank's exposure to cumulative count of wells and I obtain similar results. To be consistent with the construction of *Boom Exposure of Linkages* in the next section that uses contemporaneous deposit shares, I present results for *Own Boom Exposure* that also uses contemporaneous deposit shares. Furthermore, in unreported tables, I find that results are similar if I use deposit shares in boom counties, instead of weighted average exposure to well activity, as a measure for a bank's shock exposure as in Gilje, Loutskina, and Strahan (2016). Results are similar whether I use contemporaneous or lagged deposit shares.

Using the following model, I study how a bank changes its lending in year *t* from prior year *t-1* in a non-boom county, as a function of *Own Boom Exposure*:

$$\begin{aligned}\Delta \log\left(Mortgage\ Lending_{i,c}\right)_t \\ &= \alpha + \beta\ Own\ Boom\ Exposure_{i,t} + Bank\ Controls_{i,t-1} \\ &+ County \times Year\ F.E + \varepsilon_{i,c,t}\end{aligned} \tag{1}$$

In this model, the unit of analysis is for a bank in a non-boom county each year. $\Delta \log\left(Mortgage\ Lending_{i,c}\right)_t$ is the percent growth in mortgage 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 non-boom 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 non-local markets.

Column (1) shows that banks increase lending in local non-boom counties when they are exposed to greater degree of well activity in boom counties. I account for any confounding effect of housing market conditions of the county in question by conducting a within-market analysis using county-year fixed effects, thereby comparing banks that are exposed to the same market conditions but that have different boom exposures. In column (2), I further account for the possibility of the confounding effect of exposure to housing market conditions in *other* local markets of the bank. I do so by including 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 the inclusion of this variable does not change the results. In fact, the magnitude of *Own Boom Exposure* increases slightly after including this variable.

To understand the economic significance of the impact of *Own Boom Exposure*, consider a bank which has an average value for this variable (= 0.466), and a bank which has a standard deviation higher value (= 0.466 + 1.053 = 1.519). Column (2) implies that the latter bank increases its lending by 9.5 percent points more than the former bank (=$e^{(1.519* 0.0833)} - e^{(0.466 * 0.0833)}$).

I conduct similar tests for non-local markets and present results in columns (3) and (4). There is no evidence that banks change lending in non-local markets. The coefficients of *Own Boom Exposure* are statistically insignificant in both columns. Furthermore, the coefficient is negative in column (3). While the coefficient is positive in column (4), the economic magnitude is 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 non-local markets (Gilje, Loutskina, and Strahan (2016)).

Therefore, the results of Table 2 show that the shale shock does indeed represent a positive shock to banks and causes them to increase lending in local non-boom markets. That shocked banks increase lending only in local markets makes a further case for focusing on spillovers occurring only from local linkage banks in the next sections.

IV.2. Spillover Effect

IV.2.1. Construction of Boom Exposure of Linkages

In this subsection, I describe how I construct my main independent variable – *Boom Exposure of Linkages*. I construct this variable for each non-shocked bank each year. As defined before, two banks are geographically linked if they engage in mortgage lending in the same market (county) and if the market is local for both banks. For a non-shocked bank each year, I construct *Boom Exposure of Linkages* as the weighted average exposure of its shocked linkage banks to the log of cumulative count of wells in boom counties, where the linkage banks are local. The weights reflect the non-shocked bank's sensitivity to spillovers from its linkages, as described below.

Consider the computation of *Boom Exposure of Linkages* for a non-shocked bank X in year *t*. Let *M* be the set of all local markets for X. Then linkage banks for X are all banks that are shocked and that are local in any $m \epsilon M$. Let $w^{i}_{m,t}$ be the fraction of deposits that bank *i* holds in county *m* in year *t*. I follow the following three 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 boom counties by taking the weighted average of natural logarithm of the cumulative count of wells in boom counties, where the bank is local. The weight assigned to each market is the fraction of branch deposits that the bank holds in that market. So for a shocked linkage bank Y, exposure to well activity in boom counties is:

$$Boom\ Exposure\ of\ Linkage\ Y\ in\ year\ t = \ Boom\ Exp_t^Y = \sum_c w_{c,t}^Y \log(c\_wells_{c,t}) \tag{2}$$

where $c\_wells_{c,t}$ is the cumulative count of wells in county c in year t since the beginning of the shale well 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 well activity only in local markets of Y.

Step 2. Weigh each linkage bank's boom exposure by subject bank's sensitivity that linkage.

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 linkage banks. I do so by weighing each linkage bank's boom exposure by (a) the importance of the overlapping market to the linkage bank, and (b) 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 that captures the importance of the market to the linkage bank ensures that I give more weight to areas where X is more likely to experience spillovers. Similarly, assigning a weight that captures the importance of the overlapping 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 boom exposure as follows:

$$\begin{aligned} &weighted\ Boom\ Exposure\ of\ Linkage\ Y\ in\ County\ a\ in\ year\ t \\ &= \ w_{a,t}^X w_{a,t}^Y \ Boom\ Exp_t^Y \end{aligned} \tag{3}$$

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

$$\begin{aligned} &weighted\ Boom\ Exposure\ of\ Linkage\ Y\ in\ Counties\ a\ and\ b\ in\ year\ t \\ &= \left(w_{a,t}^X w_{a,t}^Y \ + \ w_{b,t}^X w_{b,t}^Y\right) Boom\ Exp_t^Y \end{aligned} \tag{4}$$

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

$$weighted\ Boom\ Exposure\ of\ Linkage\ Y\ in\ year\ t = \left(\sum_{m \epsilon M} w_{m,t}^X w_{m,t}^Y\right) \ Boom\ Exp_t^Y \tag{5}$$

Again, note that for a bank *i* in county *m*, $w_{m,t}^{i} > 0$ only if it has a branch in *m*. So the product of $w_{m,t}^{X}$ and $w_{m,t}^{Y}$ in equation (5) is positive only if both X and Y are local in county *m*, i.e., if X and Y are geographically linked.

Step 3. Sum up weighted boom exposures of all linkages

Finally, I consider all shocked linkages of bank X, and sum up weighted boom exposures of linkage banks computed in step 2. The final expression for *Boom Exposure of Linkages* for bank X is the following:

$$Boom\ Exposure\ of\ Linkages\ for\ X\ in\ year\ t = \sum_{i} \sum_{m \epsilon M} w_{m,t}^{X} w_{m,t}^{i}\ \ Boom\ Exp_{t}^{i} \qquad (6)$$

where *i* is a shocked bank that is geographically linked with X in year *t*. Thus, this final expression for *Boom Exposure of Linkages* captures the exposure of linkage banks to well activity in boom counties, weighted by the non-shocked subject bank's sensitivity to those linkages.

By constructing *Boom Exposure of Linkages* at the bank level, 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 non-boom county – and expect similar increases in home prices in other non-boom counties if shocked banks exist in those counties as well. Therefore, studying changes in lending behavior in a given county as a function of *Boom Exposure of Linkages* accounts for any learning that might occur in *other* counties.

Figure 1 illustrates the construction of *Boom Exposure of Linkages* using a hypothetical network of two banks – one shocked and one not shocked. Let X be a non-shocked bank, local in counties *a* and *b,* where both counties are non-boom counties. Let Y be a shocked bank, also local in *a* and *b*. In addition to *a* and *b,* Y is local in other counties, including boom counties (not shown). Solid arrows represent lending in a market, and the numbers along the arrows represent a bank's shares of deposits in the markets. For instance, X holds 60% of its deposits in county *a*. This value represents X's exposure to *a* and, thus, its exposure to the local banks in *a.*

In this example, the non-shocked bank X is the subject bank – the one that is on the receiving end of spillovers and the one whose lending behavior I study. Bank Y is X's linkage. The first step in the construction of *Boom Exposure of Linkages* is to find Y's exposure to well activity in boom counties. So I compute Y's weighted average exposure to natural logarithm of cumulative well count in boom counties in a given year, where weights are Y's deposit shares in each boom county in that year. In figure 1, $Boom\ Exp_t^Y$ is Y's exposure to well activity in year *t.*

In the second step, I assign a weight to $Boom\ Exp_t^Y$ to capture X's sensitivity to spillovers from Y. X is linked with Y via counties *a* and *b*. To capture X's sensitivity to Y via county *a*, I weigh $Boom\ Exp_t^Y$ by the product of deposit shares of X and Y in *a* (i.e., 0.6 x 0.1), and to capture X's sensitivity to Y via county *b*, I use the product of deposit shares of X and Y in *b* (i.e., 0.4 x 0.2). Thus, the markets where X is more exposed to Y and the markets where X is likely to feel the shock of Y more are weighed more. So the weighted boom exposure of linkage Y is (0.6 * 0.1 + 0.4 * 0.2)$Boom\ Exp_t^Y$. Because this is a world of only two banks, and Y is X's only linkage, this expression is the final expression for *Boom Exposure of Linkages* for X (see figure 1, part (i)).

Figure 1, part (ii) then extends this network to a network consisting an additional shocked bank Z, which is also local in counties *a* and *b.* In this case, *Boom Exposure of Linkages* for X is the weighted average of boom exposures of Y and Z. The expression for boom exposure of bank Z (i.e., $Boom\ Exp_t^Z$) weighed by X's sensitivity is (0.6 * w_a^Z + 0.4 * w_b^Z) $Boom\ Exp_t^Z$ where w_a^Z and w_b^Z are the fractions of deposits that Z holds in counties *a* and *b*. The expression for weighted boom exposure of Y is as computed previously.

