Changing the Footprint of GSE Loan Guarantees: Estimating Effects on Mortgage Pricing and Availability

Preliminary and Incomplete

Alexei Alexandrov∗ Thomas Conkling† Sergei Koulayev†

December 12, 2016

Abstract

We estimate the effects of marginal changes to the loan limits above which Fannie Mae and Freddie Mac (GSEs) are unable to guarantee and securitize loans and to the fees that the GSEs charge for guaranteeing mortgage loans (g-fees). Using a dataset of daily rate sheets by dozens of large mortgage lenders, we show that the average price difference across the loan limit is on the order of 5 basis points, though it masks considerable variation across lenders and loan characteristics. We show that changes in g-fees are close to fully passed-through to consumers; however, they are also dwarfed by existing price dispersion across lenders. We estimate the responsiveness of consumer demand to changes in interest rates of this magnitude. Finally, using our estimates above, we evaluate the effects of hypothetical marginal changes in both g-fees and loan limits.

1 Introduction

In the post-crisis years, about one trillion dollars in new residential mortgage loans are made in the United States each year. Fannie Mae and Freddie Mac (the GSEs) guarantee half of these loans: if a consumer defaults on their mortgage loan, then the GSEs pay the amount owed. One of the widely-reported reasons for the GSEs not being government agencies is the magnitude of their debt that, if to appear on the U.S. government’s books, would substantially increase outstanding U.S. government debt. Aside from guaranteeing loans, the GSEs package the guaranteed loans as securities and sell them off, with the U.S. Federal Reserve alone holding about $1.7 trillion of these securities.

With such a magnitude of risk exposure to the U.S. Government and, ultimately, the U.S. taxpayers, it is worth knowing the benefits that the GSEs provide to consumers. We analyze a

∗Amazon, email: alexei01@gmail.com.
†Consumer Financial Protection Bureau, email: thomas.conkling@cfpb.gov, sergey.kulaev@cfpb.gov. The views expressed are those of the authors and do not necessarily reflect those of the Consumer Financial Protection Bureau or the United States.
new dataset, with post-crisis and post-regulatory changes data, that we believe is more suited for estimating and identifying the benefits of GSEs at the margin than previous datasets analyzed by researchers.

The GSEs are prohibited by the U.S. Congress from guaranteeing or securitizing loans with loan amounts above a preset limit (jumbo loans), with the limit varying by county, but usually being $417,000. We show that in 2014, conditional on the relevant consumer and loan characteristics, such as credit score and loan-to-value ratio (LTV, a consumer’s financial leverage on the loan), the average pricing difference between a $417,000 loan guaranteed by a GSE and a $418,000 loan not guaranteed by a GSE is approximately 5 basis points (0.05 percentage points) per year. This average masks considerable variation across lenders. For some lenders, the difference is around 50 basis points, while for other lenders the difference is as low as negative 20 basis points: these lenders charge a lower price for jumbo loans than they do for similar loans guaranteed by the GSEs. Part of the reason for this potential negative price difference is that the GSEs charge lenders for the guarantee and the securitization, with an average upfront one-time guarantee-fee (g-fee) of approximately 55 basis points since 2013. We use the September 2015 g-fee changes to analyze the pass-through of g-fee changes to consumers. We find that the 25 basis point decrease in the upfront g-fee resulted in an average rate decrease to consumers of about 5 basis points per year (ongoing for the life of the loan): effectively, close to 100% pass-through accounting for the generally assumed duration of the mortgage of four to six years.

The 5 basis points per year due to the g-fee changes are dwarfed by the existing price dispersion across the lenders, dispersion that is on average approximately 50 basis points even for prime consumers, see Alexandrov and Koulayev (2016). Similarly, Fuster and Zafar (2014) show that consumers are typically not sensitive to interest rate changes in this range. To estimate the real impact of this interest rate increase from our data, we also analyze how much the latest increase in g-fees affected consumer demand. We show that consumer demand for mortgages changed by [Note: To be completed, waiting for release of 2015 HMDA data] in response to the 25 basis point decrease in the upfront g-fee.

Arguably, one of the most vocal debates after the crisis had been about whether the GSEs should continue to exist, especially after they were placed in conservatorship by the U.S. Government (we discuss it below). While we do not believe that our data allows us to make predictions about a drastic change like shutting down the GSEs completely, we believe our results allow us to make predictions about marginal changes. For example, our results suggest that while a gradual reduction in the loan limits (say, from $417,000 to $400,000, and for the most expensive metropolitan statistical areas from $625,500 to $575,000) may induce a substantial number of borrowers to reduce the size of their loans, a marginal increase in g-fees (say, by 50 basis points upfront, or 10 basis points ongoing), will be virtually unnoticed by consumers.

---

1 We believe that analyzing the drivers of the variation across lenders is out of scope for this paper; however, see Loutskina and Strahan (2009) for some possibilities.
2 G-fees increased for some types of loans in September 2015. However, economic theory suggests that the pass-through rates should be symmetric for decreases and increases, and that is what we find in the data as well.
Even if consumers do not react to, for example, a 10 basis point ongoing increase in interest rates, that does not mean that consumers are unaffected by it. However, the aforementioned low sensitivity of consumer demand to interest rates suggests that the effect is a transfer from consumers whose mortgages are subsidized by the GSEs to taxpayers in general. In other words, we do not believe that a noticeable fraction of consumers will refrain from getting a mortgage due to a change of interest rates of this magnitude.

Existing literature generally uses one of the two datasets to evaluate these effects: the Mortgage Interest Rate Survey (MIRS), a monthly survey filled out by selected lenders who report the terms of the loans that they originated in the last five days of the month and servicing datasets (akin to CoreLogic) that, aside from other variables, have the interest rate (but not the points and fees) for some of the mortgages in the United States. Unfortunately, using the observed prices, even if points and fees are observed, involves estimating each lender's pricing decision based on multiple continuous consumer and loan characteristics, with a dummy variable of whether the loan amount is above the GSEs' loan limit. In contrast, we have daily rate sheets from dozens of lenders, including many of the top residential mortgage originators. The rate sheets are effectively a formula for the rate that a consumer would be quoted at, say, a bank's branch, conditional on characteristics like the consumer's credit score and LTV ratio. Thus, we do not need to estimate the pricing function like previous papers – we know exactly what the pricing function is. The more recent previous work found rate differences of around 20 basis points per year: a difference considerably higher than the 5 basis points that we find. However, since the vast majority of the existing literature analyzes a completely different (pre-crisis) period, this does not necessarily indicate that the existing literature's estimates were inaccurate for that time period.³

Since we know the exact rate sheets, the September 2015 changes in g-fees provide a way to measure the pass-through of g-fee changes onto consumers. The g-fees changed only for some combinations of credit scores and LTV ratios. Assuming small fee changes of this magnitude do not substantially alter consumers' sorting into these combinations, (and that seems to be true, especially given the low prevalence of shopping for mortgages to begin with), we have all the ingredients for the standard difference-in-difference analysis: a control group of rates for consumers who had the credit score and LTV combinations for which the g-fees did not change, a treated group of rates for consumers for whom the g-fees changed, and daily data both before and after the date of the change.

