Collateral Misreporting in the RMBS Market*

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Securitized mortgage appraisals routinely target pre-specified valuations, 45% of purchase loan appraisals exactly equal purchase prices, and appraisals virtually never fall below purchase prices. As a result, appraisals exceed automated valuation model (AVM) valuations 60% of the time and are biased upward by an average of 5%. Appraisal bias predicts loan delinquency and RMBS losses and is priced at the loan level through higher interest rates, but it has essentially no impact on RMBS pricing. Selection bias simulations and unfunded loan application appraisals indicate that appraisal bias is intentional, and appraisal bias varies across loan officers, mortgage brokers, and appraisers.

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Did residential mortgage-backed security (RMBS) sponsors and mortgage originators mislead RMBS investors about collateral values? If so, how pervasive was the misinformation, what caused it, and were investors hurt by it? Over the last decade, substantial evidence has emerged of widespread fraud and misreporting in the RMBS market during the run-up to the financial crisis, culminating in over $137 billion in fines and government settlements and a multitude of investor lawsuits.[1] Collateral misvaluation due to biased appraisals played a central role in this misreporting. For example, Griffin and Maturana (2016b) estimate that as many as 45% of non-agency securitized loans have overstated appraisals, and appraisal bias is frequently cited in government settlements and private lawsuits. Yet, there remains significant disagreement about the magnitude and impact of appraisal bias, how to identify it, and what caused it.

This paper finds that appraisal bias is widespread, intentional, and harmful to investors in four ways. First, we identify and measure appraisal bias in a comprehensive sample of non-agency securitized mortgages and in internal loan data from New Century Financial Corporation by comparing appraisals to automated valuation model (AVM) valuations and property purchase prices. Based on this analysis, we conclude that non-agency securitized loan appraisals are biased upward by an average of almost 5% and that appraisals routinely target pre-specified values, resulting in inflated appraisals for half of purchase loans and a similar share of refinance loans. Second, we show that appraisal bias significantly understates loan-to-value (LTV) ratios and predicts delinquency and losses for both loans and RMBS pools. The extra risk associated with biased appraisals is priced at the loan level through higher interest rates but has essentially no impact on RMBS pricing. Third, we simulate selection bias and find that appraisal bias mainly comes from intentional inflation. Finally, we investigate who facilitated appraisal bias and find that appraisal bias varies significantly

[1] Zingales (2015) describes fraud as a major feature of the modern financial sector, particularly in the run-up to the financial crisis. Recent academic evidence of second lien, owner-occupancy status, income, and collateral misreporting includes Piskorski, Seru, and Witkin (2015), Griffin and Maturana (2016b), Jiang, Nelson, and Vytlacil (2014), Agarwal, Ben-David, and Yao (2015) and Mian and Sufi (2017). See Griffin, Kruger, and Maturana (2017) for detailed information about the banks' government settlements, including excerpts from statements of facts included in the settlements.

across loan officers, mortgage brokers, and appraisers.

Collateral valuation plays an important role in mortgage lending and securitization. For mortgage investors, collateral serves as both a protection from default (borrowers rarely default on properties with positive equity) and an insurance policy in the case of default (collateral value determines the lender's proceeds in foreclosure). As a result, origination standards and underwriting guidelines explicitly incorporate collateral value through LTV limitations, and information about LTV ratios is prominently reported to RMBS investors. For purchase loans, a property's valuation is somewhat disciplined by its purchase price, which is assumed to be from an arm's length transaction. Nonetheless, outside appraisals are required as a way to protect against overpriced transactions and potential fraud. Purchase loan properties are universally valued at the lesser of their purchase price or appraised value. For refinance loans, there are no purchase prices so valuations are based entirely on appraisals.

Appraisals are conducted by licensed appraisers, typically by valuing a property relative to recent comparable transactions. The process is inherently somewhat subjective because appraisers select what comparable transactions to use and adjust their valuations based on their assessments of differences between the properties. Moreover, there is a strong incentive to appraise properties at relatively high values because appraisers are hired by originators, and originators risk losing mortgage transactions if appraisals are low.[2] This incentive is particularly acute for securitized loans (due to less skin in the game for originators) and has been discussed in the popular media and in real estate trade publications (for example, see Andriotis (2014)). Automated Valuation Models (AVMs), which rely on mathematical modelling techniques and large databases, are an alternative valuation methodology, but

[2]Appraisers indicate that this pressure is widespread and frequently results in inflated appraisals. For example, eleven thousand appraisers signed a petition highlighting appraisal pressure during 2000 to 2007 (Financial Crisis Inquiry Commission (2011)). As of May 2009, the Home Valuation Code of Conduct requires originators to hire appraisal management companies rather than individual appraisers (see Agarwal, Ambrose, and Yao (2017) for details). This code of conduct was not in place during our sample period, and anecdotal evidence suggests that appraisal management companies pressure appraisers in much the same way as originators.

they are typically used as a due diligence tool rather than as a primary valuation tool, and their valuations are not disclosed to RMBS investors.

We analyze appraisals and AVM valuations in a large dataset consisting of U.S. non-agency securitized loans originated between 2001 and 2007. While both valuation measures are subject to error, their means and medians should be close to one another if they are unbiased. Instead, we find that appraisals are biased upward by almost 5% on average, and appraisals exceed AVM valuations 60% of the time. Evidence of appraisal bias is pervasive over time and across different types of loans and originators.

In internal data from New Century, we investigate purchase loan appraisal bias by comparing appraisals to purchase prices. Appraisals are at least as high as purchase prices 98% of the time and are exactly equal to purchase prices 45% of the time. This pattern indicates that appraisers frequently target purchase prices when constructing their valuations. Because unbiased appraisals should be evenly distributed around true property values, the fact that appraisals are almost never less than purchase prices implies that half of purchase appraisals are biased upward. Refinance loan appraisals exhibit similar targeting evidence in that a virtually identical 45% of refinance loans have appraisals that generate LTV ratios exactly equal to even five-unit LTV increments, which represent natural targets for appraisers. Similar clustering for unfunded loan applications and elevated appraisal values relative to AVM valuations at price and LTV targets indicate that these findings are due to intentional appraisal targeting as opposed to selection bias or adjustment of purchase price or loan size.

Appraisal bias generates valuations that are misleading to investors. In addition to overvaluing collateral by almost 5%, inflated appraisals significantly affect LTV ratios and combined loan-to-value (CLTV) ratios, which include junior lien loans. Reported LTV and CLTV ratios are almost never over 100%. In contrast, if LTV ratios were calculated using AVM valuations instead of appraisals, 14% of non-agency securitized loans would have origination LTV ratios above 100%. Similarly, nearly 50% of AVM-based LTV ratios are above 80%, whereas less than 23% of reported LTV ratios are above 80%. Results for CLTV ratios are even more striking. If CLTV ratios were calculated based on AVM valuations instead of appraisals, 17% of refinance loans and 25% of purchase loans would have origination CLTV ratios above 100%.

Consistent with the importance of collateral value for credit risk, appraisal bias is strongly related to delinquency and losses. At the loan level, appraisal differences and appraisal targeting both predict subsequent delinquency, and this loan performance translates into losses for RMBS investors. RMBS pools with higher appraisal differences and more appraisal targeting have higher loss rates. At the loan level, originators account for this risk to some extent through higher interest rates for loans with evidence of appraisal targeting. However, RMBS pricing, measured by yield spreads and subordination, does not vary with appraisal bias. Together, these findings indicate that appraisal bias increases credit risk. This risk was known to and somewhat priced by mortgage originators, but it was not disclosed to RMBS investors. As a result, investors in pools with elevated appraisal bias and targeting faced higher losses for which they were not compensated.

Demiroglu and James (2016) argue that indicators of appraisal bias based on AVM valuations could be due to selection bias.[3] Appraisals are somewhat noisy, and loan applications with low appraisals are potentially less likely to be completed. As a result, appraisals for completed loans could be biased upward. Importantly, selection bias is still a form of appraisal bias. If present, it understates loan risk and potentially misleads investors; and despite its simplicity and intuitive appeal, we are not aware of any RMBS disclosures to investors related to selection bias.

While selection bias cannot explain appraisal targeting, it could theoretically create some of the appraisal differences observed in the data. To assess this possibility, we start by simulating the distribution of differences between appraisals and AVM valuations under the assumption that there is no appraisal bias. We compare the empirical appraisal difference distribution to the simulated bias-free distribution based on mean appraisal differ-

[3] Ding and Nakamura (2016) and Calem, Lambie-Hanson, and Nakamura (2015) also discuss selection bias.

ence, percentage of appraisal differences that are positive, and a new measure capturing the Kolmogorov-Smirnov distance between the empirical and bias-free appraisal difference distributions. Adding selection bias to the simulation explains only a minimal amount of the appraisal bias observed in the data. This conclusion is based on both average levels of appraisal bias and the overall distribution of differences between appraisals and AVM valuations. In simulations with extreme levels of collateral-related loan denials, selection bias explains more of the average appraisal bias observed in the data, but it cannot explain the empirical rate at which appraisals exceed AVM valuations or the Kolmogorov-Smirnov measure of appraisal bias.

We conclude the paper by investigating who facilitated appraisal bias using detailed loan officer, mortgage broker, and appraiser identifiers available in the New Century data. Mean appraisal bias varies significantly, with interquartile ranges of 1.5% to 6.5% for loan officers, 0.3% to 7.3% for mortgage brokers, and 1.1% to 7.4% for appraisers. Past appraisal bias predicts subsequent appraisal bias for all three groups with particularly strong effects for appraisers. This evidence strongly suggests that appraisal bias is impacted by individual decisions made by loan officers, mortgage brokers, and appraisers.

Our analysis contributes to a growing literature documenting that RMBS misreporting is widespread and played a central role in credit expansion (Mian and Sufi (2017)), house price growth (Griffin and Maturana (2016a)), and mortgage default (Piskorski, Seru, and Witkin (2015), Griffin and Maturana (2016b), Jiang, Nelson, and Vytlacil (2014), and Garmaise (2015)).[4] With respect to appraisal bias more specifically, Griffin and Maturana (2016b) find that 45% of non-agency securitized loans have overstated appraisals.[5] Agarwal, Ben-David, and Yao (2015) identify appraisal bias in conforming mortgages using repeat sales

[4]Documented RMBS misreporting includes unreported second liens, occupancy status misreporting, income misreporting, personal asset misreporting, and appraisal bias. Additional evidence of income misreporting includes Blackburn and Vermilyea (2012) and Ambrose, Conklin, and Yoshida (2016), the latter of which uses New Century data.

[5]This finding comes from identifying appraisal overstatement based appraisals exceeding AVM valuations by more than 5%. Griffin and Maturana (2016b) also use a more conservative 20% overstatement threshold, which implies that 18% of appraisals are overstated.

and find that it is related to financial constraints and predicts subsequent default. Cho and Megbolugbe (1996) and Calem, Lambie-Hanson, and Nakamura (2015) find evidence of appraisal bias in purchase loans. Tzioumis (2016) finds that appraisal bias is unrelated to appraiser work volume and employment prospects. Conklin, Coulson, Diop, and Le (2017) find that appraisal targeting is more common when appraiser competition is high. Agarwal, Ambrose, and Yao (2017) and Ding and Nakamura (2016) find that the 2009 Home Valuation Code of Conduct reduced appraisal bias. Related evidence from Ben-David (2011) and Carrillo (2013) indicates that in some cases transaction prices are also biased upward due to fraud and collusion between buyers and sellers.

We add to this literature by using AVM valuations and appraisal targeting evidence to document that appraisal bias in non-agency securitized mortgages is widespread and harmful to investors. This appraisal bias comes from intentional inflation (as opposed to selection bias) and can be traced to specific loan officers, mortgage brokers, and appraisers. These findings also imply that AVM valuations would have provided useful information for identifying appraisal bias and predicting default if they had been disclosed to investors.

1 Are RMBS collateral values misreported?

We identify and measure collateral misreporting by comparing property appraisals reported to RMBS investors to AVM valuations and purchase prices. If appraisals and AVM valuations are unbiased and symmetrically distributed, appraisals should be equally likely to be above or below AVM valuations and purchase prices, and differences should be zero on average. We test these predictions for privately securitized loans in a general dataset that includes nearly all U.S. non-agency securitized loans and in internal loan data from New Century Financial Corporation, which includes unfunded loan applications and details missing from many other datasets.

1.1 Non-agency securitized loans, general sample

Our general loan data are from Lewtan's ABSNet Loan and HomeVal datasets. ABSNet provides loan-level information on U.S. non-agency securitized mortgages based on loan-level information in MBS servicer/trustee data tapes. ABSNet covers over 90% of non-agency securitized loans and includes detailed data on loan characteristics as of origination and ongoing monthly payment and performance information. The origination loan characteristics include appraisal values, which are reported to investors and used to calculate LTV ratios. HomeVal supplements ABSNet by providing property valuations as of loan origination date based on a proprietary AVM developed by Collateral Analytics.[6]

We analyze U.S. non-agency securitized mortgages originated between 2001 and 2007. The sample consists of first-lien loans used for purchase or refinancing with original loan balances between $30 thousand and $1 million. Following prior research, we exclude loans with original LTV ratios over 103% or CLTV ratios below 25%, as well as loans reported as being for homes of over one unit.[7] We also drop Federal Housing Administration (FHA) and Veteran Affairs (VA) loans and require all the relevant variables associated with the loans to be nonmissing.[8] Finally, we exclude loans with appraisals that are less than 33% or more than 300% of the property's AVM valuation as well as loans whose appraisals and AVM valuations are exactly the same.[9] This results in a final sample of 5.93 million loans, including 3.66 million refinance loans and 2.27 million purchase loans.

To assess appraisal bias, we analyze differences between appraisals and AVM valuations, scaled by average valuations. Specifically, we define Appraisal Difference (AD) to be:

$$AD \equiv \frac{Appraisal - AVM}{\frac{1}{2}(Appraisal + AVM)}. \quad (1)$$

[6]Collateral Analytics is a leading valuation firm and consistently ranks among the top performers for AVM accuracy. HomeVal AVM valuations are retroactive valuations based entirely on data available at the time a loan was originated.

[7]Only 0.2% of first-lien loans have LTV ratios above 103% so this restriction has no meaningful impact on our LTV analysis.

[8]The required variables, which are listed in Table 1, include loan characteristics and zip code-level data.

[9]The AVM and appraisal restrictions exclude potential data errors, decreasing the sample size by 8.9%.

If *Appraisal* and *AVM* are symmetrically distributed around the same mean, the median appraisal difference should be zero. Under the additional assumption that *Appraisal* and *AVM* have the same variance, mean appraisal difference should also be approximately zero.[10]

Table 1 summarizes the data. The mean appraisal difference for the overall sample is 4.69%, which indicates that appraisals have significant positive bias relative to AVM valuations. Additionally, 59.7% of appraisal differences are positive. Both measures of appraisal bias are moderately higher for refinance loans, which have a mean appraisal difference of 5.36% compared to 3.62% for purchase loans. Reflecting estimation errors inherent in the valuation process, appraisal differences have a standard deviation of 23.2%. Table 1 also summarizes loan characteristics, local area characteristics, and HMDA mortgage denial rates, all of which are similar to data analyzed in other mortgage studies.

[Insert Table 1 Here]

Appraisal bias persists throughout 2001 to 2007. Panel A of Figure 1 plots annual mean appraisal differences for refinance and purchase loans from 2001 to 2007. Refinance appraisal bias was 8.4% in 2001, fell to around 4.1% in 2003 to 2005, and then climbed to 10.5% in 2007. Purchase loan appraisal bias was between 2.5% and 4.7% throughout 2001 to 2007. Panel B of Figure 1 plots the fraction of loans with positive appraisal differences. Appraisal differences were positive over 55% of the time throughout the sample period for both refinance and purchase loans. For purchase loans, positive appraisal difference frequency was relatively flat over time. For refinance loans, appraisals differences were slightly more positive early and late in the sample (for example, refinance appraisal differences were positive 64.1% of the time in 2001 and 73.1% of the time in 2007). Overall, these results show that appraisal bias was a significant feature of non-agency securitized mortgages as early as 2001 and persisted

[10]The expected value of AD is approximately zero under these assumptions based on a second order Taylor expansion. This result differs from the appraisal overstatement measure used by Griffin and Maturana (2016b) and Demiroglu and James (2016), $(Appraisal - AVM)/AVM$, which has a positive expected value due to the covariance between $(Appraisal - AVM)$ and *AVM*, even if *Appraisal* and *AVM* have the same variance and are both unbiased.

throughout 2001 to 2007. If anything, appraisal bias was slightly dampened during the house price growth boom years of 2003 to 2005.

[Insert Figure **1** Here]

We next examine how appraisal bias varies across loans. Panel A of Figure **2** plots average appraisal differences by credit score for purchase and refinance loans. Appraisal bias is not confined to any particular type of borrower. For all credit score categories, mean refinance appraisal differences are at least 4.4% and mean purchase appraisal differences are at least 3.4%. For refinance loans, appraisal bias is moderately larger for medium (620-720) and high (>720) FICO score borrowers. For purchase loans, the pattern is the opposite, and low (<620) FICO score borrowers have the largest appraisal differences.

[Insert Figure **2** Here]

In Panel B of Figure **2**, we sort properties geographically based on overall house price growth between 2001 and 2007 at the zip code level. Once again, appraisal bias is pervasive across mortgages. For refinance loans, it is particularly pronounced in low house price growth areas. Specifically, the average refinance appraisal difference is 8.4% in areas with house price growth of less than 7.5%, compared to 4.7% for medium house price growth areas and 3.0% for high house price growth areas.[11]

In the internet appendix (Figure IA.**1**), we plot average appraisal differences by state and find that appraisal bias is present throughout the country and is particularly pronounced in the middle of the country. We also plot appraisal bias by loan size, local area income, population density, and number of recent transactions in the area (Internet Appendix Figure IA.**2**). Appraisal bias is positive across all types of loans, with particularly large biases for large loans and loans in areas with low income, low population density, and fewer transactions.[12]

[11]In unreported results, we find the same pattern when sorting loans by one-year lagged house price growth at the zip code level instead of overall 2001 to 2007 house price growth.

[12]The transaction evidence is consistent with Agarwal et al.'s (2017) finding that the Home Valuation Code of Conduct affected appraisals most pronounced in areas with fewer transactions.

In Figure IA.3 we find that that appraisal bias decreases with AVM confidence scores.[13] In short, appraisal bias is present everywhere and is most pronounced when appraisers have more flexibility. More generally, appraisal bias is pervasive across the country and is not restricted to any particular area or type of loan.

Appraisal bias is also pervasive across originators. Figure 3 plots mean refinance and purchase loan appraisal bias by originator for the top 20 originators.[14] With only one exception, all top originators have average appraisal differences of at least 3.9% for refinance loans and 2.5% for purchase loans, and there does not appear to be any relationship between originator size and appraisal bias. New Century's appraisal bias (4.8% for refinance loans and 4.1% for purchase loans) is similar to the appraisal bias of other major originators.

[Insert Figure 3 Here]

1.2 New Century sample

To learn more about appraisal bias, we turn next to internal data from New Century Financial Corporation. While this data is limited to a single originator, it has the advantage of including purchase prices, unfunded loan applications, and identifiers for loan officers, mortgage brokers, and appraisers. Given that New Century's appraisal bias is similar to other underwriters, this data is likely informative about appraisal practices more generally even though it is limited to a single originator. New Century's loan data includes 1.62 million loans originated between 2001 and 2007. We limit the data to first-lien loans that meet the same criteria as the ABSNet loans in the general sample, which results in 664

[13] Demiroglu and James (2016) find a similar pattern in their data and note that it is consistent with appraisal bias. This pattern is also what we would expect from appraisal targeting because there is more flexibility to manipulate valuations when a property's true value is more uncertain.

