# Bank Balance Sheets and Liquidation Values

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Abstract

*This paper investigates the impact of bank balance sheets on the liquidation value of bank-owned real estate collateral. Liquidation values are significantly lower when the selling bank is closer to insolvency or faces funding pressures. Also, buyers earn significant returns for providing liquidity to banks, as prices tend to rebound sharply after sales by illiquid banks. Lower liquidation values also depress the prices of nearby real estate transactions. This evidence suggests that balance sheet adjustments at financial institutions can explain real asset price dynamics and economic fluctuations.*

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# 1. Introduction

This paper investigates the impact of bank equity constraints and illiquidity on the liquidation value of real estate collateral. It also studies the spillover effects of depressed liquidation values onto housing markets. Prominent theories of intermediation predict that the solvency and liquidity of intermediary balance sheets might directly shape asset price dynamics through the sale of distressed assets.[1] These arguments begin with the fact that dislocations in labor and financial markets bring troubled assets onto the balance sheet of financial institutions. In 2011, nearly 25 percent of the vacant homes for sale in the US were foreclosed or became real estate owned (REO) properties held by banks and securitization trusts.

Balance sheet pressures such as binding equity constraints can cause a bank to deleverage primarily through the sale of assets with greater regulatory capital risk weights such as REO assets. Difficulties in meeting the liquidity demands of depositors can also induce a bank to sell quickly illiquid assets. Either because of equity constraints or illiquidity, the rapid liquidation of these assets when potential buyers might themselves have limited financing capacity can depress liquidation values relative to fundamentals, possibly spilling over onto the broader housing market (Shleifer and Vishny (1992), and the survey in Shleifer and Vishny (2011)).[2]

This idea that balance sheet adjustments at financial institutions can impact asset prices and the broader economy is not only at the center of models that connect intermediaries to economic fluctuations but is the main rationale for new

[1] Theoretical treatments of these ideas include Acharya, Shin and Yorulmazer (2011), Allen and Gale (1994, 2005), Brunnermeier and Sannikov (2013), Diamond and Rajan (2001, 2005), He and Krishnamurthy (2013), Rochet and Vives (2004)—see the survey in Rajan and Ramcharan (2016).

[2] Annenberg and Kung (2014), Campbell, Giglio and Pathak (2010), Geradi et. al (2012), Immergluck and Smith (2006), Lin, Rosenblatt and Yao (2009), and Mian, Sufi and Trebbi (2010) study the spillover effects of foreclosures in the period immediately around the 2008-2009 crisis. Peek and Rosengren (2000) is a classic reference on the real effects of the Japanese banking crisis. Separately, Chaney, Sraer, and Thesmar (2012) provide evidence on the importance of commercial real estate collateral for firm decisions. Also, Chu (2015) examines the impact of bank balance sheets on commercial real estate transactions.

approaches to liquidity and capital banking regulations. Motivated by these macro-prudential arguments about the potential negative effects of balance sheet illiquidity, US and international banking rules now regulate liquidity among large banks, despite concerns that these regulations might restrain lending and economic activity ((BIS (2013), Cecchetti and Kashyap (2016)). Despite similar concerns about diminished lending, Basel III capital requirements have not only increased, but countercyclical buffers are now in place to avoid procyclcial asset liquidations.

Yet causal evidence connecting the balance sheet of financial institutions to asset price declines, especially for major asset classes like real estate—the chief source of collateral in the US economy—remains limited.[3] To be sure, there is now compelling microeconomic evidence that aggregate credit availability, such as changes in banking competition within a geographic area might inflate local real asset prices (Favarra and Imbs (2015), and Rajan and Ramcharan (2015)).[4] But little is known about the underlying mechanism behind this relationship and whether in particular balance sheet illiquidity can directly affect real asset price movements (Diamond and Kashyap (2015)).

Three principal factors make it difficult to evaluate the evidence on the effects of balance sheets on the liquidation values of collateral: ex-ante endogenous matching between collateral quality and intermediaries; unobserved current economic conditions the drive balance sheet outcomes and liquidation values; and non-random selection into liquidation. In the case of endogenous matching,

[3] Beginning with Pulvino (1998), there is a sizeable literature documenting real fire sales among non-financial corporations. A recent example is Benmelech and Bergman (2008) linking the balance sheet of airlines to the value of collateral. An important literature beginning with Adrian and Shin (2008) provide time series evidence linking financial institution's balance sheets to financial asset prices. Adrian, Etula, Muir (2014) and He, Kelly and Manela (forthcoming) provide more direct tests using standard asset price models for financial assets. It is however difficult to determine causality and identify underlying mechanisms within the context of standard time series asset pricing models.

[4] Beyond real estate, Benmelech, Meisenzahl and Ramcharan (2017) provide evidence that illiquidity among non-depository institutions can affect consumer durable goods credit. Irani and Meisenzahl (2017) study banks' incentives to make syndicated loan sales while Acharya and Mora (2015) provide evidence on liquidity stress in the traditional banking system during the 2007-2010 period. Also, Rajan and Ramcharan (2016) provide evidence linking banking sector distress during the Great Depression to real local asset values.

persistent unobserved bank characteristics can both determine the quality of collateral retained on balance sheet and other balance sheet observables such as solvency. This persistence can in turn lead to spurious associations between subsequent balance sheet observables and realized liquidation values.

Similarly, current unobserved local economic conditions can simultaneously affect the liquidation values and current balance sheet outcomes, making it difficult to interpret the evidence. Weak economic conditions can for example worsen bank health, and at the same time both cause depositors to run and depress liquidation values. While in the case of selection bias, loan delinquency is often precipitated by a borrower-specific shock. But a bank's current balance sheet health could shape its incentives to renegotiate loan terms, and "select" a property into foreclosure, again leading to possibly biased estimates of the impact of balance sheet observables on liquidation values.

The research design uses detailed transaction-level information on collateral matched to the selling bank and various identification schemes to help address these endogeneity concerns. Information on the precise location of the collateral as well as the exact date of the auction allows the basic specifications to absorb most plausible controls for local economic conditions, including census tract by quarter fixed effects, as well as collateral characteristics such as the year built, the size of the property and even balance sheet health at the time the intermediary first originated the loan. In the case of selection bias, I collect information on the population of 1.6 million delinquent properties for the 680 banks in the sample—the population from which foreclosed properties are selected—in order to model directly selection into foreclosure.

The geographic diversification in the dataset--380,000 liquidations spanning some 5,000 zip codes, across 12 states and 680 banks—also aid in identification. Banks that either anticipate or directly face funding pressures often increase their deposit rates to stem deposit outflows. But many large banks set their deposit rates both at the headquarters and at regional "rate-setting" branches. Branch rates clearly reflect local economic conditions and the relative supply of deposits. But among the sample of banks operating across all 12 states, economic conditions in the zip code or census tract in which the asset is liquidated are unlikely to determine changes in the headquarter's rate (Figure 1).

I thus use this headquarter's rate to study the impact of funding pressures on liquidation values among multi-state banks. At such banks, asset liquidations are centralized; Bank of America created for example a legacy asset division to handle Countrywide asset dispositions. The exercise is analogous to estimating the impact of changes in Bank of America's deposit rate set in Charlotte, North Carolina on properties liquidated in zip-codes across California, Arizona and Florida. The headquarter's rate likely reflect funding pressures at the bank-level and provides the impetus for asset liquidations, while the absorptive capacity in the zip-code help determine liquidation values.

Either using the one quarter lag in the change in deposits scaled by assets or changes in the deposit rate as measures of a liquidity shock, there is significant evidence that increased funding pressures and lower regulatory capital ratios are associated with lower liquidation values. A one standard deviation decrease in deposits is associated with about a 1.5 percent drop in the average liquidation value of real estate collateral in the next quarter. Both quantity and price based measures of liquidity matter. For a bank at the median change in the deposit rate, a one standard deviation decrease in deposits is associated with a 1.2 percent drop in liquidation values. But for a bank at the 90$^{th}$ percentile of the 6-month rate change, and presumably trying to attract scarce liquidity by offering high rates to depositors, a similar loss of deposits is associated with a 1.9 percent drop in liquidation values.

The evidence on solvency is similar. A one standard deviation decrease in the ratio of tier 1 capital to risk weighted assets implies a 2.4 percent decline in the value of the distressed real estate collateral. But there is evidence of regulatoryinduced non-linearities. Among banks in the bottom decile of this solvency ratio and closest to regulatory insolvency, REO assets sell at about a 6 percent discount relative to otherwise identical assets sold by banks in the top solvency decile. This suggests that banks with eroding capital bases or those in need of cash to meet quickly the liquidity demands of depositors liquidate assets below their fundamental value—the firesale hypothesis.

The results on the returns to arbitrage or price rebound corroborate the firesale hypothesis. For the sample of properties that resold during the period under observation, I computed the daily internal rate of return. Under the firesale hypothesis, the size of the liquidation discount or the buyer's returns to arbitrage is related to the magnitude of the seller's distress. The estimates suggest that the returns to providing liquidity to banks are large. Buying the asset from a bank after it experiences a negative one standard deviation liquidity shock and reselling it 160 days later—the median resale time—augments returns by about 3.1 percentage points. This result is hard to reconcile with endogeneity narratives, as local economic fundamentals are highly persistent in neighborhoods with foreclosures.

The underlying mechanism appears consistent with predictions from economic theory. Banks with scarce liquidity—those experiencing deposit outflows and in need of cash—sell more quickly distressed real estate assets, helping to explain the lower liquidation values. Likewise, the impact of balance sheet pressures on liquidation values are higher in areas with less local absorptive capacity. For the same loss of deposits, liquidation values are lower in zip codes where local residents—the natural buyers—are more levered and have less capacity to buy these assets (Fostel and Geanakoplos (2008)). There is also evidence that policies such as TARP, which directly injected equity into some banks, and quantiative easing, which provided liquidity and stabilized the mortgage backed securities market, helped to lower REO discounts.

Finally, using detailed data on about 800,000 non-foreclosure market transactions, I provide evidence that REO liquidation values impact nearby house prices. A key challenge to causal inference stems from the fact that latent local economic shocks can simultaneously determine liquidation values and the price of non-REO sales. The evidence linking balance sheets to liquidation values offers a new way to address this identification challenge, and I instrument the REO liquidation value with the balance sheet of the selling bank. I find that a 10 percent decline in the liquidation value of a REO property is associated with about a 2.3 percent drop in the subsequent price of a non-REO sale located within 140 meters from the REO property.

This paper provides the first detailed evidence that asset sales by financial institutions can significantly influence the liquidation values of real estate collateral and affect the broader residential housing market. These results are thus supportive of theories that emphasize the importance of financial intermediary balance sheets in shaping asset prices and economic fluctuations (See the survey in Gertler and Kiyotaki (2010). This evidence is also suggestive that higher capital and liquidity requirements during boom times might limit the potential for asset sales that dislocate real estate markets when adverse shocks occur. When these shocks do happen, direct capital injections into financial institutions and improved access to liquidity might also reduce destabilizing asset sales.

## 2. Empirical Background and Data

### *2.A Empirical Background*

There are at least two major channels through which a financial intermediary's balance sheet might affect the liquidation value of distressed or troubled assets. First, models of financial intermediation emanating from Diamond and Dybig (1983) observe that difficulties in rolling over short term liabilities or an increase in the demand for liquidity among depositors can force a financial institution to sell quickly illiquid assets to meet the liquidity demands of creditors. When cash-in-the-market is limited, this rapid selling of illiquid assets can in turn depress liquidation values and the prices of similar assets (Allen and Gale (1994)).

Illiquidity on both the asset and liability sides of the balance sheet can also interact to shape the liquidation values of collateral: When confronted with an increase in the demand for liquidity from depositors, banks with more liquid assets might face less pressure to sell quickly illiquid assets and depress liquidation values. A related idea centers on the dual liquidity insurance function that banks provide to both borrowers and depositors (Gatev and Strahan (2006), Kashyap, Rajan and Stein (2002)). A bank with sizeable unused loan commitments to borrowers is contractually obligated to provide liquidity insurance—credit lines drawdowns—to its borrowers. If the demand for liquidity among borrowers and depositors are positively correlated, a bank with sizeable unused loan commitments might face greater pressure to sell quickly illiquid assets when confronted with an increase in the demand for liquidity from depositors.

New financial regulation proposed in the sample period could also augment REO selling pressures. In 2010, regulators for the first time proposed formal liquidity regulations such as the liquidity coverage ratio (LCR) and the net stable funding ratio (NSF) (Basel (2013, 2014). In the case of the former, REO assets are not counted as high quality liquid assets, making it harder for a bank to comply if REOs dominate its balance sheet. In the case of the NSF, the weight on REO assets is 100 percent, while that of the equivalent performing mortgage is 65 percent. Thus, once real estate collateral comes on balance sheet, it absorbs greater liquidity relative to the loan, as the bank would have to seek even more stable sources of liquidity to fund the real estate asset. If liquidity is scarce, then the incentive for rapid asset sales increase.

A second key channel centers on the high cost and slow pace of raising equity during times of crisis in conjunction with the incentives provided by risk-based capital regulation. Unable to raise outside equity easily when the financial sector is in distress, banks have powerful incentives to deleverage through asset sales, primarily of assets with greater risk weights. Figure 2 shows the extent of deleveraging in the banking system during the 2006-2015 sample period. The ratio of tier 1 capital to risk weighted assets—a key indicator of regulatory solvency—in the total banking system rises sharply beginning in 2008. But much of this increase stems from the shedding of capital intensive assets, as the ratio of risk weighted to total assets declines equally sharply over this period. Note well that this deleveraging continues well after the 2008-2009 crisis, extending through the entire sample period.

