Internet Appendix for "Did Dubious Mortgage Origination Practices Distort House Prices?"

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This appendix is divided into three sections. The first section shows that a significant portion of the twenty-five mortgage originators in our sample not only securitized loans in the private MBS market but also did business with GSEs. The second section details the sample selection process and describes the sample. The third section provides supplementary tables and figures.

A. Nonagency Securitizers and GSE Securitization

We find that twelve of the twenty-five nonagency securitizers in our sample did business with GSEs. Fannie Mae makes public a subset of the loans they have acquired since 2000. In the 7.3 million loans in the Fannie Mae sample data that were originated between 2003 and 2007, we confirm the presence of five of our top twenty-five nonagency originators in the agency market (Bank of America, Chase, GMAC-RFC, SunTrust, and Wells Fargo). However, it seems likely that at least a subset of the remaining twenty originators were also involved with agency deals because Fannie Mae simply lists the lender name as "Other" for 21.6% of the loans. We investigate this further by conducting an online search for agency MBS prospectuses that link our remaining twenty originators with GSEs and confirm that at least an additional seven lenders (Argent, BNC, Countrywide, First Franklin, Fremont, New Century, and WMC) sold loans to agency MBS as well.

B. Sample Selection and Description

First, since our main measures heavily rely on the identification of loan originators,[1] we drop ZIP codes where the originator name coverage is less than 25% as some counties may

[1] Of the 69.9 million purchase transactions (from 2003 to 2012) recorded in DataQuick, 24.7 million or 25.5% have non-missing lender names.

not commonly report originator names. Second, because we want accurate measures, we require ZIP codes to show more than five-hundred purchase transactions during the period 2003 to 2006. Third, we drop ZIP codes where the proportion of securitized (ABSNet) loans is extremely high (in the highest 2.5%) relative to county level (DataQuick) loans as those extreme values are likely due to poor coverage of the DataQuick database. Finally, since most of our specifications will rely on identification within the MSA, we drop MSAs with less than fifteen ZIP codes remaining after applying the first three filters explained above. DataQuick shows 18,909 ZIP codes with purchase transactions with originator names from 2003 to 2012. After dropping the ZIP codes with low originator name coverage, 11,096 ZIP codes remain. An additional 3,861 ZIP codes do not comply with the minimum requirement of the number of transactions, leaving 7,235 ZIP codes. Then, 1,069 ZIP codes are lost after merging the sample with Zillow and dropping ZIP codes with high values of *Fraction securitized*, or missing values for the controls. Finally, 990 ZIP codes are dropped because they are in MSAs with less than fifteen ZIP codes.

Descriptive statistics for the ZIP-code-level measures and controls are shown in Table IA.2. As mentioned in the paper, we focus on the top twenty-five lenders ranked by nonagency securitization and classify them into three groups (worse, medium, and better) based on the amount of second-lien misreporting they exhibit. The worse, medium, and better originators combined account for 34% of the loan originations between 2003 and 2006 with the remaining 66% being from originators who are not among the top twenty-five nonagency originators (unranked). Furthermore, consistent with Griffin and Maturana (2016), the three types of ranked originators (top twenty-five) account for 92.4% of privately securitized loans over the period from 2003 to 2006 (14.5% of the 15.7%), although they also sold loans to agency deals, which is why the use of the DataQuick data with all loans is important.

C. Additional Tables and Figures

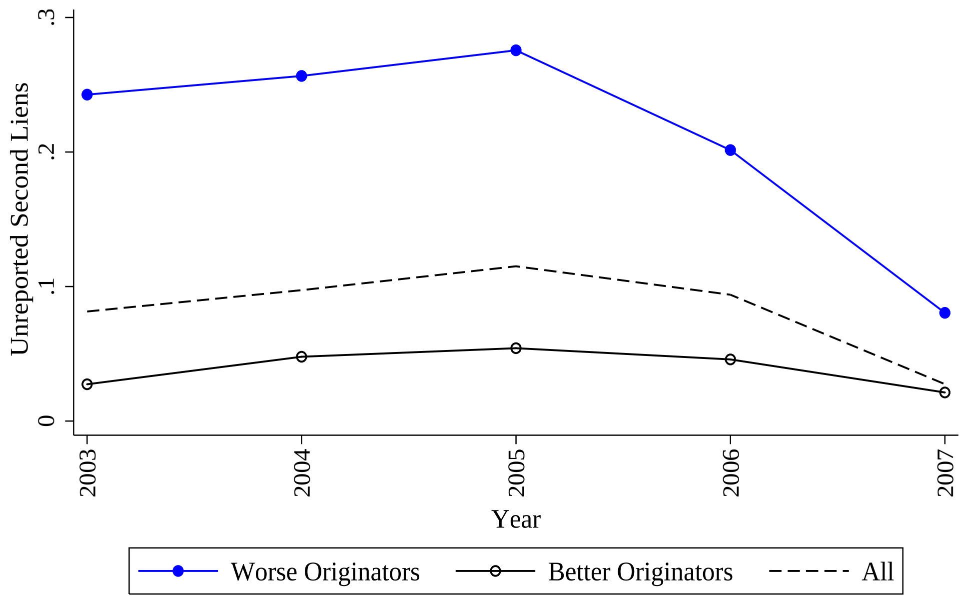


Figure IA.1
Second-Lien Misreporting by Originator Tercile
This figure shows the yearly second-lien average misreporting of the highest (blue solid circles) and lowest (hollow circles) terciles of misreporting. The dashed line shows the average for all the originators. The figure is based on the 25 loan originators with more than 2.2 million loans for purchase or refinance in Griffin and Maturana (2016).

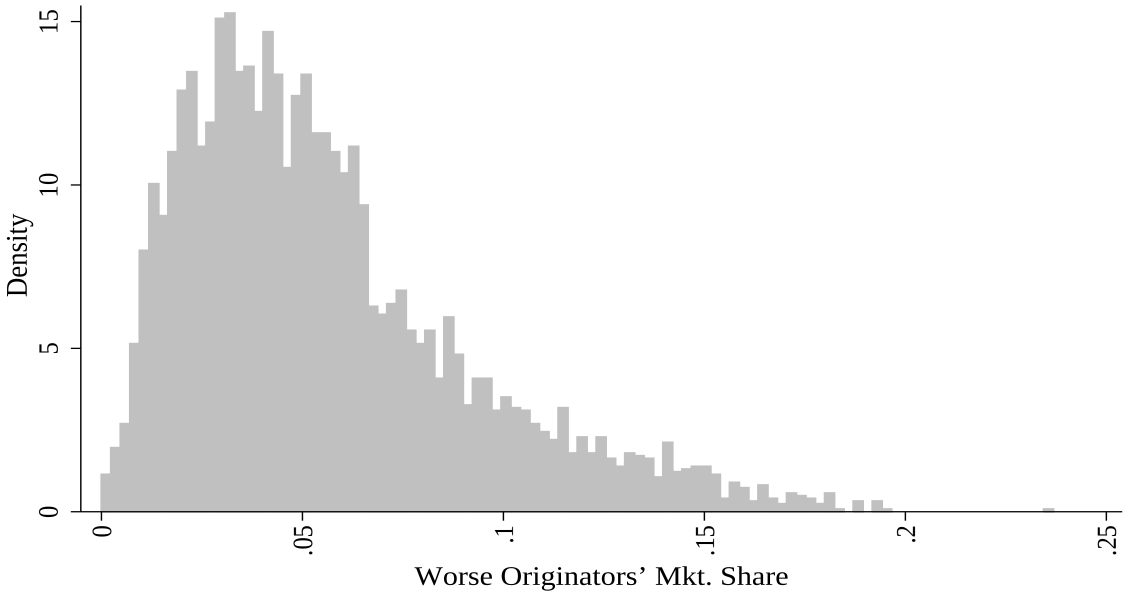


Figure IA.2
Histogram of Worse Originators' Market Share
This figure shows the histogram of frequencies of the *worse originators' market share* from 2003 to 2006. Each year the 25 loan originators in Griffin and Maturana (2016) are classified into three groups based on the cumulative fraction of loans they issued with second-lien misreporting. The amount of cumulative misreporting of each originator in year $t-1$ is used to rank the originators in year t. Originators in the tercile with the highest misreporting are referred to as the worse originators.