In the final step, I sum up weighted boom exposures of Y and Z. So the final expression for *Boom Exposure of Linkages* for X is (0.6 * 0.1 + 0.4 * 0.2) $Boom\ Exp_t^Y$ + (0.6 * w_a^Z + 0.4 * w_b^Z) $Boom\ Exp_t^Z$. This network can be extended to *n* banks, and *Boom Exposure of Linkages* for X in this network can be computed similarly.

IV.2.2. Boom Exposure of Linkages and Mortgage Lending

In this subsection, I study how a non-shocked bank in a non-boom county changes its lending as a function of the exposure of shocked linkage banks to well activity in boom counties. 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:

$$\begin{aligned}\Delta \log\left(Mortgage\ Lending_{i,c}\right)_t &\\ &= \alpha + \beta Boom\ Exposure\ of\ Linkages_{\ i,t} + Bank\ Controls_{\ i,t-1} \\ &+ County \times Year\ F.E + \varepsilon_{i,t,c}\end{aligned} \tag{7}$$

Here, $\Delta \log\left(Mortgage\ Lending_{i,c}\right)_t$ is the percent growth in mortgage lending of a non-shocked bank *i* in a non-boom county *c* at time *t*. $Boom\ Exposure\ of\ Linkages_{i,t}$ is as described before. Because $Boom\ Exposure\ of\ Linkages_{i,t}$ is constructed at the bank level each year, this variable does not vary across counties in each bank-year. For this reason, I cluster standard errors at the bank level. I also include county-year fixed effects to control for housing market conditions. These fixed effects also control for borrower demand effects that might affect bank lending. And all bank control variables are constructed as of the prior year. The coefficient of interest here is β, and any spillover effect would imply that $\beta > 0$.

Table 3 presents regression results for model (7). Column (1) studies growth in lending of a non-shocked bank in a non-boom county as a function of *Boom Exposure of Linkages*. Results show that banks increase mortgage lending when its linkages are exposed to greater well activity in boom counties. To understand the magnitude of this result, consider a bank which has an average value of *Boom Exposure of Linkages* (= 0.773) and a bank which has a standard deviation higher value for this variable (= 0.773 + 1.597 = 2.37). Column (1) implies that the latter bank increases its lending by 10.9 percent points more than the former bank (=$e^{(2.37*0.0621)} - e^{(0.773*0.0621)}$).

In column (2), I address the possibility that the increase in lending could be confounded by 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 but have different linkages in their network and, thus, different values for *Boom Exposure of Linkages*. To account for any market effect from *other* local markets of the bank, I further include *Exposure to ΔHPI(%) in Other Markets* as a control variable in column (2). *Exposure to ΔHPI(%) in Other Markets* is constructed as before and captures the subject bank's contemporaneous weighted average exposure to percent changes in home prices in local markets other than the one under consideration. As before, the weights used are the deposit shares that the bank holds in each market. Results persist even after including this variable, and, in fact, the coefficient of *Boom Exposure of Linkages* increases slightly. Specifically, a bank that has *Boom Exposure of Linkages* at a standard deviation higher than mean value increases its lending by 11.3 percent points more than a bank that has *Boom Exposure of Linkages* at the mean.

In column (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*. I define a bank to be small if it has below median size amongst the shocked banks in each overlapping market and large if it has above median size.[13] Any spillover effect implies that results are stronger coming from larger linkages. Results in column (3) show that spillovers are indeed driven by those coming from large banks. Compared to a bank which has *Boom Exposure of Large Linkages* at the mean (= 0.297), a bank that has a standard deviation higher value (= 0.297 + 0.755 = 1.052) increases its lending by 21.3 percent points more. On the other hand, *Boom Exposure of Small Linkages* is statistically insignificant and negative, inconsistent with any spillovers from small linkages.

IV.3. Retained versus Sold Loans

Next, I study whether spillover effect on mortgage lending is 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 effect improves expected future home prices and thus reduces credit exposure in mortgage lending, this should lead banks to increase lending of loans that they hold on their balance sheet 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 growth in retained loans, while columns (3) and (4) present results for sold loans. Results show that the positive impact of *Boom Exposure of Linkages* on loan growth of non-shocked banks 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 regressions of Table 3. Furthermore, spillovers occurring from large banks drive the growth in retained loans, as shown by column (2). In contrast, results in columns (3) and (4) for growth in sold loans are statistically and economically not significant. That the spillover effect from boom exposure of linkages affects lending of loans that banks retain also indicates that these spillovers have an important on-balance-sheet impact on banks.

IV.4. Placebo Test

The underlying identification assumption in model (7) is that there will be no spillovers if shocked banks are not geographically linked with non-shocked banks. In this subsection, I test the

[13] For 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 tables) if I label this bank as small such that it appears in the construction of *Boom Exposure of Small Linkages* instead.

validity of this assumption by considering placebo linkages and studying whether there are any results of spillovers via these false linkages. If the identification assumption holds, I expect no spillovers via placebo linkages. Any results of spillovers would be indicative of unobservables driving the results in previous tests.

For each non-shocked bank in each non-boom county and year, I replace all shocked geographic linkages with randomly chosen banks from the universe of all other shocked banks in that year.[14] Because these linkage banks are false and 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 the variable, *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 1000 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, thus validating the identification assumption underlying model (7). Furthermore, given this result, it is unlikely that the spillover results documented in this paper are simply due to unobservable factors.

V. Robustness Tests

In this section, I present several robustness tests.

[14] These random shocked banks could still be linked with the subject bank via other counties. However, this choice biases against finding 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.

V.1. Close Proximity to Boom Counties

In my empirical analysis, I focus on studying the lending behavior of non-shocked banks in non-boom counties, thus separating bank-to-bank spillovers from the confounding effect of a bank's own exposure to boom events and direct demand effects of boom counties. However, even if a county is not shocked, it may still experience demand spillovers from neighboring boom counties. In order to address concerns of this confounding effect, I drop all county-year observations for counties that are in close proximity to a boom county. Specifically, I drop counties that are within 100 miles of any boom county. Column (1) of table 5 presents the results and shows that results continue to hold. Moreover, the elasticity coefficient of *Boom Exposure of Linkages* increases in economic magnitude after dropping counties in close proximity to a boom county.

V.2. Selection into Counties where Shocked Banks are Located

It is also possible that banks may select into counties where shocked banks are present if they expect market conditions in those counties to improve due to the lending behavior of shocked banks. If this selection is motivated by loan demands in the area, then my results would be due to both supply and demand effects. I address this confounding effect in the following way: For every non-shocked subject bank, I find the first year that one of its linkage banks is shocked. Then, I filter for county-year observations only for those counties where this bank was local as of this year. In other words, I study lending behavior of non-shocked banks only in counties where the bank was already local when its linkages were first shocked. Column (2) of Table 5 presents the results and shows that the elasticity coefficient of *Boom Exposure of Linkages* remains statistically significant and increases slightly in economic magnitude.

V.3. Housing Market Conditions of Subject Bank's Own Markets

Next, I present robustness tests to further address potential confounding effects from the subject bank's own market exposure. Rather than responding to spillovers from linkage banks, the concern is that the subject bank increases home lending because the market under consideration is doing well. As mentioned before, all regressions include county-year fixed effects, which absorb market effects of the county in question. In this subsection, I present additional robustness tests that show that my results are not simply due to the subject bank's own market exposure.

In column (3) of Table 5, I interact my main independent variable with a dummy variable that identifies "good" and "bad" markets. Good markets are the counties that underwent above median percent changes in home prices in the prior year, and bad markets are those that underwent below median percent changes in home prices in the prior year. Over my sample period, the median lagged percent change in home prices is 2.5%. Any confounding effect from own market exposure implies that banks increase lending more in good markets. However, column (3) of Table 5 shows that this interaction term is statistically insignificant implying that spillovers in good markets are statistically indistinguishable from those in bad markets. Moreover, the magnitude of this interaction term is economically insignificant.

In column (4), I exclude 15 best performing markets each year. These markets are the counties that observe the largest percent changes in home prices in the previous year. Results continue to hold even after dropping these markets. The elasticity coefficient of *Boom Exposure of Linkages* is statistically significant and the magnitude is similar to the base regression of Table 3, column (2), implying that the results documented here are not simply due to good housing market conditions of the counties under consideration.

V.4. Market Size Effects

Furthermore, it is possible that the size of the housing markets may bias my results. One could argue that the results could be due to large markets. For instance, banks may engage in lending mostly in large markets because housing demand is generally higher in large markets, in which case my results would be confounded by demand effects. I address this concern by removing 15 largest counties by loan count in the prior year, and present results in column (5) of Table 5. I find that results persist. The elasticity coefficient of *Boom Exposure of Linkages* is statistically significant and the economic magnitude increases after removing the largest markets.

Yet another possibility is that results are driven by the smallest counties. Banks may not engage in much lending in small counties, such that the growth in lending in these counites are based on few loans, thus adding noise to my results. This could bias the magnitude of the coefficient of *Boom Exposure of Linkages*. In column (1) of Table IA.1, I remove 15 smallest counties by loan count in the previous year. I find that results persist, and that the magnitude of the coefficient is similar to the one in the base regression of Table 3, column (2). I conduct an additional test where I drop all bank-county-year observations based on fewer than 15 loans, and present results in column (2) of Table IA.1. The magnitude of the coefficient increases in this test and the result is statistically significant. Therefore, it is unlikely that my results are due to noise in the measurement of bank loan growth.