REO properties are one such capital intensive asset class. These properties migrated onto the balance sheets of banks en masse over this period, averaging about $20 billion in the banking system from the first quarter of 2008 through end-2015 (Figure 3). Given the sizeable risk weight of these assets, an intermediary facing binding equity constraints could prefer to liquidate rapidly on-balance-sheet REO assets.[5] Specifically, the risk weight on foreclosed real estate assets owned by banks is 100 percent or twice as large as real estate loans in good standing. Using the typical 8 percent minimum equity constraint before regulators mandate "prompt and corrective action", the capital requirement for bank owned real estate with a fair value of $100,000 would be $8,000; a loan of similar value would only have a capital charge of $4,000. [6]

[5] See the discussion in Kashyap, Stein and Rajan (2008) and analytical treatments of these ideas in Brunnermier and Pedersen (2008) and He and Krishnamurthy (2013)

[6] An overview of the Basel 1 risk weighting rules can be found herehttps://www.occ.gov/static/news-issuances/ots/exam-handbook/ots-exam-handbook-120ab.pdf

In some circumstances, realized losses from the sale of REO assets can offset the deleveraging benefits of these asset sales. But accounting practices generally limit this possible offsetting effect. Once an REO comes on balance sheet, losses—the gap between the cost basis and the outstanding loan amount—are immediately booked and charged against equity. Any subsequent declines in the fair market value of the asset relative to the initial cost basis are also charged to loan loss allowances. Thus, holding onto the asset in a declining market ties up both equity and leads to further charges. For a bank with scarce equity then, selling can be optimal. Banking regulations also limit the REO holding period to 5 years in most cases, so banks must eventually dispose of the asset. And for much of the sample period, banking regulators discouraged banks from property management on an ongoing basis, encouraging them to dispose of REO assets quickly. [7]

Both economic theory and the institutional details surrounding REO assets suggest that intermediary balance sheet pressures can affect liquidation values. But establishing a causal relationship between balance sheet illiquidity and solvency and liquidation values is difficult. For example, the endogenous matching between collateral quality and bank balance sheets can make it hard to differentiate the effects of balance sheet pressures from intrinsic collateral quality on observed liquidation values. "Conservative" banks for example might operate with more cash or higher levels of equity and also originate loans backed by higher quality or safer collateral ex-ante. This can then induce a positive association between book equity and liquidation values, making it hard to identify whether observed liquidation values stem from current balance sheet observables or the matching between intrinsic collateral quality and persistent unobserved bank risk preferences.

[7] The OCC's regulations describe this process in greater detail: https://www.occ.treas.gov/publications/publications-by-type/comptrollers-handbook/other-real-estate-owned/pub-ch-oreo.pdf

Contemporaneous unobserved economic conditions can also simultaneously affect the demand for liquidity or a bank's equity constraint as well as liquidation values. Adverse economic shocks for example that affect a bank's depositors could both increase the demand for liquidity and depress the liquidation value of assets sold in local markets, again making it difficult to identify a causal relationship between balance sheet pressures and liquidation values.

In principle, selection bias can also hamper causal inference. Foreclosed properties are drawn from the population of delinquent loans. And once a loan becomes delinquent, potentially unobserved balance sheet factors that affect liquidation values could also be correlated with lender-borrower negotiations and selection into the foreclosure subsample. In practice however, selection bias might be limited. In most cases, mortgage servicers interface directly with borrowers and play a central role in how delinquencies are resolved. And the incentives of servicers and banks differ. There is for example evidence that servicers tended to prioritize the foreclosure option when confronted with delinquent loans in part because of their own compensation incentives rather than driven by bank balance sheet observables.[8]

Apart from these conceptual challenges to identification, data on liquidation values, especially for real assets, are generally unavailable. Regulatory financial statements—the call report—records coarse quarterly information on charge-offs and recoveries, containing no data on the prices obtained from the sale of underlying assets and the characteristics of the collateral sold. The coarseness of public regulatory information makes it impossible to address these challenges to identification when using typical datasets. In what follows, I collect detailed

[8] See Federal Reserve System, Office of the Comptroller of the Currency, and Office of Thrift Supervision (2011) *Interagency Review of Foreclosure Policies and Practices,* report.

collateral data matched to banks and the local geography to construct a number of different identification strategies to address these endogeneity concerns.

### *2.B. Data: REO Assets*

To address these identification challenges, the analysis uses data from Zillow's ZTRAX database on the liquidation of foreclosed properties collected in 12 states, including Arizona, California, Florida—the three states with the most number of foreclosures in the United States. The ZTRAX database contains information on the near universe of housing transactions drawn from county records across the country. Importantly for the analysis, the database lists the price and date of liquidation; the property address and key collateral characteristics, including price and leverage at origination. ZTRAX also lists in text form the name of the bank that liquidated the foreclosed property, allowing a manual match with financial institutions' regulatory balance sheet and income data. The sample period runs from the first quarter of 2006 through the final quarter of 2015.

The ZTRAX database reproduces the well-known fact that foreclosures rapidly increased in 2008 and 2009 during the housing collapse, before gradually tapering off in the years after the financial crisis (Figure 4). The number of bank-owned properties in the database, about 500,000, reflects the raw count and about a third of these bank-owned properties do not have recorded prices, or lack information to match the commercial bank to the liquidation; observations with missing or non-matched data are excluded from the subsequent analysis.

For the remaining 377,000 properties that can be matched to a bank and that has a recorded liquidation value, Table 1 tabulates by state the number of bank-owned foreclosures with non-missing matched data. California, Arizona and Florida have the most number of bank liquidated properties. Panel A of Table 2 summarizes key collateral characteristics for the full sample of REO assets. It shows that across the entire distribution, foreclosed properties sold at sizeable discounts relative to their nominal origination price.

Panels B-F of Table 2 show that while banks might vary in the quality of collateral originated, this variation appears substantially smaller among the set of assets that they actually retained on balance sheet. That is, the potential for endogenous matching in the analysis might be limited. These tables report collateral characteristics by key bank observables such as tier 1 capital to risk weighted assets—a standard measure of regulatory solvency—as well as by deposits to assets—a measure of a bank's dependence on deposit financing. To avoid endogeneity, these bank variables are averaged between 2006-2001. In Table 2C, there is some evidence that banks with above median equity ratios tended to originate and retain newer homes. But across the panel of Tables, the differences in REO asset quality do not point to sizeable differences across bank types.

### *2.C. Data: Bank Data*

To measure balance sheet liquidity, in much of the analysis, I use a bank's change in deposits relative to the same quarter in the previous year and scaled by assets. This approach builds on the evidence that the traditional banking system faced significant liquidity pressures during much of the sample period, as aggregate deposit inflows weakened and funding shortfalls increased (Acharya and Mora (2015)).[9] New liquidity regulations such as the NSF and LCR also significantly raised the demand for stable funding sources, like deposits, and the relative liquidity "cost" of REO assets.

[9] As banking sector losses began to increase rapidly in 2008, many in the US congress opposed federal attempts to assist the banking system, and there was thus significant uncertainty about the health and future form of the US banking system. For example, the Troubled Asset Relief Program, which was initially intended to purchase bad assets, was originally rejected by the House of Representatives in September of 2008. Similarly, the FDIC's deposit insurance fund fell from $52.4 billion in late 2007 (a reserve ratio to deposits of 1.2%) to around $13 billion in early 2009 (a reserve ratio of just 0.27%), leading to a number of emergency measures and eroding the perception of the government guaranty. See the discussion in Bair (2013).

Figure 5 plots summary statistics for this variable from 2006 through 2015. Across the entire distribution of banks, Figure 5 shows a marked decline in deposit growth over the sample period, with the mean growth rate falling by half in 2010 relative to its 2006 peak. The growth rate measured at the 25th percentile turned negative in 2010, as a greater number of banks faced net deposit withdrawals during this period. Note this rate remained negative through most of the sample period as well.

A quantity based measure of liquidity pressures is only partially informative of underlying balance sheet funding pressures. Banks that either anticipate or directly face funding pressures could increase their deposit rates to stem deposit outflows or even induce additional flows. Ratewatch, a proprietary data source, collects information on the deposit rate for various term products at the branch-week level for a large sample of US bank. Data on deposit pricing permit more informative measures of balance sheet funding pressures.

Figure 6 plots summary statistics for the difference between a bank's interest rate on its three month certificate of deposit (CD) product—a bank specific indicator of its cost of retail deposit funds—and the three month Treasury rate. Across the distribution, this spread is predominantly negative in 2006 and 2007, as most banks could access deposit financing cheaply during the boom. But as deposit growth slowed for many banks beginning in 2008 and new liquidity regulations increased the potential demand for these funds, spreads turned sharply positive, suggesting that some banks had to increase deposit rates in order to attract deposit financing. Again, this pattern persists well beyond the immediate crisis shock.

Figure 7 illustrates more clearly how deposit flows and the cost of deposit financing relate to funding pressures over the sample period. For each of the 40 quarters in the sample beginning in 2006, I regress the change in the three month CD rate on the growth in deposits for the cross-section of banks observed in each quarter. Figure 7 plots this coefficient, observed for each quarter, along with its 95 percent confidence band.

During the boom period, the relationship between deposit flows and changes in the cost of funds is positive. But consistent with an increase demand for these funds, after 2007, this relationship becomes strikingly negative: Deposit rates tended to increase sharply when deposit flows declined. This is especially true around the crisis. However, while Acharya and Mora (2015) focus on the crisis, the relationship between deposit flows and interest rates remains significantly negative at least through early 2011. This pattern suggests that both quantity flows as well as price changes likely proxy for illiquidity. And as with deleveraging (Figure 2), for some banks at least, liquidity pressures likely remained well into the sample period.

Table 3 summarizes some of the other balance sheet variables both in 2006 and again at the end of the sample period in 2015. Consistent with the significant changes in financial regulation over the sample period, median tier 1 capital to risk weighted asset ratios are about two percentage points higher in 2015 compared to 2006. Similarly, over this period, balance sheet illiquidity, as measured by both the ratios of loans to deposits, and cash to assets appear to have decreased. Surviving banks also appear to be much larger.

## 3. Balance Sheets and Liquidation Values

### *3.A Main Results*

This subsection studies the impact of bank balance sheets on the liquidation values of real estate owned (REO) bank assets. Let $P_{ijkt}$ denote the liquidation value of property $i$ located in neighborhood $k$—zipcode or census tract—that is liquidated by bank $j$ on date $t$. To establish simply the relationship between balance sheet liquidity and liquidation values, the baseline specification uses the change in deposits relative to the same quarter in the previous year and scaled by assets as the main measure of balance sheet liquidity pressures. Illiquidity and insolvency are closely related, and the baseline specification also uses the ratio of tier 1 equity to risk weighted assets—a key regulatory measure of solvency; all bank variables are observed in the quarter before liquidation . The estimating equation is thus:

$$(1)\ P_{ijkt} = \delta_j + \delta_k + + \delta_t + \beta_1 \frac{(deposit_{jt-1} - deposit_{jt-5})}{Asset_{jt-1}} + \beta_2 \frac{tier\ 1\ equity_{jt-1}}{Asset_{jt-1}} + X_{jt-1}\Theta_1 + C_i\Theta_2$$

The parameter $\delta_j$ absorbs bank fixed effects, while $\delta_k$ and $\delta_t$ absorb neighborhood fixed effects, and year-by-quarter effects. Neighborhood fixed effects absorb location and other time invariant variation in income and other differences across neighborhoods, while $\delta_t$ control for aggregate economic shocks like monetary policy. In some specifications, I exploit the granularity of the data to construct neighborhood by year-by-quarter fixed effects, $\delta_{kt}$. These parameters can absorb non-parametrically time varying shocks at the zip code or census tract level, such as changes in income or unemployment, that might simultaneously affect liquidation values in those areas and balance sheet outcomes.

The vector $X_{jt-1}$ contains other bank observables and $C_i$ is a vector of collateral observables that proxy for the quality of the property. The date of liquidation is the date of auction for the 75 percent of cases where liquidation occurs in an auction. In the remaining cases the property is sold to an arm's length buyer, and the date is the recording date in the county deed's office.

Column 1 of Table 4 presents the most parsimonious model. The dependent variable is the log price of the liquidated property. From column 1, the point estimate is statistically significant at the one percent level and positive: a one standard deviation decrease in deposits in the previous quarter is associated with about a 0.7 percent decline in the liquidation value of the property. Column 2 includes the ratio of tier 1 capital to risk weighted assets—book equity. This variable is economically and statistically significant. A one standard deviation decrease in the tier 1 ratio is associated with a 1.8 percent drop in the liquidation value of the collateral; although illiquidity and solvency are closely related, the point estimate on balance sheet liquidity remains unchanged.

Because the effects of book equity and deposit flows could proxy for other balance sheet observables, column 3 adds other standard income and balance sheet controls such as the return on assets, the ratio of cash to assets; loans to deposits; deposits to assets as well as the size of the bank, measured in terms of log assets. These variables all enter with a one quarter lag. The point estimates on the liquidity and solvency variables increase after controlling for these additional variables. A one standard deviation decrease in deposit flows is associated with a 1.4 percent drop in liquidation values in the subsequent quarter. A similar decrease in the tier 1 ratio implies a 2.4 percent decline the value of the distressed collateral. In what follows, this will be the baseline specification. For concision, Table 4 only presents the coefficients of interest—the full table is available upon request.

The remaining columns of Table 4 address issues of measurement and non-linearities. In the case of the former, liquidity pressures can still be present even absent deposit outflows. Banks for example that either anticipate or directly face funding pressures can increase deposit rates to stem deposit outflows (Figure 6). Also, the effects of book equity on REO asset sales is likely to be non-linear. Since ratios of tier 1 capital to risk weighted assets below 8 percent automatically trigger regulatory action, banks' deleveraging incentives might increase sharply as book equity ratios approach the regulatory minimum.

Column 4 of Table 4 replaces the change in the deposits variable with the quarter on quarter change in the bank's six month certificate of deposit rate. This variable is available for a smaller number of banks, shrinking the sample size; but the point estimate is significant and negative. Consistent with illiquidity pressures leading to lower liquidation values, the coefficient implies that a one standard deviation increase the deposit rate is associated with a 0.5 percent decline in liquidation values.

Column 5 models the potential interaction between the price and quantity based measures of illiquidity. This specification includes an interaction term between the change in deposits variable and the change in the interest rate. Increased funding pressures are associated with significantly lower liquidation values. For a bank at the median change in the deposit rate, a one standard deviation decrease in deposits is associated with a 1.2 percent drop in liquidation values. But for a bank at the 90$^{th}$ percentile of the 6-month rate change, and presumably trying to conserve or attract scarce liquidity, a similar loss of deposits is associated with a 1.9 percent drop in liquidation values.

Column 6 of Table 4 considers how minimum capital requirements might non-linearly affect the price of REO assets obtained at auction. The specification parametrically models this possible non-linearity by estimating decile bins of tier 1 regulatory ratios using indicator variables that equal 1 when a bank-quarter tier 1 to risk weighted assets ratio lies within a particular decile. The 10$^{th}$ decile is the omitted category, and the coefficients measure the average price of REO assets in a particular tier 1 ratio decile bin relative to the omitted 10$^{th}$ decile bin. The point estimates and 95 percent confidence bands of these indicator variables are shown in Figure 8.

