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Within-Bank Spillovers of Real Estate Shocks*

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Abstract

By considering banks as portfolios of assets in different locations, we study how real estate shocks are transmitted across bank's business areas while controlling for local demand shocks and bank location–specific factors. Affected banks substantially alter their loan portfolios: we find evidence of real estate price declines affecting both real estate and non-real estate types of lending. Banks also roll over and fail to liquidate problematic loans, while accumulating more non-performing loans. These results provide evidence of internal contagion of real estate shocks within banks.

JEL codes: G21, G01, R30

Keywords: Banks, Real Estate, Contagion, Crisis, Zombie Lending.

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Introduction

Triggered by shocks in the real estate sector, the financial crisis of 2007–2009 was associated with a loss of real output, causing upheavals in the economy. Evidence has shown that the reduction in the aggregate credit in the US economy at the time came mostly from the reduction of bank (or intermediated) credit rather than direct credit (Adrian et al. 2012). This substitution suggests that banks' credit supply may have been substantially reduced during the crisis (especially for small firms who do not have access to the bond markets) and that banks may thus have played a major role in the transmission of the shocks coming from the real estate sector (Carvalho, Ferreira and Matos 2015).

In this paper, we study this internal contagion process, by focusing on the effects of real estate price declines on banks' loan product portfolio and on the role the mismanaged bank lending during the recent crisis played in prolonging the economic stagnation. Existing evidence suggests that such "zombie lending" took place in Japan during the 1990s (Peek and Rosengren 2005; Sekine, Kobayashi, and Saita 2003), and that this produced substantial economic damage (Caballero, Hoshi, and Kashyap 2008). In this paper, we investigate how the real estate shocks that triggered the most recent financial crisis affected the composition of the banks' loan portfolio, both in terms of the type of products on offer, and in terms of their solvency.

We find that in response to real estate price declines, banks substantially altered their loan portfolios: not only did they significantly reduce their real estate related lending, but these cuts also spilt over across business lines, including types of lending that were not directly related to real estate. The evidence suggests an interesting pattern that is informative of the portfolio implications for the deleveraging decisions of banks. Across all types of lending, interbank loans (which were relatively liquid) and commercial/industrial loans (which were relatively risky) were disproportionally more affected. This suggests that banks sold the most-liquid assets first (i.e., assets that face less-asymmetric information and are widely held by other banks). They then cut down risk exposure by lowering the holdings of the most-risky assets, consistent with the existing theory and evidence on constrained liquidation (Manconi, Massa and Yasuda 2012; Ben-David, Franzoni, and Moussawi 2012; Brown, Carlin, and Lobo 2010). We find significant effects on the treatment of existing loans: more affected banks continued to bet on the resurrection of their insolvent loans during the last crisis. Following real estate price declines, banks opted to roll over loans more frequently, recognize fewer losses and liquidate fewer loans, accumulating more non-performing loans. This suggests that a significant number of banks continued to keep toxic loans on their balance sheets, likely in fear of falling below their minimum capital levels. This continued financing, or "evergreening" (Caballero, Hoshi, and Kashyap 2008; Bruche and Llobet 2012) thus introduced additional distortions to the already shaken economy.

A relevant challenge when measuring the impact or real estate shocks on banks' policies is to differentiate their direct effect on banks policies from the effects on the demand for bank services (Jimenez, Ongena, Peydro and Saurina 2010). While the literature has offered some solutions to partial-out demand effects (see Peydro 2010 for instance), they are in general limited to the estimation of supply effects of homogeneous loans and data limitations often restrict the representativeness of the results. In this paper, we use an alternative approach and focus on identifying the effect of transmission mechanisms via banks' balance sheets from the effect of local demand, while being agnostic about the nature of the initial shocks. Using the geographical coverage of banks, we can consider each bank as a portfolio of real-estate locations. Thus, we can identify the effect of real estate losses on their lending and balance sheets, while controlling for local conditions in a given point in time.

Our approach implicitly compares the total bank-level effect of a balance sheet shock with the one that would result by adding up the individual local effects. More specifically, we measure how the aggregate exposure of a bank to real estate shocks affects its policies over and above the sum of the local effects predicted by other banks present in the same locations.[1] Using this strategy we find evidence of balance sheet contagion effects across business lines for a broad population of firms (banks) during a long period of time (the real estate crisis).

[1] We also combine this strategy with a measure of direct real estate holdings in a difference-in-differences specification.

To motivate the analysis, we first show that, banks report capital losses in line with their exposure to real estate and change their policies according to these capital losses. More importantly, we find that the aggregate exposure of a bank to real estate shocks indeed affects its policies over and above the sum of the local effects, suggesting a significant propagation effect. In particular, when compared to local single-MSA banks, multi-MSA banks that have large negative real estate exposure elsewhere cut down their lending more.[2] This set of results echo the findings in the contagion literature, where portfolio holdings of international investors are shown to be channels via which crisis spreads (Forbes and Rigobon 2002; Boyer, Kumagai, and Yuan 2006; Jotikasthira, Lundblad and Ramadorai 2012).

Although large banks are likely to spread the effect of real estate shocks across geographical locations and business lines, we find that they cut down their lending less, relative to small banks. This set of results highlights the role played by the banks' internal capital markets, indicating the resiliency of large diversified banks. It resembles the finding of differential reactions of multinationals and local firms to negative exchange rate shocks in Desai, Foley and Forbes (2008). Furthermore, resiliency, as shown by Matvos and Seru (2013), comes from the resource allocative role of the internal capital market in their study of the consequences of 2007/2008 credit shock on diversified firms' value. There is a long line of theoretical literature on the cost and benefit of internal capital markets (Stein 1997; Scharfstein and Stein 2000; Rajan, Servaes and Zingales 2000). An optimal portfolio management of location and business lines distributes the impact of economic shocks across business lines and locations. This increases the resiliency of individual banks that have diversified operations, but also creates additional channels of contagion that generate real effects beyond a particular sector or region.[3] Our research highlights both of these channels.

To measure the spillover effects of real estate price fluctuations we start by considering banks

[2] Single-MSA banks are banks that operate only in one Metropolitan Statistical Area (henceforth MSA), while multi-MSA banks operate in 2 or more MSAs.

[3] Similar contagion channels are shown in the hedge fund industry. Lo (2007) finds the margin constraints of multi-strategy hedge funds spread the negative shock in the single strategy hedge funds (e.g., in the area of subprime credit) across the hedge fund industries, causing the quant fund-wide crisis in August 2007.

as a portfolio of real estate locations. In our first approach, we construct measures of real estate shocks that take into account the different weights that each location represents in the bank's overall business and construct bank-specific real estate price indices that aggregate prices across all the locations in which the bank operates. As different banks in a given location can also operate elsewhere, we introduce time-location fixed effects to control for local business conditions, local loan demands or local credit shocks at a given point in time and bank-location fixed effects to control for any time-invariant conditions of each bank in each of its locations of operation. By saturating the model in this particular way, we measure whether the aggregate real estate prices that a bank is exposed to have a spillover effect beyond the sum of the local effects in each location. For some policies, like lending, that are likely to be partially determined locally finding an effect beyond the sum of the local parts indicates a contagion effect across geographies, while for policies that are determined bank-wide, it suggests an amplification effect.

Our second strategy uses the banks' own holdings of real estate assets in the form of property plant and equipment (PP&E) as a measure of cross-sectional exposure to real estate shocks. The distribution of PP&E across banks is a result of different forces to the specific business locations chosen by the bank, and is largely historically determined. Even if PP&E is not the main source of banks' exposure to real estate prices, it still constitutes a sizable source of exposure, and it provides a clean cross-sectional source of variation that does not suffer from endogeneity concerns. This allows for an identification strategy that is akin to a difference-in-difference estimation in which two treatment variables interact. The first difference is determined but the bank-specific real estate shocks and the second difference is determined by the bank's cross-sectional exposure to real estate shocks via PP&E.[4]

The existing literature has mainly focused on the transmission[5] of positive shocks to banks' balance sheets or on the geographical transmission per se: Gilje et al. (2016) focus on positive shocks and show that positive funding windfalls from shale discoveries are transmitted

[4] We also replace the actual variation in real estate prices with a predicted measure that uses only countrywide real estate price changes and local land supply price elasticities Saiz (2010) which is immune to reverse causality considerations.

[5] See, Gan (2007) for a related analysis of the Japanese experience in the 1990s or Puri et al. (2011) for Germany during the current crisis.

via bank branch networks to non-shale areas, and result in an increase in mortgage lending activity. Cortés and Strahan (2017) show that negative shocks, from natural disasters, result in reduced lending in areas connected via bank branch networks that are not directly affected by natural disasters. However, there is less evidence on the role of internal capital markets in propagation of these shocks and how they affect banks' loan portfolios in terms of types of loans on offer. In this paper, we fill this gap.

Our empirical set-up allows us to examine a broad set of lending outcomes (cf. Gilje et al. 2016). Our real estate shocks are likely to decrease both capital and local lending opportunities, hence our results can be unambiguously attributed to the consumption of capital rather than to increased lending in other locations (cf. Cortés and Strahan 2017).

Our paper is related to the bank lending channel literature, which examines how shocks to banks affect their ability to lend and end up affecting the firms that borrow from them (Kashyap and Stein 1995, 2000; Kishan and Opiela 2000; and Ashcraft 2006).[6] While our work covers the downturn in the real estate market after 2006, existing literature has mostly focused on the housing boom that preceded it. Analyzing the housing boom of 1998-2006, Chakraborty, Goldstein, and MacKinlay (2016) document that banks which were active in strong housing markets increased mortgage lending and decreased commercial lending. Loutskina and Strahan (2015) consider the role of financial integration among banks in amplifying housing price shocks during this period. They find that banks move mortgage capital out of low-appreciating housing markets and into high-appreciating housing markets within their own branch networks.

Several of our findings deserve attentions: first, we document substantial contagion of negative real estate shocks across banks' business lines, which has important implications for the overall transmission of shocks in the US economy. Second, we find that following real estate price declines, more liquid and more risky loans are disproportionally more reduced. This suggests that banks off-load the most-liquid assets first (i.e., assets that face less-asymmetric

[6] See also Ashcraft (2005), Khwaja and Mian (2008), Paravisini (2008), Ivashina and Scharfstein (2010), and Schnabl (2012).

information and are widely held by other banks). Third, our results suggest that banks buy time and obfuscate their losses by managing their problematic loans. More affected banks are more likely to accumulate non-performing loans and, in relative terms, are less likely to liquidate them and recognize losses.

The paper is organized as follows. In Section 1, we discuss the related literature. Section 2 presents the data, and we discuss the empirical strategy in Section 3. We present the results in Section 4 and conclude in Section 5.

