WORKING PAPERS
RESEARCH DEPARTMENT

WORKING PAPER NO. 17-23
APPRAISING HOME PURCHASE APPRAISALS

Paul S. Calem
Supervision, Regulation, and Credit Department
Federal Reserve Bank of Philadelphia

Lauren Lambie-Hanson
Supervision, Regulation, and Credit Department
Federal Reserve Bank of Philadelphia

Leonard I. Nakamura
Research Department
Federal Reserve Bank of Philadelphia

July 2017

RESEARCH DEPARTMENT, FEDERAL RESERVE BANK OF PHILADELPHIA
Ten Independence Mall, Philadelphia, PA 19106-1574 • www.philadelphiafed.org/research-and-data/

Appraising Home Purchase Appraisals

Paul S. Calem, Lauren Lambie-Hanson, and Leonard I. Nakamura

Federal Reserve Bank of Philadelphia*

July 2017

Abstract

Home appraisals are produced for millions of residential mortgage transactions each year, but appraised values are rarely below the purchase contract price. We argue that institutional features of home mortgage lending cause much of the information in appraisals to be lost: some 30 percent of recent appraisals are exactly at the home price (with less than 10 percent below it). We lay out a novel, basic theoretical framework to explain how lenders' and appraisers' incentives lead to information loss in appraisals (that is, appraisals set equal to the contract price). Such information loss is more common at loan-to-value boundaries where mortgage insurance rates increase and appears to be associated with a higher incidence of mortgage default, after controlling for pertinent borrower and loan-level characteristics. Appraisals do, in some cases, improve default risk measurement, but they are less informative than automated valuation models. An important benefit of appraisals reported below the contract price is that they help borrowers renegotiate prices with sellers.

Keywords: Information, Mortgage, Regulation, Appraisal, Mortgage Default, Foreclosure

JEL codes: D81, G14, G21, G28, L85

[*]Paul Calem is a vice president and Lauren Lambie-Hanson is a principal financial economist in the Supervision, Regulation and Credit Department, and Leonard Nakamura is a vice president and economist in the Research Department, all at the Federal Reserve Bank of Philadelphia, Ten Independence Mall, Philadelphia, PA 19106-1574; e-mails: Paul.Calem@phil.frb.org, Lauren.Lambie-Hanson@phil.frb.org, and Leonard.Nakamura@phil.frb.org.
The views expressed in this paper are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. We thank Jan Brueckner, Kris Gerardi, Paul Goldsmith-Pinkham, Tim Lambie-Hanson, Xiaoming Li, David Low, Doug McManus, Albert Saiz, and participants at the Federal Reserve System Committee Meeting on Financial Structure and Regulation, the Consumer Financial Protection Bureau Research Conference, the International Industrial Organization Conference, and seminars at Villanova University, the Federal Reserve Board of Governors Division of Consumer and Community Affairs, and Fannie Mae for helpful comments. Jeanna Kenney provided outstanding research assistance. This paper is available free of charge at www.philadelphiafed.org/research-and-data/publications/working-papers.

Home appraisals are a standard feature of the U.S. residential mortgage underwriting process. The role of an appraisal is to provide an independent estimate of the underlying home value that constitutes the collateral for the mortgage loan. The true collateral value of a home is difficult to estimate because of the uncertainty about the value of the land at the home's location and because of idiosyncratic aspects of the property. Yet, it has long been observed in regard to completed mortgage transactions that the vast majority of appraisals are at or above the purchase contract price. We present evidence that some 30% of all appraisals are reported at precisely the initial contract price.

This information loss can be attributed to the appraiser attempting to respond on behalf of the lender to two important institutional issues related to mortgage underwriting and securitization. First, the government-sponsored enterprises (GSEs) and federally regulated banking institutions set up ranges for the loan-to-value (LTV) ratio across which underwriting and mortgage insurance requirements differ. In recent years, the upper boundaries of these ranges have been 80%, 85%, 90%, 95%, and 97% LTV. The most important of these currently are 80%, 90%, and 95%. 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, which is the denominator of the LTV ratio, be calculated as the lesser of the sale price and the appraisal. As a consequence of this minimum 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 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 price from sellers). Losing a transaction would entail an opportunity cost for the lender as well as for the buyer, seller, and real estate brokers.

We model the decision of whether to report the actual appraised value versus whether to bias the appraisal upward (as high as to the contract price) as a tradeoff between the cost of potentially losing the mortgage transaction and the cost of losing informational value from the appraisal. The informational cost derives from overvaluation of the property (and associated underpricing of credit risk) specific to the transaction as well as from reduction of the longer-term value of transactional data collected for risk modeling or other business purposes. This framework — compared with a view that appraisals are systematically biased upward or simply confirm the contract price — argues that there is informational content to the negative appraisals that may be greater than what appears on the surface.

We investigate two datasets of purchase mortgage appraisals: one of loans that were intended for purchase by a GSE (that is, Fannie Mae or Freddie Mac) and one that includes prime and subprime mortgages that were not specifically tracked to the GSEs. Both datasets include some mortgages that were ultimately originated and some that never resulted in a transaction. In both datasets, less than 10% of all appraisals are below the contract price, rather than the roughly 50% that would be expected if the appraisals were unbiased. Approximately 30% of appraisals in both datasets precisely equal the contract price.

We 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 relative to the market value. 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.

Using the data, 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 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. This also may benefit lenders, since the lowered purchase price and mortgage loan will reduce their exposure. Next, using a third dataset, 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.

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, contract prices (accepted offer prices), and preappraisal LTV measures. Cho and Megbolugbe (1996) were pioneers in the study of residential mortgage appraisals, providing some of the earliest empirical evidence that appraisers rarely report values below the contract prices. However, that study relied on appraisals for completed mortgages. Agarwal, Ben-David, and Yao (2015) use a Fannie Mae database to explore the bias of appraisals for refinances, in which there is no contract price to anchor on. The potential value of appraisals is vividly illustrated in Ben-David (2011), where it is shown that means of evading LTV requirements using cash rebates and other techniques led to higher rates of default.

Ding and Nakamura (2016) utilize a special sample of premortgage transactions from the vendor FNC, Inc., to study appraisal bias or information loss. We use this same sample, although we supplement it with GSE data that cover more mortgages and time periods and allow us to examine LTV ratios and mortgage performance for the loans. Ding and Nakamura (2016) 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 contract 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 another when the lender has contracted 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 contract price when a lower value ought to be reported. Eriksen et al.'s study emphasizes the adjustments made to the comparable sales used to appraise the property, which Mayer and Nothaft (2017) also find are at work.

Despite the fact that negative appraisals are rare, they have received more public attention than the suspiciously large number of appraisals that are reported at the contract 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% that buyers and sellers renegotiate the price down and that they have a smaller, although still significant, effect on the likelihood that a sale falls through:

32% of negative-appraisal transactions fall through compared with 25% overall. They further investigate how these forces affect prices and volumes in the 20 largest metropolitan statistical areas.

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 LTV ratio, with some foreknowledge of the impact of their down payment on the cost of the mortgage and its likelihood of being underwritten (Best et al. 2015).

Others have found correlations between LTV 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.[1] We provide this precise analysis on LTV and describe how differences in appraisal bias are another pathway through which LTVs impact default risk.

2. Institutional Aspects of Appraisals

In the U.S., appraisals must be performed to provide a valuation for collateral — for the purposes of calculating the LTV ratio — when mortgages are to be guaranteed by a GSE (Freddie Mac or Fannie Mae) or the federal government (Federal Housing Administration [FHA] or Department of Veterans Affairs [VA]), or when the mortgages are originated by a federally insured commercial bank or savings and loan institution. The collateral value in these cases is required to be equated to the lesser of the sale price and the appraised value.[2]

[1] 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.

[2] These requirements are ensconced in regulations governing the real estate lending activities of federally regulated banking institutions and in the underwriting standards for loans purchased by Fannie Mae and Freddie Mac or insured by the FHA. For example, the table that gives the method for calculating the LTV ratio in Fannie Mae's 2014 *Selling Guide* reads: "Divide the loan amount by the property value. (Property value is the lower of the sales price or the current appraised value,)" (pp. 171–172).

The requirement to value the collateral at the minimum of appraised value and sale price has significant implications, because the LTV ratio is a crucial indicator of the credit risk of the mortgage and it determines the interest rate and terms the lender is willing to offer. A lowered home valuation due to an appraisal at or below the contract price can result in cancellation of the transaction if the home seller is unwilling to lower the price, the buyer is unable to provide a larger down payment, or the borrower is unwilling to pay the mortgage insurance premium and/or higher interest rate associated with a low down payment loan.

