Gender Differences in Mortgage Bunching[1]

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[1]The views expressed in this paper do not represent those of the Consumer Financial Protection Bureau or the United States. The views do not represent those of Fannie Mae or the Federal Housing Finance Agency.

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Introduction

- Accessing mortgage credit is often the largest financial transaction that individuals will undertake.
- Decisions made by individuals at the time of mortgage origination can have important financial repercussions in both the short- and long-term.
- Yet, even the savviest of mortgage borrowers may lack certain data points that would increase their financial well-being.
- This analysis informs our understanding of behavioral responses to mortgage pricing notches based on borrower gender.

Contribution

- Document substantial heterogeneity in mortgage bunching by borrower gender using an important pricing discontinuity based on loan size.
- Show that single female borrowers are less likely to bunch compared to single male and joint borrowers, which translates into lost savings.
- Explore various mechanisms that explain this heterogeneity in bunching.

High-cost counties

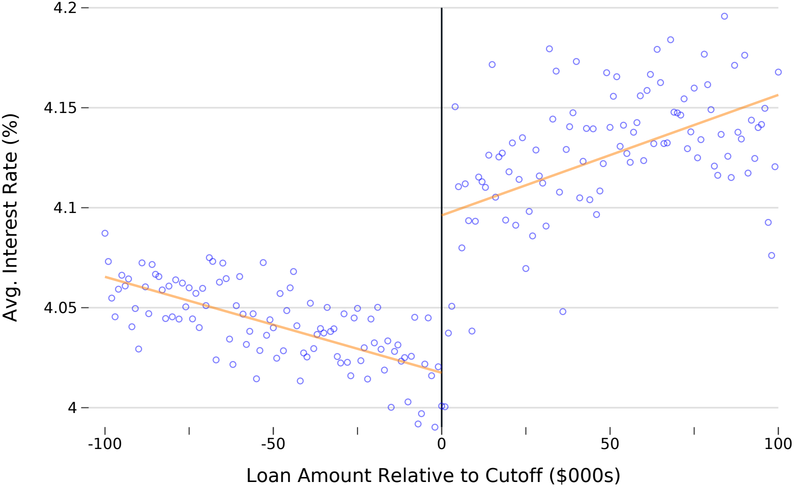
- Areas in which 115 percent of the local median home value exceeds the national conforming loan limit (Federal Housing Finance Agency).
- In 2019, there were 199 high-cost counties out of 3100+ total counties in the US.
  - Represent about 27% of first-lien, owner-occupied originations in 2019
  - Consist of large metro areas (e.g., New York City, Washington DC, San Francisco)
- High-cost counties have county-specific conforming loan limits that vary by year.
  - County-specific limits are always greater than the national conforming loan limit (NCLL).

High-balance loans

- Mortgage loans that are above the NCLL but below the county-specific conforming limit.
  - a.k.a., "super conforming", "jumbo conforming"
  - High-balance limit was $417,000 from 2010-2016; increased annually thereafter, reaching $484,350 in 2019.

- High-balance loans are eligible for securitization by the government sponsored enterprises (GSEs)
  - Subject to a 25 basis point pricing adjustment based on the GSEs guarantee fee schedule
  - Compared to standard conforming loans that are not subject to this pricing premium