1 Related Literature

At a broad level, our paper is related to the macro literature that shows how shocks to the financial system affect the credit supply (Peek and Rosengren 1997; Kashyap et al. 1993; Kashyap and Stein 2000; among others).[7] Recently, Adrian et al. (2013) showed that during the 2007–2009 crisis, there was a sharp contraction in the supply of intermediated credit through banks that contrasts with the inelastic demand for credit from firms. The shortfall is made up of direct credit, such as bond financing, indicating that financial frictions operate mainly through the credit supply. This raises the question as to whether a dollar of credit through the banking system behaves differently from a dollar of direct credit. Our paper contributes to the existing understanding of the sharp reduction of intermediated credits by revealing how intermediaries such as banks react to adverse shocks and how the various constraints they are facing affect their responses.

At the micro level, our paper is closely related to the literature that studies how shocks to banks affect the lending relationship between banks and their borrowers, i.e., firms—specifically, the amount and terms of lending (Gan 2007; Paravisini 2008; Khwaja and Mian 2008; Jimenez et al. 2012; Iyer at al. 2014). This prior literature relies on within-firm estimators to eliminate the effects of credit demand. Instead, we use the geographical reach of banks as a rich source of

[7] The literature also argues that adverse shocks may operate through the demand of credit by affecting borrower net worth and the collateral value of assets (Bernanke and Gertler 1989; Kiyotaki and Moore 1997). Studies such as Ashcraft and Campello (2007) have also shown that there is a firm balance-sheet channel of monetary policy.

variation that allows us to control for demand-side effects.[8] The within-firm approach has the appeal of dealing easily with the correlation between firm demand and bank characteristics. This requires that demand and other selection effects are constant and additive within firm and across banks. Conversely, the within-bank approach has the drawback that it cannot be used for bank policies other than lending. In particular, any aggregate policy of the bank cannot be identified with a firm. We provide complementary evidence to this literature by showing how banks cope with adverse shocks to their capital by implementing a menu of policy changes that go beyond lending, including financial and commercial policies. Relative to these two previous streams of the literature, our approach allows us to document the transmission of real estate shocks on the full population of US banks for a broad period of years.

Our paper is also broadly related to the recent literature that studies the transmission of shocks across bank branch networks. Gilje et al. (2016) show that positive funding windfalls from shale discoveries are transmitted via bank branch networks to non-shale areas, and result in an increase in mortgage lending activity. Cortés and Strahan (2017) show that negative shocks, from natural disasters, result in reduced lending in areas connected via bank branch networks that are not directly affected by natural disasters. Our paper adds to this literature in that we study how exogenous shocks to bank capital affect a *broad* set of lending outcomes, and changes in the bank lending portfolio composition, not only mortgage lending. Further, the fixed-effects structure in our empirical set up allows us to examine how real estate shocks to the whole portfolio of locations in which a bank operates affect (local) bank lending outcomes. Our results are based on all locations and real estate price fluctuations providing better extrapolability properties than those based on large location-specific shocks. (cf. Cortés and Strahan (2017)).

Similarly, Carvalho, Ferreira and Matos (2015) study the transmission of bank distress to nonfinancial firms from 34 countries during the 2007–2009 financial crisis using systemic and bank-specific shocks. They find that bank distress is associated with equity valuation losses and

[8] Drechsler et al. (2015) also use the geographical reach of banks as a source of variation to identify how bank competition affects the deposit rates of bank branches in response to monetary shocks.

investment cuts to borrower firms with the strongest lending relationships with banks and that the losses are not offset by borrowers' access to public debt markets.

Our results are also linked to the growing body of literature that studies zombie lending in Japan (Peek and Rosengren 2005; Sekine, Kobayashi, and Saita 2003). Caballero, Hoshi, and Kashyap (2008) argue that by accumulating underperforming loans, Japanese banks prevented the entry of more efficient firms and caused the Japanese "lost decade" of growth. Bruche and Llober (2014) study a solution to this problem in the context of the last financial crisis.

Further, our paper relates to the body of literature that discusses the cross-border bank amplification effects of capital shocks. Bruno and Shin (2013) study the acceleration of bank capital flows through the bank leverage channel. Cetorelli and Goldberg (2012) study the effects of the financial crisis on foreign banks' US branch lending activity.

We also analyze the downsizing of banks' assets across different business lines, similarly to the literature on the deleveraging decisions of a distressed portfolio investor. This literature is mostly motivated by the liquidity crises of 1998, starting with Scholes's presidential address at AFA (2000). It was observed that at the onset of the crisis, investors who were either facing margin constraints or regulatory constraints needed to offload assets in the portfolio to raise liquidity ratios. Empirical investigation reveals that mutual funds—and particularly hedge funds—tend to sell off liquidity assets first, and more so for those funds who face constraints that are more binding (Manconi, Massa and Yasuda 2012; Ben-David, Franzoni, and Moussawi 2012). Brown, Carlin, and Lobo (2010) study the deleveraging issue theoretically and find that the distressed investors have to make a further trade-off. That is, if the distress shock has a permanent component, distressed investors might sell off some of the illiquid assets as well so that their portfolio faces less of an impact from the liquidity downward spiral when further distress shocks strike. Empirically, this means that distressed investors might sell off liquid assets first to fend off the initial round of negative shocks. When shocks become permanent, they sell off more illiquid assets to limit the illiquidity exposure of their portfolio. Our results are informative of the portfolio implications for the deleveraging decisions of banks. One direct implication is that banks tend to liquidate assets that are most liquid, i.e., assets that face less-asymmetric information and are widely held by other banks.

Finally, although our focus is the period of housing bust, our paper is broadly related to the growing literature studying the impact of the U.S. real estate boom on the larger economy (Chaney, Sraer, and Thesmar 2012; Cvijanović 2014; and Adelino, Schoar, and Severino 2015) among others). While these papers suggest banks had an active role in the housing boom, our main finding is that banks have played a major role in potentially propagating the shocks coming from the real estate sector during the real estate downturn.

2 Data

We collect bank balance sheet data from the Federal Reserve's Report of Condition and Income ("Call Reports"). Our sample consists of quarterly data on all deposit-insured commercial banks. We include only bank-quarter observations with non-missing information on total assets, total loans, and equity. The data cover the period spanning from the last quarter of 2005 to the last quarter of 2010, giving a total of 98,497 observations covering 2,435 banks. Our dataset contains detailed information from the Schedule RC – Balance Sheet on loans and leases (total loans, C&I loans, real estate loans, consumer loans, etc.), cash and balances due from depository institutions, securities, trading assets and liabilities, deposits in domestic offices, deposits in foreign offices, other assets and liabilities, derivatives and off-balance sheet items. The data also contain information about certain flow variables related to problematic loans, such as loss recognitions, loans declared non-performing and recoveries.

Information about the geographical distribution of bank deposits is obtained from the Federal Deposit Insurance Corporation (FDIC).[9] House prices are obtained from the Federal Housing Finance Agency (FHFA) and are calculated at the level of a Core Based Statistical Area (CBSA).[10] The data contain a CBSA-level house-price index for 369 CBSAs. We obtain MSA-

[9] More specifically, we obtain the data from the Summary of Deposits. FDIC reports data on total deposits, location and ownership of all bank branches from 1994 onward (see http://www2.fdic.gov/sod/).
[10] A CBSA is a geographic area defined by the Office of Management and Budget (OMB). It is based around an urban center of at least 10,000 people and adjacent areas. CBSAs largely overlap with Metropolitan Statistical Areas (MSA), also defined by the

level land supply elasticities from Saiz (2010). Elasticities are available for 269 Metropolitan Statistical Areas (MSAs) in our sample. The MSA-level elasticities are then converted to the new CBSA definitions by employing a zip-code matching procedure.

As an alternative data source for the geographical distribution of bank loans, we use the relatively new data on small business loan originations collected under the auspices of the Community Reinvestment Act (CRA). Since 1996, larger banks have been required to report the number and amount of their (calendar-year) small business loan originations by census tract.[11] Banks and thrifts report small business and farm data and community development data if they have total assets greater than $1 billion dollars (asset level adjusted annually for inflation starting in 2005). Prior to 2005, institutions with asset levels above $250 million were required to report these data. Small business loans are defined as loans in amounts of $1 million or less. Small farm loans are defined as loans in amounts of $500,000 or less. We merge the CRA small business loans data with our sample by hand matching the Respondent IDs from the CRA data with the Bank IDs.

Summary statistics for the bank balance sheet data are shown in Table 1 (Panels A, B and C). Table 1 Panel D contains summary statistics on house prices and land supply elasticities, while Panel E contains the details of our sample banks' geographical dispersion.

The characteristics of our sample are in line with other papers that use the Call Reports as the main source of data. The mean bank in our sample had $107 billion in total assets in the last quarter of 2005, with $57 billion in total loans (corresponding to 67% of total assets). The median bank had $724 million in total assets, with $495 million in total loans (corresponding to 70% of total assets). The mean total equity capital to total assets ratio is almost 11% (with the median being 9.5%). The average tier 1 capital ratio is 9.2%, with a median of 8.1%. Real estate loans as a fraction of total assets average 46.3% in our sample, with a median of 47.1%. Property, plant and equipment constitute 1.7% of total assets on average.

OMB.

[11] Available from http://www.ffiec.gov/Cra/craproducts.htm.

As shown in Panel D, the CBSA-level land supply inelasticities range from 1 (least inelastic – Indianapolis) to 4.40 (most inelastic – Miami). Here, we define land supply inelasticity e_m as [1+max(elasticity.) - $elasticity_m$], where $elasticity_m$ is obtained from Saiz (2010). The national real estate price indices obscure the variation in the regional/CBSA real estate market conditions. In the period between the first quarter of 2006 and the end of the sample in the last quarter of 2010, the highest drop in local house prices was witnessed in San Diego (-48% over the five-year period). Over the same period, house prices in Portland fell by a mere 1.95%. Figure 1 shows the aggregate change in house prices for all CBSAs in the sample throughout the whole period. The figure shows significant variation across regions. During this same period, the Case-Schiller US House Price index recorded a drop of 31% in the national house price levels.

As shown in Panel E, there are 1,968 single-MSA banks and 487 multi-MSA banks in our sample, giving 40,595 (57,902, respectively) bank-MSA-quarter observations. Conditional on operating in more than one MSA, the median number of MSAs in which a bank operates is 17.

3 Empirical Strategy

We aim to explain the effect of losses induced by decreasing real estate prices on bank policies. The empirical strategy considers banks as conglomerates of local branches, in which the branches in each location operate as a division. Each branch is influenced by shocks that affect the bank as a whole and shocks that affect the specific location in which the branch operates. [12] However, given that multiple banks have branches in a given location, we can partial out the local shocks that homogeneously affect all banks in a given location in an additive way.