A change in the regulation of mortgages occurs during the time period covered by two of our three datasets. The New York State Attorney General's office performed an investigation in response to the recent mortgage crisis and indications that reported appraisals had been biased upward. The outcome was an agreement by the GSEs (Fannie Mae and Freddie Mac) to implement the HVCC in May 2009, an action intended to curtail practices that generate appraisal bias. One of the most significant implications of the HVCC is that it compelled lenders to hire appraisal management companies (AMCs), rather than work directly with appraisers. Ding and Nakamura (2016) use a difference-in-differences methodology to show that, in the wake of the HVCC, mortgages qualifying for GSE backing showed less bias relative to jumbo loans that were not subject to the HVCC.

AMCs are intermediaries standing between lenders and appraisers, specializing in appraisal quality control and strengthening appraiser independence. As such, AMCs are expected to reduce information loss in appraisals. AMCs proliferated in the wake of the mortgage crisis to reduce the possibility that lenders or realtors might attempt to influence appraisal reports. In particular, many lenders have turned to AMCs to help ensure compliance with the HVCC, the appraiser independence rules in the Dodd-Frank Wall Street Reform and Consumer Protection Act, and the Interagency Appraisal and Evaluation Guidelines.[3]

3. A Model of Appraisal Outcomes Taking into Account Appraiser and Lender Incentives

In this section, we construct a stylized theoretical model to demonstrate how the requirement to use the lesser of the appraised value and the contract price in the LTV calculation can lead to information loss and bias in the reported appraised values. The appraiser, serving in

[3] See, for example, National Association of Realtors (2013).

the interest of the lender, may substitute the contract price for the actual appraised value when the appraised value is lower, to preserve the opportunity for a profitable mortgage transaction.

Consider a property under contract such that the buyer and seller have agreed upon a contract price, the natural log of which we denote v_0. The buyer applies for a mortgage loan of some amount, the natural log of which we denote L_0, such that the terms of the mortgage are based on the desired LTV ratio, in accordance with the lender's loan pricing schedule. The log-transformed loan to value ratio is denoted $\lambda_0 = L_0 - v_0$

The lender proceeds to evaluate the mortgage application and commissions an appraisal of the property. The appraised value of the property, the natural log of which we denote a, would be the appraiser's best estimate of the underlying market value of the property, as in Quan and Quigley (1991) and Lang and Nakamura (1993).[4] In particular, the appraiser utilizes an efficient information collection process that takes into consideration the contract price together with information in recent comparable transactions to estimate the underlying value of the property. Recent transactions on nearby properties are a primary input into this process, as they constitute valuable information about the market value.[5]

In the absence of a regulatory requirement, the appraisal would not be binding on the lender's decision on the application, although it would be considered valuable information. The lender would take into consideration the nearness of a to v_0 and the cost implications of rejecting the requested loan terms in deciding whether to approve the requested loan terms.

However, the minimum value rule forces the lender to evaluate the application based on $v = \min(v_0, a)$ in the calculated LTV ratio. Therefore, the lender can approve the loan application at the borrower's desired LTV only if the appraiser values the property (after log transformation) at $v \geq v_0$, whereby the post-appraisal LTV ratio $\lambda = L_0 - v$ is less than or equal to λ_0.

[4] In Quan and Quigley (1991) and Lang and Nakamura (1993), appraisers use all available information in a Kalman filter, updating to arrive at an optimal (in a mean-squared-loss sense) appraised value and a confidence interval around it.

[5] The dependence on recent neighboring transactions creates a dynamic information externality, as argued in Lang and Nakamura (1993), who draw the explicit conclusion that the precision of appraisals increases with the number of recent transactions. When the flow of transactions falters, the precision of an appraisal falls and the loan becomes riskier. The empirical importance of this information externality has been explored in several papers, notably Blackburn and Vermilyea (2007) but also Calem (1996), Ling and Wachter (1998), Avery et al. (1999), and Ding (2014).

An immediate consequence of the minimum value rule is that the valuation of the property will be downward biased probabilistically. The practical impact is that, if $a < v_0$, the lender must reject the loan application or the requested loan amount and terms. We argue that the appraiser may act as agent of the lender, enabling the lender to circumvent the minimum value rule.

3.1 Downward-biased Valuation

The minimum value rule implies that if both the true (best-estimate) appraisal and the contract price each are unbiased estimates of the underlying home value, then valuation based on the lesser of the two will be biased downward. This bias may be appreciable.

For example, suppose that the appraiser's best-estimate valuation a and the accepted offer v_0, measured in logs, are distributed normally, relative to the true market value. That is, a and v_0 are distributed bivariate normally, with both means $\bar{v}$ equal to the underlying value, with variances σ_a^2 and σ_o^2, and with correlation coefficient ρ. Then the expected value of:

(1) $\min(\ln a, \ln v_o) = \bar{v} - \sqrt{\sigma_a^2 + \sigma_o^2 - 2\rho\sigma_a\sigma_o}\,\phi(0)$,

where ϕ is the pdf of a standard normal distribution, so that $\phi(0) = 1/\sqrt{2\pi} \approx 0.4$.[6] Thus, the downward bias of the estimate amounts to about 0.4 times the standard deviation of $a - v_0$ (= L). Note that we can estimate the true standard deviation of $a - v_0$ on the maintained assumption that positive appraisals are unaffected by appraisal bias. As shown later in Table 2, the underlying standard deviation is between 4% and 10%, so the bias is 1.6% to 4%.

3.2 Transactional Impact

Upon being informed of the appraised value a, the lender either approves the requested loan terms or makes a counteroffer, taking into account the contract price v_o, the requested loan amount L_o, and the implied LTV ratio $\lambda_0 = L_0 - v_0$ and the associated loan pricing. The practical impact of the minimum value rule is that it impedes the lender from making an optimal decision.

First, consider a case in which $a \geq v_0$. If not for the minimum value rule, the lender could consider whether to offer the borrower more advantageous loan terms than originally applied for. However, the impact of the minimum value rule in this situation is of secondary interest; the lender would have no reason to reject the loan application or the originally requested terms and would

[6] See Nadarajah and Kotz (2008).

have little incentive to offer more generous terms. Therefore, we shall restrict attention to the case $a < v_0$.

If $a < v_0$, the LTV ratio $\lambda^* = L_0 - a$ implied by the appraised value and the originally requested loan amount exceed $\lambda_0 = L_0 - v_0$, the LTV ratio associated with the original loan application. However, if not for the minimum value rule, the lender would not be required to use λ^* in calculating the LTV ratio for the purpose of approving the requested loan amount and for pricing the loan.[7]

Let v denote the lender's valuation for this purpose, and let $\lambda = L_0 - v$ be the corresponding LTV ratio; henceforth, we shall refer to v as the "pricing" valuation. In the absence of the minimum value rule, the appraised value and contract price would be lower and upper bounds, respectively, on the pricing valuation v:[8]

(2) $a \leq v \leq v_0$; $\lambda_0 \leq \lambda \leq \lambda^*$.

Thus, in the absence of the minimum value rule, the lender would have the option of substituting a higher property valuation, possibly as high as the contract price, for the appraised value, while agreeing to the originally requested loan amount.

In the presence of the minimum value rule, the lender's optimal decision with respect to the pricing valuation v involves the following tradeoff. On the one hand, to the extent that v exceeds the appraised value a, the property is more likely to be overvalued relative to its underlying market value, implying underpricing of credit risk.[9] On the other hand, to the extent that v falls short of v_0, there is an increasing likelihood that the transaction will not be completed.

We shall denote the undervaluation of expected credit loss due to v exceeding a as $g(v - a)$, where $g(0) = 0$.[10] Clearly, the larger the gap between a and v_0, the more severe the undervaluation of expected credit loss, so that $g'(v - a) > 0$ if $v > a$.

On the other hand, a pricing valuation v below the contract price v_0 entails risk that the transaction will not be completed. With $v < v_0$, the lender is compelled to reject either the originally

---

[7] We assume that the lender cannot deviate from a rate sheet that dictates loan pricing based on the calculated LTV ratio.

[8] The lender would have no incentive to deviate even further from the contract price by valuing the property at less than a nor any incentive to value the property at greater than the contract price.

[9] Holding constant the requested loan amount L_o, $v > a$ yields the LTV ratio $L_0 - v < L_0 - a$. Thus, the loan would be assigned a lower effective LTV ratio, corresponding to lower probability of default and expected loss given default, resulting in underpricing of the risk.

