Effects of Shadow Bank Competition on Bank Strategies and Risk *

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Abstract

Increases in the conforming ("jumbo") loan limit after 2017 increased shadow bank competition for banks with high pre-2017 jumbo exposure. Using a shift-share empirical design based on differences in weighted-average house price increase across banks' local markets, we show that banks exposed to increased shadow bank competition shift from loans to securities, increase their reliance on non-core funding, and reduce branches and staffing relative to assets which is consistent with a shift away from information-sensitive lending. These effects are stronger for small banks compared to large banks. The exposed banks also experience declines in profitability, credit quality, and supervisory ratings.

Keywords: Shadow banks; competition; bank risk; lending
JEL: G21, G23

*The results and views expressed in this paper are those of the authors and do not reflect those of the Federal Reserve Bank of Richmond, or the Federal Reserve System.

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Introduction

The share of credit originated by traditional banks has declined over the past few decades across major credit markets, including residential mortgages (Buchak et al., 2018), small business lending (Gopal and Schnabl, 2022), syndicated loans (Chernenko et al., 2022; Irani et al., 2021), and personal loans (De Roure et al., 2022), reflecting a broader shift in bank activity away from traditional lending. Over the same period, non-depository financial institutions ("nonbanks" or "shadow banks") have expanded their role in these markets, increasingly serving as key providers of credit. This shift raises critical questions about the impact of shadow bank competition on the asset allocations, financing strategies, credit policies, and risk-taking of traditional banks. To the best of our knowledge, the existing literature is yet to examine these questions, which have broader implications for credit allocation and financial stability. In this paper, we show that banks respond to an increase in shadow bank competition by shifting away from information-sensitive lending toward holding long-duration securities, and shift funding from core deposits to non-core sources. Shadow bank competition also has adverse effects on bank profitability, mortgage performance, and supervisory assessments.

The effect of banking competition on bank behavior has been studied extensively, both theoretically and empirically. However, unlike banks, shadow banks operate outside the regulatory perimeter and compete via technology-enabled, originate-to-distribute models that automate underwriting and compress decision times, particularly in the mortgage market (Fuster et al., 2019). Banks cannot easily match the process and cost advantages of shadow banks because of regulatory constraints.[1] These frictions raise banks' marginal cost of information-intensive origination, especially in the mortgage market where shadow

[1]Banking regulations impose rigorous governance and validation requirements which make it harder for banks to develop and deploy new models (see Federal Reserve's SR 11-7 on model risk management). Banks are also subject to fair-lending and supervisory constraints.

banks are highly effective. Therefore, theoretical predictions relating to the effects of increase in traditional banking competition may not apply to increase in shadow bank competition. Given the process and cost advantages of shadow banks, banks may retrench from relationship lending, reallocate toward securities that require less origination infrastructure, and scale back branches and staffing when faced with increase in shadow bank competition. These adjustments will reshape credit allocation and earnings capacity tied to deposit franchises, with implications for resilience and financial stability.

A key challenge in studying the effects of shadow bank competition on traditional banks is endogeneity: banks facing greater shadow bank competition may differ in unobservable ways that also influence their lending behavior and risk-taking. In addition, competition itself is difficult to measure, and the extent of shadow bank presence in a given market may reflect underlying demand or regulatory conditions that also shape bank strategies. We overcome these challenges by using regulatory changes in the residential mortgage market – namely, the Federal Housing Finance Administration's (FHFA) implementation of substantial increases in the conforming loan limit in the post-2017 period after holding it constant over the 2006–2016 period – which we argue generated plausibly exogenous variation in the degree of shadow bank competition faced by different banks.

Shadow banks in the residential mortgage market rely heavily on secondary market liquidity provided by government-sponsored entities (GSEs) like Fannie Mae and Freddie Mac, whose activities are regulated by the FHFA. Because FHFA regulations stipulate that GSEs may only purchase mortgages under a specified size threshold ("jumbo cutoff"), shadow banks are less likely to originate loans above this size threshold ("jumbo" loans), leading to a sharp drop off in liquidity above the jumbo cutoff (Loutskina and Strahan, 2009). After holding the jumbo cutoff unchanged over the 2006–2016 period and a small increase in 2017, the FHFA implemented a series of large annual increases in the jumbo cutoff starting in 2018. The large increase in the jumbo cutoff in the post-2017 period resulted in increased competition from shadow banks for traditional banks, especially those banks which had a high exposure to jumbo loans relative to their assets in the pre-2017 period. The increase in shadow bank competition is exogenous to local housing market conditions and bank characteristics because the jumbo cutoff changes mechanically based on changes in the average national house price, and does not respond to changes in local price conditions (see Section 2 for details).

We use a bank's balance sheet exposure to jumbo mortgages at the end of 2016 as a proxy for its exposure to the increase in shadow bank competition in the post-2017 period. We specifically focus on exposure to a segment of the jumbo market that was most affected by the increases in the jumbo limit: mortgages that lie between 100% and 125% of the jumbo limit ("Jumbo125 loans"). Of course, exposure to jumbo loans is itself endogenous, and may be affected by omitted factors, such as balance sheet strength and ability to attract low-cost deposits (e.g., see Loutskina and Strahan, 2009), which also affect bank strategies and risk. To overcome this problem, we employ an instrumental variables (IV) regression model where we use a shift-share (Bartik) instrument for a bank's 2016 jumbo exposure using the weighted average house price increase over the 2012-2016 period across local markets (identified using 3-digit zip code) in which the bank had a presence in 2011. The idea behind this instrument is as follows: because the FHFA held the jumbo cutoff constant prior to 2016, banks with a large presence in markets which saw large house price increases over the 2012-16 period will experience an *exogenous* increase (i.e., over and above what can be explained by balance sheet strength and deposit costs) in their jumbo origination over the 2012-16 period, making them more vulnerable to increase in shadow bank competition in the post-2017 period. As an alternative strategy, we also use a generalized difference-in-differences regression model to examine how bank strategies vary with their jumbo exposure before and after 2017.

We show that increased competition from shadow banks has significant effects on the composition of bank assets and liabilities. On the assets side, banks facing increased shadow bank competition decrease the proportion of loans and increase the proportion of securities. These results provide a causal interpretation for the finding that banks have been shifting away from information-sensitive loans to long-term securities on the asset side (Buchak et al., 2024; Hanson et al., 2024). The decrease in the proportion of loans is primarily driven by decrease in real estate loans, whereas there is no significant change in other categories of loans such as commercial and industrial (C&I) loans and non-mortgage individual loans.

On the liabilities side, banks facing increased shadow bank competition decrease the proportion of core deposits and increase the proportion of non-core funding (i.e., non-core deposits plus other borrowings) relative to assets. These shifts are notable because core deposits, which include checking accounts, savings accounts, money market accounts, small-denomination time deposits (below the FDIC insurance limit), and payment accounts, are considered a stable source of funding. In contrast, non-core deposits, which include brokered deposits, time deposits over the FDIC insurance limit, and foreign deposits, are typically more expensive and less stable than core deposits. A likely explanation for these patterns is that mortgage lending also enhances core deposits (see Thakor and Edison, 2024, and references therein), because banks may require mortgage borrowers to maintain checking and savings accounts with them. Therefore, a decrease in banks' mortgage lending following increased shadow bank competition is also accompanied by a drop in their core deposits, forcing them to rely more on non-core deposits and other borrowing.

Changes in the composition of bank assets and deposits also have implications for bank profitability. Because non-core funding is costlier than core deposits, increase in shadow bank competition has a positive effect on banks' interest expense scaled by assets, and consequently, a negative effect on profitability, measured using net interest income over assets and return on assets (ROA). Banks facing increased shadow bank competition also reduce their employee headcount and branches relative to assets, possibly in a bid to lower their fixed costs in response to the competitive pressures on profitability (e.g., see Sarto and Wang, 2023). Because branch infrastructure and employees are crucial for information-sensitive bank lending, these changes signal a shift away from information-sensitive lending.

Consistent with the shift away from information-sensitive lending, we find that increase in shadow bank competition has an adverse effect on the credit quality of banks' mortgage portfolios and overall loan portfolio. Specifically, banks facing increased shadow bank competition experience significant increases in the fraction of mortgage delinquencies and non-performing loans.

Finally, we use confidential supervisory data on CAMELS ratings – i.e., regulators' evaluations of capital adequacy, asset quality, management, earnings, liquidity, and market-risk sensitivity – to examine the effects of shadow bank competition on supervisory assessments. This is important because supervisory assessments provide an independent and forward-looking view of a bank's overall health, incorporating qualitative information on risk management and governance that is not captured in public data. We show that banks facing increased shadow bank competition are significantly more likely to receive a composite CAMELS downgrade from supervisors over the 2017-2023 period. The composite downgrade is driven by downgrades on the capital, management, and earnings dimensions, which indicate that increase in shadow bank competition is associated with weaker earnings generation, tighter capital headroom, and supervisory concerns about how effectively risks are being governed.

To examine the effect of bank size, we repeat the analysis for banks with assets less than \$1 billion ("small") and more than \$1 billion ("large") at the end of 2017. We find that the effects documented above regarding the changes in asset composition and reductions in branch and employee count are mainly driven by small banks, whereas large banks are less affected by the increase in shadow bank competition. There are two potential explanations for these differential patterns between small and large banks. First, large banks are more likely to be technologically equipped to compete with shadow banks compared to small banks. Second, large banks have been gradually increasing their lending to shadow banks, which partially counteracts the effects of reduction in real estate lending. Of course, large banks also experience the adverse effects of shadow bank competition on profitability, credit quality, and supervisory assessments.

1. Related Literature

Our paper relates to multiple strands of the literature which examine the evolution of banking, growth of shadow banks, and the effects of banking competition on bank credit provision and risk.

1.1. Evolution of Banking and Shadow Banks

In the traditional banking model, banks act as delegated monitors (Diamond, 1984; Ramakrishnan and Thakor, 1984), issuing demandable deposits to savers and using the proceeds to make information-sensitive loans to borrowers (Diamond and Dybvig, 1983; Diamond and Rajan, 2001). However, recent literature documents that banks have moved far away from this traditional model over the past few decades. On the asset side, there has been a notable shift away from information-intensive lending and towards longer-term securities such as MBS and long-term Treasuries (Buchak et al., 2024; Hanson et al., 2024). On the liability side, there has been a rapid growth of deposits, which has been driven mainly by the growth of uninsured deposits (Hanson et al., 2024). The growth in deposits seems to be driven by the demand for safe assets and the ability of banks to attract deposits at below-market rates (Gorton and Pennacchi, 1990; Egan et al., 2017; Drechsler et al., 2023) in exchange for other amenities such as payment services and accessible branch offices.

The decline in traditional banking has been accompanied by the rise of shadow banks in all credit markets. Buchak et al. (2018) document that the shadow bank market share in the residential mortgage market increased from 30% in 2007 to 50% in 2015, and is much higher in certain segments of this market. Demyanyk and Loutskina (2016), Gete and Reher (2021), Mian and Sufi (2022), and Drechsler et al. (2022) also highlight the roles played by shadow banks in the housing sector. Meanwhile, Erel and Inozemtsev (2024) document that nonbank financial institutions (e.g., finance companies, private equity firms, hedge funds, business development companies, etc.) have gained substantial market share in both corporate loan and bond markets: they account for 60% of small business lending secured by non-real estate collateral (Gopal and Schnabl, 2022), one-third of lending to mid-sized firms (Chernenko et al., 2022), and 80% of risky term loans to medium and large borrowers (Irani et al., 2021). The extant literature attributes the rise of shadow banks to increased regulatory burden on banks and technological innovation (e.g., see Plantin, 2015; Hanson et al., 2015; Kim et al., 2018; Farhi and Tirole, 2021; Erel and Inozemtsev, 2024; Buchak et al., 2018). Apart from these factors, Sarto and Wang (2023) find that the rise of shadow banks was also aided by the persistent decline in interest rates, which negated banks' competitive advantage in raising cheap deposit financing.

There is also a growing literature documenting the linkages between banks and shadow banks (e.g., see Acharya et al., 2024, and references therein). Banks and shadow banks finance each other, with shadow banks especially dependent on banks (Benson et al., 2023; Jiang, 2023) due to the relatively low cost of bank capital arising from the bank regulatory regime, deposit franchises, and official backstops (Donaldson et al., 2021). Apart from direct financing, banks also provide credit lines and explicit guarantees to shadow banks

(Mandel et al., 2012; Acharya et al., 2013; Kiernan et al., 2021; Acharya et al., 2024), and are increasingly including shadow bank subsidiaries inside bank holding companies (Cetorelli et al., 2012; Cetorelli and Prazad, 2024; Acharya et al., 2024). Moreira and Savov (2017) and Begenau and Landvoigt (2022) provide theory models to highlight the risks and inefficiencies created by a growing shadow banking sector, and the interesting dynamics arising from its interactions with banks.

1.2. Effects of Banking Competition

Theory offers conflicting predictions regarding the effect of banking competition on bank risk taking. The "competition-fragility" view posits that greater competition erodes franchise value, which incentivizes bank risk taking (e.g., Keeley, 1990; Hellmann et al., 2000). In contrast, the "competition-stability" view argues that greater bank market power (i.e. less competition) in the loan market exacerbates bank credit risk because higher interest rates charged to borrowers worsen loan repayment and exacerbate moral hazard and adverse selection problems (Boyd and De Nicolo, 2005). Allen and Gale (2004) and Martinez-Miera and Repullo (2010) argue that the relation between competition and bank risk taking is more complex and non-monotonic.

The effects of banking competition on risk taking are hotly debated in the empirical literature, with results varying based on the identification strategy, and the measures of competition and risk taking. Carlson et al. (2022) and Jiang et al. (2023) find that greater banking competition leads to higher risk taking (also see Jiménez et al., 2013). In contrast, Jayaratne and Strahan (1996), Carlson and Mitchener (2009), and Goetz (2018) find that greater banking competition decreases bank risk and promotes financial stability. Interestingly, Gissler et al. (2020) find that banks and nonbanks react differently to increased competition in consumer credit markets: nonbanks expand credit to riskier borrowers whereas banks specialize in relationship lending.

The literature also offers differing theoretical predictions and mixed empirical evidence regarding the effects of banking competition on credit provision. Many influential papers find that while competition increases efficiency of banks, it either leads to decrease in provision of credit to small firms (Petersen and Rajan, 1995; Marquez, 2002) or has no effect on credit provision (Jayaratne and Strahan, 1996). On the other hand, Dick and Lehnert (2010), Carlson et al. (2022) and Braggion et al. (2017) find that banks operating in more competitive (less concentrated) banking markets extend more credit to borrowers.

2. Institutional Setting

GSEs like Fannie Mae and Freddie Mac play a dominant role in enhancing mortgage liquidity. They are heavy buyers of mortgages from all types of lenders, holding some of these loans and securitizing the rest. On average, over the past 10 years, about 45% of all mortgages originated in the US were sold to GSEs after origination. When GSEs buy mortgages, they bear both credit and interest rate risks. When GSEs securitize mortgages, they either buy them and issue mortgage-backed securities (MBS) or just sell credit protection to the original lender.