V.5. Subject and Linkage Bank Size Effects

In this subsection, I address the possibility that large banks may bias my results. First, large banks, because of their size, operate in a large number of markets compared to small banks, such that they have a greater probability of having some exposure to shocked banks. Therefore, the results of my paper could be driven by large banks. Large banks also have greater capital and wider access to the capital markets, allowing them to increase lending faster than the rest of the banks, thus confounding the results of spillovers in this paper. I address this concern here.

First, in column (1) of Table 6, I include an interaction between *Boom Exposure of Linkages* and a dummy variable *Above Median Size,* which identifies banks that have above median asset size each year. Results show that this interaction term is statistically insignificant implying that the response of large banks is statistically not different from that of small banks. In column (2) of Table 6, I remove large banks from the regression. Specifically, I remove banks that have greater than $50 billion assets. This cutoff corresponds to the asset size cutoff used by the Federal Reserve to define large banks. As the results show, the elasticity coefficient on *Boom Exposure of Linkages* remains statistically significant and the magnitude of the coefficient is similar to that in the base regressions of Table 3.

Next, I test robustness of my results to size effects of linkage banks. Because large banks tend to operate in large number of markets as mentioned before, I address concerns that my results might be driven by exposure to large linkages only. I reconstruct *Boom Exposure of Linkages* by removing very large linkages, i.e., linkages that have more than $250 billion in total assets. This cutoff corresponds to the asset size cutoff used by the Federal Reserve to define very large banks. As the summary statistics in Table 1 show, shocked banks are generally larger than the non-shocked banks in my sample. Using a higher size cutoff allows me to keep enough number of shocked banks to study spillover effects. I present results in Column (3) of Table 6. Results are still statistically significant and the economic magnitude, while slightly smaller, is similar to the one in the base regression of Table 3, column (1).

Alternatively, small size banks could also bias my results. Small banks, in general, have greater variation in loan growth that could bias the magnitude of regression coefficients. I address this concern by removing very small banks – defined as banks that have smaller than $100 million in total assets. I present results in the final column of Table 6. I find that *Boom Exposure of Linkages* remains statistically significant, and that the economic magnitude is similar to the ones in the base regressions.

Finally, I address concerns that loan growth observations of banks that create small number of loans could add noise to my results. To that end, I remove 15 smallest banks by loan count (total number of loans originated at the bank level) in the previous year. I present results in Table IA.1, column (3). Results show that *Boom Exposure of Linkages* continues to remain statistically significant and is slightly larger than the coefficient in the base results of Table 3.

V.6. Alternate Independent Variable

In Table IA.2, I consider an alternate definition for my main independent variable. I reconstruct *Boom Exposure of Linkages* to capture linkage exposure to percent growth in the number of shale wells, rather than the cumulative count of shale wells. I call this variable *Boom Growth Exposure of Linkages.* The construction of this variable is similar to *Boom Exposure of Linkages* except that, now, I consider a linkage bank's exposure to log change in the count of shale wells from 2003 (the first year of shale boom). For example, in the hypothetical network of Figure 1, I compute boom growth exposure of bank Y as follows:

$$Boom\ Growth\ Exp_t^Y = \sum_c w_{c,t}^Y \left[log\ (c\_wells_{c,t}) - log(c\_wells_{c,2003})\right] \qquad (8)$$

The rest of the construction of *Boom Growth Exposure of Linkages* in regards to the assignment of weights for the importance of the overlapping market to the subject bank and the linkage banks is similar to the one for *Boom Exposure of Linkages.*

Table IA.2 presents base tests of Table 3, as well as results for retained and sold loans using this alternate independent variable. I find that my results remain. *Boom Growth Exposure of Linkages* is positive and statistically significant, and this result is driven by spillovers coming from large linkages. Compared to a bank which has *Boom Growth Exposure of Linkages* at the mean value (=0.508), a bank that has a standard deviation higher value (=0.508+1.263=1.771) increases its lending by 8.8% more. Furthermore, columns (3) and (4) indicate that results are driven by increases in retained loans, as opposed to sold loans, consistent with prior results.

In unreported tables, I consider yet another definition for my independent variable. This variable is similar to *Boom Exposure of Linkages* except that I redefine boom counties using the definition in Gilje, Loutskina, and Strahan (2016). Specifically, I redefine a boom county as the county that has more than 17 shale wells in a given year. I find that results are robust to this alternate definition as well.

VI. Spillover Mechanism

In this section, I study the mechanism underlying the positive spillovers via geographic linkages. The spillover mechanism I study posits that spillovers occur via an impact on the housing market where shocked and non-shocked banks overlap. Specifically, spillovers occur because the positive shocks on banks lead them to change their lending behavior, which has a positive impact on the current and expected future home prices of the overlapping market. The connected non-shocked banks then respond to such improvements in the housing market by expanding lending. Banks expand lending because higher expected future home prices implies higher collateral value, and thus lower credit exposure and higher expected profitability in home lending.

The proposed mechanism leads to three testable hypotheses: (1) Spillovers occur only in markets overlapping between shocked and non-shocked banks; (2) *Boom Exposure of Linkages* has a positive impact on the home prices of overlapping markets; (3) 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.

VI.1. Spillovers via the Overlapping Market

I begin by providing evidence that spillovers occur via an impact on the markets where shocked and non-shocked banks overlap. The sample in this paper includes lending by non-shocked banks in all local non-boom counties. 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 7 presents the results. Columns (1) – (3) present results for lending in markets where a shocked bank is present. Column (1) studies changes in all loans; column (2) studies changes in retained loans; while column (3) studies changes in sold loans. Results shows that in markets where shocked banks are locally present, a non-shocked bank increases its lending as its geographic linkages have higher exposure to well activity in boom counties. 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 Table 3, column (2). Furthermore, the next two columns show that the increases in lending are driven by increases in retained loans, consistent with prior results.

Columns (4) – (6) present results for lending in markets where shocked banks do not exist locally. Column (5) studies changes in all loans; column (6) studies changes in retained loans; and column (7) studies changes in sold loans. 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 spillover effect that implies a positive coefficient.

VI.2. Spillovers and Home Prices

Next, I show more directly the impact of shock exposure of geographic linkages on markets where subject and linkage banks overlap. Specifically, I show that the shock exposure of linkages has a positive impact on the subject bank's exposure to home price changes in overlapping markets.

For each bank in each year, I construct a variable *Bank Exposure to ΔHPI(%) (Overlapping Markets)* that captures overall percent changes in home prices of all local markets of the subject bank that overlap with shocked linkage banks.[15] This variable is computed as the weighted average of percent changes in home prices of those markets – and the weights are the deposit shares of the bank in those markets in a given year. Then I study how *Bank Exposure to ΔHPI(%) (Overlapping Markets)* changes as a function of *Boom Exposure of Linkages* affects.

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

[15] In 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.

$$Bank\ Exposure\ to\ \Delta HPI(\%)(Overlapping\ Markets)_{i,t} \\ = \alpha + \beta Boom\ Exposure\ of\ Linkages_{\ i,t} + Bank\ Controls_{\ i,t-1} \\ + Average\ Market\ Controls_{i,t} + Bank\ F.E + Year\ F.E + \varepsilon_{i,t} \tag{9}$$

where $Bank\ Exposure\ to\ \Delta HPI(\%)(Overlapping\ Markets)_{i,t}$ is constructed as described above for each non-shocked bank i in each year t, and $Boom\ Exposure\ of\ Linkages_{i,t}$ 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 market characteristics of the counties where a bank engages in home lending. 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 of its local markets that overlap with shocked banks, and take the weighted average, where the weights are the shares of deposits that the bank holds in each market. These market characteristics include log(population), log(per capita personal income), household debt-to-income ratio, unemployment rate, percent female population, and percent minority population.

Furthermore, I include lagged bank control variables as before. I also include bank and year fixed effects, and cluster standard errors by bank. The coefficient of interest here is β, and the spillover mechanism implies that $\beta > 0$.

Table 8 presents the results.[16] Column (1) shows that as linkages have exposure to greater well activity in boom counties, average home price changes that a subject bank is exposed to in overlapping markets increases. To understand the magnitude of this result, consider a bank which has an average value of *Boom Exposure of Linkages* (= 0.773) and a bank which has a standard deviation higher value for this variable (= 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*0.00392), the latter bank's weighted average exposure to percent changes in home prices

[16] The 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 non-shocked banks in non-boom counties used in the base regressions of model (7). There are singleton observations at the bank-county-year level that get dropped in the base regressions. The bank characteristics summarized are for the banks that remain in this sample after the singleton observations are dropped. In table 8, I use all bank-year observations, including those that get dropped in the base regressions. However, note that any singletons in the bank-year level regression of model (9) do get dropped, resulting in the differences in the number of observations here versus Table 1. In unreported tables, I rerun tests of table 8 for only those bank-year observations that are included in the sample used in the base regressions and find similar results.

is 0.93% (=2.37*0.00392). In other words, the latter bank, on average, observes 0.63 percent point more increase in home prices in the overlapping markets. This value corresponds to 26.1% of the mean value of *Bank Exposure to ΔHPI(%) (Overlapping Markets)* (=2.4%). Therefore, column (1) implies an economically significant impact of *Boom Exposure of Linkages* on a bank's exposure to home price changes in overlapping markets.

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) could be confounded by market effects. In order to address this concern, 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 effect, then this control variable should capture it and explain away the effect of *Boom Exposure of Linkages*. However, column (2) shows that the inclusion of this control variable does the change the result much – the magnitude of *Boom Exposure of Linkages* declines only slightly, while remaining statistically significant as before.

