Appraising Home Purchase Appraisals

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Abstract

Home purchase appraisals are meant to help a lender learn the underlying value of the collateral and to help a borrower avoid overpaying for a property. However, we argue that institutional features of home mortgage lending cause much of the information in appraisals to be lost: some thirty percent of all appraisals are exactly at the home price (with less than ten percent below it). We demonstrate that such information loss is more common at loan-to-value (LTV) boundaries and appears to be associated with a higher risk of mortgage default, after controlling for pertinent borrower and loan-level characteristics. Appraisals do, in some cases, help predict default risk, but they are less informative than automated valuation models. An important consequence of appraisals reported below the purchase contract price is that they help borrowers renegotiate prices with the sellers, especially if the borrowers are at LTV notches.

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A major purpose of a home purchase appraisal is to help a lender learn the underlying value of collateral when a borrower is purchasing a home. The other main purpose is to help a borrower avoid overpaying for a property. However, consistent with Calem et al. (2015), we find that institutional features of home mortgage lending cause much of the information in appraisals to be lost: we present evidence that some thirty percent of all appraisals, instead of providing an independent estimate of the value of the home, are precisely at the initial contract price.

The information loss results from the appraiser attempting to respond on behalf of the lender to two important institutional issues related to mortgage underwriting and securitization. First, the GSEs and federally regulated banking institutions set up ranges for the loan-to-value ratio (LTV) across which underwriting and mortgage insurance requirements differ. In recent years, the upper boundaries of these ranges have been 80 percent, 85 percent, 90 percent, 95 percent, and 97 percent LTV. The most important of these currently are 80, 90, and 95 percent. We call loans exactly at these boundaries "notch" loans, as borrowers bunch at these boundaries. Over half of all mortgages are made at these notch LTVs.

Second, the GSEs and federally regulated banking institutions require that the home value that is the denominator of the LTV ratio be calculated as the lesser of the selling price and the appraisal. As a consequence of this lesser value rule, an appraisal that is below the contract price (the agreed-upon offer price) may increase the down payment needed to stay within the borrower's desired LTV range.

Providing such an additional down payment is costly to households, especially to those already stretching their savings to meet the down payment requirement at a particular LTV notch. Therefore, receiving a low appraisal threatens the completion of the mortgage and the sale transaction, particularly when it pushes the LTV across a boundary, although negative appraisals do help some buyers successfully renegotiate a lower sale price from the sellers. Losing a transaction would entail an opportunity cost for the lender, and also for the buyer, seller, and real estate brokers.

The appraiser's solution to this problem, acting on behalf of the lender as laid out in Calem et al. (2015), is to bias up the reported appraisal, typically to exactly the contract price. Appraisals that fall farther short of the contract price are also biased up, but they remain below the contract price.

Calem et al., relying on a sample of (pre-origination) mortgage applications (thus free of selection effects), find that less than ten percent of all appraisals are below the contract price, rather than the fifty percent that would be expected if the appraisals were unbiased. Roughly thirty percent of all appraisals exactly equal the contract price. They refer to the cases in which the appraisals are exactly equal to the contract price as *information loss*. While some appraisals could reasonably be expected to exactly equal the contract price, it is not possible to distinguish these appraisals from those that were biased upward. For this reason, information is lost on all of the loans at this mass point. Negative reported appraisals (appraisals below the contract price), also in theory biased upward, should be comparatively informative that the buyer has overpaid.[2]

Using a new dataset, we expand on these observations with the following empirical findings that are consistent with our *a priori* argument. First, we demonstrate that more information loss and bias occur when mortgages are at LTV notches. Second, we find that when negative appraisals *are* reported, buyers are more likely to successfully renegotiate the sales prices with sellers so that they pay less—especially if the negative appraisal would otherwise catapult them into a higher LTV segment, which carries greater borrowing costs. Third, we find evidence that information loss is associated with a higher risk of mortgage default, after controlling for pertinent borrower and loan-level characteristics. Finally, we find that appraisals are less predictive of default than automated valuation model (AVM) estimates. Since these completed mortgages may be subject to selection bias, we perform this test on mortgages with LTVs below 75%, where selection due to appraisals should be minimal, and confirm our results.

1. Literature and institutional context

To our knowledge, our study is the first to rely on a national sample of presale, premortgage transactions data that includes reported appraised values, accepted offer prices, and preappraisal loan-to-value measures. Cho and Megbolugbe (1996) pioneered in the study of residential mortgage appraisals, providing some of the earliest empirical evidence that appraisers rarely report values below the offer prices. However, that study relied on appraisals for completed mortgages. Agarwal, Ben-David, and Yao (2015) use a Fannie Mae database to

[22] Moreover, to the extent that the amount of bias reflects known incentives to minimize costs and can therefore be quantified, the information loss associated with a negative appraisal is mitigated.

explore the bias of appraisals for refinances, in which there is no accepted offer price to anchor on.

Calem et al. (2015) and Ding and Nakamura (2014) utilize a special sample of premortgage transactions to study appraisal bias or information loss. However, their sample is smaller and narrower than the one used here, and it does not include loan-to-value ratios. As noted previously, Calem et al. develop a conceptual argument, supported by empirical evidence for high incidence of information loss. Ding and Nakamura (2014) focus on the impact of the 2009 Home Valuation Code of Conduct (HVCC), a regulatory change that sought to reduce appraisal bias.

All of these studies find that a large share of appraisals come in at values exactly identical or very close to the transaction price, a phenomenon Eriksen et al. (2016) refer to as “confirmation bias.” Eriksen et al. use pairs of appraisals on post-foreclosure properties, one just after the lender takes possession (which should be more objective, as it is not tied to a transaction) and an appraisal when the lender tries to sell the property to a borrower who is using mortgage financing. Comparing the two appraisals enables the authors to illustrate the common mechanics employed by appraisers to justify an appraisal that equals the transaction price when a lower value ought to be reported.

Despite the fact that negative appraisals are rare, they receive surprisingly more public attention than the suspiciously large number of appraisals that are reported at the transaction price. Fout and Yao (2016) use the Uniform Appraisal Dataset of appraisals submitted to GSEs to conduct the first scholarly investigation of how negative appraisals affect housing markets, finding that they increase the probability from 8 to 51 perecent that buyers and sellers renegotiate down the sale price down, and they have a smaller, though still significant, effect on the likelihood that a sale falls through: 32 percent of negative appraisal transactions fall throguh, as compared to 25 percent overall. They further investigate how these forces affect sales prices and volumes in the 20 largest MSAs.

We build on this prior work on appraisals by focusing on a new aspect: the role of the borrower’s desired LTV ratio in the outcome of the appraisal and, subsequently, the performance of the borrower’s mortgage, if originated. The availability of the pre-appraisal LTV ratios allows us to analyze the borrower’s ability to adjust the down payment. A mortgage down payment represents the single-largest expense most U.S. households will experience, and it is an oft-cited deterrent for homeownership (Engelhardt 1996; Lang and Hurst 2014; Acolin et al. 2016). When prospective buyers make an offer on a home, they typically would have calculated their intended down payment and loan-to-value ratio, with some foreknowledge of the impact of their downpayment on the cost of the mortgage and its likelihood of being underwritten (Best et al. 2015).