The activities of GSEs are regulated by the Federal Housing Finance Administration (FHFA), which stipulates the criteria used to determine whether a mortgage is "conforming" and thus can be sold to the GSEs. One important criterion is that GSEs may only purchase or securitize mortgages under a specified size threshold, which is referred to as the GSE conforming loan limit or the jumbo cutoff. Loans above and below this cutoff are referred to as jumbo loans and nonjumbo loans, respectively. These limitations were designed to ensure that the GSEs met the legislative goal of promoting access to mortgage credit for low- and moderate-income households. As a result, GSEs will not buy any jumbo loans, but will buy most nonjumbo loans provided they satisfy other requirements to be classified as conforming mortgages. (Apart from the size limitation, the mortgage must have a loan-to-value ratio below 0.8 or be credit enhanced with personal mortgage insurance, and there are additional income verification and property criteria.) As a result, there is a sharp drop off in liquidity above the jumbo loan cutoff (Loutskina and Strahan, 2009).[2]

Shadow banks rely heavily on secondary market liquidity provided by GSEs because, unlike banks, they lack the balance sheet strength to retain loans. For instance, while banks retained approximately 96% of jumbo and 36% of conforming mortgages they originated in 2016 on their balance sheets, shadow banks retained only 13% of the conforming mortgages they originated. Therefore, shadow banks are significantly less likely to originate jumbo loans because they cannot sell these to GSEs and will have to look for alternative sources of secondary market liquidity. For instance, in 2016, shadow banks accounted for 42% of all nonjumbo mortgages by number, but their corresponding market share in the jumbo segment was only 23%. Moreover, shadow banks sold about 64% of the jumbo loans they originated to commercial banks, credit unions, and other non-GSE institutions.

Important for our identification strategy, local housing supply or demand conditions have no effect on the jumbo cutoff or changes in this cutoff. The baseline jumbo cutoff in 2016 was $417,000 in 3,000 out of the 3,244 US counties (i.e., 92% of US counties) despite significant variation across housing markets in these counties; the cutoff was higher in "high-cost" counties[3] and was 50% higher in Alaska, Hawaii, Guam, and US Virgin Islands. Panel A of Figure 1 provides a geographical plot of the jumbo cutoff in 2016, and highlights

[2]The primary source of lending for borrowers above the conforming limit is privately held jumbo mortgages which typically carry more stringent underwriting guidelines than conforming loans. Consequently, many borrowers who may not qualify for jumbo loans must either bring extra cash to closing or take out a piggy-back second loan to keep their borrowing within the limits.

[3]High-cost counties are defined as those in which 115 percent of the local median home value exceeds the baseline jumbo cutoff. In such counties, the jumbo cutoff is a multiple of the median house value subject to a cap of 150 percent of the baseline jumbo cutoff. Visit https://www.fhfa.gov/news/news-release/fhfa-announces-increase-in-maximum-conforming-loan-limits-for-fannie-mae-and-freddie-mac-in-2017 for more details.

the counties which have a higher jumbo cutoff; Panel B provides a similar plot for 2023. In normal times, the jumbo cutoff increases each year by the percentage change in the *national* average of single-family housing prices; that is, changes in the jumbo cutoff are not driven by local market conditions. The FHFA announces the increase in jumbo cutoff during Q3 of each year to be effective the following year. However, the jumbo cutoff remained unchanged at $417,000 over the 2006–2016 period despite the significant changes in home prices at both the national and local levels during this time period. This was because the Housing and Economic Recovery Act (HERA) of 2008 restricted any additional increase in the jumbo cutoff until national home values had returned to pre-crash (i.e., 2007) levels. The FHFA announced on November 23, 2016 that it would raise raise the jumbo cutoff in 2017 because it had determined that the housing price index (HPI) in the third quarter of 2016 was higher than the corresponding value for the third quarter of 2007.

After keeping the jumbo cutoff unchanged over the 2006–2016 period, the FHFA started increasing the jumbo cutoff starting in 2017. Figure 2 shows how the baseline jumbo cutoff changed over the 2009–2023 period. We also plot the following national house price series in this figure to indicate how the distribution of national house prices changed over this period: FHFA's Housing Price Index (HPI) which denotes the national average price of single-family homes; and Zillow's top-tier and bottom-tier House Value Indices (HVI), which represent the upper and lower price brackets, respectively, within Zillow's home value data. Following a small increase of $7,000 in 2017, the jumbo cutoff saw large increases over the 2018–2023 period. There was a cumulative increase of $302,000 in the jumbo cutoff between 2018 and 2023, with the largest increase of $99,000 in 2022.

3. Data and Empirical Methodology

3.1. Data Sources

Mortgages: We obtain information on mortgage applications from the *Home Mortgage Disclosure Act (HMDA)* database which records the vast majority of home mortgage applications in the United States, and includes information on both approved and rejected loans. The extract of HMDA that we use spans the time period from 2000 to 2023. The database provides, among other things, the application outcome (i.e, whether the loan was approved), the originator's identity, loan amount, year, the county in which the property is located, the loan type and purpose, and the applicant's self-reported income and race/ ethnicity. HMDA database also records whether the originator retains the loan on its balance sheet or sells the loan within one year to a third party. During our sample period, this database does not provide information on interest rate, borrower credit scores, loan-to-value ratio, or documentation status.

We obtain information on the jumbo cutoff from the *FHFA*; this information is available at https://www.fhfa.gov/data/conforming-loan-limit-cll-values. As noted above, the jumbo cutoff could vary across counties and from year to year. Therefore, we obtain this information at the county-year level. We are able to classify each loan application in HMDA as jumbo or nonjumbo using the jumbo cutoff corresponding to the county in which the property is located and the year of the loan application. Using this information for approved loan applications, we can compute the aggregate nonjumbo lending and jumbo lending for each originator-county-year combination.

Bank Financial Variables: We obtain bank financial information on a quarterly basis from the *Reports of Income and Condition* for commercial banks (the "Call Reports" data), which we download from the website of the FFIEC Central Data Repository. We use the matching file developed by Robert Avery, which is available for download on https://sites.google.com/site/neilbhutta/data, to obtain financial information on all the banks in HMDA. This dataset matches the HMDA ID of the HMDA lender with RSSD ID bank identifier in the Call reports. In the case of a HMDA filer who is a subsidiary of a bank or thrift, the HMDA filer is matched to the parent institution. If the filer is a subsidiary of a bank holding company, the filer is matched to the (lead) largest bank of the holding company. We eliminate banks whose quarter-over-quarter growth exceeds 25% any time during our sample period because such a large growth indicates a large merger, which may have a direct effect on our outcome variables. However, we obtain qualitatively similar results even if we don't impose this restriction.

Supervisory Ratings: We obtain supervisory ratings from confidential regulatory examination records maintained withing the Federal Reserve System. These records report the CAMELS composite rating, a bank-level score ranging from 1 (strongest) to 5 (weakest), assigned following periodic on-site safety and soundness examinations. The CAMELS framework evaluates six dimensions of bank condition: Capital adequacy, Asset quality, Management quality, Earnings, Liquidity, and Sensitivity to market risk. The composite rating reflects the examiner's overall judgment of bank risk and is not a mechanical average of the six components. Ratings are updated after each examination, which typically occurs every 12 to 18 months depending on bank characteristics and condition. These supervisory assessments have been shown to incorporate non-public information and to predict future bank distress (Correia et al., 2025). We merge the CAMELS ratings with Call Reports using unique bank identifiers and assign to each bank-quarter the most recently available rating as of the quarter-end.

3.2. Measuring Exposure to Increase in Shadow Bank Competition

The increase in shadow bank competition should be higher for banks that had a greater exposure to jumbo loans in the pre-2017 period. Because the jumbo segment is very wide, we define the indicator variable, *Jumbo 125*, to identify mortgages for which the loan amount is between 100 percent and 125 percent of the jumbo cutoff in the county-year of origination. We do this to focus on the segment of the jumbo market that is most likely to experience intensification in shadow bank competition after 2017; our results are robust to using alternative cutoffs or if we use no cutoff at all and focus on the entire jumbo market. Accordingly, we measure a bank's exposure to increased competition from shadow banks using the following measure:

$$Jumbo125\ Exposure_i = \frac{\sum_{t=2012}^{2016}\left(\sum_k Jumbo125\ Lending_{ik,t}\right)}{Assets_{i,2016}} \tag{1}$$

In equation (1), subscript 'i' denotes the bank, 'k' denotes the county, and 't' denotes the year. We compute the bank's *Jumbo125 Exposure* by aggregating its *Jumbo125* lending across all counties over the 5-year period, 2012–16, and scaling it by its assets at the end of 2016. Banks retain almost all of the jumbo mortgages they originate on their balance sheets (e.g., 96% in 2016), and jumbo mortgages are refinanced less often than conforming mortgages. Therefore, we believe that *Jumbo125 Exposure* is a conservative estimate of banks' exposure to jumbo mortgages. We plot the distribution of *Jumbo125 Exposure* in Figure 3, and use darker shades to identify the portions that are above the $75^{th}-$ and $90^{th}-$percentile values. As expected, the distribution of *Jumbo125 Exposure* is highly skewed, because most banks have low exposure to the jumbo mortgage market.

As an alternative, we also compute the bank's *Jumbo Exposure* by aggregating its overall jumbo lending (i.e., without restricting to loans within 125% of jumbo cutoff) across all counties over the 5-year period, 2012–16, and scaling it by its assets at the end of 2016. We find that *Jumbo125 Exposure* is highly correlated with *Jumbo Exposure* as shown in Figure IA.1 in the Internet Appendix; the pairwise correlation between these two measures is 0.84.

3.3. Descriptive Statistics

We present descriptive statistics for the bank characteristics in Table 1. Each observation corresponds to a bank, and all the characteristics other than the instrument, *WA Price Change*, are measured at the end of 2016. As expected, the size distribution is highly skewed: while the median bank has assets of $0.28 billion, the average bank has assets of $4 billion. There is also substantial variation in the instrument, as well as *Jumbo125 Exposure* and *Jumbo Exposure*.

Loans constitute 67.3% of assets for the average bank, with real estate loans being by far the largest component. Securities account for 19.6% of the average bank's assets, and these can be further decomposed into treasury/agency securities, non-agency MBS, and other securities.[4] On the liabilities side, core deposits account for 76.8% of the average bank's assets, whereas non-core funding accounts for 12.2%. Most banks do not hold any brokered deposits (which are part of non-core deposits), but these account for more than 8.96% of assets for one-tenth of bank-quarter observations.

In Table 2, we compare bank characteristics across four categories corresponding to the four quartiles of the instrument, *WA Price Change*, where Q1 (Q4) denotes the lowest (highest) values of *WA Price Change*. As can be seen, *Jumbo125 Exposure* and *Jumbo Exposure* increase monotonically from Q1 to Q4. Banks in the Q4 group have a higher proportion of loans, different loan composition, and a lower proportion of securities compared to banks in the Q1 group, but there is no significant difference in the proportion of core deposits

[4]Apart from loans and securities, the remaining assets include fixed assets and cash.

between these two groups of banks although Q4 banks have a slightly higher proportion of non-core funding (including brokered deposits) than Q1 banks.

3.4. Jumbo Cutoff Hike and Shadow Bank Competition

Our empirical strategy rests on the assumption that the post-2017 increase in the jumbo cutoff exposed banks to increase in competition from shadow banks. We validate this assumption in this section. To do this, we define the indicator variable, *Jumbo2016*, to identify loans with amounts above the 2016 jumbo cutoff in the county of origination. Therefore, *Jumbo2016* loans represent the segment of the residential mortgage market which saw an expansion of GSE elibility after 2017 because of the increase in the jumbo cutoff. Using HMDA data, we construct a lender–county–year panel for 2012–2023 and track competition in the Jumbo2016 segment. We present the results of this analysis in Figure 4.

Panel A plots the distribution of the county-level Herfindahl–Hirschman Index (HHI) computed using market shares for Jumbo2016 originations, which serves as a measure of market concentration. We separately plot the mean, median, top quartile cutoff and bottom quartile cutoff values of county-level HHI. As can be seen, there is a steep decline in market concentration in the Jumbo2016 segment after 2017 across the distribution, which indicates that more originators competed in this segment in the post-2017 period following the expansion of GSE eligibility. Panel B plots the mean and the third quartile values of nonbank entry, which is defined as the number of new nonbank lenders that originated Jumbo2016 loans in the county during the year but did not do so in the prior year (the median value of this variable is 0 across all periods). We find that nonbank entry increases sharply beginning in 2018, signaling substantial expansions by nonbanks into this segment. Overall, the evidence in Figure 4 confirms that the increases in the jumbo cutoff after 2017 did intensify shadow bank competition.

3.5. Empirical Methodology

We wish to examine the effect of increase in shadow bank competition, which we measure using *Jumbo125 Exposure*, on bank operations and risk. An immediate concern is that *Jumbo125 Exposure* is itself endogenous. That is, omitted factors such as the bank's balance sheet strength and ability to attract low-cost deposits may affect both its exposure to the jumbo segment (e.g., see Loutskina and Strahan, 2009) and the outcome variables relating to bank operations and risk. We overcome this problem using the following *shift-share (Bartik) instrument* for *Jumbo125 Exposure*:

$$\text{WA Price Change}_i = \sum_z \frac{Deposits_{iz,2011}}{Deposits_{i,2011}} \times \text{Price Change}_{z,2012-16} \tag{2}$$

In equation (2), subscript i denotes a bank, subscript z denotes a 3-digit zip code ("Zip3") area, and *Price Change*$_{z,2012-16}$ denotes the house price change in the Zip3 area over the 2012-16 time period (the "shift"), which we compute using the FHFA House Price Index dataset.[5] We plot the distribution of *Price Change*$_{z,2012-16}$ in Panel A of Figure 5. *WA Price Change*$_i$ denotes the weighted average house price change over the 2012-16 period across all Zip3 areas in which bank i operates, where we use the 2011 deposit shares of the bank across these Zip3 areas as weights (the "share"). We plot the distribution of *WA Price Change*$_i$ in Panel B of Figure 5. The differences between panels A and B indicate that there is substantial cross-sectional variation in banks' 2011 deposit shares across Zip3 area.

To understand the intuition behind our choice of instrument, consider a Zip3 area which experiences a large house price increase over the 2012-16 period. Because the FHFA decided to keep the jumbo cutoff unchanged during this period, a bank with a large presence in this Zip3 area in 2011 will experience an *exogenous* increase (i.e., over and above what can be explained by omitted factors such as balance sheet strength and

[5]See https://www.fhfa.gov/data/hpi/datasets?tab=annual-data.

deposit costs) in its jumbo origination in this local market over the 2012-16 period. Hence, we expect *WA Price Change* to have a positive effect on *Jumbo125 Exposure*. The positive relation is clear from Figure 6 which plots the average value of *Jumbo125 Exposure* for each decile of *WA Price Change*.

We then estimate the following 2SLS instrumental variables (IV) regression:

$$Jumbo125\ Exposure_i = \gamma \times WA\ Price\ Change_i + \Psi_1 \times X_i + Bank\ Size\ FE \tag{3}$$

$$\Delta Y_{2017Q3-2020Q1} = \beta \times \widehat{Jumbo125\ Exposure_i} + \Psi_2 \times X_i + Bank\ Size\ FE \tag{4}$$

The dependent variable in the second-stage regression, $\Delta Y_{2017Q3-2020Q1}$, denotes the change in bank characteristic, Y, over the ten-quarter period from the end of 2017Q3 to the end of 2020Q1; i.e., it is the difference between Y_{2020Q1} and Y_{2017Q3}. The bank characteristics, Y, we examine are financial ratios that capture banks strategies (e.g., asset and liability composition), profitability, risk, and supervisory ratings. We focus on changes in these financial ratios in the post-2017 period because, although the FHFA announced a small increase in the jumbo cutoff for 2017, the larger jumbo cutoff increases started only in 2018 (see Figure 2). We use 2017Q3 as the starting point for our analysis because the jumbo cutoff for 2018 was announced during 2017Q3. We choose 2020Q1 as the end point because the COVID crisis, and the government interventions it engendered like the Paycheck Protection Program, directly influenced bank policies after 2020Q1. We control the first- and second-stage regressions for the following bank characteristics measured at the end of 2016: *Size* which is the natural logarithm of assets; *Liquid Assets*, which is the ratio of cash and marketable securities to assets; the ratio of interest expense to deposits to proxy for deposit costs; the ratio of single-family loans to assets; and the ratio of Tier-1 capital to assets. We also include indicator variables to differentiate between banks in the following asset size categories ("Size fixed effects"): assets less than or equal to $1 billion (the omitted category), assets greater than \$1 billion but less than or equal to \$10 billion, and assets greater than \$10 billion. Standard errors are robust to heteroskedasticity.