[14] The top-20 originators represent 62.9% of the loans in the general sample. The largest originator is Countrywide (1.11 million originations, 18.7% of the sample), followed by Residential Funding Corporation (591 thousand originations) and Washington Mutual (329 thousand originations). New Century is the 9^th largest originator in the sample with 102,907 originations. Griffin and Maturana (2016b) find similar evidence of pervasive appraisal bias across top originators and underwriters.

thousand refinance loans and 307 thousand purchase loans.[15] As described in Table 2, the New Century loans are similar to our general sample.

[Insert Table 2 Here]

In the New Century data, there are two ways we can assess appraisal bias. First, we can match loans in the New Century data to ABSNet/HomeVal data. For matched loans, we compare appraisals to AVM valuations just as we did in the general sample.[16] Consistent with Figure 3, New Century has average appraisal differences of 4.9% for refinance loans and 4.0% for purchase loans in the merged data (Table 2).

Second, and more uniquely, New Century's data allows us to compare appraisals to purchase prices. This analysis is not possible with the ABSNet data because ABSNet lacks purchase prices for most loans. If appraisals are unbiased estimates of true property values, they should be equal to purchase price on average and they should be evenly distributed around purchase prices. Instead, as reported in Table 2, appraisals exceed purchase prices by an average of 2.4%, and appraisals are greater than or equal to purchase price 98.2% of the time. Relative to an unbiased symmetric benchmark, in which appraisals should be below purchase price approximately 50% of the time, it appears that half of purchase loan appraisals are biased upwards.

1.3 Discussion

The evidence from the general sample and New Century both lead to the same conclusion: collateral misreporting in the RMBS market is large and pervasive. On average, appraisals

[15]Specifically, we keep loans with original amounts between $30 thousand and $1 million, LTV ratios under 103%, and CLTV ratios over 25%. FHA loans, VA loans, and loans reported as being for homes of over one unit are dropped. We also require appraisal and purchase price information to be nonmissing.

[16]This comparison requires merging New Century's data with ABSNet/HomeVal data at the loan level because the New Century data does not include AVM valuations. We match the loans in the two datasets based on their zip code, loan size, first payment date, purpose, type of interest rate (fixed or floating), and credit score, and we require matches to be unique. We find a match in ABSNet for 38% of the New Century funded loans. A more detailed description and evaluation of the matching procedure are available in Internet Appendix A.

are biased upwards by almost 5% relative to AVM valuations, and appraisals exceed AVM valuations 60% of the time. These patterns are persistent over time and across loan characteristics and originators. Purchase price comparisons in the New Century data indicate that appraisers routinely target purchase prices, which biases upward half of purchase loan appraisals and results in appraisals that virtually never fall below purchase prices. Given that average appraisal bias is higher for refinance loans than it is for purchase loans, the fraction of refinance loans that are biased upward may be even higher.

Do differences between appraisals and AVM valuations stem from intentional inflation bias? For the average appraisal to be on 5% higher than AVM valuations and for appraisals to exceed AVM valuations 60% of the time, either appraisals must be biased upward or AVM valuations must be biased downward. Given that automated valuation models are calibrated based on actual transactions, they should not be biased. Nevertheless, some might worry that historical comparable transactions could put downward pressure on AVM valuations in an environment with significant house price growth. The cross-sectional and time-series evidence indicate that this is not the case. Appraisal differences are smaller in zip codes with the most house price growth, and in the time series, appraisal differences are largest in 2007 after house prices started to decline. Moreover, the 5% appraisal difference we identify is in line with estimates of appraisal bias based on other methodologies. For example, Agarwal, Ben-David, and Yao (2015) estimate that appraisals are biased upward by 4.6% to 5.8% using a repeat sales approach, and Eriksen et al. (2016) find that purchase appraisals are 5.7% higher than valuation appraisals done less than six months earlier.[17]

Another possibility is that appraisals are biased due to appraiser optimism or selection bias. These explanations still result in appraisal bias and inflated collateral valuations, and both could have been identified and reported to investors by comparing appraisals to AVM valuations. The cross-sectional and time-series evidence pushes against the optimism inter-

[17] Eriksen et al.'s (2016) analysis is based on comparing appraisals conducted to assess the market value of foreclosed properties to appraisals used for purchase mortgage transactions for the same properties less than six months later with no alteration to the properties.

pretation. Appraisers are presumably most optimistic in rising home price environments, and this is where we see the lowest appraisal bias. Moreover, the Eriksen et al. (2016) comparison of two different appraisals with and without inflation incentives indicates that appraisal bias is driven by inflation incentives, not optimism. The appraisal targeting evidence in the next section also indicates that appraisal inflation was intentional. We address selection bias in detail in Section 4 and conclude that it explains only a small portion of the appraisal bias in the data.

The overwhelming tendency of appraisals to meet or exceed purchase prices is also subject to several interpretations. In addition to appraisals targeting prices, final sales prices could target appraisals or loan applications with low appraisals could be rejected. We assess these possibilities in in the next section with data on unfunded loan applications and analysis of appraisal bias at appraisal targeting thresholds. To evaluate what caused appraisal bias and how it affected investors, the remainder of the paper focuses on the following questions: do appraisals target specific valuations; were investors hurt by appraisal bias; can selection bias explain observed appraisal bias; and who facilitated appraisal bias?

2 Do appraisals target specific valuations?

Are appraisals biased upward relative to AVM valuations across the board, or do they target specific valuations? Anecdotes, popular media accounts, and industry publications indicate that appraisal targeting is widespread, and policymakers have responded with regulations such as the Home Valuation Code of Conduct to deter lenders from acting in ways that could inappropriately influence appraisals. If appraisal differences stem from appraiser optimism, selection bias, or some kind of systematic difference between appraisal and AMV valuations, there is no reason for appraisals to target specific valuations. By contrast, intentional inflation likely includes pressure for appraisers to hit certain minimum valuations in addition to general pressure for higher appraisals.

2.1 Purchase loan appraisal targeting

For purchase loans, the natural appraisal target is the purchase price because a lower appraisal could cause the transaction to fail and a higher appraisal has no benefit since LTV ratios are based on the lesser of purchase price and appraised value. If appraisers target purchase prices, we should see appraisals clustered at or above purchase prices. To assess this hypothesis, Panel A of Figure **4** plots fraction of loans by appraisal value relative to purchase price. Consistent with appraisal targeting, appraisals are almost never below purchase price, and 45.2% of loans have appraisals that are equal to purchase price.[18] Most other appraisals are above purchase price by zero to 5%. This is exactly the pattern we would expect if appraisers target their appraisals to match or slightly exceed purchase prices. While this evidence is limited to New Century, there is no reason to think appraisal targeting is unique to New Century given that New Century's average appraisal bias is similar to other originators. Moreover, Cho and Megbolugbe (1996) and Calem, Lambie-Hanson, and Nakamura (2015) find similar evidence of purchase price appraisal targeting in other samples, which suggests that it is a longstanding and widespread practice.[19]

[Insert Figure **4** Here]

Could this pattern be due to selection bias? If so, appraisals for unfunded loan applications should have lower appraisals that are clustered below purchase prices. We test this using New Century's unfunded loan application data. Applying the same criteria we used for completed loans results in a sample of 300 thousand unfunded purchase loan applications and 977 thousand unfunded refinance loan applications, which are described in the internet appendix (Table IA.**1**). Panel B of Figure **4** plots the fraction of unfunded New Century loan applications by appraisal value relative to purchase price. The results are even more extreme than the funded loan distribution in Panel A. Over two thirds (70.0%) of appraisals

[18] We treat appraisals as equal to purchase price if they are within 0.01% of one another. 99.3% of the appraisals we classify as being equal to purchase prices are exactly equal even before this rounding convention.

[19] Conklin, Coulson, Diop, and Le (2017) also document that New Century purchase appraisals cluster at and above purchase prices.

exactly equal purchase price, and once again appraisals are virtually never below purchase prices. This suggests that appraisal targeting is nearly universal for both funded loans and unfunded applications and cannot be explained by selection bias.

The unfunded loan application data is also inconsistent with the hypothesis that the 45.2% of appraisals that are exactly equal to purchase prices come from prices targeting appraisals as opposed to appraisals targeting prices. Prices in loan applications represent contract prices as opposed to final sales prices.[20] The high rate of appraisals equal to price in the unfunded loan application data suggests that appraisers regularly target contract sales prices. The moderately lower rate of appraisals equaling sales prices in the funded loan data is consistent with appraisals targeting contract prices and then prices occasionally being renegotiated downward due to home inspection issues or other contingencies.

If differences between appraisals and AVM valuations are due to random errors, selection bias, or appraiser optimism, we would expect appraisal differences to increase as appraisals increase relative to price. On average, loans with low appraisals should have negative appraisal differences, loans with high appraisals should have positive appraisal differences, and loans with appraisals equal to purchase price should have appraisal differences close to zero. By contrast, intentional appraisal targeting could push up appraisals relative to AVM valuations across the appraisal spectrum with particularly pronounced bias for properties that appraise for exactly their purchase price.

To test these predictions we turn to New Century-ABSNet merged data, which include 53,330 refinance loans and 16,995 purchase loans, described in the internet appendix (Table IA.**2**).[21] Table **3** reports the results. We calculate appraisal value relative to price using appraisal values and prices from the New Century data. Using appraisal values reported

[20]The buyer and seller in a real estate transaction first agree to a contract sales price, which is sometimes renegotiated if financing, home inspection, or other contingencies are identified prior to closing.

[21]We cannot do this analysis with New Century data alone because the New Century data does not include AVM valuations, and we cannot do this analysis in ABSNet/HomeVal alone because ABSNet lacks purchase price for most loans. The data merge is based on zip code, amount, first payment date, purpose, type of interest rate (fixed or floating), and credit score and results in matching 38% of New Century loans. See Internet Appendix A for additional details.

in ABSNet to calculate differences between appraisals and AVM valuations, appraisal differences have a positive mean throughout the appraisal distribution except when appraisal exceeds price by more than 10%. Mean appraisal difference is highest when appraisal equals purchase price, consistent with appraisal inflations targeting purchase prices. The same basic pattern also holds for excess positive appraisal difference.

[Insert Table 3 Here]

We also calculate appraisal differences using internal New Century appraisal data. The internal data reveals higher appraisal bias across the spectrum. In loan-level comparisons, we find that appraisal values reported in ABSNet typically reflect purchase price rather than internal appraisal value when New Century properties appraise for more than their purchase price.[22] This reporting convention biases observed appraisal differences in the ABSNet data downward for purchase loans and is likely part of the reason that observed appraisal bias is lower for purchase loans than for refinance loans in the ABSNet data.

2.2 Refinance loan appraisal targeting

Appraisal targeting is harder to identify for refinance loans because it is less clear what values appraisers target. Nonetheless, LTV ratio thresholds offer a window into refinance appraisal targeting. Mortgages tend to cluster at even LTV ratios, which makes these a natural target for appraisals. This is clearest for LTV ratios of 80%, which are common in the data. Because underwriting standards and interest rate policies frequently require a minimum LTV ratio of 80%, a loan for $80,000 may require a $100,000 appraisal in much the same way that a purchase loan requires an appraisal for at least the purchase price. Though the underwriting and pricing implications are less clear, LTV ratios also cluster at other five-unit LTV ratio increments, which suggests that these are also used as target valuations.

[22] Specifically, when New Century appraisals are greater than purchase prices, ABSNet appraisal value equals New Century purchase price 90% of the time.

Consistent with appraisal targeting in refinance loans, Griffin and Maturana (2016b) find that refinance loan LTV ratios cluster at increments of five and appraisal overstatement jumps at exactly these increments. Panel A of Figure 5 replicates this result. Almost half (45.2%) of refinance loans have LTV ratios that exactly equal five-unit increments such as 75, 80, or 85. This is exactly the pattern we would expect from appraisals targeting even LTV valuations, and the magnitude suggests that purchase and refinance loans have similar amounts of appraisal targeting.

[Insert Figure 5 Here]

Even LTV clustering could also stem from loan amounts targeting LTV ratios after appraisals are known. However, this explanation would not generate any particular relation between clustering and appraisal differences. As indicated in Panel A of Figure 5, average appraisal differences are 1.6 ppt higher for loans with even LTV ratios. These differences generally put even LTV appraisal differences outside of a 95% confidence interval based on fitting a fourth-order polynomial of LTV ratios. In Table IA.3 of the internet appendix, we regress appraisal difference on LTV and an indicator for even LTV ratios with similar results.

To further assess the possibility of selection bias driving the results, we next turn to unfunded loan application data from New Century. In Panel B of Figure 5, we repeat the clustering analysis in a sample restricted to just New Century loans to document that New Century's LTV clustering is similar to the rest of the sample. The picture is almost identical. If anything, appraisal targeting is slightly more common for New Century loans. Specifically, 56.0% of New Century refinance loans have even LTV ratios. In Panel C of Figure 5, we plot New Century unfunded refinance loan applications. LTV ratios are once again clustered at five-unit increments.[23] This time, 52.8% of loan applications have even LTV ratios. The consistent clustering for both funded loans and unfunded applications indicates that clustering is due to intentional targeting as opposed to selection.

[23]Panel C does not include appraisal differences because AVM valuations come from ABSNet/HomeVal data, which only include completed loans.

In the internet appendix, we examine appraisal bias for cash-out loans, where the borrower potentially wants to maximize the value of the new loan, as opposed to just repaying the old loan. This produces a larger incentive for appraisal bias and potentially leaves more flexibility to adjust loan amounts to match even LTV ratios. As expected, appraisal targeting and appraisal bias are most pronounced in cash-out refinance loans. However, non-cash-out loans also have significant appraisal bias and appraisal targeting.[24]

2.3 Discussion

Appraisal targeting is common for both purchase and refinance loans. The evidence is particularly striking for purchase loans, where we find that 45.2% of loans have appraisals that exactly equal purchase prices and 98.2% of loans have appraisals that meet or exceed purchase price. The virtually identical 45.2% of refinance loans with LTV ratios exactly equal to five-unit increments indicate that targeting is similarly pervasive in refinance loans. Appraisal difference and unfunded loan application analysis indicate that these patterns are due to appraisal targeting as opposed to selection bias, optimism, or purchase price and loan amount adjustments.

3 Did appraisal bias hurt investors?

Property valuations are of first-order importance to RMBS investors. Home equity is a major deterrent to default, and a property's underlying value determines what mortgage investors get in the case of foreclosure. As a result, LTV ratios play a central role in loan underwriting and are prominently reported to RMBS investors. Appraisal bias inflates LTV ratios and understates loan risk. In this section, we assess how much appraisal bias impacted

[24]Specifically, 49.2% of cash-out refinance loans have even LTVs compared to 34.6% even LTV clustering for non-cash-out refinance loans. Regression results comparing cash-out and non-cash-out refinance loans are reported in Table IA.3 of the internet appendix. The appraisal difference regression coefficient on an indicator for cash-out refinances is 1.3 ppt, compared to an overall mean appraisal difference of 5.4 ppt for all refinance loans.

LTV ratios and examine the impact of appraisal bias on losses and loan pricing for individual loans and RMBS pools.

3.1 Loan-to-value ratios

Biased appraisals naturally lead to biased LTV ratios. How big is the impact? To answer this question, we re-calculate LTV ratios based on AVM valuations by dividing original loan amount by AVM valuation. For refinance loans this represents the LTV ratio a loan would have had if the AVM valuation had been used instead of the appraisal. For purchase loans, our AVM-based LTV ratios are biased downward because actual purchase loan LTV ratios are based on the lesser of purchase price and appraisal value. Like appraisals, AVM valuations can be higher than purchase prices, and our AVM-based LTV ratios do not account for this.[25] Thus, our AVM-based LTV ratios underestimate the impact AVM valuations would have on purchase LTV ratios.

Panel A of Table 4 summarizes reported and AVM-based LTV ratios. For refinance loans, the mean ABSNet-reported LTV ratio is 72.9%. If LTV ratios were instead calculated based on AVM valuations, the mean refinance LTV ratio would be 79.3%. Investors also care about how many loans have elevated LTV ratios. Using reported LTV ratios, 21.2% of refinance loans have LTV ratios above 80%, 4.9% have LTV ratios above 90%, and essentially none have LTV ratios above 100%. In contrast, 45.4% of refinance loans have AVM-based LTV ratios that are above 80%, 26.0% have AVM-based LTV ratios above 90%, and 14.2% have AVM-based LTV ratios above 100%. The same basic pattern also holds for purchase loans.

[Insert Table 4 Here]

Investors also care about CLTV ratios, which include loans with junior liens (e.g., second mortgages and home equity loans). Panel B of Table 4 reports CLTV ratios based on AVM valuations using the same methodology. The results are even more extreme. While only

[25] ABSNet data has only limited coverage of purchase prices so we cannot use purchase prices when calculating AVM-based LTV ratios.

0.08% of refinance loans and 0.3% of purchase loans have reported CLTV ratios above the 100% threshold, AVM-based CLTV ratios exceed 100% for 17% of refinance loans and 25% of purchase loans. These figures suggest that true mortgage leverage was significantly higher than what was reported.

3.2 Loan delinquency and pricing

Appraisal bias inflates LTV ratios and understates loan risk. Thus, appraisal differences and appraisal targeting should predict loan delinquency. We test this hypothesis by regressing delinquency probability on our appraisal bias measures and loan-level control variables.[26] The dependent variable in the regressions is a dummy variable that takes the value of one if the loan became more than 90 days delinquent at any point in time between origination and September 2012. The regressions are OLS and include standard loan characteristic control variables and core-based statistical area (CBSA)-origination quarter fixed effects with standard errors clustered by CBSA.[27] Columns (1) to (3) of Table 5 report results for refinance loans.[28]

[Insert Table 5 Here]

In column (1), appraisal difference significantly predicts delinquency with a coefficient of 5.450, which means increasing appraisal difference by 10 ppt increases a loan's probability of becoming seriously delinquent by 0.55 ppt, relative to a mean delinquency rate of 30.2%. While this coefficient is highly significant, its economic effect is modest, potentially reflecting the fact that loan-level appraisal differences capture both appraisal bias and random errors in

[26] Griffin and Maturana (2016b) document related evidence that loan delinquency is higher for even-LTV loans and that high appraisal differences are related to delinquency and moderately higher interest rates.

[27] Specifically, the regressions control for loan size, credit score, interest rate, indicators for adjustable rates, full documentation, prepayment penalties, owner occupancy, and negative amortization, and an interaction term between interest rate and the adjustable rate indicator, which are the same control variables used by Griffin and Maturana (2016b).

[28] We focus on refinance loans because both appraisal difference and the indicator for even LTV ratios are widely available for this sample, whereas purchase price targeting is only available for purchase loans in the New Century sample. In the internet appendix (Table IA.4) we repeat all estimations for purchase loans with similar results.

appraisal and AVM valuations. Column (2) reports results from a regression of delinquency on an indicator for a loan having an even LTV. *Even LTV* has a highly significant coefficient of 9.385, which indicates that loans with even LTV ratios are 9.4 ppt more likely to become seriously delinquent, a large difference relative the mean delinquency rate of 30.2%. Column (3) reports results for a regression with both appraisal bias measures and their interaction. Appraisal difference and *Even LTV* both predict delinquency, and the interaction coefficient is also positive, indicating that appraisal difference is a stronger predictor of delinquency for loans with even LTV ratios, consistent with appraisal bias being more important for these loans.