[10] The cost of deviating from the appraised value also may depend on the precision of the appraisal. We assume that this is implicit in g and control for it in our empirical analysis.

requested loan amount L_o or the originally requested loan terms and substitute a less attractive counteroffer.[11]

Such less attractive counteroffers increase the likelihood that the property sale will be cancelled, in which case no mortgage is originated. On the one hand, the borrower may be unable or unwilling to provide the larger down payment $L_0 - L^*$ or bear the higher cost (mortgage insurance or risk premium) associated with the larger LTV ratio λ^*. On the other hand, the seller may be unwilling to reduce the price to match the appraised value. In the event that the transaction is cancelled and the mortgage is not originated, the lender incurs an opportunity cost in foregone fee income (that would offset the application processing expenses already incurred). Denoting the expected opportunity cost to the lender from potential loss of the mortgage transaction as $f(v_o - v)$, we have $f(0) = 0$ and $f'(v_o - v) > 0$ for $v_o \geq v$.

Putting together these two cost components, we have that the lender's optimal pricing valuation given $v_o \geq a$, which we denote v^*, solves the cost minimization problem:

(3) $\min_{v} f(v_o - v) + g(v - a)$.

Notice that if $f'(v_0 - a) > g'(0)$ then $a < v^* \leq v_o$. In other words, if credit losses $g(v - a)$ increase more slowly with v than the expected cost due to a cancelled transaction $f(v_o - v)$, in the neighborhood of $v = a$, the lender's preferred valuation is biased upward relative to the appraised value.[12]

Further, if $f'(0) < g'(v_0 - a)$, then $v^* = v_o$ given a sufficiently close to v_o. In other words, if the cost of possibly losing the transaction is increasing more quickly than the measured credit losses near the contract price v_0, then the lender would prefer v biased all the way up to the contract price, as long as a is not too low.

Note that, even if the lender ultimately plans to sell or securitize the loan, this basic tradeoff would still apply. A lender who originates-to-sell would face essentially the same opportunity cost of not originating the loan, which typically consists of a foregone origination fee and servicing

[11] Rather than simply reject the application outright, the lender might opt to offer the smaller amount L^* such that $L^* - a$ equals $\lambda_0 = L_0 - v_0$, the LTV ratio associated with the original loan application: $L^* = L_0 - v_0 + a$. Alternatively, the lender could agree to the requested loan amount L_0 while offering a higher-priced loan associated with the LTV ratio $\lambda^* > \lambda_0$: $\lambda^* = L_0 - a > L_0 - v_0 = \lambda_0$.

[12] It is plausible that $f'(v_0 - a) > g'(0) \approx 0$ because, on the one hand, even small changes in the offered loan amount or loan terms might significantly impact the likelihood of the transaction failing, as borrowers often have limited ability to increase their down payment. On the other hand, small deviations from the appraised value would tend to be immaterial for expected credit loss. (Many other factors, including future changes in home values, would tend to dominate.)

fees, as the originator typically becomes the servicer of both held and securitized loans. Therefore, the only source of difference between holding and securitizing would be from the cost of less accurate default risk measurement. Securitization might enable the originator to pass some of this cost along to the investor, in which case the incentive to bias the valuation above the appraisal is stronger for securitized loans compared with portfolio loans.

The minimum value rule — the requirement to use the downward-biased property valuation $v = \min(v_0, a)$ in the LTV calculation — prevents the lender from implementing the optimal pricing valuation v^*. Given $a < v_o$, the lender would be compelled to calculate the LTV ratio with $v = a < v^* \le v_o$.

3.3 Reported Appraised Value and Potential Information Loss

The appraiser (acting in the lender's interest and toward the optimal valuation) enables the lender to circumvent this distortionary effect of the minimum value rule by incorporating upward bias into the reported appraised value in the event $a < v_o$.[13] The appraiser would, in this case, report $\tilde{a} = v^*$, thereby restoring the lender's optimal pricing valuation, where we let $\tilde{a}$ denote the reported value.

Substitution of the contract price for the true appraised value (the latter being the best estimate of underlying market value) entails information loss, because the true appraised value of the property is lost in the process.[14] Although from the lender's perspective this is a good outcome given the minimum value rule, the result is socially inefficient.

One important inefficiency from information loss is that borrowers are denied the opportunity to re-evaluate their offers on the basis of the true appraised values. In addition, the lender is not able to make fine-grained distinctions across properties. For example, as we show below, there appears to be more information loss when property values have large underlying variance. As a consequence, when the underlying value is harder to know, less information is provided to the lender. The information is also lost to all subsequent consumers of appraisal data, who could use it to evaluate lending decisions, property valuations, and default risk.

[13] We opt not to complicate the model by introducing an agency problem but assume that the appraiser fully internalizes the costs faced by the lender and seeks to minimize the total cost.

[14] In theory, the reported appraisal $\tilde{a}$ remains informative provided the lender can infer the true appraised value based on knowledge of the cost minimization problem that generates v^*. However, when reported appraisals are set equal to the contract price, they are biased upward by unknown amounts. Practically speaking, databases preserve only $\tilde{a}$ and v_o.

We illustrate this aspect of our model by invoking a linear-quadratic version of the cost minimization problem (3), where we substitute $\tilde{a}$ for v^* to highlight the appraiser acting on behalf of the lender:[15]

(4) $g((\tilde{a} - a) - 1) = d((\tilde{a} - a) - 1)^2$

$f(1 - (\tilde{a} - v_o)) = b(1 - (\tilde{a} - v_o))$ if $v_o > a$ and $f(1 - (\tilde{a} - v_o)) = 0$ otherwise,

where b and d are strictly positive constants. With these costs, the appraiser determines the reported appraisal as follows:

(5-i) If $a \geq v_0$, then $\tilde{a} = a$.

(5-ii) If $a < v_o$ and $a > v_o - b/2d$, then $\tilde{a} = v_o$.

(5-iii) If $a < v_o - b/2d$, then $\tilde{a} = a + b/2d$.

The first statement follows from our initial assumption that if $a \geq v_0$ then the lender accepts the requested loan amount and terms. The second and third statements follow from solving the cost minimization problem subject to the condition $\tilde{a} \leq v_0$. The details of the proof are in the appendix.

The first statement establishes that, when the true appraisal is greater than the accepted offer price, the reported appraisal is equal to the true underlying appraisal; there is no incentive to deviate. When $a \geq v_o$, the appraiser has no incentive other than to report $\tilde{a} = a$, because the appraisal can have no adverse impact on the loan application. Because positive appraisals are reported truthfully, they can be used to estimate the standard deviation of the underlying a.

The second statement holds that, when the true underlying appraisal is below but sufficiently near the expected offer price, the reported appraisal is identical to the accepted offer price and information loss occurs. Specifically, the underlying appraisal must be within a distance of the accepted offer price such that the expected cost of a cancelled transaction exceeds the risk impact of potentially overvaluing the property.

The third statement holds that, if the true appraisal a is sufficiently below the accepted offer price v_0, the reported appraisal $\tilde{a}$ will be between the true appraisal and the accepted offer price. The difference relative to the true appraised value, $(\tilde{a} - a)$, will equal $b/2d$.

The specific situation of a borrower with limited ability to make a required minimum down payment would correspond to a relatively high opportunity cost of deviating from v_o and, hence, a larger value of $b/2d$. In this respect, the model implies a relatively high likelihood that the

---

[15] It is intuitive that g is convex: $g''(v - a) > 0$ if $v > a$, as the property valuation affects both the measured probability of default and measured loss-given default.

reported appraisal will equal the contract price a.[16] On the other hand if the borrower with a limited ability to make the required minimum down payment is also at a greater risk of default, $b/2d$ could be smaller.

Note that in the context of this model each appraiser has to estimate $b/2d$ for each appraisal. The reported appraisal becomes more informative about the true appraisal to the extent that $b/2d$ is common knowledge. Variations in this estimate across appraisals may make the actual reported appraisal less informative about the true appraisal than if $b/2d$ were common knowledge.

Finally, we note the implications of our model for the probability distribution of the reported appraised value in relation to the accepted offer price v_o. The model implies that the distribution of $\tilde{a} - v_o$ corresponds to a rightward translation of the distribution of the true appraised values a relative to v_o in the region where $a < v_o$, with a piling up of probability mass at $\tilde{a} = v_o$.