The first step of our identification strategy is to construct a bank-specific real estate price index. This is an aggregate price index across all the locations in which a bank operates. To do so, we use static weights w_{mi0} for each bank (i) - location (m) combination, according to the relative weight at the beginning of the sample, using deposits of a bank in a given location (CBSA). The weight w_{mi0} is constructed as the fraction of deposits of a bank i in location m with

[12] Note that our definition of a branch is a bank-location pair, and it may include different bank offices (that are also commonly known as branches) that operate in a given location.

respect to the total deposits of the bank at $t = 0$ (we use the fourth quarter of 2005, one quarter before our estimation sample starts).[13] The *bank specific aggregate* price index $House\ Prices_{it}$ is the weighted average of the real estate prices P_{mt} for each quarter t of each of the locations m in which the bank is located: $House\ Prices_{it} = \sum_{m=1}^{M} w_{mi0} P_{mt}$, and it measures the real estate price that affect a *given bank* in a *given quarter* across *all the locations* in which it operates.[14]

We consider outcome variables y_{mit}, which are bank policies (e.g. lending, equity issuance, etc.) and balance sheet items (e.g. tier 1 and tier 2 capital, etc.) defined at a bank-location-quarter level. The variable may be a direct panel data variable disaggregated at a bank-location level (as in the case of the CRA small business loans variables) or it may be created as the product of an outcome variable y_{it} defined for a bank i at time t (quarter) and a time-varying bank-location weight, w_{mit}. For example, y_{mit} may represent the loans outstanding of bank i in period t in location m or any other outcome variable. The weight w_{mit} is constructed as the current fraction of deposits of bank i in location m with respect to the total deposits of the bank.[15] One way to interpret this procedure is that if the outcome variables are, on average, proportional to the deposit activity of the bank, then $y_{it}w_{mit}$ is a proxy of the dependent variable of the bank in a given location at a given point in time y_{mit}. Alternatively, one can interpret this procedure as a more efficient way to estimate a bank-year level specification with multiple non-nested dummies for each location-year combination in which the bank operates. Note that, however, this specification is not equivalent to running a bank-year regression with a simple location fixed effect and year dummies, as locations cannot be captured by a single fixed effect and, instead,

[13] The deposits weight captures the relative presence of each bank in each location. Although deposit and loan activity differ across locations we only require that deposit weights are an unbiased proxy for real estate exposure. The results are robust to using number of offices as the source of the static bank weights.

[14] The measure uses cross-sectional weights determined at $t = 0$ (fourth quarter of 2005) to avoid introducing endogeneity via the weighting procedure.

[15] Becker (2007) documents the segmentation of local deposit and loan markets in the US, as well as a clear causal correlation between deposits and loans at MSA level. Note that, even if a specific deposit weight differs from a loan weight, the only necessary condition for the regressions to be unbiased is that deposit weights are an unbiased measure of loan weights. In the Appendix we show that the results are robust to using alternative weights based on the number of offices, the amount of small business loans given, or simply using 1/n (where n is the number of MSAs in which the bank operates) as the weight on the left-hand side. This is intuitive, given that in our specifications, any cross-sectional component of w_{mit} is absorbed by the bank-location dummies.

require a family of non-nested fixed effects. [16]Note that, for some of the dependent variables (such as capital), using deposit weights is just a meaningful way to allocate capital proportional to the bank's activity and check whether there are spillovers by comparing the aggregate effect to the sum of its parts. For some other variables, such as lending, there is also a local level of lending that we only observe for small business loans. It is not necessarily the case that deposit and lending activity coincide at a local level. However, it is enough to achieve consistent estimates that the deposit weights are an unbiased measure of lending activity, that is, that they do not systematically overstate or understate lending activity. We show further evidence of this lack of bias in the Appendix. Our results are robust to using the CRA database small business lending weights, or a bank's number of offices in each location or just dividing activity equally across locations in the weights construction procedure.

We use this independent variable in two specifications. The first one is a log specification. The second one is a level specification with an additional cross-sectional interaction that measures the amount of property plant and equipment (PP&E) in the bank's balance sheet. In this second specification, we also replace the actual real estate prices by a prediction that only uses aggregate nationwide shocks and cross sectional geographical measures. Both specifications are saturated with time-location fixed effects and location-bank fixed effects. All the estimations are then performed at the bank-location-quarter level and standard errors are clustered at a bank level.

Specification 1: Banks as portfolios of locations

A first specification of our regressions can then be written as:

$$\log(y_{mit}) = \alpha + \beta_1 \log(House\ Prices_{it}) + \delta_{mt} + \gamma_{mi} + \varepsilon_{mit} \qquad (1)$$

The natural logarithm of the dependent variable y_{mit} (e.g., loans in a given location) is

[16] In particular, estimating the effect using the aggregate variables and non-nested dummies would require introducing 7380 dummy variables (369 locations times 20 quarters). These dummies can take a positive value more than once per observation (i.e. banks operate in more than one location), hence they are non-nested and cannot be replicated with a combination of bank and location fixed effects, so they cannot be partialled out and would have to be estimated explicitly.

regressed against the bank-specific aggregate real estate price.[17]

The term δ_{mt} represents a collection of time-location-specific dummy variables that should capture any unobserved heterogeneity that affects a given location in a given quarter. The main advantage of considering banks as portfolios of locations is that multi-location banks allow us to estimate the effect of real-estate shocks over and above the local effects captured by δ_{mt}. In particular, these dummies should absorb any location-specific demand fluctuations. Note that the set of δ_{mt} associated with a given location also has the implicit role of a location fixed effect. This implies that β_1 is only identified by those banks that operate in more than one location. However, we include all banks in the specification, as single-location banks improve the precision in estimating δ_{mt} .

The term γ_{mi} is a bank-location fixed effect. Implicit in the specification, we are assuming that there are local effects and bank-specific effects that are proportional to all branches of a location or a bank, respectively. Note that the set of γ_{mi} associated with a given bank also has the implicit role of a bank fixed effect.

Given that the specification is in natural logs; the term β_1 measures the elasticity of the dependent variable (capital, different forms of lending, equity issuance and others) to real estate shocks, over and beyond location-time-specific and bank-specific effects. That is, the spillover effect above and beyond the individual impact in each of the locations in which a bank operates.. For example, in regard to capital losses, it is expected that the aggregate capital loss that a bank reports is close to the sum of the capital losses across each individual location, so β_1 should be close to zero. However, in regard to lending, the aggregate real estate losses of a bank affect its local lending beyond the local lending conditions, so we expect β_1 to be positive. In essence, we can interpret the coefficient β_1 as measuring the relation between aggregate bank-specific real estate prices and the part of the dependent variable unexplained by local-time-varying conditions and pure cross-sectional (bank-MSA) conditions. A significant β_1 coefficient indicates that bank

[17] The specification in (1) can be interpreted as the reduced form of an IV specification in which price exposure is calculated using running weights and then instrumented with a price variable that uses fixed cross-sectional weights.

reacts beyond what the sum of individual shocks and responses would predict and it is indicative of an amplification mechanism and a sufficient condition for some form of geographical contagion.[18]

Specification 2: Adding Cross-Sectional Exposures and Exogenous Price Shocks

A second set of specifications interacts the real estate shock variable with a cross-sectional measure of the bank's exposure to it, while controlling for the general impact of real estate shocks on all banks. This second set of regressions can be interpreted as a difference-in-differences specification that compares banks across different real estate shocks (determined by their geographical presence) and different individual exposures to them (determined by their real estate ownership). That is, the effect is identified by comparing the different reaction of banks with more or less balance sheet exposure to real estate across different levels of real estate price shocks. The measure of balance sheet exposure to real estate shocks is related to the direct holdings of productive real estate by banks. The measure of individual real estate shocks is the same one used in the previous specification. This second specification is robust to omitted variables that are simultaneously correlated with the bank's choice of the portfolio of locations and the outcome variable y_{mit}, such as some forms of time-varying matching between lenders and borrowers.

As a measure of real estate exposure, we use the fraction of property, plant and equipment (PP&E) over total assets before the beginning of the estimation sample (PP&E/Total Assets in 2005Q4). Although it is tempting to use a bank's real estate loans' portfolio as a measure of the bank's real estate exposure, this measure is correlated with the bank's lending activity and thus introduces endogeneity in to the estimation. In unreported regressions, we show that our results are robust to using this alternative real estate exposure measure and remain quantitatively unchanged.

[18] Furthermore, one can interpret β_1 as the difference in lending (or other dependent variables) of two banks that operate in the same location but have different exposures to other locations.

Most of the banks' PP&E of is composed of real estate holdings in the form of offices. This directly exposes banks to real estate fluctuations through their holdings.[19] There are two characteristics that make PP&E appealing from an empirical point of view. First, although PP&E holdings account for a low fraction of bank assets (1.7% on average), they represent a substantial exposure to real estate shocks. For example, the average decrease in real estate prices in our sample throughout the whole period (2006Q1-2010Q4) is 35%, which would entail average economic capital losses of 0.6%. Given that regulatory capital in our sample is, on average, 9.2%, this implies a reduction in capital of approximately 6 percentage points. Second, PP&E varies quite a lot across banks for historical reasons or for strategic reasons unrelated to bank lending policies. PP&E over assets has a within-sample standard deviation of 1.7%, so banks are heterogeneously exposed to real estate through their PP&E for exogenous reasons, which helps identify the effects.

Consider $House\ Prices_{it} PP\&E_{i0}$ as a dollar measure of the impact of real estate prices on a bank's balance sheet through its PP&E holdings; where $House\ Prices_{it}$ measures the aggregate bank-level real estate price index as in the previous specification and $PP\&E_{i0}$ measures the dollar value of the property plant and equipment of the bank at the beginning of the sample.[20] It is useful to re-write this measure as $House\ Prices_{it} Exp_{i0} Assets_{i0}$, where Exp_{i0} measures the fraction of PP&E in the bank's assets at the beginning of the sample ($PP\&E_{i0}/Assets_{i0}$). This measure depends on the size of the bank, so, to capture the effect of Exp_{i0} it is essential that we add as a control variable the general dollar exposure of a bank to real estate prices $House\ Prices_{it} Assets_{i0.}$ To make them comparable with the dependent variable, we re-scale both variables using the relative weight of each location w_{mi0} . Note that the variable of interest

[19] PP&E is normally reflected in bank balance sheets at historical values. Banks are required to provision losses if the value of PP&E goes below its historical value. They also realize capital gains/losses when they sell their properties. Finally, the value of PP&E is implicitly taken into account whenever banks merge or go bankrupt.

[20] A running exposure Exp_{it} would have the advantage of tracking the exposure of the bank more closely throughout the sample. However, Exp_{it} could be determined endogenously and induce biases in the estimation. Instead, we opt for a fixed Exp_{i0}, which may be a more imprecise proxy (especially for the later years of the sample), but it has the advantage of being predetermined. A similar argument can be made about the bank-location weights w_{mio} that are determined at the beginning of the sample and kept constant.

$House\ Prices_{it}Exp_{i0}Assets_{i0}$ is composed of the interaction between the firm-specific real estate shock expressed in dollars $House\ Prices_{it}Assets_{i0}$ and a cross-sectional exposure measure of the balance sheet exposure of the bank Exp_{i0}. Therefore the difference-in-differences structure is completed by including $House\ Prices_{it}Assets_{i0}$ in the regression and bank-location dummies that absorb the influence of Exp_{i0}.

