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Abstract

The 2010s saw a profound shift towards jumbo mortgage lending by large banks that are regulated under the Dodd-Frank Act. Using data from the Home Mortgage Disclosure Act, we show that the "jumbo shift" is correlated with being subject to the Comprehensive Capital Analysis and Review (CCAR) stress tests, and that financial regulation caused CCAR-regulated banks to change preference for nonconforming relative to conforming loans of similar size. We discuss potential mechanisms through which regulation could have affected bank incentives.

Key words: CCAR, mortgage lending, bunching

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1 Introduction

Mortgage lending is a core business for most banks, and a core subject of their regulation by the government. An essential aspect of mortgage finance in the U.S. is the existence of Government-Sponsored Enterprises (GSEs) that commit to purchasing all mortgages originated by banks that satisfy particular widely shared criteria. The existence of the GSEs provides an implicit (and, after the 2008 financial crisis, essentially explicit) guarantee by the government to the banks for a large class of mortgages, which is critical in overcoming the adverse selection problem in the mortgage lending market.

One of the criteria used by the GSEs is that the size of the mortgage is below a certain cutoff, known as the conforming loan limit (CLL), and which was $417,000 in 2016 for most areas of the U.S. Loans below this cutoff are known as "conforming" and may be purchased by the GSEs. "Jumbo" loans above this threshold are ineligible to be purchased by the GSEs, but can be securitized by private entities if banks do not wish to retain them on their books. Historically, most mortgage loans made in the U.S. by large and small banks alike have been conforming loans, with jumbo loans accounting for less than 10% of all mortgage originations. This jumbo share rose to 15% during the housing boom of the mid-2000s and declined to nearly zero during the financial crisis and and collapse of the private securitization market. (Calem et al. 2013). While jumbo lending has rebounded since the crisis, the recovery has been starkly bifurcated as shown in Figure 1. Large banks subject to CCAR (Comprehensive Capital Analysis and Review) stress tests under the Dodd-Frank Act (DFA) of 2010 increased their jumbo share to well above the peak in 2005 while the share at non-CCAR banks remains below the peak.

In this paper, we explore explanations for these diverging trends. First, we document that indeed, participation in CCAR is correlated with jumbo share, even conditional on bank size. We also show that the banks that participated in CCAR begin their shift towards jumbo loans only in the 2010s, after financial regulation (Dodd-Frank Act) is passed. However, looking at the jumbo share alone does not allow us to distinguish a greater preference for nonconforming loans from a greater preference for loans that are large. In particular, d'Acunto and Rossi (forthcoming) present a compelling argument that an increase in fixed and per-loan regulatory costs incentivized larger banks to make larger loans generally, although not jumbo loans in particular.

Building on the results of d'Acunto and Rossi (forthcoming), we attempt to measure the association between CCAR and lending in the jumbo market while controlling for this fixed cost story. To do so, we exploit the fact that for most banks (and nearly all banks before Dodd-Frank), the mortgage size distribution reflected pronounced bunching at the CLL, with borrowers and lenders facing strong incentives to issue conforming loans in place of jumbo loans marginally above the CLL. Considering the amount of bunching at the CLL allows us to focus explicitly on the decision to issue a nonconforming loan relative to a conforming loan of a similar size. We find that bunching at the CLL has noticeably decreased for the CCAR banks after Dodd-Frank. This finding suggests more precisely that financial regulation changed regulated banks' preference for jumbo mortgages specifically rather than large loans more generally.

Subsequently, we explore possible mechanisms whereby stress tests or other financial regulation under the Dodd-Frank Act (DFA) of 2010 may have driven the jumbo shift. We exclude a number of plausible stories related to the direct effects of stress test results (Cortes et al. 2017) and to balance sheet capacity (Buchak et al 2018). We also document that it was the set of banks subject to CCAR stress tests, rather than the larger set of banks subject to DFA stress tests or the smaller set of banks subject to Global Systemically Important Bank (GSIB) regulation that accounts for the jumbo shift. One channel through which part of the jumbo shift may have operated may be the Liquidity Coverage Regulation rule imposed on a very similar set of banks to the one covered by CCAR, although our evidence for this channel is not conclusive. To assess the stability implications of the jumbo shift, we also run a difference-in-difference analysis of the association between CCAR and the performance of banks' mortgage loan portfolios and find that the mortgage portfolios of CCAR banks have fewer nonperforming loans by volume, but not statistically significantly so.

Our paper contributes to a substantial body of research investigating the impact of stress testing. One strand of the literature considers whether test results help inform investors about the risk and value of large, potentially opaque, banks (Petrella and Resti (2013), Morgan et al. (2014), Candelon and Amadou (2015), Bird et al. (2015), Neretina et al. (2015), Flannery et al. (2017), Marcelo et al. (2020). Most find that bank asset prices respond to stress test news. Our paper is more related to a second vein of literature that studies the credit allocation effects of stress testing. Cortez et al. (2017) find that, among CCAR banks, those with lower capital ratios in stress scenario shift away from small business lending. Acharya and Berger (2018) find that CCAR banks rebalanced their portfolios toward safer loan classes broadly. Calem, Correa and Lee (2021) look specifically at jumbos and find that jumbo origination by CCAR banks fell after the first CCAR test but were not significantly affected by subsequent stress tests. Our paper complements theirs by focusing on differentials in the trends of jumbo mortgage origination, rather than changes following specific stress tests.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents the baseline jumbo share results. Section 4 provides a straightforward model of banks choosing what size loans to originate, which formally motivates the bunching specification. Section 5 presents the baseline bunching results. Section 6 explores the potential mechanisms. Section 7 concludes.

2 Data

2.1 Mortgage Loan Data

We use data collected pursuant to the Home Mortgage Disclosure Act (HMDA) to examine how lending patterns changed due to the introduction of the CCAR stress tests. The HMDA dataset includes mortgage application data as reported by mortgage lenders for approximately 80% of home lending that occurs in the United States, including, crucially, year of origination, mortgage size, location of the property and institution that originated the loan. We match that loan-level information to the parent of the bank that originated the mortgage using the HMDA lender file created by Robert Avery of the Federal Housing Finance Agency for the institutions that originated each loan. Avery et al. 2007 suggest that HMDA likely offers a representative and nearly complete sample of home lending in the U.S. Additionally, HMDA includes data on loan securitization – specifically, whether or not the originator of the loan has sold it to a third party by the end of the calendar year in which the loan was originated. We use a subsample of the HMDA dataset consisting of first-lien purchase loans on single family home equivalent properties, originated between 2000 and 2016.

We match each loan with the conforming loan limit (CLL) prevailing in the county in which the property was located at the time of origination. The CLL is the maximum size of a loan that may be sold to Fannie Mae and Freddie Mac. Loans that exceed the CLL are known as "jumbo" loans, and will generally be kept on the books of the originating institution (before the financial crisis of 2008, they also could be securitized by private entities). Loans at or below the CLL are known as "conforming" loans. We believe the effect of CCAR may differ between the "jumbo" and "conforming" loan markets, so we use the CLL to classify loans into these two categories. Historical CLL data is publicly available from Fannie Mae and the Federal Housing Finance Agency. In 2016, the CLL was $417,000 in most of the country, with the exception of high-cost counties where the CLL could be set between $417,000 and $625,500, depending on the local median home value .

Our main object of analysis will be the distribution of loan volume by lender. For each institution in HMDA, we compute the number and volume of loans made each year in bins of $30,000 around the CLL. That is, for each lender we count the number (and volume) of loans made between $29,999 and $0 below the CLL, between $1 and $30,000 above the CLL, between $30,001 and $60,000 above the CLL, etc. We collapse the dataset to the lender-year-bin level.

2.2 Lender Data

We collect annual financial information (total assets, tier 1 capital ratio, non-performing residential real estate loans, total real estate loans) on the bank holding companies (BHCs) in our sample from the FR Y-9C, FR Y9-LP, and FR Y-9SP financial reporting forms. For our sample, we consider only the institutions that reported assets in 2010 (the year before CCAR), which leaves us with 912 BHCs.

For each BHC subject to stress testing under CCAR, we use the minimum level achieved by the Tier 1 Capital Ratio, Total risk-based Capital Ratio, and Tier 1 Leverage Ratio from the 2012-2016 stress test cycles that are made publicly available by the Federal Reserve System. The data for 2012 is from the Fed's CCAR disclosure of the results that do not include the bank's capital plan, and for 2013-2016 is from the Dodd-Frank Act disclosure. Following Cortés et al. (2018), we construct measures of exposure to the stress tests based on how close each bank's minimum capital ratios were to the regulatory minimum – essentially, how close the bank was to failing the stress tests. We also use data on liquidity stress ratios from the stress tests.

3 Results for the Jumbo Share

In this section, we provide empirical evidence that bank regulation played a role in the sorting of regulated banks to jumbo mortgages relative to other banks. We first analyze the behavior of the jumbo share. To do so, we run the following specification

$$JumboShare_{b,t} = \alpha_b + \alpha_t + \gamma CCAR_{b,t} + \beta_3 \ln\left(A_{b,t}\right) + \lambda_t \times \ln\left(A_{b,2010}\right) + \varepsilon_{i,t} \qquad (1)$$

where $JumboShare_{b,t}$ is the share of mortgages originated by bank b in year t that were jumbo, α_b and α_t are bank and year fixed effects and $CCAR_{b,t}$ is an indicator variable for whether bank b was ever subject to CCAR stress tests and whether the year is after or including 2011, when CCAR stress testing became a permanent fixture of the regulatory landscape. We include several controls in this baseline specification to ensure that our results are not driven by changes in bank size over time. First, we control for the logarithm of $A_{b,t}$, the total assets of bank b in year t. Second, because the relationship between a bank's size and its jumbo share may be changing over time – purely economic and not regulatory reasons may have made it make sense for large banks to specialize in jumbo lending in the 2010s but not in the 2000s – we also control for the log of total assets of bank b in 2010, interacted with another set of year fixed effects λ_t. Our identification assumption is that conditional on these controls, the timing of a bank's entry into CCAR was exogenous to other unobserved determinants of its jumbo share. Appendix Table A2 presents estimates that also control for average loan size, which are similar.