The second marginal change we analyze is the potential consumer demand response to a reduction in the GSEs' loan limit. Consistent with the existing literature, we observe considerable bunching at the loan limit: many consumers forgo a higher loan amount (at least on the first lien) in order to remain under, or often right at, the GSEs' loan limit. Given the very small difference in the average rates between loans just below and just above the loan limit, it seems unlikely that this is a purely rational, full-knowledge consumer decision. Instead, this could be driven by the inertia of a sufficient number of consumers or their advisors (whether consumers' family, friends, [³Our findings are consistent with other industry surveys and reports; see for example Freddie Mac (2015).]
or realtors) believing that the consumer is likely to get a significantly better rate as long as the loan is under the GSEs' loan limit. Another potential reason is liquidity constraints: while jumbo loans with 20% down payment are relatively common with rates that are effectively the same as comparable conforming loans, jumbo loans with 10% or less down payment are considerably harder to find. We provide evidence that large numbers of borrowers choose low down payment loans just below the limit, while jumbos originated just above the limit are almost entirely restricted to down payments of 20% or more.

We attempt to disentangle the factors driving bunching behavior by separately estimating bunching in the data for low, medium, and high credit score borrowers, for whom interest rates and availability of loans differ. Based on our estimated propensity to bunch and observed LTV distributions for borrowers above and below the existing loan limit, we model counterfactual loan amount and LTV distributions under a new marginally lower loan limit. Our counterfactual results suggest that down payment constraints are indeed binding for many borrowers, particularly those with low or moderate credit scores. However, the majority of prime borrowers observed bunching have down payments exceeding those commonly required for jumbo loans. This suggests that a substantial amount of bunching must be due to some unobservable factors beyond interest rates and down payment constraints, potentially including preferences, beliefs, search costs, or underwriting rules. As a result, our counterfactuals predict that among the affected borrowers whose chosen loan amount is no longer conforming, 99 percent of those with low credit scores and 77 percent of those with high credit scores reduce their loan amount to below the new loan limit.

Finally, the bunching behavior above raises selection issues both regarding the consumers who bunch at the loan limit as well as about consumers who choose to take out a loan just over the loan limit, a concern often expressed in the existing literature. The lenders’ pricing practices do not lead us to believe that this is indeed an issue. Conditional on other consumer characteristics, lenders generally have the same rate for consumers whose loan amounts are between $100,000 and $417,000. This includes a sizable majority of all loans, and the fraction of consumers that appear to be bunching at $417,000 is small. Similarly, conditional on other characteristics, the lenders charge the same price for any loan amount above the GSEs’ loan limit, and the fraction of consumers that are right above the loan limit is small relative to the number of consumers taking out jumbo loans.

If any lender was concerned about selection effects around the loan limit, that lender could unilaterally create different pricing rules around the loan limit by, for example, increasing rates to consumers who appear to be bunching at the loan limit – again, there is already significant price dispersion in the market, and thus the law of one price does not hold and will not stop the lender from price discriminating. The fact that we observe no lenders implementing pricing policies that look anything like that suggests to us that the lenders are not particularly concerned about such

---

4 The argument is only slightly more involved for counties where the GSE loan limit is above $417,000 (most often $625,500). In these cases, conditional on other characteristics, the lenders generally charge four different prices: same price for any loan amount of under $100,000, same price for any loan amount that is between $100,000 and $417,000, same price for any loan amount that is between $418,000 and the loan limit, and finally same price for any loan amount above the loan limit.
selection effects, at least after controlling for characteristics such as credit score, LTV ratio, and state of residence.\(^5\) For riskier credit score and LTV combinations where selection issues may be of greatest concern, most lenders respond by offering no jumbo rates at all.\(^6\)

We do not discuss two concerns that are frequently brought up with changing g-fees or loan limits. The first concern is the availability of a 30-year fixed rate mortgage – the mainstay of the U.S. mortgage market. Even assuming that this type of a mortgage is indeed desirable from the social welfare perspective (it is most certainly desirable based on consumer choices), this type of mortgage is currently available in the prime jumbo market where the vast majority of the loans are originated and kept on portfolio by the originating institutions (usually banks), and thus a marginal change in g-fees or loan limit is unlikely to make this product unavailable.\(^7\) The second concern is adverse selection – the GSEs currently effectively cross-subsidize higher-risk (lower credit score and higher LTV ratio) consumers by charging them proportionately lower g-fees given their risk than lower-risk consumers. The concern is that increasing g-fees incentivizes the private sector to securitize loans only for lower-risk consumers, since they pay a disproportionate g-fee.\(^8\) Even if such cross-subsidization is justified, it is hard to see why the g-fee differential is the only way to accomplish this, given the multitude of other federal housing subsidies.\(^9\)

The rest of the paper is organized as follows. We discuss some of the market background and the data that we use in the following section, while tying in connections with the existing literature where appropriate. We then proceed through the three main elements of our analysis. First, we present our results on the spread between rates for loan amounts below the loan limit and above the loan limit, all else equal. This is followed by our results on the pass-through of g-fee changes to consumers. Lastly, we estimate households’ bunching at the loan limits, and calculate the effects of a counterfactual reduction of the limit.

---

\(^5\) An argument could be made that there is a binding constraint to such a price change: if the jumbo rate is only slightly above the rate just below jumbo, as it is on average, then an increase in the rates to the consumers who appear to be bunching might simply drive them to jumbo loans (the incentive compatibility constraint is binding). However, this argument overlooks the heterogeneity in the spread that we observe. There are lenders for whom the spread is much larger, for example 50 basis points, so that this constraint is unlikely to be binding at least for them. Furthermore, there are other lenders for whom the spread is negative (jumbo loans are cheaper).

\(^6\) Assuming default risk is the main dimension for selection concerns, this observation is consistent with recent literature on private information and screening in other competitive lending and insurance markets; see Hendren (2013), Einav et al. (2012), and Mahoney and Weyl (2014).

\(^7\) However, see Fuster and Vickery (2015) showing that the proportion of adjustable rate mortgages increases when securitization is more difficult. See Campbell and Cocco (2003), Campbell (2013), and Zywicki (2013) providing arguments for why, for example, a plain vanilla adjustable rate mortgage might be better from the social welfare perspective. Similarly, we do not discuss the effect on house prices. See Adelino, Schoar, and Severino (2012); however, we believe that the effects of a marginal change would be minimal.

\(^8\) See Goodman and Zhu (2013) and Securities (2014), in response to Housing Finance Agency (2014) discussed below, suggesting that this scenario might indeed occur sooner rather than later.

\(^9\) See Congressional Budget Office (2009) for other federal housing subsidies: despite all the trillion-dollar numbers referenced in this paper, “[t]he largest and most widely used tax expenditure in the housing area is the mortgage interest deduction.” See, for example, Poterba and Sinai (2008) discussing the difference between the mortgage interest deduction and not taxing the implicit rental income from living in your own house.
2 Background and Data

2.1 Background

2.1.1 GSEs before the early 2000s

Fannie Mae (Federal National Mortgage Association) was founded in 1938 in the aftermath of the Great Depression and, at the time, was a federal agency. Its main task was buying mortgage loans that were guaranteed by the Federal Housing Administration (FHA). In 1968, at least partially to keep Fannie Mae’s debt off the government’s budget, President Lyndon Johnson fully privatized Fannie Mae. The government split off a part of Fannie Mae at that time to specifically cater to buying – and at that point in time already starting to securitize – mortgage loans guaranteed by the FHA. That part, Ginnie Mae, was and still remains a part of the federal government. Around the same time Congress created Freddie Mac, which effectively became a somewhat smaller version of Fannie Mae, and allowed both Fannie and Freddie to purchase mortgages not secured by the FHA or by any other government agency.\textsuperscript{10} Even though both Fannie and Freddie had (and, technically, still have) shareholders, the two companies got significant preferential treatment from the government, including treating their debt on par with the debt of federal agencies in many contexts. At least partially due to that, there was a widely held perception that the GSEs are effectively backed by the U.S. government and would be bailed out if anything were to happen, thus lowering borrowing costs for the GSEs.