Others have found correlations between loan-to-value ratios and mortgage default rates (Foote, Gerardi, and Willen 2008; Haughwout, Peach, and Tracy 2008; Elul et al. 2010; Palmer 2015), but no one, to our knowledge, has examined the differences in default probabilities associated with micro differences in LTV.[3] We provide this precise analysis on LTV and describe how differences in appraisal bias are another pathway through which LTVs impact default risk.

2. Data

We use two datasets that come from a government-sponsored enterprise (GSE). One derives from applications for 30-year fixed-rate mortgages from 2013-2015, taken from the GSE's underwriting software. The dataset comprises loan applications for both originated mortgages subsequently purchased by the GSE and loans that ultimately were not originated or were originated but not purchased by the GSE. The second dataset, which we use to measure the ability of appraisals to predict defaults *ex post*, includes data on 30-year fixed-rate mortgages originated during 2003-2009 and ultimately guaranteed by the GSE.

The 2013-2015 loan applications data include a reported appraised value; because the observation captures the loan when the appraisal has been reported but the mortgage has not yet been approved by the lender and accepted by the borrower, selection bias is mitigated. These data also include the applied-for loan amount and the initial contract price on the home, from which the pre-appraisal LTV can be calculated. (It is standard for the appraiser to be given these pieces of information when the lender orders the appraisal.) The dataset also includes AVM estimates captured at the time the application was made.

Both datasets indicate the county in which the property is located and the quarter during which the appraisal was completed, but the data do not contain area economic characteristics.

[3] Bubb and Kaufman (2014) show localized increases in default risk associated with different credit score notches to assess the role of securitization on the riskiness of mortgages originated during the same period we study loan performance associated with information loss in appraisals.

Therefore, we supplement the GSE datasets with data from McDash Analytics on area default and foreclosure rates, Census data on community characteristics (from the 2010 decennial Census and the 2014 5-Year American Community Survey), CoreLogic public records data on area home sale characteristics, and Zillow home value indices.

3. Appraisals for notch mortgages have more information loss

The cost of mortgage insurance raises the borrower's required monthly payments by a step function at particular LTV notches (80%, 85%, 90%, 95%), providing a strong incentive to arrive at a down payment sufficient to avoid the higher cost.[4] Put differently, the marginal benefit of saving an additional one percent of the purchase price is far higher when a borrower is intending on an LTV of 81%, relative to one of 80%. The only thing to be gained by putting additional money down in the latter case (choosing a 79% LTV loan) is the interest payments prevented over the life of the loan by having a smaller principal balance. Thus, many buyers delay purchasing until they can stretch their savings to the level they need for the LTV ratio they wish to target, but not beyond that, since saving for a down payment is costly.

As a consequence, mortgages bunch at LTV notches, as shown in Table 1. Specifically, 63 percent of all mortgages fall at one of six notches, with 55 percent at the three major notches, 80, 90, and 95% LTV. To the extent that they are stretching to get to the notch, notch borrowers, relative to those residing strictly within the LTV range, are more likely to be liquidity constrained – and thus likely to be higher default risks.

Table 1 also shows that in our 2013-2015 dataset of 1.2 million appraisals for 30-year fixed rate mortgages, the overall rate of negative appraisals is 6.5 percent. Only 5.0 percent of notch mortgages have negative appraisals, as compared to 8.9 percent of non-notch mortgages. Further, negative appraisals are much more likely just above and below each notch. The five lowest values of the "percent negative" outcome are all at notch LTVs.

In contrast to the pattern observed for negative appraisals, appraisals that are equal to the contract price are more likely at the notches than at LTVs just above and below. This holds true when we consider just those appraisals that are strictly identical to the appraisal, as well as when

[4] Mortgage costs also vary depending on borrower characteristics, such as credit rating, but we are holding these other factors constant during this discussion.

we examine appraisals that are slightly positive but appear to be simply a case where the appraiser rounded the contract price up.[5]

Figure 1 displays the Table 1 data in a simple chart. The bars in Figure 1 representthe percentage of appraisals that are less than or equal to the transaction price, segmented by the applicant's desired LTV. The bars for the six notch LTVs are colored in red to distinguish them. The dotted line that is superimposed over the bars represents the percentage of appraisals that are identical to the offer price, conditional on not exeeding it, which is one metric of information loss in appraisals. At each notch there is a pronounced uptick in the dotted line, which shows the percentage of the total bar height that is made up of the appraisals that are reported at a value identical to the contract price (those which are most likely to signal information loss). After each notch, the dotted line falls off immediately, reflecting reduced information loss for applicants who are not in as great jeopardy of being pushed into a higher, costlier LTV class.

We conclude from the data in Table 1 and Figure 1 that there is more information loss for notch mortgages—the group of loans that, as we show in Section 5, also are more likely to default. To confirm that this information loss is an inherent characteristic of the LTV notches due to the increased potential for a negative appraisal to threaten the sale transaction, and not to other circumstances, we estimate a set of logit regression models for the probability of information loss.

As in Figure 1, our measure of information loss is that an appraisal is exactly equal to the accepted offer price, conditional on its being less than or equal to the accepted offer price. By focusing on this part of the distribution of appraisals to transaction prices, we intentionally ignore the positive side (appraisal > price), because that side is assumed to have no appraisal bias, as described by Calem et al. (2015).[6] The distribution of the appraisal to the purchase price can be found in Table 2.

We employ a full set of dummy variables for LTV ratios, as well as state-by-year dummy variables, controls for the prevalence of default and foreclosure in the county at the time of the appraisal, the ratio of the offer price to the county median home sales price that year, the natural

[5] These "likely rounded" appraisals are included in the last column of Appendix Table A1, "Equal or Rounded." In that table we add to the "Equal" appraisals those in which the appraisal is greater than the price but by less than $5,000 and the appraisal, unlike the purchase price, was rounded to an increment of $1,000.

[6] The share of appraisals that exceed the transaction price may vary, but it is not of consequence to this analysis, and including these appraisals in the denominator simply makes it harder to tease out the share of appraisals subject to bias that actually do experience information loss.

log of the transaction price, the past year's price appreciation in the county lagged by one year, and a dummy variable indicating the use of an appraisal management company (AMC) to facilitate the appraisal.

We display some summary statistics for these variables in Table 3. The main regression results are shown in Table 4.[7] Notch mortgages are confirmed to have sharply higher odds of information loss relative to mortgages whose LTVs are one percentage point higher or lower. We also find that higher default and foreclosure rates in the county at the time of the appraisal are negatively associated with information loss, consistent with Calem et al. (2015)'s argument that if credit risk is more salient, appraisers will apply less upward bias on values. Appraisals carried out through AMCs have less information loss, consistent with Ding and Nakamura (2015).

In Table 5 we present several robustness checks. Model 1 repeats the main model from Table 4. In Model 2 we show the results when Model 1 is estimated without control variables. Model 3 is identical to Model 2 except we broaden the set of observations to include approximately 50,000 that were omitted from the main model because they lacked a full set of control variables (and accordingly we exclude these controls). Model 4 further expands the sample to include appraisals associated with all purchase mortgages (not simply 30-year, fixed-rate purchase mortgages). We find that the results are highly robust to including or excluding controls and to using these different samples. Finally, in Models 5—7 we show that the results are similar across three geographic areas that experienced different housing market conditions during this period: the Pacific Coast, Sand States, and the Rust Belt.