We present our estimation results in Table 1. In Column 1, we display estimates of equation (1). We double-cluster standard errors by bank and year to account for correlation of errors within banks, and for common shocks to all banks in any given year. Our main interest is γ, the coefficient on the CCAR indicator variable. We estimate this coefficient to be 0.065 with a standard error of 0.019, and statistically significant at 1%. This coefficient is positive, suggesting that as banks entered CCAR, their jumbo share increased by 6.5 percentage points relative to banks that did not enter CCAR. It is also large, as the mean jumbo share of banks in the mortgage market is 14%.

It is useful to see the precise timing and nature of the evolution of the jumbo shift among CCAR relative to non-CCAR banks during the recovery from the Great Recession. Figure 2 presents estimates from a version of specification (1) in which the coefficient γ is interacted with year fixed effects, thus generating an estimate γ_t for each year t indicating how much larger the jumbo share was for the ever-CCAR banks relative to the non-CCAR banks in year t. (Since our definition of CCAR is whether a bank was ever in CCAR, it is well-defined to compute this coefficient for the time period before CCAR was enacted.) Without loss of generality, we normalize the value of γ_t in 2010 to zero, so that estimates of γ_t can be thought of as the increase or the decrease in the jumbo shift of the ever-CCAR banks relative to 2010. We see that before 2010 – the implementation of major financial reforms including CCAR following the crisis of 2008 – the parameters γ_t are flat at zero, indicating no trend for the banks that were ever in CCAR to experience a shift to jumbo lending over time. It is particularly impressive that this trend is so flat during the financial boom and bust leading up to and culminating in the financial crisis of 2008, during which many macroeconomic and financial variables behaved very cyclically. However, after 2010, γ_t grows steadily, attaining a value of greater than 0.10 by 2016 and averaging around 0.05 during this period. Hence, it appears that the jumbo shift was not a result of trends originating during the financial crisis of the 2000s, but rather a sharp response to something taking place in the early stages of the recovery, and in 2010 in particular. This is evidence that the jumbo shift might be attributable to the regulatory changes implemented after the crisis, possibly including CCAR.

In subsequent columns of Table 1 we perform robustness checks on the baseline result that regulation in 2010 played a role in the jumbo shift. First, in column 2, we show that replacing our treatment variable with a straightforward, time-varying dummy for whether bank b was in CCAR in year t does not affect the magnitude or significance of our estimate. We prefer using the "ever CCAR" dummy going forward, as there could be potential endogeneity in the timing of bank entry ginto CCAR, and as difference-in-difference estimates with variation in treatment timing typically do not recover the pure average causal effect (Goodman-Bacon 2021). Another concern could be that banks that entered CCAR had different geographical lending patterns, leading them to be differentially exposed to housing market recovery patterns than non-CCAR banks. To test this concern, in column 3, we control for the distribution of lending of bank b in year t across counties by the extent of their housing market recovery, specifically for loan-weighted and volume-weighted average house price indices and for the shares of loans by number and volume made in counties where the CLL was above the minimum CLL set in HERA 2008, which was approximately $417,000 in 2017 dollars (see Section 2). The coefficient is statistically significant and larger than in the baseline specification.

In column 4 we implement a more thoroughgoing robustness check by including bank-specific linear time trends, which decrease the CCAR coefficient to a statistically insignificant 0.035, still a sizeable magnitude with the confidence interval including the original estimate. It is worth noting that a criticism of this test may be that bank-specific time trends may mechanically absorb some of the effect of any post-2010 reforms if it takes time to be realized. In the next two columns, we assess what happens if we draw a control group of non-CCAR banks that is more comparable to the 30 CCAR banks in our analysis. First, in column 5, we limit the sample to the CCAR banks and the 30 largest non-CCAR banks by asset size in 2010. Doing so decreases the coefficient on the CCAR dummy to 0.029 and increases its standard error to 0.019, making it statistically insignificant, but similar in magnitude to the coefficient when lender linear trends are included. Second, in column 6, we perform our analysis on the 15 largest non-CCAR banks and the 15 smallest banks that are ever part of CCAR, also according to 2010 assets. The coefficient rises to 0.1, with a standard error of 0.075. While these last three robustness checks move the coefficient on the CCAR dummy, they are also very restrictive in allowing considerable heterogeneity in bank behavior over time and in narrowing the sample down to very small but comparable groups of banks. Lastly, in column 7, we perform a placebo exercise in which we remove the banks that were ever part of CCAR from the sample and label the 30 largest non-CCAR banks as "ever CCAR". We see that there is no effect after 2010 on the jumbo share of these next thirty banks relative to the smaller non-CCAR banks in our panel.

4 Theoretical Analysis of Bunching at the CLL

4.1 Motivation for Bunching Analysis

While the jumbo share remains our primary object of interest motivated by Figure 1, we also consider a more targeted measure of the way in which banks trade off making jumbo loans against making conforming loans. This is the degree of bunching at the conforming loan limit exhibited by each bank's size distribution of loans. As loans just below the CLL are almost the same size as loans just above the CLL, the extent of bunching should not reflect preference for larger or smaller loans, but should be closer to the opportunity cost of issuing a loan that is treated like a jumbo by housing market institutions relative to a loan that is treated like a conforming loan (e.g. by the GSEs). Showing an effect of CCAR on the extent of bunching at the CLL would suggest that CCAR affected this opportunity cost of jumbo lending, and therefore further strengthen the case that CCAR had a causal effect on the jumbo share of regulated banks.

Bunching at the CLL has been explored in previous literature on the mortgage market. DeFusco and Paciorek (2017) use the techniques of Kleven and Wasseem (2014) to estimate an elasticity of mortgage demand to interest rates using the bunch at the CLL and the corresponding jumbo to conforming interest rate spread. d'Acunto and Rossi (forthcoming) note that for large banks, bunching at the CLL has practically vanished in the 2010s, and argue that this is because the fixed costs of originating a loan for large banks have risen with regulation, incentivizing them to originate larger loans. However, raising fixed costs of originating a loan should not affect the incentives of banks to make a loan just below a certain value rather than just above.

Below we provide a model that reflects the intuition of d'Acunto and Rossi (forthcoming) that larger per-loan fixed costs should induce banks to seek out larger loans. Subsequently, we show that the jumbo share specification in Section 3 does not control for this channel. Therefore, if the only effect of CCAR were to increase per-loan fixed costs, we would expect to see the results that we observe in Section 3. However, under the model provided below, we show that a specification that regresses the log number of loans at the bunch on the CCAR indicator and controls for the distribution of conforming loans made by the bank in question should control for this "fixed cost story". Specifically, the coefficient on the CCAR indicator in such a regression should be equal to zero if the only effect of CCAR is to increase per-loan fixed costs.

4.2 Bank's optimization problem

Let's suppose that a bank that must lend conforming loans at rate r and jumbo loans at rate $r+\rho$. We also assume the bank incurs a per-loan regulatory cost K and an additional per-loan regulatory cost κ for jumbo loans. An increase in K can be interpreted as a general increase in regulatory burden, while an increase in κ can be interpreted as a jumbo-specific regulatory increase, or as an increase in the benefits of securitization, such as lower g-fees.

We assume that the bank faces a mortgage loan distribution $F(m)$. Then, for a mortgage of size m, the bank's profit from originating this mortgage is

$$\pi(m) = rm - K + 1(m > \bar{m})(\rho m - \kappa)$$

We assume that all mortgages are above a level m_0 such that $rm_0 > K + \kappa$ for all conceivable values of r, K and κ, so all mortgages bring positive profit to the bank.

Now, we assume that the bank takes r and ρ as given, but that it is costly for the bank to attract mortgage applications. In particular, to attract $t(m)$ applications for mortgages of size m, the bank needs to spend $c(t(m))$, a convex cost function. This structure is a reduced-form way of capturing the fact that banks may market mortgages more intensely in some areas and some market segments rather than others. Other interpretations of $t(m)$ may be hiring additional staff to work with different ends of the mortgage market, in which case costs might be linear but returns might be concave. Anecdotal evidence from bank supervision officers indicates that some major banks did expand their wealth management divisions.

The bank's optimization problem then becomes

$$\max_{t(m)} \int_{m_0}^{\infty} (\pi(m)\, t(m) - c(t(m)))\, dF(m) \tag{2}$$

The first-order condition is then

$$c'(t(m)) = \pi(m) = rm - K + 1(m > \bar{m})(\rho m - \kappa) \text{ for each } m$$

Notably, $t(m)$ is left-continuous at $\bar{m}$, with a jump immediately to its right. Differentiating the first-order condition in K and in m, we obtain

$$\frac{\partial t(m)}{\partial K} = -\frac{1}{c''(t(m))} < 0 \tag{3}$$

$$\frac{\partial t}{\partial m} = r + 1(m > \bar{m})\rho > 0 \tag{4}$$

Note that equation (4) implies that $t(m)$ is increasing in m, except possibly for a discontinuous downward jump immediately to the right of $m = \bar{m}$. However, for m large enough, it must be the case that $\pi(m) > \pi(\bar{m})$, or it would not be profit maximizing for the bank to make jumbo loans. Therefore, $t(m)$ is increasing for m large enough.

Consequently, for each mortgage level m, the bank originates $t(m)\,dF(m)$ loans, and the empirical distribution of loans has the form

$$\tilde{F}(m) = \frac{\int_{m_0}^{m} t(s)\,dF(s)}{\int_{m_0}^{\infty} t(s)\,dF(s)}$$

It follows that if $c''' > 0$ and m is large enough, then

$$\frac{\partial \tilde{F}(m)}{\partial K} \leq 0$$

because $t(s)$ is increasing in s and $1/c''(t(s))$ is decreasing in s over the interval (m, ∞) for m large enough.[1] Recall that the "fixed cost story" of d'Acunto

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[1]

and Rossi (forthcoming) is driven by changes to loan volumes for mortgage levels well above and well below the CLL.