Even by 1980, the GSEs were relatively small players in the industry, dealing with well under 10% of all mortgages. The GSEs experienced fast growth in the 1980s, taking their market share to 20% by 1990. At the end of the 1980s the GSEs (more Fannie than Freddie) got caught up in the Savings and Loans Crisis along with the thrifts, for the same reason: not managing interest rate maturity properly and getting caught by the rising interest rates in the market while having 30-year mortgages at comparatively much lower rates in portfolio. Fannie Mae was technically insolvent in the late 1980s; however, the perceived government backing allowed it to survive long enough to see interest rates decrease again, bringing Fannie back to solvency. The growth of the GSEs continued through the 1990s and the early 2000s.

There was a considerable interest in the spread between jumbo and non-jumbo loans starting from at least the late 1980s, see Hendershott and Shilling (1989). The research intensified as the GSEs were growing, see Congressional Budget Office (1996), McKenzie (2002), Passmore (2005), Passmore, Sherlund, and Burgess (2005), and Lehnert, Passmore, and Sherlund (2008). The Mortgage Interest Rate Survey (MIRS) was the dataset used most often for analysis. The dataset is a monthly survey of selected lenders, asking the lenders for loan-level information on terms, conditions, and consumer and loan characteristics for the loans made during the last five days of the month.\textsuperscript{11} The methodology often included running a regression to fit observed pricing based on

\textsuperscript{10}The term GSEs often also includes the Federal Home Loan Bank System, but we do not discuss it in this paper.

\textsuperscript{11}The survey, administered by the Federal Reserve at the time, started by asking for the first days of the month, but then switched at some point due to higher origination volume at the end of the month.
various parametric forms of consumer characteristics, usually restricted to a particular state (like California) and particular types of loans (30 year fixed) to cut down on heterogeneity. The regression also typically included a jumbo dummy (whether the loan amount is above the GSE limit) that was the coefficient of interest. The earlier findings tended to be somewhat higher, with the later findings showing a difference of approximately 20–30 basis points per year, lower differences for adjustable loans, and higher differences for higher LTV ratios.

2.1.2 GSEs from the early 2000s

The GSEs’ ramp-up of securitization in the early 2000s, up to the point where they guaranteed roughly $4 trillion of mortgage loans, their subsequent placement in conservatorship, and their role in the financial crisis had been discussed in multiple books and journal articles.\footnote{As a sample, we recommend An and Bostic (2008), Bhutta (2012), Avery and Brevoort (2015) for the articles and Angelides, Thomas, et al. (2011), Acharya, Richardson, Van Nieuwerburgh, and White (2011), and McLean (2015) for book-length treatment.} Upon placement of the GSEs in conservatorship in 2008, with the Federal Housing Finance Agency (FHFA) acting as a conservator and with the U.S. Department of Treasury receiving all the GSEs’ profits indefinitely due to the third amendment of the conservatorship agreement, there was a debate of what should be the next steps regarding the GSEs. Even before the financial crisis, there were calls for GSE reforms, for roughly the same reasons as now – GSEs enjoying implicit government guarantees not reflected in the government budget, failing to pass all of this support on to consumers, and giving profit to shareholders but losses to taxpayers – see, for example, Congressional Budget Office (1996) and various pre-crisis statements by leading policy economists such as Ben Bernanke and Larry Summers.\footnote{As a historical aside, one of the authors of Congressional Budget Office (1996) is Edward DeMarco, who then became the acting director of the FHFA from 2009 to early 2014. For the multitude of quotes from public figures, and a fascinating account of the GSEs, see Acharya, Richardson, Van Nieuwerburgh, and White (2011).}

In 2011, the Department of Treasury and the Department of Housing and Urban Development (where the FHFA is housed) jointly released President Obama’s administration’s plan for GSE reform. The plan was unequivocal about at least medium-term response: “The Obama Administration’s reform plan is designed to pave the way for a robust private mortgage market by reducing government support for housing finance and winding down Fannie Mae and Freddie Mac on a responsible timeline” (Department of Treasury and Department of Housing and Urban Development, 2011).\footnote{See also an earlier report by the Congressional Budget Office (2010) suggesting similar measures.} Two of the four suggested actions were increasing g-fees and reducing conforming loan limits.\footnote{The other two were increasing private capital, echoing a multitude of such calls for banks and other systemically important financial institutions, for example see Admati and Hellwig (2014) and winding down the GSEs’ investment portfolio, something that is currently closer to getting accomplished, although at the expense of the Federal Reserve holding much of that portfolio.}

Partially in response to these calls and Congressional action, the FHFA increased upfront (one-time) g-fees from an average of 22 basis points per loan in 2009 to 55 basis points per loan in 2013, see Housing Finance Agency (2014). However, the new director Mel Watt, appointed in early 2014,
postponed the next scheduled round of g-fee increases and instead issued a request for input for the public, with questions and analysis regarding how the g-fees should be set (Housing Finance Agency, 2014). In over a hundred of comments, the quantitative focus seemed to be on, effectively, the actuarially fair way to compute the g-fees, with the main disagreements about what should be the GSEs’ hypothetical capital ratio and return on equity – the two main components of the g-fee calculation. Many responders noted the numbers of 20-30 basis points in the GSE pricing advantage cited above from the older studies in their arguments. In more qualitative responses, commenters urged the FHFA to consider the regulatory uncertainty of the Qualified Mortgage and Qualified Residential Mortgage rules and the still recovering housing market (it is doubtful that any of the three issues are still applicable, even supposing that they were at the time). The rest of the responses were somewhat predictable: groups that favor lower mortgage rates (consumer groups, realtors, smaller lenders) urged the FHFA to decrease g-fees, while large lenders and securitizers urged caution, but were not averse to raising g-fees. In the end, the FHFA decided to lower g-fees by 25 upfront one-time basis points for a subset of loans in September 2015 – the policy variation that we are exploiting to find the pass-through rate of g-fees.

Newer research on GSEs went in two different directions. DeFusco and Paciorek (2014) uses bunching at the GSEs’ loan limit to derive the elasticity of mortgage demand to changes in interest rates. To get an estimate of the difference between jumbo and non-jumbo loans, the authors use the CoreLogic dataset described below, and find an 18 basis points per year difference – a result consistent with the previous literature, but much higher than our estimates on the order of 5 basis points. The discrepancy could be explained both by the time period studied (we analyze 2015, while DeFusco and Paciorek (2014) analyze the pre-crisis period) and by the differences in data (CoreLogic only has the interest rate, but neither points nor fees that the consumer pays).

Another strand of the literature utilizes general equilibrium macroeconomic models to model financial frictions and mortgage markets, including the GSEs, see for example Elenev, Landvoigt, and Van Nieuwerburgh (2015), Favilukis, Ludvigson, and Van Nieuwerburgh (2011), and Jeske, Krueger, and Mitman (2011), to compute the counterfactual equilibria. We believe that our data is better suited for the reduced-form approach that we utilize here; however, our results could improve the accuracy of some of the parameters of the future dynamic macroeconomic models.

2.2 Data

We utilize three datasets for our analysis. Informa rate sheets are our main source of rate information. Data collected pursuant to the Home Mortgage Disclosure Act (HMDA) is our source for market shares and the distribution of loan amounts (we utilize the agency version with loan

\[\text{\textsuperscript{16}}\text{In particular, see California Association of Realtors (2014), suggesting that at least some realtors might believe that the interest rate differential between the loans above and below the loan limit everything else equal is larger than it actually is.}\]

\[\text{\textsuperscript{17}}\text{In addition to using a semi-parametric function of consumer/loan characteristics, as opposed to the parametric functional forms in older literature described above, the authors use the appraisal value of the house as an instrument for jumbo loan status, see also Kaufman (2014). See Kleven and Waseem (2013) on the bunching technique used.}\]
origination dates). Finally, we use the CoreLogic dataset with loan-level information on consumer characteristics such as FICO credit score and LTV ratio, as well as some loan characteristics such as interest rates, for a subset of loans. The three datasets and the matching process are described below.