Columns (4) to (6) of Table 5 report results from regressions of loan interest rates on the same appraisal bias measures.[29] Column (1) shows that appraisal difference is not significantly related to interest rate. However, the statistically significant coefficient of 0.186 on *Even LTV* in column (2) indicates that even LTV loans have interest rates that are 19 bps higher than other loans. Finally, column (6) reports that the coefficient associated with the interaction between appraisal difference and *Even LTV* is positive and statistically significant. Although the coefficient's economic magnitude is a modest 0.6 bp increase in interest rates for a 10 ppt increase in appraisal difference, the direction of the relationship indicates that appraisal difference is marginally priced for loans with even LTV ratios. To further illustrate the relationship between interest rates and LTV ratios, Figure 6 plots interest rates by LTV ratio with a clear pattern of elevated interest rates for even LTV loans.

[Insert Figure 6 Here]

Overall, the results in Table 5 and Figure 6 indicate that loans with targeted appraisals and loans with larger appraisal differences are riskier. The higher interest rates for loans

[29]The regression specifications are the same except that interest rate is not a control variable (because it is the dependent variable) and we add a control variable indicator for LTV ratios above 80 because interest rates jump at this threshold, as shown in Figure 6.

with even LTVs suggest that originators are aware that these loans are riskier and respond by setting interest rates higher. In contrast, appraisal differences are less predictive of delinquency, and originators may not know the AVM valuation for all loans. As a result, appraisal targeting is priced, and appraisal differences are not, except for a modest appraisal difference price impact for even LTV loans.

3.3 RMBS losses and pricing

Until now, we have analyzed collateral misreporting and its implications at the loan level. We now turn our focus to the effect of collateral misreporting on RMBS securities. Do appraisal bias related delinquencies at the loan level translate into losses for RMBS investors? Is the lower collateral quality associated with appraisal bias priced into RMBS yields and subordination levels?

To answer these questions, we follow Piskorski et al.'s (2015) analysis of second lien misreporting and ask how differences in appraisal bias across RMBS pools relate to pool losses and pricing. Our unit of observation for this analysis is the RMBS deal pool, which is a pool of loans that support a specific set of securities within a RMBS deal. Details on sample selection and pool data calculations are in Internet Appendix B. From the ABSNet loan data, we calculate pool-level average appraisal difference, percent of refinance loans with even LTV, and control variables, including FICO, CLTV ratios, percentage of loans with low or no documentation, and percentage of loans that are refinances. We use ABSNet pool and security data to calculate pool-level losses and pricing. Losses are pool-level cumulative realized losses as of September 2014 as a percent of the pool's original balance. Yield spreads are average floating rate interest margins across all of the securities supported by the pool. AAA subordination is the fraction of the security balance in the pool that is subordinated to the AAA securities. As a control variable, we also collect pool-level overcollateralization. To eliminate outliers and potential errors in the data, we drop pools with losses, yield spreads, or AAA subordination above the 95^{th} percentile and require pools to have data on all three outcome variables. This results in a sample of 694 loan pools, which contain 2.6 million underlying loans.

Table 6 reports results for regressions of pool losses and pricing on appraisal bias measures controlling for other loan characteristics, deal year fixed effects, and fixed effects for the top six underwriters in the sample. Standard errors are clustered by deal. In the first two columns of the table, the dependent variable is cumulative loss percent. The explanatory variables of interest are the mean appraisal difference and the percentage of refinance loans with even LTV ratios.[30] Both coefficients are positive and highly significant. The average appraisal difference coefficient of 36.98 means that increasing average appraisal difference by one cross-pool standard deviation (0.024) is associated with increased losses of 0.89 ppt relative to mean losses of 20.4%. Similarly, a one standard deviation increase in percentage of loans with even LTV (0.122) as associated with increased losses of 1.87 ppt.

[Insert Table 6 Here]

Is appraisal bias priced into RMBS yield spreads and subordination? Across all four pricing regressions (Columns (3) to (6) of Table 6), the answer is no.[31] The only marginally significant pricing coefficient is the Column (6) coefficient of AAA subordination on *Percentage Even LTV*. Even this is only significant at the 10% level. Equally importantly, it is economically small. A one standard deviation increase in percentage of loans with even LTV (0.122) is associated with a 0.31 bp increase in AAA subordination relative to mean AAA subordination of 12.4%.

[30] For both regressions, we require coverage in our data for 25% of the loans in the pool. Because the even LTV targeting indicator is only for refinance loans, the 25% requirement is more restrictive for that measure, resulting in a reduced sample size for the second regression (517 pools as opposed to 694 pools).

[31] The pool pricing regression specifications are the same as the pool loss specifications discussed previously except that the pricing regressions also control for overcollateralization. Standard errors are again clustered by deal.

3.4 Discussion

The overall implication of the loan and pool analysis is that appraisal bias predicts delinquency and losses. This holds at both the loan and the RMBS pool level, particularly for the even-LTV indicator of appraisal targeting. Loan originators respond to this increased risk with higher interest rates for refinance loans with even LTV ratios. However, this loan pricing is not passed on to RMBS investors. Instead, yield spreads and subordination are largely insensitive to measures of appraisal bias, suggesting that RMBS investors were unaware of and uncompensated for collateral misreporting. This is exactly the exact same pattern that Piskorski, Seru, and Witkin (2015) find for second lien misreporting.

4 Is appraisal inflation caused by selection bias?

The leading explanation for appraisal bias is that appraisals are intentionally inflated. Appraisers obtain information about purchase prices and target refinance valuations and engineer their appraisals to come up with valuations at or above those targets. An alternative explanation advanced by Demiroglu and James (2016) is that appraisal bias is due to selection bias. Appraisals are somewhat noisy, and loan applications with low appraisals tend not to be completed. As a result, appraisals for completed loans are biased upward.

Both forms of appraisal bias understate loan risk and potentially mislead investors, but they have different implications regarding who is responsible for appraisal bias and how it can be corrected. The evidence of appraisal targeting in Section 2 establishes that intentional targeting is widespread. In this section, we simulate selection bias to assess whether selection bias can also generate observed levels of appraisal bias.

4.1 Appraisal difference simulation

We have already seen that appraisals exceed AVM valuations 59.7% of the time with an average appraisal difference of 4.7%. These are just two of many possible summary statistics for appraisal differences. To get a better sense for the full distribution of appraisal differences, Figure 7 plots appraisal difference histograms for refinance and purchase loans compared to normal distributions with means of zero and standard deviations equal to those in the data. Compared to the normal distribution benchmark, the empirical distribution exhibits significant positive bias. In particular, there are fewer observations with moderately negative appraisal differences and more observations with positive appraisal differences.

[Insert Figure 7 Here]

To estimate a counterfactual for what the distribution of appraisal differences would be without appraisal bias, we follow Demiroglu and James (2016) and model *Appraisal* and *AVM* errors as bivariate normal random variables with means equal to true property values and error standard deviations that are equal to one another with correlations of 0.25 and 0.5 respectively for refinance and purchase loans. We calibrate the standard deviations of *Appraisal* and *AVM* such that simulated appraisal difference standard deviations for refinance and purchase loans match the empirical appraisal difference standard deviations reported in Table 1.[32] The simulated bias-free appraisal difference distributions, which are plotted in Figure 7, are almost identical to normal distributions with the same standard deviations.

How different are the empirical distributions from the simulated distributions? More specifically, how much appraisal bias is necessary to explain the empirical appraisal difference distributions? Average appraisal differences are 5.36% for refinance loans and 3.62% for purchase loans, and appraisal differences are positive 61% of the time for refinance loans and 57.6% of the time for purchase loans. In the absence of appraisal bias, appraisal differences should be positive 50% of the time. This means an extra 11% of refinance loans and 7.6%

[32]The calibrated valuation error standard deviations are 24.3% for refinance loans and 21.3% for purchase loans. The means of *Appraisal* and *AVM* are irrelevant to the simulation because they do not affect appraisal difference calculations. The only difference between Demiroglu and James's (2016) simulation and ours is that we calibrate appraisal and AVM standard deviations so that simulated appraisal difference standard deviations match empirical appraisal difference standard deviations, whereas Demiroglu and James use standard deviations provided by their AVM source.

of purchase loans have positive appraisal differences compared to the bias-free benchmark. We refer to these differences as excess positive appraisal differences. Because it measures how many extra loans have positive appraisal differences, excess positive appraisal difference establishes a lower bound for how many loans must be biased in order to explain the empirical appraisal difference distribution. It is a highly conservative lower bound capturing only the number of biased appraisals needed to explain this single threshold, but it is still a useful tool for describing the distribution.

To generate more general lower bounds for appraisal bias, we employ a modified version of the Kolmogorov-Smirnov statistic, which is a distance measure commonly used to compare probability distributions. Specifically, we define the positive Kolmogorov-Smirnov (KS^+) distance between the empirical and simulated distributions as:

$$KS^+ \equiv \sup_x (F_{AD}(x) - F_{sim}(x)), \tag{2}$$

where $F_{AD}(x)$ is the empirical distribution function for appraisal differences and $F_{sim}(x)$ is the bias-free simulated cumulative distribution function for appraisal differences.[33] Intuitively, each x represents a threshold, and $F_{AD}(x) - F_{sim}(x)$ is the fraction of loans that must be biased in order to explain differences in how many loans have appraisal differences above that threshold. Like the zero appraisal difference threshold excess positive measure, each of these differences is a lower bound on the amount of appraisal bias needed to explain the empirical appraisal difference distribution. KS^+ is the maximum of these lower bounds.

Figure 8 plots empirical and bias-free simulated distribution functions for refinance and purchase loan appraisal differences. KS^+, the maximum difference between the two distributions, is 15.6% for refinance loans and 15.7% for purchase loans. These maximum differences occur at appraisal difference thresholds of -8% and -7% for refinance and purchase loans

[33]The only difference between this and the standard Kolmogorov-Smirnov test statistic is that the standard measure considers the absolute value of differences between cumulative distribution functions, whereas we consider the signed difference between $F_{AD}(x)$ and $F_{sim}(x)$. In practice, this modification does not affect our results because empirically appraisal differences are positively biased.

respectively. Thus, 15.6% is a lower bound on what fraction of refinance loans must be biased upward to explain differences between the empirical and simulated distributions. Similarly, 15.7% is a lower bound for purchase loan appraisal inflation.

[Insert Figure 8 Here]

Importantly, the extra frequency with which appraisal differences are positive and the KS^+ measure are both lower bounds on the number of loans that are biased upward. They are useful descriptions of the empirical appraisal bias distribution, but they likely significantly understate the fraction of loans with appraisal bias, which the New Century purchase loan analysis discussed earlier suggests is close to 50%.

4.2 Selection bias

Selection bias is a natural consequence of noisy appraisals. Appraisals have errors, and negative appraisal errors could derail some loan applications. If this is the case, we should expect at least some selection bias in appraisals. The main question is how much appraisal bias does selection explain? For example, we document that refinance appraisals are biased upward by 5.4% on average with a KS^+ lower bound of 15.6% for the fraction of loans that would need to be biased in order to generate the empirical appraisal difference distribution. How much of this appraisal bias is due to selection?

To quantify the importance of selection bias, we add selection bias to the simulation model described in Section 4.1. To model selection, we again follow Demiroglu and James (2016) and assume that loan completion probability is 100% if an appraisal is above the property's true value and is otherwise $max(0, 1 - \beta(V - max(0, A))/V)$, where A represents the appraisal value and V represents the property's true value (which can be normalized to one).[34] Intuitively, loan completion probability falls as appraisal value decreases relative to

[34]The two maximum operators ensure that appraisals and completion probabilities never fall below zero. In practice, they rarely bind and are not important.

a property's true value. The parameter β is calibrated such that the simulation generates a targeted denial rate, which is based on observed HMDA denial rates.

In our baseline simulations, we follow Demiroglu and James (2016) and assume: (1) appraisal and AVM errors have a correlation of 0.25 for refinance loans and 0.5 for purchase loans; and (2) denial rates are equal to observed HMDA denial rates for collateral insufficiency.[35] As reported in Table **1** the matched HMDA collateral-insufficiency denial rates for our sample are 2.5% for refinance loans and 1.7% for purchase loans. Our baseline simulations are calibrated to match these denial rates.[36]

Table **7** reports our baseline simulation results. In the data, refinance loans have average appraisal differences of 5.36%, 10.98% excess positive appraisal difference, and a KS^+ distance of 15.59% compared to the bias-free simulation. The bias-free simulation has zero appraisal bias according to all three measures. The baseline selection bias simulation has mean bias of 0.57%, 0.79% excess positive appraisal difference, and a KS^+ distance of 0.87% compared to the bias-free simulation. In short, while selection bias generates appraisal bias, it appears to be only a small part of the bias observed in the data. This result is even starker for purchase loans where baseline selection bias explains only 0.27% of the 3.62% mean appraisal difference observed in the data.[37]

[Insert Table **7** Here]

[35]HMDA denial rates are based on matching sample loans to HMDA averages by zip code, loan purpose, and year.

[36]In the simulations, collateral insufficiency is the only reason a loan is not completed, whereas in the data loan applications can be denied or withdrawn for other reasons. Calibrating the simulation to match observed collateral denial rates implicitly makes the assumption that loans are first denied for collateral-insufficiency reasons (thereby determining the appraisal difference distribution) and then complete or fail based on reasons unrelated to appraisals.

[37]These results differ from Demiroglu and James (2016) primarily because we focus on measures of appraisal bias that have an expected value of zero in the bias-free benchmark. In the internet appendix (Table IA.**5**) we report calibration parameters and additional moments, including mean levels of $(A-AVM)/AVM$ and the fraction of loans with $(A-AVM)/AVM$ above 20% and below -20%. Simulations of those statistics are closer to their empirical counterparts, consistent with the results of Demiroglu and James. We also observe HMDA collateral denial rates that are somewhat lower than those reported by Demiroglu and James (e.g., 2.5% compared to 6.5% for refinance collateral denials and 1.7% vs. 1.9% for purchase collateral denials), in part because we consider the period between 2001 and 2007, as opposed to only 2006 and 2007, when collateral denial rates were higher. Sensitivity analysis indicates that these differences are not important.

To assess the robustness of our baseline simulations, we conduct sensitivity analysis with different assumptions regarding error correlations and denial rates. Additionally, we relax the assumption that all loans with appraisals over the property's true value are originated. The baseline model assumes that all collateral-related denials come from appraisals with negative errors. In reality, a property's appraisal can also come in below a targeted value because the property's true value is lower than the target. Identifying these cases is the main purpose of requiring appraisals in the first place. Assuming some collateral-related denials are due to true value insufficiency as opposed to appraisal error, the baseline simulation overestimates selection bias. In our alternative simulations, we change the threshold for 100% origination probability from $A \geq V$ to $A \geq 1.25V$ while keeping the same linear structure for loan completion probability when appraisals are below the $1.25V$ threshold. Figure 9 plots simulated appraisal bias under different assumptions for refinance loans. The plots on the left side of the figure show average appraisal bias and the plots on the right side of the figure show KS^+ distances from the bias-free simulation. The internet appendix (Figure IA.4) includes equivalent plots for excess positive appraisal difference.

[Insert Figure 9 Here]

In Panel A of Figure 9, we consider valuation error correlation assumptions ranging from 0 to 0.5. Changing the correlation assumption has almost no impact on simulated appraisal bias. Because the simulation is calibrated to match observed appraisal difference variance, higher error correlations are offset by higher calibrated appraisal and AVM error standard deviations, leaving appraisal bias roughly constant.

In Panel B of Figure 9, we consider different denial rate assumptions. Our baseline denial rate based on HMDA denials due to collateral insufficiency could be too low if loans are denied for other reasons somehow related to collateral or if loan application withdrawals are related to appraisal valuations. In our refinance simulations we consider denial rates of up to 17.5%, which is the combined rate of withdrawals and collateral-related denials for refinance loans (see Table 1).[38] As denial rates increase, selection bias increases, and for high denial rates, the simulations get close to matching the mean appraisal difference of 5.36% that we observe in the data. However, using the alternative appraisal threshold to account for collateral denials due to true value deficiencies decreases mean appraisal difference by half, leaving it well below observed levels even with elevated denial rates. Moreover, even with a denial rate of 17.5%, the baseline selection simulation KS^+ of 6.5% falls well short of the 15.6% KS^+ observed in the data. To generate a 15.6% KS^+ statistic, the collateral related denial rate would need to be an implausible 37.5%. The alternative simulation falls even further short of explaining the observed KS^+ statistic.[39] In the internet appendix (Figure IA.4), we document similar patterns for excess positive appraisal difference. In the data, an extra 11% of loans have positive appraisal differences, whereas the highest denial rate simulation generates 6.4% excess positive appraisal difference.

We repeat the same sensitivity analysis for purchase loans in the internet appendix (Figure IA.5) with similar results. In Table IA.6, we also report results from jointly varying error correlations and denial rates. In total, we consider 15 permutations under both baseline and alternative appraisal thresholds. Consistent with Figure 9, scenarios with highly elevated denial rates come close to matching average appraisal bias but fall short with respect to excess positive appraisal difference and KS^+ statistics.

5 Who facilitated collateral misreporting?

We have already seen that appraisal bias is pervasive across major originators. The New Century data allows us to take this analysis one step further by examining how appraisal bias varies across loan officers, mortgage brokers, and appraisers. We calculate appraisal differences based on ABSNet and HomeVal data and merge them with New Century data on

[38] Denial rates are expressed as a percentage of loan applications. The 17.5% denial rate corresponds to 21.2% of completed loans.

[39] With a denial rate of 17.5% the alternative simulation generates a KS^+ statistic of 3.6%. To match a KS^+ of 15.6%, the collateral related denial rate would need to be 47.5%

the loan officers, mortgage brokers, and appraisers associated with individual loans. Figure 10 shows box plots of average appraisal difference rates for loan officers, mortgage brokers, and appraisers with at least 25 observations in the merged data. The interquartile ranges are 1.5% to 6.5% for loan officers, 0.3% to 7.3% for mortgage brokers, and 1.1% to 7.4% for appraisers, suggesting that appraisal bias varies across loan officers, mortgage brokers, and appraisers.

[Insert Figure 10 Here]

To assess whether appraisal bias is a persistent characteristic of loan officers, mortgage brokers, and appraisers, we calculate lagged appraisal bias for each loan officer, mortgage broker, and appraiser on a rolling basis using loans originated over the past 12 quarters. The lagged appraisal bias measures are standardized by scaling them by their standard deviations. To be included, lagged appraisal bias must be based on at least 25 observations. This retains most observations for loan officers, but eliminates many observations for mortgage brokers and appraisers who are only associated with a small number of loans.

Table 8 reports results for regressions of appraisal differences on lagged appraisal bias using pooled data on both refinance and purchase loans. The regressions control for CBSA-origination quarter fixed effects and the standard loan characteristic controls included in Table 5. Standard errors are clustered by CBSA. Because the lagged appraisal bias measures are standardized, the coefficients represent the appraisal difference increase associated with a one standard deviation increase in lagged appraisal bias.

[Insert Table 8 Here]

Column (1) reports results for loan officers. Lagged loan officer loan bias significantly predicts subsequent appraisal differences, but the coefficient is relatively small. A one standard deviation increase in lagged loan officer appraisal bias is associated with a 0.4 ppt increase in appraisal difference relative to a mean of 4.9%. The lagged appraisal bias of mortgage brokers (reported in column (2)) is more predictive of subsequent appraisal differences. A one standard deviation increase in lagged mortgage broker appraisal bias is associated with a 1.4 ppt increase in appraisal difference. Differences across appraisers are even larger. As reported in column (3), a one standard deviation increase in lagged appraiser appraisal bias is associated with a 2.4 ppt increase in appraisal difference.

These results imply that appraisal bias varies significantly across loan officers, mortgage brokers, and appraisers. Some individuals engaged in more (or more egregious) appraisal bias, and their past bias predicts subsequent appraisal differences. The pattern is particularly strong for appraisers, suggesting that some appraisers persistently inflate their appraisals. In addition to providing evidence that appraisal bias was intentional, this suggests that it can (at least in principle) be identified and disclosed. If we can identify individual-level appraisal bias in New Century's data, regulators ought to be able to do the same thing with data from other originators. Calculating and disclosing individual appraisal bias would likely give the market valuable information and would potentially allow appraisers to compete with one another based on their reputations for reliable appraisals.