Therefore, this model exhibits the "fixed cost story" of d'Acunto and Rossi (forthcoming), because an increase in per-loan fixed costs shifts the CDF of originated mortgages to the right.

4.3 Implications for regression specification

Therefore, a specification of the type

$$J_{b,t} = \gamma CCAR_{b,t} + \varepsilon_{i,t} \tag{5}$$

where $J_{b,t}$ is the jumbo share would fail to capture the endogenous effects of changes in $t(m)$ as we would measure

$$J_{b,t} = \frac{\int_{\bar{m}}^{\infty} t(m)\, dF(m)}{\int_{m_0}^{\infty} t(m)\, dF(m)} = 1 - \tilde{F}(\bar{m})$$

In general (e.g. when $\rho\bar{m} > \kappa$) we would expect that

$$\frac{\partial J}{\partial K} \geq 0$$

Specifically,

$$\frac{\partial}{\partial K}\left(\ln\left(\int_{m_0}^{m} t(s)\, dF(s)\right) - \ln\left(\int_{m_0}^{\infty} t(s)\, dF(s)\right)\right)$$
$$= -\frac{\int_{m_0}^{\infty} \frac{1}{c''(t(s))} dF(s)}{\int_{m_0}^{m} t(s)\, dF(s)}\left(\frac{\int_{m_0}^{m} \frac{1}{c''(t(s))} dF(s)}{\int_{m_0}^{\infty} \frac{1}{c''(t(s))} dF(s)} - \frac{\int_{m_0}^{m} t(s)\, dF(s)}{\int_{m_0}^{\infty} t(s)\, dF(s)}\right) < 0$$

Therefore, data consistent with the fixed cost story of d'Acunto and Rossi (forthcoming) could generate a positive coefficient of γ when estimating regression (5) if $CCAR_{b,t}$ is a proxy for K.

Now, consider a regression along the lines of

$$\ln B_{b,t} = \gamma CCAR_{b,t} + \sum_{j=1}^{J} \beta_j \ln F_{b,t}^{j} + \varepsilon_{i,t} \tag{6}$$

where b indexes banks, t indexes time, $B_{b,t}$ is the number of loans at the bunch, and $F_{b,t}^{j}$ is the number of loans in bin j below the CLL. Denote the bunching fraction as

$$B = F\left(\bar{m}\right) - \lim_{m \uparrow \bar{m}} F\left(m\right)$$

In terms of our model parameters,

$$\begin{aligned} B_{b,t} &= t\left(\bar{m}\right) B \\ F_{b,t}^{j} &\approx t\left(m_j\right) dF\left(m_j\right) \end{aligned}$$

for mortgage amounts $m_j < \bar{m}$.

Now, fixed costs no longer can account for a finding of a nonzero γ in the above regression. This is because

$$\ln B_{b,t} = \left(\ln\left(t\left(\bar{m}\right)\right) + \ln\left(\lim_{m \uparrow \bar{m}} dF\left(m\right)\right)\right) + \left(\ln\left(B\right) - \ln\left(\lim_{m \uparrow \bar{m}} dF\left(m\right)\right)\right)$$

and

$$\sum_{j=1}^{J} \beta_j \ln F_{b,t}^{j} = \sum_{j=1}^{J} \beta_j \left(\ln \left(t \left(m_j \right) \right) + \ln \left(dF \left(m_j \right) \right) \right)$$

The first addend of $\ln B_{b,t}$ is in the span of $\left\{ \beta_j \ln F_{b,t}^{j} \right\}_{j=1}^{\infty}$ because $t(m)$ is left-continuous at $\bar{m}$, and therefore, it should be predicted by $\sum_{j=1}^{J} \beta_j \ln F_{b,t}^{j}$ arbitrarily well. The second addend is just a function of the underlying distribution $F(m)$ and does not depend on K. Therefore, any endogenous effects on $B_{b,t}$ through changes to $t(\bar{m})$ would be controlled for in our specification as $t(m)$ is left-continuous at $\bar{m}$, and estimation of regression (6) from data coming from the solution to the optimization problem (2) should generate an estimate of zero for the coefficient γ if $CCAR_{i,t}$ is a proxy for K.[2]

5 Results for Bunching at the CLL

Armed with the intuition from the model in Section 3, we consider the association between bunching at the CLL and entry into CCAR. Figure 3 presents a pictorial version of a "difference-in-difference" analysis of the evolution of bunching at the CLL for banks that were ever in CCAR and banks that were never in CCAR before and after financial regulation was passed. In the top two panels we see the distributions of mortgage lending for CCAR and non-CCAR lenders in 2010, before regulation

[2]The model could be further complicated by making ρ a choice variable for the bank. We develop this case in the Appendix. If ρ is endogenous, we can no longer make unambiguous statements about $\partial \tilde{F}/\partial K$. However, we can show that if the cost function $c(t)$ is polynomial, then the condition $\partial^2 t/\partial m \partial K \geq 0$ (advertising for loans increases in loan size more when per-loan costs increase) for all loan sizes implies $\partial \rho/\partial K \geq 0$. This implies an increasing bunch and a lower jumbo share as per-loan costs increase, which is counterfactual to our results and therefore does not help to explain them.

went into effect. The density of mortgages by volume is decreasing through the conforming loan segment, with a sharp bunch at the CLL and a sharp drop into the space of jumbo loans. In 2010, relatively few jumbo loans were being made by either CCAR or non-CCAR banks. The bottom two panels show the same distributions in 2014. The distribution for the non-CCAR lenders looks like the distribution of either set of lenders in 2010, with a pronounced bunch and a sharp decline in loan density for immediately larger values of mortgage size. However, the distribution of the CCAR lenders now looks quite different, with a thick tail of loans stretching out into the jumbo space, with the density being almost continuous with the density of conforming loans. There still is a bunch at the CLL, but it is considerably smaller relative to the density of conforming loans close to the CLL: the number of loans in the CLL bin for CCAR lenders in 2014 is approximately twice the number of loans in the adjacent bin of conforming loans (the ones that are \$30,000 to \$60,000 below the CLL), whereas the number of loans in the CLL bin for non-CCAR lenders in 2014 and any kind of lender in 2010 is at least three times the number of loans in the adjacent conforming bin of each distribution. Therefore, we see that CCAR lenders decreased bunching at the CLL in 2014 relative to non-CCAR lenders that year and to all lenders in 2010. Correspondingly, they increased their share of jumbo originations.

Table 2 presents the same specifications that we ran for the jumbo share, now with the dependent variable being the log number of loans in the bunching bin. We also modify the set of control variables, following the results of our model in Section 3. Moreover, previous literature exploiting bunching (Saez 2010, Kleven and

Wasseem 2014) has implicitly controlled for the continuous part of the distribution of the variable in question in their analysis. To that end, we control for the log loan count and volume in every $30,000-wide bin of the loan size distribution except the bunching bin (setting these variables to zero for banks and years with no loans in a given bin) as well as for the overall log loan count and volume. In particular, we now control for the size distribution of conforming loans, and these controls would capture a reallocation of jumbo loans from smaller to larger ones if the shift of regulated banks towards jumbo were explained by an incentive to make larger loans more generally (d'Acunto and Rossi, forthcoming). Our main regression for the bunching analysis is

$$\begin{aligned} \ln\left(N_{b,t}^{Bunch}\right) &= \alpha_b + \alpha_t + \delta CCAR_{b,t} + \beta_1 \ln\left(N_{b,t}^{Total}\right) + \beta_2 \ln\left(V_{b,t}^{Total}\right) \\ &\quad + \sum_{k \neq Bunch} \zeta_k \ln\left(N_{b,t}^{k}\right) + \sum_{k \neq Bunch} \xi_k \ln\left(V_{b,t}^{k}\right) + \beta_3 \ln\left(A_{b,t}\right) \\ &\quad + \lambda_t \times \ln\left(A_{b,2010}\right) + \varepsilon_{i,t} \end{aligned} \tag{7}$$

where $N_{b,t}^{Bunch}$ is the count of loans in the bunching bin for bank b in year t, and $N_{b,t}^{k}$ and $V_{b,t}^{k}$ are the loan counts and volumes in the other bins that are used to construct the distributional controls. We expect the coefficient δ to be negative, since if CCAR incentivizes banks to shift to jumbo, it should decrease bunching at the CLL.

We present our results of the effects of CCAR on bunching at the CLL in Table 2. Column 1 presents the baseline. We see that that, on average, once CCAR began, the number of loans in the bunching bin decreases by 0.188 log points, or approximately 17% for banks that were ever part of CCAR relative to other banks, which is statistically significant at 1%. Column 2 presents the baseline results without almost all of the distributional controls. The only control that we retain is the log count of loans in the adjacent bin to the bunch (the one containing loans that are \$30,000-\$60,000 less than the CLL). The coefficient on the CCAR interaction increases in magnitude to -0.281 and retains significance at 1%, although the confidence interval includes the original estimate from column 1. Therefore, the inclusion of most of the distributional controls is not essential for our result that regulated banks experienced a decline in bunching at the CLL when the regulations took effect.