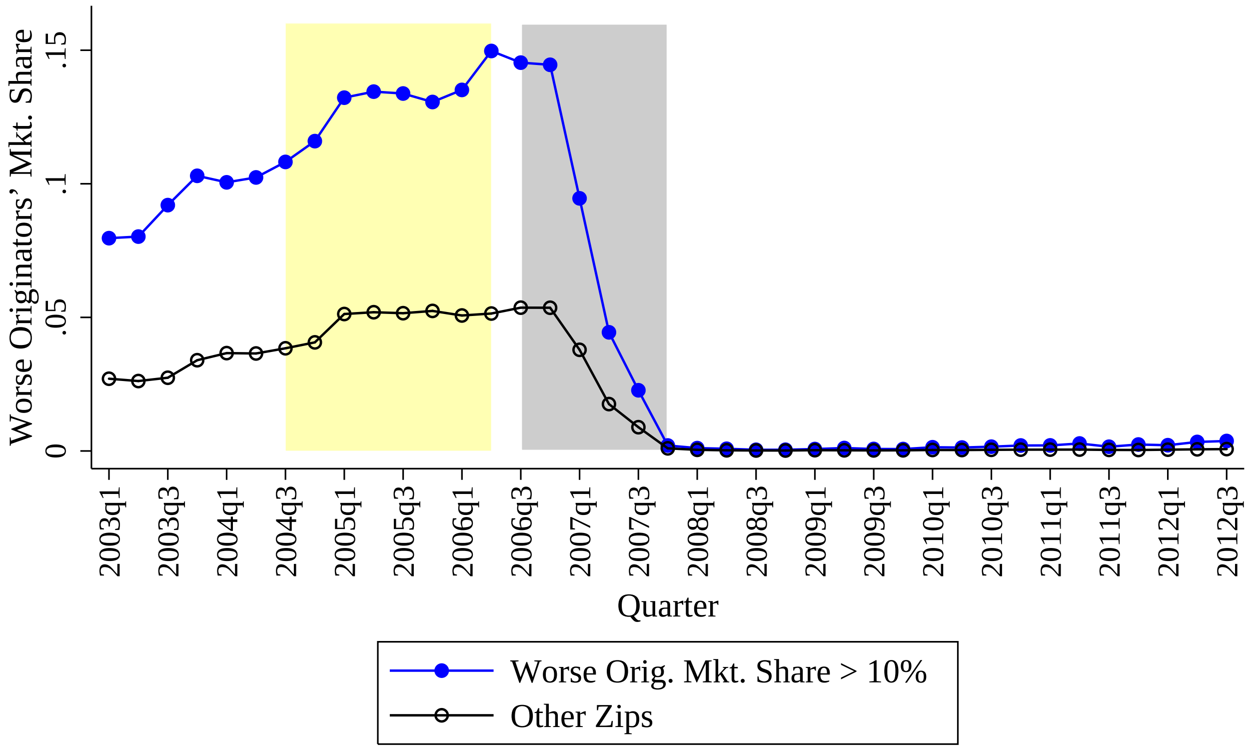
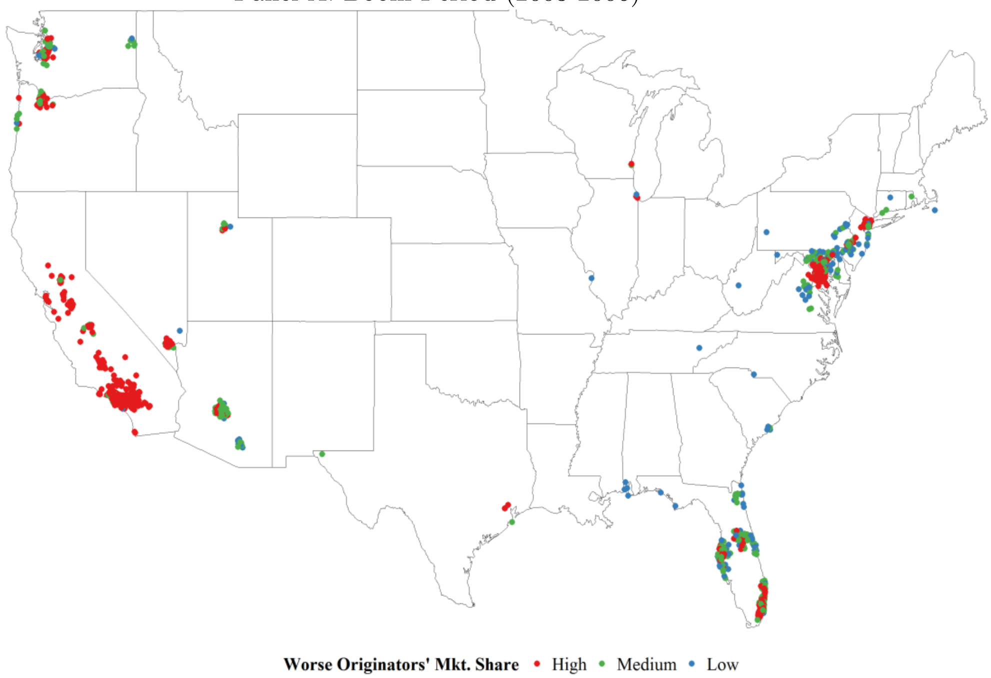


Figure IA.3
Worse Originators' Market Share
This figure shows the time-series of the average worse originators' market share for each group shown in Figure 1. ZIP codes are divided into two groups; the first group contains ZIP codes where the average market share of the worse originators during the period 2004Q3-2006Q2 (highlighted by the yellow shaded area) exceeds 10% (blue solid circles), and the second group contains the remaining ZIP codes (hollow circles). The gray shaded area highlights the period when most of the worse originators went bankrupt or lost considerable business.

Panel A: Boom Period (2003-2006)



Panel B: Bust Period (2007-2012)