In column (3), I break *Boom Exposure of Linkages* into two parts – one capturing boom exposure of linkages that have above median asset size amongst shocked banks in each overlapping market (*Large Linkages*) and the other capturing boom exposure of linkages that have below median size (*Small Linkages*). While both variables are statistically significant, the effect of *Boom Exposure of Large Linkages* is economically stronger than the effect of *Boom Exposure of Small Linkages.* For a standard deviation increase in the boom exposure of large linkages from the mean value, the subject bank observes 0.55 percent point higher increase in home prices. On the other hand, for a similar increase in boom exposure of small linkages from the mean value, the subject bank only observes a 0.17 percent point increase in home prices. Again, this is consistent with the idea that spillovers, if present, should be larger coming from large banks.

Column (4) conducts a similar test, now including a control for lagged exposure of the subject bank to percent changes in home prices in overlapping markets. Both coefficients decline in magnitude only slightly and they remain statistically significant.

VI.3. Borrower Credibility and Bank Financial Slack

According to the proposed spillover mechanism, any increase in home prices leads 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, spillover effect is *not* a shock to bank liquidity for non-shocked 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. I test these hypotheses in Table 9.

To capture the economy of a market, I use county level unemployment rates. In column (1) of Table 9, I interact *Boom Exposure of Linkages* with *Borrower Credibility,* where *Borrower Credibility* is contemporaneous unemployment rate of the county in question. And in column (2), I interact *Boom Exposure of Linkages* with *High Capital-to-Asset Ratio*, which identifies banks that have above median *Capital-to-Asset Ratio* in a given year, and, thus, have greater financial slack. I find that the interaction term in column (1) is statistically insignificant, suggesting that banks, in general, do not increase lending in bad economies as a function of boom exposure of linkages.[17] On the other hand, the interaction with *High Capital-to-Asset Ratio* 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 percent points more if it has *Boom Exposure of Linkages* at a standard deviation higher than mean value than if it has the variable 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), 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-to-Asset Ratio,* 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,

[17] Note that *Unemployment Rate* gets dropped in the regression due to its collinearity with county-year fixed effects.

such that the effect of spillovers is felt more in areas with lower borrower credibility. But because spillovers do not affect bank liquidity and only improves housing market conditions making home lending more attractive, only banks with financial slack respond with increased lending.

Additionally, that the interaction term in column (1) 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), consider a bank that has high financial slack (i.e., *High Capital-to-Asset Ratio*=1). In markets with 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 percent points more. In markets with a standard deviation higher unemployment rate, the response is higher. A similar increase in *Boom Exposure of Linkages* leads the bank to increase lending by 32.8 percent points more.[18] So the difference in the response of this bank to a standard deviation increase in *Boom Exposure of Linkages* in these two markets is 8.1 (=32.8-24.7) percent points. Now, consider a bank that has low financial slack (i.e., *High Capital-to-Asset Ratio*=0). In markets with 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 percent points more, while in a market with a standard deviation higher unemployment rate, a similar increase in *Boom Exposure of Linkages* actually leads the bank to decrease lending by 11.8 percent points more.[19] As per column (3), such response of a bank with high financial slack is statistically different from that of the bank with low financial slack.

So far, I have presented results that show that banks with high financial slack increase lending more in bad economies as their linkages have higher boom exposure. This is consistent with the spillover mechanism, which implies an improvement in credit exposure in home lending

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[18] This 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 $e^{(2.37(0.285-4.736*0.06-0.268+6.561*.0.06))} - e^{(0.773(0.285-4.736*0.06-0.268+6.561*.0.06))}$=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.

[19] This 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 $e^{(2.37(0.285-4.736*0.06))} - e^{(0.773(0.285-4.736*.06))}$=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.

due to spillovers. Next, I provide additional evidence that is consistent with this mechanism. If the proposed mechanism is true, one can also expect banks that, on average, operate more in bad economies to respond more to spillovers. I test this hypothesis in columns (4) and (5) of Table 9.

For each bank in each year, I construct *Bank Unemployment Exp*, which is the weighted average of unemployment rates in all local markets of the subject bank. The weights are deposit shares 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.* Results show that the interaction term is not statistically significant, consistent with the results in column (1). These results imply that banks that operate more in bad economies, in general, 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-to-Asset Ratio,* where *Borrower Credibility* is *Bank Unemployment Exp.* I find that this term is statistically significant. Therefore, banks that operate more in bad economies increase lending more as a function of shock exposure of linkages, if they are not financially constrained.

To understand the economic significance of the results in column (5), consider a bank that has high financial slack (i.e., *High Capital-to-Asset Ratio*=1). In response to a standard deviation increase in *Boom Exposure of Linkages* from the mean, a bank with average *Bank Unemployment Exp* increases its lending by 23.9 percent points more. For a similar increase in *Boom Exposure of Linkages,* the response of a bank with a standard deviation higher than mean *Bank Unemployment Exp* is higher. This bank increases lending by 32.9 percent points more. So the difference in the responses of these two banks to a standard deviation increase in *Boom Exposure of Linkages* is 9 (=32.9-23.9) percent points. If the two banks had low financial slack, a similar difference in their responses to a standard deviation increase in *Boom Exposure of Linkages* is -8.9%.

Thus, the results in this subsection show that as linkages experience larger positive shocks, banks that are not financially constrained increase lending more in areas where borrower credibility is low. Similarly, banks that operate more in areas with low borrower credibility increase lending more if they are not financially constrained. These results are consistent with improvements in credit exposure in home lending due to spillovers.

VI.4. Alternate Mechanisms

In this subsection, I address the possibility of alternate spillover mechanisms.

VI.4.1. Liquidity Channel

First, I discuss the possibility that the same mechanism that causes shocked banks to increase lending in non-boom counties also causes spillovers from shocked to non-shocked banks. Gilje, Loutskina, and Strahan (2016) argue that banks "export" liquidity from boom counties to non-boom counties because a liquidity shock allows banks to originate loans that were previously difficult to originate due to contracting frictions. In the context of this paper, one could argue, for example, that the increases in home prices due to the lending behavior of shocked banks could lead homeowners to sell their homes, resulting in prepayments, and, thus, an influx of liquidity for banks. Increased liquidity could then lead banks to originate loans with contracting frictions ("liquidity channel").

However, the results already presented contradict this argument. First, banks increase lending only in markets where shocked banks exist locally. However, if spillovers were to occur via the "liquidity" channel, there is no obvious reason why banks would increase lending only in markets where shocked banks are present and not where they are not present. Banks should be able to "export" liquidity from one market to another irrespective of whether shocked banks exist or not. Second, the "liquidity channel" also implies that financially constrained banks increase lending more. These banks should have more trouble originating new loans, and increased liquidity should allow them to increase lending to a greater extent than those that have financial slack. However, I find that spillovers are driven by banks with financial slack.

VI.4.2. Investor Channel

Alternatively, one could argue that results are due to investors who provide funds to banks. Specifically, these investors could learn from the lending behavior of shocked banks and the subsequent positive impact on home prices. They could then increase their funds to banks, who then expand lending. In other words, results could be investor effects as opposed to bank effects. In order to test this hypothesis, I consider the behavior of banks dependent on wholesale funds and study how they respond to spillovers. Because wholesale funds are short term and less risky, it is easy for wholesale fund investors to quickly increase their supply of funds to banks if they believe spillovers have a positive impact on the housing markets. In this case, banks dependent on wholesale funds would respond more strongly to spillovers.

Therefore, for each bank in each year, I construct *Wholesale-to-Assets Ratio*. Wholesale funds include large-time deposits, deposits booked in foreign offices, subordinated debt and debentures, gross federal funds purchased, repos, and other borrowed money (includes commercial papers) (Acharya and Mora (2015)). Then I construct a dummy variable *High Wholesale-to-Assets Ratio*, which identifies banks having above median *Wholesale-to-Assets Ratio* in a given year. In column (1) of Table 10, I include an interaction between *Boom Exposure of Linkages* and *High Wholesale Dependence,* where *High Wholesale Dependence* is the variable *High Wholesale-to-Assets* just described. I find that this interaction term is statistically and economically insignificant.

Given prior results where banks with financial slack increase lending only in bad economies, I test whether wholesale fund dependent banks behave similarly and increase their lending only in bad economies. To that end, in column (2), I include a triple interaction between *Boom Exposure of Linkages, Borrower Credibility,* and *High Wholesale Dependence,* where *Borrower Credibility* is *Unemployment Rate* and *High Wholesale Dependence* is *High Wholesale-to-Assets Ratio*. However, this interaction term is not statistically significant. Moreover, this interaction term is negative, inconsistent with wholesale dependent banks increasing lending in bad economies as a function of boom exposure of linkages.

Following the same vein of tests as before, I now consider *Bank Unemployment Exp,* and ask whether banks that operate more in bad economies and that are dependent on wholesale funds increase lending more in response to shock exposure of linkages. Specifically, in column (3), I include a triple interaction between *Boom Exposure of Linkages, Borrower Credibility,* and *High Wholesale Dependence,* where *Borrower Credibility* is *Bank Unemployment Exp* and *High Wholesale Dependence* is *High Wholesale-to-Assets Ratio.* Again, this term is statistically insignificant and negative.