The evidence is consistent with the deleveraging hypothesis: Undercapitalized banks sell at steep discounts. Figure 8 shows that for the most undercapitalized banks, those in the bottom decile, the price obtained on the sale of REO assets is about 5.6 percent lower than bank-quarter observations in the top decile. Banks with eroding capital bases or one in need of cash to meet quickly the liquidity demands of depositors might liquidate assets below their fundamental value (Diamond and Kashyap (2015), Diamond and Rajan (1999)).

Therefore, if these results reflect the causal effect of bank balance sheet distress on liquidation values—the firesale hypothesis—then the price bounce or capital gain from resale should be largest for those assets sold by the most illiquid or under-capitalized banks. Liquidations by distress sellers create an arbitrage opportunity for unconstrained buyers, allowing these buyers to purchase the liquidated property at a discount. They can then resell the property at its higher fundamental value ((Shleifer and Vishny (1997)). And because the size of the discount is related to the magnitude of the seller's distress, under the firesale hypothesis, the buyer's returns to arbitrage is proportional to the seller's distress.

If however these results are driven by latent economic fundamentals that jointly drive liquidation values and balance sheets, then any subsequent capital gains should be unrelated to the balance sheet of the seller at the time of liquidation. If anything, given that fundamentals are highly persistent in neighborhoods with foreclosures—the autoregressive coefficient for house price changes at the quarterly frequency in these areas is 0.96—under the latent fundamentals hypothesis, observed capital gains should be lower for properties sold by illiquid banks: The unobserved negative fundamentals that weakened balance sheets and liquidation values in the first place should also keep subsequent resale prices low.

To test whether balance sheet variables might explain subsequent capital gains, I collected data on the date of the first resale and the price obtained for the subset of liquidated properties in the sample that subsequently resold by end 2015. There are about 121,000 such cases. I do not have data on any improvements made after purchase or any leverage used by buyers, and for each of these properties I calculate the daily unlevered internal rate of return (IRR) :

$$\left(\frac{resale\ price_{t+n}}{liquidation\ value_t}\right)^{\frac{1}{n}} - 1.$$

Where *n* is the number of days elapsed from liquidation by the bank to subsequent resale by the buyer. Column 7 of Table 4 regresses this internal rate of return on the baseline set of balance sheet variables observed in the quarter before liquidation.

The evidence is striking: properties sold by more illiquid banks are associated with an economically and statistically large price bounce. A one standard deviation decrease in deposit growth in the quarter before a bank sells an asset increases the buyer's subsequent daily IRR by 0.02 percentage points. Note that the median property is resold in about 160 days, and the median daily IRR is 0.08 percent. Equally striking is the fact that using the change in the deposit rate as the measure of illiquidity gives identical results (column 8). A one standard deviation increase in the deposit rate in the quarter before liquidation increases a buyer's daily IRR by 0.02 percentage points.

These estimates suggest that the returns to "dry powder" are large. Buying from an illiquid bank—defined as one that in the previous quarter experienced a negative one standard deviation liquidity shock—and reselling the asset 160 days later augments returns by about 3.1 percentage points. This result is hard to reconcile with narratives about latent fundamentals that drive liquidations and balance sheets. Note also this result is robust to including measures of collateral quality such as the year built; an indicator for whether the property has been remodeled in the last 10 year; square footage; number of bedrooms and number of bathrooms—these are available upon request. All this suggest that balance sheet pressures might depress liquidation values below fundamentals. There are however a number of endogeneity concerns, and before assessing the robustness of the main results, the next subsection uses economic theory to first identify the underlying mechanism.

## 4. Mechanism

### *4A. Balance-Sheet Heterogeneity, Policy and Local Absorptive Capacity*

*Balance-Sheet Liquidity*

Economic theory observes that illiquidity on both sides of the balance sheet can interact to shape liquidation values. If these results reflect the causal effect of funding pressures on liquidation values, then the impact of a loss of deposit financing on liquidation values should be larger among banks with less liquid assets. Unable to meet easily the liquidity demands of depositors, banks with less cash face greater pressures to liquidate quickly troubled assets To wit, asset illiquidity would be expected to amplify the effect of an adverse liquidity shock on liquidation values.

Table 5 test this prediction using various sample splits based on the cash to assets ratio measured using data from 2001-2006 to avoid endogeneity. The dependent variable throughout is the log liquidation value, as the sample of IRR observations are too small for the sample splits exercise. Column 1 uses the baseline specification but for banks that entered the sample period in the bottom quartile of the cash to asset ratio, while column 2 restricts the sample to those banks in the top quartile. For the cash poor subsample, a one standard deviation decrease in deposit growth is associated with a 1.9 percent drop in the liquidation value (column 1). But for the sample of banks with cash ratios above the 75$^{th}$ percentile, the implied effect is 50 times smaller and statistically insignificant. This difference is hard to reconcile with the possible endogeneity stories.

Columns 3 and 4 use sample splits based on those banks below and above the median cash ratios respectively. The implied effect of the below median subsample is again larger. These differences across the median sample splits is even more visible when using changes in the deposit rate (columns 5 and 6). The below median cash subsample is statistically significant and about twice as large as the point estimate obtained in the above median cash subsample; the latter itself is not significant. These splits also show that among banks with plentiful balance sheet liquidity, the implied effects of solvency on liquidation values is much larger. That is, for these more liquid banks, concerns about solvency rather than illiquidity feature more prominently in the liquidation decision.

The concurrent off-balance sheet commitments of a bank also provides a powerful source of variation to identify the channels through which illiquidity might affect liquidation values (Gatev and Strahan (2006), Acharya and Mora (2015). If concurrent off-balance sheet commitments are drawn down rapidly, a bank will have to issue new liabilities or equity, or rapidly sell other assets to finance the expansion in its loan portfolio. Thus, banks with substantial existing off-balance sheet loan commitments and little cash assets are likely to be especially sensitive to a loss of deposits, and we would expect an even bigger relationship between the change in deposits and liquidation values for these banks.

Columns 7 and 8 of Table 5 evaluate this hypothesis, interacting the change in deposits with a measure of off-balance sheet commitments: the ratio of off-balance sheet loan commitments plus assets to assets, all observed in the previous quarter. Column 7 restricts the sample to banks with below median cash assets, and column 8 uses those banks with above median cash ratios. In the case of the former, the interaction terms are jointly significant at the one percent level, and the evidence suggests that larger off-balance sheet commitments might amplify the impact of illiquidity on liquidation values, especially in the case of banks with less liquid assets.

For example, from column 7 a one standard deviation decrease in deposits is associated with a 2.9 percent decline in average liquidation values the next quarter for a bank at the $90^{th}$ percentile of the off-balance sheet commitment ratio. The implied effect is about a third smaller for a bank at the $10^{th}$ percentile of this ratio.

This pattern is not present in column 8—the interaction terms are jointly insignificant (p-value=0.56)—and the magnitudes are substantially smaller. Note that I have used sample splits based on the Berger and Bouwman (2009) liquidity measures, but these results, available upon request, are not significant, suggesting that a shortage of cash itself was key.

*Policy*

During the sample period, policy makers directly injected capital into some banks—the Troubled Asset Relief Program (TARP)—and purchased assets—QE1, QE2, and QE3 among others. This subsection uses the variation in some of these programs across time and banks to understand better the underlying mechanism behind REO discounts and balance sheet observables.

In the case of TARP, eligible institutions sold equity interests to the US Treasury in amounts equal to 1 percent to 3 percent of the institution's risk-weighted assets.[10] Eligibility was in part determined by the regulator's assessment of a bank's solvency. To limit taxpayer losses, banks in poor health, those with plentiful bad assets or those close to insolvency, were ineligible for TARP funds. And to remove any stigma associated with these injections and encourage other banks to apply, the Treasury first injected capital into the largest banks.

TARP likely had to two key effects. First, these capital injections mechanically increased a bank's distance to insolvency. Second, since weaker banks were ineligible for TARP funds, Treasury equity purchases likely conveyed positive information about a bank's solvency, helping recipients more easily raise outside equity. These effects suggest that for a given distance to insolvency—the tier 1 ratio—a bank that received TARP funds, and now viewed as solvent, might have

[10] An overview of TARP can be found here: https://www.treasury.gov/initiatives/financial-stability/TARP-Programs/bank-investment-programs/cap/Pages/default.aspx

less incentive to dispose of REO assets at a discount, as it would now have the balance sheet capacity to potentially wait for a rebound in prices. Of course, recipient banks could use the capital injection to realize losses and clean up their balance sheets.

To evaluate the effects of TARP then, I use a simple difference-in-difference model, creating an indicator variable that equals 1 in the quarters after a bank receives TARP funds, and 0 otherwise. I also interact this variable with a bank's tier 1 to risk weighted assets ratio. The evidence in column 9 of Table 5 suggests that after a bank receives TARP, the relationship between the equity constraint and liquidation values weakens. The interaction term is negative, and both variables are significant at the one percent level (p-value=0.01).

Together, a one standard deviation decrease in the tier 1 ratio is associated with a 2.9 percent drop in the price of the asset. But in the period after a bank receives TARP, and is now widely seen as solvent and presumably can raise outside equity more easily, the same decline in the solvency ratio is associated with a 1.9 percent decline in REO price. While this evidence is suggestive that equity injections might help contain destabilizing asset sales, unobserved heterogeneity that determine selection into TARP could bias the inference and this evidence should be interpreted cautiously.[11]

Quantitative easing—the purchases of assets such as mortgage backed securities (MBS) and Treasuries of various maturities by central banks—can also affect banks' incentives to sell assets and equilibrium liquidation values. In the most direct channel, the solvency of banks with significant on-balance sheet exposures to MBS and Treasuries improves when central banks purchase these assets and inflate their prices. Improved solvency could then reduce a bank's incentive to sell REOs at a

[11] In evaluating the effects of TARP, a sizeable literature has pursued a diverse range of emprical strategies. See for example (Berger, Makaew, and Roman (2018) and Duchin and Sosyura (2014))

discount. Central bank purchases of MBS can also improve the liquidity of these assets, again reducing the need for banks to sell REOs at a discount. There are other channels through which QE can affect liquidation values, including through demand and expectations—see (Foley-Fisher, Ramcharan and Yu (2015), and the surveys in Williamson (2017) and Krishnamurthy and Vissig-Jorgensen (2013)).[12]

To gauge the impact of these asset purchases on liquidation values, I follow Rodnyansky and Darmouni (2016) and compute each bank's exposure to QE asset purchases based on the bank's holdings of MBS and Treasury securities in 2007, expressed as a share of assets. This ratio is then interacted with indicators that equal 1 for the various QE policy interventions; these indicator variables also appear linearly in the regressions, while the cross-sectional exposure to QE—the ratio of MBS and Treasuries to assets in 2007—is absorbed in the bank fixed effects.

Column 10 reports these results. During QE1 and QE2, there is significant evidence that liquidation values are higher when a bank has more MBS and Treasury holdings. For a bank at the 10$^{th}$ percentile of this ratio, liquidation values during QE1 are about 0.3 basis points higher than otherwise. But for a bank at the 90$^{th}$ percentile, and thus heavily exposed to QE1's attempt to stabilize the MBS market, liquidation values are 0.96 percentage points higher on average. While QE1 was unexpected, QE2 and QE3 were largely anticipated by markets, and the effect in QE2 is about 22 percent smaller relative to QE1 and insignificant in the case of QE3. Again, while this evidence is suggestive of the balance sheet channel in determining liquidation values, other explanations, including unobserved demand or changes in expectations, remain possible.

*Local Absorptive Capacity*

[12] In the case of bank lending, the evidence is mixed. Rodnyansky and Darmouni (2016) find that QE1 and QE3—MBS purchases—led to more lending to firms. Using a similar methodology, Chakraboty, Goldstein and Mackinlay (2016) find that banks more exposed to QE1 and QE2 through their MBS holdings increased mortgage lending, but decreased lending to firms.

Apart from the balance sheet of the bank, the variation in the local capacity to absorb asset sales can also provide another source of heterogeneity that can help identify the underlying mechanism. In zip codes with a larger number of non-bank asset sales that absorb the local cash available in the market, there may be more limited capacity to absorb additional bank asset sales without dislocating prices (Allen and Gale (1994)). Sales of bank collateral in these areas should then be associated with even lower liquidation values: The impact of balance sheet pressures on liquidation values should be larger when the local capacity to absorb more asset sales is limited and the bank also has less cash.

For the below-median cash subsample, column 1 of Table 6 adds the interaction between the deposit growth variable with the log of the number of non-bank foreclosures within the zip code—I also include all variables linearly. The interaction term is positive and significant—both variables are jointly significant at the 1 percent level—and suggests that asset sales by non-bank institutions amplify the impact of bank balance sheet liquidity on liquidation values. For a zip code-quarter observation at the 10$^{th}$ percentile of non-bank foreclosure sales, a one standard deviation decrease in deposit growth is associated with a 1.6 percent drop in liquidation values. But at the 90$^{th}$ percentile of non-bank foreclosure sales, a similar loss of funding is associated with a 2.5 percent drop in the liquidation value of the distressed collateral. Column 2 restricts the sample to the more liquid banks. A similar pattern emerges, but the economic magnitudes are about 30 percent smaller.

Distress among natural buyers can also shape the variation in the local capacity to absorb asset sales and provide another source of heterogeneity to help identify the underlying mechanism (Shleifer and Vishny (1997) and Fostel and Geanakoplos (2008)). These arguments observe that during booms, the most optimistic buyers become the natural buyers, as they most want the asset and use the most leverage to obtain it. During a price downturn, losses to these highly leveraged natural buyers can limit their credit access and sideline these buyers from local housing markets. The sidelining of natural buyers can in turn depress liquidation values even further when banks engage in forced sales.[13]

To understand the role of natural buyers in shaping these results, I compute the median leverage—loan to value ratio—of all property transactions in the zip-codes in the sample over the boom period of 2004-2007. In zip-codes with high leverage during the boom, local residents, the natural buyers of local real estate, likely do not have any remaining borrowing capacity to absorb asset sales by banks in the bust. But in areas that used less leverage during the boom, local natural buyers are less likely to be sidelined from the housing market, and the rapid sales of assets is less likely to dislocate the price.