To understand how the effects of shadow bank competition vary with bank size, we estimate the IV regression model (4) separately for banks in the following two size categories based on total assets at the end of 2017: "small banks" defined as those with assets of less than or equal to \$1 billion, and "large banks" defined as those with assets of more than \$1 billion. As per this classification, there are 2,847 small banks and 509 large banks in our sample. It is not feasible to estimate the IV regression separately for banks with assets over \$10 billion because there are only 73 such banks.

We present the results of the first-stage regression in Table 3. As can be seen, *WA Price Change* has a strong positive effect on both *Jumbo125 Exposure* and *Jumbo Exposure*, and the $F-$statistics are large.[6] Columns (3) and (4) demonstrate that this relationship is robust across subsamples, with the instrument remaining a significant and strong predictor for both small and large banks separately. Therefore, our instrument satisfies the relevance criterion. On the other hand, because it is based on the bank's deposit shares across Zip3 areas in 2011 and house price changes over the 2012-16 period in these Zip3 areas, *WA Price Change*$_i$ is unlikely to have a direct effect on the *changes* in bank financial ratios in the post-2017 period. Therefore, we believe that the instrument satisfies the exclusion restriction.[7]

As an alternative to the IV regression model, we also implement the following dynamic

[6]We also estimate a non-parametric version of the first-stage regression after replacing *WA Price Change* with indicator variables identifying the deciles of *WA Price Change*. The coefficient estimates on the second through tenth decile dummies plotted in Figure IA.3 also indicate a positive relation between *WA Price Change* and *Jumbo125 Exposure*.

[7]One potential threat to the exclusion restriction arises from the possibility of mean reversion in local house price growth and local economic growth after 2017. That is, if the Zip3 areas that experienced high house price growth and economic growth over the 2012-2016 period experience a reversal in fortunes after 2017, then the exclusion restriction could be violated. However, we show in Figure IA.2 in the internet appendix that there is no evidence of mean reversion in local house price growth and local economic growth after 2017.

generalized difference-in-differences (DiD) regression to estimate the within-bank quarter-by-quarter effects of *Jumbo125 Exposure* on bank strategies and risk in the quarters prior to and after 2017Q4:

$$Y_{iq} = \alpha + \mu_i + \mu_q + \sum_{\tau=-8,\tau\neq 0}^{\tau=8} \beta_\tau \times Q_\tau \times \mathit{Jumbo125\ Exposure}_i + X_{i,q-1} \cdot \Gamma + \epsilon_{iq} \tag{5}$$

We estimate regression (5) on a panel dataset that has one observation for each bank (indexed by i) and calendar quarter-year (indexed by q) combination, includes all banks that feature in the HMDA data, and spans the time period from 2015Q4 to 2020Q1. We begin the analysis in 20154Q because a series of regulatory changes implemented during the 2011–2015 period directly influenced bank policies;[8] and as noted above, we end the analysis in 2020Q1 to avoid picking up the effects of the COVID crisis which began in the US in 2020Q2. Q_τ for are identifiers for quarters, where the omitted quarter, Q_0, denotes 2017Q3 and Q_τ with positive (negative) values of τ denotes quarters after (before) 2017Q3. We include fixed effects for the bank (μ_i) and the quarter-year (μ_q). The lagged bank characteristics (X_{q-1}) that we control for are *Size*, *Equity Capital*, and indicator variables to differentiate between banks in the following asset size categories: assets less than or equal to \$1 billion (the omitted category), assets greater than \$1 billion but less than or equal to \$10 billion, and assets greater than \$10 billion. Standard errors are robust to heterogeneity and clustered at the bank level.

Note that whereas the IV regression model (4) examines changes in outcome variables

[8]The Comprehensive Capital Analysis and Review (CCAR) stress tests of 2011 and 2012 had a significant negative effect on the provision of mortgage credit, especially jumbo mortgage credit, by US banks (see Gete and Reher, 2018; Calem et al., 2020). Buchak et al. (2018) also point to a series of regulatory changes implemented during the 2011–15 period which had an adverse effect on banks' mortgage origination activity: tightening of risk-weighted capital requirements under Basel III; mortgage-related lawsuits pertaining to banks' conduct during the financial crisis; and closure of the Office of Thrift Supervision (OTS) which had the reputation of being a lax regulator. Next, the 2013 Supervisory Guidance on Leveraged Lending (GLL) and the subsequent 2014 FAQ notice, which clarified expectations on the GLL, had a negative effect on speculative-grade term-loan origination by banks (Calem et al., 2020).

in the post-2017 period (i.e., $\Delta Y_{2017Q4-2020Q1}$), the dependent variable in equation (5), Y_{iq}, is the outcome variable for bank i in year-quarter q. Hence, the coefficient β_τ captures the *within-bank* change in the outcome variable Y between quarters 0 and τ as a function of the bank's *Jumbo125 Exposure*. If omitted factors drive the relationship between Jumbo125 Exposure and Y, we would expect β_τ to be significant even in the pre-period (negative values of τ), indicating a violation of parallel trends. Conversely, a causal response to increased shadow bank competition implies that β_τ should be statistically significant only in the post-period (positive values of τ), while remaining indistinguishable from zero in the pre-period. In sum, the coefficients β_τ trace out the differential evolution of the outcome variable relative to the base quarter (2017Q3) that is attributable to cross-sectional variation in Jumbo125 Exposure.

4. Effects of Shadow Bank Competition on Bank Strategies

4.1. Effect on Composition of Bank Assets

In this section, we present the results of regressions aimed at understanding the effect of increased competition from shadow banks on the composition of bank assets. We present the results of the second-stage regression of the IV model (4) in Panel A of Table 4, which capture the effect of increase in shadow bank competition on changes in composition of bank assets over the period from 2017Q3 to 2020Q1. For each outcome variable, we also plot the quarter-by-quarter β_τ coefficients from the dynamic DiD regression (5) in Figure 7.

The dependent variables in columns (1) and (2) denote the change in $Loans$ and $Securities$, respectively, over the period from 2017Q3 to 2020Q1. Recall that $Loans$ denotes total loans and leases as a percentage of assets, whereas $Securities$ denotes total securities – i.e., sum of held-to-maturity securities, available-for-sale securities, and equity securities not held for trading – as a percentage of assets. The results indicate that banks respond to increase in shadow bank competition by decreasing the proportion of loans and increasing the proportion of securities on their balance sheet. These effects are economically significant, and indicate that a 1% increase in *Jumbo125 Exposure* is associated with a 1.38% decrease in the proportion of loans and a 1.7% increase in the proportion of securities relative to assets in the post-2017 period.

The corresponding dynamic plots for $Loans$ and $Securities$ are in panels A and B of Figure 7. In both these panels, it is clear that β_τ is insignificant prior to 2017Q4 (i.e., for negative τ) which indicates that these variables did not vary with *Jumbo125 Exposure* prior to 2017Q4. By contrast, β_τ is negative and significant in Panel A for 2019Q1 (i.e., $\tau = 5$) and beyond; and is positive and significant in Panel B for 2018Q4 (i.e., $\tau = 4$) and beyond. We note that the economic magnitudes in these plots are smaller than those in the corresponding columns of Table 4, which is to be expected because equation (5) includes bank fixed effects.

In columns (3) through (5) in Panel A of Table 4, we separately examine post-2016 changes in the following categories of loans (expressed as percentage of assets) to understand what is driving the overall reduction in the proportion of loans: *SFR Loans* which include all single-family residence loans (column (3)); *Other RE Loans* which include all real estate loans other than SFR loans (column (4)); and *Other Loans* which include commercial and industrial loans and consumer loans to individuals, such as auto loans and credit cards (column (5)). We find that the decrease in $Loans$ following increased competition from shadow banks is driven by decreases in both SFR loans and other real estate loans, whereas there is no significant change in non-real estate loans.

The corresponding dynamic plots for *SFR Loans*, *Other RE Loans* and *Other Loans* are in panels C through E of Figure 7. The plot in panel C indicates a small increase in SFR lending in early 2018 following by a sharp decline beginning in early 2019. The plot in panel D also points to a significant decline in other real-estate loans in response to the increase in shadow bank competition, whereas the plot in panel E shows that there is no significant change in non-real-estate lending. Overall, these patterns are consistent with the corresponding IV regression results in Panel A of Table 4.

Next, we estimate the IV regressions in Panel A separately for small and large banks. Recall that we use $1 billion as the cutoff to classify banks into these two categories based on their total assets at the end of 2017. For each of the outcome variables in Panel A, we report the coefficient on $\widehat{Jumbo125\ Exposure}$ separately for small and large banks in Panel B. The coefficients in column (1) indicate that small banks banks facing increased shadow bank competition decrease the proportion of loans and increase the proportion of securities on their balance sheet in the post-2017 period, and that the decrease in the proportion of loans is driven by both SFR loans and other real estate loans. On the other hand, the insignificant coefficients in column (2) indicate that the asset composition of large banks does not change significantly in response to the increase in shadow bank competition.

Past literature has highlighted that large US banking institutions reduced their provision of mortgage credit in response to post-crisis tightening of banking supervision (e.g., Calem et al., 2020). In contrast, the results in Panel B show that smaller US banks are more likely to reduce their loan exposures following increase in shadow bank competition. There are two potential explanations for these differential patterns between small and large banks. First, large banks are more likely to be technologically equipped to compete with shadow banks compared to small banks. Second, large banks have been gradually increasing their lending to shadow banks (e.g., see Jiang, 2023; Cetorelli and Prazad, 2024), which partially counteracts the effects of reduction in real estate lending.

4.2. Effect on Composition of Bank Liabilities

Next, we present the results of regressions aimed at understanding the effect of increased competition from shadow banks on the composition of bank liabilities, that is, the split between core deposits, non-core deposits, and other (i.e., non-deposit) borrowings. Core deposits form a stable source of funds for banks, and include the following categories of non-brokered domestic deposits: checking accounts, savings accounts, money market accounts, and time deposits of $250,000 or less (i.e., at or below the deposit insurance limit). In contrast, non-core deposits are typically more expensive and less stable than core deposits, and include brokered deposits, large denomination time deposits, and all foreign deposits. We combine non-core deposits and other borrowings into a single category which we refer to as "non-core funding" because these account for a small fraction of liabilities, on average; the results are qualitatively similar if we examine these two categories separately.

We present the results of the second-stage IV regression in Panel A of Table 5, which capture the effect of increase in shadow bank competition on changes in composition of bank liabilities over the period from 2017Q3 to 2020Q1. The dependent variables in columns (1) and (2) measure the changes in the proportion (as percentage of assets) of core deposits and non-core funding, respectively, over the period from 2017Q3 to 2020Q1. The results indicate that banks respond to increase in shadow bank competition by decreasing the proportion of core deposits and increasing the proportion of non-core funding. These effects are economically significant: a 1% increase in *Jumbo125 Exposure* is associated with a 2% reduction in $Core\ Deposits$ over the 10 quarters following 2017Q3, which is large in comparison to its average value of 76.8%; and this is compensated by a 2.3% increase in $Non-core\ Funding$ over the same period.

A likely explanation for the drop in the proportion of core deposits and the corresponding increase in the proportion of non-core funding in the post-2017 period for banks with high *Jumbo125 Exposure* is the linkage between mortgage lending and core deposits. That is, banks may require some of their mortgage borrowers to maintain checking and savings accounts with them, both of which constitute core deposits. Therefore, a decrease in banks' mortgage lending following increased competition from shadow banks is also accompanied by a drop in core deposits, causing them to increase their reliance on non-core deposits and other borrowings.

One category of non-core deposits that are of special interest to regulators are brokered deposits, which are considered to be unstable and highly sensitive to interest rate movements. Regulators worry that brokered deposits could facilitate a bank's rapid growth in risky assets without adequate controls; and once problems arise, a problem bank could use such deposits to fund additional risky assets to attempt to "grow out" of its problems (Correia et al., 2024). Accordingly, the dependent variable in column (3) is $\Delta Brokered\ Deposits$ which denotes the change in the ratio of brokered deposits to assets. The results indicate that there is no significant change in the reliance on brokered deposits in response to increase in shadow bank competition.

We plot the results of the corresponding dynamic DiD regression in Figure 8. The plots for $Core\ Deposits$ and $Non-core\ Funding$ in panels A and B, respectively, are consistent with the corresponding results in the table, but the economic magnitudes are lower because the dynamic DiD regression captures within-bank changes in these ratios. On the other hand, the plot in panel C indicates a small within-bank increase in reliance on brokered deposits in the first few quarters of 2018 in response to increase in shadow bank competition, but this effect is reversed in subsequent quarters.

Next, we estimate the IV regressions in Panel A separately for small and large banks. For each of the outcome variables in Panel A, we report the coefficient on $Jumbo\widehat{125\ Exposure}$ separately for small and large banks in Panel B. The coefficients in columns (1) and (2) have similar signs, and indicate that both small and large banks decrease their reliance on core deposits and increase reliance on non-core funding in the post-2017 period in response to increased competition from shadow banks. In case of large banks, we find that the increased reliance on non-core funding is mainly driven by increased reliance on other borrowings, but the proportion of non-core deposits does not change.

4.3. Effect on Labor Intensity and Branch Intensity of Bank Operations

In this section, we examine the effect of increased shadow bank competition on the labor intensity and branch intensity of bank operations, which we measure using assets per employee and assets per branch, respectively. The dependent variables are changes in labor intensity and branch intensity of bank operations from the end of 2017Q3 to the end of 2020Q1, and are as follows: Δ*Log(Assets/Employees)* in column (1), where *Log(Assets/Employee)* is the natural logarithm of the ratio of assets to employees; and Δ*Log(Assets/Branches)* in column (2), where *Log(Assets/Branches)* is the natural logarithm of the ratio of assets to number of branches.

We present the results of the second-stage IV regression model in Panel A of Table 6. The positive and significant coefficients on $Jumbo\widehat{125\ Exposure}$ in both the columns indicate that banks respond to increase in shadow bank competition by significantly decreasing their employee count and branch count relative to assets. Taken together, these results are consistent with our earlier findings that banks respond to increase in shadow bank competition by moving away from information-sensitive lending and toward securities. Because lending is labor-intensive and relies on branch networks, the shift from loans to securities allows banks to grow their assets while decreasing their branches and employee headcount.