It is useful to see that the timing of the decline in bunching at the CLL among the CCAR banks aligns with the implementation of CCAR. To this end, in Figure 4, we present a year-by-year version of this regression in which the coefficient δ is allowed to vary by t, and plot the path of δ_t over time. We normalize the value of δ_{2010} to zero without loss of generality. We find that before 2010, including through the years of the housing boom and bust between 2003 and 2009, the γ_t coefficients are not significantly different from zero, pointing to there not being a differential trend in the extent of bunching at the CLL for banks that would eventually become part of CCAR relative to banks that didn't. This finding is notwithstanding the strong variation in bunching at the CLL over the 2000s, with bunching in aggregate being muted during the boom but very prominent both in the pre-boom period and during the bust (when the market for jumbo loans dried up nearly completely). However, after 2010, as CCAR became a feature of the regulatory landscape, the δ_t

coefficients become sharply negative, declining to about -0.25 log points by 2015. The δ_t coefficients rise somewhat in 2016, but still remain significantly negative.

It is also important to verify that our dependent variable – the log of the count of loans in the bunching bin – is not proxying for other shifts in the size distribution of mortgages that have not been accounted for by the distributional controls. In Figure 5 we present estimates of equation (7) in which we replace the dependent variable with the log count of other bins to the left of the CLL and control for the log count of the bunching bin on the right hand-side. We see that the only other bin for which the CCAR coefficient δ is statistically significant is the bin that is adjacent to the bunching bin (containing loans that are between \$30,000 and \$60,000 lower than the CLL). The magnitude of δ when the log loan count in that bin is the dependent variable is roughly half of the magnitude of δ when the dependent variable is the bunching bin. The values of δ when the dependent variable is formed by any other bin are all small and statistically insignificant. Hence, the data shows that the bunching bin is special relative to the other parts of the size distribution of mortgages to the left of the CLL, giving us greater confidence in the analysis.

The remaining columns of Table 2 reproduce the same robustness checks as columns 2 through 7 of Table 1. We see that when the log number of loans in the bunching bin is the dependent variable, the coefficient estimate varies considerably less than it does when the dependent variable is the jumbo share. For example, when we add bank linear trends in column 5, the coefficient on the "ever CCAR" variable becomes -0.209, very close to the coefficient in the baseline specification. In columns 6 and 7, in which we perform our analysis on the 60 largest banks and on the 30 banks nearest to the CCAR cutoff of $50 billion, thus substantially reducing the sample and the control group, we obtain coefficients of -0.145 and -0.184 respectively, both of which are close in magnitude to the baseline coefficient in column 1. We verify that being a CCAR bank, rather than being a large bank, is what is driving our results by presenting versions of Figure 3 for the 60 largest banks and the 30 banks nearest to the CCAR cutoff in the top three panels of Figure 6. We see that the number of loans in the bunching bin relative to the overall number of conforming loans is smaller for the CCAR banks than for similarly sized non-CCAR banks in 2014, while, in 2010, the reverse was the case. In the bottom three panels of Figure 6 we present trends in this "relative bunch" measure (the ratio of the number of loans in the bunching bin to the total number of conforming loans) for CCAR and non-CCAR banks for the duration of our analysis for the all bank sample, the 60 bank sample and the 30 bank sample. It is clear that the relative bunch for the non-CCAR banks in either sample is increasing through the sample period, while the relative bunch for CCAR banks falls after a turning point around 2010. Finally, in column 9, we perform the placebo check of removing the "ever CCAR" banks from the regression and labeling the largest 30 banks by 2010 assets as the "ever CCAR" banks. Reassuringly, we find no effect on the bunching behavior of these large non-CCAR banks relative to their smaller non-CCAR counterparts.

The fact that entry into CCAR (rather than merely being large) is associated with a decline in bunching at the CLL provides evidence against the idea that regulation affected bank behavior by creating fixed costs of regulations that were most economically managed by taking out large loans. Mortgages just above the

CLL are not appreciably larger than mortgages just below the CLL, but they are very different from an institutional perspective because they can be securitized. The finding that upon the beginning of the stress testing regime in earnest, large banks began disproportionately favoring the first type of loans suggests that something about regulations at that time spurred them to that alternative institutional regime.

6 Potential Mechanisms

While we find that entry into CCAR statistically explains a considerable part of the "jumbo shift" it is by no means evident that entry into CCAR causally explains it. . The CCAR banks also faced stricter regulation in addition to stress tests, including a new liquidity rule and higher capital requirements. Regulation of other banks in our control group also changed, including an alternative Dodd Frank Test (DFAST). In the next section, we invesigate if these non-CCAR regulations explain the CCAR jumbo shift.

6.1 Other Concurrent Regulations on Large Banks

Table 3 presents estimates of equation (1) and Table 4 presents estimates of equation (7) augmented by various controls to get at different channels through which regulation could have incentivized banks to expand jumbo lending as a share of their mortgage portfolio and to decrease bunching at the CLL. (We present a version of Table 3 augmented by log average mortgage loan size in Appendix Table A3.) Column 1 in each table replicates the baseline. First, we investigate whether our findings are driven by different groups of banks exposed to different regulations by asset volume. CCAR banks were not the only banks to undergo stress tests – banks with assets as low as \$10 billion had to undergo annual Dodd-Frank Act Stress Tests (DFAST). While both test banks' capital plans, DFAST uses a standard plan for covered banks while CCAR uses the banks' own plans). If taking any kind of stress test incentivized banks to increase their relative preference for jumbo over conforming loans, we should see similar increases in the jumbo share and similar decreases in the bunch for the DFAST banks as well as for the CCAR banks. Similarly, the largest banks, those with assets of \$250 billion and more, were subject to even more stringent regulations and designated as Globally Systemically Important Banks (GSIBs). In theory, the CCAR effects that we computed in Section 3 could be driven by this small group of 8 enormous banks.

Column 2 of Table 3 presents estimates of equation (1), including an additional interaction between the year being 2011 or later and the bank having assets greater than \$10 billion in 2010, and another interaction between the time period dummy and the bank having assets of greater than \$250 billion in 2010. Various post-GFC bank regulations are activated at those thresholds.We see that, conditional on the CCAR interaction, the coefficient on the \$10 billion interaction is statistically insignificant and tiny (-0.008), while the estimate on the CCAR interaction remains large, significant and close to the baseline estimate (0.058). The coefficient on the \$250 billion interaction is also large (0.046), suggesting that GSIBs might have experienced a greater jumbo shift than other CCAR banks, but is not statistically significant. The corresponding estimates in Column 2 of Table 4 have the same implications: the estimate of the CCAR interaction is a statistically significant −0.144, and the estimates of the $10 billion and $250 billion interactions are insignificant and small. Therefore, the shift to jumbo by CCAR banks appears unique to CCAR stress tests specifically and is not a general large bank effect.

6.2 Capital and Balance Sheet Capacity

An important channel through which regulation may have affected the propensity of regulated banks to originate jumbo mortgages by requiring them to hold more capital. Buchak, Matvos, Piskorski and Seru (2019) argue that increased capital requirements gives banks a comparative advantage (over non-banks) in holding mortgages rather than selling them. They find that banks with higher capital ratios originate more jumbo mortgages than banks with lower capital ratios.

To investigate whether higher capital requirements account for our baseline findings above, we add banks' risk-weighted capital ratio and their leverage ratio to the model. The former equals (Tier I) capital divided by total risk-weighed assets. The latter equals (Tier I) capital divided by total (unweighted) assets. Both are bounded from below by regulators and either, if binding, can affect banks' lending decisions. Only 697 of the 911 banks in our original sample are required to report the Tier I ratios (which involves performing a risk-weighting of the bank's assets). In column 3 of Tables 3 and 4 we reproduce our baseline results on this smaller sample of 697 banks. We see that the coefficient on the CCAR interaction declines in magnitude from 0.065 to 0.033 (losing significance) in the jumbo share specification and from −0.188 to −0.121 (significant at 10%) in the bunching specification. Therefore, while this sample is less favorable to our initial findings, we still can reproduce our results in the smaller sample of banks with Tier I ratios. In column 4 of Tables 3 and 4 we conduct the test that we propose. We find that the coefficients on the Tier I ratios are statistically insignificant, with the coefficient on the Tier 1 Capital Ratio carrying the right sign, and the coefficient on the Tier 1 Leverage Ratio carrying the wrong sign (negative in the jumbo share specification and positive in the bunching specification). In both tables, the coefficient on the CCAR interaction is essentially unchanged from the baseline for the sample of 697 banks. Therefore, greater capitalization does not explain the CCAR effect.[3]

6.3 Direct Effects of Stress Test Scores

Another channel that could explain the shift of regulated banks to jumbo could be the outcome of the stress tests themselves. Cortes et al. (2019) use scores from the CCAR stress tests to show that banks that came closer to failing to meet the quantitative targets of the tests made fewer small business loans and more mortgage loans, as the latter were treated as safer by the stress tests. It could be the case that jumbo loans were also treated as safer than conventional loans. Column 5 of Tables 3 and 4 reestimates the baseline equations (1) and (7) on the original sample of over 900 banks, controlling for additional interactions of the currently CCAR indicator with stress test scores, normalized as the distance between each stress test score and its passing threshold, with passing scores set to be negative and failing scores

[3]We find that CCAR banks do experience an increase in their Tier I Capital Ratios, but this correlation goes away when one controls for the log asset by year fixed effects. Results are available on request

set to be positive. We consider stress tests for Tier 1 Capital, Tier 1 Leverage and Tier 1 Risk-Based Capital, as well as a variable equal to the stress test score closest to failing (the Min Exposure measure). We find essentially no role for stress test outcomes in driving the jumbo shift. The CCAR interaction remains statistically significant at 5% and close to the baseline estimate in both Table 3 (0.05) and in Table 4 (-0.159). The interactions of the stress test scores with the CCAR indicator are almost always statistically insignificant, except for the one with Tier 1 Leverage Distance in the jumbo share specification, which is consistent with banks that are closer to failure increasing their jumbo share.