The results in columns 3 and 4 of Table 6 are consistent with the natural buyer hypothesis: The price effects of illiquidity are higher in areas with more leveraged homeowners. From column 3, among banks with below median cash, a one standard deviation decrease in deposits is associated with a 1.9 percent drop in liquidation values in zip codes at the 10$^{th}$ percentile of median leverage. But the same deposit shock suggests a 2.3 percent drop in the liquidation value in zip codes at the 90$^{th}$ percentile of leverage. Among banks with above median cash, and thus the capacity to absorb better a funding shock, the effects are trivial. A one standard deviation decrease in deposits is associated with a 1.3 percent drop in liquidation values regardless of whether leverage is at the 10$^{th}$ or 90$^{th}$ percentile. Sidelined natural buyers then, and the overhang of future sales itself, appear to amplify the effects of balance sheet illiquidity on liquidation values.

[13] Note that this approach is similar to Granja, Matvos and Seru (2017) who show that local intermediary leverage affected the disposition of failed bank assets.

Differences in state foreclosure laws provide a source of plausibly exogenous variation in local absorptive capacity that can also help identify how the local supply of distressed assets might interact with balance sheet pressures to shape liquidation values. Foreclosures are much slower in states that require lenders to use the courts in order to foreclose upon real estate collateral (judicial foreclosure states). While in "power of sale" states, lenders can in many cases seize and liquidate collateral after due notice of default, without going through the courts (Pence (2006)).

There is already evidence that foreclosure rates in "power of sale" states are higher, and that the impact of these laws can affect local prices (Mian, Sufi and Trebbi (2010), Rajan and Ramcharan (2016)). And we would expect then that balance sheet pressures should have a bigger effect on liquidation values in "power of sale" states. To this end, columns 5 and 6 estimate separately the baseline regression for liquidations in judicial and power of sale states. In the latter states, a one standard deviation decrease in deposit growth is associated with a 1.4 percent decline in the liquidation value. But in judicial foreclosure states, where legal frictions preclude rapid asset disposition, the same decrease in deposit growth is associated with only a 0.7 percent price decline in the liquidation value of the collateral.

*Timing*

Data on the timing of asset sales can provide further corroboratory evidence on the mechanism underlying the relationship between bank balance sheets and liquidation values. If the positive relationship between deposit flows and liquidation values reflect the causal impact of liquidity, then banks with plentiful liquidity—those experiencing deposit inflows or those with sizeable cash on the balance sheet—would be expected to sell less quickly REO assets in order to obtain higher liquidation values. That is, under the liquidity hypothesis, the coefficient on deposits flows should be negative: Sales are more likely when deposit flows decline. If however deposit growth proxies for good local economic fundamentals and plentiful cash in the local market, then positive deposit growth should positively affect both liquidation values as well as the probability that a foreclosed asset sells: Sales are are more likely when deposit flows increase and there is plentiful cash in the local market.

To test this hypothesis, Table 7 uses a linear probability model to understand how illiquidity might affect the probability of selling available-for-sale REO assets in a given quarter. Using information on the date the property first became available for sale along with the actual date of sale, Table 7 creates an unbalanced panel. The dependent variable equals 0 in the quarters when the property is available for sale and 1 in the quarter when the property is finally sold. The median property takes about three quarters to sell. Column 1 models the probability that an available-for-sale property is sold as a function of the baseline bank balance sheet variables.

Consistent with the balance sheet channel, illiquidity increases the probability of observing a sale. A one standard deviation decrease in deposit growth is associated with a 1 percent increase in the probability that a property is sold in next the quarter. The tier 1 capital coefficient is however insignificant. Column 2 next includes the rich set of hedonic controls. There is little change in the deposit growth point estimate. Finally, columns 3 and 4 split the sample into those banks with above median (column 3) and below median (column 4) cash to asset ratio in the period before the sample begins. Among the banks that began the sample period with scare liquidity (column 4), the deposit growth coefficient is about 75 percent larger than the coefficient obtained in column 3. Thus, given that deposit outflows are associated with a greater probability of sale, it seems unlikely that the deposit flows variable proxies for local economic conditions.

## 5. Robustness: The Endogeneity Concern

The evidence on the price bounce, along with the heterogeneity in predetermined balance sheet liquidity and local absorptive capacity in shaping liquidation values and the timing of sales is hard to reconcile with omitted fundamentals, reverse causality or endogenous selection. But these remain important concerns and this subsection develops a variety of robustness checks to evaluate the endogeneity concern.

### *5.A. Unobserved current economic conditions*

*Local controls*

The first series of tests exploit the geospatial detail in the data to help gauge the potential for biased estimates due to unobserved local economic conditions. Poor local economic conditions could for example cause depositors to run on a weak local bank, helping to explain both deposit outflows or higher deposit rates and depressed liquidation values. To this end, since the dataset observes the property's address, column 1 of Table 8 includes zip code-level house price changes observed from one month before the transaction and up to six months prior to help assess the extent to which local economic conditions might drive these results.

House price changes at this fine level of spatial disaggregation are likely to be a useful proxy for local economic conditions. The number of observations decline slightly as zip code level house price data are not uniformly available for all zip codes. Unsurprisingly, there is some evidence that local house price dynamics is positively related to liquidation prices. Over the six-month window, a one standard deviation increase in the house price index is associated with a 2.1 percent increase in liquidation values—these coefficients are omitted for concision. The impact of illiquidity and solvency continues to be unchanged.

To non-parametrically absorb more general time varying zip code-level shocks, column 2 uses zip code—there are 4,582 zip codes in this sample--by year-quarter fixed effects—the period spans 31 quarters. The balance sheet variables remain unchanged. While the marketing of residential real estate tends to occur at the zip code level, census tracts are more compact geographic regions that tend to contain households with similar economic and demographic characteristics. Column 3 thus uses tract interacted with year by-by-quarter fixed effects to absorb time-varying shocks at this level of geography. Census tract data are not available for all properties, but the main results are again unchanged.

*Multi-State Banks*

The remaining tests try to parse the influence of local economic conditions by using the fact that the vast majority of foreclosure observations in the sample come from banks that operate across multiple markets, such as Bank of America and Wells Fargo. For these large multi-state banks, local economic conditions in any given market will likely have a small or negligible impact on bank balance sheet outcomes. But for banks that operate within a single market, often smaller community banks, current local economic shocks are more likely to jointly influence both the balance sheet of the bank and subsequent liquidation values.

Systematically excluding the smaller less geographically diversified banks thus provides a way to limit any biases from unobserved current local economic conditions. There are 12 states in the sample, and to exploit this geographic diversification, column 4 of Table 8 uses the baseline specification from column 3 of Table 4, but excludes observations from banks that operate within only a single state. The results are unchanged. Conversely, about 90 percent of foreclosure observations in the sample come from banks that operate across all 12 states in the sample, and column 5 restricts the sample to this geographically diversified group. The results again remain unchanged. Column 6 measures geographic range at the county level. About 95 percent of liquidations in the sample stem from banks that have liquidated at least one foreclosure across 112 counties or more. For this subsample of banks operating across such a large geographic range, county-level unobserved economic shocks are unlikely to both influence liquidation prices and bank balance sheet outcomes.

Column 7 of Table 8 focuses on the finer zip code level outcomes. At this level of spatial disaggregation, unobserved local shocks are even less likely to be a source of bias for diversified banks. Using the same 95 percent threshold, column 7 restricts attention to the top 95 percent of liquidations: banks with foreclosures spread across more than 553 zip codes. The results remain robust.

Finally, column 8 more directly addresses the endogenous run concern. Some banks set their deposit rates at the headquarters, while other banks allow for "rate-setting" branches. In the latter case, local branches are allowed to set deposit rates based on local economic conditions and the relative supply of local deposits. Asset liquidations are however centralized; Bank of America created for example a legacy asset division to handle Countrywide asset dispositions.

Therefore, using the sample of multi-state banks, column 8 studies the impact of deposit rates set at headquarters on liquidation values. Concretely, this exercise is analogous to estimating the impact of  Bank of America's deposit rate set in Charlotte, North Carolina on properties liquidated in zip-codes across California, Florida, Arizona and the other disparate states in the sample. For this sample of banks, the headquarter's rate is clearly not driven by local economic conditions in California zipcodes. And it is extremely unlikely in this sample that that unobserved poor local economic conditions cause depositors to withdraw from the local bank, simultaneously pushing up deposit rates and depressed liquidation values. The negative impact of deposit rates on liquidation values remain, suggesting that latent fundamentals story is unlikely to explain the results.

*5.B Selection*

The endogenous selection of delinquent properties into foreclosure is a potential source of bias. Once a loan becomes delinquent, the bank and borrower can agree to revise the loan terms and return the loan to current status. Otherwise, failing agreement, the bank can foreclose upon the property; the property then enters the sample of liquidated bank collateral. This sequence of decisions implies that unobserved bank-level characteristics that drive selection into foreclosure could also be correlated with the balance sheet variables, leading to biased estimates in the pricing equation. For example, banks with limited equity or those concerned that realized losses could signal deeper balance sheet problems and exacerbate funding pressures might only foreclose upon higher quality collateral. [14] This could bias downwards the relationship between solvency or illiquidity and liquidation values in the pricing equation.

To be sure, the set of collateral and balance sheet controls can help mitigate these selection concerns. And institutional features of the foreclosure process also weigh against selection bias. Mortgage servicers—not necessarily banks—often managed the resolution of delinquent loans. And financial regulators observed that these servicers became so overwhelmed by the volume of loan delinquencies that significant backlogs occurred, as computer systems designed to process routine payments during boom times proved unable to track delinquencies. If anything, to maximize the net present value of their servicing fee, servicers tended to foreclose

[14] In the context of models of bank runs such as Diamond and Dybvig (1983), low liquidation values can also act as a coordinating mechanism for beliefs about the bank's ability to honor the sequential service constraint, inducing runs. Variations of this idea center on only some individuals being partially informed about solvency and the future returns to deposits, as proxied for by low liquidation values. This again can induce a run, as less informed agents observe the "length of the withdrawal line" and run on the bank (Chari and Jaganathan (1988), Bhattacharya and Gale (1987). He and Manela (2016) models depositors' endogenous acquisition of noisy information about bank liquidity, such as observing liquidation values in the current context, when there is uncertainty about the bank's capacity to honor the sequential service constraint. This approach creates rich withdrawal dynamics and endogenous failure rates based on the quality of the information.

upon delinquent borrowers too quickly.[15] The large volume of delinquent properties and the incentives facing servicers both suggest that servicers likely had little capacity or incentive to strategically select which borrowers to foreclose upon in response to bank balance sheet observables.

Nevertheless, to address more directly selection bias concerns, for each bank in the sample, I collected data on its population of delinquent loans. Together, the number of delinquent properties is about 1.6 million for the 680 banks in the sample. The delinquency data include the usual underlying collateral characteristics; the date the property first became delinquent, and of course the date when the property is foreclosed upon and liquidated or the date that the property is no longer delinquent. These data allow us to model directly the selection into foreclosure decision.

Using the population of delinquent loans, column 1 of Table 9 examines whether the balance sheet liquidity and solvency measures help predict whether a delinquent property is selected into foreclosure. The dataset is an unbalanced quarterly panel of delinquent properties that begins in the quarter of delinquency and ends if the property is either liquidated or is no longer delinquent; the data are censored when the sample ends in 2015 Q4. The dependent variable equals 1 in the quarter when the property is foreclosed upon and liquidated, and 0 otherwise.

Consistent with the institutional details surrounding the delinquency crisis and mortgage servicers, there is no significant evidence that the one quarter lagged liquidity and solvency measures are related to whether a delinquent property is selected into foreclosure (column 1 of Table 9). The remaining columns of Table 9

[15] The Federal Housing Finance Agency (FHFA) (2011) notes that on a performing loan, costs to servicers are small, and for these loans, the typical 25 basis point servicing fee and other revenue easily exceed the cost of servicing. But for nonperforming loans, the costs associated with collections, advancing principal and interest to investors, loss mitigation, foreclosure and the maintenance and disposition of the REO assets can be both substantial and unpredictable, easily exceeding the servicing fee. See "Alternative Mortgage Servicing Compensation Discussion Paper (FHFA (2011): https://www.fhfa.gov/PolicyProgramsResearch/Research/Pages/Alternative-Mortgage-Servicing-Compensation-Discussion-Paper.aspx

investigate further the extent of any sample selection bias in the pricing equation. The main exclusion restriction uses the duration of the mortgage contract. Buyers using short-term mortgage contracts are more likely to be short term speculative investors who intend to flip or resell quickly the house. Given declining prices, these investors would be expected to be more willing to allow a property to enter foreclosure, conditional on delinquency (Bernanke (2010), Geanakoplos (2010)).

Information on duration is available for only a subset of the delinquent properties, of which about 80,000 became REO assets. Column 2 includes the log of the number of days from origination until the first mortgage interest rate reset in the selection-into-foreclosure equation: The dependent variable equals 1 in the quarter the delinquent property is foreclosed upon. As before, the balance sheet variables are not significant in the linear probability model, but the maturity of the mortgage reset enters negatively: a 10 percent decrease in the number of days from origination until the first reset is associated with a 0.01 percent increase in the probability that delinquency culminates in foreclosure. The implied economic effects using the probit model in column 3 is similar to those obtained in column 2.

The inverse Mills ratio is significant, but despite the considerably smaller sample—only 78,286 properties in the pricing equation—the liquidity and tier 1 equity point estimates are nearly identical to that observed in the full sample of 377,000 observations (column 2 of Table 4). Indeed, these balance-sheet point estimates are also nearly identical to those obtained using the same 78,286 properties, but without correcting for selection bias (column 5). Hence, both the narratives around mortgage servicing and the statistical evidence suggest that any bias from non-random selection into the pool of foreclosed properties is likely to be small.

### *5.C. Collateral Quality*

The evidence in Table 2 suggests that the endogenous matching between retained collateral and bank type might be limited, but to help address concerns about biased estimates due to endogenous matching, column 1 of Table 10 takes advantage of the detailed information on collateral characteristics and include several hedonic variables to control for quality. These variables include the age of the property; an indicator for whether the property was remodeled in the last 10 years; the log of the square footage; the log of the total number of bathrooms; and the log of the total number of bedrooms. These variables could be noisy as they do not record renovations not registered with the county, but they all enter with their expected signs. For instance, liquidation values are about 8 percent higher for properties remodeled in the last 10 years. The sample size shrinks by about 20 percent as not all of these variables are available for every transaction, but the liquidity and solvency point estimates remain unchanged.

Information about the loan contract at origination can help up further gauge the relevance of endogenous matching. In particular, the choice of leverage at loan origination can be closely related to a bank's business model and its subsequent exposure to illiquidity or losses. At the same time, leverage can also itself proxy for collateral quality. For example, the debt capacity might be greater for collateral perceived to be more liquid, resulting in higher loan to value (LTV) ratios at origination and possibly higher ex-post liquidation values (Shleifer and Vishny (1992)). Alternatively, because of debt overhang, high LTV ratios could depress the liquidation value of troubled assets.