We plot the results of the corresponding dynamic DiD regression in Figure

9. The dependent variables in panels A and B are $Log(Assets/Employees)$ and $Log(Assets/Branches)$, respectively. Both these plots show that some of the β_τ coefficients in the pre-treatment period are negative, which indicates that banks with higher $Jumbo125\ Exposure$ had more employee-intensive and branch-intensive operations (i.e., lower assets per employee and lower assets per branch) in the pre-2017 period. This is to be expected because expansion of jumbo lending would have required these banks to also increase their employee count and number of branches. In contrast, the β_τ coefficients in the post-2017 period are weakly positive in panel A (starting in $\tau = 6$) and are statistically insignificant in panel B. Overall, it appears that the IV regression results in Panel A of Table 6 are driven by pre-treatment differences in employee-intensity and branch-intensity of operations between banks with high and low $Jumbo125\ Exposure$, which are reversed after 2017.

Next, we estimate the IV regressions in Panel A separately for small and large banks, and report the coefficients on $Jumbo\widehat{125\ Exposure}$ separately for these categories in Panel B. The significant coefficients in column (1) indicate that small banks facing increased competition from shadow banks significantly decrease their employee count and branch count relative to assets in the post-2017 period. However, large banks do not change the labor-intensity or branch-intensity of their operations in response to increase in shadow bank competition, as evidenced by the insignificant coefficients in column (2). This is consistent with our earlier findings that small banks respond more strongly to increase in shadow bank competition.

5. Effects of Shadow Bank Competition on Bank Profitability and Risk

5.1. Effects on Bank Profitability

In this section, we present the results of regressions aimed at understanding the effect of increased competition from shadow banks on bank profitability. We present the results of the second-stage IV regression in Panel A of Table 7, which capture the effect of increase in shadow bank competition on changes in bank profitability over the period from the end of 2017Q3 to the end of 2020Q1.

A major driver of bank profits is net interest income, which is defined as the difference between interest income and interest expense. Accordingly, the dependent variable in column (1) is ΔNII, where *NII* is defined as the net interest income as a percentage of bank assets. We find that increase in shadow bank competition has a negative effect on banks' net interest income ratio. The coefficient estimate translates to a 0.18% decline in *NII* for a 1% increase in *Jumbo125 Exposure*, which is large compared to the average *NII* of 3.4%.

In columns (2) and (3), we separately examine changes in *Interest Expense* and *Interest Income* (both as a percentage of assets), respectively, to understand what is driving the reduction in *NII*. We find that increase in shadow bank competition has a positive effect on interest expense as percentage of assets, but no significant effect on interest income as percentage of assets. Taken together with our results in Panel A of Table 5, it appears that the increase in interest expense ratio following increase in shadow bank competition may be driven by the change in bank deposit composition toward non-core deposits and other borrowings, which are more expensive than core deposits.

The dependent variable in column (4) is ΔROA, where return on assets (ROA) is an aggregate measure of profitability. We find that increase in shadow bank competition has a negative effect on banks' ROA. The coefficient estimate translates to a 0.21% reduction in ROA for a 1% increase in *Jumbo125 Exposure*, which is large compared to the average ROA of 0.88%.

The corresponding dynamic plots for NII, *Interest Expense*, *Interest Income*, and ROA are in panels A through D, respectively, of Figure 10. We compute these profitability measures over the past four quarters in order to smooth out seasonal variation. The plots in panels A and B point to a significant decrease in *NII* and significant increase in interest expense (scaled by assets), respectively, in the post-2017 period; the β_τ coefficients prior to 4Q 2017 are either statistically or economically insignificant. Similarly, the plot in panel D points to a weak decrease in *ROA* in the post-2017 period, with no significant pre-trends prior to 2017Q4. On the other hand, the plot in panel D shows that there was no significant change in net interest income (scaled by assets) after 2017.

We estimate the IV regressions in Panel A separately for small and large banks, and report the coefficients on $Jumbo\widehat{125\ Exposure}$ separately for these categories in Panel B. We find that both small and large banks experience a decline in net interest income and an increase in interest expenses scaled by assets when faced with increase in shadow bank competition, although the magnitude of the effect seems larger for small banks compared to large banks. The increase in shadow banks also results in a decline in ROA for small banks, but there is no significant effect on the ROA of large banks.

5.2. Effects on Bank Credit Quality

Next, we examine the effect of increased competition from shadow banks on the credit quality of banks. If banks shift away from information-sensitive lending when faced with increased competition from shadow banks, then we expect weaker loan performance over time resulting in a worsening of credit quality. Because loan performance takes time to deteriorate, in these regressions, we extend the post-2017 period till 2020Q4 (i.e., 12 quarters) to allow for sufficient time to detect potential deterioration in loan performance. The COVID crisis in early 2020 is the ideal setting to test this hypothesis because inadequate screening or monitoring prior to 2020 is more likely to result in delinquencies and defaults after the onset of the COVID crisis. We obtain qualitatively similar, albeit weaker, results if we limit the post-2017 period till 2020Q1.

We present the results of the second-stage IV regression in Panel A of Table 8, which capture the effect of increase in shadow bank competition on changes in bank credit quality over the period from the end of 2017Q3 to the end of 2020Q4. The dependent variables we examine are: $\Delta Delinquent\ Mortgages$ in column (1), where $Delinquent\ Mortgages$ denotes the percentage of the bank's residential mortgage holdings that are delinquent; and ΔNPL in column (2), where NPL denotes the ratio of non-performing loans to loan (expressed as a percentage). The positive and significant coefficients on $Jumbo\widehat{125\ Exposure}$ in these columns indicate that increase in shadow bank competition has an adverse effect on the quality of banks' mortgage portfolio and the overall credit quality. When we estimate these regressions separately for small and large banks in Panel B, we find that both small and large banks experience deterioration in mortgage portfolio following increase in shadow bank competition, whereas the corresponding effects for overall credit quality in these subsamples are not statistically significant.

In Figure 11 we plot the quarter-by-quarter β_τ coefficients estimated using the dynamic DiD regression for each measure of credit quality. The plot in Panel A indicates that, while there is some evidence of deterioration in mortgage portfolio quality within two quarters after 4Q 2017, the larger effects materialize after the onset of the COVID crisis. We find similar patterns with respect to deterioration of overall credit quality in Panel B.

5.3. Effects on Supervisory Ratings

Finally, we examine whether the effects of shadow bank competition extend to regulators' assessments of bank condition. The supervisory CAMELS ratings provide regulators' confidential evaluations of a bank's overall safety and soundness along six dimensions, combining both quantitative indicators and qualitative assessments of management and governance. In particular, the supervisors evaluate whether boards and senior management identify, measure, monitor, and control risks commensurate with the institution's size and complexity; and respond to changing business conditions. We showed above that banks exposed to shadow bank competition pivot from information-sensitive loans to securities, increase reliance on non-core funding, and experience decline in credit quality and profitability. These shifts are likely to increase supervisory scrutiny of interest-rate risk management, liquidity risk management, and capital adequacy. If supervisors judge that risk management practices and forward-looking planning did not fully keep pace with the altered asset-liability mix and profitability pressures, then we expect adverse effects on supervisory assessments of bank condition.

We present the results of the second-stage IV regression in Panel A of Table 9, which capture the effect of increase in shadow bank competition on the likelihood of a supervisory rating downgrade over the period from the end of 2017Q3 to the end of 2023Q4. We extend the estimation window to 2023Q4 because CAMELS ratings are highly persistent and are typically updated only following an on-site examination every 12–18 months. Accordingly, the dependent variable in each column is an indicator variable to identify whether the bank's corresponding supervisory rating worsened (i.e., increased to a higher numeric value) during this period, and zero otherwise. We obtain qualitatively similar results if we use the change in the numeric rating as the dependent variable, but the interpretation is easier with an indicator variable. We exclude banks that already had the weakest composite rating of 5 in 2017Q3, since these institutions have limited scope for further deterioration and are subject to exceptional supervisory oversight. Each regression additionally includes a fixed effect for the bank's 2017Q3 rating in the corresponding dimension to account for differences in baseline supervisory condition and rating transition probabilities.

The dependent variable in column (1) is an indicator for a downgrade of the composite rating, whereas the dependent variables in columns (2) through (7) indicate downgrade in the following six categories: capital, asset quality, management, earnings, liquidity, and sensitivity to market risk, respectively. We find in column (1) that increase in shadow bank competition increases the likelihood of a composite rating downgrade. The coefficient estimate indicates that a 1% increase in $Jumbo125\ Exposure$ is associated with a 5.7% increase in the likelihood of a composite rating downgrade, which is an economically meaningful effect given that only 12.3% of banks were downgraded over the period. Banks facing greater shadow-bank competition are also significantly more likely to be downgraded on the dimensions of capital (column (2)), management (column (4)), and earnings (column (5)), indicating that competitive pressure is associated with weaker earnings generation, tighter capital headroom, and supervisory concerns about how effectively risks are being governed. The results in Panel B indicate that large banks are more likely to receive a composite rating downgrade and rating downgrades on more dimensions compared to small banks following the increase in shadow bank competition. This may be due to the fact that large banks receive greater regulatory scrutiny compared to small banks, both in terms of the frequency and scope of supervisory examinations.

Figure 12 presents the corresponding dynamic regressions. The patterns we see in these plots are consistent with the results presented in Panel A of Table 9, although the economic magnitudes are substantially lower since these plots show within-bank effects compared to cross-sectional differences in Table 9.

6. Conclusion

How does increased competition from shadow banks affect bank strategies and risk taking? We address these questions using the sharp increases in the jumbo cutoff in the post-2017 period following a long period in which the jumbo cutoff was unchanged, which we argue resulted in a significant increase in shadow bank competition for traditional banks which had high exposure to the jumbo loan market in the pre-2017 period. The increase in shadow bank competition is exogenous to local housing market conditions and bank characteristics because the jumbo cutoff does not respond to changes in local house price conditions.

We show that banks with high exposure to the increased competition from shadow banks decrease the proportion of loans and increase the proportion of securities on the asset side. On the liabilities side, we find that banks with high exposure to the increased competition from shadow banks decrease the proportion of core deposits and increase the proportion of non-core deposits and other borrowings relative to assets. Consistent with a shift away from information-sensitive lending, these banks reduce branches and staffing relative to assets. All these effects are stronger for small banks with assets under $1 billion compared to large banks.

Increase in shadow bank competition has an adverse effect on banks' profitability because of an increase in interest expenses (scaled by assets), possibly due to the shift away from cheaper core deposits to the relatively expensive non-core funding. Increase in shadow bank competition also has an adverse effect on the mortgage quality and overall credit quality of the exposed banks, and leads to worsening of supervisory assessments of overall bank condition and safety.

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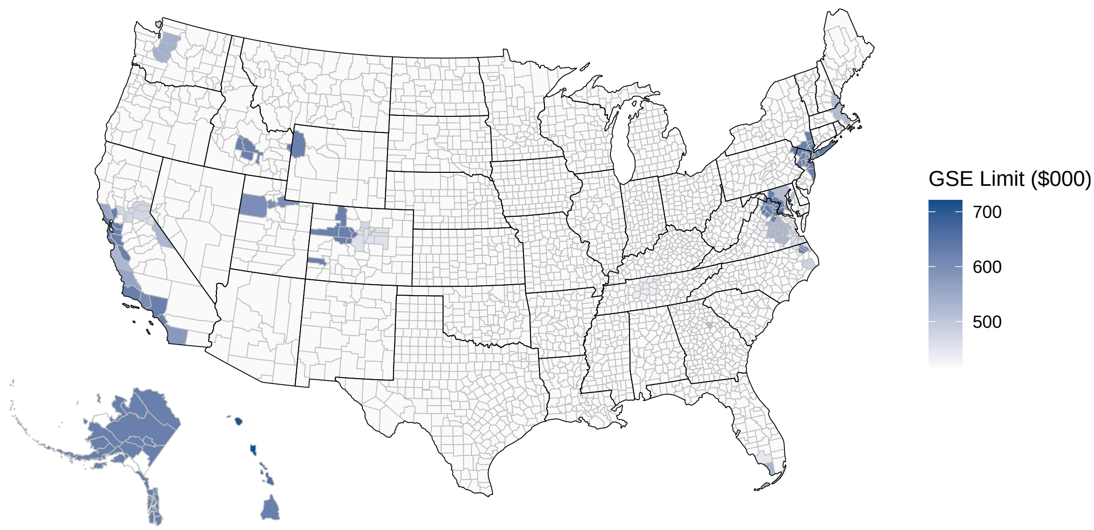
Figure 1: Geography of the Jumbo Cutoff

This figure illustrates the geographical distribution of the GSE jumbo loan cutoff across counties in the United States. Panel A depicts the jumbo cutoff limits in 2016. The darker shades of blue represent higher jumbo loan cutoffs. Panel B shows the updated limits in 2023.

Panel A: 2016



Panel B: 2023

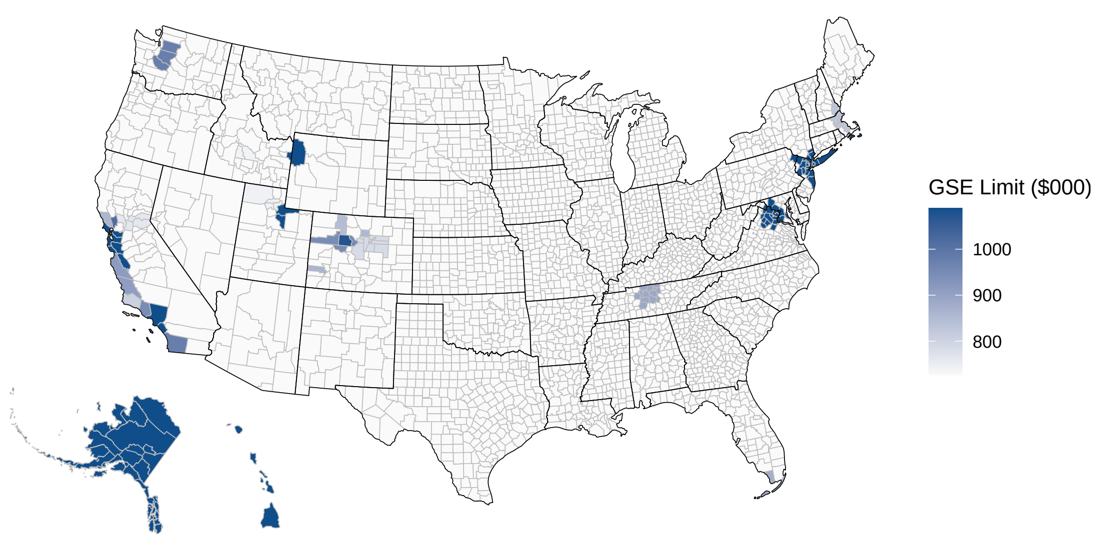


Figure 2: Jumbo Cutoff Over the Years

This figure illustrates the annual GSE jumbo loan limit for "normal" counties (excluding high-cost areas) from 2009 to 2023. The Federal Housing Finance Agency (FHFA) Housing Price Index (HPI), shown as an overlay, serves as the basis for adjusting the GSE cutoff level in response to changes in the national average price of single-family homes. The figure also presents Zillow's Top and Bottom Tier House Value Indices (HVI), which reflect the upper and lower segments of home prices, respectively, within Zillow's housing data