Informa Research Services provide us with daily downloads of retail mortgage price sheets from 31 creditors starting in summer 2014, including seven of the top ten creditors by HMDA market share. This data allows us to look up the available price options for a borrower based on FICO, LTV (LTV) ratio, loan size, property state, loan type (both fixed vs adjustable and FHA, conventional, jumbo, etc.), and loan purpose (for example, purchase loans) for these creditors. Generally, pricing adjustments for FICO occur every 20 points, and pricing adjustments for LTV occur every 5%. Moreover, these thresholds tend to be the same across creditors: for example, for most creditors there is no within-creditor price dispersion for FICO scores between 720 and 740, holding other consumer characteristics constant (similarly for LTV between 80% and 85%). Pricing is conducted at the state level by each creditor, though many creditors offer little to no variation across groups of states or price nationally. Since borrowers can negotiate their price and creditors can charge overages, these prices, theoretically, may vary from transacted prices. This data does not include information about upfront fees and other closing costs. We cannot reveal the lenders in the Informa dataset. Thus, we do not show any graphs or tables with market shares of Informa lenders: even masking the name of the lender might not prevent a diligent researcher from backing out the lender’s identity based on the public HMDA information.

HMDA was originally enacted by Congress in 1975. HMDA data contains information about approximately 90 – 95% of originated mortgages at the loan level, including creditor, origination date, loan type (e.g., FHA versus conventional), property type, property location, loan purpose, loan size, and other fields. These data allow us to calculate market share at a granular level – e.g. what a creditor’s market share was during the month of August (or even during a particular day) for home purchase, first-lien, owner-occupied FHA loans in Massachusetts. Market shares, both within specific segments and at a high level, tend to be small. The largest creditor nationally, Wells Fargo, has a roughly 6% market share among conventional purchase loans. The top five creditors have a combined market share of under 15%, and the top 20 creditors have around 25%. The median creditor has 0.002% market share. See Bhutta and Ringo (2015) for more.

HMDA data does not, however, have detailed pricing information (it contains information on loans priced more than 150 basis points above the APOR, but only around 5% of recorded loans fall under this designation and they are originated disproportionately by much smaller creditors). The loan-level data do not have credit score or LTV. Moreover, HMDA does not distinguish between mortgage channels – broker, correspondent, and retail. Our pricing data only covers retail prices, so HMDA market shares are an approximation only.

CoreLogic Loan Level Market analytics contains both origination and performance data on loans serviced by 17 top servicers. We use the origination data, which contains FICO and LTV at origination, origination data, loan size, property state, and loan purpose to match with the
Informa data, filtering by number of units, occupancy, and lien. This allows us to weight the various consumer profiles tested in Informa by actual market share (since HMDA lacks FICO and LTV information). These data do not, however, have detailed pricing information. In particular, while the interest rate is available, the points and fees that a consumer pays are not: in other words, any price dispersion in CoreLogic could have a simple explanation of consumers paying different points and fees. Moreover, we approximate that these 17 servicers account for less than 50% of the first-lien market captured by HMDA, though this varies by loan type and loan purpose.

The HMDA-CoreLogic match is relatively familiar to researchers of the U.S. mortgage market, and thus we do not spend the time to describe it in detail, except that we note that we use the agency version of HMDA, with the origination date significantly improving the accuracy, and that in 2014 first-lien originations in CoreLogic were only one third of those in the HMDA data. We know the lenders in the Informa data, and match them by name to the lenders in HMDA.

3 Interest Rates and Guarantee Fees

The first step of our analysis is to calculate the average interest rate spread between conforming loans guaranteed by the GSEs, and jumbo loans above the GSE loan limits. The calculation weights the posted Informa rates by HMDA lender market shares, using CoreLogic data to control for the distribution of loan and borrower types within-lender.

We then proceed to assess marginal changes along two policy levers available to the GSEs: g-fees and loan limits. The marginal effect of g-fees is identified by a September 2015 policy change which changed g-fees for some loans, while maintaining the status quo for others. The impact of the policy change on the Informa rates identifies the pass-through of marginal fee changes. Loan origination data is then used to test for any resulting demand effects [Note: To be completed, waiting for release of 2015 HMDA data]. The following section evaluates the impact of marginal changes in loan limits, based on the observed bunching at current limits.

3.1 Average Interest Rates

Throughout our analysis, we focus on conventional, thirty year, fixed rate, single family, purchase mortgages in non-high cost counties. These are among of the most popular mortgage products, are offered by nearly all lenders, and are a common benchmark in previous studies. As described in Section 2.2, within this narrow mortgage category lenders’ posted interest rates vary based on characteristics including FICO, LTV, and loan amount. Additionally, the distributions of these loan and borrower characteristics vary across lenders. Our method for calculating the interest rate spread aims to control for differences in loan types and market shares between loans above and below the GSE loan limits. As such, the relevant comparison is between average rates above and below the limit for loans with the same FICO and LTV.

\footnote{We observe the full rate curve offered by lenders (including points and fees), but since we do not have data on points paid by consumers in our data, we calculate all rates with zero points.}
When using loan originations to weight prices, the total number of originations for the calendar year is used. For interest rates, we use a simple annual average of within-lender, within-loan type interest rates. The simplifying assumption is that all borrowers received this annual average rate. Given the relative strengths of each dataset, the approach follows in three steps. First, CoreLogic originations data are used to calculate within-lender, across-loan type weights:

\[ a = \text{loan amount bin} \ (\$ \text{ thousands}) \in \{350 - 417, 418 - 500\} \]
\[ f = \text{FICO score bin} \in \{\leq 680, 680 - 740, \geq 740\} \]
\[ l = \text{LTV bin} \in \{\leq 80, > 80 - 85, > 85 - 90, > 90\} \]

For each lender \( j \), the cross product of these 3 categories creates 24 bins of loans. If \( n_{jafl} \) is the number of loans within a given bin, then the relative share of loans made by a firm that fall into each category is:

\[ w_{jafl} = \frac{n_{jafl}}{\sum_{a,f,l} n_{jafl}} \]

The assumption here is that although CoreLogic does not have representative coverage across lenders, we assume that the coverage within-lender, across-loan type is representative.

The second step uses HMDA to calculate each lender’s national market share, distinguishing across loan amounts above and below the conforming limit:

\[ m_{ja} = \sum_{j} \frac{n_{ja}}{n_{ja}} \]

We use HMDA in this way because of its more accurate across-lender coverage relative to CoreLogic. By restricting to loans originated near the loan limits, our shares are representative of the observed distribution of lenders chosen by borrowers just above and just below the limits.

Finally, we combine both weights to calculate our weighted average prices by loan type. The Informa rate sheets contain loan prices for all combinations of lender, loan amount, FICO, and LTV, so we define \( p_{jafl} \), by choosing \( \tilde{a}, \tilde{f}, \tilde{l} \) from within the bins specified above:

\[ \tilde{a} \in \{417, 418\} \]
\[ \tilde{f} \in \{670, 710, 750\} \]
\[ \tilde{l} \in \{80, 85, 90, 95\} \]

There is a small amount of cross-state price variation, so \( p_{jafl} \) is actually the median within-lender.

\[ ^{19} \text{The HMDA data includes application dates, but not LTV or FICO, which precludes us from mapping the appropriate Informa rate from that application date directly to the originated loan.} \]
within-loan type price across all states served. Combining the prices and weights, we calculate $\bar{p}_{afl}$:

$$
\bar{p}_{afl} = \frac{\sum_j w_{jafl} m_{ja} p_{jafl}}{\sum_j w_{jafl} m_{ja}}
$$

which is a within-FICO, within-LTV, within-loan amount average price.