6 Conclusion

Appraisal bias is large, widespread, intentional, and identifiable based on appraisal targeting and differences between appraisals and AVM valuations. Appraisals exceed AVM valuations 60% of the time and are on average almost 5% higher than AVM valuations. New Century purchase loan appraisals are at least as high as purchase prices 98% of the time, indicating that half of purchase loan appraisals are biased upward, and even LTV clustering suggests that appraisal targeting is similarly widespread for refinance loans. Simulations and appraisal targeting evidence indicate that this bias comes from intentional inflation as opposed to selection bias. Consistent with appraisal bias being an intentional decision, it varies significantly across loan officers, mortgage brokers, and appraisers; and past appraisal bias predicts subsequent appraisal bias.

Appraisal bias is harmful to RMBS investors in that loans with inflated appraisals and appraisal targeting are more likely to become seriously delinquent, and RMBS pools with more of these loans have higher loss rates. Increased default risk is reflected in loan level pricing through higher interest rates for loans with evidence of appraisal targeting. However, RMBS pricing, measured with yield spreads and AAA subordination, is generally insensitive to measures of appraisal bias, suggesting that RMBS investors were unaware of and uncompensated for appraisal bias. If they had been disclosed, AVM valuations would have been useful to RMBS investors both for identifying appraisal bias and for estimating default risk. Although welfare assessment and policy evaluation are outside the scope of this paper, we speculate that the pervasiveness of appraisal bias and its harm to investors likely justify a regulatory response. The Home Valuation Code of Conduct is a step in this direction. Loan-level AVM disclosures and monitoring of appraisal differences for individual loan officers, mortgage brokers, and appraisers may also be warranted. To make informed investment decisions, RMBS investors need reliable information. Collateral valuations during the run-up to the financial crisis clearly fell short of that requirement.

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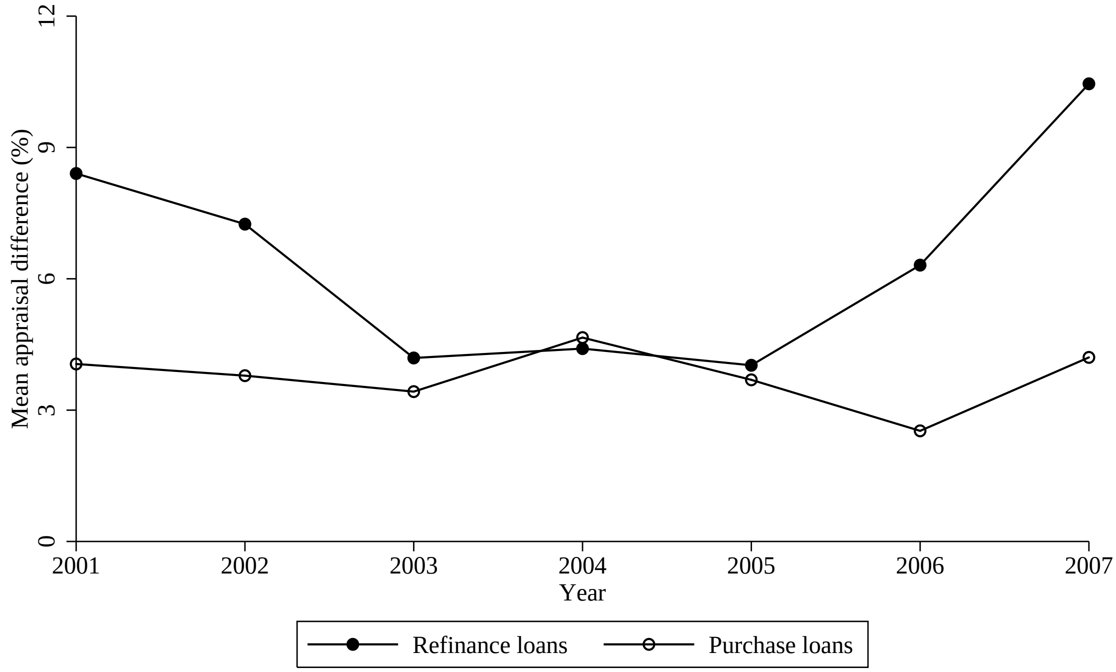
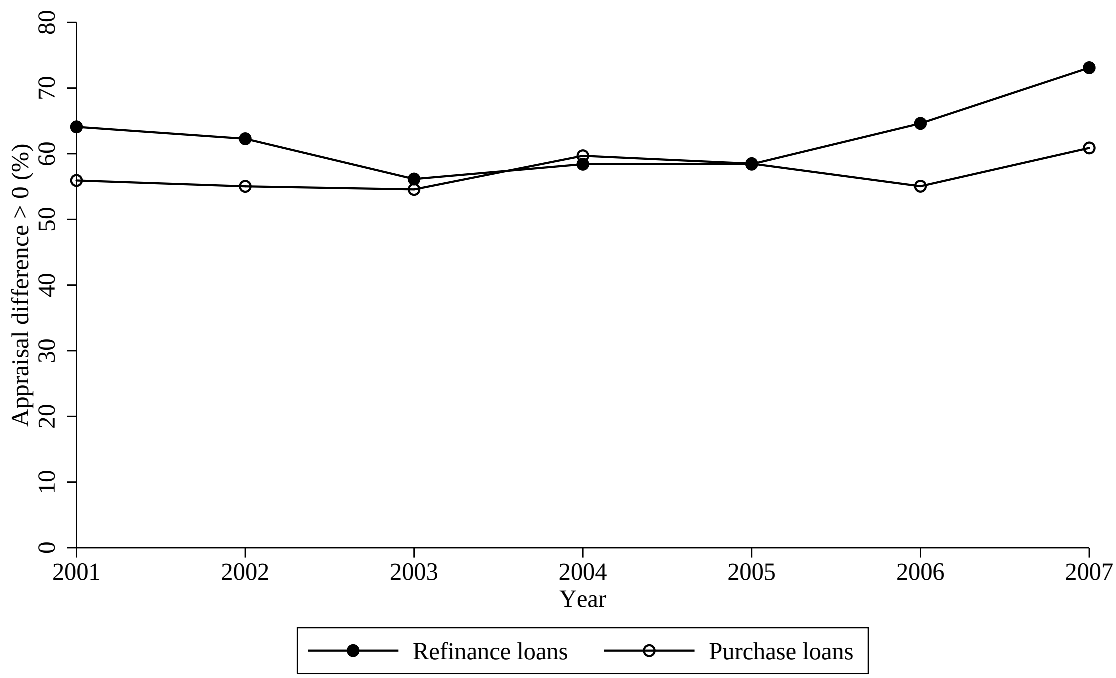
Figure 1. Time-series of appraisal differences

Panel A: Mean appraisal difference



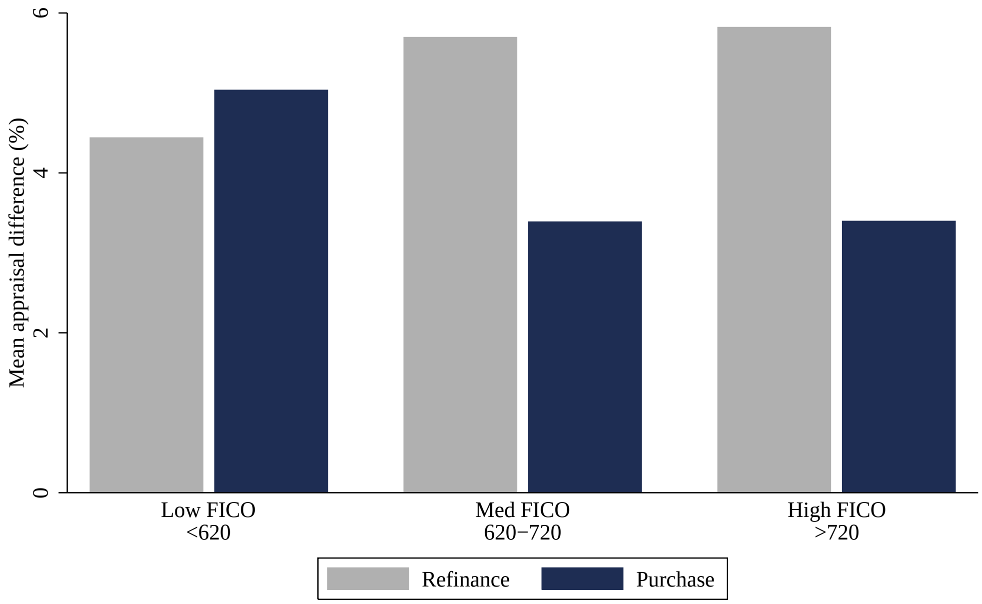
Panel B: Appraisal difference greater than zero



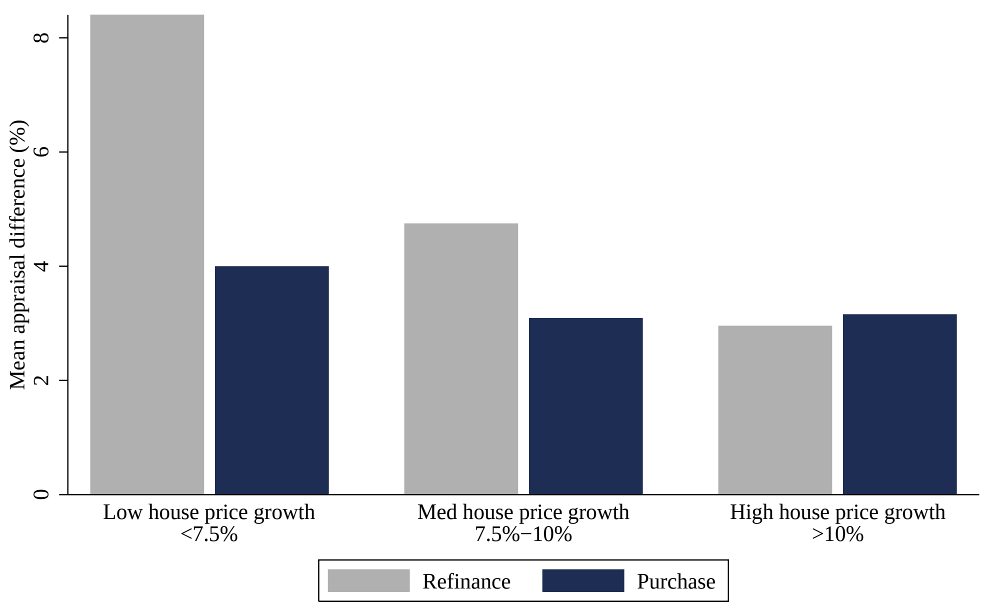
This figure plots the mean appraisal difference and the fraction of loans with an appraisal difference greater than zero for refinance loans and purchase loans by year. Appraisal difference is defined as the difference between appraised value and AVM value, divided by the average of both values.

Figure 2. Cross-sectional description of appraisal differences

Panel A: Credit score

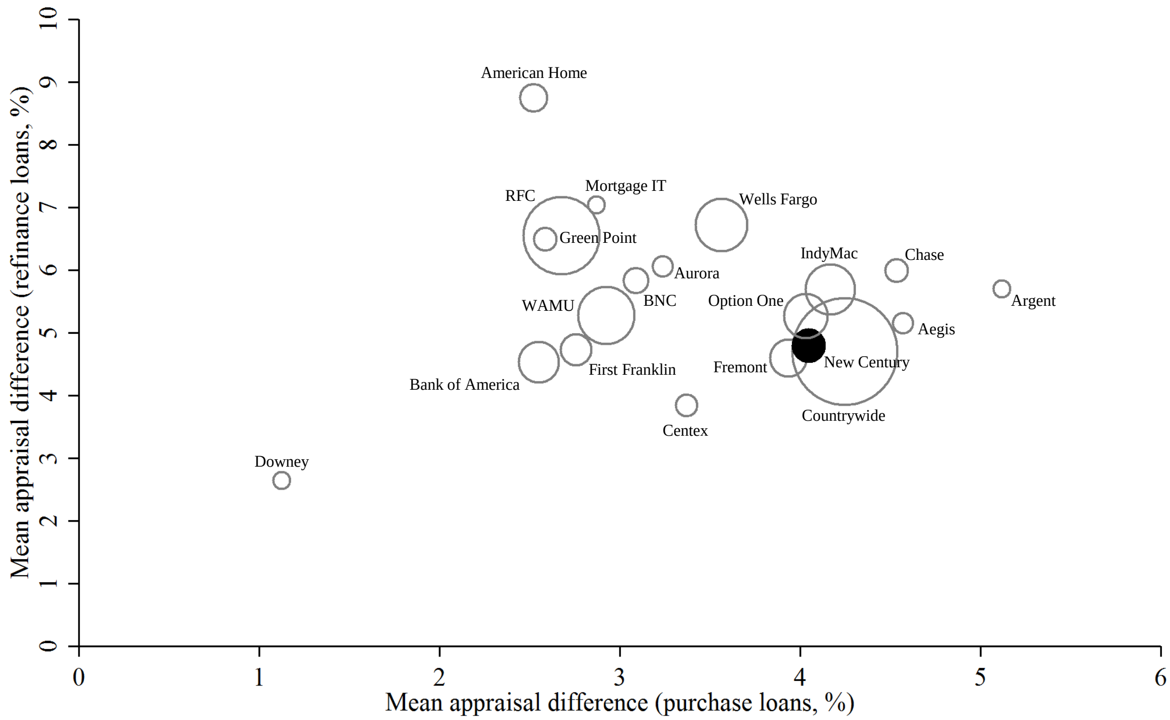


Panel B: Past house price growth



This figure plots the average appraisal difference by credit score at origination and zip code-level house price growth from 2001 to 2007 (from Zillow). Appraisal difference is defined as the difference between appraised value and AVM value, divided by the average of both values.

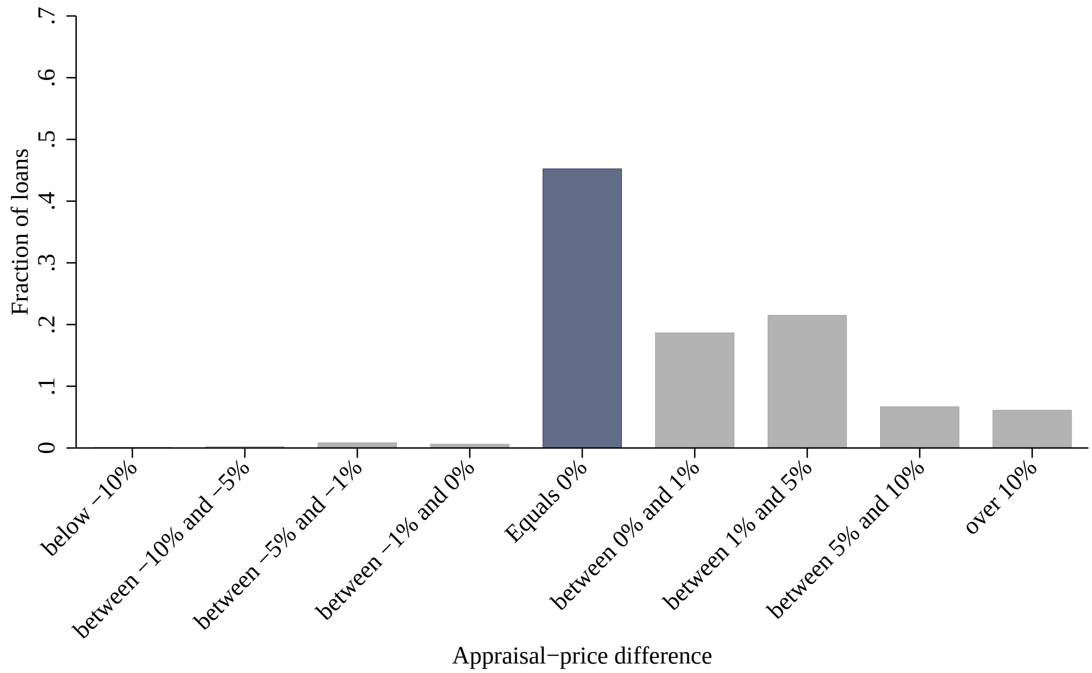
Figure 3. Appraisal difference by loan originator



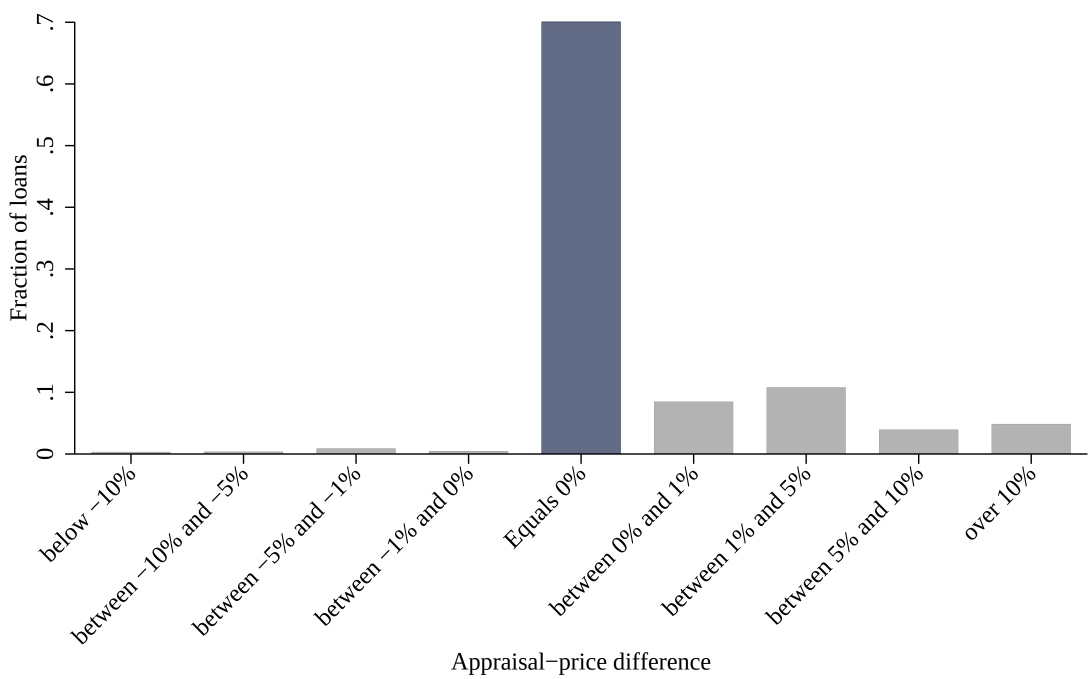
This figure plots average refinance and purchase loan appraisal differences by loan originator for the top-20 originators. The size of the circles represents number of originations in the sample.