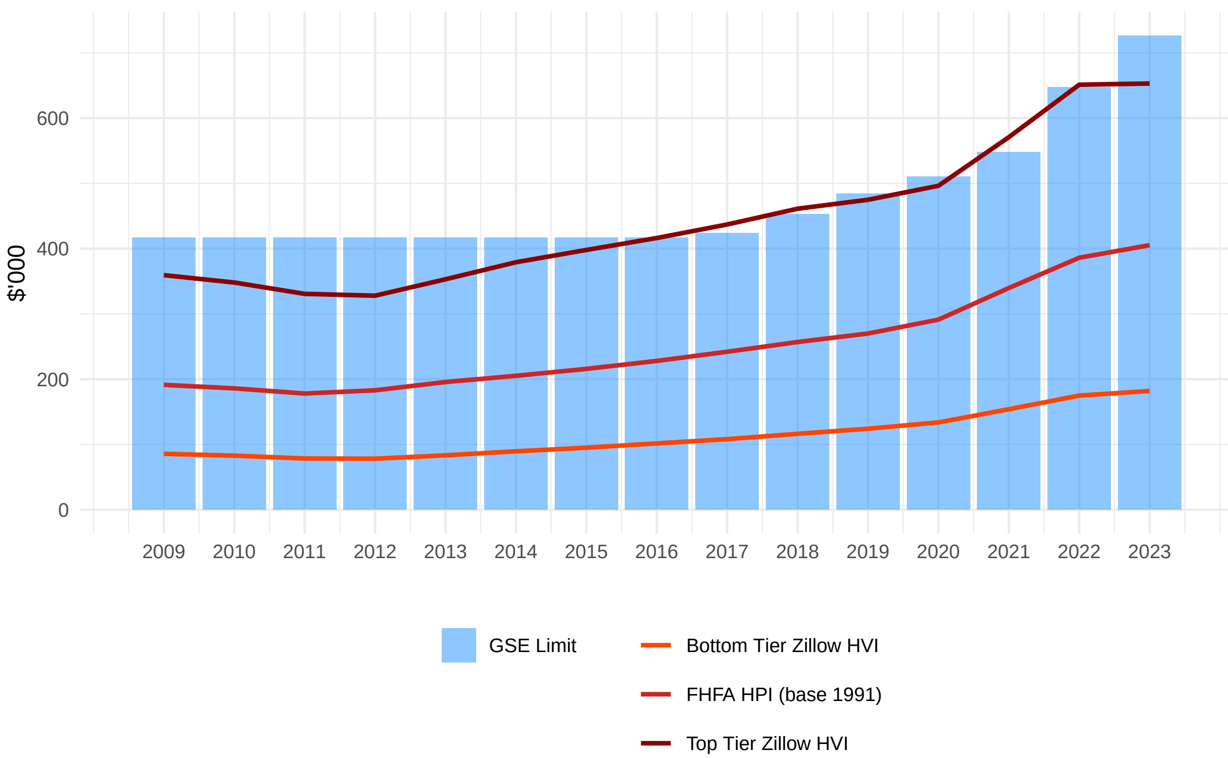


Figure 3: Distribution of *Jumbo125 Exposure*

This figure shows the distribution of *Jumbo125 Exposure*, which measures the exposure of banks to the jumbo loan segment in the pre-2017 period, as defined in equation 1. *Jumbo125 Exposure* is calculated by aggregating a bank's Jumbo125 loan originations across all counties over the 2012–2016 period and scaling the total by the bank's assets at the end of 2016. The measure reflects the relative importance of the jumbo loan market for each bank prior to the 2017 increase in the jumbo cutoff. Specifically, Jumbo Exposure for bank i is given by:

$$Jumbo125\ Exposure_i = \frac{\sum_{t=2012}^{2016} \left(\sum_k Jumbo125\ Lending_{ik,t} \right)}{Assets_{i,2016}}$$

where t denotes the year and k denotes the county.

We use darker shades to indicate banks that fall above the 75th and 90th percentiles of Jumbo Exposure, highlighting those with the highest exposure.

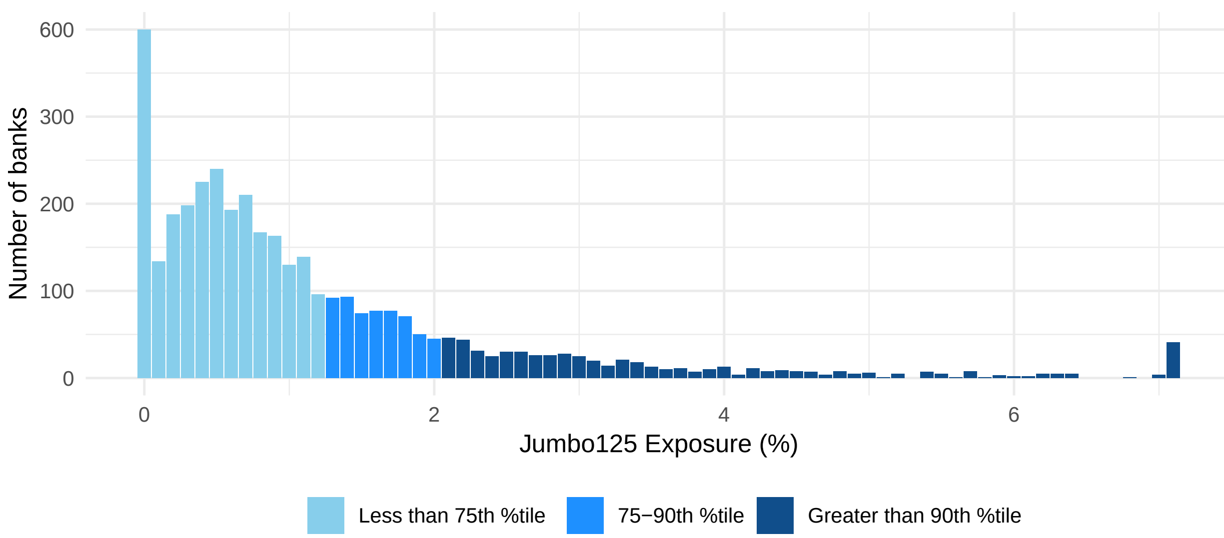


Table 1: Descriptive Statistics

This table provides descriptive statistics for key bank characteristics. Each observation corresponds to a bank, and all the bank characteristics, other than the instrument *WA Price Change*, are measured as of 2016. For each variable, the table reports the number of observations (Obs), mean, standard deviation (SD), and selected percentiles (P10, P25, P50, P75, P90). All the variables are defined in Table IA.1.

Variable	Obs	Mean	SD	P10	P25	P50	P75	P90
Assets ($bn)	3,356	4.030	61.560	0.080	0.140	0.280	0.610	1.530
WA Price Change (%)	3,356	15	10.940	4.240	7.680	11.620	19.140	33.460
Jumbo125 Exposure	3,356	1.140	1.330	0	0.260	0.730	1.530	2.760
Jumbo Exposure	3,356	5.150	6.230	0.240	1.380	3.220	6.430	12.110
Loans (%)	3,356	67.290	15.080	46.330	58.930	69.960	78.550	84.010
Total Securities (%)	3,356	19.570	14.330	3.270	9.010	16.880	26.930	39.340
SFR Loans (%)	3,356	19.000	14.210	4.750	9.090	15.500	24.980	38.430
Other RE Loans (%)	3,356	33.460	14.900	13.360	23.130	33.540	43.320	52.540
Other Loans (%)	3,356	14.820	10.900	2.940	7.250	12.810	20.220	28.310
Core Deposits (%)	3,356	76.750	9.550	64.580	71.800	78.610	83.530	87.060
Non-Core Funding (%)	3,356	12.220	9.290	2.760	5.380	10.140	16.830	24.180
Brokered Deposits (%)	3,356	2.760	5.670	0	0	0	3.400	8.960
Mortgage Delinquency (%)	3,356	2.230	2.930	0	0.550	1.410	2.870	5
NPL (%)	3,356	1.080	1.630	0.030	0.250	0.640	1.350	2.370
NII (%)	3,356	3.390	0.690	2.650	3	3.360	3.730	4.130
Interest Expense (%)	3,356	0.430	0.240	0.160	0.250	0.390	0.550	0.740
Interest Income (%)	3,356	4.150	0.810	3.310	3.700	4.110	4.530	4.990
ROA (%)	3,356	0.880	0.740	0.290	0.550	0.850	1.170	1.580
Assets per Branch ($mn)	3,356	341.260	4,914.780	30.440	42.200	60.870	95.390	163.410
Assets per Employee ($mn)	3,356	5.620	8.070	3.110	3.740	4.630	6.050	8.320
CAMELS Composite Rating	3,356	1.860	0.680	1	1	2	2	2

Table 2: Descriptive Stats - By IV Quartiles

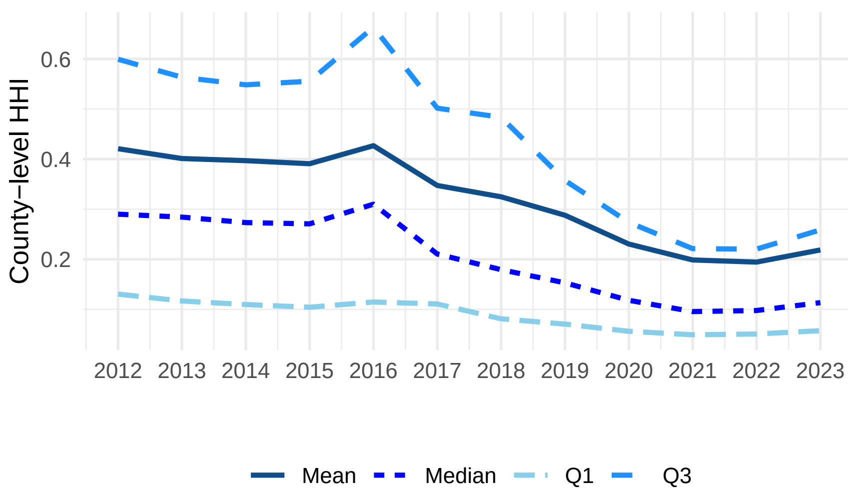
This table reports mean values of key bank characteristics separately for banks sorted into four quartiles by the instrument, *WA Price Change*. Columns Q1 through Q4 denote the four quartiles, where Q1 denotes the lowest quartile and Q4 denotes the highest quartile of *WA Price Change*. All bank characteristics are measured as of 2016. All variables are defined in Table IA.1.

Variable	Q1	Q2	Q3	Q4	t-test p val (Q4-Q1)
WA Price Change (%)	4.447	9.597	14.855	31.091	0.00
Jumbo125 Exposure	0.901	1.155	1.138	1.349	0.00
Jumbo Exposure	3.664	4.858	5.007	6.920	0.00
Loans (%)	65.667	67.745	67.248	68.669	0.00
Total Securities (%)	21.976	19.466	19.298	17.177	0.00
SFR Loans (%)	21.811	20.622	17.345	15.962	0.00
Other RE Loans (%)	29.985	32.586	33.042	38.016	0.00
Other Loans (%)	13.489	14.303	16.650	14.392	0.12
Core Deposits (%)	77.233	76.948	76.611	76.518	0.17
Non-Core Funding (%)	11.676	11.687	12.336	12.806	0.06
Brokered Deposits (%)	2.290	2.365	3.049	2.886	0.02
Mortgage Delinquency (%)	2.686	2.313	2.031	1.630	0.00
NPL (%)	1.165	1.123	1.028	0.852	0.00
NII (%)	3.318	3.383	3.366	3.456	0.11
Interest Expense (%)	0.431	0.439	0.422	0.401	0.21
Interest Income (%)	4.099	4.154	4.115	4.182	0.22
ROA (%)	0.826	0.894	0.910	0.912	0.01
Assets per Branch ($mn)	66.316	67.850	103.932	169.023	0.00
Assets per Employee ($mn)	4.723	4.853	5.503	6.147	0.00
CAMELS Composite Rating	1.819	1.785	1.845	1.963	0.00

Figure 4: Non-bank Competition in the Jumbo2016 Segment

This figure presents trends in non-bank competition at the county-year level. Panel A shows the Herfindahl-Hirschman Index (HHI) for Jumbo 2016 lending, calculated based on the market share of each lender in a given county-year. The figure plots the mean (solid dark blue line), median (dashed blue line), first quartile (Q1, light blue dashed line), and third quartile (Q3, light blue dashed line) over time. Panel B displays the number of new non-bank entrants into the Jumbo 2016 market in each county-year, defined as lenders that did not participate in this segment in the previous year. The figure presents the mean (solid dark blue line) and Q3 (light blue dashed line) of new non-bank entrants across counties.

Panel A: County-level Jumbo2016 HHI



Panel B: Non-bank Entry to Jumbo2016 Segment

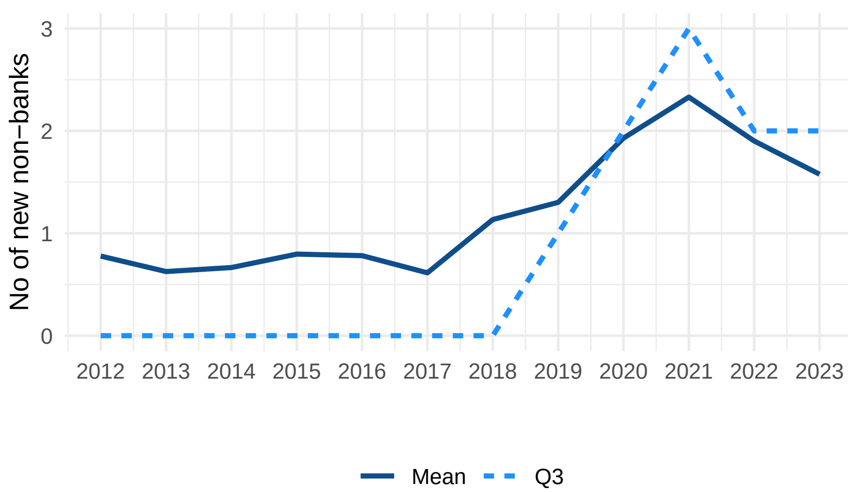
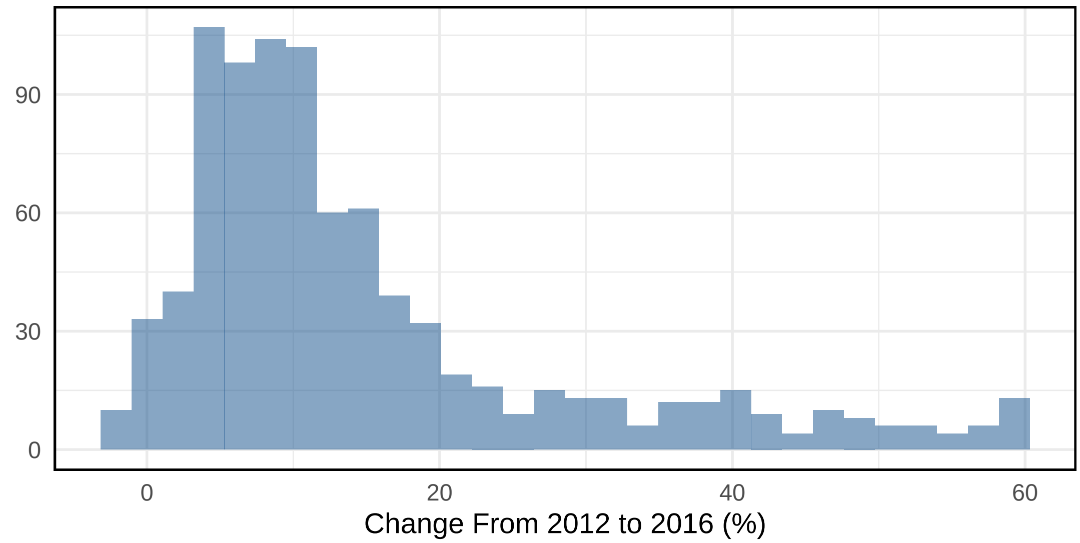


Figure 5: Distribution of Shift and Shift-Share Components of the Instrument

Panel A shows the distribution of house price changes from 2012 to 2016 across 3-digit zip code (Zip3) areas, which represent the "shift" component in our Bartik-style instrument. Panel B plots the corresponding distribution of our instrument—the bank-level, deposit-weighted average house price change over the same period—constructed using each bank's 2011 deposit shares across Zip3 areas.