Therefore, the second specification takes the form:

$$y_{mit} = \alpha + \beta_1 House\ Prices_{it}Assets_{i0}w_{mi0} + \beta_2 House\ Prices_{it}Exp_{i0}Assets_{i0}w_{mi0} + \delta_{mt} + \gamma_{mi} + \varepsilon_{mit} \quad (2)$$

Again, we saturate the model using location-time dummies δ_{mt} and bank-location dummies γ_{mi} and they have the same interpretation and in the first specification. This allows for estimating the effects at a bank-location-quarter level. Given that there are interactions with variables determined cross-sectionally at a bank level, this second specification is run in levels (dollars) and not logs.

The main coefficient of interest is β_2, which measures the differential impact of real estate prices for two banks that experience similar real estate price fluctuations in their portfolio of assets (i.e., the same $House\ Prices_{it}Assets_{i0}w_{mi0}$), but have different levels of exposure to real estate prices in their balance sheet. The term $House\ Prices_{it}Assets_{i0}w_{mi0}$ controls for the effect the general price fluctuations may have on the bank's policies, and as such it is an implicit control for bank size. In particular, it captures any bank-specific demand factors that are correlated with real estate price fluctuations and that affect the bank as a whole. It also captures any supply factors that are correlated with prices and affect all banks simultaneously, for example, a generalized decrease in the creditworthiness of the borrowers when the real estate prices drop. Note that β_1 is positive by construction, as both the dependent variable and the measure of aggregate bank exposure are measured in dollars and related to the size of the bank, however, β_2 depends only on the effect of Exp_{i0} (which is unitless) on this relationship.

Again, some of our dependent variables, such as Tier 1 capital, are not explicitly allocated to any location. However, if one aggregates expression (2) at the bank-year level (i.e. aggregating across bank-locations in a given year), the specification becomes one in which observations are defined at the bank-year level and we introduce fractional dummies according to the bank location weights and their interaction with year dummies. Note that our approach is, however, computationally more efficient than this equivalent specification, which would require estimating a large set of non-nested fixed-effect variables. The effect measured is the effect of prices when the bank is considered a portfolio of locations, net of the individual local effects estimated using the whole population of banks.

We introduce a further modification in this last specification. We use an alternative measure of local real estate price variation. In this specification, we replace the actual real estate prices P_{jt} with predicted prices in regressions that use the product of local real estate price elasticities and the aggregate countrywide variation in prices. The real estate elasticities are constructed based on cross-sectional geographical data from Saiz (2010), so the predicted price, once we control for aggregate time effects, is not affected by the lending of banks in that particular region. Following Mian and Sufi (2010), Chaney et al. (2012) and Cvijanović (2014), to obtain an exogenous source of variation in local real estate prices, we use a measure of land supply inelasticity interacted with aggregate (national) real estate prices (as measured by the Case-Shiller US House Price Index) as our instrument for local MSA-level real estate prices.

The intuition for this instrument is straightforward: MSAs with elastic land supply should experience small real estate price appreciation in response to increases in aggregate real estate demand (as proxied by the aggregate real estate prices), since land supply is relatively easy to expand. On the other hand, inelastic land supply MSAs should witness large real estate price appreciation in response to the same aggregate real estate demand shock (Glaeser, et. al, 2008). [21] [22]As a result, the predicted real estate prices are highly correlated with the actual prices. However, as they are constructed by interacting a pure cross-sectional and a pure time-series variable, they

[21] Two main factors restrict land supply. First, there may be topological constraints that impede real estate construction, such as steepness of terrain or presence of water bodies. Two, regulation plays an important role in restricting land development and new construction. Environmental regulation, urban planning, and zoning are just a few issues that restrict the amount of land supply.

[22] Glaeser et al. (2008) and Hilber and Vermeulen (2014) also provide evidence that the level of mean-reversion in house prices was enormous in highly inelastic places during the 1989–1996 period in the U.S., that is during 1974–1977, 1981–1982, 1990–1996 and in 2008 in the UK, thus providing further justification for using the instrument.

are not driven by temporary location-specific shocks or by the feedback from local lending to real estate prices. For this same reason, we estimate this second specification in levels, as a log structure with time-location and bank-location fixed effects would absorb all the relevant variation.

The specification in Equation (1) would have a similar interpretation as some of the conglomerates literature that estimates the reaction of one division to exogenous shocks to another division (see, for example, Lamont and Polk 2002; and Chang and Dasgupta 2007; among others). More closely related is the work by Murfin (2012), Gilje et al (2016) and Chakraborty et al. (2016), who also isolate the effects of shocks in a given location on bank outcomes in other locations.[23] By adding a further interaction with the level of cross-sectional exposure of the bank to real estate shocks in Equation (2), the effect is identified by banks with the same aggregate shocks but with different exposure to them.

4 Results

Using the two proposed specifications, we provide evidence of the internal contagion of real estate shocks within banks both across geographical areas of operations and across business divisions.

We proceed by stages: In section 4.1 we start by documenting the impact of real estate shocks on the capital of banks. Section 4.2 focuses on total lending as well as lending to small businesses, where for the latter variable, we have an exact geographical identification down to the census tract level. These first two sections show some first-order effects of real estate shock on bank policies and also provide auxiliary results to establish the validity of our estimation strategy. Our main results are shown in Sections 4.3 to Section 4.5. In particular, section 4.3 studies the disaggregated effects on different types of loans, showing how banks adjust their portfolio of loans. Section 4.4 discusses how banks address problematic loans when faced with a real-estate-

[23] More specifically, Murfin (2012) focuses on unexpected liquidity shocks, Gilje et. al. (2016) on oil and natural gas shale discoveries and Chakraborty et al. (2016) on the rise in real estate prices during the housing bubble. Our identification strategy can also be seen as the mirror image of that in Ashcraft and Campello (2007). While they aim to isolate local effects, controlling for bank-aggregate effects, our objective is exactly the opposite.

induced loss. In Section 4.5, we explore how real estate losses are transmitted to a bank's other business areas. Finally, in Section 4.6, we explore the cross-sectional heterogeneity in banks' responses to real estate market shocks in terms of their size.

4.1 Capital

In this section, we start by providing motivating evidence that confirms the findings of the existing literature on the effects of exogenous shocks on banks' balance sheets (Gilje et al. 2016; Chakraborty et al. 2016). We begin by exploring the effect of real estate shocks on bank's capital the two different proposed specifications. Panel A of Table 2 shows the results of a log specification that measures elasticities (see Equation (1)), while Panel B shows a specification in levels in which the exposure of banks to real estate loans is measured using their property plant and equipment (PP&E) and with instrumented real estate prices (along the lines of Equation (2)).

In Column 1 and 2 of panel A, the point estimates indicate that that a 10% reduction in real estate prices reduces, on average, Tier 1 capital by 1.4% relative to itself. This is a modest reduction in capital, and it is not statistically significant. This is an interesting result. The coefficient on $\log(House\ Prices_{it})$ in specification 1 can be interpreted as the effect of the aggregate bank-specific real estate shock over and above what the sum of the individual local effects predict. The result show that the sum of the local capital losses is a good predictor of the aggregate capital reduction reported by the bank. That is, there is no evidence of capital savings through diversification across geographical regions (that would imply a negative coefficient on $\log(House\ Prices_{it})$, nor a strong sign of an amplification effect, given the small positive point estimate and the lack of statistical significance. This is an intuitive result, as capital losses are likely to be additive. If a bank recognizes a capital loss in one location, it does not affect the way in which the bank needs to calculate capital losses in a different location. Similarly, the effects on Tier 2 capital are not significant in the first panel.

The results in Panel B show capital losses across banks with different levels of real estate ownership. The estimation captures the fact that banks with more PP&E in their balance sheet should recognize higher capital losses when facing real estate shocks. This is because the PP&E

exposure measure generates cross-sectional heterogeneity that is not captured by the location composition of a bank. The resulting coefficients are positive and significant for both Tier 1 and Tier 2 capital. As expected, banks with a higher cross-sectional exposure to real-estate prices recognize a larger fraction of capital losses. The quantitative impact of the effect can be interpreted as 3 cents of Tier 1 capital depleted per dollar of real estate losses, although, again, these have to be interpreted as over and above the common losses that other banks in the same MSA report. This second set of results is important to validate the use of PP&E as a useful measure of real estate exposure. Although the direct economic impact of real estate prices on the creditworthiness of a bank via its real estate holdings is mechanical, it is also important to establish whether banks are able to offset this impact and whether they actually recognize it from an accounting point of view. Comparing two banks with the same real estate shock, the one with a higher exposure to PP&E recognizes higher losses. These may be due to realized capital gains when real estate is sold or to loss recognition when the value of real estate assets is below its historical purchase value.

Overall, this section presents several preliminary results for the rest of the paper. First, overall capital losses of banks seem to be aligned with what the local effects predict. However, banks with a higher exposure to real estate shocks through their PP&E do recognize higher losses than those less exposed.

4.2 Total Loans

Following the previous evidence regarding the significant capital losses banks experienced following negative shocks (see also Cortes and Strahan 2015), we next examine the effects on banks' overall lending policies. Namely, we estimate the effect of real estate market spillovers on bank "branch" lending. Column 3 in Panel A of Table 2 shows the results with respect to total lending. A positive coefficient indicates a reduction in total lending when real estate prices drop. Effects are measured over and above the sum of the MSA-quarter effects predicted by other banks. The effect is statistically significant; an additional 10% drop in the portfolio of real estate locations of a bank reduces the flow of small business loans by 1.8% over and above the local reduction by other banks. This suggests that there is an overall balance sheet amplification mechanism of real estate shocks in our sample. It is important to establish the existence of this amplification for the particular shock and channel in this paper before approaching a more detailed analysis of the transmission across business lines and different types on lending.

In Column 3 of Panel B of Table 2 we report the results regarding total lending for the difference in differences specification. Here the results focus on the heterogeneous exposure of banks to real estate for a given combination of regions. The results show that banks that are more exposed to real estate shocks through their own real estate ownership also cut loans more intensely[24].

To further establish the validity of the proposed channel, we explore the effect of real estate prices on small business loans. This is shown in Columns 4 and 5 of Table 2. The dependent variables in these specifications are obtained from the CRA database and are measured directly at a local level rather than constructed using dynamic weights. The results using this alternative source of data are also positive and significant and are very consistent with the results that use an imputed dependent variable using deposit weights. The effect is, in fact, larger in terms of elasticities than for the total loans variable. A reduction of 10% in real estate prices implies a reduction in small business loans of 7% relative to themselves. This result is important to validate the rest of the analysis in the paper, as it establishes that there is geographical contagion across regions in bank lending. This is a sustained assumption throughout the rest of the paper.