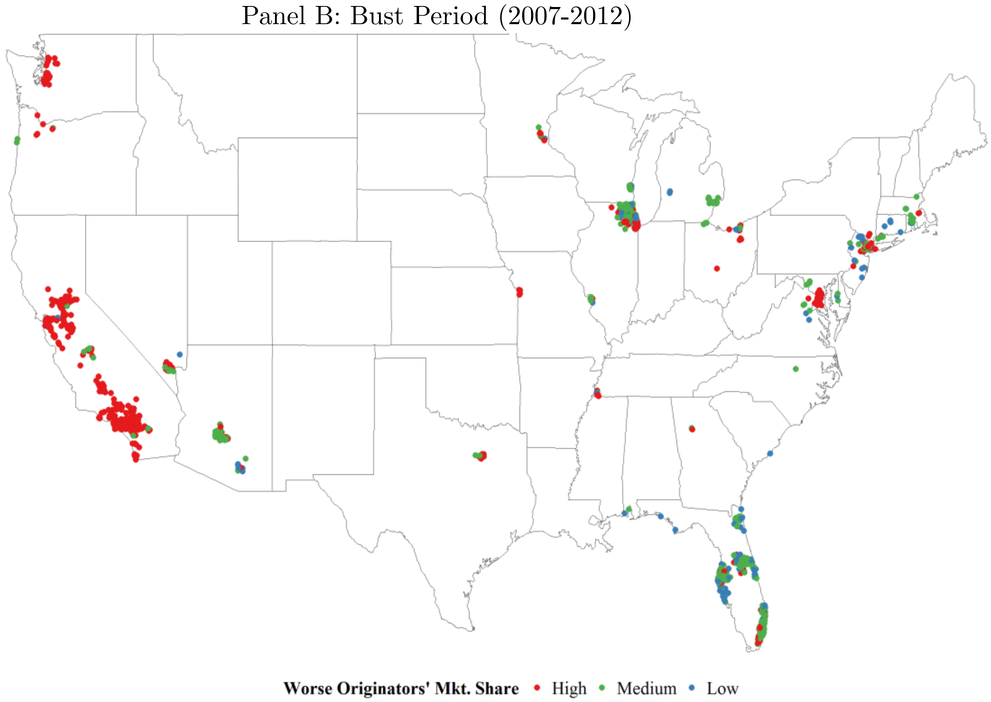


Figure IA.4
Extreme House Price Movements and Worse Originators' Market Share
The above maps report the ZIP codes with the most extreme house returns during the boom and the bust, as well as the presence of bad originators within these ZIP codes. ZIP codes are first divided into three equal terciles based on market share of the worse originators. ZIP codes with the highest presence of the worse originators are in red, those with a moderate presence are in green, and those with the lowest presence are in blue. Additionally, ZIP codes are classified into four equal quartiles based on house price returns during the boom and the bust. In the boom (Panel A), only ZIP codes in the highest quartile of house returns are displayed, representing the largest gains. Similarly, in the bust (Panel B), only ZIP codes in the lowest quartile of house returns are displayed, representing the largest losses.

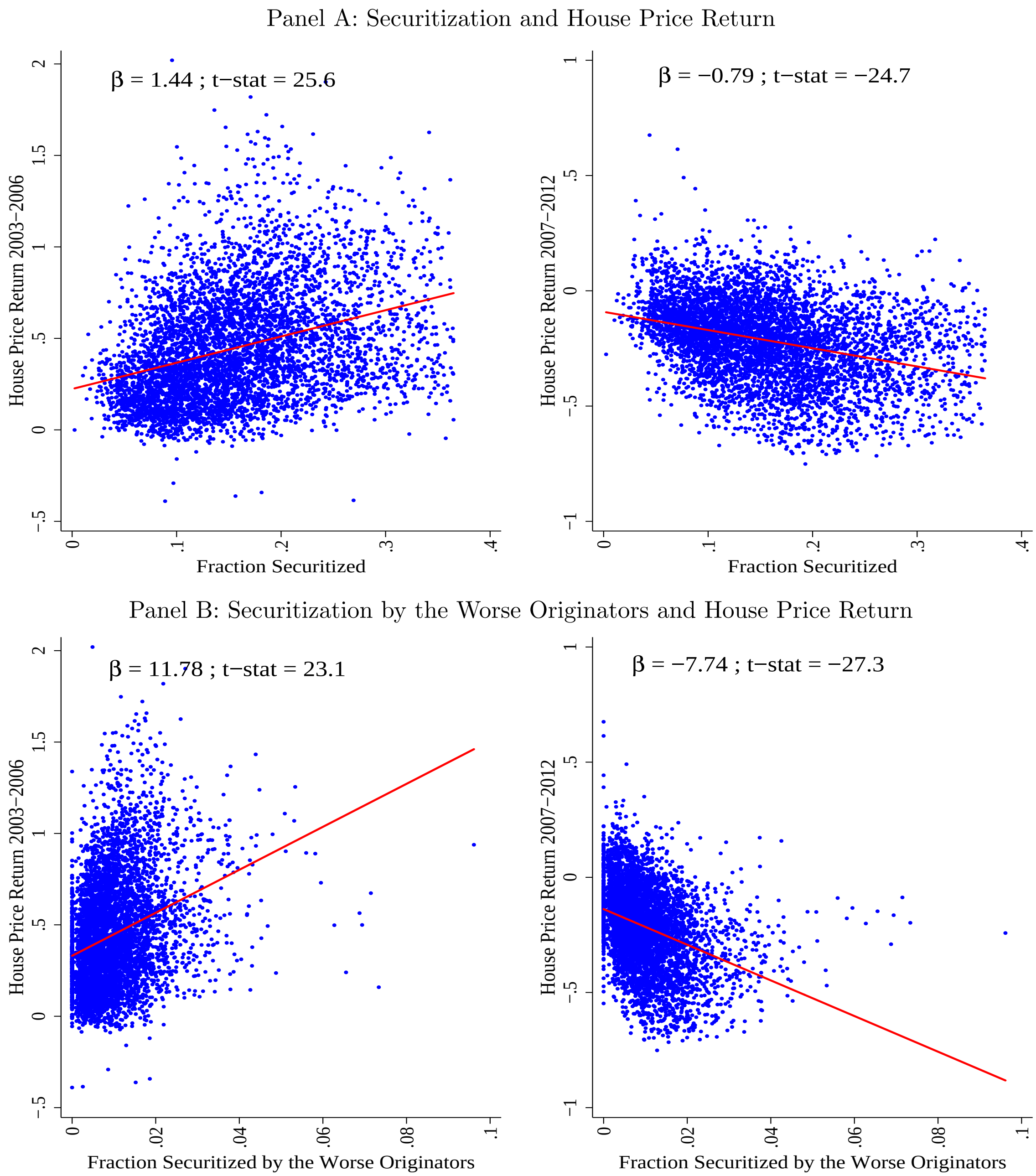


Figure IA.5
Non-Agency Securitization and House Returns
This figure shows the correlation between non-agency securitization activity and house price returns. Panel A shows the relation between the fraction of loans privately securitized in each ZIP code from 2003 to 2006 (left graph) and from 2007 to 2012 (right graph) and the returns of the corresponding ZIP code house price indices. Panel B shows the relation between the fraction of loans privately securitized in each ZIP code during the period 2003-2006 by the worse originators based on second-lien misreporting and the return of the corresponding ZIP code house price index. The red lines fit pooled linear regressions. Coefficient estimates and t-statistics are presented at the top of each graph.

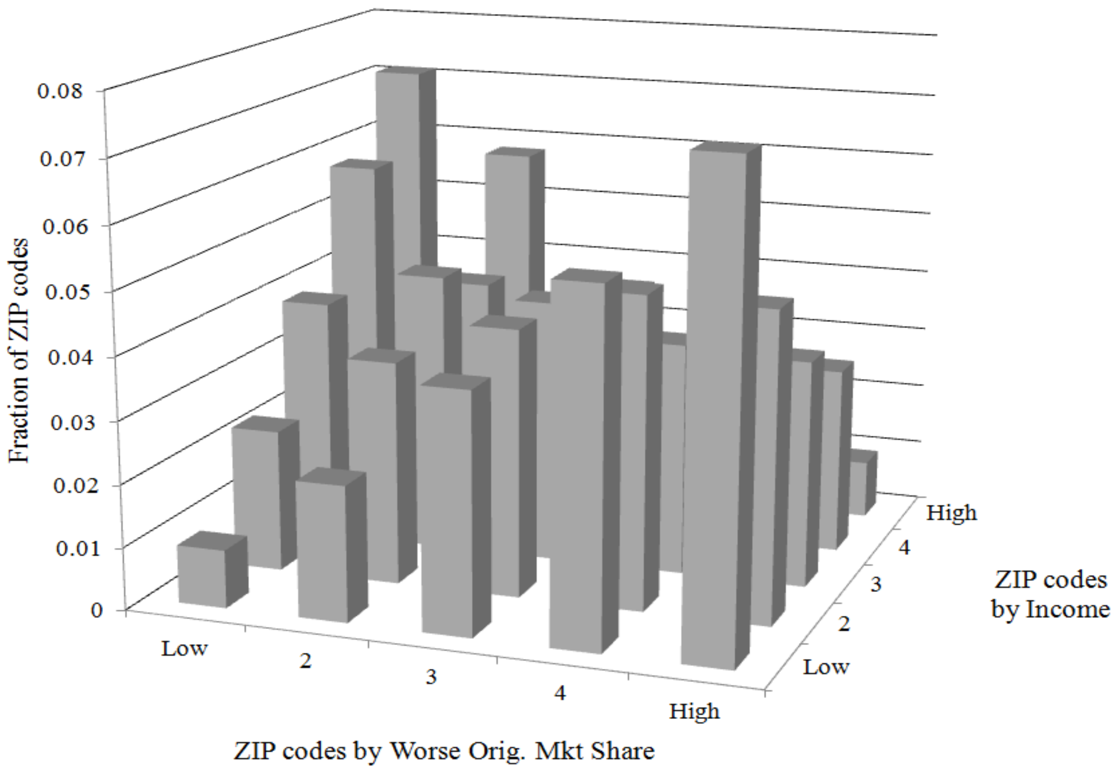


Figure IA.6
Fraction of ZIP codes per Group in Table 1
This figure shows the fraction of ZIP codes in each of the income-worse originators' market share bins in Table 1.