Figure 4. Appraisal values of New Century purchase loans and unfunded purchase loan applications

Panel A: Purchase loans



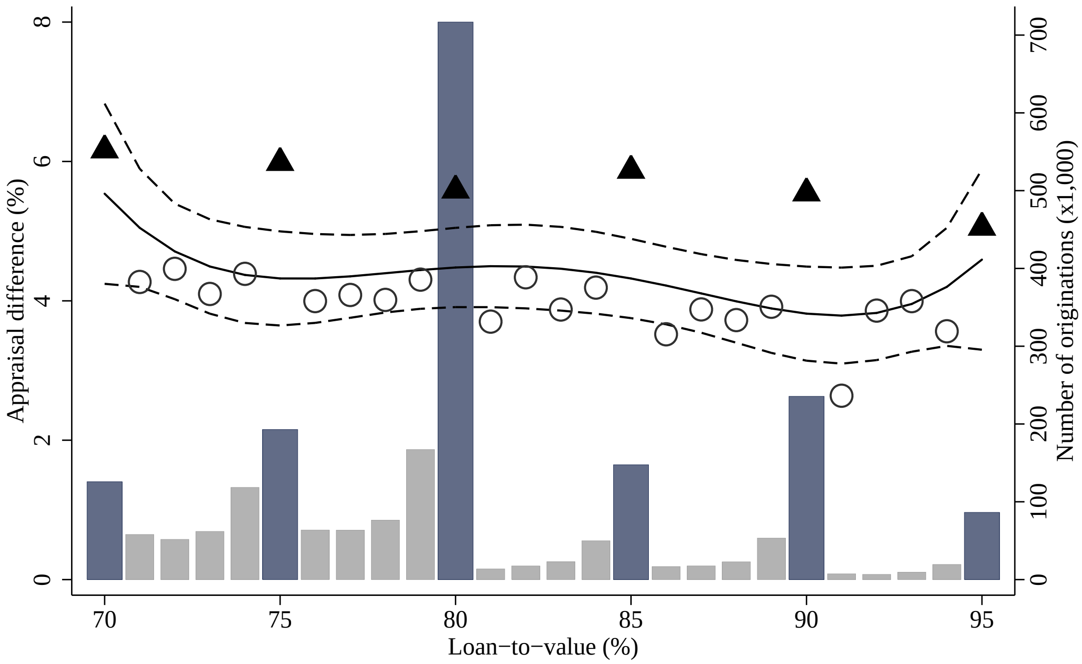
Panel B: Unfunded purchase loan applications



Panels A and B plot the fraction of New Century purchase loans by appraisal value relative to purchase price and the fraction of unfunded purchase loan applications by appraisal value relative to purchase price, respectively. The dark blue bar highlights appraisals that are equal to purchase prices. Data comes from New Century's internal records. Appraisal-price difference is the difference between New Century's (internal data) appraisal and the property's purchase price divided by the purchase price.

Figure 5. LTV ratio clustering of refinance loans

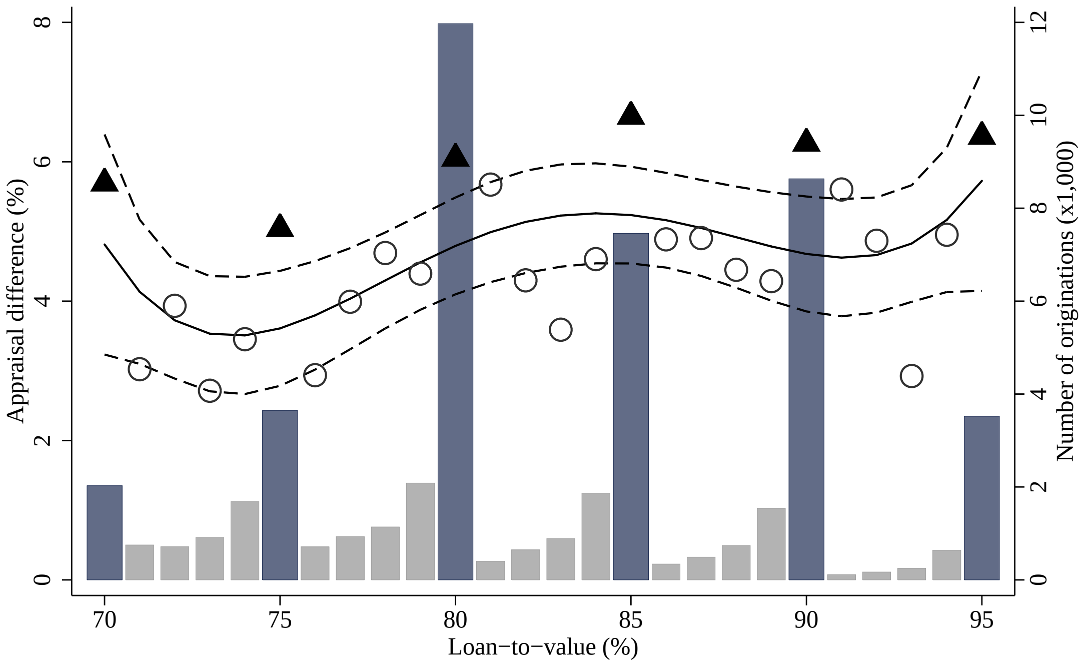
Panel A: All refinance loans



Panels A and B plot number of observations and the mean appraisal difference for refinance loans by LTV ratio using the full sample of ABSNet loans and the subsample comprised by those loans originated by New Century, respectively. Loans at five-unit LTV ratios are required to have LTV ratios exactly equal to those values. The bars show the number of loan originations by LTV ratio. Dark blue bars highlight originations at five-unit LTV ratios. The circles and triangles show mean appraisal differences. Triangles highlight mean appraisal differences at five-unit LTV ratios. The black line fits a fourth-order polynomial for appraisal difference and the dashed lines delimit the 95% confidence interval. Panel C plots the number of unfunded refinance loan applications by LTV ratio in New Century's internal records.

Figure 5 (continued). LTV ratio clustering of refinance loans

Panel B: New Century refinance loans



Panel C: New Century unfunded refinance applications

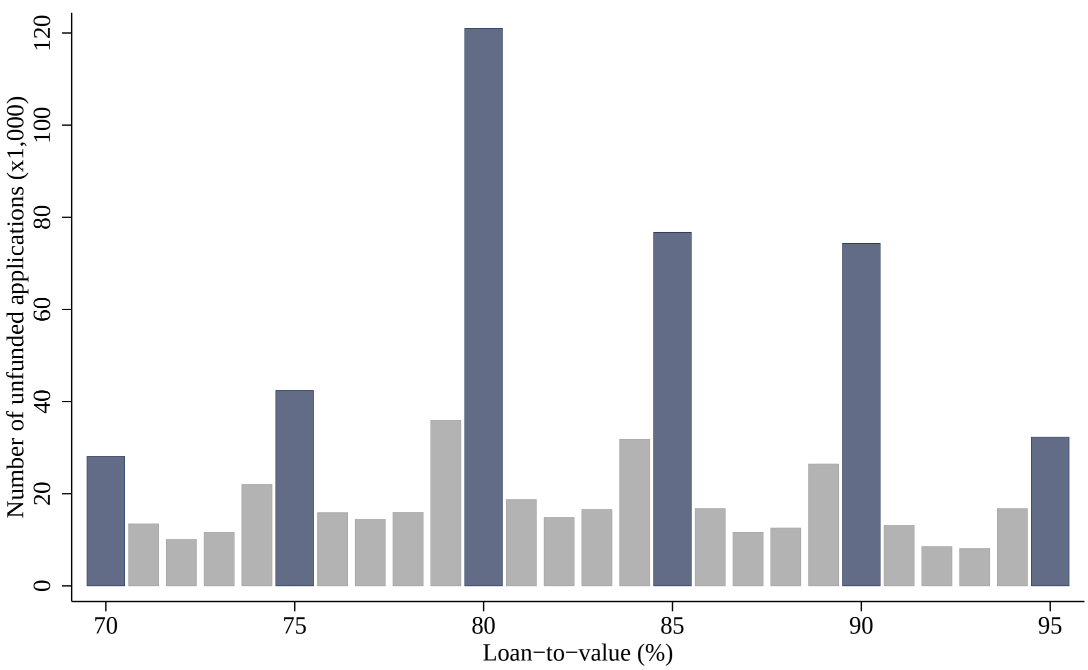
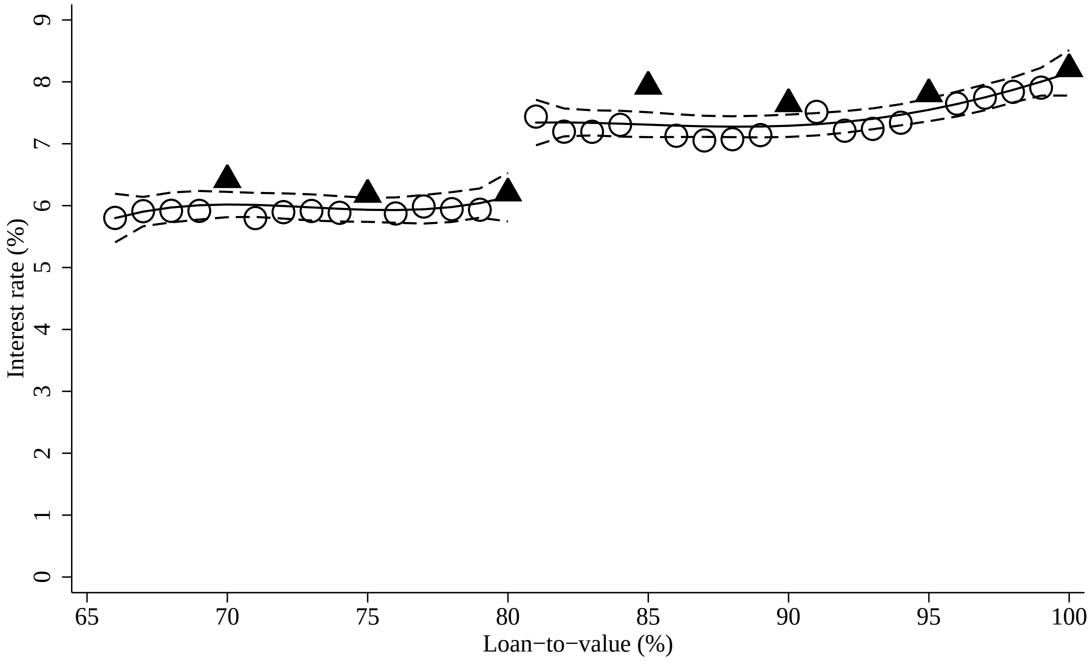


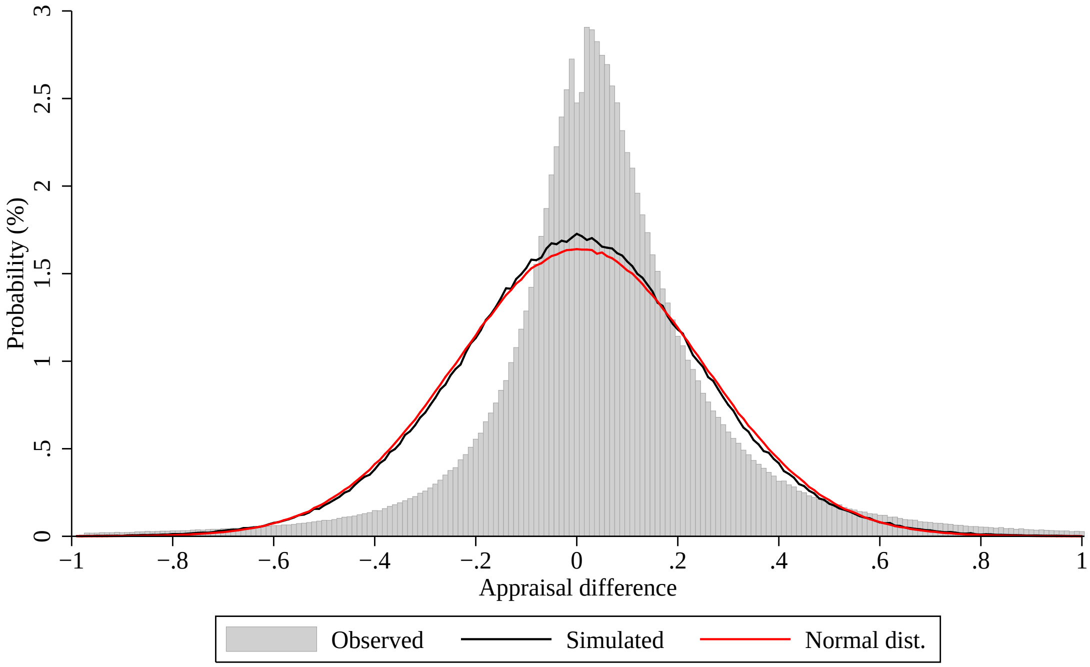
Figure 6. **Interest rates of refinance loans**



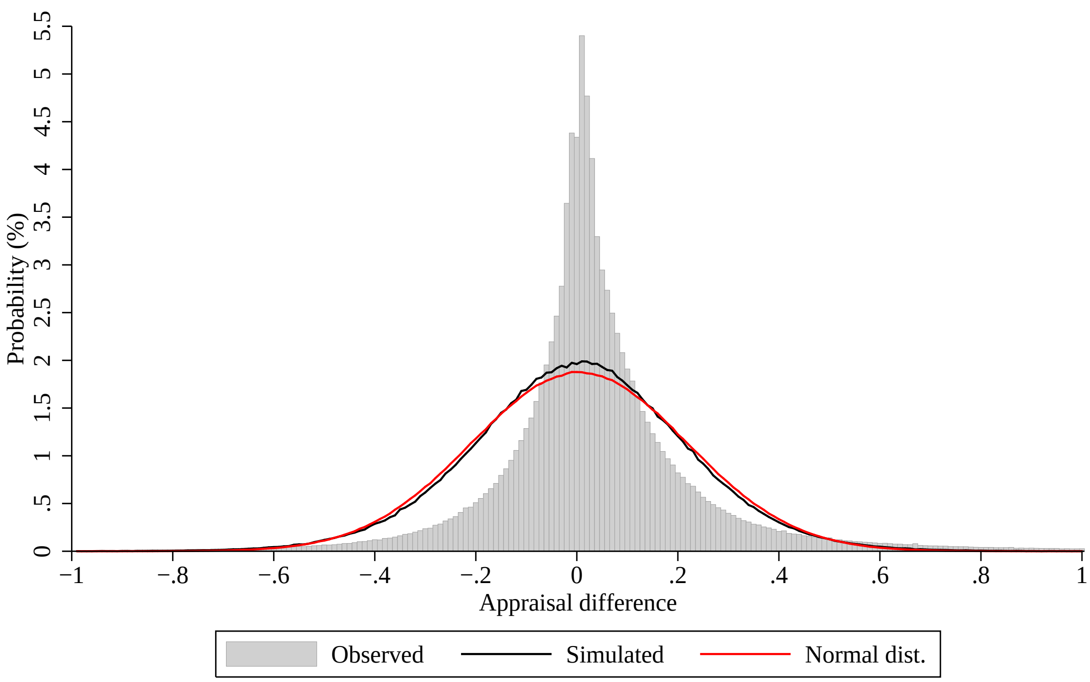
This figure plots interest rates at origination for refinance loans by LTV ratio, respectively. Loans at five-unit LTV ratios are required to have LTV ratios exactly equal to those values. Triangles highlight delinquency probabilities and mean interest rates at five-unit LTV ratios. The black line fits a fourth-order polynomial and the dashed lines delimit the 95% confidence interval.

Figure 7. Probability distribution of appraisal differences

Panel A: Refinance loans

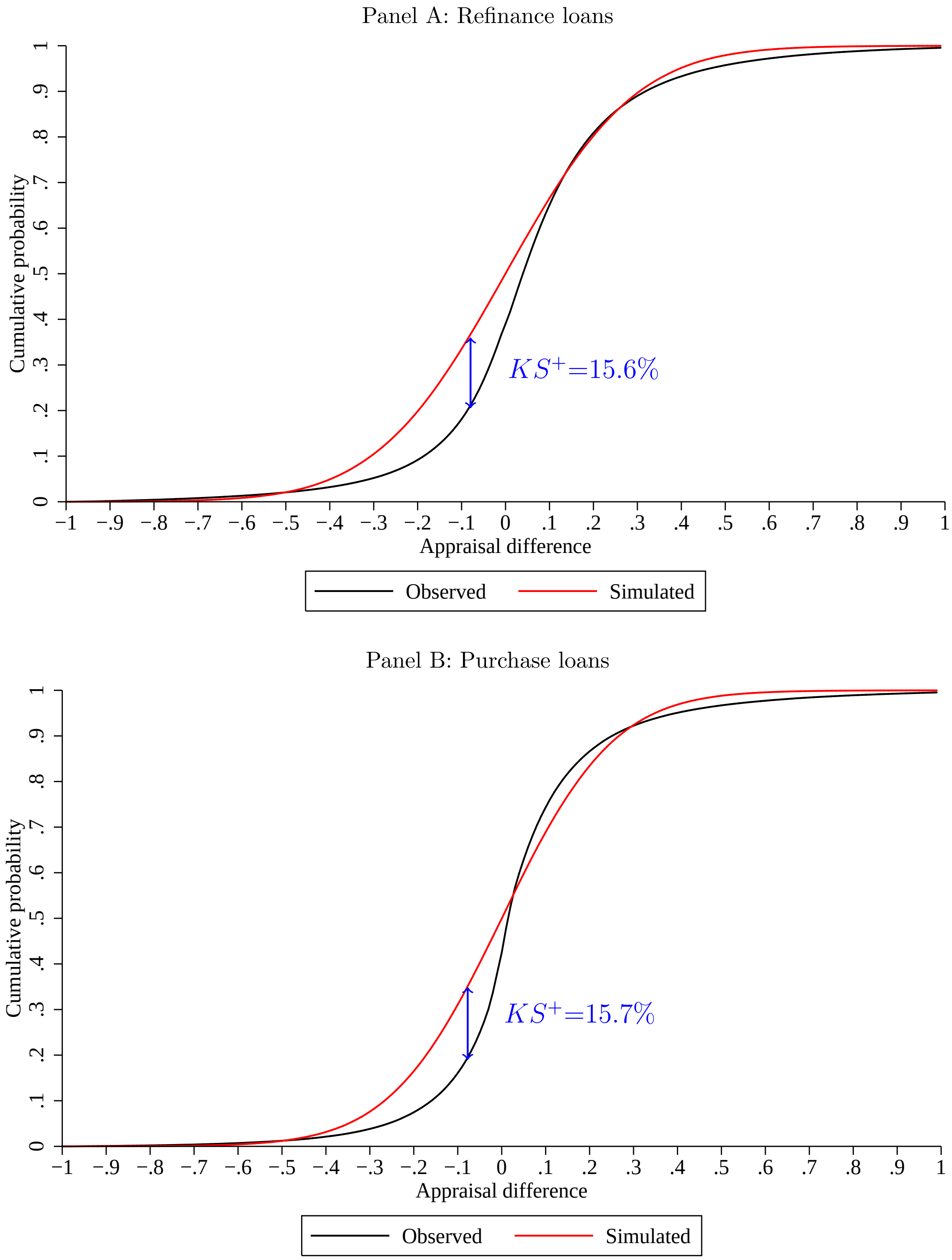


Panel B: Purchase loans



This figure plots histograms of appraisal differences for refinance and purchase loans. The observed frequencies are compared to bias-free simulated appraisal difference probability distribution functions and to normal distributions with means of zero and standard deviations equal to those of the data. In the simulations, appraisal and AVM values are modelled as bivariate normal random variables with means of zero and correlations of 0.25 and 0.5 respectively for refinance and purchase loans. We calibrate the standard deviations of Appraisal and AVM such that the simulated appraisal difference standard deviations for refinance and purchase loans match their empirical counterparts.