Summing up, this section shows that total lending is reduced due to aggregate real estate losses over and above the local effects that affect all banks. This is suggestive of contagion across geographical regions, but we also check this contagion using data on small business loans. Finally the loan reduction is more intense for those banks more exposed to shocks via their PP&E holdings. These results are in line with Gan (2007) and Loutskina and Strahan (2015), who also

[24] During the 2006-10 period, there has been a significant M&A activity in the banking sector. There were also more than 300 bank failures during this time. To address the concern that not including bank failures might underestimate our results, we also estimate our main specifications while dropping the bank*MSA fixed effects, as if every bank was re-born every period. As it can be seen from the Appendix, our results remain unchanged.

show a transmission of real estate shocks throughout the balance sheet of banks. In our application, we are able to extend this idea to the whole population of US banks during the crisis using an estimation strategy that is reminiscent of the conglomerates literature. Following this intuition, in the next section, we explore the contagion of real estate shocks across different loan types.

4.3 Loan Portfolio

In the previous section, we showed evidence of an overall a drop in lending that ensued when the real estate market collapsed. In the following few paragraphs, we investigate whether this effect was felt across different types of loans. This is an important objective, as it would indicate a form of transmission of real estate shocks across business areas that occurs through the balance sheet of banks. The results of this section are intuitively linked to the problem of how to optimally downsize a portfolio of investments, taking into account the liquidation costs and the reversibility of this downsizing. They are also related to the literature on internal capital markets and how firms allocate funds across divisions.

Table 3 shows disaggregated results for different types of loans. By looking at the results presented in Panel A, we can see that the real estate market collapse had a ripple effect on various types of lending at the bank "branch" level. We decompose total lending into Real Estate Loans, Loans to Depositors, Agricultural Loans, Commercial and Industrial Loans, Foreign Loans, Obligations, Loans to non-Depositors and Leases. These are mutually exclusive categories used in the CALL reports that together comprise the total loans variable.

The results show that banks reduce their lending across different types of loans, although the effects are not homogeneous across all categories. In the log specification (Panel A), the riskier forms of lending (unsecured loans to depositors and commercial loans) are the most affected. A reduction of real estate prices of 10% implies a reduction of loans to depositors of 10% and a reduction in commercial loans of 7%. Real estate loans are also affected, but to a lower extent, with a reduction of 3% associated with a 10% reduction in real estate prices. Other loan categories, such as agricultural loans, leases, loans to foreign institutions and any other types of loans, show elasticities that are not statistically different from zero. Optimally downsizing a portfolio of loans involves taking into account transaction costs and the reversibility and price elasticities of the different types of loans among other variables. The fact that some lending categories are being cut more severely than real estate loans as a result of a real estate shock reflects the results of this optimization.

The results for the difference-in-difference specification (Specification (2)) shown in Panel B are largely consistent with the previous results. In overall dollar terms, real estate loans are the most affected category, followed by commercial and industrial loans and individual loans. However, the relative size of each of these categories in the balance sheet of banks is not homogeneous, so one needs to rescale the effect accordingly (see Panel C in Table 1). In relative terms, commercial and industrial loans and loans to depositors are again the most affected. Loans to non-depositors which are mostly interbank loans are also highly affected, in relative terms, in this second specification.

These results draw a picture of how economic shocks are transmitted through the banking system back to the real economy. By construction, our paper establishes the contagion of shocks across geographical locations via banks; this is at the heart of our identification strategy. This section also indicates a channel of contagion and amplification within the different business areas of a bank.[25] Given that we measure the real estate shocks at the aggregate bank level, our specifications allow for the real estate shocks to be transmitted from one bank location to another. The results shown in Table 3 indicate that there is both a geographical transmission effect and a spillover of the real estate shock from one banking business area (i.e., real estate) to another (i.e., loans to other depository institutions, personal loans, commercial and industrial lending or consumer loans).

[25] This result resembles similar effects in the literature of internal capital markets (see, for example, Lamont and Polk 2002; or, more recently, Matvos and Seru 2013). It also contrasts with the results in Chakraborty et al. (2016), who find a substitution effect across bank business lines during the real estate boom. However, both results are mutually consistent with standard financing constraint models, in which firms are constrained either when their investment opportunities expand beyond their financing capabilities (as in Chakraborty et al. 2016) or when their financing capabilities shrink faster than their investment opportunities (our results). In both situations, non-real estate loans are expected to shrink.

A consistent pattern appears across all these analyses: deleveraging banks reduce interbank and commercial/industrial lending significantly. The common understanding is that interbank loans are the most liquid and less relationship-based, while commercial/industrial loans are the most risky. This is consistent with the existing literature on constrained financial institutions' investment decisions to sell the most-liquid assets first to raise capital and then cut down risk exposure by lowering the holdings of the most-risky assets.

4.4 Loss Recognition

In this section, we measure how affected banks address problematic loans when they are more affected by real estate losses. While the real economic impact of real estate prices on mortgages is determined by their exposure to real estate and real estate prices, banks may have an incentive to manipulate or time the apparent losses they recognize from an accounting and regulatory point of view. By rolling over loans with dubious prospects of repayment, banks can postpone the recognition of losses from an accounting point of view as well as gamble on the improvement of the loans' repayment odds. Conversely, by foreclosing and liquidating some loans early, banks can provide themselves with additional liquidity. Banks also have some flexibility with respect to which particular loans they liquidate and which ones they keep as non-performing loans in their balance sheets. Table 4 shows the effects on loss recognition, loan recoveries and non-performing loans.

The first results in Columns 1, 2 and 3 of Panel A of Table 4 show how banks that are more affected by real estate prices, perform less charge offs and less loan recoveries than what is predicted by the sum of their parts. Overall, the effect on net recoveries is also negative. Moreover, in columns 1 to 7 of Panel B of Table 4, the results show that more affected banks are also having higher levels of non-performing loans. Given that these effects are in addition to the local effects and are related to the overall bank losses, this result indicates that affected banks were postponing the recognition of losses and not tidying up their balance sheet, even in locations in which they were not directly affected. This behavior is similar to the documented "zombie" lending activities of banks during the Japanese banking crisis, as documented by Caballero et al.

(2008).

As we can see from Panel B, banks particularly increase the total amount of outstanding non-performing loans (Column 1). Moreover, this increase is felt substantially across different loan categories, such as commercial and industrial non-performing loans (Column 2) and commercial real estate loans (Column 6), indicating that the effort to recognize less losses is done across business lines and is not restricted to new policies relative to mortgage lending. Jointly, these two effects show that the more-affected banks are rolling-over more dubious loans instead of pushing for an earlier resolution that would imply recognizing some losses, but which would also generate additional liquidity.

The first results in Columns 4, 5 and 6 of Panel A of Table 4 show a slightly different picture. Banks that are more exposed to real estate prices in the cross section, over-react to real estate prices when it comes to loan recoveries and charge-offs. That is, they recover more loans and recognize more losses. As we show in Table 2, these are precisely the banks that suffer higher capital losses. This is consistent with a notion of more capital constrained banks recognizing more losses so as to alleviate uncertainty about their future capital requirements. The results in Panel C are consistent with those in Panel B, showing that more affected banks in the cross-section also have more non-performing loans (Column 1, Panel C). Jointly, the results on this second specification provide a mixed picture. While it seems that more affected banks are managing their capital losses more actively, they are also accumulating more non-performing loans. Note that these two results are not mutually exclusive, since banks have some flexibility in determining non-performing loans and in choosing the quality of the loans that they decide to foreclose. In particular, these results imply that more affected banks are postponing the liquidation of higher quality loans, but liquidating more actively the lower quality ones.

The evidence in the previous two sections jointly indicates that banks that are more affected by real estate shocks in given locations take actions in their overall business portfolio that allow them to postpone the recognition of losses and the need for additional capital. Our results suggest that banks buy time and obfuscate their losses by managing their problematic loans. More affected banks are more likely to accumulate non-performing loans and, in relative terms, are less likely to liquidate them and recognize losses. Our results are in line with the existing evidence that suggests that such "zombie lending" took place in Japan during the 1990s (Peek and Rosengren 2005; Sekine, Kobayashi, and Saita 2003; Caballero, Hoshi, and Kashyap 2008). While we cannot directly observe the impact of these actions on bank profits, it is reasonable to conjecture that some of these policies are efforts to increase liquidity and current cash flows at the expense of future and aggregate discounted profits and that they may destroy value.[26]

4.5 Cost Reductions, Equity Issuance and Liquidity

In the previous sections, we have shown that in response to negative shocks to the value of their productive real estate (and their portfolios of real estate loans), banks experienced substantial capital losses that were followed by a significant cut in their aggregate lending. This shock had a ripple effect on bank business operations that involve the real estate sector, and the shock was transmitted to other banks' business operations. An advantage of our estimation strategy, relative to the state of the art within-firm estimators is that we can focus on bank outcomes other than lending. In this section, we explore the effects of real estate shocks in the funding and operational decisions of banks.

We start by focusing on equity issuance (Column 1 in Table 5). More affected banks do not seem to have accessed equity markets more intensely. Both Panel A and B show small and statistically insignificant results.

The next set of results (Columns 2 to 4) focuses on several measures of operational expenses. The results on PPE exposure show that more-affected banks reduce their operational expenses at different levels of aggregation: expenses on premises, interest expenses, and non-interest expenses. The effect is also very large when we pool interest and non-interest expenses. Even though the decrease in creditworthiness may increase the per unit cost of borrowing of banks, more affected banks managed to cut their borrowing needs in line with their reduction in loans.

[26] See Garicano and Steinwender (2013) for a detailed analysis of similar policies at a firm level.

The elasticity results are more imprecisely estimated and only show statistically significant results when we pool all the interest and non-interest expenditures together.

Finally, we show results on the different liquid assets that banks keep (Columns 5 to 7). Again, only the relative exposure specification shows positive and statistically significant results. Positive coefficients in all of them indicate a reduction in these liquid assets. That is, banks are selling some of their liquid assets to create liquidity that helps them address their real estate losses.

Overall, the results in Table 5 show a general inability of more-affected banks to replenish core capital with the additional issuance of equity. Moreover, more-affected banks reduce their operational costs and deplete their liquidity as part of their effort to address real estate shocks.

4.6 The Case of Large Banks

In this section, we explore the cross-sectional heterogeneity in banks' responses to the real estate market collapse in terms of their size. For example, the top 5 banks in the US have 40% of deposits nationwide and the top 20 US banks (bank holding companies - BHCs) hold assets equal to 84.5% of the nation's entire economic output. Large banks are also the ones with more diversified geographical portfolios. It is important to examine these banks separately to assess which part of our results is driven by the largest banks in the economy.

To identify the "mega banks" in our sample, we rank them in Q42005 based on their total assets. The top 99th percentile contains the 20 largest banks (BHCs).[27] For each bank-location combination ("branch"), we then assign a value of 1 for the dummy variable LARGE if its parent holder (BHC) is one of the top 20 BHCs listed above. We interact the variable LARGE with the variables of the specification in (2).