To assess the impact of leverage, column 2 of Table 10 includes the price of the property at origination, while column 3 adds the loan to value ratio, also observed at origination. The coefficient on the price at origination documents the low recovery rates obtained when selling distressed collateral during the bust. A 10 percent increase in the price at origination is associated with only a 1.7 percent increase in the subsequent liquidation value (column 2). There is also significant evidence that increased leverage at origination depresses liquidation values (column 3). There is no change however in the liquidity and solvency point estimates.

Rather than using information about the loan contract at origination to gauge the impact of endogenous matching, column 4 uses the information about the bank's balance sheet itself at origination. The endogenous matching concern centers on the possibility that the ex-ante variation in bank balance sheets might determine jointly the choice of collateral quality, the subsequent liquidation values of REO assets and the bank's exposure to liquidity and equity shocks during the liquidation period. The analysis has already controlled for hedonic characteristics and loan terms that might indicate collateral quality. But directly observing key balance sheet variables around loan origination can help further gauge the extent of any bias emanating from the endogenous matching between bank type and collateral quality.

Column 4 thus includes asset liquidity, the tier 1 capital to risk weighted assets ratio, total assets and the deposit to asset ratio, all observed in the quarter before loan origination. The regression also includes year-by-quarter loan origination fixed effects. There is some evidence that asset liquidity at the time of origination is correlated with subsequent liquidation values, but there is again little change in the deposit flows or the book equity point estimates observed in the quarter before liquidation. This evidence suggests then that balance sheet liquidity and solvency might shape liquidation values, even after controlling for key collateral characteristics and the potential for endogenous matching at origination.

Finally, in results available upon request I examine the relative importance of market versus book equity in shaping liquidation values. Using data from the Center for Research on Security Prices, the first test replaces the book equity variable with the average quarter on quarter change in the bank's stock price, lagged one quarter.

Only 190 banks are public in the sample, reducing the sample of liquidated properties. But the change in market equity is positively associated with liquidation values. A one standard deviation decrease in market equity is associated with about a one percent drop in liquidation values. Rather than reflecting information in book equity, the next test includes both book and market equity, showing that they independently affect liquidation values.

## 6. Spillovers

The impact of illiquidity and solvency on the liquidation values of REO sales. can have broader consequences. Because pricing in real estate is based in part on the price of previous sales of comparable assets, low liquidation values among bank owned properties could also depress the subsequent price of otherwise similar non-bank owned properties (Annenberg and Kung (2015), Murfin and Pratt (2016)). In this way, bank balance sheet pressures could negatively spill over onto the prices of nearby non-foreclosure or arms-length home sales, depressing collateral values more widely and impeding economic activity (Rajan and Ramcharan (2016)). This subsection now examines whether the liquidation values among bank-owned properties might affect the prices of other nearby properties.

To understand then the spillover effects of REO sales, the analysis turns to transaction level data on all residential arms-length real estate sales for the 5 states in the sample the provide the latitude and longitude of the house.[16] Using the date of sale and location of each of these arms-length transactions, I match each arms-length transaction to an REO sale using a simple nearest neighbor approach: I identify the geographically closest REO sale within the previous 18 months that is located no further than one kilometer away from the arms-length transaction. This

[16] The five states are Arizona, California, Colorado, Florida, Nevada, and Washington.

criteria yields about 805,000 unique real estate transactions that match to one of the 167,000 REO transactions in these 5 states. The median distance is about 140 meters—the same block— while the median REO sale precedes its nearest arms-length neighbor by about 240 days. Given this relative geographic and temporal proximity, the nearest REO sale is likely to be a relevant comparable for the pricing of the subsequent non-bank sale.

Using this simple nearest neighbor approach, column 1 of Table 11 regresses the price obtained in the arms-length transaction on the liquidation value of the nearest REO sale within the eighteen month and one kilometer window. Not surprisingly given the geographic and temporal proximity, the coefficient is positive and significant. A one percent increase in the liquidation value is associated with a 0.4 percent increase in the price of the nearest subsequent sale. The regression includes zip code and year-by-quarter fixed effects.

But time-varying local unobserved shocks that simultaneously affect liquidation values and the sale price of homes in the area is a significant challenge to causal inference within this empirical design. Notably, positive shocks—local fundamentals—for example that increase liquidation values could also increase the price of nearby arms-length transactions, imparting an upwards bias. The existing literature has used hedonic controls and spatial disaggregation to help address these concerns, and building on this existing work, column 2 includes hedonic details about the house to control better for its "fundamental" value. These variables enter with their expected signs, and the point estimate on the log liquidation value of the nearest neighbor REO sale declines by about 36 percent, suggesting that these hedonic variables might reasonably control for the fundamental value of the asset.

But in order to limit the influence of broader economic shocks that might drive both liquidation values and arms-length prices, column 3 narrows the distance window between an REO sale and the subsequent arm's length transaction to be no more than 140 meters apart—the median distance in the full sample. The median distance in this subsample is now 70 meters, resulting in many properties that are either physically adjacent or located in the same physical structure as their matched REO sale. The point estimates on the REO liquidation value across the two samples are nearly identical.

Using this narrow distance window, column 4 includes the monthly change in house prices, observed in the current month and one month prior to the sale. The effects of common economic shocks in the local area on prices are likely to be nearly identical for two properties located less than 140 meters apart. Thus, if these results reflect the simultaneous impact of latent local housing market conditions on the price of non-foreclosure and REO sales, then the REO point estimate should weaken when conditioning on zip code-level house prices. The point estimate is in fact unchanged.

While this evidence is reassuring, the previous evidence on the impact of liquidity and solvency on liquidation values offer a new way to estimate causally the impact of REO sales on nearby properties.  Column 5 builds on this previous balance sheet evidence, instrumenting the liquidation value of the REO asset with the deposit flows and tier 1 equity ratio of the bank. The 2SLS estimate in column 5 is less precisely estimated than its OLS counterpart in column 4, but is only about 15 percent smaller, suggesting that the influence of omitted local shocks might indeed be limited.

The 2SLS estimate can however be biased if local economic shocks that affect liquidation and home values are also correlated with these balance sheet variables. For example, the balance sheet of banks that earn most of their revenues in a local area could be affected by the same unobserved shocks that also drive liquidation values and transactions prices. Put differently, in zip codes where liquidating banks had bigger market shares, unobserved shocks to the balance sheet of these banks could also affect the prices of non-bank transactions. Column 5 uses zip code-by-bank fixed effects to non-parametrically absorb the pre-existing variation in individual bank market shares across zip codes. The 2SLS estimate is only marginally smaller.

More generally, the robustness exercises in Table 8 already suggest that biases from current unobserved economic shocks are likely very small in this empirical design. But to assuage concerns, in results available upon request I use only REOs sold by banks active in more than one state, as well as separately, I use REOs from banks that are active in all 5 states. These specifications thus include only geographically diverse banks, making it extremely unlikely that their balance sheet outcomes in previous quarters—the instruments—are conditionally correlated with local economic shocks inside a zip code. Consistent with this logic, the 2SLS point estimates are little changed across the samples. The results in Table 11 suggest that liquidity and solvency pressures at banks can lead to discounts on the sale of REO properties that in turn can also lower the prices of nearby homes.

## 7. Conclusion

This paper studies the relationship between bank balance sheets and the liquidation value of real estate collateral. I find that the balance sheet of financial institutions significantly influence the liquidation values of disposed collateral. Liquidation values tend to decline and the probability of an asset sale tends to increase when banks lose deposits or are forced to increase deposit rates to attract liquidity. Bank illiquidity is also associated with an economically large price rebound and these effects are substantially larger when asset liquidity is limited or when banks have large off-balance sheet exposures. Similarly, declining equity buffers or falling stock prices are also associated with lower liquidation values

Low liquidation values among bank-owned properties also spillover onto non-bank owned sales. These effects are especially large for recent nearby non-bank owned sales. All this suggests that the sharp and extended deflation in real estate prices common after crisis events reflect both the effects of household deleveraging as well as ongoing balance sheet adjustments at financial institutions. Empirical studies focused on causal inference cannot measure the general equilibrium effects of policy interventions. But these results suggest that despite their potential economic costs, regulations that constrain balance sheet choices during boom times might in turn limit the potential for prolonged asset price busts when adverse shocks occur. Relatedly, efforts at recapitalizing banks or providing liquidity during times of distress might forestall asset sales and more general asset price deflation.

## Figures and Tables

### *V.A Figures*

Figure 1. Multi-State Banks and the Local Endogeneity Concern

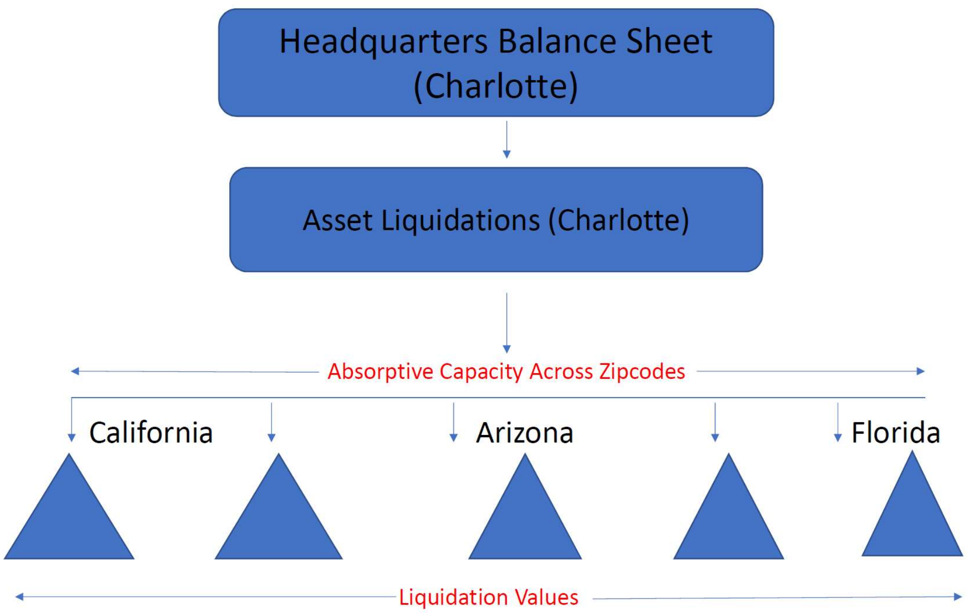
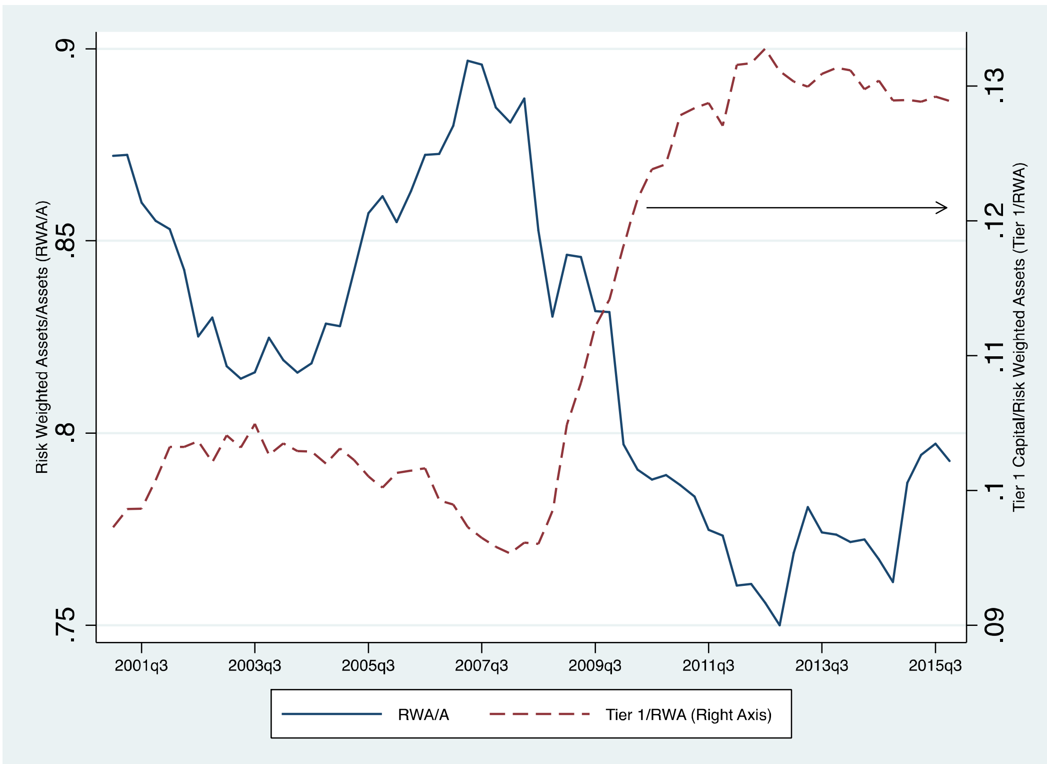


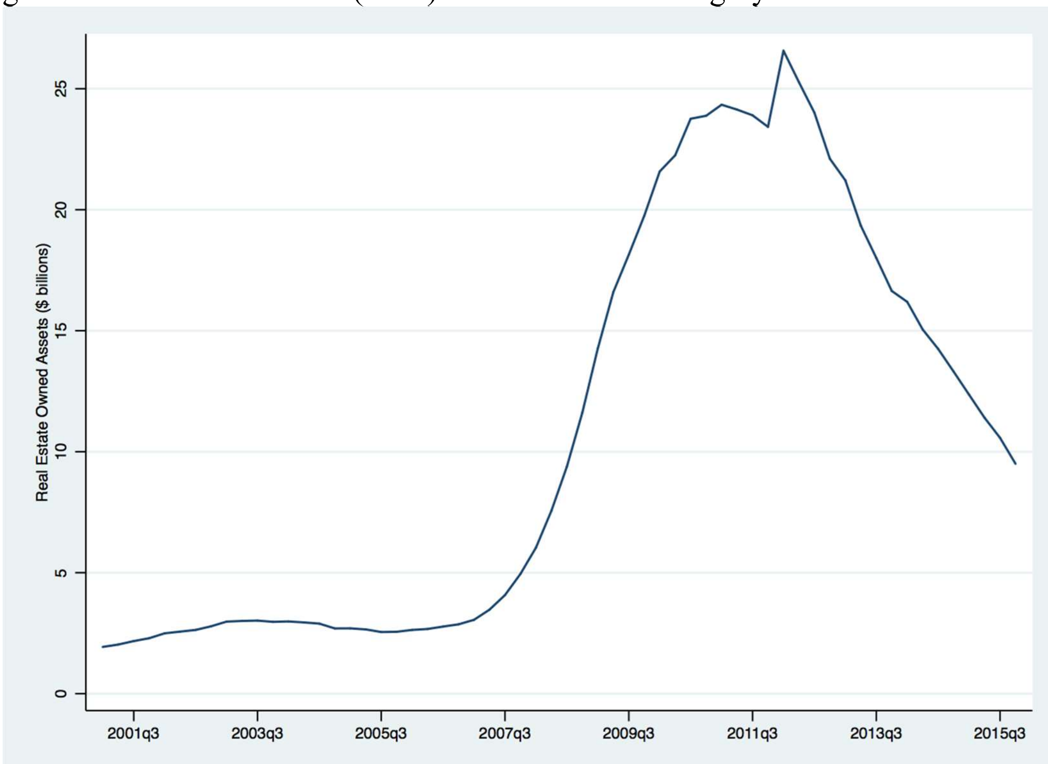

Figure 1 illustrates the research design used in Table 8 to address the concern that unobserved local shocks simultaneously impact balance sheet outcomes and liquidation values. Large banks such as Bank of America set their deposit rates both at the headquarters (Charlotte) and at regional "rate-setting" branches. At such banks, asset liquidations are centralized. The research design estimates the impact of changes in Bank of America's deposit rate set in Charlotte, North Carolina on properties liquidated in zip-codes across California, Arizona and Florida. The headquarter's rate likely reflect balance sheet pressures at the bank-level and provide the impetus for asset liquidations, while the absorptive capacity in the zip-code help determine liquidation values.