6.4 Liquidity Coverage Rule

A final channel that we consider is the Liquidity Coverage Rule regulation (LCR). Banks subject to LCR were required to have a sufficient quantity of suitably defined liquid assets (for example, deposits that were expected to be stable) relative to liabilities. The value of this ratio for a bank in a stressed scenario is known as the Liquidity Stress Ratio (LSR). Importantly, bank accounts of individuals who had mortgages with the bank were considered to be "stable deposits" from the point of view of LCR, whereas bank accounts of individuals with no other ties to the bank were generally not. This feature of the LCR made it appealing for banks to issue mortgages to wealthy individuals, who might then hold large accounts with these banks that would be counted as stable deposits. As many of the banks that were subject to the LCR also were subject to CCAR, we investigate heterogeneity within this set of banks by interacting the LCR dummy with a measure of the liquidity stress ratio (LSR) in 2010 for the banks subject to the rule. Column 6 of Tables 3 and 4 presents the resulting estimates. We see that the coefficient on the CCAR interaction in the jumbo share specification remains statistically significant and somewhat larger than the baseline coefficient (0.096), however the coefficient on the CCAR interaction in the bunching specification shrinks to -0.097 (roughly half of the baseline) and becomes statistically insignificant. However, its confidence interval is large and includes the baseline coefficient. The coefficients on the LCR and LCR-LSR interactions are statistically insignificant in the bunching specification, suggesting that it is not clear whether CCAR or LCR may be driving the decline in bunching at the CLL for the banks that fall under CCAR.

6.5 Impacts on Nonperforming Loans

A natural follow-up question to the finding that regulation has driven CCAR banks to increase jumbo lending is whether this jumbo shift has made the CCAR banks safer along some dimension. In Table 5 we reestimate equations (1) and (7), replacing the dependent variable with the fraction of residential real estate loans on the bank's books that are nonperforming. We find no statistically or economically significant effects of CCAR on nonperforming loans.

7 Conclusion

We show that that recovery in jumbo mortgage lending since the 2010 is bifurcated, with stress tested banks shifting to jumbo far more than others. We use lender-loan level data from the Home Mortgage Disclosure Act as well as regulatory variables for the largest bank holding companies present in the mortgage market to show that the jumbo shift of the 2010s took place for the banks subject to CCAR stress tests, and through our analysis of changes in bunching behavior at the CLL, that financial regulation changed incentives for these banks to issue nonconforming vs. conforming loans conditional on the size of the loan. We provide evidence against a number of plausible mechanisms for this phenomenon. While we do not find clear evidence in support of any specific mechanism, one mechanism that appears to explain the data better than others may be the Liquidity Coverage Rule regulation. We also find that participation in CCAR made banks' mortgage loan portfolios have an insignificantly lower fraction of nonperforming loans, although this is not the only dimension of bank portfolio safety that is relevant.

Our paper shows that financial regulation is capable of reshaping bank incentives in the mortgage market, and, in theory, allocating credit. While we do not explore the normative effects of the jumbo shift in this paper, policymakers should be careful in designing future regulations to avoid generating consequences that may not fit with their original objectives.