The results are shown in Table 6. Column 1 of Panel B shows the results for tier 1 capital. We

[27] These are, in in descending order: JPMorgan Chase & Co, Bank of America Corporation, Citigroup Inc., Wells Fargo & Company, Goldman Sachs Group, Morgan Stanley, US Bancorp, Bank of New York Mellon, HSBC North America Holdings, PNC Financial Services Group, Capital One, TD Bank US Holding Company, State Street Corporation, Ally Financial, BB&T Corporation, Suntrust Banks, Principal Financial Group, American Express Company, Ameriprise Financial and RBS Citizens Financial Group.

can see that the estimated coefficient on the interaction term (β_4) is negative but very small and not statistically significant. In Column 2, we see a different effect for large banks in terms of tier 2 capital depletion that is only significant in the log specification (Panel A), reducing the impact by 15%.

The specification in Column 3 measures the effect on total lending and shows a slightly different picture. A large negative coefficient indicates that large banks were able to cut loans proportionally less than smaller banks. The effect is 26% of the size of the general effect. This is an interesting result: while the qualitative result is the same for both large and small banks, it seems that the transmission of shocks via lending for large banks is much smaller than for small banks. The smaller overall effect for large banks is important, given the trend toward a more concentrated banking market nationwide.

One possible interpretation of the relatively smaller effect on lending for large banks could be that larger banks are also ones that are moving away from the originate and distribute mortgage business and are returning to a more traditional *on balance sheet* business. However, the results in Table 3 seem to go against this hypothesis. The relatively lower reduction in lending operates across all business lines and is not restricted to real estate lending. Another possible interpretation is that large banks had better access to equity markets. In Column 3, we explore the differences in equity issuance across bank sizes. The result is both economically and statistically non-significant, so it does not seem that equity issuance is an important factor in the relatively smaller effect found in larger banks. A third possible interpretation is that large banks are able to better distribute the negative shocks across more locations, thus having a lower amplification effect than more concentrated multi-location banks.

Overall, the results in this section do not show important qualitative differences between large banks and the rest. Quantitatively, large banks exhibit a slightly smaller sensitivity to real estate shocks. These results suggest that the nature of the real estate market price depreciation transmission on bank financing, operating and payout policy decisions was not qualitatively driven by their relative size differences. However, quantitatively, this combination of results shows that the consolidation of banks in the US has potentially contributed to a more resilient banking system.

5 Conclusion

In this paper, we examine the effects of real estate price declines on banks' loan product portfolio and on the role the mismanaged bank lending during the recent crisis played in prolonging the economic stagnation. We investigate how the real estate shocks that triggered the most recent financial crisis affected the composition of the banks' loan portfolio, both in terms of the type of products on offer, and in terms of their solvency. We find that in response to real estate price declines, banks substantially altered their loan portfolios: not only did they significantly reduce their real estate related lending, but these cuts also spilt over across business lines, including types of lending that are not directly related to real estate. We find significant effects on the treatment of existing loans: more affected banks continued to bet on the resurrection of their insolvent loans during the last crisis. Following real estate price declines, banks opted to roll over loans more frequently, recognize fewer losses and liquidate fewer loans, accumulating more non-performing loans.

Using the geographical coverage of banks, we consider each bank as a portfolio of real-estate locations; this enables us to identify the effect of real estate losses on their lending and balance sheets, while controlling for local conditions in a given point in time. Our approach implicitly compares the total bank-level effect of a balance sheet shock with the one that would result by adding up the individual local effects. More specifically, we measure how the aggregate exposure of a bank to real estate shocks affects its policies over and above the sum of the local effects predicted by other banks present in the same locations. Using this strategy we find evidence of balance sheet amplification effects for a broad population of firms (banks) during a long period of time (the real estate crisis).

The results are important to understand how banks address shocks that deplete their regulatory and economic capital. Some of the results show a transmission mechanism through bank lending to final borrowers and transmission mechanisms across locations and within banks. Banks operating in multiple locations and business areas can be a source of economic resiliency by diversifying the impact of economic shocks. However, we also show that their overall reaction is amplified beyond the sum of their individual parts in several dimensions and that they can be a source of contagion.

The reaction of banks' internal capital markets to real estate shocks is also relevant to the macroeconomic transmission of shocks. On the one hand, the internal contagion of shocks within the banks is related to the geographic transmission of economic shocks. A recent stream of recent explores the geographic transmission of shocks in the US economy (Caliendo et al. (2016), Fogli et al. (2013)). This research documents important regional linkages in the US, but it is still a challenge to identify the specific channels through which regions influence each other. Our results can be seen as suggestive of banks as one of the possible channels of such contagion. On the other hand, even if we observe contagion and a certain degree of amplification within a bank, this could actually make the whole economy more resilient. To the extent that banks are able to absorb local losses by transferring their effects to less affected locations, they are smoothing local shocks and making themselves more resilient. This additional resiliency has a geographical dimension, but it is also present when we analyze banks as a conglomerate of business lines. Focusing on the whole population of US banks during a financial crisis with a marked real estate component is particularly relevant to understand this resiliency.

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Tables and Figures

Figure 1

CBSA Real Estate Price Growth 2005–2011

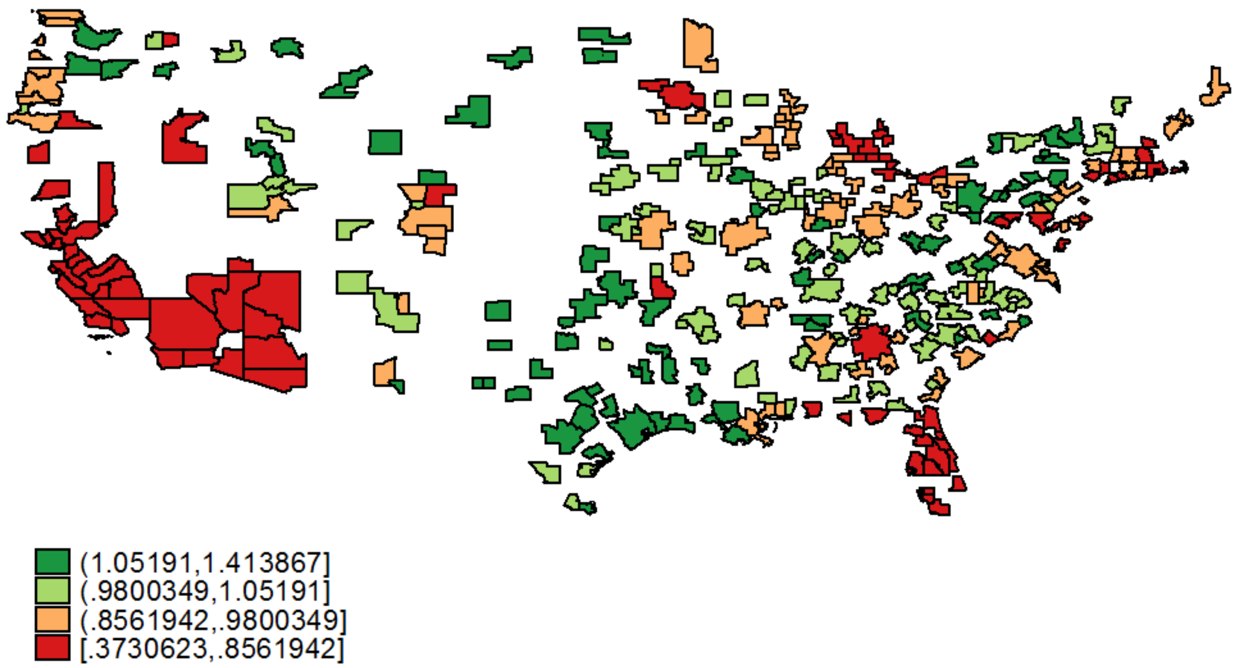

Table 1: Summary statistics

This table presents summary statistics of the sample of bank holding companies, obtained from Call Reports, merged with the geographical distribution of bank deposits as obtained from the Federal Deposit Insurance Corporation (FDIC). House prices are obtained from the Federal Housing Finance Association (FHFA). Our sample consists of quarterly data on all deposit-insured commercial banks. We include only bank-quarter observations with non-missing information on total assets, total loans, and equity. The data cover the period spanning from the first quarter of 2005 to the last quarter of 2010.

Panel A: Bank summary statistics (as of Q42005)

	mean	sd	p25	p50	p75
Total Assets	107,000,000	271,000,000	159,986	723,580	36,300,000
Total Loans	57,600,000	134,000,000	110,145	494,696	25,100,000
MBS	13,700,000	41,100,000	2,037	39,248	3,002,975
PP&E	841,408	1,934,679	2,890	12,304	411,273
Total Equity Capital	10,100,000	24,900,000	16,086	69,927	3,563,262
Tier 1 Capital	6,778,542	17,000,000	15,527	66,208	2,151,723
Tier 2 Capital	2,185,870	5,197,550	1,215	6,314	577,367

Panel B: Bank summary statistics, scaled by total assets (as of Q42005)

	mean	sd	p25	p50	p75
Total Loans	0.669	0.150	0.599	0.691	0.762
MBS	0.081	0.084	0.01	0.062	0.125
PP&E	0.017	0.014	0.008	0.013	0.022
Total Equity Capital	0.109	0.073	0.083	0.095	0.111
Tier 1 Capital	0.092	0.058	0.067	0.081	0.096
Tier 2 Capital	0.013	0.009	0.007	0.009	0.015

Panel C: Types of lending

Scaled by total assets

	Real estate loans	Loans to depository inst.	Agri loans	Commercia l & industrial loans	Individual loans	Foreign loans	Obligations	Loans to non-depository inst.	Leases
Mean	0.4666	0.0033	0.0096	0.0765	0.0555	0.0001	0.0045	0.0082	0.0075

Scaled by total lending

	Real estate loans	Loans to depository inst.	Agri loans	Commercia l & industrial loans	Individual loans	Foreign loans	Obligations	Loans to non-depository inst.	Leases
Mean	0.6883	0.0071	0.0150	0.1169	0.0862	0.0001	0.0074	0.0145	0.0114

Panel D: Real estate price summary statistics

	Mean	SD	Min	p25	p50	p75	Max
Case-Shiller US house price index	162.68	22.61	130.84	135.98	170.49	186.26	190.5
MSA House Prices Index	186.43	39.84	114.94	159.14	175.01	200.14	365.1
Inelasticity	2.93	0.88	1	2.29	2.7	3.76	4.4

Panel E: Bank location summary statistics

By bank-MSA	**Avg number of MSAs**	**Median number of MSAs**
Whole sample	29.8	2
Single-MSA banks	1	1
Multi-MSA banks	49.9	17
By bank		
Whole sample	1.97	1
Single-MSA banks	1	1
Multi-MSA banks	6.22	2

	Unique bank-MSA-date	**Total Observations (bank-MSA-date)**
Whole sample	2,435	98,497
Single-MSA banks	1968	40,595
Multi-MSA banks	487	57,902
Avg MSA weight	0.448	
Median MSA weight	0.198	