4. Negative appraisals help borrower renegotiate—especially when at an LTV notch

Although they can threaten the sale, negative appraisals can serve the borrowers (purchasers) well by helping them avoid overpaying for a property. Most purchase contracts include an appraisal contingency, which allows the buyer to back out of the transaction and be returned any earnest money paid if the appraisal falls short of the transaction price. This clause helps facilitate these renegotiations when appraisals come in lower than anticipated.

[7] Table 4 includes model results for the 433,807 appraisals with values less than or equal to the contract price. This is consistent with the 37% of the 1,176,895 appraisals in Table 3, Panel A which are non-positive.

In fact, in 57 percent of the sales in our dataset that come to completion in spite of a negative appraisal, the borrower and seller renegotiate the price downward.[8] The frequency of renegotiation in response to a negative appraisal is even higher for borrowers bumped into a higher LTV class by the appraisal—71 percent of those sales are renegotiated.

In contrast, only 2 percent of sales with appraisals equal to or greater than the contract price are renegotiated for any reason after the appraisal. Thus, to the extent that appraisers bias upward property valuations, buyers appear to have less ability to renegotiate prices with the sellers. The more the appraisal falls short of the contract price, the more likely the buyer and seller are to renegotiate, as shown in Figure 2. However, the importance of being catapulted to a higher LTV class persists whether the appraisal is only slightly below the contract price or when the difference is large.

The savings to borrowers from renegotiation can be considerable. Among the negative-appraisal loans in our sample in which the price was renegotiated, buyers saved 2.5% or $6,000 at the median.

5. Default risk is higher at LTV notches, where information loss is more prevalent

Upwardly biased valuations will tend to increase the rate at which borrowers default and the losses that the lenders experience. Given that information loss is more common at notches, a logical next question is whether more borrowers at notch LTVs do, in fact, default. For this analysis, we turn to the sample of mortgages originated in 2003-2009 to evaluate the relationship between information loss, LTV, and the likelihood that a loan becomes 180 or more days delinquent in the first 5 years after it was originated.[9]

In our 2003-2009 dataset, we have information about the sale price, the appraisal, and the AVM at the point that mortgage was originated, along with information on subsequent payment performance. Unlike the loan application database, however, we do not have information on the applied-for LTV or the initial contract price, and as a result, this sample suffers from a selection problem. We observe fewer negative appraisals, and the borrowers who had a negative appraisal and yet still appear in our dataset may be different from the group who had a negative appraisal

[8] This is close to the 51 percent found by Fout and Yao (2016).
[9] Our 2013-2015 mortgage sample is not seasoned enough to assess mortgage performance.

and subsequently walked away from the transaction.[10] These limitations make it impossible to know the overall contribution of appraisals in helping predict (and prevent) defaults. We discuss this issue further in the next section.

The performance analysis restricts attention to 30-year, fixed-rate mortgages taken out by owner-occupants to purchase homes to serve as their primary residences. We exclude loans with a piggyback (second lien) mortgage at purchase and loans with LTVs less than 50% or greater than 97%.[11]

Descriptive statistics in Table 6 show the characteristics of the sample overall and broken down by whether the mortgage is observed to default. Figure 3 shows the proportions of loans originated in 2007 that became 180 or more days delinquent in the initial five years of the loan history, by LTV. The 2007 vintage was selected as a benchmark because it was the worst performing vintage of loans during the recent mortgage crisis. The figure shows elevations in the default rate at most notches, with the exception of the 80% LTV, which, while higher than LTVs several percentage points lower, resembles closely loans at 78-79% LTV.

In Table 7, we present the results from the probability-of-default regressions, structured as linear probability models. This analysis accounts for house price changes after origination and borrower and loan characteristics displayed in Table 6. In Table 7, Model 1 we show that the risk of default increases at the notches 85, 90, and 95%. In Models 2, 3, and 4 we break out the sample by the outcome of the appraisal: below the sale price, equal to the sale price, and above the sale price, respectively.

The increased default risk at the notches is strongest for the loans where the appraisal was identical to the transaction price (Model 3). We conduct F-tests and find that the coefficients at the 85, 90, and 95% notches in Model 3 are larger, statistically, than those at adjacent LTVs.[12] These loans with an appraisal equal to the transaction price are most subject to information loss. Realistically, some of these homes could have been truthfully appraised at a value exactly equal

[10] Also, since we do not observe the contract price, we cannot rule out that negative appraisals were initially reported but the buyer and seller renegotiated, resulting in a smaller difference between the appraisal and the price than captured in the appraisal-vs-contract price measure. Table 2 compares the 2013-2015 dataset to the 2003-2009 dataset, which suffers from the selection problem. However, the 2003-2009 figures shown there do not exclude loans for which the full set of control variables (e.g., AVMs, house price indices, etc.) were not available.

[11] We also exclude unusual product types, such as interest-only loans.

[12] P-values for an F-test of equality of the coefficients are as follows: 83.5-84.5% vs. 85% = 0.0061; 85% vs. 85.5-86.5% = 0.0016, 88.5-89.5% vs. 90% = 0.0298; 90% vs. 90.5-91.5% = 0.0075; and 93.5-94.5% vs. 95% = <0.0001. The one exception is that there is no statistically significant difference in the coefficients for 95% and 95.5-96.5% (p = 0.1708).

to the transaction price, but others have been biased upward to encourage the completion of the transaction, and it is not possible to distinguish those appraisals with bias from those without. Given the greater incentives to bias appraisals upward when applications are at the notch LTVs, it is not surprising that loans at those LTVs would experience substantially higher default risk than loans at just higher and lower LTVs.

We find a more muted relationship between being at a notch and greater default risk among loans with positive appraisals. For these loans, default risk differs statistically only around the 90 and 95% notches. And at those notches, the coefficients show a smaller increase in default risk than in Model 3 (0.007 vs. 0.015 for 90% LTV, 0.008 vs. 0.019 for 95% LTV).

The increased default probability at LTV notches is not indicated for the segment with negative appraisals (Model 2). Non-robustness in this segment may reflect the small and highly selected nature of this sample. Negative appraisals are comparatively uncommon and most lead to renegotiation or cancellation of the transaction, so that originated loans with negative appraisals relative to the sale price are likely to suffer from selection bias.

An additional, possible explanation for higher default risk at notch mortgages is that borrowers who are at notches are more financially constrained, and that this information is passed along to the appraiser, who inflates the appraisal to the transaction price. This would explain why we see some evidence of increased default risk at notches even in loans with positive appraisals, where information loss should be much less common. The models control for the amount of savings the borrower has on hand at the time of the mortgage application (after accounting for the down payment and closing costs), which is an indicator of how much ability the borrower had to stretch to a lower, less costly LTV loan or to make up the down payment shortfall imposed by a negative appraisal. In our data, borrowers at notch mortgages tend to closely resemble their counterparts just below the notches in terms of savings on hand, while borrowers just above the notch are (intuitively) less likely to have cash on hand.[13] So while financial constraints may be at play in the higher default risk at notches, our findings indicate that appraisal bias also plays a role.

[13] Consider the percentage of borrowers who had enough savings at origination to cover the equivalent of three months of mortgage principal and interest payments. At 94% and 95% LTVs, 74% of borrowers had enough savings to cover three months of payments, versus 56% of borrowers at 96% and 57% of borrowers at 97%. If borrowers had large amounts of savings, the rational thing to do would generally be to make larger down payments and avoid higher mortgage interest payments.