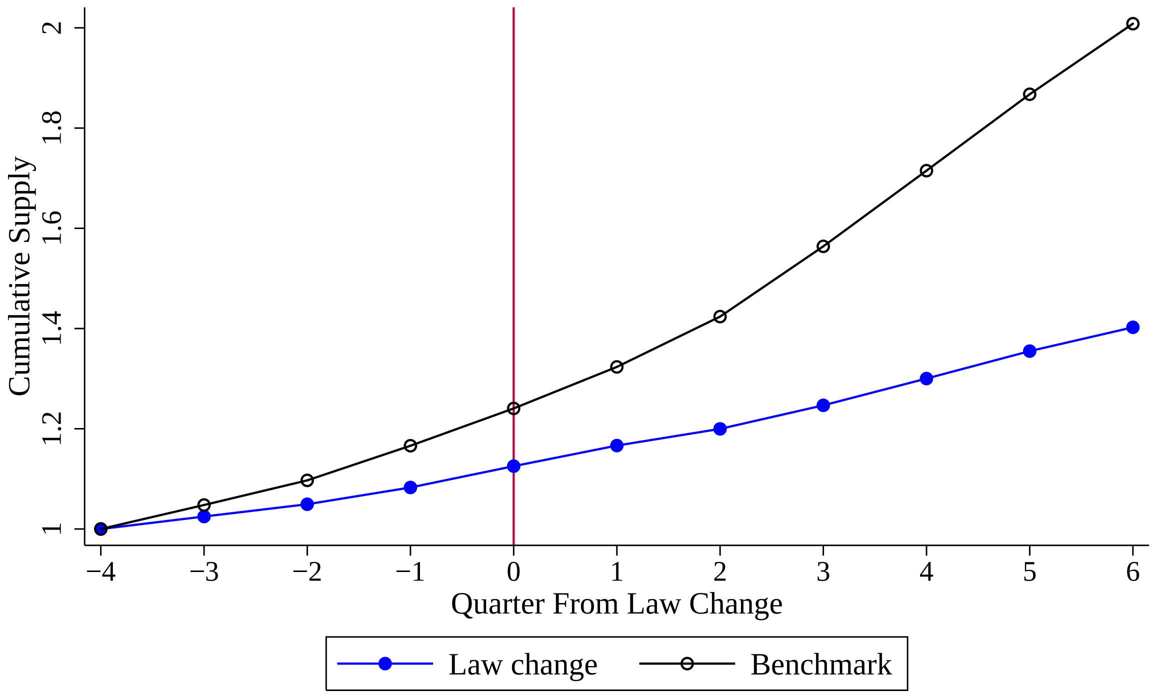


Figure IA.7
Loan Supply by the Worse Originators Before and After APLs
This figure compares the cumulative loan supply by the worse originators of ZIP codes in states that passed restrictive anti-predatory lending laws (APLs) between 2004 and 2005 (solid circles) with the cumulative loan supply by the worse originators of a benchmark of ZIP codes in states that did not pass any APLs before 2006 (hollow circles), before and after the law changes. The states in the first group are Indiana, Massachusetts, New Mexico, South Carolina, and Wisconsin. The states in the benchmark are Arizona, Delaware, New Hampshire, Montana, Oregon, Washington, and Tennessee.

Panel A: 2004Q1, New Mexico and South Carolina

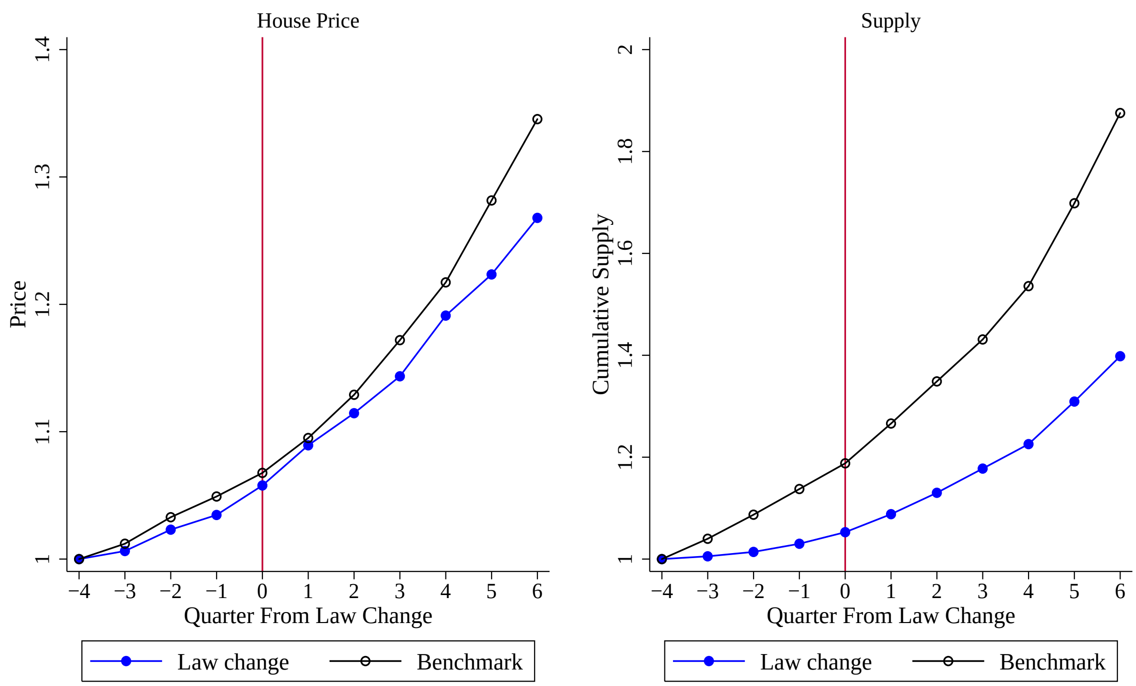
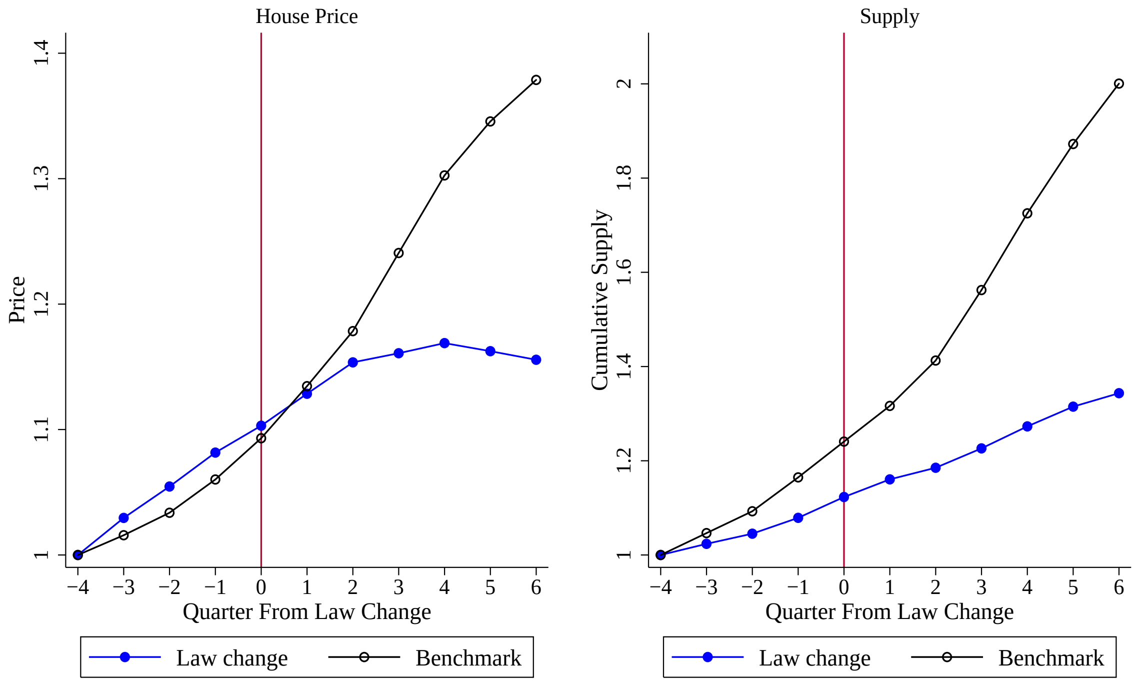