4. Data

We explore the model's conclusions using three datasets of appraisals:

(1) Acquired from a GSE, this dataset includes 3.6 million mortgage applications made in 2013–2015, including both those that resulted in a transaction and those that did not. We compare the appraised value with the contract price. We also focus on the 1.3 million single-family purchase mortgage applications that were flagged as intended for sale to a GSE, while the rest were originated using the GSE's underwriting platform but may have been intended to be held in portfolio.

(2) Also acquired from a GSE, this dataset includes 900,000 single-family purchase mortgages originated in 2003–2009. Since these loans are well-seasoned, we can use them to study how appraisal loss relates to mortgages' ultimate outcomes. Because the contract price is not available, we must compare the appraised value with the final sale price.

(3) Acquired from the vendor FNC, a real estate mortgage technology company, this dataset includes 1.1 million single-family purchase mortgage applications made in 2013–2015, including both those that resulted in a transaction and those that did not. This sample includes applications made to a number of subprime lenders that became

[16] This increased likelihood corresponds to a wider range of appraised values a generating $\tilde{a} = v_o$.

bankrupt during the recent mortgage crisis. For each application, we compare the appraised value to the contract price.

4.1. The Empirical Distribution of Appraised Values Relative to Contract Prices

Using these three datasets, we examine the distribution of reported ratios of appraised values relative to contract prices for elements of consistency with our stylized model. Specifically, we calculate the natural log of the ratio of the reported appraised value to the price (contract or sale price, as available). Table 1 summarizes the distribution of these values (the appraised value relative to the price) by dataset, and Figure 1 displays the distribution of the 2013–2015 sample intended for sale to a GSE. Figure 2 shows the distribution by loan application year for the two datasets in which we observe the contract price. In each year from 2007–2015, 25% to 30% of mortgage applications had an appraised value that was exactly identical to the contract price.

Significant bunching at this mass point where $a = v_o$ is consistent with our model's predictions. Figure 3 displays this effect for the linear-quadratic version of the model, showing that bunching is particularly common when *b* is large relative to *d* (Panel B) and when the variance of $\tilde{a}$ - v_o is small (Panel C).

Bunching appraised values at the contract price may also be driven by other factors. Appraisers are given the contract price as part of the appraisal order process for a reason: it is seen as pertinent information for the value of the home. One might argue that the bunching is driven by appraisers estimating a close to v_o and deferring to v_o for reporting $\tilde{a}$. However, note the asymmetry in the Figure 1 distribution just above and below the mass point of $\tilde{a} = v_o$: 25.6% of appraised values exceeded the contract price by no more than 1%, but only 0.7% of appraised values fell below the contract price, although within 1%.

If appraisers are indeed making such small adjustments, defaulting to the contract price, they appear to be doing so systematically when their own valuation *a* was lower than the contract price. The part of the distribution just above $\tilde{a} = v_o$ looks relatively smooth. If anything, slightly more records reside just above $\tilde{a} = v_o$ than we might expect.[17]

[17] This could be due to appraisers defaulting to v_o but then rounding their appraisal up to a cleaner number (e.g., an increment of $1,000 or $5,000), or appraisers may even report $\tilde{a}$ slightly > v_o when $a = v_o$ if there is a common perception that appraisals are upwardly biased to v_o, and the appraisers want to send a clear signal that they believe the appraised value is not less than the contract price. For example, Kartik (2009) presents a model in which equilibrium lying behavior results in systematically upwardly biased communication.

Negative appraisals have been rare over time, making up just 5.1% of observations in 2007 and 6.9% in 2008. Due to increased perceived risks of default in 2008–2009, even before the HVCC and associated policy interventions, negative appraisals began to become more common, peaking at 12.8% in 2009. We argue that, throughout this period, the small number of negative appraisals stems from the biasing of appraisals upward, typically, although not always, to the contract price.

4.2. Characteristics of GSE data

We focus our analysis on the two GSE datasets, because they include richer characteristics of the mortgages. However, we also incorporate the FNC data where possible (such as in Table 1 and in model robustness) to be more confident that our findings are not isolated to GSE-targeted loans. The 2013–2015 applications data include 1.3 million 30-year, fixed-rate, single-family, owner-occupied purchase mortgage applications, taken from the GSE's underwriting software. The dataset contains 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 GSE dataset, which we use to measure the ability of appraisals to predict defaults *ex post*, includes data on approximately 900,000 30-year, fixed-rate mortgages originated during 2003–2009 and ultimately guaranteed by the GSE. The loans used in the default models are restricted to fully amortizing, single-family, owner-occupied purchase mortgages with full documentation at underwriting and no prepayment penalties. HARP loans, loans with streamlined processing, and loans with other types of credit variances are excluded.

The 2013–2015 loan applications data include AVM estimates captured at the time the application was made and 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. When ordering appraisals, lenders routinely provide both the contract price and the amount the borrower intends to borrow, thus communicating the applied-for LTV ratio. These fields are displayed on typical appraisal order forms, which are publicly accessible online.

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. Therefore, we supplement the GSE datasets with data from McDash Analytics on area default and foreclosure rates, CoreLogic public records data on area home sale characteristics, and Zillow home value indices.

5. LTV Notches

A borrower's choice of how much money to borrow when buying a house is strongly influenced by the mortgage insurance requirements set by lenders and the GSEs, and their corresponding monthly costs. The cost of mortgage insurance raises the borrower's required monthly payments by a step function at particular LTV notches (80%, 85%, 90%, and 95%), as demonstrated through an example in Figure 4. This provides a strong incentive to arrive at a down payment sufficient to avoid the higher cost that sets in just above a notch.[18]

Put differently, the marginal benefit of an additional one percentage point down payment is far higher for a borrower who would otherwise face an LTV of 81%, compared with a borrower who would otherwise face an LTV of 80%. The only thing to be gained by putting additional money down in the latter case (therefore, 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 2. Specifically, 63% of all 2013–2015 mortgage applications in our dataset fell at one of six notches, with 55% at the three major notches of 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.

Before an appraisal is ordered, the borrower has selected his target LTV, calculated as the loan amount divided by the contract price. If the appraisal turns out to equal or exceed the contract

[18] Mortgage costs also vary depending on borrower characteristics, such as credit score, but we are holding these other factors constant during this discussion. The reason insurance costs increase dramatically just above the notches is that mortgage insurance coverage increases. Specifically, standard mortgage insurance coverage required by the GSEs for 30-year mortgages is 12% of the outstanding principal balance for 80.01–85% LTV, 25% coverage for 85.01–90% LTV, and 30% for 90.01–95% LTV loans. Since higher LTV loans are likely to have greater losses, requiring greater coverage for these loans helps to equalize the GSE's expected losses across different LTVs.

price, it has no impact on the LTV.[19] However, in the event of a negative appraisal, the buyer (borrower) must decide how to proceed, because the LTV is now higher than the borrower had targeted (since the LTV denominator is the lesser of the price and the appraised value). He may decide to make a larger down payment to keep the LTV the same as the loan for which he applied, accept a higher LTV loan (at a greater cost), or renegotiate the price with the seller. He may also do a combination of these things (e.g., split the difference with the seller), or he may choose to walk away from the transaction. All of these outcomes are undesirable to someone: the buyer, the seller, the lender, or all three parties.

Accepting a higher LTV loan is particularly undesirable to the borrower, especially if the new LTV requires a greater amount of mortgage insurance coverage. Given that most borrowers apply for loans at LTV notches, an appraisal that falls at all short of the contract price and leads to a higher LTV would result in significantly more spending on mortgage insurance each month. Lenders (and the appraisers they hire) might therefore expect borrowers at notches to be more likely to back out of a transaction if the appraisal is negative. As we shall see, loans at LTV notches experience more information loss (more cases where appraised value matches contract price) relative to loans just above or below the notches. This suggests that appraisers find the concern that the loan will fall through (higher *b*) more salient than default concerns (higher *d*). As we shall see in Section 8, this can lead to more defaults as a consequence of information loss.

6. Information Loss at Notch LTVs

Objective, independent appraisals might be expected to fall short of (or exceed) the contract price roughly half the time, but in reality negative appraisals are reported only rarely. In our 2013–2015 dataset of 1.3 million appraisals for 30-year fixed rate mortgages summarized in Table 3, only 6% were reported below the contract price. Only 5% of notch mortgages have negative appraisals, as compared to 9% 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.