In columns (4), (5), and (6), I repeat the tests using an alternate measure for wholesale dependence of banks. I use *Core Deposits-to-Assets* ratio, which I construct for each bank each year. Literature argues that banks that rely less on core deposits rely more on wholesale funds and use core deposits-to-assets ratio as a measure to capture reliance on wholesale funding (Dagher and Kazimov (2015)). Core deposits include transaction deposits, savings deposits, and time deposits less than $100,000 (Acharya and Mora (2015)). I then construct a dummy variable *High CDA*, which identifies banks having above median *Core Deposits-to-Assets Ratio* in a given year.

Column (4) considers the double interaction between *Boom Exposure of Linkages* and *High CDA;* column (5) considers a triple interaction between *Boom Exposure of Linkages, Unemployment Rate,* and *High CDA;* and column (6) considers a triple interaction between *Boom Exposure of Linkages, Bank Unemployment Exp,* and *High CDA.* Again, none of these interaction terms are statistically significant. While the signs of the interaction terms are consistent with arguments of investor effects, the statistical insignificance of these terms, combined with the results in columns (1) through (3), render these arguments weak.

VII. Aggregate Effects

VII.1. Bank Aggregates

The results in this paper have shown that a non-shocked bank increases its lending in non-boom counties as its linkages have greater shock exposure. In this subsection, I study the impact of spillovers on an aggregate bank level. It is possible that a bank may be reallocating lending from other markets to markets where shocked banks are present in order to take advantage of the improved housing market conditions. In this case, there may be no aggregate increase in lending at the bank level. While reallocation of lending is interesting in its own right, I show in this subsection that the spillover effect does not just lead banks to reallocate loan supply from one area to another, but it has an economically significant impact on an aggregate 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 each of the subject bank's local non-boom markets. The weights are the shares of deposits that the bank holds in the respective markets. Then I study how *Boom Exposure of Linkages* affects loan growth at this aggregate bank-year level. Because the aggregate loan growth varies by bank-year, the unit of analysis in this study is for a given bank in a given year. I estimate the following model:

$$\begin{aligned}\Delta\log\left(Mortgage\ Lending_{i,t}\right) \\ &= \alpha + \beta Boom\ Exposure\ of\ Linkages_{\ i,t} + Bank\ Controls_{\ i,t-1} \\ &+ Average\ Market\ Controls_{i,t} + Bank\ F.E + Year\ F.E + \varepsilon_{i,t}\end{aligned} \tag{10}$$

where $\Delta\log\left(Mortgage\ Lending_{i,t}\right)$ is constructed as described above for each non-shocked bank i in each year t, and $Boom\ Exposure\ of\ Linkages_{i,t}$ is constructed as before. I also control for contemporaneous weighted average market characteristics of the subject bank's local markets, like the ones included in model (9). The construction of these market characteristics in model (10) includes all local markets of the bank, as opposed to the construction in model (9), which includes only markets overlapping between shocked and non-shocked banks. Furthermore, I include lagged bank control variables, bank and year fixed effects, and cluster standard errors by bank.

Table 11 presents the results.[20] Column (1) presents results for growth of all loans in the sample; column (2) presents results for retained loans; and column (3) presents results for sold loans. As column (1) shows, there is an aggregate increase in lending at the bank level due to *Boom Exposure of Linkages.* A bank that has a standard deviation higher than mean value for *Boom Exposure of Linkages* increases its lending by 15.9 percent points more than a bank that has *Boom Exposure of Linkages* at the mean. Columns (2) and (3) show that these results are being driven by growth of retained loans, consistent with prior results. Therefore, these results show that positive spillovers have a significant on-balance sheet impact at the aggregate bank level.

VII.2. County Aggregates

In this subsection, I study aggregate lending of all non-shocked banks in each county. Such a study will shed light on the aggregate economic magnitude of spillovers in a county. It is possible that banks that have higher *Boom Exposure of Linkages* simply outcompete others with lower *Boom Exposure of Linkages* in picking up loan demand. They may be able to do so if they happen to have stronger branch presence (and, therefore, higher *Boom Exposure of Linkages*) in areas where shocked banks are present. Stronger branch presence implies easier access to borrowers and greater information advantage. If banks compete away loans from one another, there may be no net increase in lending on an aggregate county level amongst the non-shocked banks. In this subsection, I show that there is an economically significant impact of spillovers at the county level and that banks are not simply outcompeting one another.

To that end, I first construct loan growth at the county level. As before, I only consider non-shocked banks in non-boom counties in order to separate the impact of own shock exposure from the impact of spillovers. I take the size weighted average of loan growth (log change in loans originated) of all non-shocked banks in a non-boom county each year. I also construct *Boom Exposure of Linkages* at the county level. I construct this variable as the size weighted average of

[20] For reasons similar to the ones described in footnote 14, the number of observations in this table is different than the ones in the summary statistics of Table 1. Just as in footnote 14, I rerun the tests of Table 11 for only those county-year observations that are included in the sample in the base regressions and find similar results (in unreported tables).

Boom Exposure of Linkages of all non-shocked banks in each county and year. Then I study how this county level *Boom Exposure of Linkages* affects county level growth in lending.

Because this study is at a county-year level, there is no way to fully absorb market effects as in the base regressions that include county-year fixed effects. Instead, I include state-year fixed effects. Specifically, I estimate the following model:

$$\begin{aligned} \Delta\log\left(Mortgage\ Lending_{c,t}\right) &= \alpha + \beta County\ Boom\ Exposure\ of\ Linkages_{c,t} \\ &+ Market\ Controls\ _{c,t} + State - Year\ F.E + \varepsilon_{c,t} \end{aligned} \tag{11}$$

where $\Delta\log\left(Mortgage\ Lending_{c,t}\right)$ and $County\ Boom\ Exposure\ of\ Linkages_{c,t}$ are constructed as described above for each non-boom county *c* in each year *t*. In addition to state-year fixed effects, I also include controls for contemporaneous market characteristics, which include log(population), log(per capita personal income), household debt-to-income ratio, unemployment rate, percent female population, percent minority population, and lagged percent change in home prices. And I cluster standard errors by county.

Table 12 presents the results.[21] Column (1) presents results for growth of all loans in the sample; column (2) presents results for retained loans; and column (3) presents results for sold loans. As column (1) shows, there is an aggregate increase in lending at the county level as a function of *County Boom Exposure of Linkages.* A county that has a standard deviation (=0.949) higher than mean (=0.479) value for *County Boom Exposure of Linkages* observes 19 percent points more growth in lending than a county that has *County Boom Exposure of Linkages* at the mean. Columns (2) and (3) show that these results are being driven by growth in retained loans, consistent with prior results. Therefore, these results show that positive spillovers have a significant on-balance sheet impact on an aggregate county level, and that non-shocked banks are not simply outcompeting one another.

VIII. Conclusions

In this paper, I provide the first evidence of positive spillovers between banks. I show that geographic linkages that form between banks when they engage in home lending in the same

[21] For reasons similar to the ones described in footnote 14, this table has more observations than the ones in the summary statistics of Table 1. Just as in footnote 14, I rerun the tests of Table 12 for only those county-year observations that are included in the sample used in the base regressions and find similar results (in unreported tables).

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 non-shocked banks that are geographically linked with shocked banks experience spillovers. Specifically, a non-shocked bank in a non-boom county increases lending more if its linkages are exposed to greater well activity in boom counties.

For each non-shocked 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 which has a standard deviation higher than mean value for *Boom Exposure of Linkages* increases its lending by 11.3 percent points more than a bank which has this variable at the mean.

The study of the underlying spillover mechanism suggests that positive spillovers occur via an impact on the markets overlapping between shocked and non-shocked banks. Specifically, *Boom Exposure of Linkages* has a positive impact on the home prices of 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 non-shocked banks increase lending.

This study is important for two reasons. First, as mentioned earlier, it provides the first evidence of positive bank-to-bank spillovers. Second, the underlying spillover mechanism has not been explored in the literature before, and this paper adds to the literature by identifying a novel mechanism of transmission of shocks between banks.

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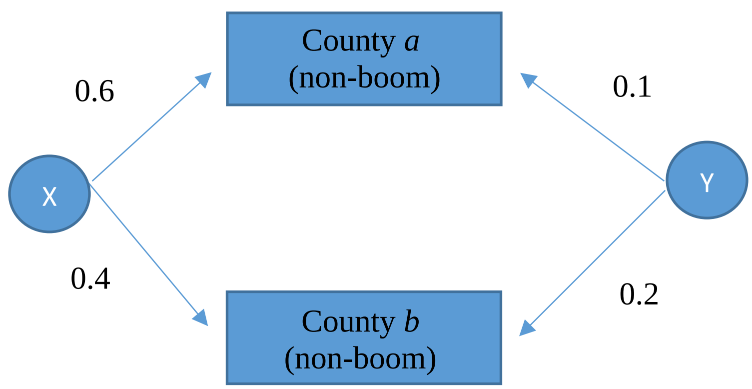
Figure 1. Illustration of Measure Construction

This figure presents an illustration of the construction of *Boom Exposure of Linkages.* It shows a stylized network of two hypothetical banks – a non-shocked bank X and a shocked bank Y – in counties (markets) *a* and *b* that are both non-boom 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 * 0.1 + 0.4 * 0.2) $Boom\ Exp_t^Y$