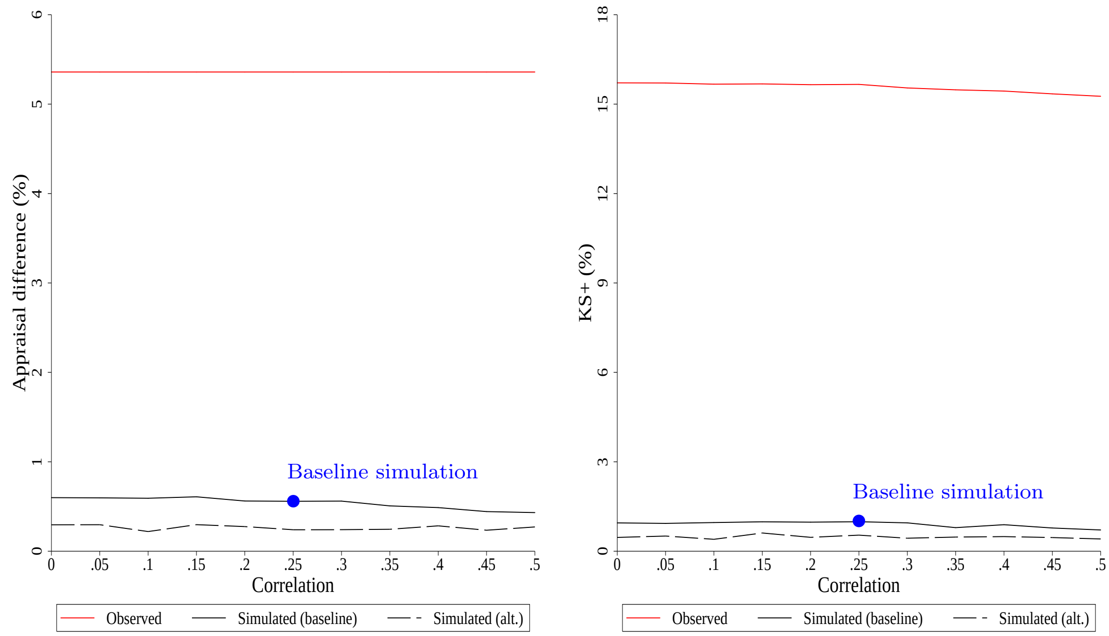
Figure 8. Cumulative distribution of appraisal differences



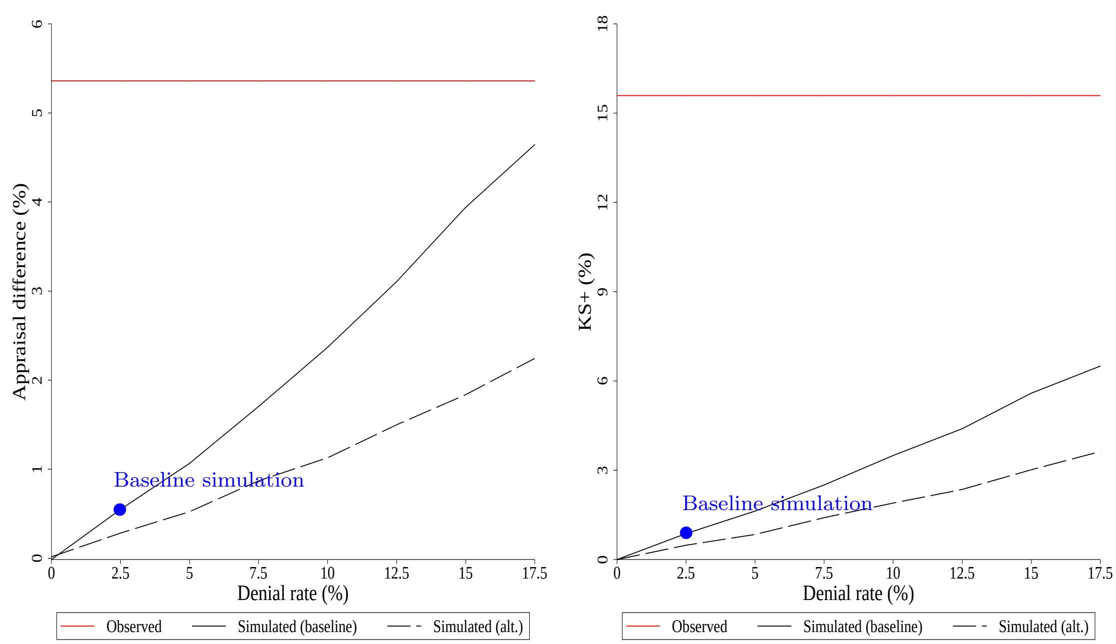
This figure plots empirical and bias-free simulated distribution functions of appraisal differences for refinance and purchase loans. Appraisal and AVM values are modelled as bivariate normal random variables with means of zero and correlations of 0.25 and 0.5 respectively for refinance and purchase loans. We calibrate the standard deviations of Appraisal and AVM such that the simulated appraisal difference standard deviations for refinance and purchase loans match their empirical counterparts. KS^+ measures the maximum difference between the distributions.

Figure 9. Simulation sensitivity analysis for refinance loans

Panel A: Sensitivity with respect to error correlations



Panel B: Sensitivity with respect to denial rates



This figure plots refinance simulation results under different assumptions regarding error correlations and denial rates. In the alternative simulations, we change the threshold for 100% origination probability from $A \geq V$ to $A \geq 1.25V$ while keeping the same linear structure for loan completion probability when appraisals are below the $1.25V$ threshold. Appraisal difference is defined as the difference between appraised value and AVM value, divided by the average of both values. KS^+ measures maximum difference from the bias-free simulated distributions. Because KS^+ is computed relative to the bias-free simulation, observed KS^+ changes slightly across the correlation scenarios in Panel A.

Figure 10. Appraisal difference distribution of loan officers, mortgage brokers, and appraisers

This figure summarizes mean appraisal differences across loan officers, mortgage brokers, and appraisers. Individuals are included if they were involved with at least 25 loans in the merged New Century data between 2001 and 2007. The boxes plot mean appraisal difference medians and quartiles, and the lines represent 10^{th} and 90^{th} percentiles.

Table 1. General sample summary statistics

	All loans N = 5,934,938		Refinance loans N = 3,662,156		Purchase loans N = 2,272,782	
Variables	Mean	SD	Mean	SD	Mean	SD
Appraisal bias measures						
Appraisal difference (AD) (%)	4.69	23.2	5.36	24.3	3.62	21.3
AD≥0 (d,%)	59.7	-	61.0	-	57.6	-
Loan/borrower characteristics						
Purchase loan (d,%)	38.3	-	-	-	-	-
Loan amount ($000s)	290.3	188.1	291.9	186.0	287.9	191.4
FICO score	673.7	72.7	661.8	75.3	692.9	63.8
LTV (%)	75.9	13.3	72.9	14.3	80.8	9.6
ARM (d,%)	66.7	-	63.4	-	71.9	-
Full documentation (d,%)	44	-	47.2	-	38.7	-
Prepayment penalty (d,%)	37.4	-	38.5	-	35.7	-
Owner occupied (d,%)	86.3	-	89.4	-	81.4	-
Complex (d,%)	11.2	-	13.2	-	8.0	-
Interest rate (%)	6.5	2.2	6.4	2.3	6.6	2.0
Loan performance						
Delinquent 90+ before Sep. 2012 (d,%)	32.9	-	30.2	-	37.3	-
HMDA denial rates (zip code level)						
Denial due to collateral (%)	2.2	1.4	2.5	1.5	1.7	1.2
Denial due to collateral or withdrawal (%)	15.2	5.0	17.5	4.5	11.3	3.1
Denial for any reason (%)	18.9	7.6	21.4	7.5	15.0	5.9
Geographic characteristics (zip code level)						
Average household income ($000s)	54.8	35.9	55.0	36.0	54.4	35.7
Population density (habitants/SqMile)	3,963	5,865	4,062	5,409	3,803.8	6,529.7
House price change 1 year before (%)	13.9	11.2	13.9	11.1	11.2	11.2

This table reports summary statistics for the general sample of U.S. non-agency securitized mortgages from ABSNet. The sample consists of first-lien loans originated between 2001 and 2007 used for purchase or refinancing with original loan balances between $30k and $1 million. Loans with original LTV ratios over 103% or with CLTV ratios below 25%, as well as loans reported as being for homes of over one unit are excluded. FHA and VA loans are also dropped. Finally, all of the relevant variables associated with the loans are required to be nonmissing, and we exclude loans with appraisals that are less than 33% or more than 300% of, or exactly equal to the property's AVM valuation. Appraisal difference (AD) is defined as the difference between appraised value and AVM value, divided by the average of both values.

Table 2. New Century sample summary statistics

	Refinance loans N = 664,137		Purchase loans N = 307,738	
Variables	Mean	SD	Mean	SD
Appraisal bias measures				
Appraisal-price difference (%)	-	-	2.4	20.7
Appraisal-price difference≥0 (d,%)	-	-	98.2	-
AD (%,only available for the merged sample)	4.9	22.5	4.0	21.7
AD≥0 (d,%,only available for the merged sample)	62	-	56.7	-
Loan/borrower characteristics				
Loan amount ($000)	187.5	120.3	205.7	130.3
LTV (%)	77.5	12.7	83.0	8.2
ARM (d,%)	66.3	-	78.6	-
Prepayment penalty (d,%)	73.4	-	69.4	-
Owner occupied (d,%)	93.9	-	87.8	-
Interest rate (%)	7.8	1.4	7.7	1.3

This table presents summary statistics for the sample of funded loans from New Century internal records. The sample consists of first-lien loans originated between 2001 and 2007 used for purchase or refinancing with original loan balances between $30k and $1 million. Loans with original LTV ratios over 103% or with CLTV ratios below 25%, as well as loans reported as being for homes of over one unit are excluded. FHA and VA loans are also dropped. Appraisal-price difference is the difference between appraisal and the property's purchase price divided by the purchase price. Appraisal difference (AD) is the difference between appraised value and AVM value, divided by the average of both values, and is computed using New Century-ABSNet merged data.

Table 3. New Century appraisal bias

	Reported ABSNet Appraisals		Internal NC Appraisals		
	Mean AD	Excess Positive AD	Mean AD	Excess Positive AD	*N*
Overall	4.0%	6.7%	6.1%	12.5%	16,995
Appraisal-Price Difference:					
Below -10%	1.4%	2.6%	3.8%	2.6%	19
Between -10 and -5%	2.0%	9.5%	3.2%	9.5%	42
Between -5 and -1%	5.3%	6.1%	5.4%	6.1%	180
Between -1 and 0%	4.6%	7.5%	4.7%	8.3%	127
Equals 0%	5.7%	11.2%	5.8%	11.2%	7,987
Between 0 and 1%	5.2%	11.0%	5.5%	12.7%	3,050
Between 1 and 5%	3.1%	4.2%	5.4%	13.3%	3,429
Between 5 and 10%	1.5%	-4.6%	8.0%	16.8%	1,125
Over 10%	-7.9%	-20.0%	10.4%	16.8%	1,036

This table reports mean appraisal differences for New Century purchase loans by appraisal value relative to purchase price in the New Century-ABSNet merged data. Appraisal difference (AD) is defined as the difference between appraised value and AVM value, divided by the average of both values. Appraisal differences for New Century loans are calculated based on both reported loan-level data (from ABSNet) and internal loan-level data (from New Century). Appraisal-price difference is the difference between New Century's (internal data) appraisal and the property's purchase price divided by the purchase price.

Table 4. Reported LTVs vs. AVM-based LTVs

Panel A: Loan-to-value ratios

	Refinance N=3,662,156		Purchase N=2,272,782	
	Reported LTV	AVM-based LTV	Reported LTV	AVM-based LTV
Mean (%)	72.9	79.3	80.8	85.6
Median (%)	75.9	78.0	80.0	81.0
% of loans with LTV over:				
80%	21.2	45.4	22.5	53.9
90%	4.9	26.0	11.5	27.8
100%	0.06	14.2	0.2	14.5

Panel B: Combined loan-to-value ratios

	Refinance N=3,662,156		Purchase N=2,272,782	
	Reported CLTV	AVM-based CLTV	Reported CLTV	AVM-based CLTV
Mean (%)	74.2	80.8	86.4	91.5
Median (%)	77.2	79.0	88.6	88.4
% of loans with CLTV over:				
80%	28.6	47.9	52.9	67.6
90%	8.5	29.6	36.4	46.0
100%	0.08	16.8	0.3	25.1

This table describes reported and AVM-based LTV and CLTV ratios for refinance and purchase loans. Reported LTV and CLTV ratios are from ABSNet data. AVM-based LTV and CLTV ratios are calculated by dividing original loan amounts and combined loan amounts by AVM valuations.

Table 5. Appraisal bias and loan performance and pricing

	Delinquent			Interest rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Mean (%)	30.2	30.2	30.2	6.4	6.4	6.4
AD	5.450***		3.499***	0.016		-0.024*
	(0.332)		(0.355)	(0.012)		(0.014)
Even LTV		9.385***	4.191***		0.186***	0.183***
		(0.250)	(0.161)		(0.008)	(0.008)
AD×Even LTV			4.080***			0.068***
			(0.515)			(0.019)
			(0.536)			(0.019)
Controls	yes	yes	yes	yes	yes	yes
CBSA×Quarter FE	yes	yes	yes	yes	yes	yes
N	3,662,156	3,662,156	3,662,156	3,662,156	3,662,156	3,662,156
R^2	0.27	0.26	0.27	0.67	0.67	0.67

Columns (1) to (3) report results from OLS regressions where the dependent variable is a dummy variable that takes the value of one if the loan became more than 90 days delinquent at any point in time between origination and September 2012, and zero otherwise. The explanatory variables of interest are the loan's appraisal difference and an indicator for even LTV. Control variables include indicators for full-doc loans, the presence of a prepayment penalty, owner occupied properties, complex loans, adjustable-rate loans, as well as credit score, loan amount, LTV, interest rate at origination, and an interaction term between interest rate and the adjustable rate indicator. Columns (4) to (6) report results from OLS regressions where the dependent variable is the loan interest rates at origination. The regression specifications are the same as in columns (1) to (3) except that interest rate is not a control variable (because it is the dependent variable) and an additional control variable indicator for LTV ratios above 80 is included. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by CBSA. ***$p<0.01$, **$p<0.05$, *$p<0.1$. *$p<0.1$.

Table 6. Appraisal bias and RMBS pool performance and pricing

	Losses		Yield spread		Subordination	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean (%)	20.4	20.5	0.29	0.30	12.0	12.4
Average AD	36.978***		0.054		1.769	
	(10.367)		(0.139)		(4.764)	
Percentage Even LTV		15.324***		0.039		2.515*
		(3.027)		(0.048)		(1.310)
Controls	yes	yes	yes	yes	yes	yes
Underwriter FE	yes	yes	yes	yes	yes	yes
Deal year FE	yes	yes	yes	yes	yes	yes
N	694	517	694	517	694	517
R^2	0.81	0.83	0.56	0.53	0.84	0.86

This table reports results of RMBS pool-level OLS regressions. Columns (1) and (2) report results from regressions where the dependent variable is the pool-level cumulative realized loss as of September 2014 as a percent of the pool's original balance. The explanatory variables of interest are the pool's mean appraisal difference and the pool's percentage of refinance loans with even LTVs. Control variables are average FICO score, average CLTV ratio, percentage of loans with low or no documentation, and percentage of loans that are refinance. Columns (3) and (4) report results from OLS regressions where the dependent variable is yield spread. Yield spreads are average floating rate interest margins across all of the securities supported by the pool. Columns (5) and (6) report results from OLS regressions where the dependent variable is AAA subordination. AAA subordination is the fraction of the security balance in the pool that is subordinated to the AAA securities. The regression specifications are the same as in columns (1) and (2) except that an additional control for overcollateralization is included. Overcollateralization is based on the difference between subordination and total credit support. All regressions include deal year fixed effects and underwriter fixed effects for the top six underwriters in our sample. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by deal. ***$p<0.01$, **$p<0.05$, *$p<0.1$. *$p<0.1$.

Table 7. Baseline simulation results

	Refinance loans			Purchase loans		
	Mean AD	Excess positive AD	KS^{+}	Mean AD	Excess positive AD	KS^{+}
Data	5.36	10.98	15.59	3.62	7.56	15.67
Bias-free simulation	-0.04	-0.05	0	0.01	0.08	0
Selection bias simulation	0.57	0.79	0.87	0.27	0.47	0.74

This table reports mean appraisal differences (AD), excess positive appraisal differences, and KS^{+} statistics for the baseline bias-free and the baseline selection bias simulations for refinance and purchase loans. Appraisal and AVM errors are modeled as bivariate normal random variables with means of zero, equal error standard deviations, and correlations of 0.25 and 0.5 respectively for refinance and purchase loans. We calibrate the standard deviations of Appraisal and AVM such that simulated appraisal difference standard deviations for refinance and purchase loans match their empirical counterparts. To model selection, we assume that loan completion probability is one if an appraisal is above the property's true value and is otherwise $max(0, 1 - \beta(V - max(0, A))/V)$, where V represents the property's true value and can be normalized to one. The parameter β is calibrated such that the simulation generates targeted denial rates of 2.5% for refinance loans and 1.7% for purchase loans, which are based on observed HMDA collateral denial rates. Excess positive appraisal difference measures the amount of appraisals that are higher than the AVM in excess of 50% and KS^{+} measures the maximum differences from the bias-free simulated distributions.

Table 8. Appraisal bias persistence of loan officers, mortgage brokers, and appraisers

	(1)	(2)	(3)
Mean appraisal difference	0.049	0.048	0.052
Loan Officer Lagged AD	0.004**		
	(0.002)		
Broker Lagged AD		0.014***	
		(0.003)	
Appraiser Lagged AD			0.024**
			(0.012)
Control Variables	Yes	Yes	Yes
CBSA×Quarter FE	Yes	Yes	Yes
N	35,737	6,728	1,507
R^2	0.117	0.159	0.116

This table reports results from OLS regressions where appraisal difference is the dependent variable and the independent variables of interest are lagged mean appraisal differences by loan officers, brokers, and appraisers. Lagged appraisal difference is calculated over the previous twelve quarters with the requirement that there be at least 25 observations. Coefficients are standardized to reflect one-standard-deviation changes in the explanatory variables. Control variables include indicators for full-doc loans, the presence of a prepayment penalty, owner occupied properties, complex loans, adjustable-rate loans, as well as credit score, loan amount, LTV, and interest rate at origination. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by CBSA. ***p <0.01, **p <0.05, *p <0.1.

Internet Appendix For "Collateral Misreporting in the RMBS Market"

A. New Century-ABSNet matching description

We merge funded first-lien loans associated with single-unit properties in New Century data with those loans in ABSNet whose originator is either New Century Mortgage Corporation or its subsidiary, Home123 Corporation. We keep loans for which the lien position or the number of units in the underlying property are missing. This results in initial samples of 952,289 loans in the New Century data and 577,899 loans in ABSNet. We first match the loans based on their zip code, first payment date, interest rate type (fixed- or adjustable-rate mortgage), and purpose of transaction (purchase or refinance). Second, we require the New Century's status date to be within 30 days from the loan origination date in ABSNet, and loan amounts and credit scores to be within a $1,000 and 10 points, respectively. Third, we only consider the remaining loan pairs a match when it is unique. This procedure results in 363,623 unique matches, which represents 38.2% on the initial New Century data sample. Restricting the sample based on the criteria described in Section 1.1 results in a sample of 70,325 matched loans, which are described in Table IA.**2**.

To confirm the accuracy of our matching procedure, we repeat the matching exercise with all loans in ABSNet regardless of their originator. Using this methodology, we match 468,676 pairs of loans. Of the 363,623 pairs that we obtained through the original matching, 363,434 (99.95%) coincide with those obtained through the less restrictive matching procedure, which provides reassurance about the accuracy of the database merge.