One puzzle is why borrowers at 80% LTV do not face greater default risk than their counterparts at 78.5-79.5% and 80.5-81.5% LTV. Although the 80% LTV notch would have relatively high incidence of appraisal bias, it is also the case that there are many borrowers who opt to limit their down payment to 20% even though they can afford a substantially higher down payment. Such borrowers may have superior investment opportunities or stronger precautionary motives, which also make them intrinsically lower default risks. On balance, then, the 80% LTV notch would have an ambiguous relationship to default risk. All in all, this finding deserves further investigation.

6. Appraisals inform the risk of default, but not consistently, and not as well as AVMs

Despite the fact that appraisals are often subject to bias, they sometimes contain information that can help a lender assess a loan's default risk. We evaluate the informational value of appraisals in predicting defaults by estimating another set of linear probability models, similar to those in Table 7. Specifically, we estimate the probability of becoming 180 or more days delinquent within the first five years after origination, controlling for the same characteristics as before, except excluding the dummy variables around the LTV notches. The results are reported in Table 8.

In Models 1-3 we focus on just the mortgages in which the appraisal exceeded the transaction price. For these observations, we would expect appraisals to be predictive of default risk, since they are a truthful (bias-free) estimate of home values. Model 1 is the baseline model; Model 2 adds a measure of the amount by which the appraisal differed from the price, ln(appraisal/sale price); and Model 3 includes instead the difference between the AVM and the price, ln(AVM/sale price). We include the baseline model to show the marginal increase in default explanatory power from adding each of the new variables.

For this sample, we find a significant, negative relationship between ln(appraisal/sale price) and risk of becoming 180+ days delinquent. In other words, the higher the appraisal was relative to what the borrower paid, the lower the borrower's risk of default—a logical conclusion given the assumption that the appraisals are unbiased measures of default risk. Substituting the difference between the AVM and the price, ln(AVM/sale price), the model becomes slightly more predictive, as evidenced by the change in the r^2 values.

In Models 4-6 we switch our focus to mortgages in which the appraisal was reported at a value equal to or less than the sale price. For this sample, adding ln(appraisal/sale price) in Model 4 yields no improvement in model fit, though appraisals exactly identical to the transaction price are shown to be at higher default risk. The magnitude of the increase in risk for loans with equal appraisals is 0.36 percentage points; this is a significant increase, given that the overall default rate in this sample is 5.8%. Adding even this variable, however, has no discernable effect on the model's r^2 value.

While appraisals are not a consistently strong predictor of default risk, AVMs inform default risk regardless of whether an appraisal comes in above or below the transaction price (Models 3 and 6). Including the AVM term also produces a larger improvement in the r^2 of each model than does including appraisals, though even AVMs make only a modest contribution to model fit. While the t-statistic for the appraisal term is small, the AVM term's t-statistic is of similar magnitude to other conventional predictors of mortgage default included in the model, such as DTI, property type, or amount of savings the borrower has on-hand, which could be used as reserves for the mortgage payments.

In this data set, we observe only completed mortgages, so one could argue that these results stem from selection bias. If many negative appraisals were reported on high-risk loans and the low appraisals resulted in mortgages being not completed, we might simply not capture the usefulness of appraisals in predicting mortgage defaults.

To address this concern, we estimate Models 4-6 again, focusing on just the sample of mortgages with LTVs below 75%, labeled in Table 8 as Models 7-9. At these low LTVs, borrowers have a substantial cushion of equity and the LTV is not a significant determinant of loan cost, so a negative appraisal should not affect the likelihood of a transaction falling through, and selection bias should be minimal. In Model 8, we find just that: the coefficient on the "equal appraisal" dummy variable falls to less than 0.0012 and loses statistical significance.

Another reason the equal appraisal dummy variable is less predictive of default risk is simply that property values matter less for defaults when borrowers have more equity. However, the ln(AVM/sale price) is still a significant predictor of default risk in Model 9: its coefficient is -0.012, about one-quarter its size in Model 6, but still strongly significant. Including the AVM term also generates a modest improvement in the r^2. Taken in sum, these results indicate that property values are indeed less informative of default risk for low-LTV borrowers; however, AVMs still offer more predictive power than appraisals.

7. Conclusion

Recent shortages of appraisers have made national news headlines, as have charges that negative appraisals have worked to stall house price recovery. These concerns over appraisals raise the question of what their informational value is to lenders and to the borrowers who are paying for them. Answering that question is a critical first step before considering policy responses in this $10.1 trillion industry, where $6.0 trillion in mortgage debt is backed by FHA, VA, or one of the two GSEs in federal conservatorship, Fannie Mae and Freddie Mac (Urban Institute 2016).

We argue that the reporting biases in home purchase appraisals result in substantial information loss. This does not mean, however, that appraisals have no value. Positive appraisals do have significant information. Negative appraisals, while biased, contain information that can be extracted. Also, negative appraisals frequently result in renegotiation of the purchase price, which is of benefit to the lender as well as the borrower.

The information loss from biased appraisals is greatest at notch-LTV mortgages, where borrowers are at greatest risk of mortgage default. A consequence is that appraisals have little overall value in predicting default for the notch-LTV mortgages, which comprise a large share of mortgages originated. The information loss in the appraisals constitutes a cost to lenders mortgage insurers, GSEs, and ultimately borrowers, since it makes it more difficult to efficiently price mortgage default risk.