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8 Figures

Figure 1

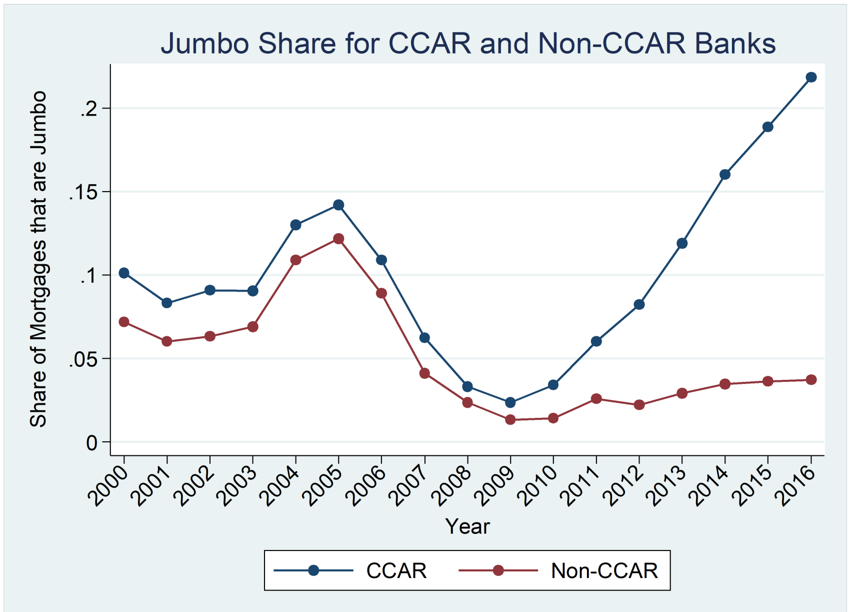


Figure 2

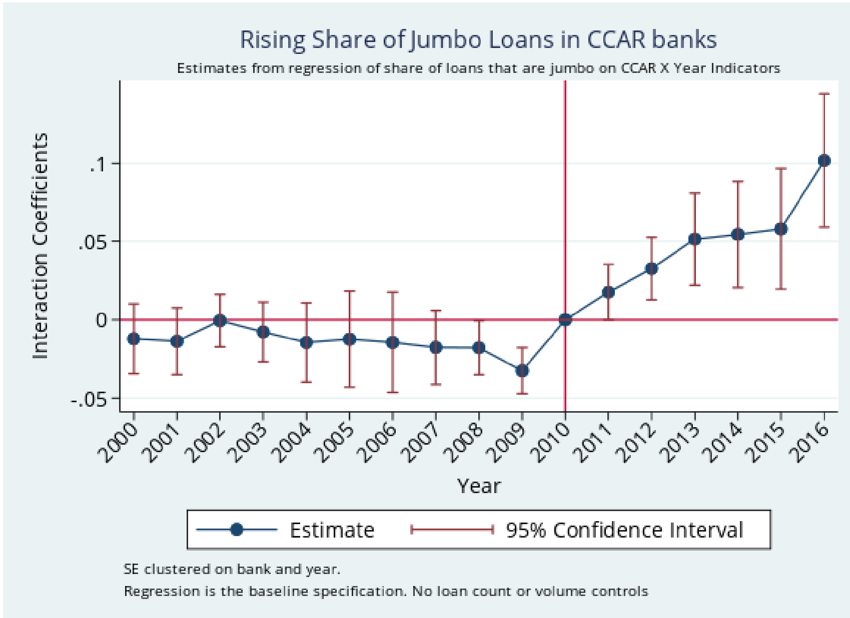


Figure 3

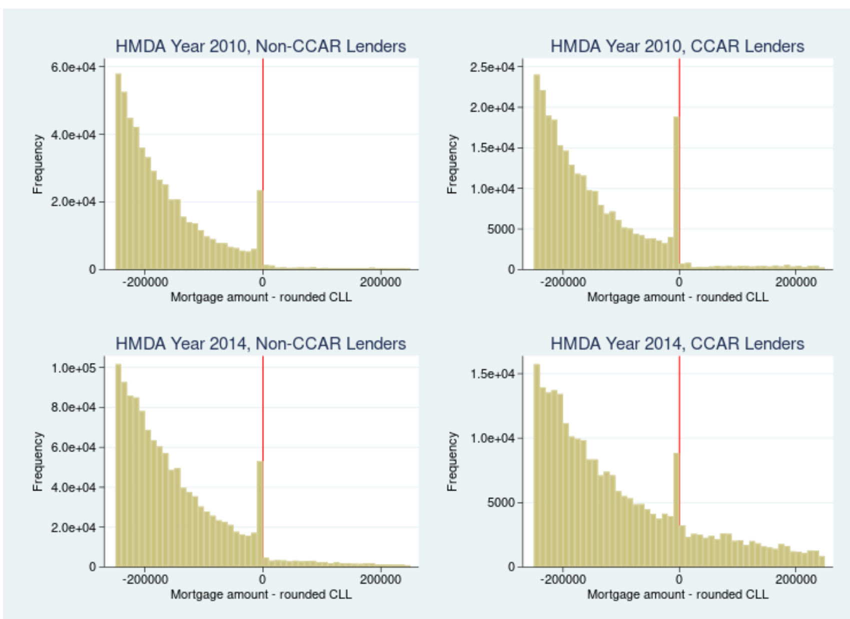


Figure 4

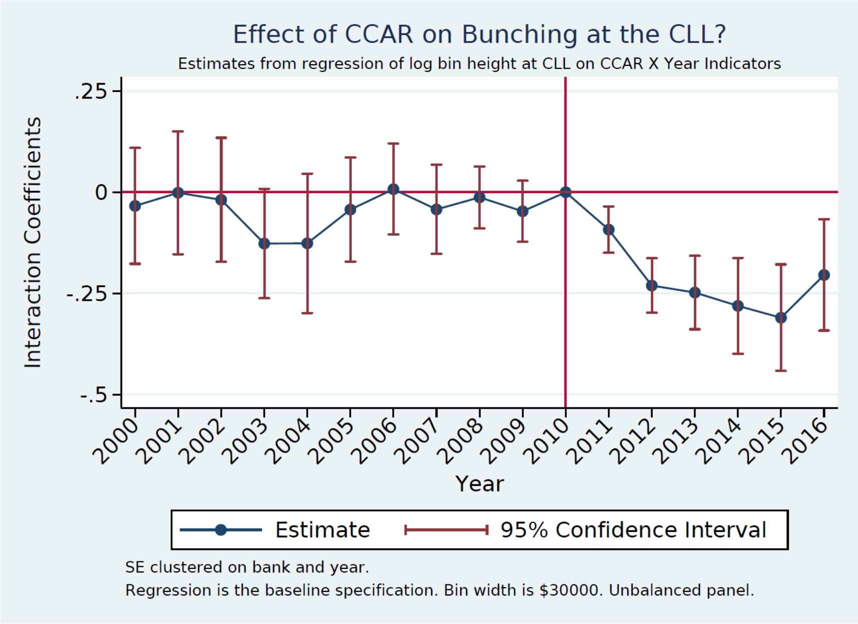


Figure 5

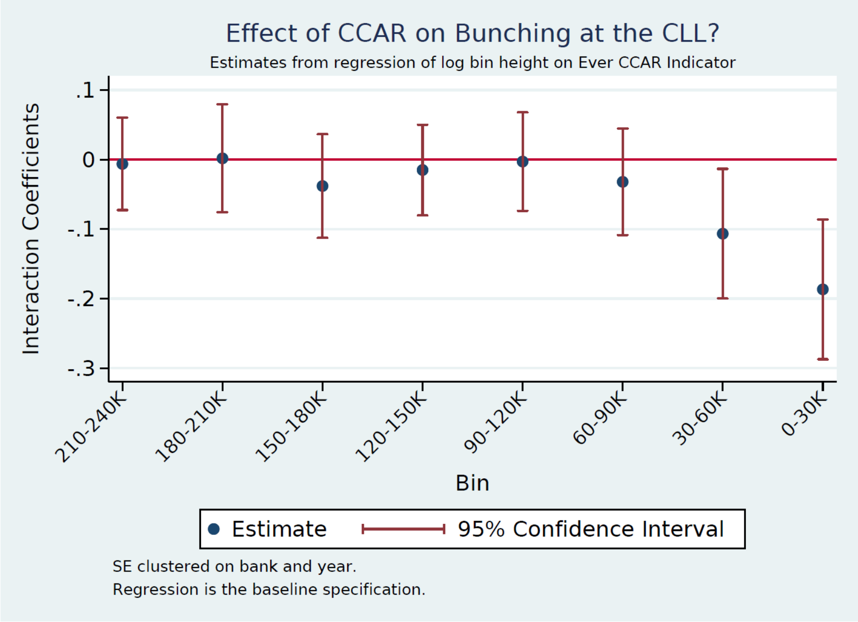
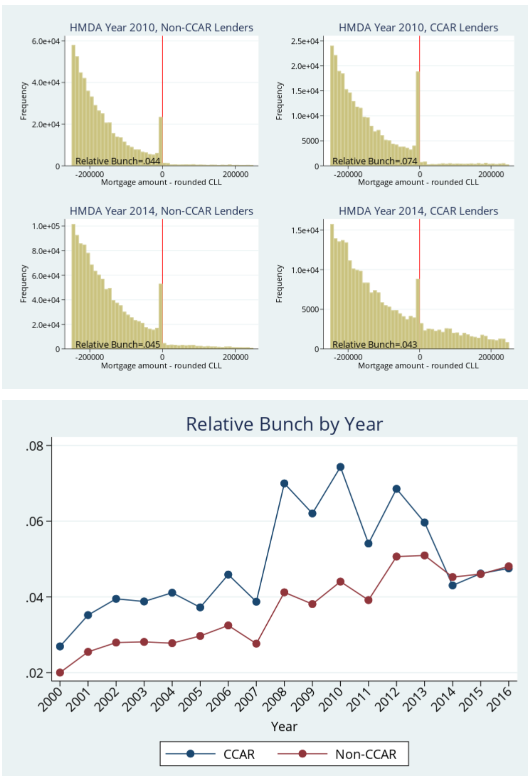
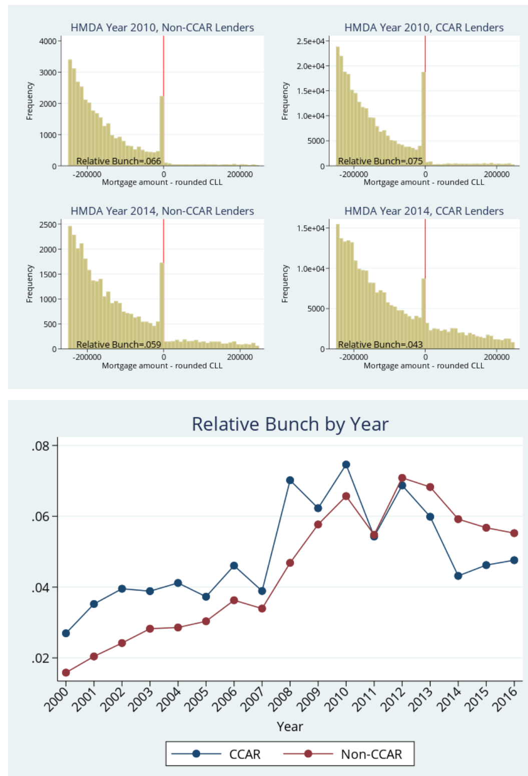


Figure 6

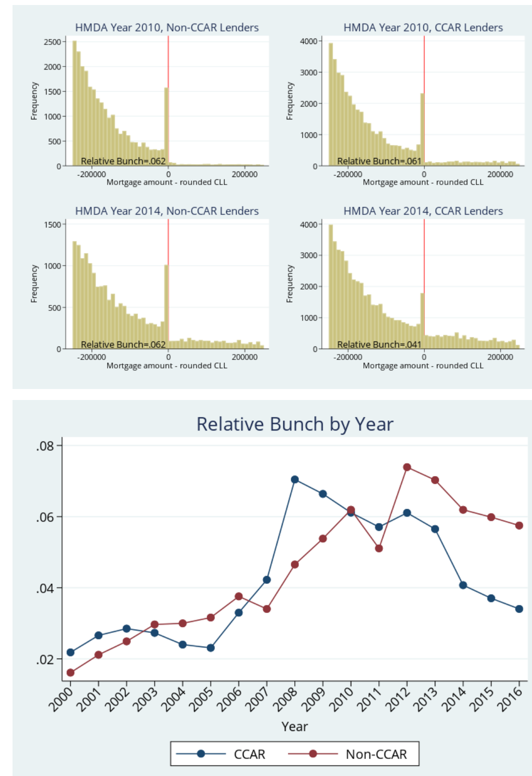
Full Sample



Top 60 Banks



Closest 30 Banks



9 Tables

Table 1

Baseline Jumbo Share Specification
Dependent variable is the share of mortgages originated by a bank that are jumbo.

	(1) Ever CCAR	(2) Currently CCAR	(3) Bank Exp Controls	(4) Lender Linear Trends	(5) 60 Largest Banks	(6) 30 Nearest Margin	(7) CCAR Placebo
(Ever CCAR)* (Year>2010)	0.065***	0.063***	0.085***	0.035	0.029	0.103	-0.010
	(0.019)	(0.018)	(0.019)	(0.022)	(0.039)	(0.075)	(0.018)
N	11982	11982	11905	11982	926	464	11556
# Lenders	909	909	907	909	60	30	879

Each regression includes bank and year fixed effects and controls for yearly log assets and log assets in 2010 multiplied by year fixed effects.
Observations at the Lender/Year level. Double-Clustered Standard Errors (Lender and Year) in Parentheses.
Coefficients on (Ever CCAR)*(Year>2010) represent γ in Equation 1.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2

Baseline Bunching Specification

Dependent variable is the log number of loans between \$0 and \$30,000 less than the Conforming Loan Limit.

	(1) Ever CCAR	(2) Ever CCAR	(3) Currently CCAR	(4) Bank Exp Controls	(5) Lender Linear Trends	(6) 60 Largest Banks	(7) 30 Nearest Margin	(8) CCAR Placebo
(Ever CCAR)* (Year>2010)	-0.188***	-0.281***	-0.167***	-0.182***	-0.209**	-0.145	-0.184	-0.050
	(0.050)	(0.089)	(0.056)	(0.049)	(0.080)	(0.100)	(0.175)	(0.053)
Dist. Ctrls.	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
N	11982	11982	11982	11905	11982	926	464	11556
# Lenders	909	909	909	907	909	60	30	879

Each regression includes bank and year fixed effects and controls for yearly log assets, log assets in 2010 multiplied by year fixed effects, and log loan counts and volume in all other bins.

Observations at the Lender/Year level. Double-Clustered Standard Errors (Lender and Year) in Parentheses.

Coefficients on (Ever CCAR)*(Year>2010) represent δ in Equation 7.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3

Mechanisms for Baseline Jumbo Share Specificiation
Dependent variable is the share of mortgages originated by a bank that are jumbo.

	(1) Baseline Specification	(2) Other Regulations	(3) Baseline 697 Bank Sample	(4) Balance Sheet Capacity	(5) Stress Test Measures	(6) Liquidity Coverage Ratio
(Ever CCAR)* (Year>2010)	**0.065***** **(0.019)**	**0.058**** **(0.023)**	**0.033** **(0.025)**	**0.033** **(0.025)**	**0.050**** **(0.018)**	**0.096***** **(0.019)**
Currently CCAR					0.027 (0.019)	
(Assets>10B)* (Year>2010)		-0.008 (0.017)				
(Assets>250B)* (Year>2010)		0.046 (0.028)				
Tier 1 Leverage Ratio (1 yr lag)				-0.215 (0.181)		
Tier 1 Capital Ratio (1 yr lag)				0.070 (0.105)		
Currently CCAR Min. Exposure					-0.017 (0.019)	
Currently CCAR* Tier 1 Capital Distance					-0.006 (0.014)	
Currently CCAR* Tier 1 Leverage Distance					0.030** (0.011)	
Currently CCAR* Tier 1 Risk-Based Capital Distance					-0.007 (0.013)	
LCR Treatment						-0.175*** (0.059)
LCR Treatment LSR 2010						0.244 (0.143)
N	11982	11982	8888	8888	11982	9643
# Lenders	909	909	697	697	909	700

Each regression includes bank and year fixed effects and controls for yearly log assets and log assets in 2010 multiplied by year fixed effects.

Observations at the Lender/Year level. Double-Clustered Standard Errors (Lender and Year) in Parentheses.

Coefficients on (Ever CCAR)*(Year>2010) represent γ in Equation 1.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4

Mechanisms for Baseline Bunching Specification
Dependent variable is the log number of loans between $0 and $30,000 less than the Conforming Loan Limit.