Loan availability is an important concern to address when calculating the jumbo-conforming interest rate spread. Lenders in the Informa dataset post rates for conforming loans at all combinations of FICO and LTV described above. However, rates for jumbo loans are only consistently available for low LTV, and medium to high FICO scores. This lack of posted prices is consistent with CoreLogic originations data (discussed in detail below), which suggest that while many high LTV and low FICO conforming loans are originated, jumbo loans are largely restricted to mortgages with an LTV less than or equal to 80, and to borrowers with good credit. Anecdotally, the same loan types that are missing in our data also generate messages stating they are unavailable when entered into rate calculators on lenders’ websites.

Our calculated average interest rates, shown in Table 1, suggest that the jumbo-conforming interest rate spread is small and in fact slightly negative for the most commonly chosen loan types.\(^{20}\) For a borrower with good credit (FICO of 750) and a twenty percent down payment (LTV of 80), lenders on average offer a jumbo loan without a government guarantee for 2 basis points less than a guaranteed conforming loan. For a borrower with a FICO score of 710, the jumbo loan is 6 basis points cheaper.

Although lenders avoid any default risk when making conforming loans, they do pay the added cost of g-fees assessed by the GSEs. The next step in our analysis estimates the pass through of observed g-fee changes to the rates paid by consumers.

3.2 Marginal Changes to G-Fees

3.2.1 Pass-through rate of g-fee changes

The difference-in-differences estimates of the g-fee pass-through rate that follow are based on granular pricing data in the Informa rate sheets. Figure 1 shows a sample time-series of lender-level posted interest rates for $416,000, 30-year, fixed rate loans with zero points to California borrowers with an LTV ratio of 80 and a FICO credit score of 750. Interest rates largely move parallel to one-another, leaving the relative price rankings across firms fairly stable. On a given day, the spread across lenders can be as large as 50 basis points (.5 percentage points).

The upfront guarantee fees charged by the GSEs vary along the same loan and borrower char-

Table 1: Average Interest Rates by Loan Type

<table>
<thead>
<tr>
<th>FICO</th>
<th>LTV</th>
<th>Conforming, $417k (%)</th>
<th>Jumbo, $418k (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>750</td>
<td>80</td>
<td>4.12</td>
<td>4.09</td>
</tr>
<tr>
<td>710</td>
<td>80</td>
<td>4.24</td>
<td>4.17</td>
</tr>
<tr>
<td>670</td>
<td>80</td>
<td>4.55</td>
<td>4.18**</td>
</tr>
<tr>
<td>750</td>
<td>85</td>
<td>4.13</td>
<td>4.22*</td>
</tr>
<tr>
<td>710</td>
<td>85</td>
<td>4.24</td>
<td>4.19*</td>
</tr>
<tr>
<td>670</td>
<td>85</td>
<td>4.60</td>
<td>-</td>
</tr>
<tr>
<td>750</td>
<td>90</td>
<td>4.15</td>
<td>4.57**</td>
</tr>
<tr>
<td>710</td>
<td>90</td>
<td>4.27</td>
<td>4.57**</td>
</tr>
<tr>
<td>670</td>
<td>90</td>
<td>4.49</td>
<td>-</td>
</tr>
<tr>
<td>750</td>
<td>95</td>
<td>4.16</td>
<td>-</td>
</tr>
<tr>
<td>710</td>
<td>95</td>
<td>4.28</td>
<td>-</td>
</tr>
<tr>
<td>670</td>
<td>95</td>
<td>4.55</td>
<td>-</td>
</tr>
</tbody>
</table>

* Rates available from fewer than 30% of Informa lenders
** Rates available from fewer than 10% of Informa lenders

Note: Average annual interest rates in 2014, weighted by within-lender distribution of loan types, and across-lender market shares. A rate is defined as available if a lender offers loans of that type on their rate sheets, and at least one origination is observed. The symbol ‘-’ indicates that no lenders in the Informa data listed rates and originated loans for this loan type.
Figure 1: Lender-Level Daily Interest Rates, California, LTV = 80, FICO = 750

Note: Each colored dot or symbol represents the daily posted interest rate for a given lender. All rates shown are for a $416,000 loan in California, with zero points, LTV = 80, FICO = 750. The data cover January 1st to October 14th of 2015. All data come from Informa rate sheets. The vertical line at September 1st indicates the effective date of the upfront guarantee fee changes used in the differences-in-differences analysis.
Note: Each colored dot or symbol represents the interest rate for an LTV = 85 loan minus the interest rate for an LTV = 80 loan for a given lender. All rate differences shown are for $416,000 loans in California, with zero points, FICO = 750. The data cover January 1st to October 14th of 2015. All data come from Informa rate sheets. The vertical line at September 1st indicates the effective date of the upfront guarantee fee changes used in the differences-in-differences analysis. For FICO scores of 750, the upfront fee on LTV = 85 loans decreased by 25 basis points (.25 percentage points), while the upfront fee was unchanged for loans with LTV = 80.
acteristics observed in the Informa rate sheets data. The fee changes implemented on Sept. 1st, 2015 varied across these characteristics, which allow us to measure the pass-through of fee changes to consumers. Figure 2 plots an example rate spread between two otherwise identical loans with LTVs of 85 and 80. On September 1st the upfront guarantee fee for the LTV 85 loans was reduced by 25 basis points, while the fee remained unchanged for loans with LTV of 80. Nearly all lenders had zero spread between these loans prior to the fee change, meaning they charged the same rate for both borrower types. As the effective date approaches, lenders begin lowering the rate on LTV 85 loans relative to LTV 80 loans, passing the lower guarantee fee through to consumers. For this particular loan type, we see most lenders reducing spreads by between three and seven basis points.

To assess how the degree of pass-through may vary with borrower characteristics, we conduct a series of difference-in-differences regressions comparing rates on loans in neighboring LTV bins offered to borrowers with different FICO scores. Table 2 presents the estimated treatment effects of the upfront fee changes. For borrowers with high FICO scores, who make up the bulk of the mortgage market, the FICO and LTV combinations with a relative fee reduction see interest rates approximately 5 basis points lower, with quite consistent effect sizes. This change in annual rates would suggest average pass-through in the range of 100% of the 25 basis point upfront fee, given the generally assumed four to six year average duration of a mortgage. For lower credit scores, the pass-through is less clear. This may reflect the thinner market of borrowers with these scores.

As a test of the identification strategy, we estimate the same model on numerous FICO and LTV combinations with no relative fee changes. In the thicker, high credit score segment of the market, we estimate precise zero treatment effects. This suggests that our estimates are not being driven by a policy change coincident with the upfront fee reduction, though again the results are less conclusive at lower credit score levels.

3.2.2 Effect of g-fee changes on loan demand

[Note: Difference-in-differences estimates of g-fee policy change on loan originations, to be completed. Waiting for release of 2015 HMDA data.]

4 Marginal Changes to Loan Limits

The previous section documents the interest rates and availability of loans above and below the GSEs loan limits, and the effects of marginal changes to the g-fees charged to guarantee these loans. This section estimates the effects of marginal changes to the loan limits themselves, changing the set of loans eligible for a GSE guarantee. While g-fee changes result in small interest rate changes for large numbers of borrowers, loan limit changes may substantially alter the set of available loans for those borrowers near the existing limits.