Figure IA.8
Effect of APLs on House Price Movements and Loan Supply by the Worse Originators
This figure compares the house price movements (on the left) and the cumulative loan supply by the worse originators (on the right) of ZIP codes in states that passed restrictive anti-predatory lending laws (APLs) between 2004 and 2005 (solid circles) with the house price movements and the cumulative loan supply by the worse originators of a benchmark of ZIP codes in states that did not pass any APLs before 2006 (hollow circles). In each panel, ZIP codes share the same quarter when APLs were passed. In Panel A, the ZIP codes in the "Law Change" group are from New Mexico and South Carolina (APL in 2004Q1). In Panel B, the ZIP codes in the "Law Change" group are from Massachusetts (APL in 2004Q3). In Panel C, the ZIP codes in the "Law Change" group are from Indiana and Wisconsin (APL in 2005Q1).

Panel B: 2004Q3, Massachusetts



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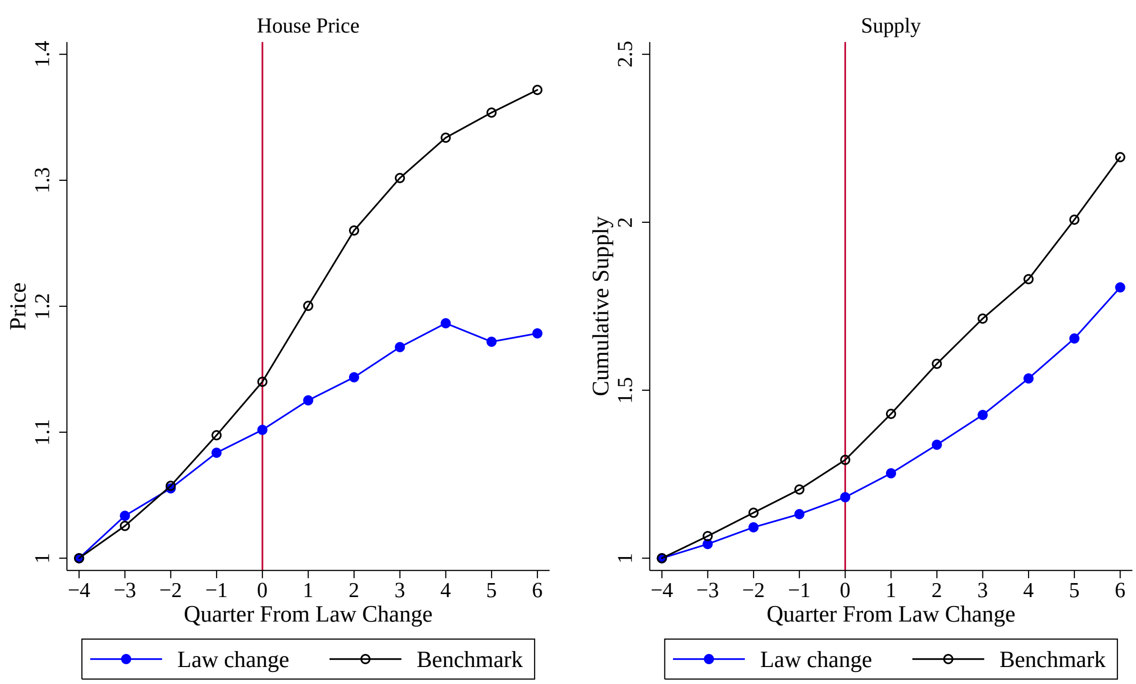
Panel C: 2005Q1, Indiana and Wisconsin



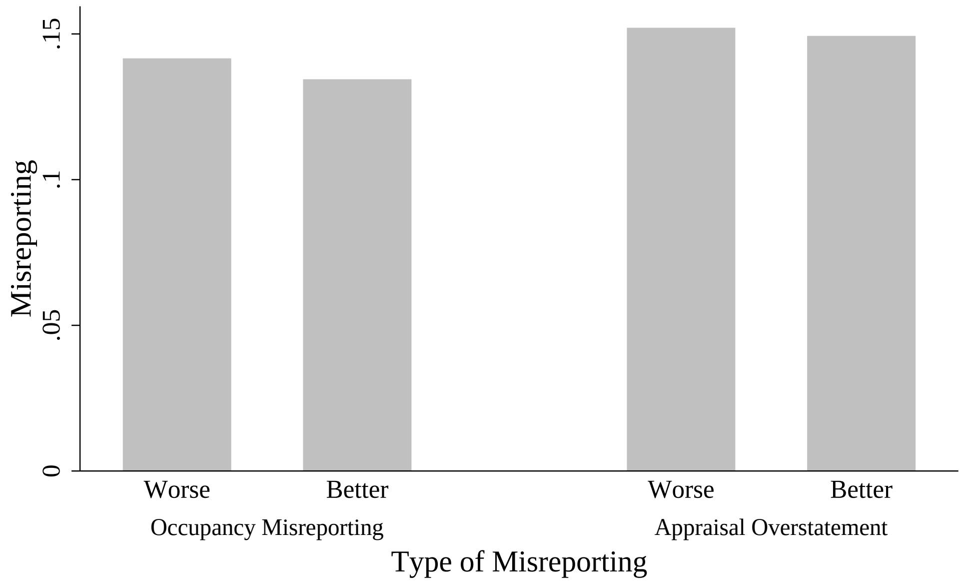


Figure IA.9
Occupancy Misreporting and Appraisal Overstatements by Originator Type
This figure shows the amount of occupancy misreporting and appraisal overstatements by originator type (worse and better). The two misreporting indicators are defined in Griffin and Maturana (2016).