High-balance pricing discontinuity, 2010-2019



Source: NMDB 11.1

Relevant literature on mortgage pricing differentials

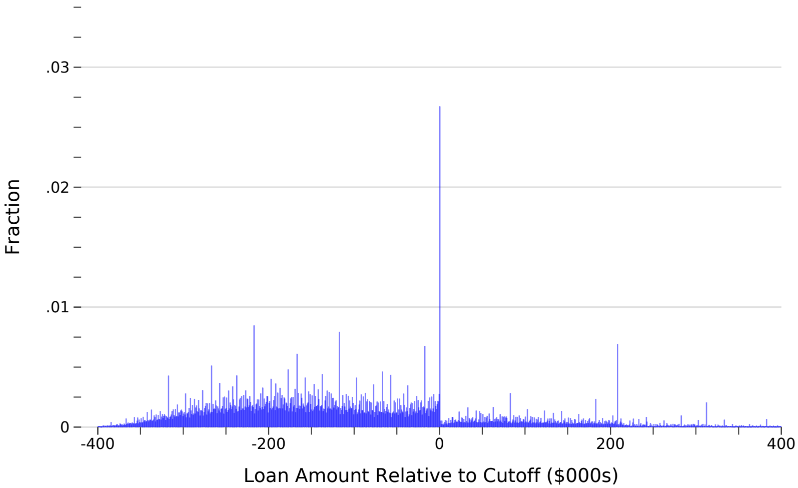
Existing literature has used the jumbo limit (loans above the county-specific limit) to

- estimate the interest rate elasticity of demand (Sherlund, 2007; DeFusco and Paciorek, 2017)
- impacts on housing prices (Adelino et al., 2012)
- the availability of fixed-rate mortgages (Fuster and Vickery, 2015), and
- the distribution of loan amount and pass through of fees to consumer mortgages rates (Alexandrov et al., 2019)

High-balance versus jumbo limit

- The high-balance limit sits near the 75th percentile of the mortgage loans distribution, whereas the jumbo limit represents the far right tail of the distribution.
- Compared to jumbo loans, high-balance loans are
  - more representative of the typical mortgage borrower,
  - have loan characteristics similar to conforming loans (e.g., similar LTV requirements), and
  - can be securitized through the GSEs.

High-balance bunching, 2010-2019



Source: NMDB 11.1

Differences by borrower gender

- Follows from a substantial and growing literature in housing economics that documents gender differences in housing transaction outcomes (Harding et al, 2003; Anderson et al, 2018; Goldsmith-Pinkham and Shue, 2020).
- We focus on how behavioral responses to this pricing discontinuity vary by gender with the goals of
  - documenting bunching differences and
  - exploring mechanisms to explain these differences.

Data

- National Mortgage Database (NMDB)
  - Nationally representative, 1-in-20 sample of first-lien mortgages pulled from consumer credit records.
  - Includes detailed borrower and loan information, including borrower gender, loan amount, property value, interest rate, etc.
- Home Mortgage Disclosure Act (HMDA)
  - All loan transactions from HMDA filing institutions.
  - Includes limited origination information on borrower and loan for 2010-2017. Detailed information for, comparable to NMDB, for 2018-2019.
  - Merge to HMDA Reporter panel to classify by institution type.
- Focus on a sample of first-lien, owner-occupied, fixed rate mortgages loans over the period 2010-2019.
  - Restrict to +/- $400k from high-balance limit, covers about 96% of the distribution of mortgage loans in any given year.

HMDA Summary statistics, 2010-2019

	All	Female	Male	Joint
	(1)	(2)	(3)	(4)
Income at Origination ($000s)	131	92	119	152
Loan Amount ($000s)	322	271	322	342
Purchase	.32	.34	.37	.28
Refi	.68	.66	.63	.72
Conforming	.78	.88	.79	.74
High-Balance	.16	.10	.16	.19
Jumbo	.05	.02	.05	.07
Non-depository	.48	.49	.53	.46
Bank	.46	.45	.43	.48
Credit Union	.06	.06	.05	.07
Single Female	.21	1	0	0
Single Male	.27	0	1	0
Joint	.52	0	0	1
Observations	10,260,282	2,086,063	2,695,963	5,225,195