[19] In this case, in which the appraisal is greater than or equal to the transaction price, the LTV will ultimately be the loan amount divided by the final sale price. This will generally be the same as the LTV at the time of the mortgage application or possibly less if the buyer and seller renegotiate the price down, such as after receiving negative findings in the home inspection. It is very unlikely that the purchase price is adjusted *up* and the LTV increased.

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 we examine appraisals that are equal or within one percent above the contract price.

Figure 5 displays the Table 2 data in a simple chart. The bars in Figure 5 represent the percentage of appraisals that are less than or equal to the contract 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 on the bars represents the percentage of appraisals that are identical to the contract price, conditional on not exceeding 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 that 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 2 and Figure 5 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 linear probability models for the probability of information loss. Our measure of information loss is that an appraisal is exactly equal to the contract price, conditional on its being less than or equal to the contract price (the same measure displayed in the dotted line in Figure 5). By focusing on this part of the distribution of appraisals to contract prices, we intentionally ignore the positive side (appraisal > price), because that side is assumed to have little or no appraisal bias.[20] However, as we show, the choice to model information loss in this way is not driving our result. If we instead consider three possible outcomes (appraisal exceeding, falling short of, or equaling the contract price) in a multinomial framework, we find consistent results.

[20] The share of appraisals that exceed the contract 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.

We employ a full set of dummy variables for LTV ratios as well as state-by-appraisal-year dummy variables, controls for the prevalence of default and foreclosure in the county at the time of the appraisal, the ratio of the contract price to the county median home sales price that year, the natural log of the contract price, 12-month price appreciation in the county lagged by one year, and a dummy variable indicating the use of an AMC to facilitate the appraisal. We display summary statistics for these variables in Table 3.

The main regression results are shown in Table 4.[21] Notch mortgages are confirmed to have a sharply higher incidence of information loss relative to mortgages with one percentage point higher or lower LTV. On average, notch mortgages are about 9 percentage points more likely than non-notch mortgages to have the appraisal equal the contract price, conditional on not exceeding it. 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 our 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 (2016).

The results are robust to controlling for the identity of the appraiser (Table 5, Models 3 and 4). In other words, the practice of reporting appraisals identical to contract price holds even within-appraiser.[22] Interestingly, controlling for the identity of the appraiser also dramatically increases the model fit, as evidenced by the R^2, suggesting strong between-appraiser differences in the tendency to report equal appraisals. Results are also robust to instead including lender controls (Table 5, Models 5 and 6). While these controls also improve model fit over the baseline model, the improvement is much more modest than when including appraiser controls.

The elevation in information loss at LTV notches can be found across the United States, in areas with different housing market conditions during this period. In Table 6, we show the results for three groupings of states: the West Coast (California, Oregon, and Washington), Sand States (Arizona, Florida, and Nevada), and the Rust Belt (Indiana, Michigan, and Ohio). We also show that the pattern persists when we restrict the sample to appraisals in rural areas, defined as counties that are located outside metropolitan statistical areas. Overall, the effects at notches are a bit

[21] Table 4 includes model results for the 472,960 appraisals with values less than or equal to the contract price. This is consistent with the 36% of the 1,318,074 appraisals in Table 3, Panel A, which are non-positive. Results for all the control variables can be found in Table A1.

[22] Approximately 3,300 appraisals do not have information on the appraiser who conducted the appraisal, so those observations are omitted from Models 3 and 4 of Table 5.

weaker in rural areas. This is particularly true at the 75% LTV notch, which is most notably tied to increases in mortgage pricing for condominiums and investment properties, both of which are less common in rural areas.

Our results are not driven by our decision to model information loss as the probability of an appraisal being reported equal to the contract price, conditional on not exceeding it. To test this, we present Table 7, in which we specify the information loss model as a multinomial logit, where the three possible outcomes are: (1) appraisal < contract price, (2) appraisal = contract price (the outcome of interest, information loss), or (3) appraisal > contract price. As with the linear probability model estimated on the sample of non-positive appraisals, we find that information loss is significantly more common at LTV notches. However, because the linear probability model is easier to interpret, we present the majority of our results using that specification.

We provide additional robustness checks in the appendix. Table A2 shows that our results are not sensitive to excluding control variables or extending our sample to adjustable-rate mortgages and mortgages with terms other than 30 years in length. In Table A3, we relax the definition of information loss to include appraisals that came in identical to or slightly above (but within 1% of) the contract price, which generates similar results to our main model.

One lingering question is about the generalizability of our results to earlier periods or to loans that may not have been intended for GSE sale. The FNC dataset offers insights into these questions. Although we cannot observe LTV in the FNC dataset, in Table 8 we estimate our information loss model on the GSE and FNC datasets, removing the LTV controls. We find qualitatively similar results for the log contract price, county median home value, and AMC controls. Interestingly, while house price change is not a strong driver of information loss among the GSE dataset's appraisals, in the FNC dataset having greater house price appreciation leading up to an appraisal makes it more likely that the appraiser will report the contract price than a negative appraisal. Also, while having a county default rate of 5–7% is a significant negative predictor of information loss in the GSE dataset, it is not significant for the FNC appraisals. However, in both datasets we see a significant negative effect of foreclosure rates over 7% on information loss.

7. Negative Appraisals and Renegotiations between Buyer and Seller

Although they can threaten the sale, negative appraisals can serve the borrowers (purchasers) well by helping them avoid overpaying for a property. The extent to which the borrower pays less for the property will tend to mitigate the risk to the lender. 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 contract price.[23] This clause helps facilitate these renegotiations when appraisals come in lower than anticipated.

In fact, in 58% of the sales in our dataset that come to completion despite a negative appraisal, the borrower and seller renegotiate the price downward.[24] The frequency of renegotiation in response to a negative appraisal is even higher for borrowers who would be bumped into a higher LTV class by the appraisal: 71% of those sales are renegotiated.

In contrast, only 2% 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 6. 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.

Negative-appraisal transactions in hot market counties (those with year-over-year appreciation of more than 10% leading up to the date of the appraisal) are less likely by a few percentage points to result in renegotiations, which could perhaps be caused by buyers waiving the appraisal contingency clause in their purchase and sale agreements to provide more competitive offers. However, as shown in Table 9, the fundamental pattern is the same: a negative appraisal that has a material impact on the buyer's LTV is more likely to result in a renegotiation.

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

8. Default Likelihood at LTV Notches

[23] The appraisal contingency is a standard, commonly used clause in purchase and sale agreements, although buyers can waive it to make their offers more competitive, similar to waiving a mortgage financing or inspection contingency (Chism 2016, Colley 2015).

[24] This is close to the 51% found by Fout and Yao (2016).

Upward bias in collateral valuations will tend to increase the rate at which borrowers default and the losses that the lenders experience in relation to measured LTV. Given that information loss and the associated upward bias are more common at notches, a logical question is whether observed default frequencies are higher at notches compared with neighboring observations, particularly when information loss is directly indicated (by appraised value equal to contract price).

To address this question, we turn to the sample of mortgages originated in 2003–2009 and evaluate the relationship between the LTV and the likelihood that a loan becomes 120 or more days delinquent in the first 3 years after it was originated.[25] To simplify the analysis with respect to LTV, we exclude loans with a second-lien mortgage at origination (i.e., a piggyback mortgage). We also limit the sample loans with LTVs of 50–90% and that were 30-year, fixed-rate mortgages taken out by owner-occupants to purchase homes to serve as their primary residences.

In our 2003–2009 dataset, we have information about the ultimate sale (transaction) price, the appraisal, and the AVM at the point the mortgage was originated, along with information on subsequent payment performance. Unfortunately, we lack panel data on the mortgages and observe only three metrics for performance: the loan becoming 90+ days delinquent within the first two years after origination, 120+ days delinquent within the first three years, or 180+ days delinquent within the first five years. Because of this data limitation, we must study loan performance at the different snapshots in time for each loan, rather than estimating default hazards.

Another limitation is that, unlike the 2013–2015 loan application dataset from the GSE, 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 and subsequently walked away from the transaction.[26] 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.

[25] Our 2013–2015 mortgage sample is not seasoned enough to assess mortgage performance.

[26] Also, because 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 transaction price than would have been captured in an 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.

Descriptive statistics in Table 10 show the characteristics of the sample overall and are broken down by whether the mortgage is observed to default. Figure 7 shows the proportion of loans originated in 2007 that became 120 or more days delinquent in the initial three 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 at the 80% LTV, which, while higher than LTVs several percentage points lower, resembles closely loans at 78–79% LTV.