	(1) Baseline Specification	(2) Other Regulations	(3) Baseline 697 Bank Sample	(4) Balance Sheet Capacity	(5) Stress Test Measures	(6) Liquidity Coverage Ratio
(Ever CCAR)* (Year>2010)	**-0.188***** **(0.050)**	**-0.144**** **(0.059)**	**-0.121*** **(0.068)**	**-0.121*** **(0.068)**	**-0.159**** **(0.066)**	**-0.097** **(0.083)**
Currently CCAR					-0.082 (0.085)	
(Assets>10B) (Year>2010)		-0.058 (0.052)				
(Assets>250B) (Year>2010)		-0.012 (0.092)				
Tier 1 Leverage Ratio (1 yr lag)				1.031 (0.797)		
Tier 1 Capital Ratio (1 yr lag)				-0.458 (0.534)		
Currently CCAR* Min. Exposure					0.008 (0.069)	
Currently CCAR* Tier 1 Capital Distance					-0.014 (0.036)	
Currently CCAR Tier 1 Leverage Distance					-0.035 (0.053)	
Currently CCAR Tier 1 Risk-Based Capital Distance					0.024 (0.020)	
LCR Treatment						0.158 (0.217)
LCR Treatment xLSR 2010						-0.489 (0.385)
N	11982	11982	8888	8888	11982	11982
# Lenders	909	909	697	697	909	909

Each regression includes bank and year fixed effects and controls for yearly log assets, log assets in 2010 multiplied by year fixed effects, and log loan counts and volume in all other bins.

Observations at the Lender/Year level. Double-Clustered Standard Errors (Lender and Year) in Parentheses.

Coefficients on (Ever CCAR)*(Year>2010) represent δ in Equation 7.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5

Baseline Jumbo Share and Bunching Specifications
on Nonperforming Loans
Dependent variable is the fraction of mortgage loans that are nonperforming.

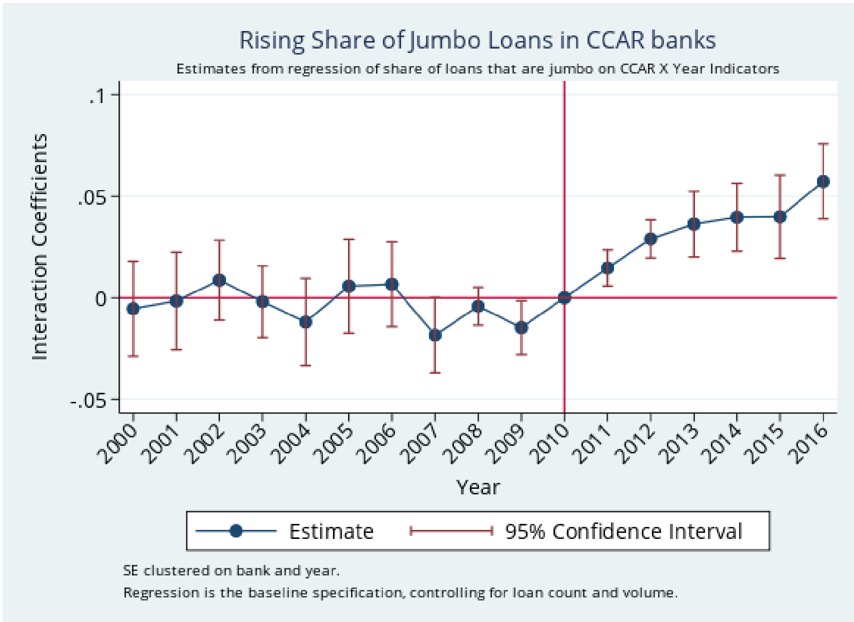
	(1) Bunching Specification	(2) Jumbo Specification
(Ever CCAR)*(Year>2010)	-0.007	-0.007
	(0.008)	(0.008)
Distributional Controls	Yes	No
Log(2010 assets) X Year FE	Yes	Yes
N	9627	9627
Number of Lenders	700	700

Right hand-sides of columns (1) and (2) correspond to baseline specifications in Tables 1 and 2 respectively.
Coefficients on (Ever CCAR)*(Year>2010) represent γ of Eq. 1 in Column (1)
and δ of Eq. 7 in Column (2).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

10 Appendix

10.1 Appendix Figures

Figure A1



10.2 Appendix Tables

Table A1

CCAR Banks by Entry Year

Bank Name	Year Entered CCAR
Ally	2011
Bankwest	2015
BB&T	2011
BBVA	2013
BMO Harris	2013
BNY Mellon	2011
Bank of America	2011
Capital One	2011
Citi	2011
Citizens	2013
Comerica	2013
Deutsche Bank	2014
Discover	2013
Fifth Third	2011
Goldman	2011
HSBC	2013
Huntington	2013
JP Morgan Chase	2011
KeyCorp	2011
Morgan Stanley	2011
M&T	2013
MUFG	2013
Northern Trust	2013
PNC	2011
Regions	2011
Santander	2013
SunTrust	2011
TD	2015
US Bancorp	2011
Wells Fargo	2011
Zions	2013

Last observed in 2016. All banks entering CCAR remain until last observation.

Table A2

Baseline Jumbo Share Regression, Controlling for Average Loan Size
Dependent variable is the share of mortgages originated by a bank that are jumbo.

	(1) Ever CCAR	(2) Currently CCAR	(3) Bank Exp Controls	(4) Lender Linear Trends	(5) 60 Largest Banks	(6) 30 Nearest Margin	(7) CCAR Placebo
(Ever CCAR)*(Year>2010)	0.041***	0.042***	0.060***	0.026*	0.024	0.040	-0.007
	(0.012)	(0.011)	(0.011)	(0.013)	(0.020)	(0.034)	(0.012)
Log(Avg Loan Size)	0.198***	0.198***	0.190***	0.201***	0.262***	0.303***	0.196***
	(0.014)	(0.014)	(0.013)	(0.014)	(0.035)	(0.049)	(0.014)
Log(2010 assets) X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11982	11982	11905	11982	926	464	11556
Number of Lenders	909	909	907	909	60	30	879

Each regression includes bank and year fixed effects and controls for yearly log assets and log assets in 2010 multiplied by year fixed effects.
Observations at the Lender/Year level. Double-Clustered Standard Errors (Lender and Year) in Parentheses.
Coefficients on (Ever CCAR)*(Year>2010) represent γ in Equation 1.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3

Mechanisms for Baseline Jumbo Share Specificiation, Controlling for Average Loan Size
Dependent variable is the share of mortgages originated by a bank that are jumbo.

	(1) Baseline Specification	(2) Other Regulations	(3) Baseline Bank Sample	(4) Balance Sheet Capacity	(5) Stress Test Measures	(6) Liquidity Coverage Ratio
(Ever CCAR)* (Year>2010)	**0.041*** **	**0.042** **	**0.026** **	**0.026* **	**0.029** **	0.060***
	(0.012)	**(0.014)**	**(0.014)**	**(0.014)**	**(0.011)**	**(0.012)**
Currently CCAR					0.029*	
					(0.014)	
(Assets>10B)* (Year>2010)		-0.004				
		(0.011)				
(Assets>250B)* (Year>2010)		0.007				
		(0.017)				
Tier 1 Leverage Ratio (1 yr lag)				-0.247*		
				(0.124)		
Tier 1 Capital Ratio (1 yr lag)				0.063		
				(0.076)		
Currently CCAR* Min. Exposure					-0.009	
					(0.010)	
Currently CCAR* Tier 1 Capital Distance					-0.018**	
					(0.007)	
Currently CCAR* Tier 1 Leverage Distance					0.024***	
					(0.008)	
Currently CCAR* Tier 1 Risk-Based Capital Distance					0.004	
					(0.007)	
LCR Treatment						-0.064*
						(0.031)
LCR Treatment* LSR 2010						0.068
						(0.073)
N	11982	11982	8888	8888	11982	9643
Number of Lenders	909	909	697	697	909	700

Each regression includes bank and year fixed effects and controls for yearly log assets and log assets in 2010 multiplied by year fixed effects.

Observations at the Lender/Year level. Double-Clustered Standard Errors (Lender and Year) in Parentheses.

Coefficients on (Ever CCAR)*(Year>2010) represent γ in Equation 1.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

10.3 Appendix Theory

10.3.1 Borrower optimization problem

We assume that borrowers with unobservable characteristics θ have a utility function $U(m, r, \theta)$ over mortgage amounts m and interest rates r. We assume this function to satisfy the following properties:

$$U_{mm} < 0,\ U_r < 0,\ U_{mr} < 0$$

Then, mortgage demand $m(r)$ satisfies

$$U_m(m(r, \theta), r, \theta) = 0$$

and, in particular, is decreasing in r

$$m_r(r, \theta) = -U_{mr}/U_{mm} < 0$$

The consumer's value function is defined by

$$V(r, \theta) = U(m(r, \theta), r, \theta)$$

and by the envelope theorem,

$$V_r = U_r < 0$$

Now consider the setup in which there is a mortgage level $\bar{m}$ that is the

CLL: for mortgages under the CLL the interest rate is r, while the interest rate for mortgages over the CLL is $r+\rho$. It is clear that some borrowers will prefer to bunch at the CLL instead of applying for a nonconforming (jumbo) loan. We can divide borrowers into three groups: conforming, bunchers and jumbo, defined by the three sets below

$$\begin{aligned} C(r) &= \{\theta : m(r,\theta) \leq \bar{m}\} \\ B(r,\rho) &= \{\theta : m(r,\theta) > \bar{m} \;\&\; U(\bar{m}, r, \theta) \geq V(r+\rho,\theta)\} \\ J(r,\rho) &= \{\theta : m(r,\theta) > \bar{m} \;\&\; U(\bar{m}, r, \theta) < V(r+\rho,\theta)\} \end{aligned}$$

It is clear that the set of conforming borrowers $C(r)$ does not depend on ρ, the jumbo-conforming spread.