Consistent with previous studies, we observe considerable bunching of loan amounts at the GSE loan limit, suggesting borrowers will be sensitive to this policy lever. This is despite the evidence of small price differences between jumbo and conforming loans. One potential explanation is loan
Table 2: Diff-in-Diff Treatment Effects of 25 Basis Point Upfront Guarantee Fee Decrease

<table>
<thead>
<tr>
<th>FICO = 750</th>
<th>LTV 65 over 60 Fee Diff</th>
<th>Effect</th>
<th>LTV 75 over 70 Fee Diff</th>
<th>Effect</th>
<th>LTV 80 over 75 Fee Diff</th>
<th>Effect</th>
<th>LTV 85 over 80 Fee Diff</th>
<th>Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-</td>
<td>-.000</td>
<td>-</td>
<td>-.000</td>
<td>-</td>
<td>-.000</td>
<td>-25bp</td>
<td>-.046</td>
</tr>
<tr>
<td></td>
<td>(.002)</td>
<td></td>
<td>(.000)</td>
<td></td>
<td>(.002)</td>
<td></td>
<td>(.006)</td>
<td></td>
</tr>
<tr>
<td>FICO = 730</td>
<td>-</td>
<td>.001</td>
<td>-</td>
<td>-.001</td>
<td>-</td>
<td>.001</td>
<td>-25bp</td>
<td>-.052</td>
</tr>
<tr>
<td></td>
<td>(.003)</td>
<td></td>
<td>(.002)</td>
<td></td>
<td>(.004)</td>
<td></td>
<td>(.007)</td>
<td></td>
</tr>
<tr>
<td>FICO = 710</td>
<td>-25bp</td>
<td>-.043</td>
<td>+25bp</td>
<td>.036</td>
<td>-</td>
<td>-.007</td>
<td>-25bp</td>
<td>-.050</td>
</tr>
<tr>
<td></td>
<td>(.005)</td>
<td></td>
<td>(.005)</td>
<td></td>
<td>(.002)</td>
<td></td>
<td>(.008)</td>
<td></td>
</tr>
<tr>
<td>FICO = 690</td>
<td>-</td>
<td>-.005</td>
<td>-</td>
<td>-.021</td>
<td>-</td>
<td>-.015</td>
<td>-</td>
<td>.011</td>
</tr>
<tr>
<td></td>
<td>(.004)</td>
<td></td>
<td>(.007)</td>
<td></td>
<td>(.006)</td>
<td></td>
<td>(.005)</td>
<td></td>
</tr>
<tr>
<td>FICO = 670</td>
<td>-</td>
<td>-.017</td>
<td>+25bp</td>
<td>-.006</td>
<td>-</td>
<td>-.006</td>
<td>-25bp</td>
<td>-.031</td>
</tr>
<tr>
<td></td>
<td>(.009)</td>
<td></td>
<td>(.016)</td>
<td></td>
<td>(.005)</td>
<td></td>
<td>(.008)</td>
<td></td>
</tr>
<tr>
<td>FICO = 650</td>
<td>-</td>
<td>-.024</td>
<td>+25bp</td>
<td>-.005</td>
<td>-25bp</td>
<td>-.029</td>
<td>-</td>
<td>-.010</td>
</tr>
<tr>
<td></td>
<td>(.008)</td>
<td></td>
<td>(.018)</td>
<td></td>
<td>(.006)</td>
<td></td>
<td>(.005)</td>
<td></td>
</tr>
</tbody>
</table>

All regressions include lender-by-state, date, and LTV fixed effects.

Note: Robust standard errors (in parentheses) are clustered at the lender level. Dependent variable is the interest rate in percentage points on a $416,000 loan with zero points offered by a given lender in a given state, based on Informa rate sheets data. Daily data is used from 2015, excluding the period between the announcement date of the rate changes (April 17th) and the implementation date (September 1st). The results presented are the diff-in-diff treatment effects for 24 separate regressions, which vary based on FICO credit score and LTV (loan-to-value) percentage. The treatment is a 25 basis point (.25 percentage point) reduction in upfront guarantee fees for loans with certain LTV and FICO combinations, while fees on other combinations remained unchanged. The Fee Diff columns show the changes in the guarantee fee spreads between loans, and the Effect columns show estimated changes in rate spreads between loans.
availability, as our pricing analysis suggests that jumbo loans may be largely unavailable for low credit scores and high LTVs. We first document that loan availability likely explains some, but not all, of the observed bunching in loan amounts. Given the sizeable portion of observed loan choices which are not explained by either interest rates or availability, we use a reduced form, non-parametric approach to estimate the distribution of loan amounts in a counterfactual scenario with a marginally lower GSE loan limit.

4.1 Loan Choices Near the GSE Loan Limit

The price that borrowers pay for their home, in combination with the GSE loan limits, determines how much down payment is required while still qualifying for a conforming loan. If borrowers are constrained by their funds available for a down payment, this could contribute to bunching at the GSE loan limits. Conforming loans are generally available with LTVs up to 95.21 Figure 3 shows the LTV and loan amounts chosen by borrowers for three separate ranges of home purchase prices; those eligible for a conforming loan with a maximum LTV of 95, those eligible for a conforming loan with a maximum LTV between 80 and 95, and those eligible for conforming loans with a maximum LTV below 80. All of these borrowers have the option to choose a jumbo loan as well. For the first group of home prices, we observe substantial bunching at LTVs of 80, 90, and 95. The GSE loan limit is not binding for this range, and we observe no bunching in loan amounts. For the second group, the GSE loan limit binds at some LTV level between 80 and 95. Considerable bunching is observed at the loan limit ($417,000 for this set of non-high cost counties). The LTV distribution above 80 is smoother, consistent with each of these borrowers having a different maximum conforming LTV. The final group, for whom the GSE loan limit binds at an LTV below 80, has a large mass at the loan limit. These borrowers contribute to the thicker density of borrowers below LTV 80 for this group. The mass at LTV 80 constitutes the jumbo borrowers in the smooth loan amount distribution seen above the GSE loan limit. Very few jumbo borrowers choose loans above LTV 80.

This figure suggests a few intuitions about borrowers’ choice of loan amount. The large mass of conforming loans above LTV 80 (when available) would indicate that higher LTV is a desired characteristic, and some borrowers are likely down-payment constrained.22 This may indicate that an important marginal effect of the GSEs is to permit borrowers to make smaller down payments. However, even for high-priced homes, we still see borrowers choosing loans at the conforming limit with LTVs below 80, despite the availability of jumbos with higher LTVs and (based on evidence from Section 3.1) essentially equal interest rates. This seems to suggest that either (a) jumbo loans are not actually available to these borrowers due to unobserved underwriting requirements, or (b) borrowers have imperfect information about the availability or interest rates of jumbo loans.

---

21 For now we are abstracting from the unobserved underwriting requirements of both conforming and jumbo loans.
22 This large mass above LTV 80 is observed even if the sample is restricted to loans near the GSE loan limit.
Figure 3: Original LTV and Loan Amounts by Borrowers’ Home Price

Note: All data come from CoreLogic 2014 loan originations in non-high cost counties (GSE loan limit = $417,000). Each row represents loans originated on homes priced within the specified range. The first column depicts the LTV distribution for the loans within the home price range. The second column depicts the total number of loans originated, in $5,000 bins, for the specified price range. Loans with LTV less than 60 or greater than 100 have been excluded from figures, as have loans for homes priced above $800,000.
4.2 Counterfactual Loan Sizes

The evidence presented so far suggests substantial bunching at the GSE loan limits, despite small rate differences between conforming and jumbo loans. This motivates our largely reduced-form, or non-parametric approach to simulating borrower behavior under a marginally lower counterfactual loan limit. At the household level, bunching imposes an adjustment cost of either raising additional funds for a down payment, or choosing a cheaper home. These costs should be increasing in the loan size reduction required to bunch, and likely vary across borrowers based on observable factors like credit scores, and unobservable preferences, beliefs, liquidity constraints, or underwriting requirements. The primary assumption we impose is that conditional on the observable credit scores, the distribution of these unobservable factors, and hence the propensity to bunch and the resulting distribution of chosen LTVs, is the same for borrowers near the new counterfactual limit as it is for borrowers near the existing limit.