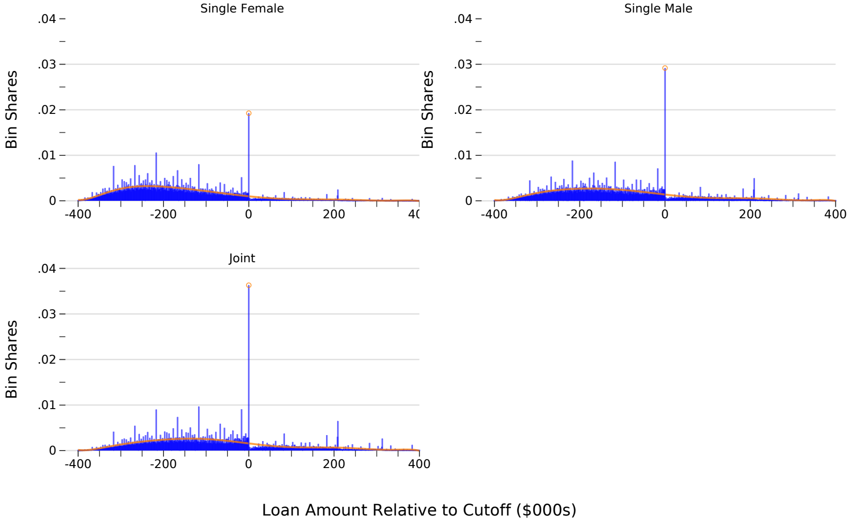
Note: Reported as shares unluss indicated otherwise.

Estimate bunching at high-balance limit

$$S_b = \sum_{k=0}^{P} \beta_k \times (V_b)^k + \delta \times 1[V_j = L] + \epsilon_b \tag{1}$$

- S_b: Share of loans in value bin b
- V_b: Bin loan value
- L: Bin containing high-balance limit
- P: Degree of polynomial (10)
- δ: Excess bunching at high-balance limit

Polynomial bunching estimates by gender



Source: HMDA

Estimates of bunching differences

Panel A: HMDA, 2010 - 2019					
	(1)	(2)	(3)	(4)	(5)
	Female	Male	Joint	Male - Female	Joint - Female
Bunching	0.0183***	0.0278***	0.0347***	0.0095***	0.0164***
	(0.0007)	(0.0007)	(0.0008)		
R-sqr	0.794	0.803	0.792		

Panel B: NMDB, 2010 - 2019					
	(1)	(2)	(3)	(4)	(5)
	Female	Male	Joint	Male - Female	Joint - Female
Bunching	0.0173***	0.0244***	0.0330***	0.0071***	0.0157***
	(0.0006)	(0.0006)	(0.0007)		
R-sqr	0.827	0.818	0.813		

Note: Number of observations is 801 for all regressions, which is equal to the number of bins.

Can we explain away these differences?

- Next, we use loan-level data to explain factors that drive this differential bunching behavior.

- Estimate loan-level LPM of the form:

$$AtLimit_{ijt} = \alpha_i Male_i + \beta_i Joint_i + \gamma_i X_i + \mu_t + \iota_t + \lambda_j + \epsilon_{ijt} \quad (2)$$

  - $AtLimit_{ijt}$: Indicator of the loan amount being within \$1000 to the left of the HBL
  - $Male_i$ and $Joint_i$: Indicators of loan taken out by single male or joint borrowers, respectively (relative to single female)
  - X_i: Vector of borrower and loan attributes
  - μ_t, ι_t, and λ_j: Month of origination, year of origination, and county fixed effects

Property value vs. Loan amount samples

- To estimate equation (2), we restrict to a sample of loans that could reasonably end up at the HBL.
- Property value (PV) sample: NMDB, HMDA 2018-2019
  - Minimum PV equal to the HBL divided 0.97 and maximum PV not greater than HBL times 1.25
  - Restricts to properties where the HBL falls between an LTV of 80-97%
  - Results in sample with PVs of roughly $430-521k for 2010-2016
- Loan amount (LA) sample: HMDA, 2010-2019
  - Restrict so that the loan amount range for each county-by-year cell in HMDA matches that of the NMDB property value sample above.