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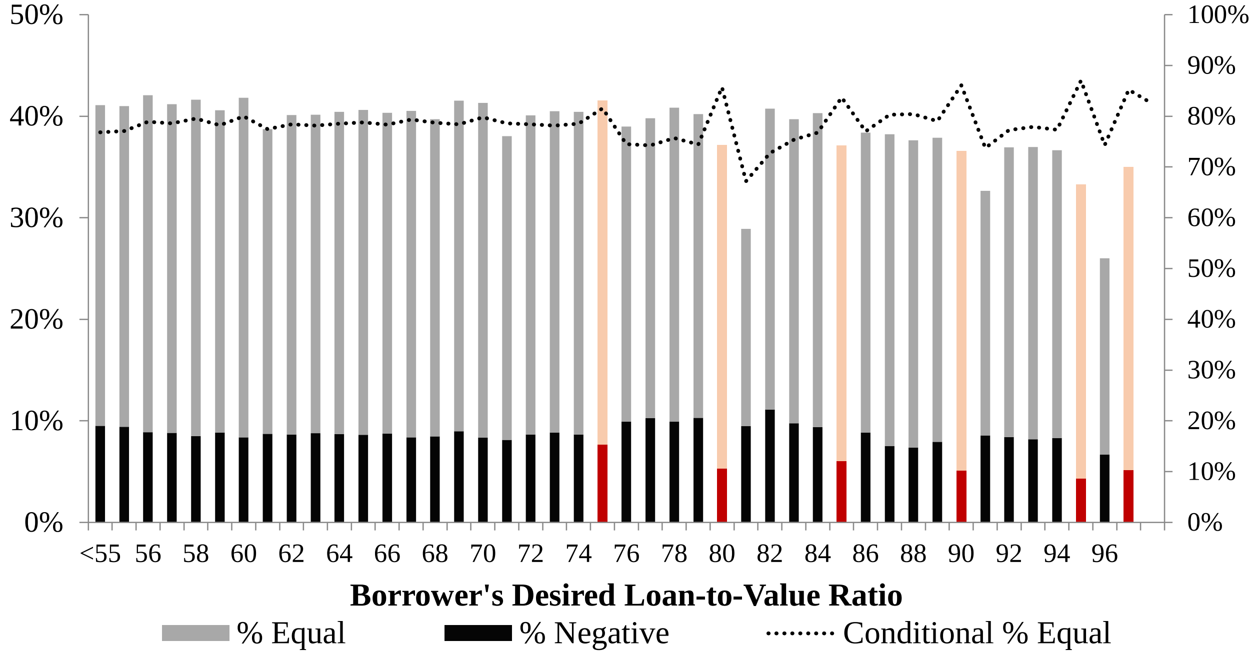
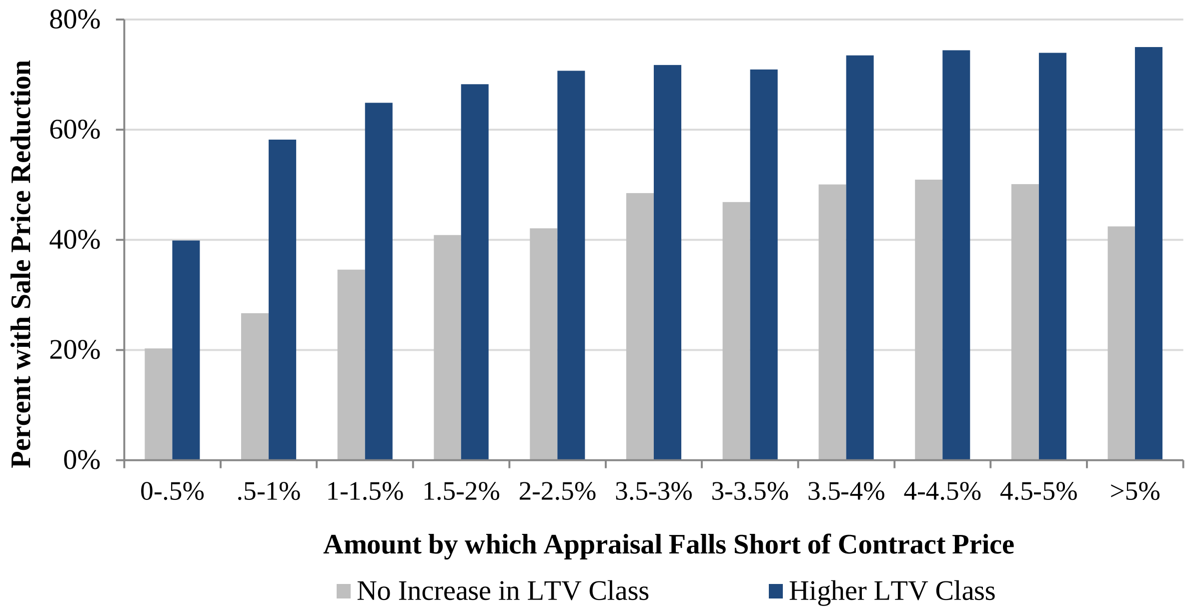
Figures

Figure 1: Appraisal Outcomes by Applicant's Desired Loan-to-Value Ratio



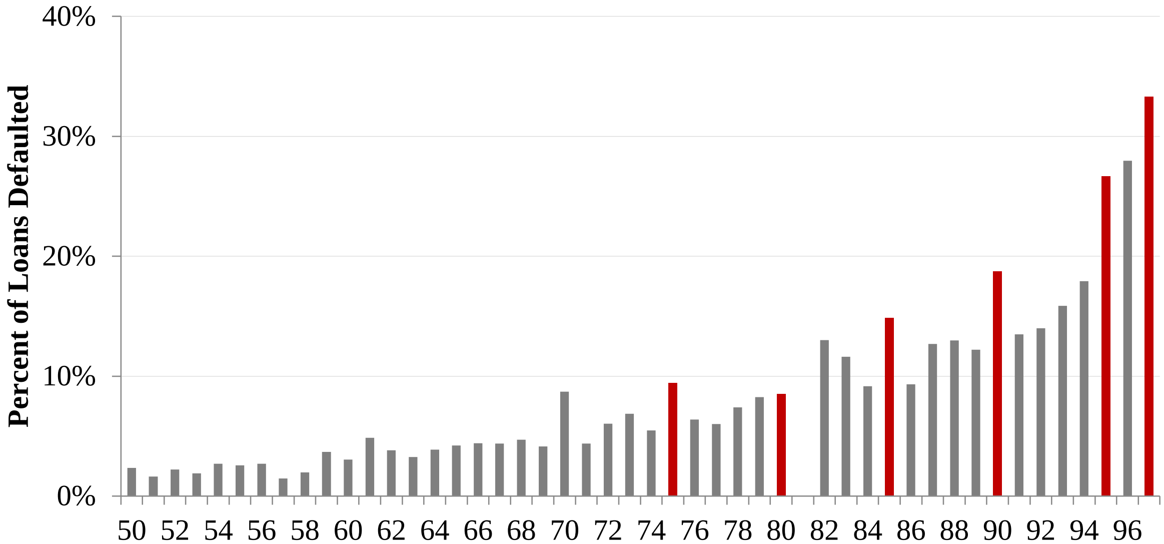
Source: Authors' calculations based on data from GSE

Figure 2: Incidence of buyer-seller price renegotiation following negative appraisals, by whether negative appraisal would catapult borrower to a higher LTV class



Source: Authors' calculations based on data from GSE

Figure 3: Percentage of 2007 Vintage Loans that Became 180+ Days Delinquent
During Initial 5 Years, by Loan-to-Value Ratio



Source: Authors' calculations based on data from GSE. Note: Data not displayed for 81% LTV, because only 43 mortgages in our dataset were at this LTV. The next smallest group was 82% LTV, which had 146 observations.

Tables

Table 1: Appraisal Outcomes by Anticipated Loan-to-Value Ratio (2013-2015)

Applied-for LTV	Total	% of Appraisals	% Negative	% Equal	% Positive
< 70	142,965	12.1	9.0	31.8	59.1
70	14,813	1.3	8.3	33.0	58.7
71	7,960	0.7	8.1	29.9	62.0
72	9,966	0.8	8.7	31.4	59.9
73	9,864	0.8	8.9	31.7	59.5
74	10,637	0.9	8.7	31.8	59.6
75	26,061	2.2	7.7	33.9	58.5
76	10,331	0.9	9.9	29.0	61.0
77	12,340	1.0	10.3	29.5	60.2
78	15,229	1.3	9.9	30.9	59.2
79	17,712	1.5	10.3	29.9	59.8
80	278,977	23.7	5.3	31.9	62.8
81	16,937	1.4	9.5	19.4	71.1
82	14,473	1.2	11.1	29.6	59.3
83	12,057	1.0	9.8	29.9	60.3
84	12,207	1.0	9.4	30.9	59.7
85	28,415	2.4	6.1	31.1	62.9
86	10,657	0.9	8.8	29.6	61.6
87	12,560	1.1	7.5	30.7	61.8
88	13,799	1.2	7.4	30.3	62.4
89	15,054	1.3	7.9	29.9	62.1
90	114,610	9.7	5.1	31.5	63.5
91	14,052	1.2	8.6	24.1	67.4
92	15,811	1.3	8.4	28.5	63.1
93	18,981	1.6	8.2	28.8	63.0
94	19,592	1.7	8.3	28.3	63.3
95	258,730	22.0	4.3	29.0	66.7
96	11,385	1.0	6.7	19.3	74.0
97	30,720	2.6	5.2	29.8	65.0
Total	1,176,895	100.0	6.5	30.4	63.1
Major Notches (80, 90, 95)	652,317	55.4	4.9	30.6	64.5
All Notches	737,513	62.7	5.0	30.7	64.2
Non-Notches	439,382	37.3	8.9	29.8	61.3