In Table 11, 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 10. In Model 1, we show that the risk of default increases at the notches of 85%, 90%, and 95%.[27] In Models 2, 3, and 4, we break out the sample by the outcome of the appraisal: below the transaction price, equal to the price, and above the price, respectively.

In support of our argument that information loss in appraisals should be linked to increased defaults, we find that the increased default likelihood at the notches is strongest for the loans where the appraisal was identical to the 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.[28] These loans with an appraisal equal to the price are most subject to information loss. Realistically, some of these homes could have been truthfully appraised at a value exactly equal to the 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 LTV and greater default risk among loans with positive appraisals. For these loans, measured default likelihood differs

[27] Extended results, including coefficients for all the control variables, can be found in Table A4 of the appendix. Our finding that default risk is elevated at most LTV notches is robust to changing the definition of default to at least 180 days delinquent within the first 5 years of the loan's history (Table A5) or at least 90 days delinquent within the first 2 years of the loan's history (Table A6).

[28] P-values for an F-test of equality of the coefficients are as follows: 83.5–84.5% vs. 85.0% = 0.0164; 85.0% vs. 85.5–86.5% = 0.0001; 88.5–89.5% vs. 90.0% = 0.0003; 90.0% vs. 90.5–91.5% = 0.0054; 93.5–94.5% vs. 95.0% < 0.0001; and 95.0% vs. 95.5–96.5% = 0.0090.

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.

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 transaction price are likely to suffer from selection bias.

Another possible explanation for why notch mortgages default at higher rates is that borrowers at notches are more financially constrained and that this information is passed along to the appraiser, who inflates the appraisal to the contract 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 has to stretch to a lower, less costly LTV loan or to make up the down payment shortfall that would be 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.[29]

When we look at the loans separately by the time period in which they were originated (Table 12), we find evidence of higher default likelihood at the notches across time periods (2003–2005, 2006–2007, and 2008–2009). However, during 2006 and 2007, widely acknowledged to be the two worst-performing vintages of mortgages nationwide in the recent mortgage crisis, the effects at notches appear particularly strong. In the other years, some notches do not have significant increases in default risk (particularly, the 95% LTV notch in 2003–2005 and the 85% notch in 2008–2009).

[29] Consider the percentage of borrowers who had enough savings at origination to cover the equivalent of at least three months of mortgage principal and interest payments. At 94% and 95% LTVs, 74% of borrowers had enough savings to cover at least 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, in any of these periods, borrowers at 80% LTV are not observed to have higher default frequency than their counterparts at 78.5–79.5% and 80.5–81.5% LTV. Although the 80% LTV notch would have a 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 observed incidence of default. All in all, this finding deserves further investigation.

9. Measuring Default Risk with Appraisals vs. AVMs

Although we know that appraisals suffer from information loss, they sometimes contain information that can help a lender assess a loan's default risk. How do these relatively costly appraisals compare in informational value to relatively inexpensive results from an AVM? Are the appraisals of substantial value despite their bias?

We begin to evaluate the informational value of appraisals in predicting defaults by estimating another set of linear probability models, similar to those in Tables 11 and 12. Specifically, we estimate the probability of becoming 120 or more days delinquent within the first three 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 13.

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 the risk of becoming 120+ 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 transaction price. For this sample, adding ln(appraisal/sale price) in Model 4 yields no improvement in model fit, although appraisals exactly identical to the price are shown to be at higher default risk. The magnitude of the increase in risk for loans with equal appraisals is 40 basis points; this is a material increase, given that the overall default rate in this sample is 4.4%. 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 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, although 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 or amount of savings the borrower has on-hand, which could be used as reserves for the mortgage payments.

In this dataset, 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 13 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 0.001 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 -0.0094, 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.

10. 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 the FHA, the VA, or one of the two GSEs in federal conservatorship, Fannie Mae and Freddie Mac (Urban Institute 2016).

Bias and information loss in appraisals are very common: fewer than 1 in 10 reported appraisals are below the contract price, and one-third are equal to the contract price. We argue that this asymmetric distribution and mass point of appraised values in relation to the contract price is a consequence of a tradeoff between the cost of potentially losing the mortgage transaction and the cost of losing informational value from the appraisal. This tradeoff, in turn, arises because of institutional factors, including the minimum value rule that compels mortgage lenders to base the LTV ratio on the lower of the contract price and appraised value. Appraisers will bias up the appraisal even so far as setting it equal to the contract price in order to mitigate the risk of a lost transaction.

We have presented a novel theoretical model of appraisals that highlights the conflict, combined with an analysis of appraisal outcomes at LTV notches. Our analysis suggests that the concern for losing the mortgage transaction is more salient than the one for default risks.

Consistent with upward bias in the reported appraised value and corresponding downward bias in measured LTV, we observe an economically and statistically significant increase in defaults at LTV notches. Moreover, we find that AVMs, on average, are more predictive of default risk than are appraisals. Overall, the empirical findings suggest that appraisals have little value in predicting default for notch-LTV mortgages, which comprise a large share of mortgages originated.

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. Information can be extracted from negative appraisals, despite their tendency to be biased upward, and they frequently result in renegotiation of the price, which is of benefit to the lender as well as the borrower. But when appraisals are reported equal to the contract price, it is hard — if not impossible — to glean information.

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. Given that the incentive to report a biased appraised value derives from the minimum value rule for calculating the LTV, the analysis suggests reconsideration of this policy. It may be preferable to set property value equal to contract price when calculating LTV, with appraisal reported as an additional characteristic of property considered in underwriting. Alternatively, appraisers can be directed to report appraisals as a range of values, with the lender free to select a particular value within that range.

References

Agarwal, Sumit, Itzhak Ben-David, and Vincent Yao. 2015. "Collateral Valuation and Borrower Financial Constraints: Evidence from the Residential Real Estate Market," *Management Science* 61(9): 2220–2240.

Acolin, Arthur, Jesse Bricker, Paul Calem, and Susan Wachter. 2016. "Borrowing Constraints and Homeownership," *American Economic Review Papers & Proceedings* 106(5): 625–629.

Avery, Robert B., Patricia E. Beeson, and Mark S. Sniderman. 1999. "Neighborhood Information and Home Mortgage Lending," *Journal of Urban Economics* 45: 287–310.

Ben-David, Itzhak. 2011. "Financial Constraints and Inflated Home Prices during the Real Estate Boom," *American Economic Journal: Applied Economics* 3: 55–87.

Best, Michael, James Cloyne, Ethan Ilzetzki, and Henrik Kleven. 2015. "Interest Rates, Debt and Intertemporal Allocation: Evidence from Notched Mortgage Contracts in the UK," Bank of England Working Paper No. 543.

Blackburn, McKinley, and Todd Vermilyea. 2007. "The Role of Information Externalities and Scale Economies in Home Mortgage Lending Decisions," *Journal of Urban Economics* 61: 71–85.

Bubb, Ryan and Alex Kaufman. 2014. "Securitization and Moral Hazard: Evidence from Credit Score Cutoff Rules," *Journal of Monetary Economics* 63, 1–18.

Calem, Paul S. 1996. "Mortgage Credit Availability in Low- and Moderate-Income Minority Neighborhoods: Are Information Externalities Critical?" *Journal of Real Estate Finance and Economics* 13: 71–89.

Chism, Patrick. 2016. "What's an Appraisal Contingency, and Why Should I Care?" Quicken Loans Blog. Available at: https://www.quickenloans.com/blog/whats-an-appraisal-contingency-and-why-should-i-care.

Cho, Man, and Isaac F. Megbolugbe, 1996. "An Empirical Analysis of Property Appraisal and Mortgage Redlining," *Journal of Real Estate Finance and Economics* 13: 45–55.

Colley, Angela. 2015. "Protect Yourself—and Your Finances—with These Creative Contingency Clauses," National Association of Realtors Blog. Available at: http://www.realtor.com/advice/finance/protect-yourself-with-creative-contingency-clauses/.

Ding, Lei. 2014. "Information Externalities and Residential Mortgage Lending in the Hardest Hit Housing Market: The Case of Detroit," *Cityscape* 16: 233–252.

Ding, Lei, and Leonard I. Nakamura, 2016. "The Impact of the Home Valuation Code of Conduct on Appraisal and Mortgage Outcomes," *Real Estate Economics* 44(3): 658–690.

Elul, Ronel, Nicholas S. Souleles, Souphala Chomsisengphet, Dennis Glennon, and Robert Hunt. 2010. "What 'Triggers' Mortgage Default?" *American Economic Review Papers & Proceedings* 100(2): 490–494.