Effect on Probability of Bunching at Limit, NMDB PV Sample

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	1(At Limit)	1(At Limit)	1(At Limit)	1(At Limit)	1(At Limit)
Single Male	0.0076***	0.0055***	0.0037*	0.0036*	0.0035*
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Joint	0.0041***	-0.0006	0.0013	0.0008	0.0008
	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
White Non-Hispanic		0.0008	0.0014	0.0012	0.0010
		(0.0011)	(0.0011)	(0.0011)	(0.0011)
Ln(Borrower Income)		0.0150***	0.0109***	0.0116***	0.0131***
		(0.0010)	(0.0010)	(0.0010)	(0.0010)
Refi			-0.0276***	-0.0293***	-0.0250***
			(0.0018)	(0.0020)	(0.0020)
Cash-out Refi			-0.0336***	-0.0351***	-0.0333***
			(0.0013)	(0.0014)	(0.0014)
Month FE	NO	NO	NO	YES	YES
Year FE	NO	NO	NO	YES	YES
County FE	NO	NO	NO	YES	YES
NMDB Controls	NO	NO	NO	NO	YES
R-sqr	0.0003	0.0027	0.0156	0.0191	0.0210

Note: Sample size for all regressions is 71,815 loans. NMDB-specific controls include borrower credit score at origination and loan term.

Effect on Probability of Bunching at Limit, HMDA LA Sample

	(1)	(2)	(3)	(4)
Dependent Variable:	1(At Limit)	1(At Limit)	1(At Limit)	1(At Limit)
Single Male	0.0121***	0.0029***	0.0024***	0.0031***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Joint	0.0209***	-0.0008***	0.0001	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
White Non-Hispanic		-0.0046***	-0.0043***	0.0016***
		(0.0002)	(0.0002)	(0.0002)
Ln(Borrower Income)		0.0504***	0.0504***	0.0505***
		(0.0002)	(0.0002)	(0.0002)
Refi			-0.0058***	-0.0140***
			(0.0002)	(0.0002)
Non-Depository			0.0140***	0.0159***
			(0.0003)	(0.0003)
Bank			0.0045***	0.0033***
			(0.0003)	(0.0003)
Month FE	NO	NO	NO	YES
Year FE	NO	NO	NO	YES
County FE	NO	NO	NO	YES
R-sqr	0.0020	0.0213	0.0224	0.0332

Note: Sample size for all regressions is 7,012,310 loans.

Overall effects

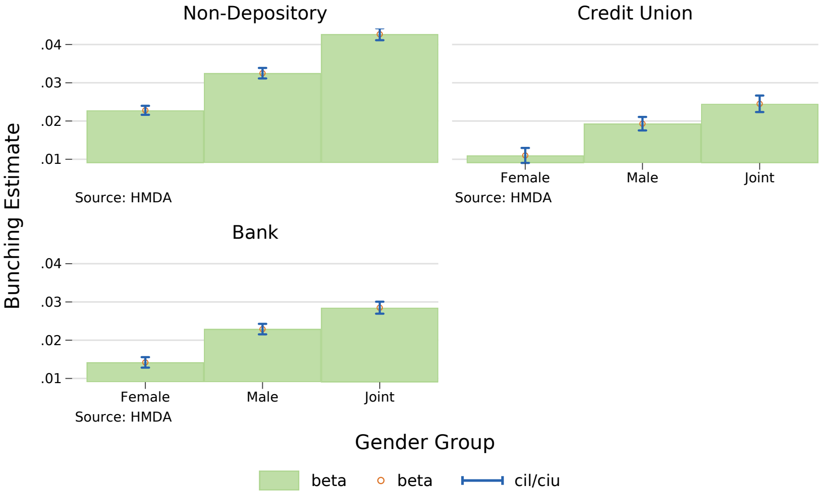
- A male-female bunching difference of 0.31 p.p. in HMDA and 0.35 p.p. in NMDB remains after including a robust set of borrower, loan, and geographic controls.
  - Single male borrowers are 14.1-18.6% more likely to bunch compared to single female borrowers.
- Differences in bunching between single female and joint borrowers can be entirely explained by differences in borrower income and race.

Mechanisms

- Two mechanisms we consider:
  - Institution type, which can inform us on borrower behavior (e.g., shopping, time constraints)
  - Values of the HBL over time, which can inform us about financial knowledge and literacy

- Modify equation (2) to include an interaction term between gender dummies and (a) depository institution and (b) post-2016 indicator.