Panel A: Zip3-Level Price Change from 2012 to 2016, Shift



Panel B: Bank-Level 2011 Deposit-Weighted Price Change from 2012 to 2016, Shift-Share (Instrument)

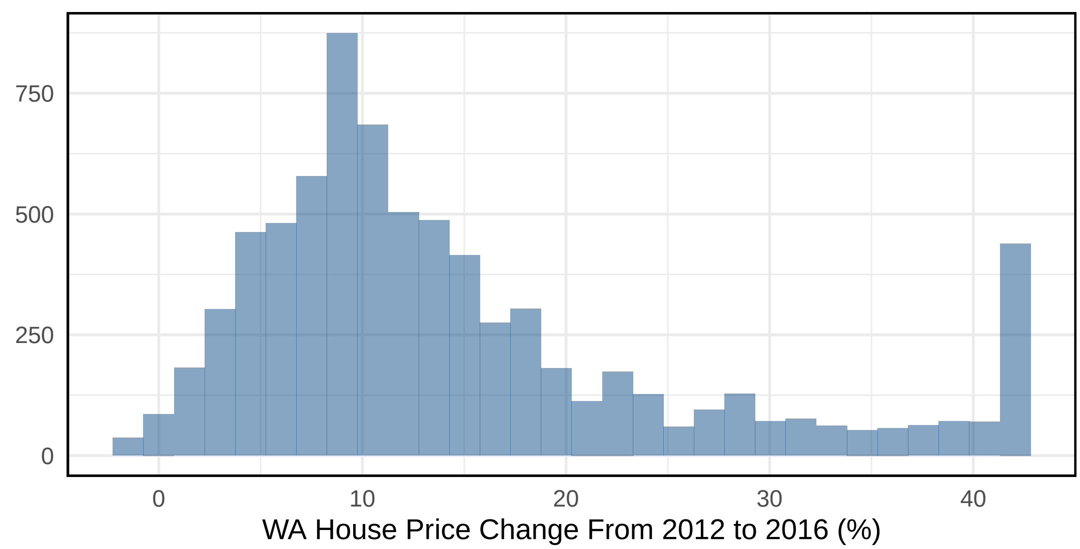


Figure 6: First Stage - Univariate

This figure plots the average value of the treatment variable, Jumbo125 Exposure, by deciles of the instrument—bank-level weighted average house price change from 2012 to 2016. The plot illustrates a positive first-stage relationship: banks operating in areas with higher pre-2017 house price growth tend to have greater exposure to loans just above the 2016 conforming loan limit. The blue line shows the fitted linear trend, and the shaded area represents the 95% confidence interval.

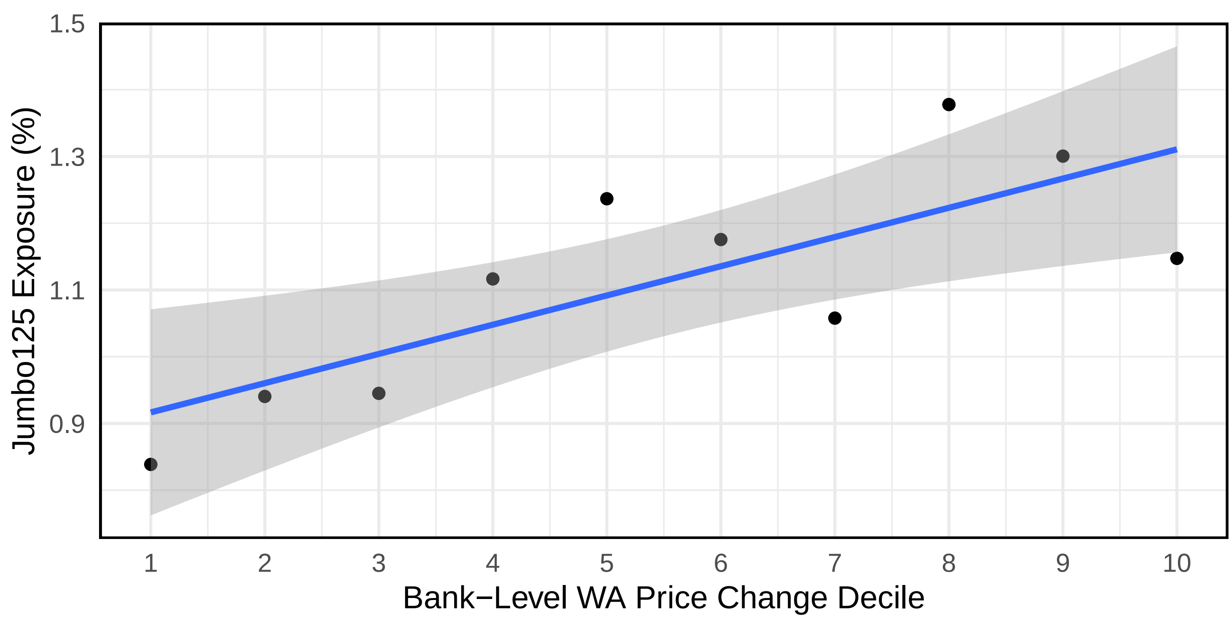


Table 3: First Stage Regression

This table reports results from the first-stage regressions used to instrument for bank exposure to the jumbo mortgage segment. Columns (1) and (2) present results for the full sample. Column (1) uses Jumbo125 Exposure—the main endogenous variable in our baseline analysis—as the dependent variable, while Column (2) uses an alternative measure, Jumbo Exposure. Columns (3) and (4) repeat the specification from Column (1) for subsamples of small and large banks, respectively. The instrument, WA Price Change, is the deposit-weighted average house price change across Zip3 areas from 2012 to 2016. All control variables are measured at the end of 2016. Bank size fixed effects are included in all specifications. Robust standard errors are in parentheses.

	Full Sample		Small Banks	Large Banks
	(1)	(2)	(3)	(4)
Dependent Variable	Jumbo125 Exposure	Jumbo Exposure	Jumbo125 Exposure	Jumbo125 Exposure
WA Price Change	1.791***	11.95***	1.641***	2.139***
	(0.1698)	(1.021)	(0.1865)	(0.3729)
log(Assets)	0.1054***	0.9687***	0.1289***	-0.0323
	(0.0255)	(0.1289)	(0.0282)	(0.0597)
Liquid Assets (%)	-0.0025	-0.0117	-0.0018	0.0055
	(0.0024)	(0.0121)	(0.0026)	(0.0054)
Interest Expense/Deposits (%)	0.1668**	1.402***	0.1610*	0.2088
	(0.0807)	(0.3980)	(0.0902)	(0.1866)
Tier 1 Capital Ratio (%)	-0.0213***	-0.1461***	-0.0207***	-0.0267
	(0.0069)	(0.0288)	(0.0070)	(0.0260)
SFR Loans (%)	0.0476***	0.1517***	0.0435***	0.0726***
	(0.0021)	(0.0097)	(0.0022)	(0.0058)
Observations	3,356	3,356	2,847	509
R^2	0.30993	0.20686	0.27715	0.50781
F-test	187.90	109.12	181.48	73.843
Bank size fixed effects	✓	✓	✓	✓

Table 4: IV: Shadow Bank Competition and Composition of Bank Assets

This table reports second-stage estimates from the instrumental variables (IV) regression examining the effect of shadow bank competition on bank asset composition. Panel A presents results for the full sample, while Panel B reports the estimated coefficient on Instrumented Jumbo125 Exposure separately for small banks (total assets < 1 billion) and large banks (total assets > 1 billion). We instrument for a bank's *Jumbo125 Exposure* using its deposit-weighted average house price change across Zip3 areas from 2012 to 2016 (see Equation (2)). The dependent variable in each column denotes the change in a measure of the bank's asset composition over the period from the end of 2017Q3 to the end of 2020Q1. All control variables are measured at the end of 2016. The specification includes bank size category fixed effects. Standard errors (in parentheses) are heteroskedasticity-robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full Sample

	Δ Loans (%) (1)	Δ Securities (%) (2)	Δ SFR Loans(%) (3)	Δ Other RE Loans (%) (4)	Δ Other Loans(%) (5)
$\widehat{\text{Jumbo125}}$ Exposure	-1.375**	1.696***	-0.5880**	-1.095**	-0.1295
	(0.5882)	(0.5197)	(0.2911)	(0.4251)	(0.3274)
log(Assets)	0.4000**	0.2001	-0.0589	0.2581**	0.3651***
	(0.1790)	(0.1581)	(0.0886)	(0.1293)	(0.0996)
Liquid Assets (%)	0.0454***	0.0886***	-0.0011	0.0217*	0.0051
	(0.0170)	(0.0150)	(0.0084)	(0.0123)	(0.0095)
Single Family Loans/Assets (%)	0.0588**	-0.0604**	-0.0193	0.0664***	0.0330**
	(0.0298)	(0.0263)	(0.0148)	(0.0216)	(0.0166)
Interest Expense/Deposits (%)	-1.429***	1.732***	-0.6853***	-0.6795**	-0.1740
	(0.4085)	(0.3610)	(0.2022)	(0.2952)	(0.2274)
Tier 1 Capital Ratio (%)	0.1331***	-0.1106***	0.0876***	-0.0016	0.0040
	(0.0415)	(0.0367)	(0.0205)	(0.0300)	(0.0231)
Observations	2,813	2,813	2,813	2,813	2,813
F-test (1st stage)	98.865	98.865	98.865	98.865	98.865
Bank size fixed effects	✓	✓	✓	✓	✓

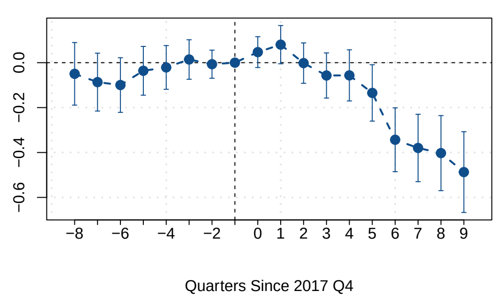
Panel B: By Size

	Δ Loans (%)	Δ Securities (%)	SFR Loans(%)	Δ Other RE Loans(%)	Δ Other Loans(%)	Δ NBFI Loans(%)	Obs	F-test
Small banks	-2.308***	2.478***	-0.8476**	-1.897***	-0.1732	0.0780	2,379	59.70
	(0.8636)	(0.7145)	(0.4051)	(0.6571)	(0.4680)	(0.0575)		
Large banks	0.241	0.359	-0.202	0.093	0.192	0.284**	434	34.22
	(0.8069)	(0.7527)	(0.4723)	(0.6309)	(0.5388)	(0.1355)		

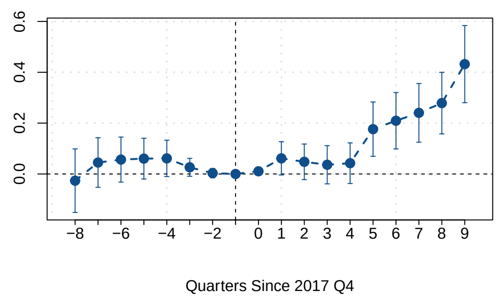
Figure 7: Shadow Bank Competition and Composition of Bank Assets– Dynamic Effects

This figure presents the results of dynamic DiD regressions (equation (5)) estimating the within-bank quarter-by-quarter effects of *Jumbo125 Exposure* on bank asset composition in the quarters prior to and after 2017Q4. In each panel, we plot the β_τ estimates corresponding to the dependent variable indicated in the panel's header. The error bars indicate 90% confidence intervals for each coefficient estimate. The regressions include fixed effects for the bank (μ_i), quarter-year (μ_q), and size category. Standard errors are clustered at the bank level.

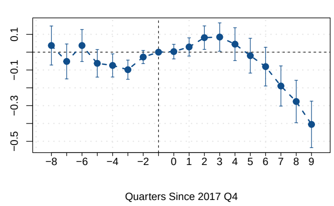
Panel A: Loans (%)



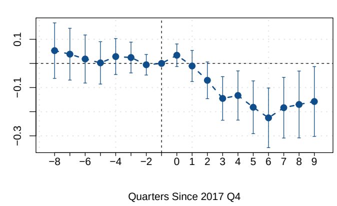
Panel B: Securities (%)



C: SFR Loans (%)



D: Other RE Loans (%)



E: Other Loans (%)

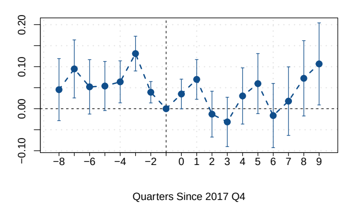


Table 5: IV: Shadow Bank Competition and Composition of Bank Liabilities

This table reports second-stage estimates from the instrumental variables (IV) regression examining the effect of shadow bank competition on bank liability composition. Panel A presents results for the full sample, while Panel B reports the estimated coefficient on Instrumented Jumbo125 Exposure separately for small banks (total assets < 1 billion) and large banks (total assets > 1 billion). We instrument for a bank's *Jumbo125 Exposure* using its deposit-weighted average house price change across Zip3 areas from 2012 to 2016 (see Equation (2)). The dependent variable in each column denotes the change in a measure of the bank's liability composition over the period from the end of 2017Q3 to the end of 2020Q1. All control variables are measured at the end of 2016. The specification includes bank size category fixed effects. Standard errors (in parentheses) are heteroskedasticity-robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full Sample

	Δ Core Deposits (%) (1)	Δ Non-Core Funding (%) (2)	Δ Brokered Deposits (%) (3)
$\widehat{\text{Jumbo125 Exposure}}$	-1.996***	2.314***	0.1195
	(0.5234)	(0.5380)	(0.3381)
log(Assets)	0.4883***	-0.5527***	-0.4037***
	(0.1592)	(0.1637)	(0.1029)
Liquid Assets (%)	-0.0757***	0.0647***	0.0244**
	(0.0152)	(0.0156)	(0.0098)
Single Family Loans/Assets (%)	0.0602**	-0.0764***	0.0251
	(0.0265)	(0.0273)	(0.0171)
Interest Expense/Deposits (%)	0.6102*	-0.4275	-0.8867***
	(0.3635)	(0.3737)	(0.2348)
Tier 1 Capital Ratio (%)	-0.1078***	0.1966***	0.0580**
	(0.0369)	(0.0380)	(0.0239)
Observations	2,813	2,813	2,813
F-test (1st stage)	98.865	98.865	98.865
Bank size fixed effects	✓	✓	✓

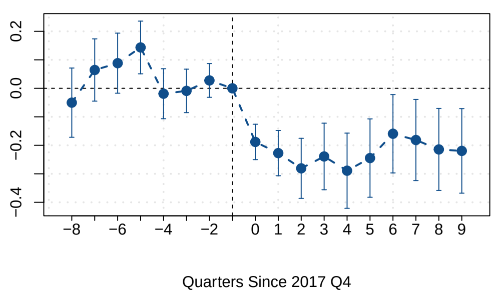
Panel B: By Size

	Δ Core Deposits (%)	Δ Non-Core Funding (%)	Δ Brokered Deposits (%)	Obs	F-test
Small banks	-1.769***	2.239***	-0.208	2,379	59.70
	(0.7552)	(0.7490)	(0.290)		
Large banks	-2.77**	2.742**	1.038	434	34.22
	(1.082)	(1.090)	(1.245)		

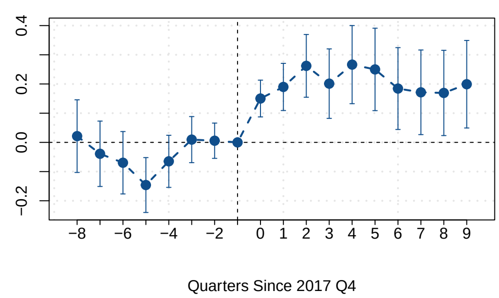
Figure 8: Shadow Bank Competition and Composition of Bank Liabilities– Dynamic Effects

This figure presents the results of dynamic DiD regressions (equation (5)) estimating the within-bank quarter-by-quarter effects of *Jumbo125 Exposure* on bank liability composition in the quarters prior to and after 2017Q4. In each panel, we plot the β_τ estimates corresponding to the dependent variable indicated in the panel's header. The error bars indicate 90% confidence intervals for each coefficient estimate. The regressions include fixed effects for the bank (μ_i), quarter-year (μ_q), and size category. Standard errors are clustered at the bank level.