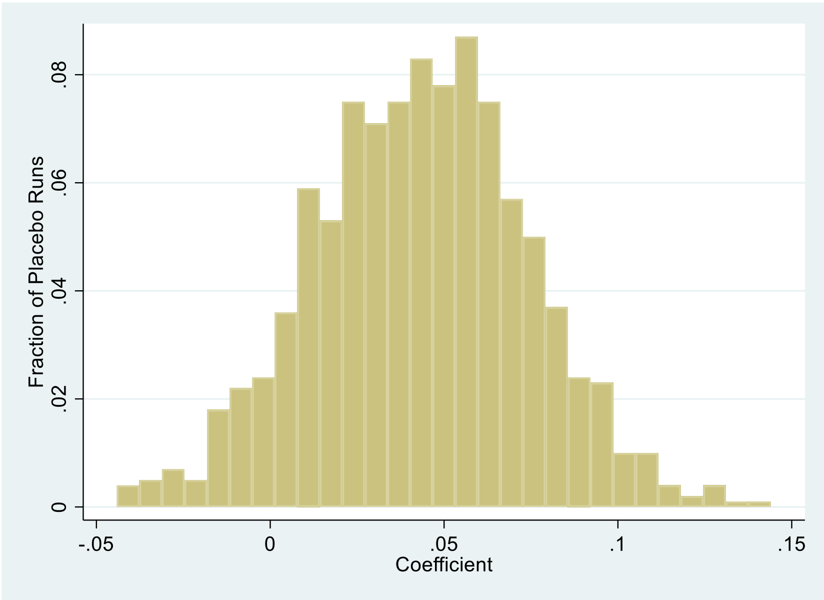
(ii) In a world of banks X, Y, and Z, where Z is local and engages in home lending in counties *a* and *b*:

Boom Exposure of Linkages for X:
(0.6 * 0.1 + 0.4 * 0.2) $Boom\ Exp_t^Y +$ (0.6 * w_a^Z + 0.4 * w_b^Z) $Boom\ Exp_t^Z$

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

Figure 2. Placebo Test

This figure 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 1000 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

Table 1. Summary Statistics

This table presents summary statistics for the variables used in the regressions of this paper. Unless otherwise noted, the sample consists of non-shocked banks in non-boom counties from the year 2003 to 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 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. *Δlog(Loans Originated)* is the percent growth in loans originated from time *t-1 to t*. *Δlog(Loans Retained)* and *Δlog(Loans Sold)* are defined similarly for loans that are retained in bank portfolios and loans that are sold respectively.

	Panel A: Bank Characteristics		
	N	Mean	SD
All Banks	(Bank-Year Variation)		
#Branches	6785	2.69	3.142
#Loans Originated	6785	183.354	564.343
Lagged #Loans Originated	6785	176.832	676.839
log(Total Assets)	6785	12.532	1.343
Net Income/Assets	6785	0.009	0.007
Capital/Assets	6785	0.101	0.023
Asset Quality	6785	0.004	0.005
Mortgages/Assets	6785	0.176	0.101
Liquidity Ratio	6785	0.223	0.128
Unused Commitments Ratio	6785	0.093	0.056
ALL/Assets	6785	0.009	0.004
C&I Loans/Assets	6785	0.107	0.07
Wt Avg of log(Population)	6785	11.942	1.42
Wt Avg of log(Personal Income)	6785	10.481	0.249
Wt Avg of Debt-to-Income	6785	1.328	0.692
Wt Avg of Percent Female Population	6785	0.507	0.01
Wt Avg of Percent Minority Population	6785	0.169	0.129
Bank Unemployment Exposure	6785	0.058	0.017
All Banks			
Bank Exposure to ΔHPI(%)	6785	0.027	0.036
Lagged Bank Exposure to ΔHPI(%)	6785	0.027	0.035
Banks local in Counties where #Shocked Banks>0			
Bank Exposure to ΔHPI(%) (Overlapping Markets)	6082	0.024	0.034
Lagged Bank Exposure to ΔHPI(%) (Overlapping Markets)	6082	0.024	0.034
All Banks	(Bank-County-Year Variation)		
Exposure to ΔHPI(%) in Other Markets	16539	0.018	0.028

Panel B: Market Characteristics			
	N	Mean	SD
All Counties	(County-Year Variation)		
Median Bank (non-shocked) Branch Count	3349	5.431	4.932
Median Bank (non-shocked) Size	3349	13.14	1.175
#Shocked Banks	3349	3.453	4.96
Counties where #Shocked Banks>0			
Median Bank (shocked) Branch Count	2393	42.761	25.448
Median Bank (shocked) Size	2393	17.066	1.996
All Counties			
#Loans Originated	3349	1158.065	2624.537
Lagged #Loans Originated	3349	1160.316	2615.758
log(Population)	3349	11.073	1.25
log(Personal Income)	3349	10.389	0.258
Debt-to-Income	3349	1.483	0.818
Unemployment Rate	3349	0.06	0.018
Percent Female Population	3349	0.505	0.014
Percent Minority Population	3349	0.145	0.141
Lagged ΔHPI(%)	3349	0.027	0.039

Panel C: Boom Exposure Variables			
	N	Mean	SD
Non-Shocked Banks	(Bank-Year Variation)		
Boom Exposure of Linkages	6785	0.773	1.597
Boom Exposure of Large Linkages	6785	0.297	0.755
Boom Exposure of Small Linkages	6785	0.462	0.887
Shocked and Non-Shocked Banks			
Own Boom Exposure (Local subsample)	9410	0.466	1.053
Own Boom Exposure (Non-Local subsample)	13706	0.601	1.359
County Level (Non-Shocked Banks)	(County-Year Variation)		
County Boom Exposure of Linkages	3349	0.479	0.949

Panel D: Mortgage Lending Variables			
	N	Mean	SD
	(Bank-County-Year Variation)		
Percent Change in Loans Originated	16539	0.655	2.115
Percent Change in Loans Retained	16539	0.639	2.141
Percent Change in Loans Sold	16539	0.337	2.275
Fraction Loans Retained	16539	0.794	0.293
	(Bank-Year Variation)		
Percent Change in Loans Originated	6785	0.65	2.064
Percent Change in Loans Retained	6785	0.642	2.053
Percent Change in Loans Sold	6785	0.223	1.946
	(County-Year Variation)		
Percent Change in Loans Originated	3349	0.617	1.576
Percent Change in Loans Retained	3349	0.575	1.601
Percent Change in Loans Sold	3349	0.463	1.877

Table 2. Own Boom Exposure

This table 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. Sample in this regression includes both shocked and non-shocked banks in non-boom 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 non-local counties. All regressions include county-year fixed effects. Standard errors are clustered by bank, and t-statistics are reported in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Δlog(Loans Originated)			
	Local		Non-local	
	(1)	(2)	(3)	(4)
Own Boom Exposure	0.0816**	0.0833**	-0.0213	0.0128
	(2.409)	(2.435)	(-0.855)	(0.511)
Exposure to ΔHPI(%) in Other Markets		-0.993		-10.99***
		(-0.571)		(-5.734)
log(Total Assets)	-0.0225	-0.0201	-0.170***	-0.158***
	(-0.799)	(-0.675)	(-7.536)	(-7.472)
Net Income/Assets	-18.85***	-18.79***	-17.70***	-19.41***
	(-3.254)	(-3.238)	(-2.888)	(-3.113)
Capital/Assets	5.532***	5.508***	2.670*	2.422
	(3.610)	(3.578)	(1.762)	(1.571)
Asset Quality	12.46	12.23	-6.766	-9.149
	(1.509)	(1.465)	(-0.698)	(-0.912)
Mortgages/Assets	-0.844**	-0.857**	-0.924**	-1.325***
	(-2.446)	(-2.449)	(-2.114)	(-3.296)
Liquidity Ratio	-0.318	-0.322	-1.366***	-1.198***
	(-1.221)	(-1.229)	(-3.492)	(-3.216)
Unused Commitments Ratio	0.690	0.696	0.246	0.273
	(0.599)	(0.604)	(0.371)	(0.422)
ALL/Assets	7.830	7.539	-11.76	-14.50
	(0.598)	(0.581)	(-0.958)	(-1.206)
C&I Loans/Assets	-0.475	-0.471	-0.0950	-0.198
	(-0.836)	(-0.832)	(-0.164)	(-0.338)
Constant	0.641	0.633	5.687***	5.867***
	(1.561)	(1.534)	(14.873)	(15.942)
County-Year Fixed Effects	Y	Y	Y	Y
Observations	34142	34142	132205	132205
Adjusted R-squared	0.107	0.107	0.064	0.071

Table 3. Boom Exposure of Linkages
This table 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). Sample in this regression includes non-shocked banks in non-boom counties from 2003 to 2017. Column (1) presents results for the regression that does not include *Exposure to ΔHPI(%) in Other Markets*, while column (2) presents results for the regression that includes it. *Exposure to ΔHPI(%) 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 amongst 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 parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Δlog(Loans Originated)		
	(1)	(2)	(3)
Boom Exposure of Linkages	0.0621**	0.0642**	
	(2.003)	(2.075)	
Exposure to ΔHPI(%) in Other Markets		2.145	1.982
		(1.571)	(1.454)
Boom Exposure of Large Linkages			0.240***
			(2.646)
Boom Exposure of Small Linkages			-0.0779
			(-0.978)
log(Total Assets)	-0.0310	-0.0372	-0.0372
	(-0.946)	(-1.136)	(-1.138)
Net Income/Assets	-39.71***	-39.88***	-39.70***
	(-6.454)	(-6.465)	(-6.432)
Capital/Assets	9.334***	9.422***	9.275***
	(4.115)	(4.138)	(4.047)
Asset Quality	-24.24***	-23.92***	-23.49***
	(-3.488)	(-3.439)	(-3.379)
Mortgages/Assets	-0.984**	-0.971**	-0.940**
	(-2.159)	(-2.130)	(-2.059)
Liquidity Ratio	-0.731**	-0.710**	-0.699**
	(-2.139)	(-2.078)	(-2.049)
Unused Commitments Ratio	-0.281	-0.296	-0.304
	(-0.423)	(-0.443)	(-0.456)
ALL/Assets	-11.70	-11.95	-12.24
	(-1.157)	(-1.181)	(-1.211)
C&I Loans/Assets	0.286	0.302	0.293
	(0.592)	(0.625)	(0.603)
Constant	1.023**	1.054**	1.074**
	(2.232)	(2.306)	(2.354)
County-Year Fixed Effects	Y	Y	Y
Observations	16539	16539	16539
Adjusted R-squared	0.066	0.066	0.067