Figure 2. Risk Weighted Assets and Tier 1 Capital in the Banking System, 2001-2015



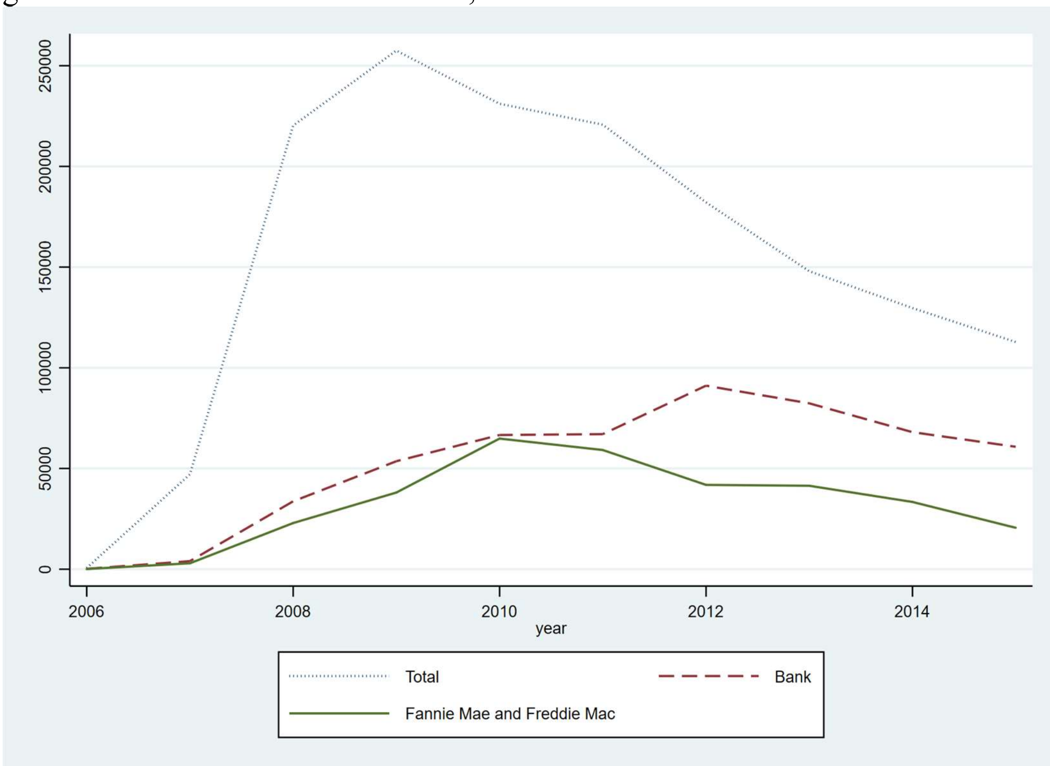

The solid line is the sum of risk weighted assets in the U.S. banking system divided by the sum of total assets. The dotted line is the total of tier 1 capital divided by the sum of total risk-weighted assets. The data are from the Call Report.

Figure 3. Real Estate Owned (REO) Assets in the Banking System



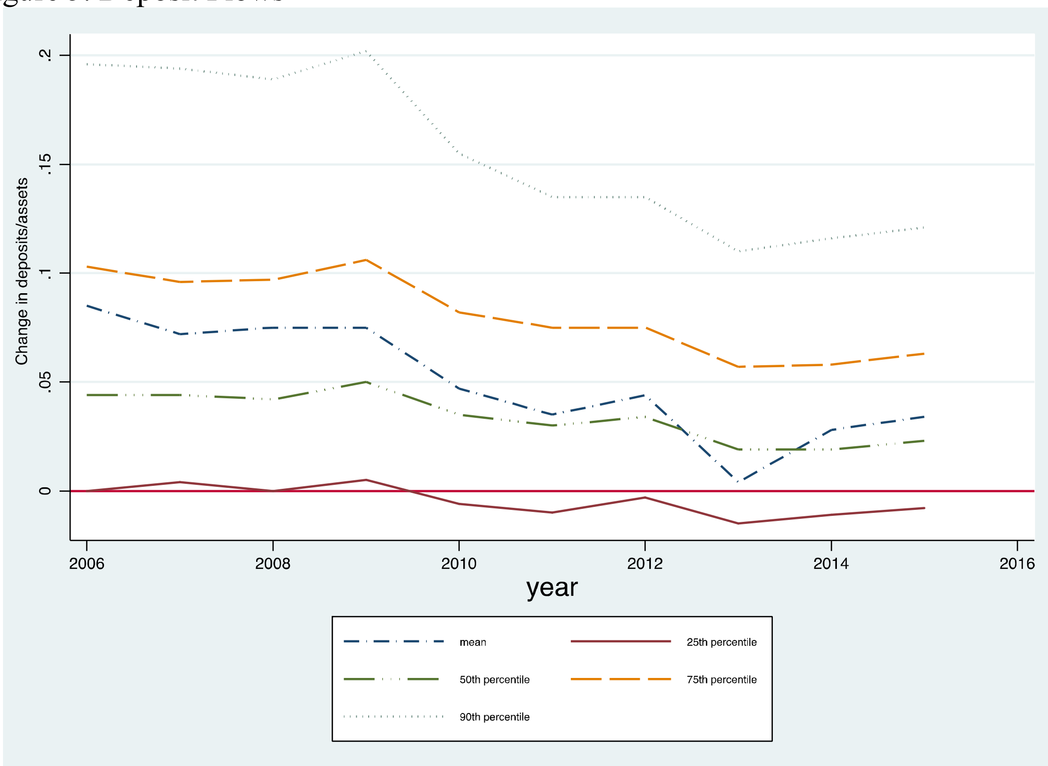

This figure plots the total REO assets held on the balance sheet of commercial banks from 2001 Q2 through 2015 Q4.

Figure 4. The Number of Foreclosures, 2006-2015.



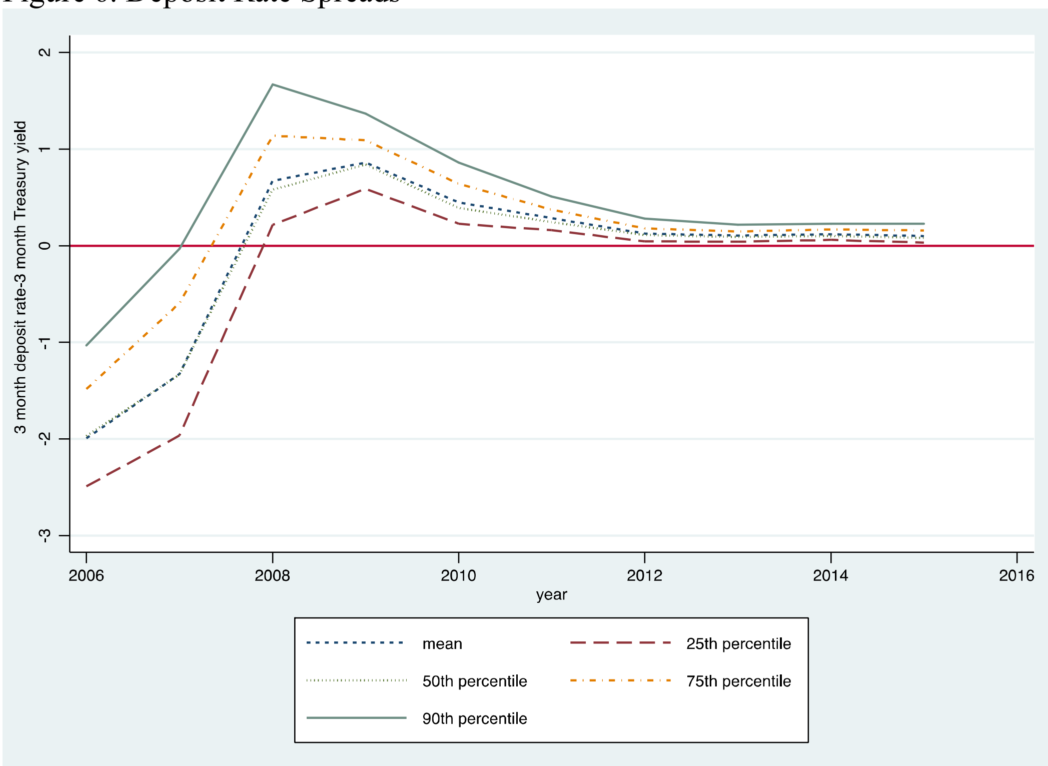

This figure plots the annual total number of foreclosures, the number from Fannie and Freddie Mac (agency) trusts, and the number of bank foreclosures in the ZTRAX database over the sample period. The states in the sample are Arizona, California, Colorado, Florida, Illinois, Michigan, New Jersey, Nevada, Ohio, Pennsylvania, Texas and Washington.

Figure 5. Deposit Flows



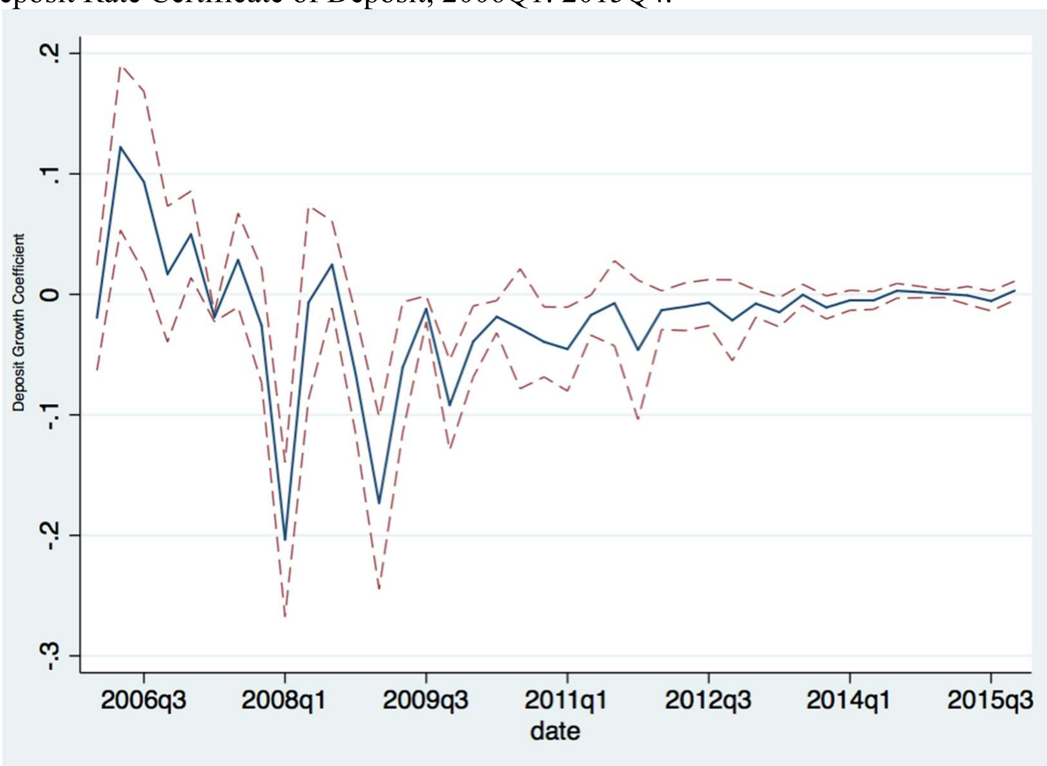

This figure shows the year-on-year change in deposit flows divided by assets in the previous year in each quarter from 2006 Q1 through 2015 Q4 for banks at various points in the cross-section distribution. For example the "50$^{th}$ percentile" plots the median deposit change observed in a given quarter among the cross-section of banks in that quarter.

Figure 6. Deposit Rate Spreads




This figure shows the spread between the three month certificate of deposit rate offered by a bank and the yield on the three month Treasury bill in each quarter from 2006 Q1 through 2015 Q4 for banks at various points in the distribution. For example the "50th percentile" plots the median spread observed in the quarter among the cross-section of banks.