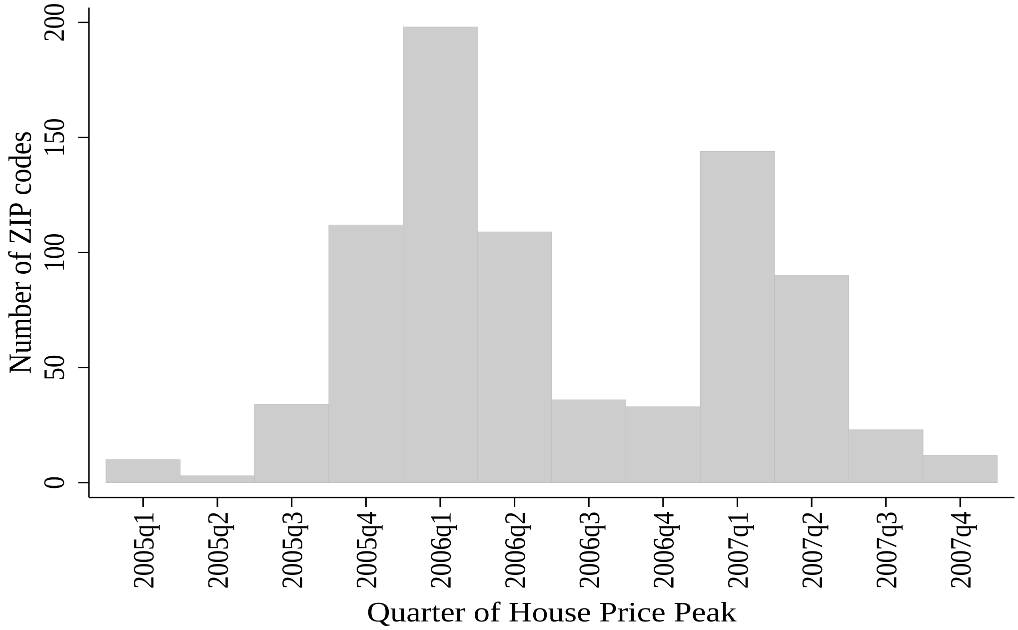


Figure IA.10
Frequency Histogram of House Price Peaks
This figure shows the frequency histogram for the house price peaks of the ZIP codes considered in Figure 7 and Table I.A.15.

Table IA.1
Originator Names and Second-Lien Misreporting Ranking Frequencies

	Tercile of Second-Lien Misreporting		
Originator	1	2	3
Fieldstone	0	0	6
First Franklin	0	0	6
Fremont	0	0	6
GreenPoint	0	0	6
WMC	0	0	6
Aegis	0	2	4
Mortgage IT	1	2	3
Ownit	0	0	3
American Home	0	4	2
BNC	0	4	2
New Century	0	4	2
People's Choice	0	4	2
Argent	5	1	0
Bank of America	4	2	0
Chase	2	4	0
Countrywide	2	4	0
Downey	6	0	0
IMPAC	6	0	0
Indymac	6	0	0
National City	3	3	0
Option One	3	3	0
GMAC RFC	6	0	0
SunTrust	1	5	0
Washington Mutual	5	1	0
Wells Fargo	1	5	0

This table shows the number of years between 2003 and 2008 that each of the 25 originators in the sample entered the different terciles of second-lien misreporting.

Table IA.2
Sample Descriptive Statistics

	Mean	p10	p50	p90
Worse Originators' Mkt. Share (03-06)	5.6	1.7	4.8	10.8
Medium Originators' Mkt. Share (03-06)	17.3	11.0	16.9	23.9
Better Originators' Mkt. Share (03-06)	11.1	6.6	10.6	16.2
Unranked Originators' Mkt. Share (03-06)	66	51.4	67.4	77.6
Fraction Securitized (03-06)	15.7	7.2	14.7	26.1
Fraction Securitized by the Worse Originators (03-06)	1.0	0.2	0.8	2.0
Fraction Securitized by the Medium Originators (03-06)	6.8	2.9	6.4	11.3
Fraction Securitized by the Better Originators (03-06)	6.7	2.8	6.2	11.4
Fraction Securitized by the Unranked Originators (03-06)	1.2	0.4	1.0	2.2
Population (2000), th.	24.6	6.4	21.7	46.3
Housing Units (2000), th.	9.7	2.5	8.8	18.0
Housing Vacancy Rate (2000)	6.0	2.2	4.5	10.7
Average Household Income (2001), th.$	56.7	30.6	47.6	88.9
Change Average Household in Income (01-06), th.$	12.9	2.4	7.8	27.3
House Price Return (03-06)	44.8	10.0	39.0	86.9
House Price Return (07-12)	-21.5	-45.5	-20.2	-0.5
Number of Zip Codes	5,176			

This table shows descriptive statistics for the 5,176 ZIP codes in the sample. To obtain the final sample, ZIP codes where the originator name coverage is less than 25% are dropped, and ZIP codes are required to show more than 500 purchase transactions from 2003 to 2006. Additionally, ZIP codes with the highest 2.5% fraction of loans securitized are dropped. Finally, MSAs with less than 15 ZIP codes are also dropped.

Table IA.3
Effect of Securitization on House Price Returns (Pooled Regressions)

	2003-2006		2007-2012	
Fraction Securitized	1.44***		-0.79***	
	(25.62)		(-24.70)	
Fraction Securitized by the Worse Originators		7.73***		-5.97***
		(12.81)		(-17.54)
Fraction Securitized by the Medium Originators		1.86***		-0.54***
		(10.45)		(-5.37)
Fraction Securitized by the Better Originators		0.17		-0.31***
		(0.94)		(-2.96)
Constant	0.22***	0.23***	-0.09***	-0.10***
	(23.12)	(24.36)	(-16.55)	(-18.18)
Observations	5,176	5,176	5,176	5,176
Adj. R-squared	0.11	0.13	0.11	0.14

This table shows OLS estimates for regressions in which ZIP code house price returns is the dependent variable, on the ZIP code-level of securitization and on the fraction of securitized loan originations by the various types of originators from 2003 to 2006. Columns 1 to 2 show the results for the boom period (2003-2006), columns 3 to 4 show the results for the bust period (2007-2012), and t-statistics are presented in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table IA.4
Effect of Securitization on House Returns

	2003-2006				2007-2012			
Fraction Securitized	0.181***		0.198***		-0.432***		-0.444***	
	(3.28)		(2.78)		(-5.58)		(-8.87)	
Fraction Securitized by the Worse Originators		7.420***		5.130***		-5.309***		-2.699*
		(4.77)		(4.71)		(-3.15)		(-1.89)
Fraction Securitized by the Medium Originators		-0.365*		-0.121		0.021		-0.216
		(-1.93)		(-0.75)		(0.12)		(-1.38)
Fraction Securitized by the Better Originators		-0.586		-0.378		-0.070		-0.332
		(-1.54)		(-1.19)		(-0.24)		(-1.33)
Population			0.007***	0.006***			-0.004***	-0.004***
			(3.19)	(2.87)			(-5.14)	(-5.82)
Housing Units			-0.017***	-0.015***			0.011***	0.011***
			(-3.16)	(-2.95)			(5.40)	(5.96)
Housing Vacancy Rate			0.704***	0.658***			-0.209***	-0.187***
			(4.10)	(3.99)			(-4.14)	(-3.99)
Average Household Income			-0.001***	-0.001***			0.001***	0.001***
			(-3.32)	(-3.00)			(7.03)	(6.61)
Change in Avg. Household Income			0.000	0.001			0.001***	0.000***
			(0.78)	(1.20)			(2.85)	(3.32)
Constant	0.420***	0.438***	0.430***	0.432***	-0.147***	-0.159***	-0.196***	-0.197***
	(48.56)	(47.60)	(24.92)	(29.69)	(-12.14)	(-12.68)	(-15.03)	(-13.76)
MSA FE	Y	Y	Y	Y	Y	Y	Y	Y
SE Clustered by MSA	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,176	5,176	5,176	5,176	5,176	5,176	5,176	5,176
Adj. R-squared	0.77	0.79	0.80	0.81	0.66	0.69	0.73	0.73

This table shows OLS estimates for regressions in which ZIP code house price returns is the dependent variable, on the ZIP code-level of securitization and on the fraction of securitized loan originations by the various types of originators from 2003 to 2006. Columns 1 to 4 show the results for the boom period (2003-2006), and columns 5 to 8 show the results for the bust period (2007-2012). Columns 3, 4, 7 and 8 include demographic controls. All regressions have MSA fixed effects. Reported t-statistics in parentheses are heteroscedasticity robust and clustered by MSA. ***p<0.01, **p<0.05, *p<0.1.