Table 4. Retained versus Sold Loans

This table 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). Sample in this regression includes non-shocked banks in non-boom 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 amongst 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 parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Δlog(Loans Originated)			
	Retained Loans		Sold Loans	
	(1)	(2)	(3)	(4)
Boom Exposure of Linkages	0.0614**		0.0197	
	(1.981)		(0.802)	
Boom Exposure of Large Linkages		0.187**		-0.0181
		(2.038)		(-0.227)
Boom Exposure of Small Linkages		-0.0385		0.0522
		(-0.488)		(0.611)
Exposure to ΔHPI(%) in Other Markets	1.737	1.621	2.899**	2.931**
	(1.300)	(1.214)	(1.982)	(1.994)
County-Year Fixed Effects	Y	Y	Y	Y
Control Variables	Y	Y	Y	Y
Observations	16539	16539	16539	16539
Adjusted R-squared	0.059	0.059	0.023	0.023

Table 5. Robustness Test: Market Effects

This table 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* in various robustness specifications. *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). Sample in this regression includes non-shocked banks in non-boom counties from 2003 to 2017. Column (1) excludes counties that are within 100 miles of boom counties. Column (2) only keeps counties where the subject bank is local as of the first year one of its linkages is shocked. Column (3) includes an interaction between *Boom Exposure of Linkages* and a dummy variable *Good Market*, which identifies markets that have above median percent changes in home prices in the previous year. Column (4) excludes 15 best performing markets (of the subject bank); these are markets that observe the largest percent changes in home prices in the previous year. Column (5) excludes 15 largest markets by loan count each year. All regressions include county-year fixed effects and bank control variables. Standard errors are clustered by bank, and t-statistics are reported in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Δlog(Loans Originated)				
	Drop Markets Close to Boom Markets	Local Markets as of the year of First Linkage Shock	Good vs Bad Markets	Remove Best Markets	Remove Largest Markets by Loan Count
	(1)	(2)	(3)	(4)	(5)
Boom Exposure of Linkages	0.862**	0.0767*	0.0641	0.0628**	0.136***
	(2.131)	(1.891)	(1.324)	(1.987)	(2.605)
Boom Exposure of Linkages X Good Market			0.000176		
			(0.003)		
Exposure to ΔHPI(%) in Other Markets	-0.0267	1.502	2.145	2.635*	1.616
	(-0.016)	(1.085)	(1.572)	(1.844)	(1.015)
County-Year Fixed Effects	Y	Y	Y	Y	Y
Control Variables	Y	Y	Y	Y	Y
Observations	8684	14002	16539	15976	13555
Adjusted R-squared	0.084	0.079	0.066	0.068	0.074

Table 6. Robustness Test: Bank Size Effects

This table presents robustness of results to bank size effects. 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). Sample in this regression includes non-shocked banks in non-boom counties from 2003 to 2017. Column (1) includes an interaction between *Boom Exposure of Linkages* and a dummy variable *Above Median Size*, which identifies banks that have above median size in total assets. Column (2) excludes large subject banks, defined to be banks larger than $50 billion in total assets. Column (3) excludes very large linkage banks, defined to be banks larger than $250 billion in total assets. Column (4) drops small size subject banks, defined to be banks smaller than $100 million in total assets. All regressions include county-year fixed effects and bank control variables. Standard errors are clustered by bank, and t-statistics are reported in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Δlog(Loans Originated)			
	Large vs Small Banks (1)	Remove Large Subject Banks (2)	Remove Very Large Linkages (3)	Remove Small Subject Banks (4)
Boom Exposure of Linkages	0.0544	0.0624**	0.0569*	0.0624*
	(1.353)	(1.992)	(1.689)	(1.883)
Exposure to ΔHPI(%) in Other Markets	2.346*	3.062**	2.133	1.955
	(1.726)	(2.242)	(1.562)	(1.353)
Boom Exposure of Linkages X Above Median Size	0.0205			
	(0.503)			
County-Year Fixed Effects	Y	Y	Y	Y
Control Variables	Y	Y	Y	Y
Observations	16539	15743	16539	14568
Adjusted R-squared	0.068	0.068	0.066	0.057

Table 7. Spillovers via the Overlapping Market

This table 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). Sample in this regression includes non-shocked banks in non-boom 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 parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Δlog(Loans Originated)					
	Shocked Bank Present			Shocked Bank Not Present		
	(1) All Loans	(2) Retained Loans	(3) Sold Loans	(4) All Loans	(5) Retained Loans	(6) Sold Loans
Boom Exposure of Linkages	0.0689**	0.0649**	0.0212	-0.210	-0.210	0.0940
	(2.210)	(2.070)	(0.878)	(-1.353)	(-1.447)	(0.533)
Exposure to ΔHPI(%) in Other Markets	2.615*	2.383*	2.059	0.311	-0.834	6.616
	(1.879)	(1.731)	(1.506)	(0.093)	(-0.251)	(1.364)
County-Year Fixed Effects	Y	Y	Y	Y	Y	Y
Control Variables	Y	Y	Y	Y	Y	Y
Observations	12819	12819	12819	3720	3720	3720
Adjusted R-squared	0.056	0.050	0.016	0.112	0.102	0.028

Table 8. Boom Exposure of Linkages and Home Prices

This table reports regressions of a bank's exposure to percent changes in home prices (*Bank Exposure to ΔHPI(%)*) 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). Sample in this regression includes non-shocked banks from 2003 to 2017. *Bank Exposure to ΔHPI(%)* 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). 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 amongst 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 parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Bank Exposure to ΔHPI (%) (Overlapping Markets)			
	(1)	(2)	(3)	(4)
Boom Exposure of Linkages	0.00392***	0.00338***		
	(8.196)	(8.574)		
Boom Exposure of Large Linkages			0.00727***	0.00600***
			(8.191)	(7.457)
Boom Exposure of Small Linkages			0.00194**	0.00182**
			(2.050)	(2.285)
Lagged Bank Exposure to ΔHPI(%) (Overlapping Markets)		0.215***		0.211***
		(6.661)		(6.492)
Bank Control Variables	Y	Y	Y	Y
Average Market Control Variables	Y	Y	Y	Y
Bank Fixed Effects	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
Observations	6032	6032	6032	6032
Adjusted R-squared	0.624	0.641	0.625	0.642

Table 9. Boom Exposure of Linkages, Financial Slack, and Borrower Credibility

This table 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). Sample in this regression includes non-shocked banks in non-boom 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 local counties of the subject bank. 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 parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Δlog(Loans Originated)				
	Unemployment Rate			Bank Unemployment Exp	
	(1)	(2)	(3)	(4)	(5)
Boom Exposure of Linkages	0.114	0.0311	0.285*	0.0745	0.214
	(0.806)	(0.887)	(1.827)	(0.517)	(1.369)
Boom Exposure of Linkages X Borrower Credibility	-0.727		-4.736*	0.0569	-3.348
	(-0.290)		(-1.740)	(0.023)	(-1.229)
Boom Exposure of Linkages X High Capital/Assets		0.0838**	-0.268*		-0.215
		(2.382)	(-1.844)		(-1.367)
Boom Exposure of Linkages X Borrower Credibility X High Capital/Assets			6.561**		5.490**
			(2.511)		(1.968)
High Capital/Assets X Borrower Credibility			-0.206		0.246
			(-0.065)		(0.064)
High Capital/Assets	0.221***	0.171**	0.174	0.218***	0.146
	(3.065)	(2.216)	(0.899)	(3.022)	(0.638)
Borrower Credibility				7.085*	7.167*
				(1.864)	(1.870)
Exposure to ΔHPI(%) in Other Markets	1.820	1.767	1.799	1.870	1.850
	(1.332)	(1.288)	(1.319)	(1.369)	(1.355)
County-Year Fixed Effects	Y	Y	Y	Y	Y
Control Variables	Y	Y	Y	Y	Y
Observations	16539	16539	16539	16539	16539
Adjusted R-squared	0.060	0.061	0.062	0.061	0.062

Table 10. Boom Exposure of Linkages, Wholesale Dependence, and Borrower Credibility