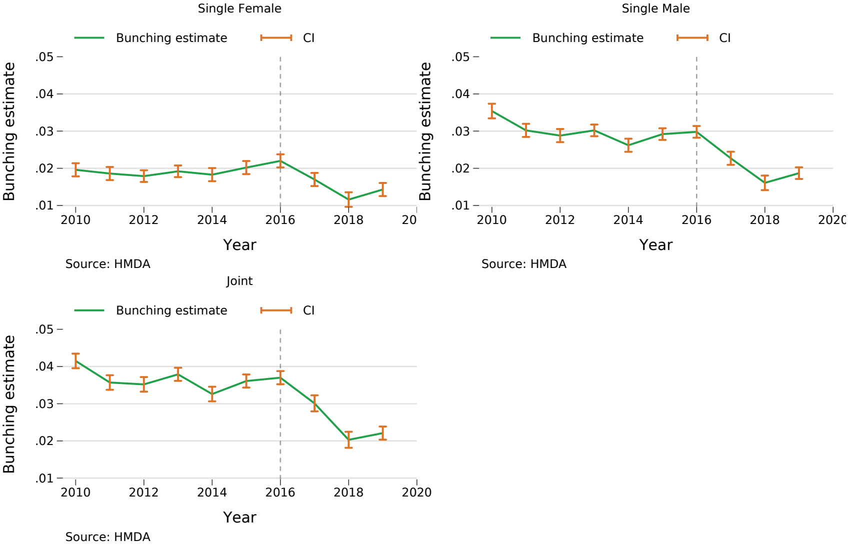
Polynomial bunching estimate by institution type



Difference-in-differences by Institution Type, HMDA LA Sample

	(1)
Dependent Variable:	1(At Limit)
Single Male	0.0025**
	(0.0009)
Joint	-0.0043***
	(0.0007)
Non-depository	0.0109***
	(0.0006)
Bank	0.0012
	(0.0007)
Single Male # Non-depository	0.0012
	(0.0009)
Single Male # Bank	-0.0003
	(0.0009)
Joint # Non-depository	0.0077***
	(0.0008)
Joint # Bank	0.0018*
	(0.0008)
Borrower Controls	YES
Loan Controls	YES
Month FE	YES
Year FE	YES
County FE	YES
# of Observations	7,520,007
R-sqr	0.0292

Bunching estimate over time



Difference-in-differences by Pre v Post 2016, HMDA LA Sample

	(1)
Dependent Variable:	1(At Limit)
Male	0.0043***
	(0.0002)
Joint F-M	0.0028***
	(0.0002)
Post Limit Changes	-0.0232***
	(0.0004)
Male # Post Limit Changes	-0.0074***
	(0.0005)
Joint F-M # Post Limit Changes	-0.0131***
	(0.0005)
Borrower Controls	YES
Loan Controls	YES
Month FE	YES
Year FE	NO
County FE	YES
# of Observations	7,520,007
R-sqr	0.0286

Note: Borrower controls include white non-Hispanic indicator, log income at origination. Loan controls include loan purpose group indicators and depository institution type.

Summary

- Our analysis shows significant differences in bunching by borrower gender at the HBL limit.
- Differences in borrower, loan, and geographic characteristics can explain about 54-74% of the male-female bunching difference, but a significant difference remains.
- We posit that the remaining difference might be explained through a few channels, namely differences in: borrower mortgage shopping behavior; borrower engagement with the lender; financial literacy; or financial capacity.

Conclusions and Policy Implications

- Our estimates indicate that if single female borrowers bunched at a rate similar to single male borrowers, they would have saved roughly $407 million by taking advantage of this pricing adjustment between 2010 - 2019.
- Policies that lead to smaller differences in borrower attributes by gender could allow single female borrowers to take advantage of mortgage pricing breakpoints.
- Even if these known attribute differences can be equalized, there still remains a significant amount of savings that can be gained by single female borrowers compared to their male counterparts.
- We still have left to consider the extent to which other policies that, e.g., improve financial literacy and shopping behavior, may further equalize these savings differences.