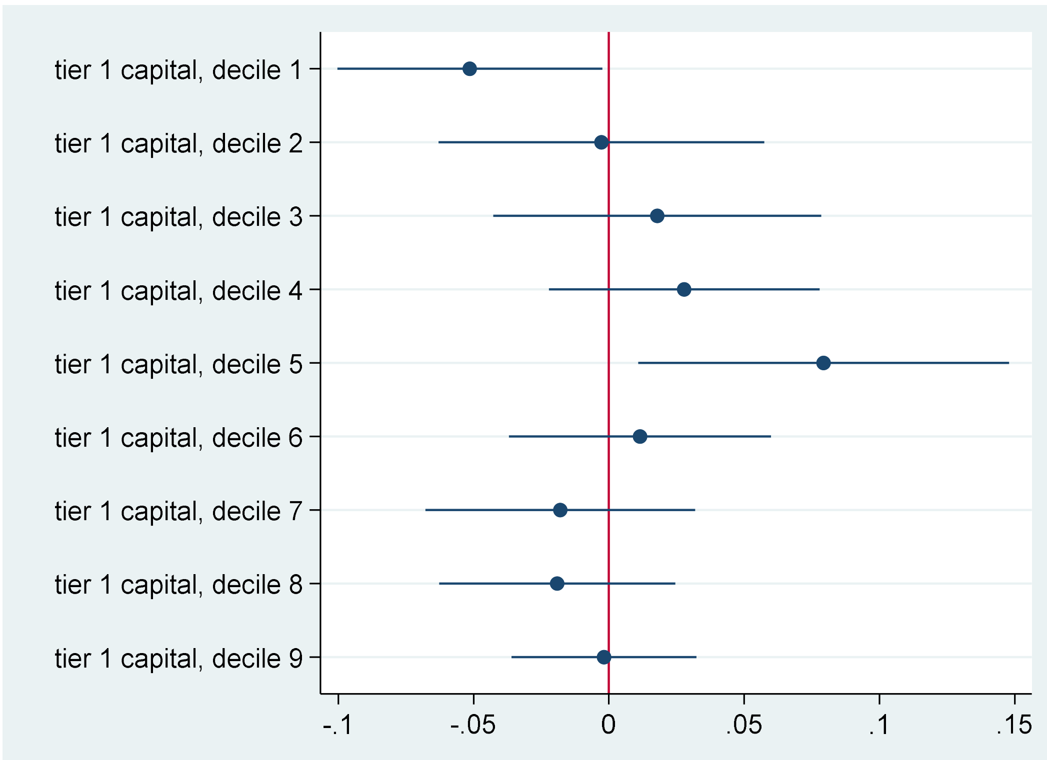
Figure 7. Relationship Between Deposit Growth and Change in Three Month Deposit Rate Certificate of Deposit, 2006Q1: 2015Q4.




For each quarter in the sample period, the regression $Change\ in\ three\ month\ deposit\ rate\ CD = \beta_0 + \beta_1 change\ in\ deposits + \epsilon$ is performed for the crossection of banks. The figure plots $\beta_1$--the solid line—along with the 95 percent confidence band using robust standard errors.

Figure 8. Non-Linear Impact of Equity Constraints on Liquidation Values

This figure reports the point estimates (dot) and 95% confidence bands for indicator variables that equal 1 if a bank-quarter observation is in a given decile and 0 otherwise. The omitted category is the top or 10th decile of tier capital to risk weighted assets: Assets liquidated by banks in the bottom decile sell at a 5.6% discount relative to those sold by banks in the top decile. The other covariates in the regression are reported in column 6 of Table 4.



## *V.B Tables*

Table 1. Bank-Owned Properties in the Sample, by State

| State | Freq. | Percent |
|---|---|---|
| AZ | 54,296 | 16.19 |
| CA | 86,830 | 25.90 |
| CO | 13,632 | 4.07 |
| FL | 75,335 | 22.47 |
| IL | 14,663 | 4.37 |
| MI | 9,914 | 2.96 |
| NJ | 1,903 | 0.57 |
| NV | 10,500 | 3.13 |
| OH | 38,103 | 11.37 |
| PA | 7,478 | 2.23 |
| TX | 11,376 | 3.39 |
| WA | 11,234 | 3.35 |

This table lists the number of liquidated bank-owned properties by each state in the sample. The states in the sample are Arizona, California, Colorado, Florida, Illinois, Michigan, New Jersey, Nevada, Ohio, Pennsylvania, Texas and Washington.

Table 2 Panel A. Collateral Characteristics, Real Estate Owned (REO) Assets, Full Sample

| | Price per square feet, at origination | Price per square feet, at foreclosure | Foreclosure price | Lot size (square feet) | Total bedrooms | Total bath | Year built |
|---|---|---|---|---|---|---|---|
| mean | 46 | 17 | 157,816 | 58,873 | 2 | 2 | 1976 |
| 25th percentile | 13 | 7 | 64,000 | 5,980 | 0 | 1 | 1957 |
| 50th percentile | 24 | 14 | 117,400 | 7,474 | 3 | 2 | 1980 |
| 75th percentile | 42 | 27 | 198,000 | 10,276 | 3 | 2 | 2000 |
| 90th percentile | 70 | 45 | 312,000 | 19,994 | 4 | 3 | 2005 |
| standard deviation | 4079 | 2431 | 920,797 | 486,439 | 2 | 1 | 27 |

This table reports summary statistics for the sample REO sold by banks.

Table 2 Panel B. Below median tier 1 capital to risk weighted assets ratio, 2006

| | Price per square feet, at origination | Price per square feet, at foreclosure | Foreclosure price | Lot size (square feet) | Total bedrooms | Total bath | Year built |
|---|---|---|---|---|---|---|---|
| mean | 35 | 12 | 150,248 | 80,182 | 2 | 2 | 1974 |
| 25th percentile | 13 | 6 | 59,000 | 6,000 | 1 | 1 | 1956 |
| 50th percentile | 24 | 13 | 109,000 | 7,500 | 3 | 2 | 1978 |
| 75th percentile | 43 | 25 | 185,000 | 10,375 | 3 | 2 | 1999 |
| 90th percentile | 72 | 43 | 310,000 | 19,166 | 4 | 3 | 2005 |
| standard deviation | 3422 | 2421 | 576,911 | 614,465 | 2 | 1 | 27 |

This table reports summary statistics for the sample REO sold by banks with below median tier 1 to risk weighted assets, averaged 2006-2001, in the sample.

Table 2 Panel C. Above median tier 1 capital to risk weighted assets ratio, 2006

| | Price per square feet, at origination | Price per square feet, at foreclosure | Foreclosure price | Lot size (square feet) | Total bedrooms | Total bath | Year built |
|---|---|---|---|---|---|---|---|
| mean | 36 | 26 | 159,848 | 53,115 | 2 | 2 | 1976 |
| 25th percentile | 13 | 7 | 65,200 | 5,952 | 0 | 1 | 1958 |
| 50th percentile | 24 | 15 | 120,000 | 7,440 | 3 | 2 | 1981 |
| 75th percentile | 42 | 27 | 200,100 | 10,243 | 3 | 2 | 2001 |
| 90th percentile | 69 | 45 | 312,958 | 20,000 | 4 | 3 | 2005 |
| standard deviation | 4249 | 2434 | 993,027 | 707,444 | 2 | 1 | 27 |

This table reports summary statistics for the sample REO assets sold by banks with above median tier 1 to risk weighted assets, averaged 2006-2001, in the sample.

## Table 2D. Below median deposits to assets ratio, 2006

| | Price per square feet, at origination | Price per square feet, at foreclosure | Foreclosure price | Lot size (square feet) | Total bedrooms | Total bath | Year built |
|---|---|---|---|---|---|---|---|
| mean | 32 | 17 | 159,460 | 63,044 | 2 | 2 | 1975 |
| 25th percentile | 13 | 7 | 64,000 | 6,000 | 0 | 1 | 1957 |
| 50th percentile | 25 | 14 | 116,000 | 7,492 | 3 | 2 | 1980 |
| 75th percentile | 45 | 26 | 196,280 | 10,237 | 3 | 2 | 2000 |
| 90th percentile | 75 | 45 | 320,000 | 19,540 | 4 | 3 | 2005 |
| standard deviation | 4194 | 2377 | 1,215,297 | 117,840 | 2 | 1 | 27 |

This table reports summary statistics for the sample of REO assets sold by banks with below median deposits to assets, averaged 2006-2001, in the sample.

## Table 2E. Above median deposits to assets ratio, 2006

| | Price per square feet, at origination | Price per square feet, at foreclosure | Foreclosure price | Lot size (square feet) | Total bedrooms | Total bath | Year built |
|---|---|---|---|---|---|---|---|
| mean | 28 | 18 | 155,951 | 54,104 | 2 | 2 | 1976 |
| 25th percentile | 12 | 6 | 64,000 | 5,876 | 0 | 1 | 1958 |
| 50th percentile | 23 | 14 | 119,000 | 7,425 | 3 | 2 | 1981 |
| 75th percentile | 40 | 27 | 199,732 | 10,324 | 3 | 2 | 2001 |
| 90th percentile | 63 | 44 | 305,000 | 20,038 | 4 | 3 | 2005 |
| standard deviation | 3932 | 2492 | 366,124 | 632,335 | 2 | 1 | 27 |

This table reports summary statistics for the sample of REO assets sold by banks with above  median deposits to assets, averaged 2006-2001, in the sample.

Table 3. Summary Statistics: Bank Balance Sheet Variables, 2006 and 2015

| | Tier 1 Capital /Risk Weighted Assets | Loans/Deposits | Deposits/Assets | Cash/Assets | Return on Assets | Assets (log) |
|---|---|---|---|---|---|---|
| | | | 2006 | | | |
| mean | 0.166 | 0.63 | 0.8 | 0.046 | 0.007 | 11.789 |
| median | 0.134 | 0.665 | 0.836 | 0.033 | 0.006 | 11.663 |
| standard deviation | 0.103 | 0.182 | 0.145 | 0.062 | 0.023 | 1.383 |
| | | | 2015 | | | |
| mean | 0.179 | 0.604 | 0.823 | 0.098 | 0.007 | 12.271 |
| median | 0.153 | 0.635 | 0.85 | 0.066 | 0.005 | 12.112 |
| standard deviation | 0.092 | 0.18 | 0.121 | 0.104 | 0.026 | 1.403 |

## Table 4. The Impact of Banks' Balance Sheets on Liquidation Values and Price Rebound.

Columns 1-6 investigate the impact of bank balance sheet variables, observed the quarter before liquidation, on the liquidation value of bank-owned real estate. In columns 1-6, the dependent variable is the log price of the property obtained in liquidation—the liquidation value. All specifications include zip-code, bank and year-by-quarter fixed effects, and standard errors, in parentheses, are clustered by zip code and bank. Columns 3-8 include the loan to deposits, deposits to total assets, cash to total assets, the log of total assets, the return to assets, all lagged one quarter as additional controls. The equity decile point estimates from column 6 are plotted in Figure 8. The dependent variable in columns 7 and 8 is the unlevered internal rate of return based on the liquidation price and the next resale price. This is defined as $\left(\frac{resale\ price_{t+n}}{liquidation\ value_t}\right)^{\frac{1}{n}} - 1$, where *n* is the number of days elapsed from liquidation by the bank to subsequent resale by the buyer.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | change in | | balance sheet | | Price and | non-linear | Price Rebound: Unlevered IRR | |
| VARIABLES | deposits | solvency | controls | deposit rate | quantity | equity | Change in deposits | Deposit rate |
| Year on year change in deposits, scaled by assets, lagged one quarter | 0.0581* | 0.0579* | 0.0694* | | 0.193*** | -0.00311 | -0.00142*** | |
| | (0.0330) | (0.0335) | (0.0356) | | (0.0401) | (0.0441) | (0.000395) | |
| Tier 1 Capital/Risk Weighted Assets, lagged one quarter | | 0.288*** | 0.241* | 0.829 | 0.731 | | 0.00176 | 0.000829 |
| | | (0.101) | (0.138) | (0.547) | (0.654) | | (0.00294) | (0.00740) |
| Change in 6 month CD rate, lagged one quarter | | | | -0.0530*** | -0.0859*** | | | 0.000952*** |
| | | | | (0.00969) | (0.0104) | | | (0.000150) |
| Change in 6 month CD rate* Year on year change in deposits, scaled by assets, lagged one quarter | | | | | 0.628*** | | | |
| | | | | | (0.182) | | | |
| Observations | 377,944 | 377,944 | 377,944 | 294,621 | 294,621 | 377,944 | 120,787 | 95,075 |
| R-squared | 0.549 | 0.549 | 0.550 | 0.543 | 0.543 | 0.551 | 0.113 | 0.123 |

# Table 5. Mechanism I: Balance Sheet Liquidity.

The dependent variable is the log liquidation price. The "below (above) "x$^{th}$ " percentile" restricts the sample to those banks with cash/assets ratios, averaged over 2001-2006, below (above) the x$^{th}$ percentile. From column 7, the sum of the coefficients for "year on year change in deposits, scaled by assets"+ "year on year change in deposits, scaled by assets*off-balance sheet comittments+assets/assets" is 0.140 (p-value=0.00). In column 8, this sum is -0.04 (p-value=0.56). In column 9, the variable "TARP" equals 1 after a bank receives TARP funds and 0 otherwise. QE "i" are indicator varaibles that equal 1 in the quarters in which the specific program was in place. "MBS and Treasury" holdings is the ratio of these assets to total assets in 2008. All specifications include the baseline control from column 3 of Table 4: loan to deposits, deposits to total assets, cash to total assets, the log of total assets, the return to assets, all lagged one quarter All specifications include zip code, bank and year-by-quarter fixed effects, and standard errors, in parentheses, are clustered by zip code and bank.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | cash | | | | | | | | | |
| VARIABLES | bottom quartile | top quartile | below median | above median | above median | above median | below median | above median | TARP | QE |
| Year on year change in deposits, scaled by assets | 0.220*** | 0.00455 | 0.174*** | 0.140*** | | | 0.0354 | -0.452 | 0.106*** | 0.121*** |
| | (0.0425) | (0.0771) | (0.0295) | (0.0224) | | | (0.154) | (0.320) | (0.0352) | (0.0306) |
| Change in 6 month CD rate, lagged one quarter | | | | | -0.0388*** | -0.0183 | | | | |
| | | | | | (0.0129) | (0.0222) | | | | |
| off-balance sheet comittments+assets/assets | | | | | | | 0.268*** | 0.495*** | | |
| | | | | | | | (0.0886) | (0.0734) | | |
| year on year change in deposits, scaled by assets*off-balance sheet comittments+assets/ | | | | | | | 0.105 | 0.410 | | |
| | | | | | | | (0.144) | (0.249) | | |
| Tier 1 Capital/Risk Weighted Assets, lagged one quarter | 0.386*** | 0.149 | 0.197 | 0.646*** | 1.710** | 1.498** | 0.345** | 0.408* | 0.479** | 0.519*** |
| | (0.137) | (0.199) | (0.149) | (0.227) | (0.828) | (0.671) | (0.146) | (0.246) | (0.229) | (0.157) |
| Tier 1 Capital/Risk Weighted Assets*TARP | | | | | | | | | -0.172 | |
| | | | | | | | | | (0.410) | |
| TARP | | | | | | | | | -0.00685 | |
| | | | | | | | | | (0.0410) | |
| QE 1*MBS and Treasury holidngs | | | | | | | | | | 1.237** |
| | | | | | | | | | | (0.550) |
| QE 2*MBS and Treasury holidngs | | | | | | | | | | 0.968** |
| | | | | | | | | | | (0.430) |
| QE 3*MBS and Treasury holidngs | | | | | | | | | | -0.360 |
| | | | | | | | | | | (0.297) |
| QE 1 | | | | | | | | | | -0.0648*** |
| | | | | | | | | | | (0.0169) |
| QE 2 | | | | | | | | | | -0.00161 |
| | | | | | | | | | | (0.00788) |
| QE 3 | | | | | | | | | | 0.0347*** |
| Observations | 50,614 | 95,509 | 137,868 | 196,272 | 85,040 | 173,363 | 137,868 | 196,272 | 335,264 | 211,455 |
| R-squared | 0.666 | 0.633 | 0.622 | 0.609 | 0.629 | 0.608 | 0.622 | 0.609 | 0.605 | 0.609 |