Table IA.5
Relative House Price Drop Difference Between Run-up Matched ZIP Codes

	2003-2012	
Worse Orig. Mkt. Share > 10% × Post2006	-0.144***	-0.146***
	(-6.74)	(-6.57)
Post2006	-0.680***	-0.681***
	(-12.53)	(-12.43)
Worse Orig. Mkt. Share > 10%	0.030***	-0.006
	(2.94)	(-0.57)
Fraction Securitized		0.657***
		(3.95)
Population		-0.002
		(-1.32)
Housing Units		0.007
		(1.68)
Housing Vacancy Rate		0.185
		(1.68)
Average Household Income		-0.001***
		(-3.21)
Change in Avg. Household Income		0.002***
		(3.62)
Constant	0.477***	0.390***
	(9.50)	(7.03)
Observations	1,472	1,435
Adj. R-squared	0.78	0.79

This table shows OLS estimates for a specification in which the dependent variable is vector with house price returns (with two returns per ZIP code, one for the boom and one for the bust). *Worse Orig. Mkt. Share > 10%* is an indicator that identifies the 858 ZIP codes in the first group graphed in Panel A of Figure 2, and *Post2006* is a dummy variable that takes the value of one if the date of the price corresponds to the year 2007 or later, and zero otherwise. Reported t-statistics in parentheses are heteroscedasticity robust and clustered by MSA. ***p<0.01, **p<0.05, *p<0.1.

Table IA.6
Falsification Test for the Effect of APLs

	All ZIP Codes		High Worse Orig. Supply	
	House Returns	Supply	House Returns	Supply
Post Law (False)	-0.005	-0.019***	-0.005	-0.024***
	(-1.31)	(-3.12)	(-1.18)	(-4.37)
Fraction Securitized	0.018	0.232***	0.006	0.164***
	(1.52)	(6.57)	(0.57)	(3.98)
Population	-0.000	0.001	0.000	0.001
	(-0.18)	(1.48)	(0.36)	(1.22)
Housing Units	0.000	-0.001	-0.000	-0.002
	(0.21)	(-1.11)	(-0.22)	(-1.19)
Housing Vacancy Rate	0.030***	0.002	0.035***	0.002
	(4.11)	(0.08)	(3.52)	(0.07)
Average Household Income	-0.000	-0.000***	0.000	-0.000**
	(-1.15)	(-5.81)	(1.04)	(-2.88)
Constant	0.011**	0.003	0.010	0.019**
	(2.31)	(0.55)	(1.75)	(2.39)
Quarter FE	Y	Y	Y	Y
Observations	8,458	8,120	4,440	4,440
Adj. R-squared	0.093	0.263	0.133	0.208

This table shows a falsification test for the regressions in Table 3. The change in anti-predatory lending laws is falsely assumed to have occurred three quarters before the true date of the change. The regression is estimated from the first quarter of 2003 to the second quarter of 2005 to mitigate the effects of overlapping with quarters where the laws were already implemented. All regressions include quarter fixed effects. Reported t-statistics in parentheses are heteroscedasticity robust and clustered by CBSA. ***p<0.01, **p<0.05, *p<0.1.

Table IA.7
The Effect of the HB4050 Program on House Prices

	July 2006-April 2007	July 2006-April 2007 Ex Oct. 2006-Nov. 2006
Treatment×Post	-0.019***	-0.021***
	(-4.42)	(-4.28)
ZIP code FE	Y	Y
Month FE	Y	Y
Observations	242	198
Adj. R-squared	0.73	0.70

This table shows the effect of the implementation of the Illinois Predatory Lending Database Pilot Program (HB4050) on house prices. The table presents OLS estimates for regressions in which ZIP code house price is the dependent variable. The independent variable is the interaction of two dummy variables, *treatment* and *post*. The dummy *treatment* takes the value of one if the ZIP code is in the HB4050 area, and zero if the ZIP code is in the control group unaffected by the program. The twelve ZIP codes in the control group resemble the ZIP codes in the HB4050 area in terms of pretreatment socioeconomic characteristics and housing market conditions (see Agarwal et al. (2014) for details). The dummy *post* takes the value of one from three months after the HB4050 program was implemented (December 2009) and zero before. Column 1 shows the result for the period from July 2006 to April 2007. In Column 2, the months immediately following the implementation of the program (October and November of 2006) are dropped. All regressions include ZIP code and month fixed effects. Reported t-statistics in parentheses are heteroscedasticity robust (we do not cluster by ZIP code due to the reduce number of ZIP codes in the regression). ***p<0.01, **p<0.05, *p<0.1.

Table IA.8
Effect of Worse Originator Activity in Elastic and Inelastic ZIP Codes (Boom)

	Elastic MSAs		Inelastic MSAs	
	2003-2006		2003-2006	
	Top 50%	Top 25%	Bottom 50%	Bottom 25%
Worse Originators' Mkt. Share	0.924	-1.032**	1.093***	1.315***
	(0.80)	(-2.19)	(2.78)	(3.44)
Medium Originators' Mkt. Share	0.147	-0.209	-0.423***	-0.253**
	(0.77)	(-1.28)	(-4.74)	(-2.73)
Better Originators' Mkt. Share	0.256	0.185	-0.925**	-1.212***
	(1.25)	(0.80)	(-2.43)	(-2.95)
Fraction Securitized	0.009	0.024	0.094	0.109
	(0.08)	(0.16)	(0.65)	(0.61)
Population	0.001	0.003	0.005***	0.005***
	(0.77)	(1.37)	(3.92)	(3.87)
Housing Units	-0.004	-0.007	-0.012***	-0.011***
	(-1.36)	(-1.66)	(-3.29)	(-3.07)
Housing Vacancy Rate	0.870***	0.637***	0.631***	0.579***
	(2.81)	(4.06)	(4.03)	(3.52)
Average Household Income	-0.002***	-0.001***	-0.001***	-0.001***
	(-3.77)	(-4.12)	(-2.88)	(-3.83)
Change in Avg. Household Income	0.002***	0.002***	0.000	0.001**
	(5.48)	(4.49)	(0.66)	(2.28)
Constant	0.319***	0.267***	0.586***	0.616***
	(6.98)	(9.95)	(15.94)	(12.16)
MSA FE	Y	Y	Y	Y
SE Clustered by MSA	Y	Y	Y	Y
Observations	1,796	633	2,871	2,111
Adj. R-squared	0.80	0.67	0.82	0.80

This table shows OLS estimates for regressions in which ZIP code house price returns during the boom is the dependent variable, on the ZIP code-level market share of the various types of originators from 2003 to 2006, for different subsamples of ZIP codes based on housing supply elasticities from Saiz (2010). The regressions include different combinations of demographic controls and MSA fixed effects. Column 1 shows the estimates for the ZIP codes in MSAs in the most elastic half. Column 2 shows the regression for ZIP codes in MSAs in the most elastic quartile. Column 3 considers the most inelastic half and column 4 the most inelastic quartile. Reported *t*-statistics in parentheses are heteroscedasticity robust and clustered by MSA. ***p<0.01, **p<0.05, *p<0.1.