Table 2: How Appraisals Vary Across Selection

Percent of Values Falling Within Each Band of ln(Appraisal/Price)			
	Empirical Samples:		
Percentile Range:	Full sample of scored applications (2013-2015)	Subsample intended for sale to GSE (2013-2015)	Historical sample of originations (2003-2009)
< -0.1	1.1	0.6	0.3
< -0.05 and ≥ -0.1	1.8	1.4	0.5
< -0.01 and ≥ -0.05	3.9	3.8	1.4
< 0 and ≥ -0.01	0.7	0.7	0.8
Exactly = 0	28.8	28.9	39.1
> 0 and ≤ 0.0025	7.8	8.2	6.6
> 0.0025 and ≤ 0.005	6.2	6.6	4.8
> 0.005 & ≤ 0.0075	5.5	5.8	4.1
> 0.0075 and ≤ 0.01	4.7	5.0	3.4
> 0.01 and ≤ 0.05	30.5	31.1	24.4
> 0.05 and ≤ 0.1	6.4	5.9	7.4
> 0.1	2.5	2.1	7.3

Source: Authors' calculations based on data from GSE. The full sample of scored applications includes 3.8 million loans, for which the appraised value is compared to the final sale price, as contract price is not available. For the subsample intended for sale to the GSE, 1.2 million loans, the contract price is available and is used in the calculation. The historical sample covers 9.2 million appraisals conducted 2003-2009 and has only the final sale price.

Table 3: Appraisal Outcomes and Characteristics of 2013-2015 Vintage Loans

Panel A, All Appraisals in Sample

	Percentage of Appraisals				
	Negative	**Equal**	**Positive**	**Total**	**n**
Year of appraisal:					
2013	8	31	61	100	350,726
2014	5	30	64	100	385,270
2015	6	30	64	100	440,899
Appraisal management company used?					
No	5	29	66	100	441,955
Yes	7	31	61	100	734,940
Regions:					
West coast (CA, OR, WA)	9	46	46	100	205,277
Sand states (AZ, FL, NV)	12	27	61	100	134,263
Rust belt (IN, MI, OH)	6	28	66	100	104,804
All	6	30	63	100	1,176,895

Panel B, Appraisals Less than or Equal to Contract Price

	Percentage		
Appraisal management company used in transaction	65.5		
Property in rural county	2.0		
Loans 90+ days delinquent or in foreclosure:			
5-7%	17.0		
> 7%	19.7		
County Population in poverty:			
10-20%	69.5		
> 20%	6.2		
	Median	**Mean**	**Std. Dev.**
ln contract price	12.6	12.6	0.5
Ratio of contract price to county median	1.2	1.3	0.6
1-year lagged house price appreciation	4.5	5.6	7.3

County default and foreclosure rate is calculated as the share of first-lien mortgages that are 90+ days delinquent, in foreclosure, or in bank ownership. Lagged house price appreciation captures the change in the Zillow county-level home value index from 24 to 12 months before the appraisal. County median house prices are found using sales of residential properties in the same quarter as the appraisal (from CoreLogic). Rural counties are considered to be those not located within a metropolitan statistical area. Source: Authors' calculations based on data from GSE, McDash Analytics, 2010 Census, 2014 5-Year American Community Survey, CoreLogic, and Zillow.

Table 4: Odds ratios for likelihood that appraisal identically contract price, 2013-2015

	(1)	(2) No AMCs	(3) AMCs
Applied-for LTV			
74	1.109*	1.242**	1.053
	(2.50)	(2.79)	(1.06)
75	1.333***	1.425***	1.290***
	(9.56)	(6.37)	(7.12)
76	0.898**	0.888~	0.903*
	(-2.65)	(-1.69)	(-2.06)
79	0.865***	0.804***	0.896**
	(-4.51)	(-3.87)	(-2.80)
80	1.854***	2.025***	1.782***
	(33.13)	(21.13)	(25.69)
81	0.601***	0.660***	0.577***
	(-14.40)	(-6.50)	(-12.94)
84	0.991	1.053	0.962
	(-0.24)	(0.74)	(-0.84)
85	1.515***	1.810***	1.402***
	(13.19)	(10.11)	(9.02)
86	0.993	1.073	0.956
	(-0.17)	(0.94)	(-0.91)
89	1.132***	1.090	1.148**
	(3.34)	(1.31)	(3.08)
90	1.860***	2.121***	1.752***
	(28.42)	(19.02)	(21.37)
91	0.833***	0.786***	0.857***
	(-4.76)	(-3.61)	(-3.30)
94	1.003	0.924	1.054
	(0.10)	(-1.39)	(1.26)
95	2.113***	2.237***	2.054***
	(37.89)	(22.97)	(30.09)
96	0.909*	0.882	0.918
	(-2.05)	(-1.55)	(-1.51)
97	1.753***	2.074***	1.608***
	(17.14)	(12.62)	(11.93)
Appraisal Management Company (AMC) used	0.824***		
	(-21.29)		
Count default/foreclosure rate 5-7%	0.840***	0.843***	0.836***
	(-11.45)	(-6.49)	(-9.60)
County default/foreclosure rate over 7%	0.750***	0.734***	0.755***
	(-14.37)	(-8.83)	(-11.44)
Other county and home characteristics	Yes	Yes	Yes
State-by-Year Controls	Yes	Yes	Yes
Observations	433,807	149,459	284,348
Log likelihood	-190,020.50	-59,697.51	-130,023.39

Odds ratios displayed with z-statistics in parentheses. ~ denotes 0.10 level of significance, * 0.5, ** 0.01, *** 0.001. † Omitted category: LTV < 55. For brevity, results suppressed for LTVs of 55-73, 77-78, 82-83, 87-88, 92-93. Notch LTVs are shaded in gray. Other county and home characteristics include those displayed in Table 3. Sample includes observations with appraisal and contract price. Model 2 (3) excludes (is restricted to) appraisals conducted by AMC.