Now, $P(B(r,\rho))$ is increasing in ρ, because

$$\begin{aligned} \rho_1 &> \rho_0 \Rightarrow V(r+\rho_1,\theta) < V(r+\rho_0,\theta) \\ &\Rightarrow P(U(\bar{m},r,\theta) \geq V(r+\rho_0,\theta)) \\ &\leq P(U(\bar{m},r,\theta) \geq V(r+\rho_1,\theta)) \end{aligned}$$

Similarly, it is clear that $P(J(r,\rho))$ is decreasing in ρ, because $P(B(r,\rho)) + P(J(r,\rho)) = 1 - P(C(r))$, which does not depend on ρ.

We can define $m(r,\rho,\theta) = m(r,\theta) \times 1(\theta \in C(r)) + \bar{m} \times 1(\theta \in B(r,\rho)) + m(r+\rho,\theta) \times 1(\theta \in J(r,\rho))$

We can abstract from θ by writing down the CDF for m

$$F(m, r, \rho) = P(m(r, \rho, \theta) \leq m)$$

Then, for $m < \bar{m}$,

$$F(m, r, \rho) = C(m, r)$$

for $m = \bar{m}$

$$F(\bar{m}+, r, \rho) - F(\bar{m}-, r, \rho) = P(B(r, \rho))$$

and for $m > \bar{m}$,

$$F(m, r, \rho | \theta \in J(r, \rho)) = G(m, r, \rho)$$

In particular,

$$\frac{\partial G}{\partial \rho}(m, r, \rho) = \frac{\partial}{\partial \rho} P(m(r + \rho, \theta) \leq m \;\&\; U(\bar{m}, r, \theta) < V(r + \rho, \theta)) < 0 \text{ for all } m$$

Abusing notation, we can then talk of $C(m, r)$ and $G(m, r, \rho)$ as the CDFs of conforming and jumbo loans. An example of a model of this style is presented in DeFusco and Paciorek (2019).

10.3.2 Bank's optimization problem

Let's suppose that a bank that must lend conforming loans at rate r (set in competitive equilibrium) but that may change the jumbo-conforming spread ρ to maximize profit faces borrowers as described in Section 1 of the Appendix. We assume that there is a minimum loan size m_0 such that all loans above m_0 are profitable and no type ever wants to borrow less than m_0 (in particular, $m_0 > 0$ and $C(m_0, r) = 0$ for any reasonable r). We also assume the bank incurs a per-loan regulatory cost K and an additional per-loan regulatory cost κ for jumbo loans. An increase in K can be interpreted as a general increase in regulatory burden, while an increase in κ can be interpreted as a jumbo-specific regulatory increase.

The bank's profit function can then be written as

$$\Pi(r,\rho) = \int_{m_0}^{\infty} \left[(rm - K) + 1(m > \bar{m})(\rho m - \kappa)\right] dF(m, r, \rho)$$

and the first-order condition for maximization is given by

$$\begin{aligned} \Pi_\rho = & \int_{\bar{m}}^{\infty} m dF(m, r, \rho) + (r\bar{m} - K)\frac{\partial P(B(r,\rho))}{\partial \rho} \\ & + \int_{\bar{m}}^{\infty} \left[(rm - K) + (\rho m - \kappa)\right] dG_\rho(m, r, \rho) = 0 \end{aligned}$$

which is equivalent to

$$0=\int_{\bar{m}}^{\infty} mdF\left(m,r,\rho\right)+r\bar{m}\frac{\partial P\left(B\left(r,\rho\right)\right)}{\partial\rho}+\int_{\bar{m}}^{\infty}\left[rm+\left(\rho m-\kappa\right)\right]dG_{\rho}\left(m,r,\rho\right)$$

since

$$\frac{\partial B}{\partial\rho}+\frac{\partial J}{\partial\rho}=\frac{\partial C}{\partial\rho}=0$$

Therefore, $\Pi_{\rho K}=0$, so

$$\frac{\partial\rho}{\partial K}=-\frac{\Pi_{\rho K}}{\Pi_{\rho\rho}}=0$$

and a change in the fixed cost K therefore does not affect the jumbo-conforming spread ρ. As ρ is the only endogenous variable in the model, it follows that an increase in K does not affect the fraction of bunchers B or the jumbo share J.

On the other hand, an change in jumbo-specific per-loan costs κ does have such effects. In particular,

$$\Pi_{\rho\kappa}=-\int_{\bar{m}}^{\infty} dG_{\rho}\left(m,r,\rho\right)=-\frac{\partial P\left(J\left(r,\rho\right)\right)}{\partial\rho}>0$$

Therefore,

$$\frac{\partial\rho}{\partial\kappa}=-\frac{\Pi_{\rho\kappa}}{\Pi_{\rho\rho}}>0$$

and

$$\frac{\partial P\left(B\left(r,\rho\right)\right)}{\partial\kappa}=\frac{\partial B}{\partial\rho}\frac{\partial\rho}{\partial\kappa}>0$$

Thus, observing that the bunching fraction B declines, the jumbo-conforming spread falls and the jumbo share rises would be naturally predicted by a decrease in jumbo-specific loan costs κ.

10.3.3 A richer model of the fixed cost story

One problem with the model in section 3 is that it does not present is no "fixed cost story": changes to K are irrelevant to the bank's only choice variable ρ, and therefore, to the distribution of realized mortgages. The reason for this is that in this model, every consumer originates a loan (possibly of a size that depends on the bank) so the bank will always pay K in fixed costs regardless of what it does. A richer model can endogenize the bank's seeking out of larger or smaller loans by allowing the bank to advertise to individuals demanding a mortgage of size m at a cost. Specifically we assume that for every mortgage level m, the bank can pay $\frac{1}{k}t\left(m\right)^{k}$ per mortgage to multiply the number of loans attracted by $t\left(m\right)$. The bank's problem becomes

$$\Pi\left(t,r,\rho\right)=\int_{m_0}^{\infty}\left\{\left[\left(rm-K\right)+1\left(m>\bar{m}\right)*\left(\rho m-\kappa\right)\right]t\left(m\right)-\frac{1}{k}t\left(m\right)^{k}\right\}dF\left(m,r,\rho\right) \quad (8)$$

We assume classic convex costs, such that $k>1$. Our original model from Section 3 is a special case of this model in which $k\to\infty$, so that costs are zero up to $t(m) = 1$ and infinitely high thereafter. Other interpretations of $t(m)$ may be hiring additional staff to work with different ends of the mortgage market, in which case costs might be linear but returns might be concave. Anecdotal evidence from bank supervision officers indicates that some major banks did expand their wealth management divisions.

The first-order condition in $t(m)$ is

$$\frac{\partial \Pi}{\partial t(m)} = (rm - K) + 1(m > \bar{m}) * (\rho m - \kappa) - t(m)^{k-1} = 0$$

A "fixed cost story" would imply that an increase in fixed costs K should increase advertising by more for high values of m than for low values of m. In other words, we must have

$$\frac{\partial^2 t(m)}{\partial m \partial K} \geq 0 \tag{9}$$

We now show that for any $k > 1$, if $\frac{\partial \rho}{\partial K} < 0$, then inequality (9) must be violated for large enough values of m.

Differentiating the FOC in $t(m)$ over K and accounting for the fact that $\rho = \rho(K)$ depends on K but is common for all m, we obtain

$$
\begin{aligned}
t(m)^{k-1} &= (rm - K) + 1(m > \bar{m}) * (\rho m - \kappa) \\
(k-1)\, t(m)^{k-2} \frac{\partial t(m)}{\partial K} &= 1(m > \bar{m}) \frac{\partial \rho}{\partial K} m - 1 \\
(k-1)\, t(m)^{k-2} \frac{\partial t}{\partial m} &= r + 1(m > \bar{m}) * \rho \\
(k-1)\, t(m)^{k-2} \frac{\partial^2 t(m)}{\partial m \partial K} &= 1(m > \bar{m}) \frac{\partial \rho}{\partial K} v - (k-1)(k-2)\, t(m)^{k-3} \frac{\partial t}{\partial m} \frac{\partial t(m)}{\partial K}
\end{aligned}
$$

In particular, the marginal cost $t(m)^{k-1}$ is linearly increasing in m (except possibly for a notch to the right of the CLL). The schedule $t(m)$ is also increasing in m.

We can simplify the expression for the cross partial $\frac{\partial^2 t(m)}{\partial m \partial K}$ for $m \leq \bar{m}$,

$$
(k-1)\, t(m)^{2k-3} \frac{\partial^2 t(m)}{\partial m \partial K} = \frac{(k-2)}{(k-1)} r
$$

And for $m > \bar{m}$

$$
(k-1)\, t(m)^{k-2} \frac{\partial^2 t(m)}{\partial m \partial K} = \frac{1}{k-1} \frac{\partial \rho}{\partial K} + \frac{(k-2)}{(k-1)} \frac{1}{t(m)^{k-1}} \left(1 - (K + \kappa) \frac{\partial \rho}{\partial K}\right) [r + \rho]
$$

substituting in the first-order condition.

The first term is constant in m and positive iff $\partial \rho / \partial K > 0$. The second term goes to zero as m goes to infinity. Therefore, for m large enough, the sign of $\frac{\partial^2 t(m)}{\partial m \partial K}$ is given by the sign of the first term. Hence, any model explaining the behavior of ρ and $t(m)$ by optimization of equation (8) that features a fixed cost story, with

$\partial^2 t\,(m)\,/\partial m \partial K \geq 0$ for all m, must involve $\partial\rho/\partial K \geq 0$, and an increase in fixed costs must increase the jumbo-to-conforming spread as well as the density at the bunch, and decrease the jumbo share. In contrast, to rationalize our findings of a declining bunch and rising jumbo share, we would need $\partial\rho/\partial K > 0$. Therefore, even if the fixed cost story has implications for the behavior of ρ, they should go counter to what we observe in the data.