Table IA.9
Housing Net Worth, Housing Supply Elasticity, and Worse Originators' Market Share

	Δ Housing Net Worth, 2006-09	Δ Housing Net Worth, 2006-09	Δ Housing Net Worth, 2006-09
Housing Supply Elasticity	0.054***		0.023***
	(6.67)		(3.01)
Worse Originators' Mkt Share		-0.065***	-0.057***
		(-11.71)	(-9.46)
Constant	0.956	2.521**	1.658
	(0.73)	(2.29)	(1.48)
Industry Controls	Y	Y	Y
Observations	254	254	254
R-squared	0.52	0.64	0.66

This table shows OLS regressions in which changes in housing net worth is regressed on housing supply elasticity and worse originators' market share (both independent variables are standardized). To add independency to the test we use data from Mian and Sufi (2014). Reported t-statistics in parentheses are heteroscedasticity robust and clustered by state. ***p<0.01, **p<0.05, *p<0.1.

Table IA.10
Unmet Demand and Market Share

	Worse Originators' Mkt. Share		Medium Originators' Mkt. Share		Better Originators' Mkt. Share	
Unmet Demand	0.161***	0.110***	-0.045***	-0.036*	-0.121***	-0.009
	(19.41)	(5.47)	(-3.76)	(-1.83)	(-13.10)	(-0.56)
Fraction Securitized		0.187***		0.126***		0.040**
		(10.57)		(5.94)		(2.07)
Population		0.000***		-0.000**		-0.000***
		(7.56)		(-2.49)		(-5.54)
Housing Units		-0.000***		0.000***		0.000***
		(-6.84)		(2.76)		(5.63)
Housing Vacancy Rate		0.000		-0.000		-0.000
		(1.17)		(-1.18)		(-0.36)
Avg. Household Income		-0.000***		0.000***		0.000***
		(-5.54)		(2.73)		(4.21)
Change in Avg. Household Income		0.000		-0.000		0.000
		(0.82)		(-1.08)		(0.44)
Constant	0.030***	0.024***	0.179***	0.147***	0.131***	0.057***
	(20.26)	(6.26)	(83.42)	(30.98)	(79.54)	(15.64)
Observations	3,939	3,939	3,939	3,939	3,939	3,939
Adj. R-squared	0.09	0.76	0.00	0.65	0.04	0.65

This table shows the relation between the market share of the different types of originators and ZIP code-level loan rejection rates (unmet demand). Reported *t*-statistics in parentheses are heteroscedasticity robust and clustered by MSA. ***p<0.01, **p<0.05, *p<0.1.

Table IA.11
Variable Contribution to R^2

	Worse originators			Better originators		
	Without the variable	With the variable	Relative Change in R^2	Without the variable	With the variable	Relative Change in R^2
Interest Rate	0.236	0.243	0.030	0.2787	0.2793	0.002
CLTV	0.238	0.243	0.021	0.262	0.279	0.065
Full-Doc	0.239	0.243	0.017	0.273	0.279	0.022

This table compares the effect of variables that capture the interest rate, the combined loan-to-value ratio, or the documentation type on the R^2 of delinquency regressions using the loans issued by the worse originators versus using the loans issued by the better originators. The regressions also include credit score, the log of loan amount, and indicators for whether the loan is an ARM and has a prepayment penalty.

Table IA.12
Loan Characteristics by Originator Type (Matched Sample)

	Worse Originators	Better Originators
CLTV (perc.)	90.1	91.0
Full-Doc	42.0%	32.0%
Interest Rate (perc.)	7.30	7.28
Non-owner Occupied	17.6%	19.9%
Credit Score	677	686
Loan Amount	257,079	277,674
ARM	80.7%	78.5%
Prepayment Penalty	50.6%	50.6%
Delinquent 90+	63.2%	54.4%

This table compares the characteristics of the loans issued by the worse originators with the characteristics of the loans issued by the better originators in the matched sample. For each loan issued by a worse originator, we find another loan issued by a better originator in the same ZIP code-year that also has similar propensity score. To compute the propensity score, we estimate a logit regression in which the dependent variable is a dummy that takes the value of one if the loan was issued by one of the worse originators and takes the value of zero if the loan was issued by one of the better originators, and the explanatory variables are combined LTV, credit score, interest rate, the log of the loan amount, and indicators for low-doc, non-owner occupied property, arm loan, and the existence of a prepayment penalty. Also, we impose a maximum distance between propensity scores of 1%. We are able to impose such a tight criteria because there are many more loans from the better originators and we match with replacement up to a maximum of five times.

Table IA.13
Explanatory Power of Loan-Level Variables - Separate Subsamples

	Delinquency 90+	
	Worse	Best
CLTV	0.351***	0.803***
	(16.19)	(28.98)
Full-Doc	-7.559***	-9.680***
	(-7.19)	(-11.16)
Interest Rate	1.635***	0.827***
	(8.03)	(4.34)
Non-owner Occupied	-0.656	0.167
	(-0.52)	(0.14)
Credit Score	-0.139***	-0.154***
	(-14.36)	(-14.90)
ln(Loan Amount)	9.221***	5.661***
	(8.41)	(6.29)
ARM	4.737***	2.137***
	(5.69)	(3.32)
Prepayment Penalty	5.598***	11.578***
	(6.93)	(13.51)
Constant	-2.725	7.008
	(-0.24)	(0.62)
ZIPxYear FE	Y	Y
Observations	86,822	86,822
Adj. R-squared	0.25	0.35

This table shows OLS loan-level regressions in which the dependent variable is an indicator for whether the loan became 90 days or more delinquent and the explanatory variables are a set of loan characteristics. Also included are ZIP Code interacted with year of origination fixed effects. Column 1 shows the results for the loans issued by the worse originators while column 2 shows the results for the loans issued by the better originators. For each loan issued by a worse originator, we find another loan issued by a better originator in the same ZIP code-year that also has similar propensity score. To compute the propensity score, we estimate a logit regression in which the dependent variable is a dummy that takes the value of one if the loan was issued by one of the worse originators and takes the value of zero if the loan was issued by one of the best originators. The explanatory variables are combined LTV, credit score, interest rate, the log of the loan amount, and indicators for low-doc, non-owner occupied property, arm loan, and the existence of a prepayment penalty. Also, we impose a maximum distance between propensity scores of 1%. We are able to impose such a tight criteria because there are many more loans from the better originators and we match with replacement up to a maximum of five times. Reported t-statistics in parentheses are heteroscedasticity robust and clustered by CBSA. ***p<0.01, **p<0.05, *p<0.1.

Table IA.14
Alternative Sorting Using HMDA Income

Avg. Household Income (HMDA)	Worse Originators' Market Share Low	2	3	4	High	High - Low	t-stat
Low	0.049	0.053	0.061	0.059	0.103	0.054	3.42
2	0.022	0.024	0.034	0.054	0.102	0.080	11.28
3	0.005	0.011	0.023	0.040	0.090	0.085	16.40
4	-0.007	0.008	0.008	0.031	0.074	0.081	13.10
High	-0.041	-0.037	-0.017	-0.003	0.031	0.073	8.76
High - Low	-0.091	-0.090	-0.078	-0.062	-0.072		
t-stat	-8.62	-10.53	-7.17	-8.16	-5.59		

This table shows repeats the estimation in Panel A of Table 7 with the only difference that average HMDA income in 2002 is used to classify the ZIP codes, instead of IRS income. ZIP codes are double sorted independently based on their average income in 2002 (as reported in the HMDA database) and *worse originators' market share*.

Table IA.15
Proportion Peaks

	Number of ZIP codes	Pct. of ZIP codes where supply by worse originators peaked before house price peak	Pct. of ZIP codes where supply by better originators peaked before house price peak	Difference in proportions	z-statistic
All house price peak-years	804	90.0	65.8	24.3	11.72
House price peaks in 2005	159	80.5	69.8	10.7	2.21
House price peaks in 2006	376	87.0	62.2	24.7	7.79
House price peaks in 2007	269	100.0	68.4	31.6	10.05

This table compares the proportion of ZIP codes where loan supply by the worse originators peaked before the ZIP code house price with the proportion of ZIP codes where loan supply by the better originators peaked before the ZIP code house price. The z-statistic of a proportion test is reported in the last column.

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