Table 5: Odds ratios for likelihood that appraisal identically matches contract price, robustness (2013-2015)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Applied-for LTV							
74	1.109*	1.104*	1.103**	1.089*	1.140~	0.941	1.101
	(2.51)	(2.45)	(2.58)	(2.48)	(1.82)	(-0.60)	(0.56)
75	1.334***	1.334***	1.323***	1.340***	1.376***	1.133~	1.326*
	(9.59)	(9.82)	(10.04)	(11.84)	(6.28)	(1.66)	(2.17)
76	0.899**	0.881**	0.874***	0.871***	0.949	0.879	0.963
	(-2.63)	(-3.21)	(-3.64)	(-4.13)	(-0.69)	(-1.31)	(-0.23)
79	0.865***	0.876***	0.876***	0.893***	0.967	0.791**	0.902
	(-4.49)	(-4.23)	(-4.45)	(-4.21)	(-0.58)	(-2.88)	(-0.77)
80	1.856***	1.804***	1.804***	1.795***	1.869***	1.699***	2.061***
	(33.18)	(32.75)	(34.53)	(40.58)	(18.85)	(12.14)	(8.68)
81	0.601***	0.617***	0.620***	0.613***	0.722***	0.635***	0.618***
	(-14.38)	(-14.11)	(-14.79)	(-16.74)	(-4.72)	(-4.99)	(-3.65)
84	0.992	0.994	1.005	1.010	1.053	0.861	1.148
	(-0.22)	(-0.16)	(0.14)	(0.30)	(0.65)	(-1.63)	(1.01)
85	1.516***	1.548***	1.555***	1.548***	1.581***	1.367***	1.814***
	(13.21)	(14.23)	(15.21)	(16.44)	(7.15)	(4.11)	(5.04)
86	0.994	1.009	1.005	1.002	1.052	0.866	1.218
	(-0.15)	(0.21)	(0.13)	(0.07)	(0.59)	(-1.43)	(1.34)
89	1.132***	1.135***	1.142***	1.154***	1.290***	1.012	1.071
	(3.35)	(3.50)	(3.93)	(4.54)	(3.41)	(0.14)	(0.52)
90	1.862***	1.862***	1.861***	1.878***	1.899***	1.684***	1.993***
	(28.46)	(29.47)	(31.05)	(35.68)	(15.46)	(10.09)	(7.69)
91	0.834***	0.847***	0.858***	0.876***	0.954	0.758**	0.892
	(-4.74)	(-4.50)	(-4.40)	(-4.08)	(-0.57)	(-2.94)	(-0.85)
94	1.004	1.026	1.035	1.053~	1.153~	0.866~	1.201
	(0.12)	(0.79)	(1.13)	(1.83)	(1.90)	(-1.81)	(1.52)
95	2.114***	2.026***	2.014***	2.031***	2.226***	2.059***	2.443***
	(37.92)	(37.79)	(39.72)	(46.43)	(19.90)	(15.95)	(10.74)
96	0.910*	0.873**	0.871***	0.888**	0.923	1.110	1.172
	(-2.03)	(-3.03)	(-3.31)	(-2.99)	(-0.73)	(0.91)	(1.00)
97	1.753***	1.740***	1.781***	1.779***	1.877***	1.528***	1.856***
	(17.15)	(17.65)	(19.59)	(20.78)	(8.46)	(5.47)	(5.37)
Controls							
County/home traits	Yes	No	No	No	Yes	Yes	Yes
State-by-year controls	Yes	No	No	No	Yes	Yes	Yes
Observations in Sample							
State	All	All	All	All	CA, OR, WA	AZ, FL, NV	IN, MI, OH
Loan types	FRM 30	FRM 30	FRM 30	All	FRM 30	FRM 30	FRM 30
Null values on controls	No	No	Yes	Yes	No	No	No
Observations	433,807	433,807	485,038	552,858	111,769	52,586	35,920
Log likelihood	-190,007	-198,454	-224,441	-259,391	-47,367	-31,162	-15,675

Odds ratios displayed with z-statistics in parentheses. ~ denotes 0.10 level of significance, * 0.5, ** 0.01, *** 0.001. † Omitted category: LTV < 55. For brevity, results suppressed for LTVs of 55-73, 77-78, 82-83, 87-88, 92-93. Notch LTVs are shaded in gray. Other county and home characteristics include a dummy for whether the county is rural, ln contract price, the ratio of the contract price to the county median sale price that quarter, and lagged house price captured as the change in the Zillow county-level home value index from 24 to 12 months before the appraisal. Sample includes observations with appraisal and contract price.

Table 6: Appraisal Outcomes and Characteristics of 2003-2009 Vintage Loans

	All Loans (n = 1,013,714)			No Default (n = 954,707; 94%)			Default (n = 59,007; 6%)		
	Median	Mean	SD	Median	Mean	SD	Median	Mean	SD
FICO	737	724	64	741	728	61	659	660	71
Back-end DTI	39	40	12	39	40	12	46	45	11
House price change (%) †	-2.0	-0.7	21.6	-1.1	0.3	21.3	-17.4	-17.4	20.7
House price trough (%) †	-7.6	-11.5	12.8	-7.2	-10.8	12.2	-20.4	-22.6	16.8
Reserves (months of mortgage payments)									
< 3 months		19%			19%			30%	
3-11 months		30%			30%			37%	
12+ months		51%			52%			33%	
Co-borrower		48%			49%			29%	
Condo		9%			9%			9%	
New Construction		1%			1%			1%	
Appraisal < Price		2%			2%			2%	
Appraisal = Price		45%			46%			45%	
Appraisal > Price		52%			52%			54%	

Note: Percentages at times do not sum to 100% due to rounding. For 12% of observations, county house price indices were not available for the study period. For these, we assigned the state-level house price index.

Table 7: Linear Probability Models for Default Risk at and Near LTV Notches, 2003-2009 Vintage Loans

	(1) All	(2) Negative	(3) Equal	(4) Positive
Dummies for LTVs at or Near a Notch				
78.5-79.5	0.0017	-0.0015	0.003	-0.0006
	(0.89)	(-0.18)	(1.10)	(-0.21)
80.0	0.0001	0.0031	-0.0002	-0.0011
	(0.12)	(0.61)	(-0.14)	(-0.81)
80.5-81.5	0.0201~	0.0309	0.0167	0.0179
	(1.96)	(1.49)	(0.99)	(1.16)
83.5-84.5	-0.0039	0.0028	-0.0121*	0.0024
	(-1.02)	(0.15)	(-2.13)	(0.44)
85.0	0.0065**	0.0049	0.0051~	0.0070*
	(3.02)	(0.33)	(1.65)	(2.24)
85.5-86.5	-0.0077*	-0.0101	-0.0135*	-0.0029
	(-2.14)	(-0.49)	(-2.55)	(-0.58)
88.5-89.5	0.0004	-0.0306~	0.0068~	-0.0041
	(0.14)	(-1.87)	(1.65)	(-1.06)
90.0	0.0112***	-0.0035	0.0152***	0.0074***
	(7.70)	(-0.37)	(6.67)	(3.82)
90.5-91.5	-0.004	0.0301~	0.0003	-0.0083~
	(-1.17)	(1.84)	(0.05)	(-1.89)
93.5-94.5	-0.0099***	-0.0085	-0.0094*	-0.0109**
	(-3.89)	(-0.64)	(-2.28)	(-3.26)
95.0	0.0129***	-0.0078	0.0193***	0.0079***
	(14.85)	(-1.21)	(13.88)	(6.95)
95.5-96.5	0.0187***	-0.0045	0.0088	0.0256***
	(3.93)	(-0.19)	(1.15)	(4.07)
House price change†	-0.0002***	-0.0004***	-0.0002***	-0.0002***
	(-9.13)	(-4.34)	(-5.83)	(-7.30)
House price trough†	-0.0032***	-0.0018***	-0.0033***	-0.0031***
	(-108.89)	(-11.22)	(-75.92)	(-75.99)
Constant	0.5472***	0.3684***	0.5696***	0.5378***
	(90.09)	(13.11)	(66.22)	(59.86)
Vintage and lender dummies	Included	Included	Included	Included
Borrower, loan, and house traits	Included	Included	Included	Included
Observations	1,013,714	23,101	460,908	529,705
R^2	0.137	0.097	0.144	0.133

Coefficients displayed with t-statistics in parentheses. ~ denotes 0.10 level of significance, * 0.5, ** 0.01, *** 0.001. Borrower, loan, and house traits include: the minimum FICO score of borrower/co-borrower (captured at origination), the back-end debt-to-income ratio of the borrowers, a dummy for the presence of co-borrower(s) on the loan, the number of months of saving "reserves" the borrowers have which might be used for mortgage payments, a linear spline of LTV (with notches at 70%, 80%, and 90%), a dummy for condos, and a dummy for new construction. †House price change and house price trough are measured at the county level (or state, if county-level data unavailable). The fields track house price changes from origination to 5 years post origination.