This table studies the interaction between boom exposure of linkages, wholesale dependence, 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). Sample in this regression includes non-shocked banks in non-boom counties from 2003 to 2017. Columns (1) through (3) use wholesale funds-to-assets ratio to capture bank dependence on wholesale funds, while columns (4) through (6) use core deposits-to-assets ratio. Columns (1) and (4) include an interaction between *Boom Exposure of Linkages* and *High Wholesale Dependence,* which takes the value 1 for banks having above median wholesale dependence each year. Columns (2) and (5) include a triple interaction between *Boom Exposure of Linkages, Unemployment Rate,* and *High Wholesale Dependence*. Columns (3) and (6) include a triple interaction between *Boom Exposure of Linkages, Bank Unemployment Exp,* and *High Wholesale Dependence*. *Bank Unemployment Exp* is the weighted average of unemployment rates in subject bank's local markets. Weights are the shares of deposits that the bank holds in each market. All regressions include county-year fixed effects and bank control variables. Standard errors are clustered by bank, and t-statistics are reported in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Δlog(Loans Originated)					
	Wholesale-to-Assets Ratio			Core Deposits-to-Assets Ratio		
		Unemp Rate	Bank Unemp Exp		Unemp Rate	Bank Unemp Exp
	(1)	(2)	(3)	(4)	(5)	(6)
Boom Exposure of Linkages	0.0480	0.0270	-0.0339	0.0690**	0.0464	0.00856
	(1.134)	(0.147)	(-0.173)	(2.027)	(0.299)	(0.055)
High Wholesale Dependence	0.0343	0.171	0.0321	0.0112	-0.137	-0.0667
	(0.481)	(0.854)	(0.133)	(0.162)	(-0.719)	(-0.293)
Boom Exposure of Linkages X High Wholesale Dependence	0.0213	0.0911	0.122	-0.0128	0.159	0.148
	(0.505)	(0.561)	(0.694)	(-0.296)	(1.082)	(0.936)
Boom Exposure of Linkages X Borrower Credibility		0.452	1.617		0.389	1.127
		(0.136)	(0.465)		(0.142)	(0.415)
High Wholesale Dependence X Borrower Credibility		-2.361	0.138		2.684	1.409
		(-0.718)	(0.035)		(0.836)	(0.367)
Boom Exposure of Linkages X Borrower Credibility X High Wholesale Dependence		-1.354	-1.916		-3.274	-2.999
		(-0.459)	(-0.613)		(-1.277)	(-1.090)
Borrower Credibility			6.537			5.963
			(1.411)			(1.462)
Exposure to ΔHPI(%) in Other Markets	2.169	2.174	2.225	2.142	2.134	2.185
	(1.588)	(1.596)	(1.630)	(1.569)	(1.566)	(1.600)
County-Year Fixed Effects	Y	Y	Y	Y	Y	Y
Control Variables	Y	Y	Y	Y	Y	Y
Observations	16539	16539	16539	16539	16539	16539
Adjusted R-squared	0.066	0.066	0.066	0.066	0.066	0.066

Table 11. Bank Aggregates

This table 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). Sample in this regression includes non-shocked banks from 2003 to 2017. Column (1) presents results for all loans; column (2) presents results 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 parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Δlog(Loans Originated)		
	All Loans	Retained Loans	Sold Loans
	(1)	(2)	(3)
Boom Exposure of Linkages	0.0870**	0.110***	0.0198
	(2.157)	(2.748)	(0.643)
log(Total Assets)	-0.793***	-0.812***	-0.0741
	(-4.074)	(-4.221)	(-0.498)
Net Income/Assets	-32.65***	-28.35***	-15.55**
	(-4.080)	(-3.578)	(-2.322)
Capital/Assets	13.13***	11.40***	4.410*
	(4.434)	(3.938)	(1.827)
Asset Quality	-27.28***	-22.55***	-19.74***
	(-3.651)	(-3.065)	(-2.885)
Mortgages/Assets	-4.322***	-4.613***	-0.315
	(-4.293)	(-4.785)	(-0.384)
Liquidity Ratio	0.738	0.995*	-0.693*
	(1.434)	(1.962)	(-1.681)
Unused Commitments Ratio	0.750	0.413	0.435
	(0.554)	(0.305)	(0.403)
ALL/Assets	-32.98**	-28.49**	-13.76
	(-2.333)	(-2.025)	(-1.182)
C&I Loans/Assets	-0.410	0.153	-1.540*
	(-0.397)	(0.144)	(-1.840)
Wt Avg of log(Population)	-0.511***	-0.465***	-0.109
	(-4.007)	(-3.552)	(-1.273)
Wt Avg of log(Personal Income)	0.823	0.656	0.884*
	(1.483)	(1.193)	(1.774)
Wt Avg of Debt-to-Income	0.0810	0.100	0.0427
	(0.580)	(0.724)	(0.399)
Bank Unemployment Exposure	10.66**	9.218**	5.749
	(2.311)	(2.063)	(1.447)
Wt Avg of Percent Female Population	13.41	8.090	14.18
	(0.978)	(0.606)	(1.178)
Wt Avg of Percent Minority Population	1.501	1.093	2.524*
	(0.669)	(0.493)	(1.756)
Lagged Bank Exposure to ΔHPI(%)	0.124	0.947	-2.370*
	(0.099)	(0.756)	(-1.894)
Constant	0.0860	4.359	-14.55*
	(0.009)	(0.464)	(-1.733)
Bank Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y
Observations	6726	6726	6726
Adjusted R-squared	0.113	0.098	-0.015

Table 12. County Aggregates

This table reports regressions at the aggregate county-year level. It presents regressions of county level growth in home lending on county level *Boom Exposure of Linkages.* County level loan growth is the size weighted average of loan growth (log change in loans originated) of all non-shocked banks in a non-boom county and year. *County Boom Exposure of Linkages* is the size weighted average of *Boom Exposure of Linkages* of all non-shocked banks in a non-boom county and year. *Boom Exposure of Linkages* for each bank captures the exposure of the bank's shocked geographic linkages to well activity in boom counties (described in detail in the text). Sample in this regression includes non-boom counties from 2003 to 2017. Column (1) presents results for all loans; column (2) presents results retained loans; and column (3) presents results for sold loans. All regressions include state-year fixed effects. Standard errors are clustered by county, and t-statistics are reported in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Δlog(Loans Originated)		
	All Loans	Retained Loans	Sold Loans
	(1)	(2)	(3)
County Boom Exposure of Linkages	0.170***	0.156***	0.00550
	(3.780)	(3.521)	(0.187)
log(Population)	-0.142***	-0.136***	0.0661***
	(-5.264)	(-5.257)	(3.249)
log(Personal Income)	0.0549	0.138	0.0321
	(0.275)	(0.772)	(0.197)
Debt-to-Income	-0.0684*	-0.0557*	-0.0514*
	(-1.947)	(-1.667)	(-1.922)
Unemployment Rate	-2.810	-0.789	-4.260**
	(-1.121)	(-0.334)	(-2.171)
Percent Female Population	4.705**	3.902**	2.577
	(2.380)	(2.181)	(1.597)
Percent Minority Population	0.836**	0.673**	0.192
	(2.543)	(2.181)	(0.810)
Lagged ΔHPI(%)	-0.744	-1.151	1.259
	(-0.838)	(-1.254)	(1.314)
Constant	-0.631	-1.296	-1.646
	(-0.322)	(-0.719)	(-1.016)
State-Year Fixed Effects	Y	Y	Y
Observations	5008	5008	5008
Adjusted R-squared	0.141	0.114	0.111

Internet Appendix

Positive Bank-to-Bank Spillovers

Shasta Shakya

Table IA.1: Small Size Effect

This table 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* in various robustness specifications. *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). Sample in this regression includes non-shocked banks in non-boom counties from 2003 to 2017. Column (1) drops 15 smallest counties by loan count each year. Column (2) drops bank-county-year observations based on fewer than 15 loans. Column (3) drops 15 smallest banks by loan count each year. All regressions include county-year fixed effects and bank control variables. Standard errors are clustered by bank, and t-statistics are reported in parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Δlog(Loans Originated)		
	Drop Smallest 15 Markets by Loan Count	Drop Bank-County-Year obs with <15 loan count	Drop Smallest 15 Banks by Loan Count
	(1)	(2)	(3)
Boom Exposure of Linkages	0.0640**	0.121**	0.0662**
	(2.057)	(2.314)	(2.137)
Exposure to ΔHPI(%) in Other Markets	2.140	4.491**	3.293**
	(1.567)	(2.435)	(2.508)
County-Year Fixed Effects	Y	Y	Y
Control Variables	Y	Y	Y
Observations	16481	11150	16043
Adjusted R-squared	0.059	0.122	0.071

Table IA.2: Alternate Independent Variable

This table reports regressions of a bank's percent growth in home lending in a given county and year on the bank's *Boom Growth Exposure of Linkages*. *Boom Growth Exposure of Linkages* captures the exposure of a bank's shocked geographic linkages to growth in well activity in boom counties (described in detail in the text). Sample in this regression includes non-shocked banks in non-boom counties from 2003 to 2017. Column (2) breaks *Boom Growth Exposure of Linkages* into two parts: *Boom Growth Exposure of Large Linkages* that captures boom growth exposure of linkages that have above median asset size amongst shocked banks in a given county, and *Boom Growth Exposure of Small Linkages* that captures boom growth 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 parenthesis. *, ** and *** indicate significance at 10%, 5% and 1% level respectively.

	Δlog(Loans Originated)			
	All Loans (1)	All Loans (2)	Retained Loans (3)	Sold Loans (4)
Boom Growth Exposure of Linkages	0.0647**		0.0626**	0.0180
	(2.078)		(1.986)	(0.767)
Boom Growth Exposure of Large Linkages		0.163*		
		(1.921)		
Boom Growth Exposure of Small Linkages		-0.0240		
		(-0.303)		
Exposure to ΔHPI(%) in Other Markets	2.137	2.050	1.731	2.894**
	(1.566)	(1.503)	(1.296)	(1.979)
County-Year Fixed Effects	Y	Y	Y	Y
Control Variables	Y	Y	Y	Y
Observations	16539	16539	16539	16539
Adjusted R-squared	0.066	0.066	0.059	0.023