B. Pool selection and pool data calculation description

The unit of observation for our RMBS analysis is the RMBS deal pool, which is a pool of loans that support a specific set of securities within a RMBS deal. For deals with a "Y" structure, we conduct our analysis at the more general loan pool level corresponding to the subordinated securities. From the ABSNet loan data, we calculate pool-level average appraisal difference, percent of refinance loans with even LTV, and control variables, including average FICO score, average CLTV ratio, percentage of loans with low or no documentation, and percentage of loans that are refinance. Like Piskorski, Seru, and Witkin (2015), we restrict our sample to loan pools with at least 25% of loans in our loan sample. In addition, we only consider loan pools for which at least 95% of the underlying loans have both FICO score and CLTV ratio information. Our regressions also control for deal year and fixed effects for the top six underwriters in the sample. The remaining underwriters, which jointly correspond to 247 pools, are grouped together.

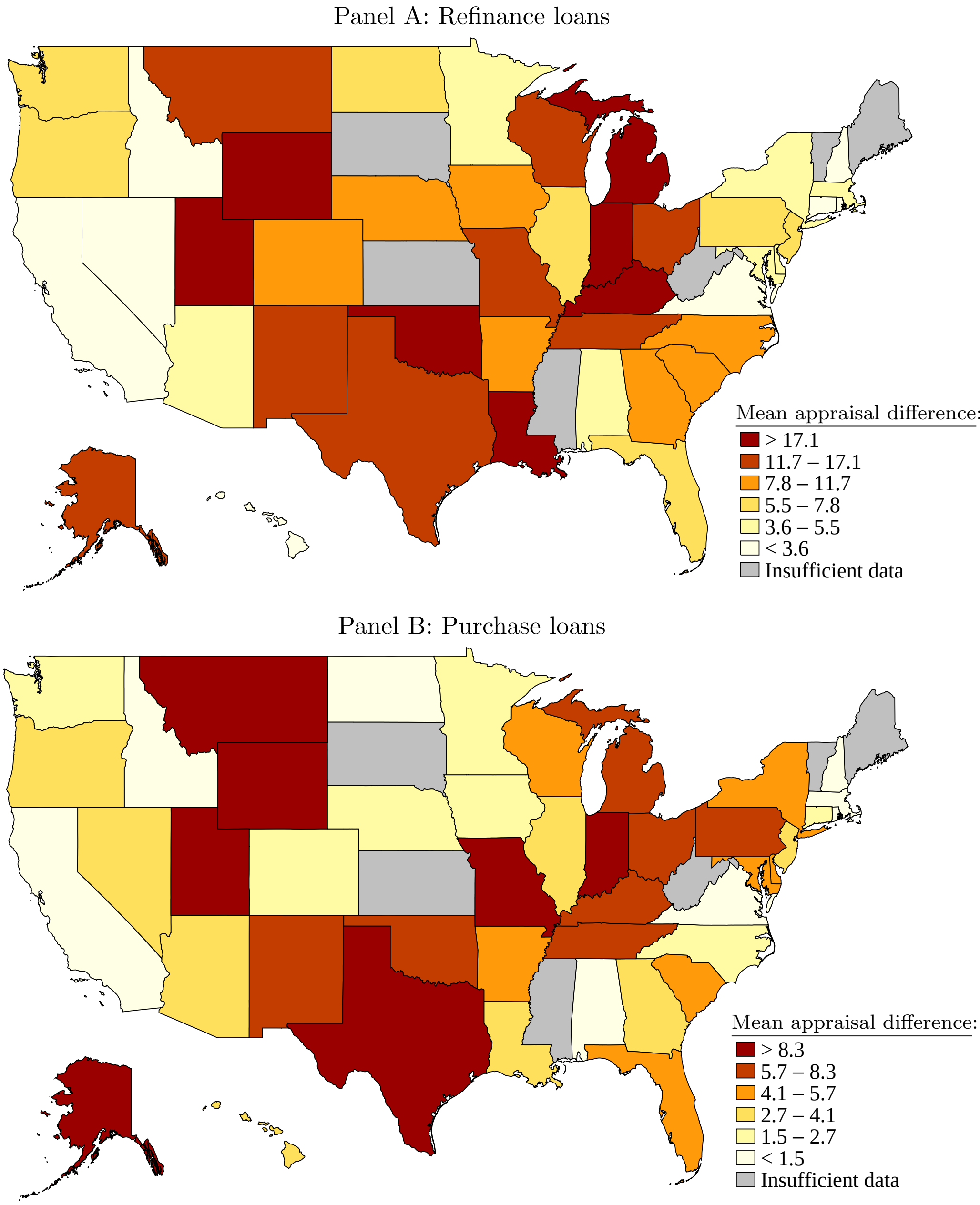
We use ABSNet pool and security data to calculate pool-level losses and pricing. Losses are pool-level cumulative realized losses as of September 2014 as a percent of the pool's original balance. Yield spreads are average floating rate interest margins across all of the securities supported by the pool. Because this data is limited to floating rate securities, we limit our analysis to pools in which at least 90% of pool security value comes from floating rate securities with available interest rate margin data. AAA subordination is the fraction of the security balance in the pool that is subordinated to the AAA securities. We calculate this as the minimum subordination of any AAA security in the pool. Security-level credit ratings come from Standard & Poor's, supplemented by Moody's. Because we need credit ratings for this calculation, we limit our analysis to pools in which we have credit ratings for at least 90% of the security value in the pool.

As a control variable, we also collect pool-level overcollateralization. Overcollateralization is based on the difference between subordination and total credit support. We also compute overcollateralization based on reported overcollateralization tranches with similar results.

To eliminate outliers and potential errors in the data, we drop pools with losses, yield spreads, or AAA subordination above the 95^{th} percentile and require pools to have data on all three outcome variables. This results in a sample of 694 loan pools, which come from 681 deals and contain 2.6 million underlying loans.

C. Supplemental figures and tables

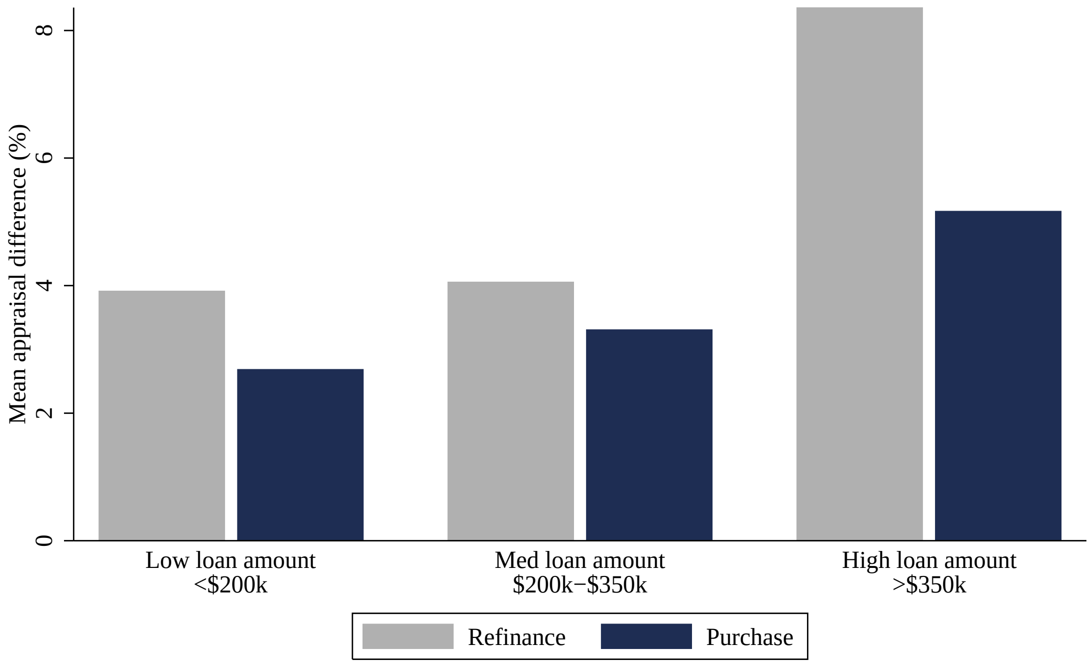
Figure IA.1. Geographic distribution of appraisal differences



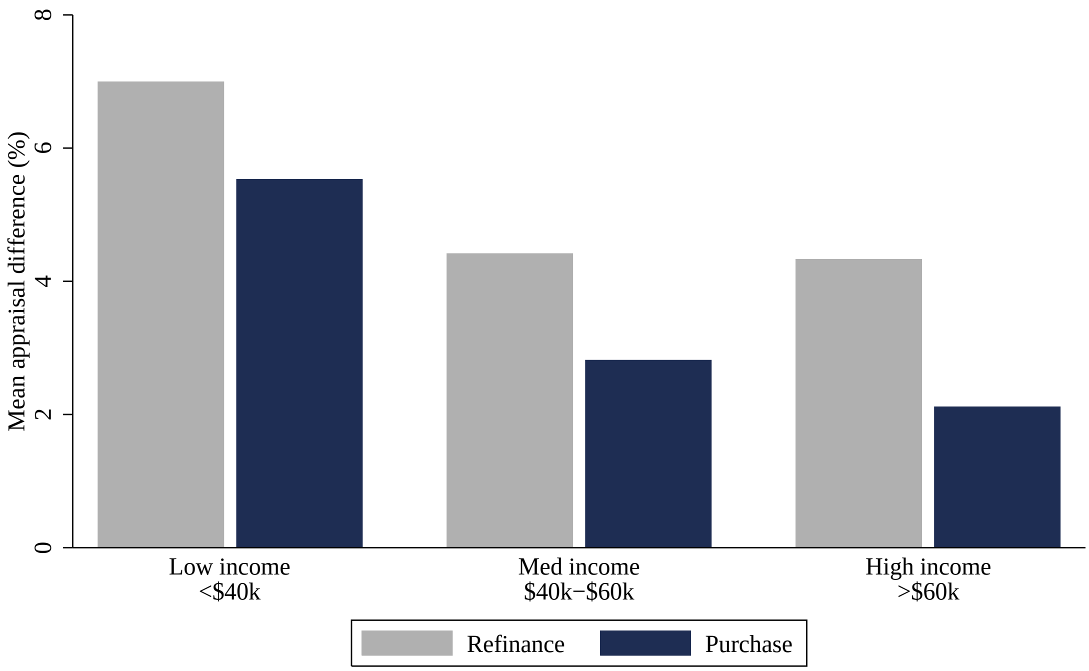
This figure plots average appraisal differences for refinance loans and purchase loans by state. Appraisal difference is defined as the difference between appraised value and AVM value, divided by the average of both values. States with less than one hundred observations are omitted.

Figure IA.2. **Additional cross-sectional description of appraisal differences**

Panel A: Loan amount



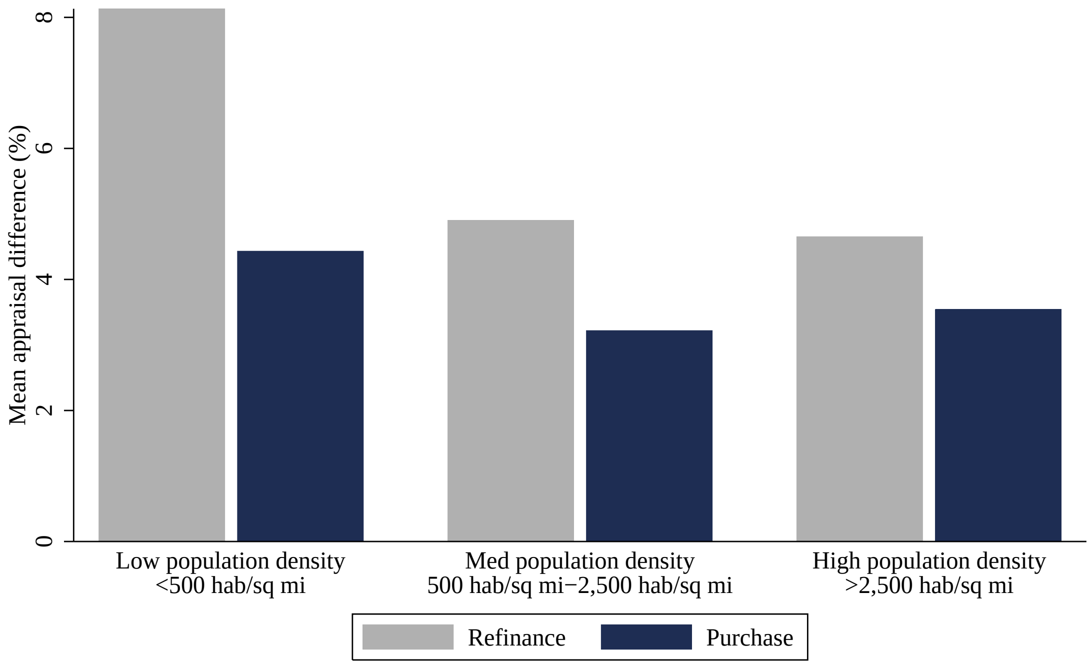
Panel B: Household income



This figure plots the average appraisal difference by loan amount, zip code-level income in 2001 (from the SOI IRS database), zip code-level population density (from the 2000 Decennial Census), and zip code-level house market liquidity (measured as the number of purchase transactions reported by DataQuick in the loan's zip code during the 12 months prior to loan origination month). Appraisal difference is the difference between appraised value and AVM value, divided by the average of both values.

Figure IA.2 (continued). Additional cross-sectional description of appraisal difference

Panel C: Population density



Panel D: House market liquidity

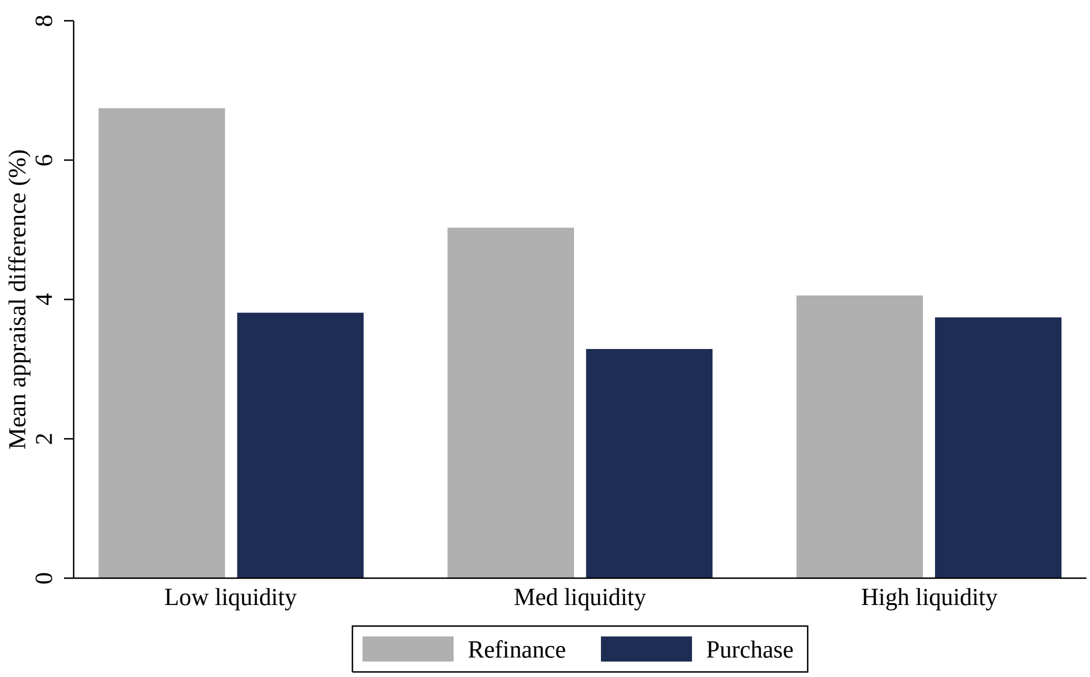
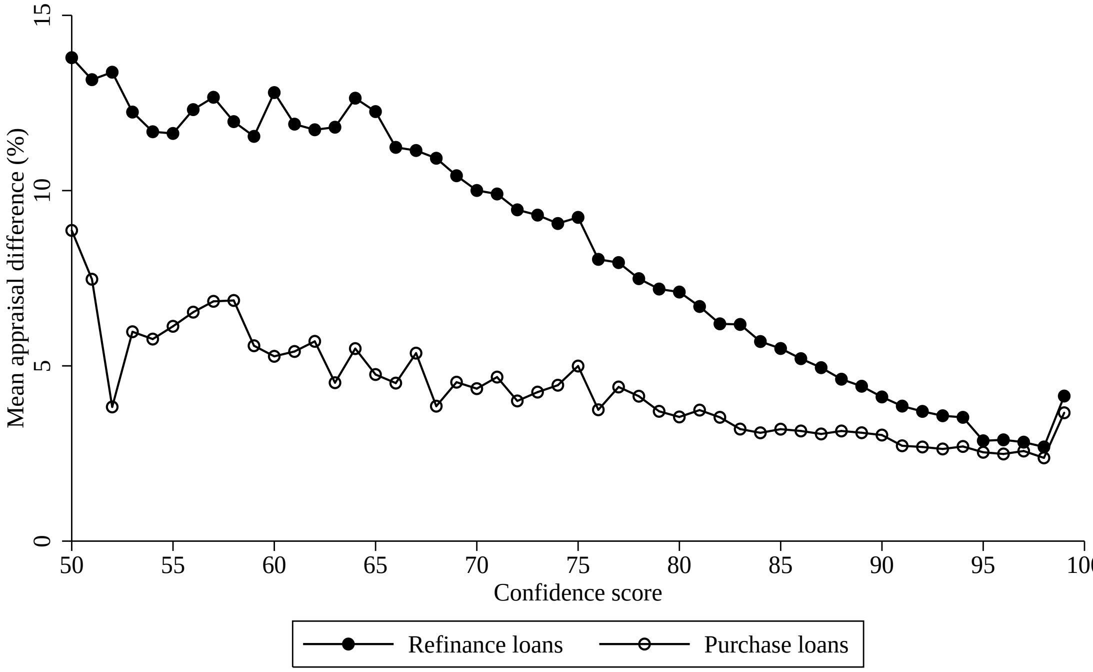
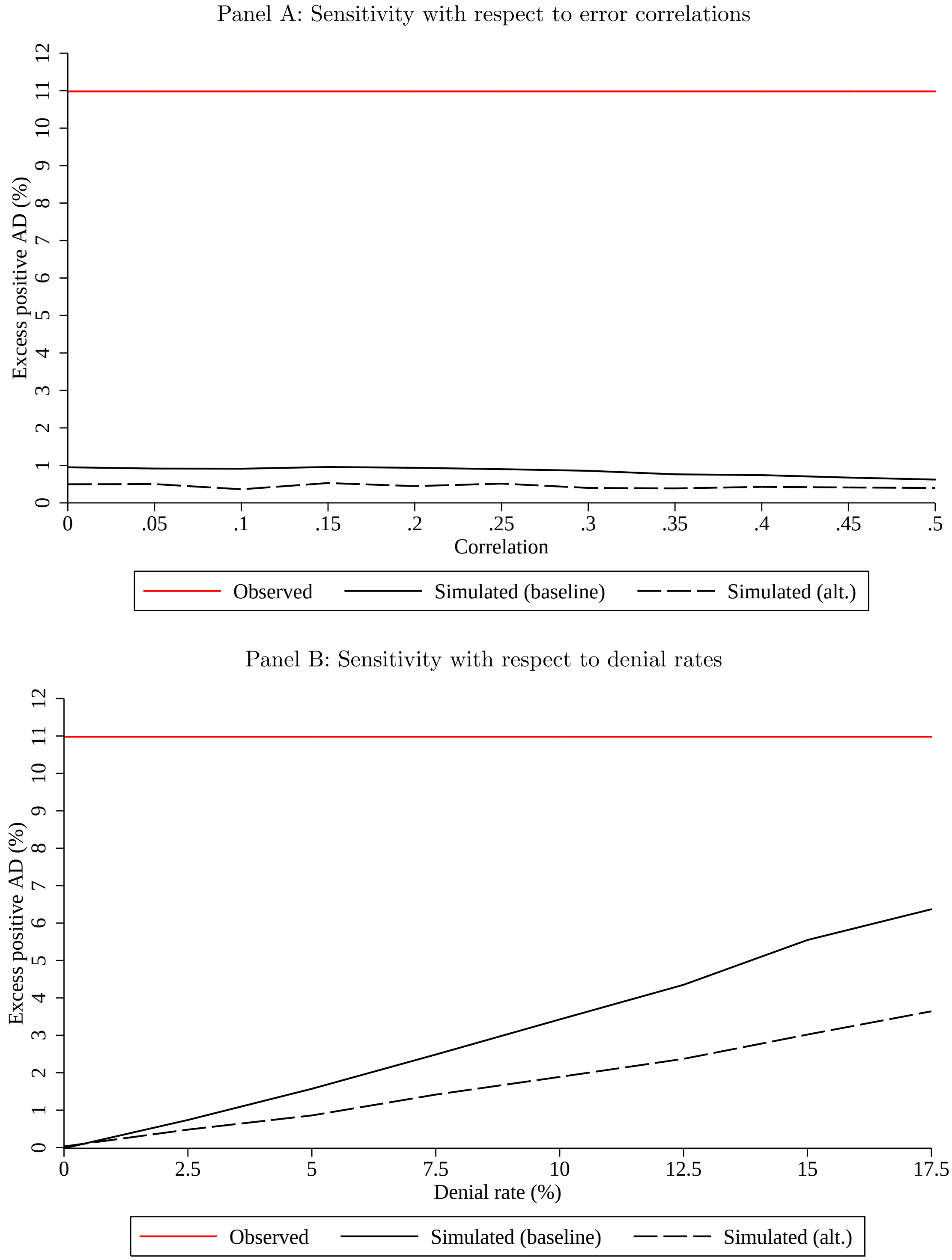


Figure IA.3. **Appraisal difference by confidence score**



This figure plots the mean appraisal difference for refinance loans and purchase loans by AVM confidence score. Appraisal difference is the difference between appraised value and AVM value, divided by the average of both values.