Table 8: Improvements in Default Model Fit Taking into Account Appraisals and AVMs, 2003-2009 Vintages

	Appraisal > Price			Appraisal ≤ Price			Appraisal ≤ Price and LTV < 75%		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FICO at purchase	-0.0008***	-0.0008***	-0.0008***	-0.0008***	-0.0008***	-0.0008***	-0.0005***	-0.0005***	-0.0005***
	(-158.21)	(-158.56)	(-158.83)	(-157.41)	(-157.43)	(-156.51)	(-61.83)	(-61.83)	(-61.73)
DTI	0.0008***	0.0008***	0.0008***	0.0005***	0.0005***	0.0005***	0.0001***	0.0001***	0.0001***
	(30.40)	(30.19)	(30.18)	(19.08)	(19.11)	(18.71)	(3.95)	(3.96)	(3.87)
3-11 months of reserves	-0.0089***	-0.0090***	-0.0089***	-0.0105***	-0.0105***	-0.0104***	-0.0091***	-0.0091***	-0.0091***
	(-10.192)	(-10.28)	(-10.21)	(-11.48)	(-11.48)	(-11.45)	(-5.59)	(-5.59)	(-5.59)
12+ months of reserves	-0.0141***	-0.0141***	-0.0141***	-0.0160***	-0.0159***	-0.0158***	-0.0141***	-0.0140***	-0.0141***
	(-16.83)	(-16.86)	(-16.80)	(-18.51)	(-18.46)	(-18.27)	(-9.99)	(-9.98)	(-9.99)
Co-borrower	-0.0338***	-0.0342***	-0.0346***	-0.0370***	-0.0370***	-0.0375***	-0.0171***	-0.0171***	-0.0173***
	(-54.77)	(-55.30)	(-55.93)	(-58.90)	(-58.89)	(-59.75)	(-19.09)	(-19.09)	(-19.30)
Condo	-0.0078***	-0.0080***	-0.0070***	-0.0126***	-0.0125***	-0.0115***	-0.0049***	-0.0049***	-0.0046**
	(-6.80)	(-6.99)	(-6.15)	(-12.49)	(-12.42)	(-11.49)	(-3.37)	(-3.35)	(-3.15)
New construction	0.0143***	0.0141***	0	0.0077**	0.0077**	-0.0012	-0.0007	-0.0006	-0.0032
	(5.13)	(5.06)	(-0.02)	(2.82)	(2.84)	(-0.43)	(-0.19)	(-0.19)	(-0.92)
House price change†	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	< 0.0001	< 0.0001	< 0.0001
	(-7.23)	(-7.09)	(-7.24)	(-6.39)	(-6.33)	(-6.85)	(-0.76)	(-0.74)	(-0.87)
House price trough†	-0.0032***	-0.0032***	-0.0032***	-0.0032***	-0.0032***	-0.0032***	-0.0012***	-0.0012***	-0.0012***
	(-76.23)	(-76.76)	(-77.32)	(-77.13)	(-77.18)	(-77.51)	(-19.87)	(-19.89)	(-19.85)
LTV Linear Spline									
< 70% LTV	0.0005***	0.0005***	0.0005***	0.0006***	0.0006***	0.0007***	0.0008***	0.0008***	0.0008***
	(3.81)	(3.85)	(3.96)	(5.79)	(5.78)	(6.04)	(9.87)	(9.86)	(9.99)
70-80% LTV	0.0002	0.0002	0.0002	0.0002	0.0002	0.0003	-0.0004	-0.0004	-0.0005
	(0.87)	(0.92)	(1.04)	(1.05)	(0.99)	(1.29)	(-0.93)	(-0.92)	(-0.99)
80-90% LTV	0.0017***	0.0017***	0.0017***	0.0016***	0.0016***	0.0015***			
	(9.45)	(9.29)	(9.22)	(9.17)	(9.22)	(8.86)			
> 90% LTV	0.0015***	0.0016***	0.0016***	0.0017***	0.0017***	0.0016***			
	(5.76)	(5.89)	(5.95)	(6.10)	(6.11)	(5.67)			
ln(appraisal/sale price)		-0.0367***			0.008			0.0055	
		(-11.02)			(0.33)			(0.19)	
Appraisal = sale price					0.0036*			0.0012	
					(2.07)			(0.57)	
ln(AVM/sale price)			-0.0270***			-0.0473***			-0.0117***
			(-23.23)			(-36.07)			(-6.04)
Constant	0.5366***	0.5396***	0.5356***	0.5592***	0.5559***	0.5494***	0.3209***	0.3199***	0.3188***
	(60.31)	(60.62)	(60.22)	(68.63)	(66.87)	(67.48)	(40.05)	(38.79)	(39.77)
Vintage & lender dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	529,705	529,705	529,705	484,009	484,009	484,009	100,833	100,833	100,833
R^2	0.1332	0.1334	0.1341	0.1413	0.1413	0.1436	0.0686	0.0686	0.0689

Linear probability model coefficients displayed with t-statistics in parentheses. ~ denotes 0.10 level of significance, * 0.5, ** 0.01, *** 0.001.

Appendix

Table A1: Appraisal Outcomes by Anticipated Loan-to-Value Ratio (2013-2015)

Applied-for LTV	Total	Negative	Equal	Equal or Rounded
< 70	142,965	9.0	31.8	44.6
70	14,813	8.3	33.0	45.3
71	7,960	8.1	29.9	44.5
72	9,966	8.6	31.4	45.0
73	9,864	8.9	31.7	45.5
74	10,637	8.7	31.8	45.4
75	26,061	7.7	33.9	45.7
76	10,331	9.9	29.0	45.0
77	12,340	10.3	29.5	44.4
78	15,229	9.9	30.9	44.7
79	17,712	10.3	29.9	44.6
80	278,977	5.3	31.9	46.3
81	16,937	9.5	19.4	45.5
82	14,473	11.1	29.6	43.0
83	12,057	9.8	29.9	44.3
84	12,207	9.4	30.9	45.4
85	28,415	6.0	31.1	46.3
86	10,657	8.8	29.6	46.4
87	12,560	7.5	30.7	46.9
88	13,799	7.4	30.3	46.1
89	15,054	7.9	29.9	46.8
90	114,610	5.1	31.5	47.5
91	14,052	8.6	24.1	46.9
92	15,811	8.4	28.5	46.0
93	18,981	8.2	28.8	47.1
94	19,592	8.3	28.3	46.9
95	258,730	4.3	29.0	47.9
96	11,385	6.7	19.3	51.7
97	30,720	5.2	29.8	50.4
Total	1,176,895	6.5	30.4	46.5
Major Notches (80, 90, 95)	652,317	4.9	30.6	47.1
All Notches	737,513	5.0	30.7	47.2
Non-Notches	439,382	8.9	29.8	45.4