Engelhardt, Gary V. 1996. "Consumption, Down Payments, and Liquidity Constraints," *Journal of Money, Credit and Banking* 28(2): 255–271.

Eriksen, Michael D., Hamilton B. Fout, Mark Palim, and Eric Rosenblatt. 2016. "Contract Price Confirmation Bias: Evidence from Repeat Appraisals." Working paper, available at: http://www.fanniemae.com/resources/file/research/datanotes/pdf/working-paper-102816.pdf.

Fannie Mae, 2014. *Selling Guide: Fannie Mae Single Family*. Washington, D.C.: Fannie Mae, April 15.

Foote, Christopher L., Kristopher Gerardi, and Paul S. Willen. 2008. "Negative Equity and Foreclosure: Theory and Evidence." *Journal of Urban Economics* 64(2): 234–245.

Fout, Hamilton and Vincent Yao. 2016. "Housing Market Effects of Appraising Below Contract." Working paper, available at: http://www.fanniemae.com/resources/file/research/datanotes/pdf/fannie-mae-white-paper-060716.pdf.

Haughwout, Andrew, Richard Peach, and Joseph Tracy. 2008. "Juvenile Delinquent Mortgages: Bad Credit or Bad Economy?" *Journal of Urban Economics* 64(2): 246–257.

Kartik, Navin. 2009. "Strategic Communication with Lying Costs." *Review of Economic Studies* 76(4): 1359–1395.

Lang, Bree J. and Ellen H. Hurst. 2014. "The Effect of Down Payment Assistance on Mortgage Choice," *Journal of Real Estate Finance and Economics* 49(3): 329–351.

Lang, William W., and Leonard I. Nakamura. 1993. "A Model of Redlining," *Journal of Urban Economics* 33: 223–234.

Ling, David C., and Susan M. Wachter. 1998. "Information Externalities and Home Mortgage Underwriting," *Journal of Urban Economics* 44(3): 317–332.

Mayer, Yanling and Frank E. Nothaft. 2017. "Home Appraisals: Analysis of the Accuracy, Selection, and Adjustments to Comparable Sales Data." Working paper.

Nadarajah, Saralees, and Samuel Kotz. 2008. "Exact Distribution of the Max/Min of Two Gaussian Random Variables," *IEEE Transactions on Very Large Scale Integration (VLSI) Systems* 16: 210–212.

National Association of Realtors. 2013. NAR Issue Brief: Appraisal Management Company Q&A, July 2, Washington, DC. Available at: https://www.nar.realtor/appraisal/nar-issue-brief-appraisal-management-company-qa.

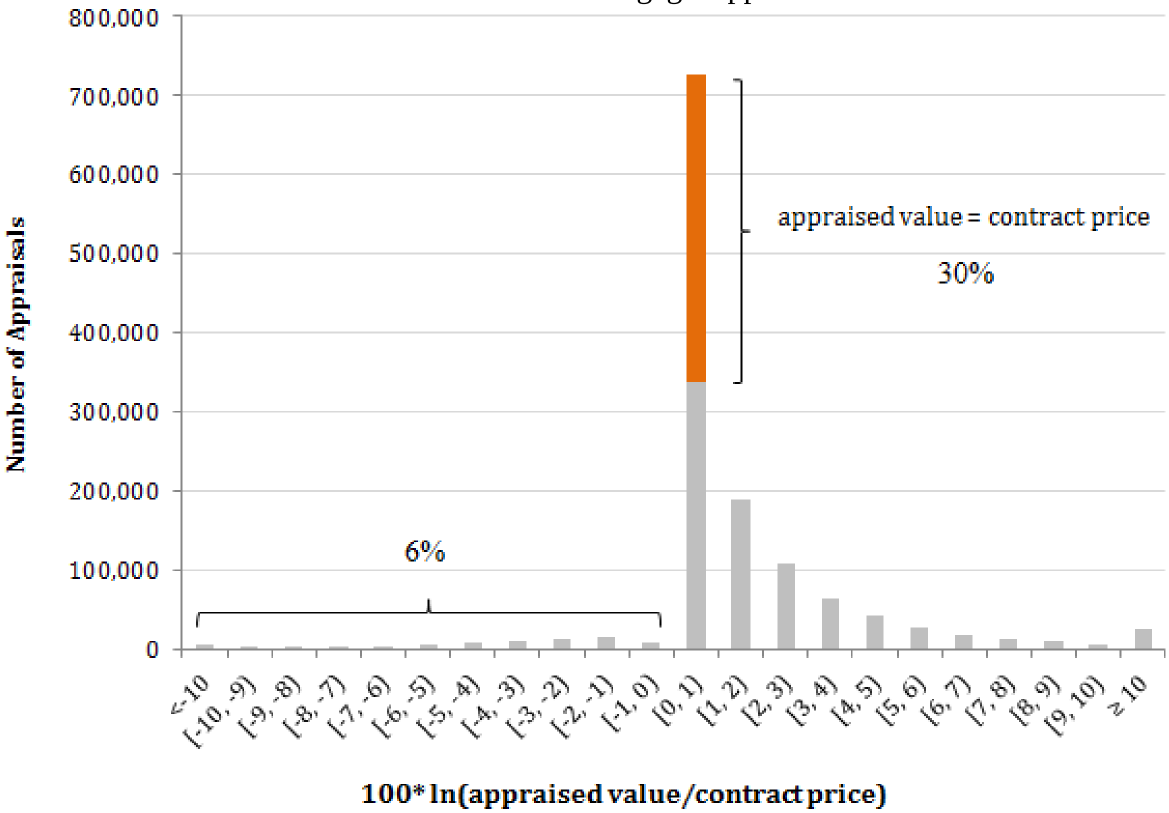
Quan, Daniel C., and John M. Quigley. 1991. "Price Formation and the Appraisal Function in Real Estate Markets," *Journal of Real Estate Finance and Economics* 4: 127–146.

Palmer, Christopher. 2015. "Why Did So Many Subprime Borrowers Default During the Crisis: Loose Credit or Plummeting Prices?" Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2665762.

Urban Institute. 2016. "Housing Finance at a Glance: A Monthly Chartbook," October. Available at: http://www.urban.org/sites/default/files/publication/85166/housing-finance-at-a-glance-a-monthly-chartbook-october-2016.pdf.

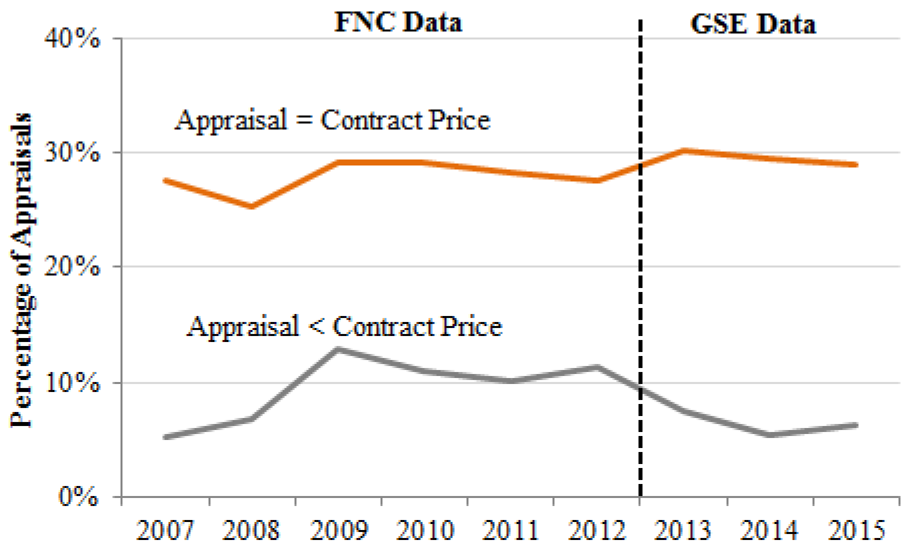
Figures

Figure 1: Distribution of Appraised Values Relative to Contract Price, 2013–2015 First-Lien Mortgage Applications