Our estimation and notation directly follows DeFusco and Paciorek (2014), assuming that in the absence of GSE loan limits, the distribution of loan amounts would be smooth. The data show that bunching at the loan limit is accompanied by a dip in the distribution of loan amounts just above the limit. Our model is estimated to minimize the difference between the missing mass of borrowers just above the limit and the excess mass bunching at the limit.

For our calculations, all dollar loan amounts are measured in logs, and normalized to zero at the GSE loan limit in the county of origination. All loans are assigned to bins \( j = \{-J, \ldots, L, \ldots, 0, \ldots, U, \ldots, J\} \), reflecting their distance from the loan limit, in intervals of a fixed width. We use a flexible polynomial of degree \( p \) to fit the distribution of loan counts \( n_j \) within each bin, with additional indicator variables for those bins immediately surrounding the loan limit, \( \{m_L, \ldots, m_U\} \), to estimate the amount of bunching relative to the smooth polynomial. The full regression is

\[
n_j = \sum_{i=0}^{p} \beta_i (m_j)^i + \sum_{k=L}^{U} \gamma_k \mathbb{1}(m_k = m_j) + \epsilon_j.
\]

The estimated polynomial, excluding the indicators, yields the predicted smooth distribution of loan amounts without bunching

\[
\hat{n}_j = \sum_{i=0}^{p} \hat{\beta}_i (m_j)^i.
\]

Both the missing mass of borrowers above the limit, \( \hat{M} \), and the excess mass of borrowers bunching at the limit, \( \hat{B} \), are calculated as differences between the borrower counts predicted by the smooth distribution and the data:

\[
\hat{M} = \sum_{j=1}^{U} (\hat{n}_j - n_j) = -\sum_{j=1}^{U} \hat{\gamma}_j,
\]

and

\[
\hat{B} = \sum_{j=L}^{0} (n_j - \hat{n}_j) = \sum_{j=L}^{0} \hat{\gamma}_j.
\]

After estimating the above model separately for borrowers with low, medium, and high credit scores, we use the smooth polynomial distribution of loan amounts and the indicator coefficients...
$\gamma_k$ to calculate the fraction of borrowers missing from each of the $U$ bins above the limit:

$$f_k = -\frac{\gamma_k}{\hat{n}_k}.$$

These fractions trace out the dip in originations above the existing loan limit, and form the basis for our counterfactual predictions.

Our counterfactual shifts the loan limit downward by $S$ bins, using $f_k$ to model the number of borrowers bunching at given distances from the new loan limit. We assume that borrowers now bunch from the full range of loan sizes in $\{-S+1, \ldots, U\}$. Given the larger interval of loan sizes covered, we define a wider set of bins $j_c = \{1, \ldots, U\}$ such that it covers the same interval as $j = \{-S+1, \ldots, U\}$, and then apply the fractions $f_k$ to these wider bins. This method traces out our counterfactual dip, and then allocates the total counterfactual mass of missing loans,

$$M_c = \sum_{j_c=1}^{U} f_{j_c} \hat{n}_{j_c},$$

below the new loan limit on the interval from $j = \{L - S, \ldots, -S\}$. Like our estimation algorithm, this counterfactual does not allow for the extensive margin choice to not take out a mortgage.

Figure 4 shows the distribution of loan sizes centered around the existing GSE loan limit, the fitted values of our regression model, the smooth loan size distribution implied by the polynomial coefficients of the model, and finally the counterfactual loan distribution under a new GSE loan limit which has been reduced by four log points (approximately four percentage points, or down to $400,000$ from $417,000$). The fitted values are the summation of separately estimated models on the groups of low, medium, and high FICO borrowers. Under the assumption that this small marginal change in loan limits does not induce any supply response from lenders, the only borrowers affected by the limit change are those with loan sizes between the old and new limits. For borrowers below the new limit, or above the old limit, the counterfactual only removes an unchosen option from their choice set.\(^{23}\)

Affected borrowers between the old and new limits have three possible responses. They may continue to borrow a loan amount between the limits and pay jumbo rates instead of conforming. They may bunch below the new limit, reducing their loan amount and continuing to pay conforming rates. Finally, those borrowers who had already reduced their loan amount to bunch at the old limit may now “unbunch,” switching to a larger jumbo loan. The availability and attractiveness of these options will vary with borrowers’ credit scores, initial LTV ratios, and unobservable preferences or underwriting requirements.

Consistent with the evidence from lenders’ rate sheets in Table 1, Figure 5 suggests that jumbo loans are largely unavailable for borrowers with low credit scores. The level of bunching is more pronounced for these borrowers than for the population as a whole, and 99 percent of those affected

\(^{23}\)We ignore the possibility that, given jumbo rates below conforming, the limit reduction could induce some borrowers below the new limit to shift upward.
Figure 4: Distribution of Loan Amounts Near GSE Loan Limit, Full Sample

Note: Loan originations in 2014 for non-high cost counties, matched CoreLogic-to-HMDA data. All dollar loan amounts are measured in logs, and normalized to zero at the GSE loan limit in the county of origination. Bin width is .01 in log thousands of dollars. A polynomial of degree $p = 13$ is used to fit the distribution of loan counts over a range of $J = 150$ bins above and below the limit. Results reflect the sum of separately estimated models for low, medium, and high credit score borrowers. Counterfactual distribution based on loan limit reduction of four bin widths (approximately four percentage points).
by the limit reduction bunch below the new limit in our counterfactual results. Lowering the loan limit would appear to have a substantial effect on these marginal borrowers.

For affected borrowers with high credit scores, who make up the majority of the market taking out loans near the GSE limit, the expected impact of a lower limit is less clear. Those with LTV 80 may be able to pay the same or less for a jumbo loan, while those with LTV 95 will be forced to adjust. To get a fuller picture of the heterogeneous impacts across borrowers, we supplement our counterfactual loan amounts with modeled LTV choices and interest rates paid. Our results then conclude with a summary of changes in loan amounts, LTVs, and interest rates paid for the borrowers affected by our counterfactual limit reduction.

4.3 Counterfactual LTV Ratios

As with the distribution of loan amounts, we assume that the LTV distribution immediately above (below) the new limit would be the same as that observed immediately above (below) the existing limit, \( f(l, \text{above}) \). The included ranges of \( U \) bins above and \( L \) bins below are the same as used in the loan amount bunching estimation. While this method does not model loan choice at the borrower level, it provides a sense of where borrowers are switching from and switching to relative to the observed data.

Consider the high credit score borrowers observed choosing loan amounts between the new and existing limits. In our counterfactual, 19 percent of these borrowers remain between the limits after the shift. We allocate these borrowers according to \( f(l, \text{above}) \), as shown in Figure 6 alongside the observed distribution. The results indicate that 75 percent of borrowers with an LTV of 80 or less would adjust their loan amounts as a result of the shift, compared to 95 percent of those with higher LTVs. Among borrowers with good credit, the GSEs have a larger effect on the availability of high LTV loans. However, many borrowers at lower LTVs adjust as well, suggesting that unobserved factors like stricter underwriting or incomplete information are economically important even for those with good credit.