Panel A: Core Deposits



Panel B: Non-Core Funding (%)



Panel C: Brokered Deposits (%)

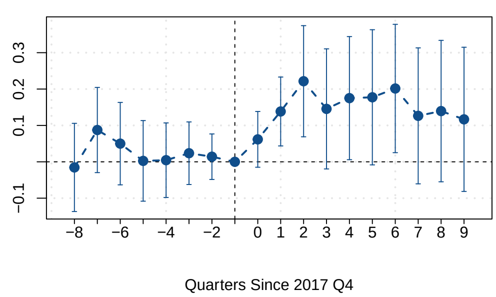


Table 6: IV:Shadow Bank Competition and Bank's Labor and Branch Intensity

This table reports second-stage estimates from the instrumental variables (IV) regression examining the effect of shadow bank competition on bank labor and branch intensity. Panel A presents results for the full sample, while Panel B reports the estimated coefficient on Instrumented Jumbo125 Exposure separately for small banks (total assets < 1 billion) and large banks (total assets > 1 billion). We instrument for a bank's *Jumbo125 Exposure* using its deposit-weighted average house price change across Zip3 areas from 2012 to 2016 (see Equation (2)). The dependent variable in each column denotes the change in a measure of the bank's labor and branch intensity over the period from the end of 2017Q3 to the end of 2020Q1. All control variables are measured at the end of 2016. The specification includes bank size category fixed effects. Standard errors (in parentheses) are heteroskedasticity-robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full Sample

	Δ log(Assets/Employees) (1)	Δ log(Assets/Branches) (2)
$\widehat{\text{Jumbo125 Exposure}}$	0.0411***	0.0830***
	(0.0132)	(0.0194)
log(Assets)	0.0030	0.0095
	(0.0040)	(0.0058)
Liquid Assets (%)	-0.0004	0.0003
	(0.0004)	(0.0005)
Single Family Loans/Assets (%)	-0.0020***	-0.0046***
	(0.0007)	(0.0010)
Interest Expense/Deposits (%)	0.0048	-0.0232*
	(0.0092)	(0.0132)
Tier 1 Capital Ratio (%)	-0.0002	-0.0006
	(0.0009)	(0.0013)
Observations	2,813	2,781
F-test (1st stage)	98.865	94.126
Bank size fixed effects	✓	✓

Panel B: By Size

	Δ log(Assets/Employees)	Δ log(Assets/Branches)	Obs	F-test
Small banks	0.053***	0.118***	2,379	59.70
	(0.0202)	(0.0310)		
Large banks	0.014	-0.007	434	34.22
	(0.0207)	(0.0284)		

Figure 9: Shadow Bank Competition and Bank's Labor and Branch Intensity– Dynamic Effects

This figure presents the results of dynamic DiD regressions (equation (5)) estimating the within-bank quarter-by-quarter effects of *Jumbo125 Exposure* on bank bank scale metrics in the quarters prior to and after 2017Q4. In each panel, we plot the β_τ estimates corresponding to the dependent variable indicated in the panel's header. The error bars indicate 90% confidence intervals for each coefficient estimate. The regressions include fixed effects for the bank (μ_i), quarter-year (μ_q), and size category. Standard errors are clustered at the bank level.

Panel A: log(Assets per Employee)

Panel B: log(Assets per Branch)

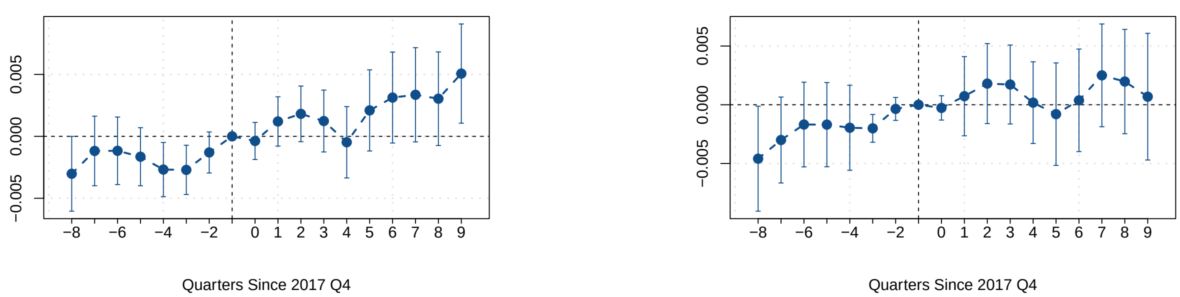


Table 7: IV: Shadow Bank Competition and Profitability

This table reports second-stage estimates from the instrumental variables (IV) regression examining the effect of shadow bank competition on bank profitability. Panel A presents results for the full sample, while Panel B reports the estimated coefficient on Instrumented Jumbo125 Exposure separately for small banks (total assets < 1 billion) and large banks (total assets > 1 billion). We instrument for a bank's *Jumbo125 Exposure* using its deposit-weighted average house price change across Zip3 areas from 2012 to 2016 (see Equation (2)). The dependent variable in each column denotes the change in a measure of the bank's profitability over the period from the end of 2017Q3 to the end of 2020Q1. All control variables are measured at the end of 2016. The specification includes bank size category fixed effects. Standard errors (in parentheses) are heteroskedasticity-robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full Sample

	Δ NII (%) (1)	Δ Int. Exp. (%) (2)	Δ Int. Inc (%) (3)	Δ ROA (%) (4)
$\widehat{\text{Jumbo125 Exposure}}$	-0.1804***	0.0901***	-0.0354	-0.2084**
	(0.0355)	(0.0182)	(0.0336)	(0.0865)
log(Assets)	0.0319***	-0.0092*	0.0139	0.0206
	(0.0108)	(0.0055)	(0.0102)	(0.0263)
Liquid Assets (%)	0.0065***	-0.0020***	0.0040***	0.0002
	(0.0010)	(0.0005)	(0.0010)	(0.0025)
Single Family Loans/Assets (%)	0.0086***	-0.0052***	0.0026	0.0097**
	(0.0018)	(0.0009)	(0.0017)	(0.0044)
Interest Expense/Deposits (%)	-0.2621***	0.2029***	-0.0626***	-0.2646***
	(0.0247)	(0.0126)	(0.0233)	(0.0601)
Tier 1 Capital Ratio (%)	-0.0112***	0.0049***	-0.0074***	-0.0365***
	(0.0025)	(0.0013)	(0.0024)	(0.0061)
Observations	2,813	2,813	2,813	2,813
F-test (1st stage)	98.865	98.865	98.865	98.865
Bank size fixed effects	✓	✓	✓	✓

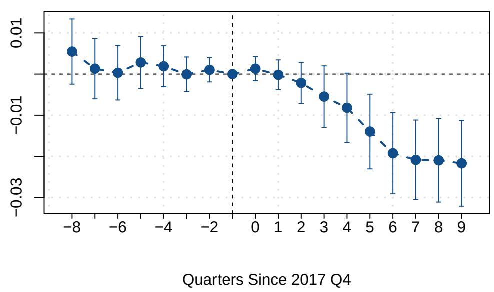
Panel B: By Size

	Δ NII (%)	Δ Int. Exp. (%)	Δ Int. Inc (%)	Δ ROA (%)	Obs	F-test
Small banks	-0.21***	0.11***	-0.026	-0.249**	2,379	59.70
	(0.0576)	(0.0323)	(0.0398)	(0.1187)		
Large banks	-0.111**	0.054**	-0.051	-0.184	434	34.22
	(0.0498)	(0.0236)	(0.0368)	(0.2020)		

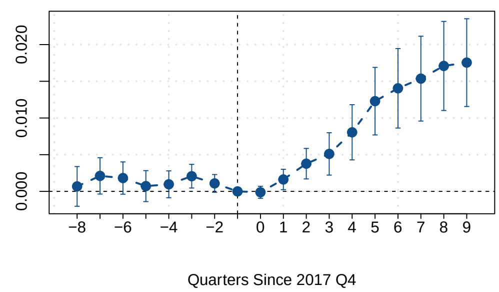
Figure 10: Shadow Bank Competition and Bank Profits– Dynamic Effects

This figure presents the results of dynamic DiD regressions (equation (5)) estimating the within-bank quarter-by-quarter effects of *Jumbo125 Exposure* on bank profitability metrics in the quarters prior to and after 2017Q4. In each panel, we plot the β_τ estimates corresponding to the dependent variable indicated in the panel's header. The error bars indicate 90% confidence intervals for each coefficient estimate. The regressions include fixed effects for the bank (μ_i), quarter-year (μ_q), and size category. Standard errors are clustered at the bank level.

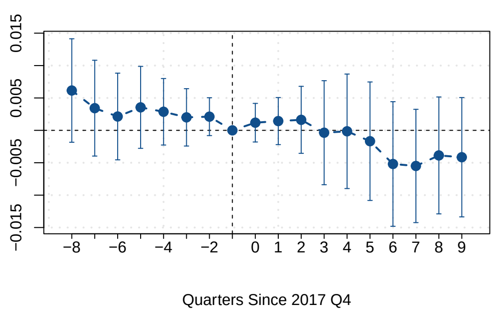
Panel A: Net Interest Income (%)



Panel B: Interest Expense (%)



Panel C: Interest Income (%)



Panel D: Return on Assets (%)

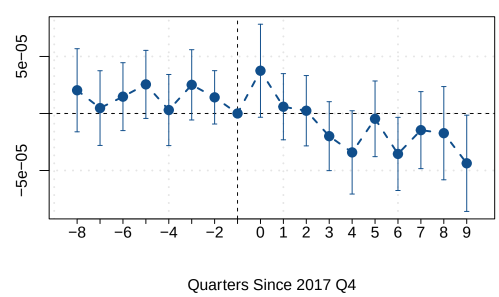


Table 8: IV: Shadow Bank Competition and Credit Quality

This table reports second-stage estimates from the instrumental variables (IV) regression examining the effect of shadow bank competition on bank credit quality. Panel A presents results for the full sample, while Panel B reports the estimated coefficient on Instrumented Jumbo125 Exposure separately for small banks (total assets < 1 billion) and large banks (total assets > 1 billion). We instrument for a bank's *Jumbo125 Exposure* using its deposit-weighted average house price change across Zip3 areas from 2012 to 2016 (see Equation (2)). The dependent variable in each column denotes the change in a measure of the bank's credit quality over the period from the end of 2017Q3 to the end of 2021Q4. All control variables are measured at the end of 2016. The specification includes bank size category fixed effects. Standard errors (in parentheses) are heteroskedasticity-robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full Sample

	Δ Mtg. Delinquency (%) (1)	Δ NPL (%) (2)
$\widehat{\text{Jumbo125 Exposure}}$	0.7586***	0.3105**
	(0.2573)	(0.1439)
log(Assets)	0.0451	-0.0013
	(0.0784)	(0.0423)
Liquid Assets (%)	-0.0093	-0.0059
	(0.0077)	(0.0039)
Interest Expense/Deposits (%)	-0.3906*	-0.2594**
	(0.2128)	(0.1115)
Tier 1 Capital Ratio (%)	-0.0131	-0.0029
	(0.0181)	(0.0138)
Single Family Loans/Assets (%)	-0.0268**	-0.0134**
	(0.0125)	(0.0066)
Observations	2,648	2,648
F-test (1st stage)	92.080	92.080
Bank size fixed effects	✓	✓

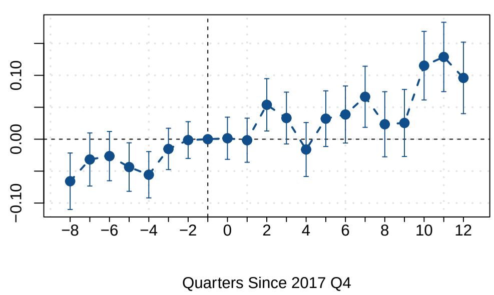
Panel B: By Size

	Δ Mtg. Delinquency (%)	Δ NPL (%)	Obs	F-test
Small banks	0.53*	0.313	2,234	61.54
	(0.3350)	(0.1969)		
Large banks	0.846**	0.3506*	414	32.64
	(0.4426)	(0.1921)		

Figure 11: Shadow Bank Competition and Bank Risk– Dynamic Effects

This figure presents the results of dynamic DiD regressions (equation (5)) estimating the within-bank quarter-by-quarter effects of *Jumbo125 Exposure* on bank risk metrics in the quarters prior to and after 2017Q4. In each panel, we plot the β_τ estimates corresponding to the dependent variable indicated in the panel's header. The error bars indicate 90% confidence intervals for each coefficient estimate. The regressions include fixed effects for the bank (μ_i), quarter-year (μ_q), and size category. Standard errors are clustered at the bank level.