Panel F: Bank-specific aggregate real estate price index *House Prices$_{it}$*

House Prices$_{it}$

By bank, across quarters	Avg Single-MSA	Demeaned Single-MSA	Avg Multi-MSA	Demeaned Multi-MSA
mean	220.70	-6.03×10^{-7}	227.31	-5.01×10^{-6}
sd	49.84	27.87954	34.90	26.31

By quarter, across banks	Avg Single-MSA	Demeaned Single-MSA	Avg Multi-MSA	Demeaned Multi-MSA
mean	220.7	2.17×10^{-6}	227.32	1.40×10^{-6}
sd	0.67	57.11	0.71	43.71

Table 2: The effect of real estate prices on bank capital and lending policies

Panel A shows the results of estimating the log specification as in Equation (1), while Panel B shows the results of estimating Equation (2). The dependent variables y_{mit} are obtained from the FDIC call reports and CRA small business loans. From FDIC call reports we obtain: tier 1 capital (RCFD8274), total loans (RCFD2122), tier 2 capital (RCFD8275). From the CRA small business loans data set we obtain the total originated and purchased small business loans and total originated small business loans. Dependent variables y_{mit} are defined at a bank-location-quarter level that is created as the product of an outcome variable y_{it} defined for bank *i* at time *t* (quarter) and a time-varying bank-location weight, w_{mit}. For example, y_{mit} may represent the loans outstanding of bank *i* in period *t* in location *m* or any other outcome variable. The weight w_{mit} is constructed as the fraction of deposits of bank *i* in location *m* with respect to the total deposits of the bank. The independent variable in Panel A, *Log(House Prices$_{it}$)*, is the main independent variable that captures the real estate shock that a given bank is facing. It can be written as $House\ Prices_{it} = \sum_{m=1}^{M} w_{mi0} P_{mt}$ It measures the weighted average of the real estate prices P_{mt} of each of the locations in which the bank is located, using as weights the relative importance of each location in terms of deposits (w_{im0} is a static weight at t_0). In Panel B, P_{mt} (local MSA-level real estate price) is predicted using land supply inelasticity interacted with aggregate (national) real estate prices (as measured by the Case-Shiller US House Price Index). All specifications include bank-MSA and MSA-quarter fixed effects. In all specifications, we report robust standard errors that cluster at the bank level.

Panel A

	(1)	(2)	(3)	(4)	(5)
All dep. variables in logs	Tier 1 Capital	Tier 2 Capital	Loans	Total Loans (Originated + Purchased)	Total Loans (Originated)
Log(House Prices$_{it}$)	0.144	-0.061	0.185*	0.689*	0.708*
	(1.30)	(-0.40)	(1.65)	(1.72)	(1.72)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes	Yes
Obs	97,565	97,048	97,239	15,683	15,683
R^2	0.674	0.787	0.712	0.782	0.802

Panel B

	(1) Tier 1 Capital	(2) Tier 2 Capital	(3) Loans	(4) Total Loans (Originated + Purchased)	(5) Total Loans (Originated)
House $Prices_{it}$ * $PP\&E_{branch,2005}$	0.031***	0.013***	0.254***	2.184***	2.187***
	(14.06)	(9.87)	(6.61)	(3.30)	(3.30)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes	Yes
Obs	95,987	95,987	95,987	15,683	15,683
R^2	0.699	0.707	0.714	0.513	0.512

Table 3: The effect of real estate prices on banks' loan composition

Panel A shows the results of estimating the log specification as in Equation (1), while Panel B shows the results of estimating Equation (2). The dependent variables y_{mit} are: real estate loans (RCFD1410), loans to depository institutions and acceptances of other banks, agricultural and farmers loans (RCFD1590), commercial and industrial loans, individual loans (RCFD1975), loans to foreign governments and official institutions (including foreign central banks), obligations (other than securities and leases) of states and political subdivisions in the U.S., and lease financing receivables (RCON2165). Dependent variable y_{mit} is defined at a bank-location level that is created as the product of an outcome variable y_{it} defined for bank *i* at time *t* (quarter) and a time-varying bank-location weight, w_{mit}. The independent variable in Panel A, *Log(House Prices$_{it}$)*, is the main independent variable that captures the real estate shock that a given bank is facing. It can be written as $House\ Prices_{it} = \sum_{m=1}^{M} w_{mi0} P_{mt}$. It measures the weighted average of the real estate prices P_{mt} of each of the locations in which the bank is located, using as weights the relative importance of each location in terms of deposits (w_{im0} is a static weight at t_0). In Panel B, P_{mt} (local MSA-level real estate price) is predicted using land supply inelasticity interacted with aggregate (national) real estate prices (as measured by the Case-Shiller US House Price Index). All specifications include bank-MSA and MSA-quarter fixed effects. In all specifications, we report robust standard errors that cluster at the bank level.

Panel A

All dep. variables in logs	(1) ReLoans	(2) LoansTo Dep	(3) AgriLoans	(4) CILoans	(5) Individual Loans	(6) Foreign Loans	(7) Obligations	(8) Loans-NonDep	(9) Leases
Log(House Prices$_{it}$)	0.313***	1.012**	0.281	0.703***	0.075	0.455	-0.265	-0.135	0.241
	(3.63)	(1.98)	(1.63)	(2.98)	(0.66)	(1.30)	(-1.59)	(-0.67)	(0.81)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	92,202	92,202	92,202	92,202	92,202	92,202	92,202	92,202	92,202
R^2	0.970	0.937	0.947	0.942	0.964	0.874	0.938	0.916	0.966

Panel B

	(1) ReLoans	(2) LoansTo Dep	(3) AgriLoans	(4) CILoans	(5) Individual Loans	(6) Foreign Loans	(7) Obligations	(8) Loans-NonDep
House Prices$_{it}$ * PP&E$_{branch,2005}$	0.142***	0.006***	0.001**	0.054***	0.029***	0.001***	0.002***	0.011***
	(5.27)	(4.07)	(2.33)	(7.10)	(11.72)	(4.38)	(3.95)	(4.81)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	90,356	90,356	90,356	90,356	90,356	90,356	90,356	90,356
R^2	0.727	0.057	0.342	0.699	0.101	0.120	0.463	0.662

Table 4: The effect of real estate prices on loan loss recognition, recoveries and non-performing loans

In Panel A, we report estimation results of Equation (2) in columns 1 and 2, and estimation results of Equation (1) in columns 3 and 4. The dependent variables y_{mit} in Panel A are: loan recoveries (RIAD4605), loan charge offs (RIAD4635) and net charge offs, defined as the difference between loan recoveries and loan charge offs. In Panels B and C, we show the results for total non-performing loans (defined as the sum of total loans past due 90 days or more and non-accruals). We split them by type of non-performing loans: commercial and industrial non-performing loans, farmer non-performing loans, restructured non-performing loans, other non-performing bank assets, commercial real estate non-performing loans, and credit card non-performing loans. Panel B shows the results of estimating Equation (1), and Panel C shows the results of estimating Equation (2). Dependent variable y_{mit} is defined at a bank-location level that is created as the product of an outcome variable y_{it} defined for bank *i* at time *t* (quarter) and a time-varying bank-location weight, w_{mit}. The weight w_{mit} is constructed as the fraction of deposits of bank *i* in location *m* with respect to the total deposits of the bank. The independent variable in Panel B, *Log(House Prices$_{it}$)*, is the main independent variable that captures the real estate shock that a given bank is facing. It can be written as $House\ Prices_{it} = \sum_{m=1}^{M} w_{mi0} P_{mt}$. It measures the weighted average of the real estate prices P_{mt} of each of the locations in which the bank is located, using as weights the relative importance of each location in terms of deposits (w_{im0} is a static weight at t_0). In Panel A and Panel C, P_{mt} (local MSA-level real estate price) is predicted using land supply inelasticity interacted with aggregate (national) real estate prices (as measured by the Case-Shiller US House Price Index). All specifications include bank-MSA and MSA-quarter fixed effects. In all specifications, we report robust standard errors that cluster at the bank level.

Panel A

	(1) log(Loan recoveries)	(2) log(Loan charge offs)	(3) log(Net charge offs)	(4) Loan recoveries	(5) Loan charge offs	(6) Net charge offs
Log(House Prices$_{it}$)	0.000***	0.002***	0.001***			
	(5.81)	(6.17)	(6.11)			
House Prices$_{it}$ * PP&Ebranch,2005				-0.364**	-1.709***	-2.083***
				(-1.97)	(-5.63)	(-6.50)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Obs	97,969	97,969	91,362	95,987	95,987	95,987
R^2	0.879	0.858	0.855	0.647	0.443	0.412

Panel B

All dep. variables in logs	Non-performing loans by type						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Non-performing loans	Commercial and Industrial	Farmer	Restructured loans	Other non-performing assets	Commercial real estate	Credit card
Log(House $Prices_{it}$)	-2.365***	-1.686***	-2.171***	-5.633***	-2.059***	-2.996***	-0.687*
	(-6.76)	(-4.96)	(-2.60)	(-6.79)	(-5.21)	(-4.68)	(-1.65)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	97,930	97,969	97,969	97,924	97,969	97,969	97,889
R^2	0.785	0.974	0.774	0.713	0.917	0.825	0.776

Panel C

	Non-performing loans by type						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Non-performing loans	Commercial and Industrial	Farmer	Restructured loans	Other non-performing assets	Commercial real estate	Credit card
House $Prices_{it}$ * $PP\&E_{branch,2005}$	-0.006**	-0.002***	-0.001	-0.001***	-0.001**	-0.001***	-0.003
	(-2.12)	(-2.88)	(-0.63)	(-4.14)	(-2.00)	(-3.67)	(-1.37)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	95,987	95,987	95,987	95,987	95,987	95,987	95,987
R^2	0.072	0.021	0.063	0.061	-0.024	0.091	0.036

Table 5: The effect of real estate prices on banks' financing and operating activities.

Panel A shows the results of estimating the log specification as in Equation (1), while Panel B shows the results of estimating Equation (2). The dependent variables y_{mit} are: equity issuance (defined as the quarterly change in tier 1 capital), expenses on premises (RIAD4217), non-interest expense (RIAD4093), interest and non-interest expense (RIAD4130), trading assets (RCFD3545), investment securities (RCFD0391) and cash and balances (RCFD0010). Dependent variable y_{mit} is defined at a bank-location level that is created as the product of an outcome variable y_{it} defined for bank i at time t (quarter) and a time-varying bank-location weight, w_{mit}. The weight w_{mit} is constructed as the fraction of deposits of bank i in location m with respect to the total deposits of the bank. The independent variable in Panel A, *Log(House Prices$_{it}$)*, is the main independent variable that captures the real estate shock that a given bank is facing. It can be written as $House\ Prices_{it} = \sum_{m=1}^{M} w_{mi0} P_{mt}$. It measures the weighted average of the real estate prices P_{mt} of each of the locations in which the bank is located, using as weights the relative importance of each location in terms of deposits (w_{im0} is a static weight at t_0). In Panel B, P_{mt} (local MSA-level real estate price) is predicted using land supply inelasticity interacted with aggregate (national) real estate prices (as measured by the Case-Shiller US House Price Index). All specifications include bank-MSA and MSA-quarter fixed effects. In all specifications, we report robust standard errors that cluster at the bank level.