# Table 6. Mechanism II: Local Absorptive Capacity

In all specifications, the dependent variable is the log price of the foreclosed property. All specifications include as controls the loan to deposits, deposits to total assets, cash to total assets, the log of total assets, the return to assets, all lagged one quarter; other controls include zip code, bank and year-by-quarter fixed effects, and standard errors, in parentheses, are clustered by zip code and bank. Below (above) median cash restricts the sample to banks with below (above) median cash/asset ratios, averaged over 2001-2006. The "median ltv ratio in zip code, 2004-2007" is the median loan to value ratio of all mortgages originated in the zip code between 2004-2007. This variable is absorbed in the zip-code fixed effect. "Non-Judicial" or "Power of Sale" states restricts the sample to liquidations in states with non-judicial foreclosure laws.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Non-bank foreclosures | | Leverage | | State law | |
| VARIABLES | below median cash | above median cash | below median cash | above median cash | Non-judicial | Judicial |
| Year on year change in deposits, scaled by assets | 0.0990*** | 0.127** | -0.191 | 0.169*** | 0.106*** | 0.0627** |
| | (0.0318) | (0.0530) | (0.119) | (0.0417) | (0.0246) | (0.0291) |
| Tier 1 Capital/Risk Weighted Assets, lagged one quarter | 0.242 | 0.768** | -0.407 | -0.308* | 0.417*** | 0.418** |
| | (0.187) | (0.377) | (0.295) | (0.180) | (0.152) | (0.194) |
| Year on year change in deposits, scaled by assets *log of non-bank foreclosures in zipcode | 0.0219** | 0.00551 | | | | |
| | (0.0102) | (0.0189) | | | | |
| Tier 1 Capital/Risk Weighted Assets*log number of non-bank foreclosures in zip code | 0.0234 | -0.0455 | | | | |
| | (0.0498) | (0.136) | | | | |
| Year on year change in deposits, scaled by assets *median ltv ratio in zipcode, 2004-2007 | | | 0.436*** | -0.0774** | | |
| | | | (0.146) | (0.0337) | | |
| Tier 1 Capital/Risk Weighted Assets*median ltv ratio in zipcode, 2004-2007 | | | 0.963** | 0.703** | | |
| | | | (0.443) | (0.307) | | |
| log number of non-bank foreclosures in zipcode | -0.0724*** | -0.0527*** | | | | |
| | (0.00528) | (0.0195) | | | | |
| Observations | 134,221 | 191,008 | 99,740 | 125,976 | 197,752 | 137,463 |
| R-squared | 0.619 | 0.608 | 0.563 | 0.575 | 0.587 | 0.499 |

## Table 7. Mechanism III: Timing

The dependent variable equals 1 if a property is sold in the quarter and 0 otherwise. The sample begins in 2006 Q1 and ends in 2015 Q4. All specifications include as controls the loan to deposits, deposits to total assets, cash to total assets, the log of total assets, the return to assets, all lagged one quarter; other controls include zip code, bank and year-by-quarter fixed effects, and standard errors, in parentheses, are clustered by zip code and bank. Above (below) median cash denote the sample of banks whose cash to asset ratio, averaged from 2001-2006, is above (below) the median.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | | Hedonic Controls | |
| | Full Sample | Full Sample | Above median cash | Below median cash |
| Year on year change in deposits, scaled by assets, lagged one quarter | -0.0709*** | -0.0751*** | -0.0810*** | -0.139*** |
| | (0.0193) | (0.0206) | (0.0170) | (0.0381) |
| Tier 1 Capital/Risk Weighted Assets, lagged one quarter | 0.194 | 0.189 | 0.0557 | -0.0212 |
| | (0.147) | (0.145) | (0.130) | (0.213) |
| Lot size, square feet, logs | | -0.0115*** | -0.0116*** | -0.0113*** |
| | | (0.000631) | (0.000737) | (0.000712) |
| Total number of bedrooms, logs | | 0.000828 | 0.00211 | 0.000246 |
| | | (0.00172) | (0.00370) | (0.00116) |
| Total number of baths, logs | | -0.00702*** | -0.00702* | -0.00745*** |
| | | (0.00189) | (0.00399) | (0.00210) |
| Year built, logs | | 0.0120 | 0.0717 | -0.0256 |
| | | (0.0462) | (0.0878) | (0.0428) |
| Observations | 1,173,942 | 975,498 | 397,068 | 578,423 |
| R-squared | 0.126 | 0.129 | 0.144 | 0.127 |

## Table 8. Robustness Checks I: Latent Fundamentals

In all specifications, the dependent variable is the log price of the foreclosed property. All specifications include as controls the loan to deposits, deposits to total assets, cash to total assets, the log of total assets, the return to assets, all lagged one quarter. Column 1 includes monthly zip-code level prices, observed over the previous 6 months along with zip-code, bank and year-by-quarter fixed effects. Column 2 includes zip code-by-year-quarter fixed effects. Column 3 census tract-by-year-quarter fixed effects. Column 4 incudes banks operating in more than one state. Column 5 includes those banks with REO sales across all 12 states. Column 6 includes banks with REO sales across 95 percent of the counties (112) in the sample. Column 7 includes banks with REO sales across 95 percent (553) of the zip codes. Column 8 uses the interest rate set at the bank's headquarters for the sample of banks operating across all 12 states.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | zip code house price changes | zip code*year-quarter fixed effects | Census tract*year-quarter fixed effects | multi-state banks | all-state banks | banks active in >112 counties | banks active in >553 zip codes | Head-quarter's interest rate and all-state banks |
| Year on year change in deposits, scaled by assets | 0.0951*** | 0.114*** | 0.155*** | 0.113*** | 0.121*** | 0.117*** | 0.120*** | |
| | (0.0339) | (0.0322) | (0.0293) | (0.0364) | (0.0393) | (0.0390) | (0.0388) | |
| Tier 1 Capital/Risk Weighted Assets, lagged one quarter | 0.400*** | 0.205** | 0.199 | 0.390*** | 0.544** | 0.396** | 0.386** | 1.504** |
| | (0.150) | (0.104) | (0.166) | (0.136) | (0.251) | (0.163) | (0.156) | (0.674) |
| Change in 6 month CD rate, lagged one quarter | | | | | | | | -0.030*** |
| | | | | | | | | (0.010) |
| Observations | 301,236 | 301,757 | 249,894 | 330,764 | 312,004 | 319,183 | 319,036 | 245,216 |
| R-squared | 0.592 | 0.693 | 0.555 | 0.605 | 0.604 | 0.605 | 0.605 | 0.602 |

## Table 9. Robustness Checks II: Selection into Foreclosure

For a delinquent mortgage, the dependent variable in columns 1-3 equals 1 if the mortgage is foreclosed upon in the quarter and 0 otherwise. Column 1 uses the full sample of delinquent properties. Columns 2 and 3 use the sample of delinquent loans that also have information on the maturity of the mortgage. The dependent variable in columns 4 and 5 is the log liquidation value. Column 4 includes the Inverse Mills Ratio obtained from column 3. For comparison, column 5 reports the benchmark OLS specification without the sample correction, but for the same sample of properties as in column 4.

| | Probability of foreclosure | | | Log Liquidation Value | |
|---|---|---|---|---|---|
| | Linear Probability Model | | Probit | | |
| | (1) | (2) | (3) | (4) | (5) |
| Year on year change in deposits, scaled by assets | 0.00265 | 0.00114 | 0.042 | 0.046 | 0.043 |
| | (0.00249) | (0.00329) | (0.039) | (0.053) | (0.052) |
| Tier 1 Capital/Risk Weighted Assets, lagged one quarter | 0.00240 | 0.00378 | 0.348 | 0.321* | 0.307* |
| | (0.0185) | (0.0321) | (0.269) | (0.188) | (0.173) |
| Mortgage Maturity: Log Number of Days Until the Mortgage Interest Rate Resets | | -0.00105*** | -0.022*** | | |
| | | (0.000221) | (0.003) | | |
| Inverse Mills Ratio | | | | 0.343** | |
| | | | | (0.164) | |
| Observations | 18,753,374 | 3,585,020 | 3,411,863 | 78,286 | 78,286 |
| R-squared | 0.013 | 0.021 | | 0.65 | 0.65 |

## Table 10. Robustness Checks III: Collateral Characteristics

The dependent variable is the log price of the foreclosed property. All specifications include as controls the loan to deposits, deposits to total assets, cash to total assets, the log of total assets, the return to assets, all lagged one quarter and zip code, bank and year-by-quarter fixed effects, and standard errors, in parentheses, are clustered by zip code and bank. Bank balance sheet variables at origination (column 4) are observed in the quarter before origination. The table continues on the next page.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | collateral characteristics | price at origination | leverage at origination | balance sheet at origination |
| Year on year change in deposits, scaled by assets | 0.0967** | 0.104*** | 0.104*** | 0.123*** |
| | (0.0374) | (0.0391) | (0.0393) | (0.0367) |
| Tier 1 Capital/Risk Weighted Assets, lagged one quarter | 0.351*** | 0.336** | 0.340** | 0.557** |
| | (0.123) | (0.147) | (0.146) | (0.222) |
| Lot size, square feet, logs | 0.216*** | 0.200*** | 0.199*** | |
| | (0.00557) | (0.00562) | (0.00568) | |
| Total number of bedrooms, logs | 0.0532*** | 0.0373*** | 0.0373*** | |
| | (0.0135) | (0.0128) | (0.0127) | |
| Total number of baths, logs | 0.504*** | 0.427*** | 0.425*** | |
| | (0.0167) | (0.0143) | (0.0142) | |
| Year built, logs | 18.67*** | 17.28*** | 17.24*** | |
| | (0.673) | (0.687) | (0.689) | |
| Remodeled in last 10 years | 0.0826*** | 0.0724*** | 0.0722*** | |
| | (0.0155) | (0.0162) | (0.0162) | |
| Previous Market Sales Price, log | | 0.167*** | 0.172*** | |
| | | (0.00474) | (0.00459) | |
| Loan to Value Ratio, at Origination | | | -0.0500*** | |
| | | | (0.00542) | |
| Tier 1 Capital/Risk Weighted Assets, at loan origination | | | | -0.0203 |
| | | | | (0.0951) |
| Deposits/Total Assets, at loan origination | | | | 0.0442 |
| | | | | (0.0465) |
| Cash/Total Assets, at loan origination | | | | 0.313*** |
| | | | | (0.103) |
| Log of Total Assets, at loan origination | | | | 0.00477 |
| | | | | (0.00971) |
| Return on Assets, at loan origination | | | | -0.876** |
| | | | | (0.442) |

Table 10. Robustness Checks III: Collateral Characteristics, Cont'd.

| | | | | |
|---|---|---|---|---|
| Observations | 273,846 | 220,838 | 220,838 | 220,749 |
| R-squared | 0.694 | 0.706 | 0.706 | 0.607 |

## Table 11. Spillovers: The Impact of Bank Liquidation Values on Non-Bank Sales

The dependent variable is the log price of a non-foreclosure transaction. In columns 1 and 2, the liquidation value of a REO asset is obtained using the nearest REO sale that is no further away than 1 kilometer from the non-foreclosure transaction and that occurred within the last 18 months. Columns 3-6 shrink the distance window to less than 140 meters. Columns 5-6 instrument the liquidation value of the REO sale with the Year on year change in deposits, scaled by assets in the previous quarter, and tier 1 capital to assets, again in the previous quarter (column 2 of Table 4). All specifications include year-by-quarter and zip code fixed effects; columns 4-6 also include bank fixed effects. Standard errors are clustered at the REO matched sale and year-by-quarter level. Column 6 includes zip code by bank fixed effects.

| | OLS | | | | 2SLS | |
|---|---|---|---|---|---|---|
| | Less than 1 km apart | | Less than 140 meters apart | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| VARIABLES | no controls | hedonic controls | hedonic controls | monthly house prices | | zip code*bank fixed effects |
| liquidation value of REO asset, logs | 0.402*** | 0.250*** | 0.271*** | 0.276*** | 0.232* | 0.188* |
| | (0.00689) | (0.00628) | (0.00888) | (0.00878) | (0.114) | (0.101) |
| Lot size, square feet, logs | | 0.216*** | 0.234*** | 0.234*** | 0.242*** | 0.256*** |
| | | (0.00438) | (0.00673) | (0.00684) | (0.0343) | (0.0386) |
| Total number of bedrooms, logs | | 0.0299*** | 0.0151 | 0.00927 | 0.0133 | 0.0109 |
| | | (0.00967) | (0.0105) | (0.00985) | (0.0129) | (0.0135) |
| Total number of baths, logs | | 0.499*** | 0.427*** | 0.432*** | 0.440*** | 0.448*** |
| | | (0.0130) | (0.0133) | (0.0139) | (0.0507) | (0.0557) |
| Year built, logs | | 14.79*** | 14.88*** | 14.65*** | 15.58*** | 16.46*** |
| | | (0.489) | (0.491) | (0.490) | (2.696) | (3.111) |
| House price change in zip code, current month | | | | 0.381 | | |
| | | | | (0.346) | | |
| House price change in zip code, previous month | | | | 2.353*** | | |
| | | | | (0.579) | | |
| Observations | 804,801 | 737,896 | 380,776 | 364,119 | 380,749 | 377,707 |
| R-squared | 0.571 | 0.667 | 0.633 | 0.636 | 0.633 | 0.657 |

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