Panel A: Mortgage Delinquencies (%)



Panel B: Non-performing Loans (%)

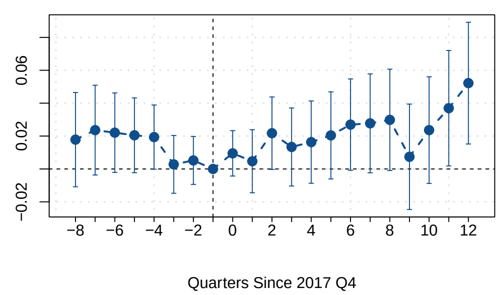


Table 9: IV: Shadow Bank Competition and Supervisory Ratings

This table reports second-stage estimates from the instrumental variables (IV) regression examining the effect of shadow bank competition on bank supervisory ratings (CAMELS ratings) downgrades. Panel A presents results for the full sample, while Panel B reports the estimated coefficient on Instrumented Jumbo125 Exposure separately for small banks (total assets < 1 billion) and large banks (total assets > 1 billion). We instrument for a bank's *Jumbo125 Exposure* using its deposit-weighted average house price change across Zip3 areas from 2012 to 2016 (see Equation (2)). The dependent variable in each column denotes the change in a measure of the bank's supervisory ratings (CAMELS ratings) downgrades over the period from the end of 2017Q3 to the end of 2023Q4. All control variables are measured at the end of 2016. The specification includes bank size category fixed effects. Standard errors (in parentheses) are heteroskedasticity-robust. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Full Sample; Dependent Variable = Downgrade Indicator

	Composite	Capital	Asset Quality	Management	Earnings	Liquidity	Sensitivity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\widehat{\text{Jumbo125}}$ Exposure	0.0569*	0.0739***	0.0138	0.0677**	0.0803***	0.0493	0.0191
	(0.0303)	(0.0286)	(0.0268)	(0.0325)	(0.0295)	(0.0333)	(0.0319)
log(Assets)	-0.0077	-0.0148	0.0115	-0.0073	-0.0223**	-0.0068	-0.0069
	(0.0096)	(0.0092)	(0.0087)	(0.0101)	(0.0099)	(0.0110)	(0.0106)
Liquid Assets (%)	-0.0013	-0.0020**	-0.0015*	-0.0007	-0.0027***	-0.0082***	-0.0011
	(0.0009)	(0.0009)	(0.0008)	(0.0010)	(0.0009)	(0.0011)	(0.0009)
Single Family Loans/Assets (%)	-0.0029**	-0.0040***	-0.0018	-0.0029*	-0.0017	-0.0030*	-0.0003
	(0.0015)	(0.0014)	(0.0013)	(0.0016)	(0.0014)	(0.0016)	(0.0016)
Interest Expense/Deposits (%)	0.0447*	0.0371	0.0548***	0.0306	0.0505**	0.1014***	0.0372
	(0.0229)	(0.0233)	(0.0211)	(0.0243)	(0.0237)	(0.0250)	(0.0232)
Tier 1 Capital Ratio (%)	-0.0029	-0.0195***	0.0007	0.0016	0.0007	-0.0069**	-0.0038
	(0.0024)	(0.0025)	(0.0023)	(0.0026)	(0.0025)	(0.0030)	(0.0025)
Observations	2,494	2,495	2,491	2,493	2,487	2,505	2,506
F-test (1st stage)	98.132	95.593	97.233	98.596	102.06	92.681	90.606
Bank size fixed effects	✓	✓	✓	✓	✓	✓	✓
CAMELS Rating	✓	✓	✓	✓	✓	✓	✓

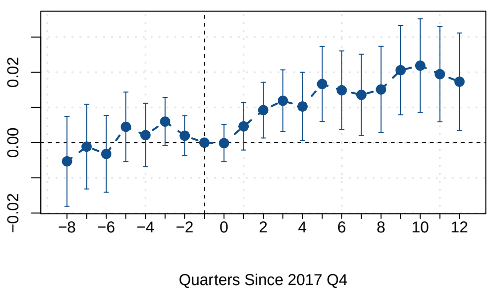
Panel B: By Size

	Composite	Capital	Asset Quality	Management	Earnings	Liquidity	Sensitivity
Small banks	0.034	0.068**	0.032	0.069*	0.057	0.023	0.025
	(0.0358)	(0.0340)	(0.0363)	(0.0414)	(0.0425)	(0.0427)	(0.0381)
Large banks	0.11*	0.114**	0.034	0.061	0.232***	0.133**	0.024
	(0.0606)	(0.0523)	(0.0479)	(0.0596)	(0.0746)	(0.0616)	(0.0592)

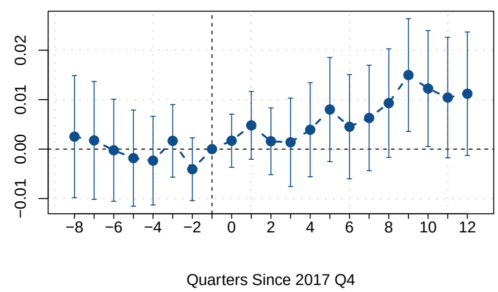
Figure 12: Shadow Bank Competition and CAMELS Ratings– Dynamic Effects

This figure presents the results of dynamic DiD regressions (equation (5)) estimating the within-bank quarter-by-quarter effects of *Jumbo125 Exposure* on bank CAMELS ratings in the quarters prior to and after 2017Q4. In each panel, we plot the β_τ estimates corresponding to the dependent variable indicated in the panel's header. The error bars indicate 90% confidence intervals for each coefficient estimate. The regressions include fixed effects for the bank (μ_i), quarter-year (μ_q), and size category. Standard errors are clustered at the bank level.

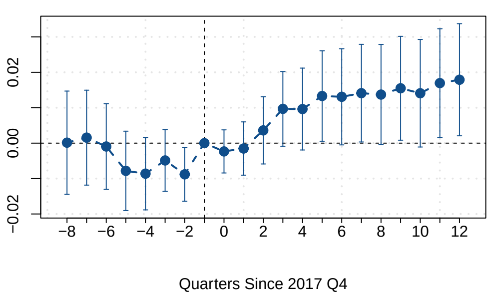
Panel A: Composite Rating



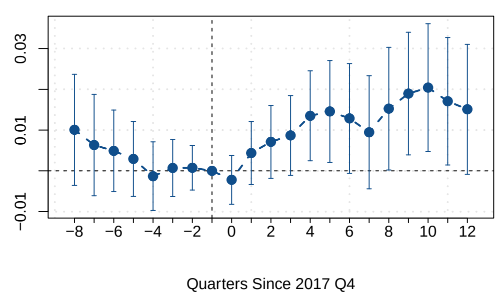
Panel B: Capital Rating



Panel C: Management Rating



Panel D: Earnings Rating



Internet Appendix

For

"Effects of Shadow Bank Competition on Bank Strategies and Risk"

Table IA.1: Variable Definitions

Variable	Description
Jumbo125 Exposure	Measures the exposure of banks to the jumbo loan segment in the pre-2017 period. Calculated as $\frac{\text{Total jumbo loans originated 2012-2016}}{\text{Total assets in 2016}}$ for each bank
Total assets	Total assets at the end of the quarter (UBPR2170)
Loans (%)	Total loans and leases (UBPRE386) as a percent of total assets (UBPR2170)
Real Estate Loans (%)	Loans secured by real estate (UBPR1410) as a percent of total assets (UBPR2170)
Individual Loans (%)	Loans to individuals (UBPRD665) as a percent of total assets (UBPR2170)
C&I Loans (%)	Commercial loans (UBPRE116) as a percent of total assets (UBPR2170)
Securities (%)	Average Total Investment Securities Percentage of Average Assets (UBPRPN08)
Treasury/Agency (%)	Average US Treas & Agency (Excl MBS) Percentage of Average Assets (UBPRPN09)
Non-Agency MBS (%)	Average Non-Agency Mortgage Backed Securities Percentage of Average Assets (UBPRPN10)
Deposits (%)	Total deposits (UBPR2200) as a percent of total assets (UBPR2170)
Other Borrowings (%)	Other borrowed money (RCFD3190) as a percent of total assets (UBPR2170)
Core Deposits (%)	Demand, NOW, ATS, MMDA, and deposits below insurance limit less fully insured brokered deposits (UBPRK434) as a percent of total assets (UBPR2170)
Non-core Deposits (%)	Total deposits (UBPR2200) - Core deposits (UBPRK434) as a percent of total assets (UBPR2170)
Brokered Deposits (%)	Brokered deposits (UBPR2365) as a percent of total assets (UBPR2170)
Equity (%)	Total equity (UBPR3210) as a percent of total assets (UBPR2170)
Tier I Capital Ratio	Total risk-based capital to adjusted risk weighted assets (UBPRD488)
Liquid Assets (%)	Cash and Marketable Securities (UBPRE582) as a percent of total assets (UBPR2170)
Non-performing Loans (%)	The sum of loans and lease financing receivables past due at least 90 days, plus those in nonaccrual status, divided by gross loans and lease-financing receivables outstanding (UBPR7414)
Mortgage delinquencies (%)	The sum of loans secured by mortgages secured by 1-4 family properties that are 90 days or more past due and still accruing interest and loans secured by mortgages secured by 1-4 family properties that are on nonaccrual status divided by total single family mortgages (UBPRE488)
Net Interest Income (%)	Net interest income as a percent of average assets (UBPRKX40)
Interest Income (%)	Interest income as a percent of average earnings assets (UBPRE678)
Interest Expense (%)	Intereset expense as a percent of average assets (UBPRE002)
Return on Assets (%)	Return on equity (UBPRE630) * Total Equity (UBPR3120)/Total Assets (UBPR2170)
Annual Asset Growth (%)	(Total assets (UBPR2170) - total assets year ago)/Total assets year ago
Assets per Employee (mn)	Assets per employees in USD millions (UBPRE090)

Figure IA.1: Correlation of Jumbo Exposure Measures

This figure plots the relationship between two exposure measures used in the analysis: Jumbo Exposure (x-axis), defined as the share of mortgages exceeding the conforming loan limit based on 2016 thresholds, and Jumbo125 Exposure (y-axis), which focuses on mortgages between 100% and 125% of the 2016 limit and serves as the treatment variable in the IV analysis.

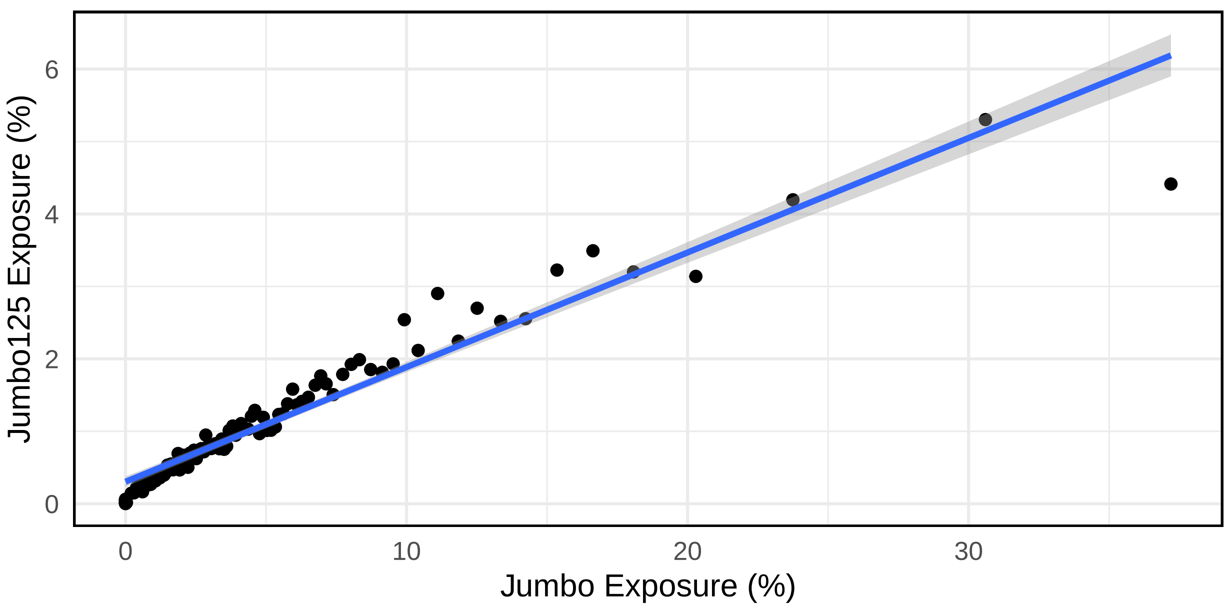
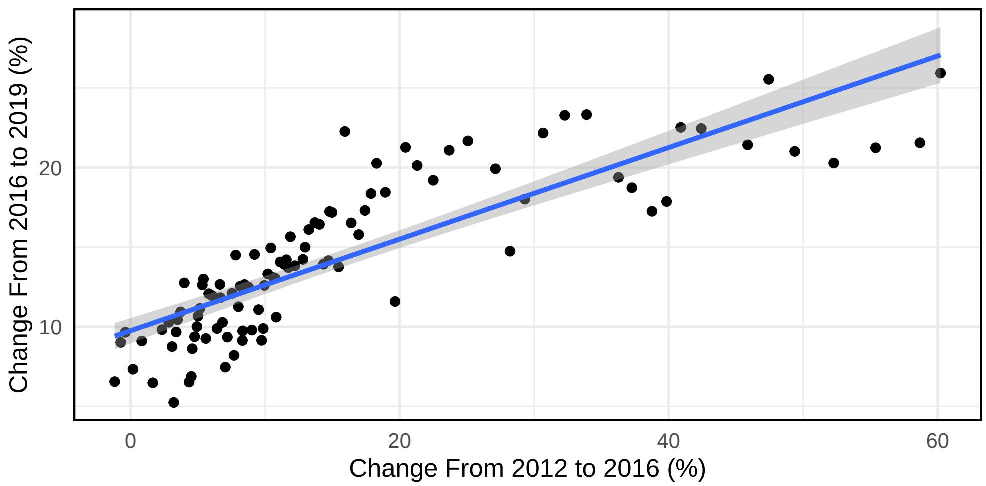


Figure IA.2: Correlation of Economic Conditions

This figure plots the relationship between average house price changes across percentiles of the county-level distribution in two periods: 2012–2016 (x-axis) and 2016–2019 (y-axis) in Panel A and GDP Growth in Panel B. Each point represents a percentile bin of counties, with the coordinates reflecting the mean change within that percentile for each time period. The fitted line and shaded 95% confidence interval indicate a strong positive correlation, suggesting that counties with higher pre-2017 house price appreciation and GDP growth tended to maintain elevated growth post-2016. This persistent correlation reduces concerns about mechanical mean reversion and supports the exclusion restriction underlying the instrument.

Panel A: House Price



Panel B: GDP Growth

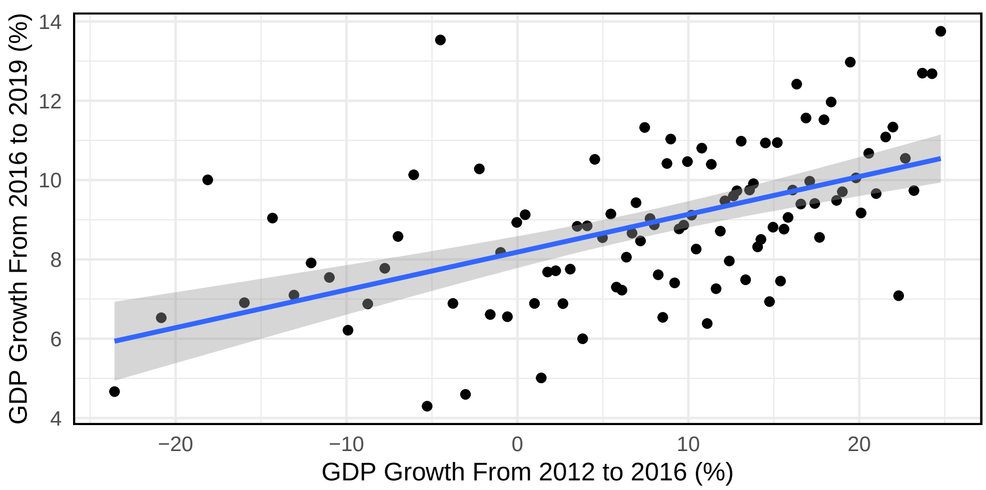


Figure IA.3: Nonparametric First-Stage Estimates Using WA Price Change Deciles

This figure plots the coefficients and 90% confidence intervals from a first-stage regression where the dependent variable is Jumbo125 Exposure, and the key regressor is a set of indicator variables for deciles of the bank-level WA Price Change (2012–2016). This specification is analogous to column (1) of Table 2 but replaces the continuous WA Price Change with decile dummies to allow for nonparametric estimation of the first-stage relationship.