Panel A

All dep. variables in logs	(1) Equity Issuance	(2) Expenses on premises	(3) Non-interest expense	(4) Interest and non-interest expense	(5) Trading assets	(6) Investment securities	(7) Cash and balances
Log(House Prices$_{it}$)	-0.011	0.091	0.166	0.341**	-0.198	0.153	-0.035
	(-0.04)	(0.66)	(1.20)	(2.27)	(-0.57)	(0.31)	(-0.20)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	49,569	97,954	97,969	97,969	97,969	93,440	97,967
R^2	0.694	0.940	0.936	0.933	0.962	0.904	0.918

Panel B

	(1) Equity Issuance	(2) Expenses on premises	(3) Non-interest expense	(4) Interest and non-interest expense	(5) Trading assets	(6) Investment securities	(7) Cash and balances
House Prices$_{it}$ * PP&Ebranch,2005	0.001	0.001***	0.008***	0.014***	0.055***	0.069***	0.021***
	(1.36)	(21.37)	(20.14)	(20.79)	(2.77)	(6.26)	(10.03)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	91,436	95,987	95,987	95,987	95,987	91,522	95,987
R^2	0.012	0.709	0.779	0.776	0.612	0.705	0.433

Table 6: The effect of real estate prices on banks' operations: large banks

Panel A shows the results of estimating the log specification as in Equation (1), while Panel B shows the results of estimating Equation (2). The dependent variables y_{mit} are: tier 1 capital (RCFD8274), total loans (RCFD2122), tier 2 capital (RCFD8275) and equity issuance (defined as the quarterly change in tier 1 capital). Dependent variables y_{mit} are defined at a bank-location level that is created as the product of an outcome variable y_{it} defined for bank i at time t (quarter) and a time-varying bank-location weight, w_{mit}. The weight w_{mit} is constructed as the fraction of deposits of bank i in location m with respect to the total deposits of the bank. Dummy variable *Large* takes the value 1 if the bank-branch belongs to a top-20 bank holding company in terms of total assets. The independent variable in Panel A, *Log(House Prices$_{it}$)*, captures the real estate shock that a given bank is facing. It can be written as $House\ Prices_{it} = \sum_{m=1}^{M} w_{mi0} P_{mt}$. It measures the weighted average of the real estate prices P_{mt} of each of the locations in which the bank is located, using as weights the relative importance of each location in terms of deposits (w_{im0} is a static weight at t_0). In Panel B, P_{mt} (local MSA-level real estate price) is predicted using land supply inelasticity interacted with aggregate (national) real estate prices (as measured by the Case-Shiller US House Price Index). All specifications include bank-MSA and MSA-quarter fixed effects. In all specifications, we report robust standard errors that cluster at the bank level.

Panel A

All dep. variables in logs	(1) Tier 1 Capital	(2) Tier 2 Capital	(3) Loans	(4) Equity Issuance
Log(House Prices$_{it}$)	0.142	-0.059	0.182*	0.023
	(1.28)	(-0.39)	(1.67)	(0.10)
Log(House Prices$_{it}$)*Large bank	0.010	-0.009**	0.014	-0.010
	(1.32)	(-2.05)	(0.93)	(-0.23)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes
Obs	97,565	97,048	97,239	49,569
R^2	0.674	0.787	0.712	0.566

Panel B

	(1) Tier 1 Capital	(2) Tier 2 Capital	(3) Loans	(4) Equity Issuance
House Prices$_{it}$ * PP&Ebranch,2005	0.031***	0.014***	0.269***	0.000
	(12.64)	(8.17)	(6.92)	(1.23)
Large bank*House Prices$_{it}$ * PP&Ebranch,2005	-0.001	-0.002	-0.069***	0.001
	(-0.79)	(-0.85)	(-3.01)	(0.65)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes
Obs	95,987	95,987	95,987	91,436
R^2	0.851	0.785	0.814	0.083

External Appendix:

To test whether our assumption that a bank's lending activity in a certain location is correlated with its deposit activity in the same location, we run several tests, as shown in Table A.1 – Table A.5

In **Table A.1** we show results of estimating Equation (1) in Panel A, and Equation (2) in Panel B, whereby in our weighting procedure to construct the dependent variables we use the loan-based bank-MSA weights obtained from the CRA database, instead of calculating bank MSA weights using deposits. As we can see from Panel A and Panel B, our results remain unchanged.

Table A1:

Panel A

	(1)	(2)	(3)
All dep. variables in logs	Tier 1 Capital	Tier 2 Capital	Loans
Log(House Prices$_{it}$)	1.188**	1.441*	1.374**
	(2.06)	(1.95)	(2.32)
Bank*MSA fixed effect	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes
Obs	3,947	3,948	3,948
R^2	0.825	0.841	0.827

Panel B

	(1)	(2)	(3)
	Tier 1 Capital	Tier 2 Capital	Loans
House Prices$_{it}$ * PP&E$_{branch,2005}$	0.029***	0.010***	0.266***
	(3.53)	(2.63)	(3.40)
Bank*MSA fixed effect	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes
Obs	3,827	3,827	3,827
R^2	0.669	0.612	0.629

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In **Table A.2,** we show correlations between actual CRA and deposit-based MSA weights (both static – computed using deposit shares in 2005Q4; and running – computed using the current quarter), for all banks, and for single-MSA and multi-

MSA banks. In the whole sample, we can see that the correlations between CRA-based and deposit-based weights are positive and highly significant, ranging from 0.69 for running weights, to 0.71 for static weights. For multi-MSA banks, the correlation between CRA-based and deposit-based running weights 0.52, while for static weights it is 0.54

Table A.2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All Banks			Single-MSA Banks	Multi-MSA Banks		
	Loans	MSA Weight	Static MSA Weight	Loans	Loans	MSA Weight	Static MSA Weight
CRA Loans	0.259***			0.851***	0.159***		
	(37.52)			(62.30)	(25.26)		
CRA MSA Weight		0.694***				0.519***	
		(79.45)				(44.68)	
Static CRA MSA Weight			0.709***				0.535***
			(80.01)				(44.94)
Observations	3,953	3,953	3,953	708	3,245	3,245	3,245
R-squared	0.263	0.615	0.618	0.846	0.164	0.381	0.384

In **Table A.3** we show results of estimating Equation (1) for Table 3 from the main text, whereby in our weighting procedure to construct the dependent variables we use the number of offices a bank has in an MSA (scaled by total number of offices that a bank operates) in Panel A, and by using 1/n, where n is the number of MSAs in which the bank operates, as the weights in our dependent variable construction in Panel B, instead of calculating bank MSA weights using deposits. As we can see from Panel A and Panel B, our results remain unchanged.

Table A.3:

Panel A: Office weights

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All dep. variables in logs	ReLoans	LoansToDep	AgriLoans	CILoans	Individual Loans	Foreign Loans	Obligations	Loans-NonDep
Log(House Prices$_{it}$)	0.217***	2.868**	0.267	0.008	-0.013	-1.333	-0.632***	-0.255
	(2.71)	(2.31)	(1.14)	(0.08)	(-0.12)	(-0.56)	(-2.58)	(-1.29)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	91,169	30,865	66,469	60,199	91,137	14,082	59,305	80,072
R^2	0.949	0.853	0.921	0.963	0.955	0.846	0.880	0.903

Panel B: 1/n weights

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All dep. variables in logs	ReLoans	LoansToDep	AgriLoans	CILoans	Individual Loans	Foreign Loans	Obligations	Loans-NonDep
Log(House Prices$_{it}$)	0.214***	2.878**	0.271	0.015	-0.014	-1.308	-0.627**	-0.258
	(2.66)	(2.31)	(1.16)	(0.15)	(-0.14)	(-0.55)	(-2.55)	(-1.31)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	91,169	30,865	66,469	60,199	91,137	14,082	59,305	80,072
R^2	0.949	0.853	0.921	0.963	0.955	0.846	0.880	0.903

In **Table A.4** we show results of estimating Equation (1) for Table 4 from the main text, whereby in our weighting procedure to construct the dependent variables we use the number of offices a bank has in an MSA (scaled by total number of offices that a bank operates) in Panel A, and by using 1/n, where n is the number of MSAs in which the bank operates, as the weights in our dependent variable construction in Panel B, instead of calculating bank MSA weights using deposits. As we can see from both panels, our results remain unchanged.

Table A.4

Panel A: Office weights

	Non-performing loans by type						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All dep. variables in logs	Non-performing loans	Commercial and Industrial	Farmer	Restructured loans	Other non-performing assets	Commercial real estate	Credit card
Log(House $Prices_{it}$)	-2.263***	-1.560***	-1.777***	-3.361***	-0.697***	-1.931***	-0.611
	(-6.56)	(-6.41)	(-3.88)	(-6.48)	(-2.75)	(-5.30)	(-1.52)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	97,930	97,969	97,969	97,961	97,969	97,969	97,889
R^2	0.785	0.949	0.671	0.601	0.753	0.590	0.783

Panel B: 1/n weights

All dep. variables in logs	Non-performing loans by type						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Non-performing loans	Commercial and Industrial	Farmer	Restructured loans	Other non-performing assets	Commercial real estate	Credit card
Log(House $Prices_{it}$)	-2.351***	-1.686***	-2.185***	-4.579***	-1.026***	-2.610***	-0.678
	(-6.75)	(-6.00)	(-3.05)	(-6.75)	(-3.02)	(-5.56)	(-1.62)
Bank*MSA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA*quarter fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	97,930	97,969	97,969	97,924	97,969	97,969	97,889
R^2	0.750	0.962	0.684	0.629	0.845	0.706	0.759

During the 2006-10 period, there has been a significant M&A activity in the banking sector. Additionally, there were more than 300 bank failures during this time. To address the concern that not including bank failures might underestimate our results, we estimate our main specifications, but drop the bank*MSA fixed effects, so banks are treated as being re-born every period and, in particular, merged banks are treated as new banks.

Table A.5: Mergers

Panel A

All dep. variables in logs	(1) Tier 1 Capital	(2) Tier 2 Capital	(3) Loans
Log(House $Prices_{it}$)	0.975***	1.117***	2.528***
	(2.77)	(3.55)	(4.59)
Bank*MSA fixed effect	No	No	No
MSA*quarter fixed effect	Yes	Yes	Yes
Obs	97,565	97,239	97,048
R^2	0.162	0.148	0.166

Panel B

	(1) Tier 1 Capital	(2) Tier 2 Capital	(3) Loans
House $Prices_{it}$ * $PP\&E_{branch,2005}$	0.036***	0.013***	0.271***
	(8.97)	(11.01)	(6.734)
Bank*MSA fixed effect	No	No	No
MSA*quarter fixed effect	Yes	Yes	Yes
Obs	95,987	95,987	95,987
R^2	0.624	0.615	0.679