To see where the switching borrowers end up, we apply the same method to assign LTVs to all borrowers bunching below the new limit in our counterfactual, based on the distribution observed just below the existing limit, \( f(l, \text{below}) \). Note that if the purchase price of homes is held constant, our counterfactual limit reduction of four percentage points would force any bunching borrowers to reduce their loan amount (and hence LTV) by at most four percentage points. Figure 7 shows that the counterfactual distribution has less pronounced peaks at the focal values of 80 and 95, and increased mass elsewhere. The regions where the number of counterfactual loans exceeds that in the data are suggestive of the LTVs that bunching borrowers would choose. First, we see an increase in loans taken out with LTV above 80, but below 95. This would be expected from the population of borrowers who preferred high LTV conforming loans near the old limit, and now must

\[ \text{We round LTVs, } l, \text{ up to the nearest whole number, and additionally impose that borrowers' cannot choose loans for which we observe no rates in our Informa data. This results in only a small change relative to the empirical distribution of LTVs, and allows us to calculate counterfactual rates.} \]
Figure 5: Distribution of Loan Amounts Near GSE Loan Limit, Low FICO Borrowers

Note: Loan originations in 2014 for non-high cost counties, matched CoreLogic-to-HMDA data. Sample restricted to borrowers with FICO scores ≤ 680. All dollar loan amounts are measured in logs, and normalized to zero at the GSE loan limit in the county of origination. Bin width is .01 in log thousands of dollars. A polynomial of degree $p = 13$ is used to fit the distribution of loan counts over a range of $J = 150$ bins above and below the limit. Counterfactual distribution based on loan limit reduction of four bin widths (approximately four percentage points).
Figure 6: LTV Distribution for Borrowers Between New and Existing GSE Loan Limits, High FICO Borrowers

Note: Data restricted to high credit score borrowers below existing GSE loan limit, and above new, counterfactual loan limit. For counterfactual, total number of borrowers is the model prediction from loan amount counterfactual, distributed according to the observed LTV distribution of jumbo loans above the existing loan limit.
Note: Data restricted to high credit score borrowers immediately below new, counterfactual GSE loan limit. For counterfactual, total number of borrowers is the model prediction from loan amount counterfactual, distributed according to the observed LTV distribution of jumbo loans immediately below the existing loan limit.

marginally reduce their loan amount to maintain conforming status. The second region where we observe substantial bunching is for LTVs below 80. This likely reflects many of the borrowers already bunched at the old limit, who reduce their loan even further. Based on credit score and LTV, these borrowers are eligible for jumbo loans priced at or below conforming rates.

### 4.4 Summary of Loan Limit Counterfactual Results

As a whole, these exercises suggest that while stricter jumbo LTV requirements explain some of the bunching observed in the data, there are still large numbers of prime borrowers whose bunching cannot be explained by either interest rates or down payment constraints. With this caveat in mind, we summarize our counterfactual’s impacts on low, medium, and high credit score borrowers in Table 3. Within each group, we calculate the percentage of affected borrowers making each of
Table 3: Summary of GSE Loan Limit Counterfactual, Affected Borrowers

<table>
<thead>
<tr>
<th></th>
<th>Low FICO, up to 680</th>
<th>Medium FICO, 680-740</th>
<th>High FICO, 740 and up</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Rate</td>
<td>4.54</td>
<td>4.25</td>
<td>4.13</td>
</tr>
<tr>
<td>Initial LTV</td>
<td>76.9</td>
<td>78.4</td>
<td>76.8</td>
</tr>
</tbody>
</table>

**Choose Conforming**

<table>
<thead>
<tr>
<th></th>
<th>99%</th>
<th>92%</th>
<th>77%</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Bunching Below New Limit</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interest Rate</td>
<td>4.54</td>
<td>4.25</td>
<td>4.12</td>
</tr>
<tr>
<td>LTV</td>
<td>72.4</td>
<td>75.5</td>
<td>73.2</td>
</tr>
<tr>
<td>Change in Loan Amt</td>
<td>-$14,700</td>
<td>-$14,800</td>
<td>-$15,100</td>
</tr>
</tbody>
</table>

**Switch to Jumbo**

<table>
<thead>
<tr>
<th></th>
<th>2%</th>
<th>6%</th>
<th>19%</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Remain at Initial Loan Amt</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interest Rate</td>
<td>4.18</td>
<td>4.18</td>
<td>4.12</td>
</tr>
<tr>
<td>LTV</td>
<td>73.5</td>
<td>76.2</td>
<td>75.8</td>
</tr>
<tr>
<td>% Unbunching to Larger Jumbo</td>
<td>0%</td>
<td>3%</td>
<td>4%</td>
</tr>
<tr>
<td>Change in Loan Amt</td>
<td></td>
<td>$40,800</td>
<td>$61,700</td>
</tr>
</tbody>
</table>

| Number of Affected Borrowers   | 575     | 2,972   | 7,298   |

*Note: Affected borrowers defined as those with loan amounts above the new counterfactual limit, up to and including the existing limit. Percentages may not add to one due to rounding and discrete nature of bunching estimation algorithm.*

the three possible responses discussed above; remaining at their current loan amount, bunching below the new limit, or “unbunching” to a larger jumbo loan. We use our counterfactual LTV distributions to calculate average interest rates and LTVs for each subset of borrowers.

To calculate the average initial rates, we assign the average conforming rate for the applicable FICO score and LTV (from Table 1) to each affected borrower. This gives an average rate over the observed LTV distribution for each credit score range. As would be expected, rates are declining in FICO score, with low credit score borrowers paying 42 basis points more than those with high credit scores.

Similarly, our loan amount counterfactual predicts that 99 percent of Low FICO affected borrowers and 77 percent of High FICO affected borrowers would bunch at the new limit. These borrowers all reduce their loan amounts by about $15,000, reflected in the three to four percentage point reduction in average LTVs. The LTV distribution is approximated by the difference between the counterfactual and actual loan distributions below the new limit, as shown in Figure 7. Despite reducing loan amounts, these borrowers see essentially no change in rates, given the limited price variation by LTV in the conforming market.

Most of the affected borrowers switching to jumbo loans remain at their current loan amounts between the new and existing limits. These borrowers have lower LTVs than the affected population.
as a whole, and pay essentially the same or lower rates for jumbo loans as they had paid for conforming. Although our model predicts that Low FICO jumbo borrowers pay about 35 basis points less than those who bunch, this reflects an extremely small population (about 10 borrowers in our sample) and is based on the rates of fewer than ten percent of Informa lenders who offer these loans. The average rate for the roughly 1,400 High FICO borrowers reflects a large number of low LTV borrowers paying a slightly lower rate, and a small number with higher LTVs paying significantly more.

Finally, a small number of borrowers who had previously chosen loans right at the limit now switch to larger jumbo loans under our counterfactual. Because we do not explicitly model which affected borrowers (from the LTV distribution) make this switch, we do not calculate their resulting LTVs or interest rates. However, from the difference between the observed and counterfactual loan amount distributions above the existing limit, we calculate that Medium and High FICO “unbunchers” choose on average $40,800 and $61,700 higher loan amounts, respectively. These large totals reflect the substantial loan size range over which borrowers bunch in our estimates.
References


California Association of Realtors. Comment in response to the FHFA’s request for input on guarantee fee policy, 2014.


Congressional Budget Office. Assessing the public costs and benefits of Fannie Mae and Freddie Mac, 1996.

Congressional Budget Office. An overview of federal support for housing, 2009.

Anthony A. DeFusco and Andrew Paciorek. The interest rate elasticity of mortgage demand: Evidence from bunching at the conforming loan limit. 2014.

Department of Treasury and Department of Housing and Urban Development. Reforming america’s housing finance market: A report to congress, 2011.


RBS Securities. Comment in response to the FHFA’s request for input on guarantee fee policy, 2014.