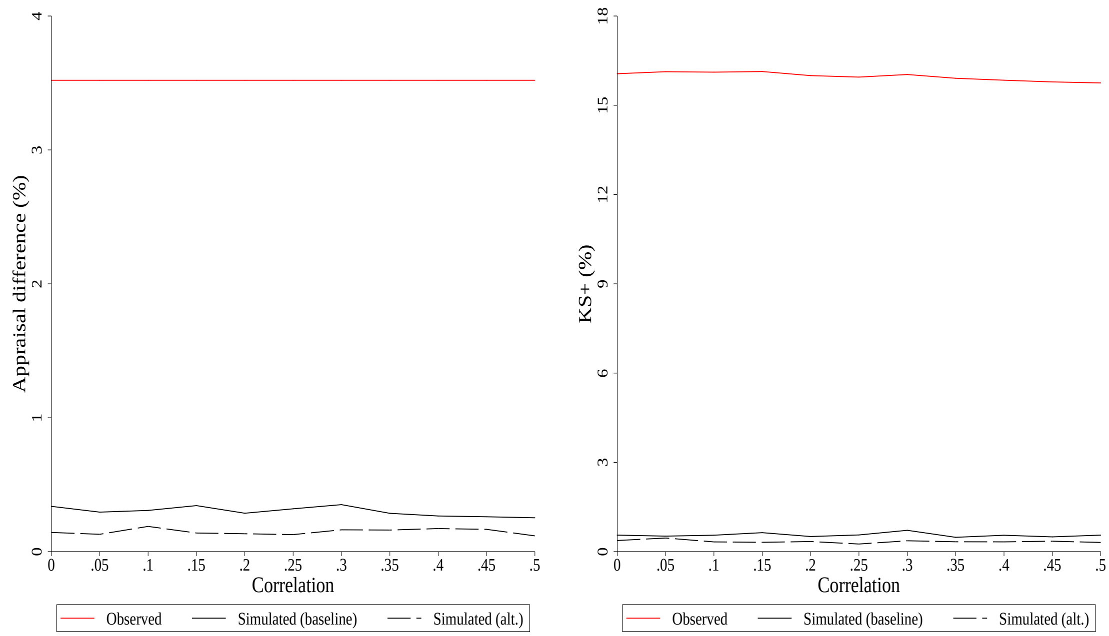
Figure IA.4. Simulation sensitivity analysis for refinance loans



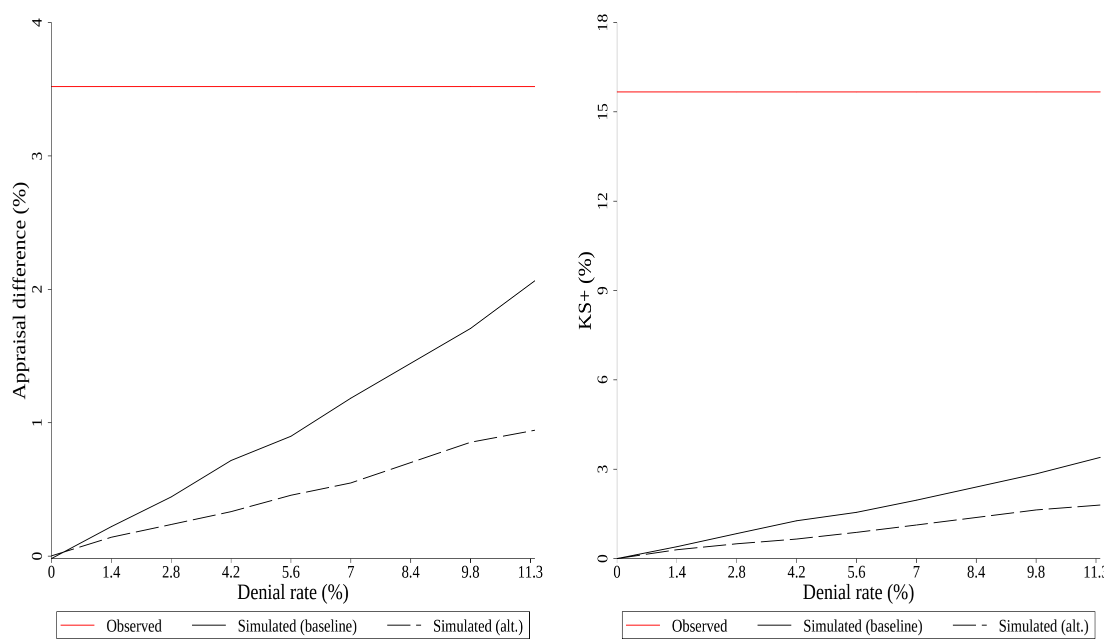
This figure plots refinance simulation results for excess positive AD under different assumptions regarding error correlations and denial rates. In the alternative simulations, we change the threshold for 100% origination probability from $A \geq V$ to $A \geq 1.25V$ while keeping the same linear structure for loan completion probability when appraisals are below the $1.25V$ threshold. Excess positive appraisal difference measures the amount of appraisals that are higher than the AVM in excess of 50%.

Figure IA.5. Simulation sensitivity analysis for purchase loans

Panel A: Sensitivity with respect to error correlations



Panel B: Sensitivity with respect to denial rates



This figure plots purchase simulation results under different assumptions regarding error correlations and denial rates. In the alternative simulations, we change the threshold for 100% origination probability from $A \geq V$ to $A \geq 1.25V$ while keeping the same linear structure for loan completion probability when appraisals are below the $1.25V$ threshold. Appraisal difference is defined as the difference between appraised value and AVM value, divided by the average of both values. KS^+ measures maximum difference from the bias-free simulated distributions. Because KS^+ is computed relative to the bias-free simulation, observed KS^+ changes slightly across the correlation scenarios in Panel A.

Table IA.1. New Century unfunded loan application summary statistics

	Refinance loans N = 976,737		Purchase loans N = 300,223	
Variables	Mean	SD	Mean	SD
Appraisal bias measures				
Appraisal-price difference (%)	-	-	2.0	20.4
Appraisal-price difference≥0 (d,%)	-	-	98.0	-
Loan/borrower characteristics				
Loan amount ($000)	172.8	124.8	201.5	143.4
LTV (%)	77.3	14.57	85.6	9.8
ARM (d,%)	65.5	-	78.5	-
Prepayment penalty (d,%)	71	-	72.1	-
Owner occupied (d,%)	95.8	-	79.7	-
Interest rate (%)	7.5	2.1	7.6	2.0

This table reports summary statistics for the sample of unfunded loan applications from New Century internal records. The sample consists of first-lien loan applications submitted between 2001 and 2007 for purchase or refinancing with original loan balances between $30k and $1 million. Loans with original LTV ratios over 103% or with CLTV ratios below 25%, as well as loans reported as being for homes of over one unit are excluded. FHA and VA loans are also dropped. Appraisal-price difference is the difference between appraisal and the property's purchase price divided by the purchase price.

Table IA.2. New Century-ABSNet merged data summary statistics

	All loans $N = 70{,}325$		Refinance loans $N = 53{,}330$		Purchase loans $N = 16{,}995$	
Variables	Mean	SD	Mean	SD	Mean	SD
Appraisal bias measures						
Appraisal difference (AD) (%)	4.63	22.3	4.85	22.5	3.96	21.7
AD>0 (d,%)	60.7	-	62.0	-	56.7	-
Loan/borrower characteristics						
Purchase loan (d,%)	24.2	-	-	-	-	-
Loan amount ($000s)	223.3	130.8	217.7	125.9	240.8	143.6
FICO score	608.8	59	598.5	56.3	641.3	56.6
LTV (%)	78.8	11.9	77.5	12.8	82.5	7.2
ARM (d,%)	74.5	-	70.5	-	87	-
Full documentation (d,%)	58.7	-	63.3	-	44.1	-
Prepayment penalty (d,%)	58	-	56.3	-	63.5	-
Owner occupied (d,%)	92.7	-	94.4	-	87.6	-
Complex (d,%)	0.003	-	0.000	-	0.012	-
Interest rate (%)	7.8	1.2	7.8	1.2	7.9	1.2
Loan performance						
Delinquent 90+ before Sep. 2012 (d,%)	48.9	-	44.6	-	62.5	-

This table reports summary statistics for the sample of New Century-ABSnet matched loans. We match the loans in the two datasets based on their zip code, loan size, first payment date, purpose, type of interest rate (fixed or floating), and credit score, and we require matches to be unique. A more detailed description is available in Internet Appendix A

Table IA.3. Cash-out vs. non-cash-out refinance loans

	Appraisal Difference			Even LTV
	(1)	(2)	(3)	(4)
Mean (%)	5.4	5.4	5.4	45.2
Even LTV	1.518***		1.435***	
	(0.103)		(0.098)	
Cashout		1.319***	1.208***	7.689***
		(0.126)	(0.124)	(0.430)
Controls	yes	yes	yes	yes
CBSA×Quarter FE	yes	yes	yes	yes
N	3,662,156	3,662,156	3,662,156	3,662,156
R^2	0.11	0.11	0.11	0.25

Columns (1) to (3) report results from OLS regressions where the dependent variable is the loan's appraisal difference. The explanatory variables of interest are indicator for even LTV and an indicator for cash-out refinance. Control variables include indicators for full-doc loans, the presence of a prepayment penalty, owner occupied properties, complex loans, adjustable-rate loans, as well as credit score, loan amount, LTV, interest rate at origination, and an interaction term between interest rate and the adjustable rate indicator. Column (4) reports the result from an OLS regression where the dependent variable the indicator for even LTV. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by CBSA. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. *$p < 0.1$.

Table IA.4. **Appraisal bias and loan performance and pricing of purchase loans**

	Delinquent			Interest rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Mean (%)	48.9	48.9	48.9	7.8	7.8	7.8
AD	7.569***		6.224***	-0.051**		-0.060***
	(0.975)		(1.055)	(0.023)		(0.023)
A=Price		15.341***	13.980***		0.219***	0.220***
		(0.743)	(0.782)		(0.015)	(0.017)
AD×A=Price			8.109***			0.012
			(3.084)			(0.053)
Controls	yes	yes	yes	yes	yes	yes
CBSA×Quarter FE	yes	yes	yes	yes	yes	yes
N	70,325	70,325	70,325	70,325	70,325	70,325
R^2	0.28	0.27	0.29	0.60	0.60	0.60

This table reports results analogous to Table **5**, for purchase loans instead of refinance loans. Columns (1) to (3) report results from OLS regressions where the dependent variable is a dummy variable that takes the value of one if the loan became more than 90 days delinquent at any point in time between origination and September 2012, and zero otherwise. The explanatory variables of interest are the loan's appraisal difference and an indicator for appraisal being equal to purchase price. Control variables include indicators for full-doc loans, the presence of a prepayment penalty, owner occupied properties, complex loans, adjustable-rate loans, as well as credit score, loan amount, LTV, interest rate at origination, and an interaction term between interest rate and the adjustable rate indicator. Columns (4) to (6) report results from OLS regressions where the dependent variable is the loan interest rates at origination. The regression specifications are the same as in columns (1) to (3) except that interest rate is not a control variable (because it is the dependent variable) and an additional control variable indicator for LTV ratios above 80 is included. Reported t-statistics in parentheses are heteroscedasticity-robust and clustered by CBSA. ***p <0.01, **p <0.05, *p <0.1. *p <0.1.

Table IA.5. Baseline simulation calibration parameters and appraisal bias moments

Panel A: Refinance loans

	Data	Bias free simulation	Selection bias simulation
Calibration parameters			
σ_A	-	19.10	19.30
σ_{AVM}	-	19.10	19.30
β	-	0	0.33
Appraisal bias moments			
σ_{AD}	24.26	24.28	24.35
d	2.50	0	2.54
Mean AD	5.36	-0.04	0.57
AD>0−0.5	10.98	-0.05	0.79
KS^+	15.59	-	0.87
Mean (A-AVM)/AVM	9.28	3.07	3.74
(A-AVM)/AVM>0.20	21.28	21.96	22.70
(A-AVM)/AVM<-0.20	8.02	17.37	16.77

Panel B: Purchase loans

	Data	Bias free simulation	Selection bias simulation
Calibration parameters			
σ_A	-	20.30	20.30
σ_{AVM}	-	20.30	20.30
β	-	0	0.21
Appraisal bias moments			
σ_{AD}	21.27	21.39	21.29
d	1.70	0.00	1.70
Mean AD	3.62	0.01	0.27
AD>0−0.5	7.56	0.08	0.47
KS^+	15.67	-	0.74
Mean (A-AVM)/AVM	6.69	2.41	2.65
(A-AVM)/AVM>0.20	14.95	18.80	19.06
(A-AVM)/AVM<-0.20	6.41	14.06	13.72

This table reports the parameter values and appraisal bias moments from the baseline simulations. Appraisal and AVM values are modeled as bivariate normal random variables with means of zero, equal error standard deviations, and correlations of 0.25 and 0.5 respectively for refinance and purchase loans. We calibrate error standard deviations for Appraisal and AVM such that the simulated appraisal difference (AD) standard deviations for refinance and purchase loans match their empirical counterparts. To model selection, we assume that loan completion probability is one if an appraisal is above the property's true value and is otherwise $max(0, 1 - \beta(V - max(0, A))/V)$, where V represents the property's true value and can be normalized to one. The parameter β is calibrated such that the simulation generates targeted denial rates of 2.5% for refinance loans and 1.7% for purchase loans, which are based on observed HMDA collateral denial rates. Excess positive appraisal difference measures the amount of appraisals that are higher than the AVM in excess of 50% and KS^+ measures the maximum differences from the bias-free simulated distributions.

Table IA.6. Simulation sensitivity analysis

Panel A: A≥V threshold for 100% loan completion probability

		Refinances				Purchases		
		Mean AD	Excess positive AD	KS$^+$		Mean AD	Excess positive AD	KS$^+$
$\rho = 0$	d = 0	-0.01	0.03	0	d = 0	0.01	-0.01	0
	d = 2.5	0.57	0.89	0.89	d = 1.7	0.34	0.62	0.64
	d = 7.5	1.93	2.87	2.85	d = 4.9	1.04	1.83	1.86
	d = 12.5	3.50	5.08	5.05	d = 8.1	1.88	3.19	3.23
	d = 17.5	5.31	7.47	7.53	d = 11.3	2.72	4.56	4.58
$\rho = 0.25$	d = 0	-0.04	-0.05	0	d = 0	0.01	0.03	0
	d = 2.5	0.57	0.79	0.87	d = 1.7	0.32	0.53	0.52
	d = 7.5	1.67	2.48	2.54	d = 4.9	0.93	1.58	1.55
	d = 12.5	3.09	4.39	4.47	d = 8.1	1.62	2.71	2.71
	d = 17.5	4.67	6.47	6.58	d = 11.3	2.40	3.98	3.96
$\rho = 0.5$	d = 0	-0.06	-0.12	0	d = 0	0.01	0.08	0
	d = 2.5	0.44	0.60	0.74	d = 1.7	0.27	0.47	0.74
	d = 7.5	1.42	2.00	2.14	d = 4.9	0.78	1.29	2.14
	d = 12.5	2.62	3.57	3.70	d = 8.1	1.36	2.21	3.70
	d = 17.5	3.94	5.27	5.51	d = 11.3	2.03	3.17	5.51

Panel B: A≥1.25V threshold for 100% loan completion probability

		Refinances				Purchases		
		Mean AD	Excess positive AD	KS$^+$		Mean AD	Excess positive AD	KS$^+$
$\rho = 0$	d = 0	0.02	0.05	0	d = 0	-0.04	-0.07	0
	d = 2.5	0.26	0.47	0.46	d = 1.7	0.12	0.18	0.42
	d = 7.5	0.88	1.50	1.50	d = 4.9	0.44	0.84	0.95
	d = 12.5	1.60	2.67	2.66	d = 8.1	0.80	1.47	1.59
	d = 17.5	2.38	3.91	3.90	d = 11.3	1.11	2.07	2.16
$\rho = 0.25$	d = 0	0.00	0.01	0	d = 0	-0.02	-0.04	0
	d = 2.5	0.26	0.43	0.49	d = 1.7	0.15	0.28	0.40
	d = 7.5	0.80	1.31	1.34	d = 4.9	0.41	0.77	0.83
	d = 12.5	1.47	2.40	2.41	d = 8.1	0.77	1.47	1.51
	d = 17.5	2.28	3.69	3.68	d = 11.3	1.08	2.02	2.07
$\rho = 0.5$	d = 0	0.02	0.00	0	d = 0	0.04	0.06	0
	d = 2.5	0.29	0.52	0.53	d = 1.7	0.14	0.27	0.53
	d = 7.5	0.79	1.23	1.24	d = 4.9	0.36	0.69	1.24
	d = 12.5	1.30	2.10	2.10	d = 8.1	0.67	1.24	2.10
	d = 17.5	2.12	3.40	3.40	d = 11.3	0.98	1.77	3.40

This table reports sensitivity analysis for the correlation, denial rate, and appraisal thresholds assumptions discussed in Section 3.1. In total, we consider 15 permutations under both baseline and alternative appraisal thresholds. Appraisal and AVM values are modelled as bivariate normal random variables with means of zero and equal error standard deviations. We calibrate error standard deviations for Appraisal and AVM such that the simulated appraisal difference (AD) standard deviations for refinance and purchase loans match their empirical counterparts. To model selection, we assume that loan completion probability is one if an appraisal is above the property's true value and is otherwise $max(0, 1 - \beta(V - max(0, A))/V)$, where V represents the property's true value and can be normalized to one. The parameter β is calibrated such that the simulation generates a targeted denial rate. Excess positive appraisal difference measures the amount of appraisals that are higher than the AVM in excess of 50% and KS^+ measures the maximum differences from the bias-free simulated distributions.