Source: Authors' calculations based on data from GSE

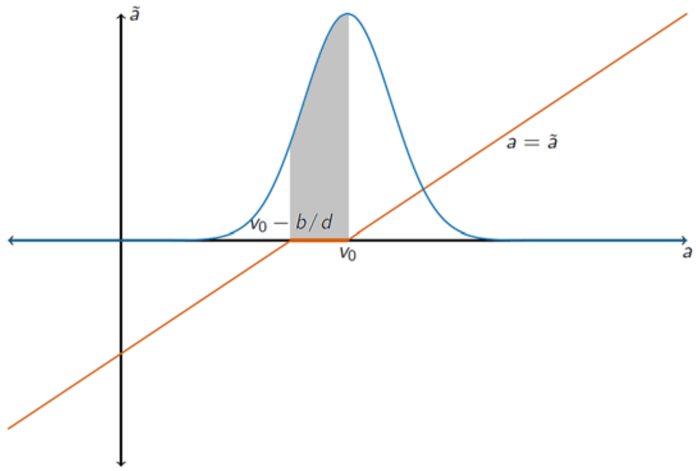
Figure 2: Appraisal Outcomes by Year, 2007–2015 First-Lien Mortgage Applications



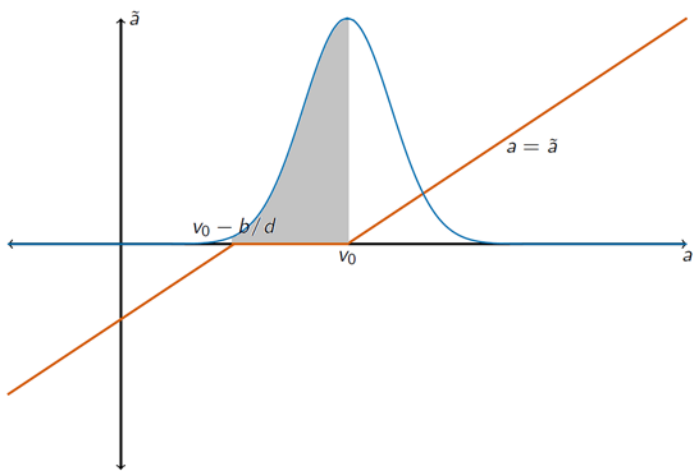
Source: Authors' calculations based on data from GSE and FNC

Figure 3: Biased Appraisals under Different Model Assumptions

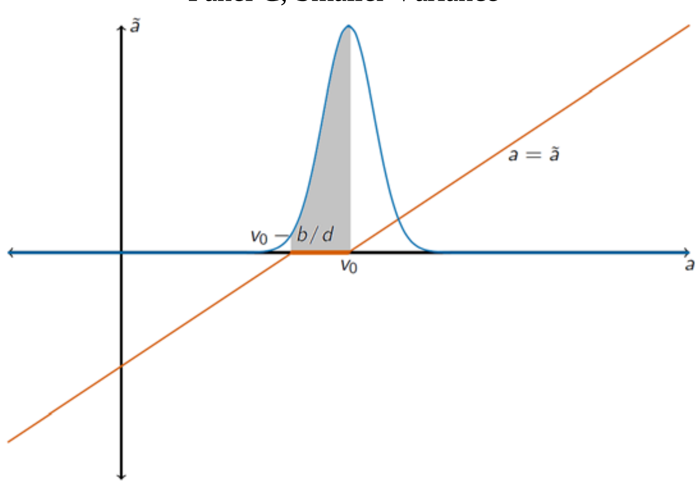
Panel A, Baseline



Panel B, Greater Value of *b* Relative to *d*

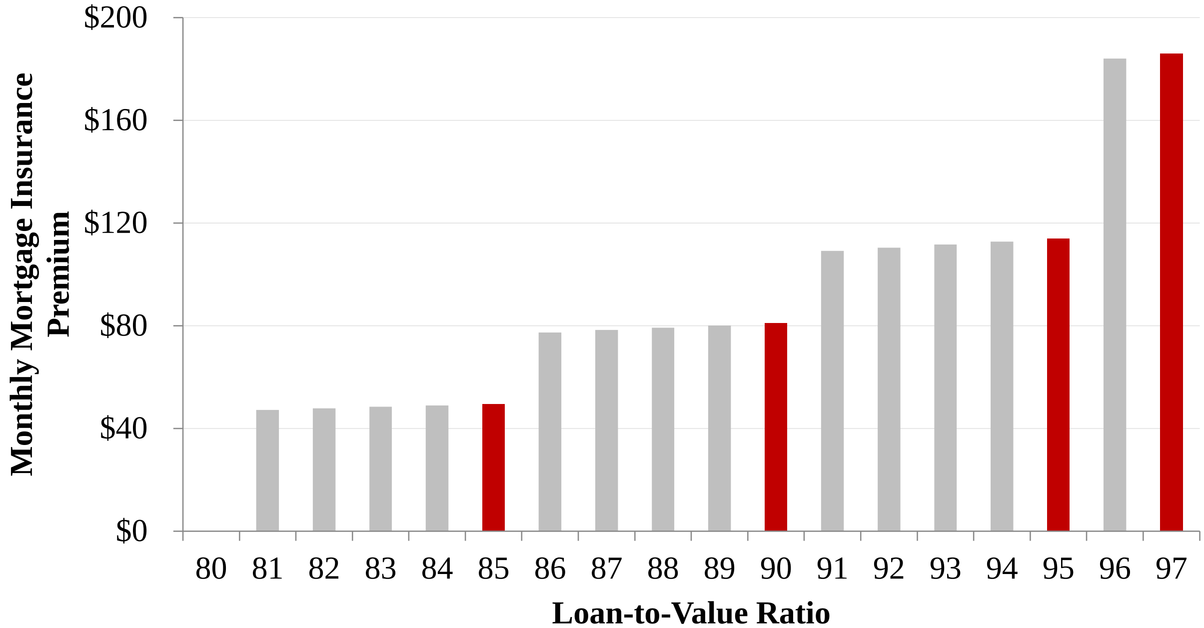


Panel C, Smaller Variance



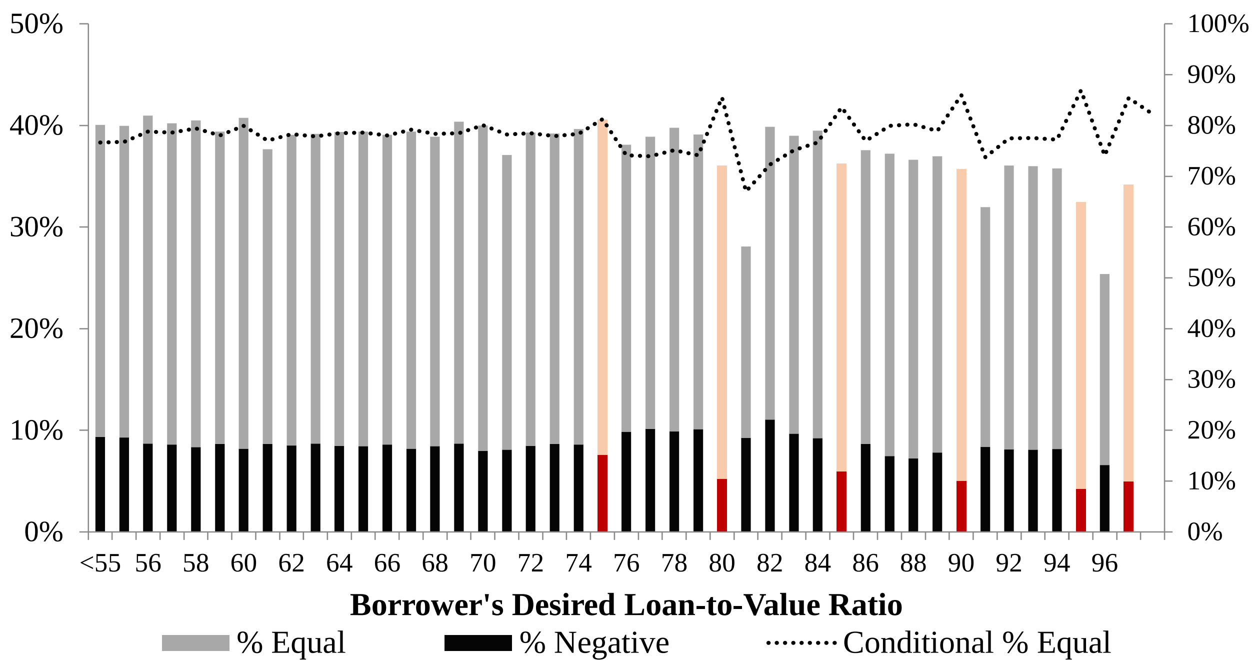
Note: The authors thank Paul Goldsmith-Pinkham for creating an initial version of this figure.

Figure 4: Monthly Mortgage Insurance Premium Costs by LTV
for a Borrower Purchasing a $200,000 Home



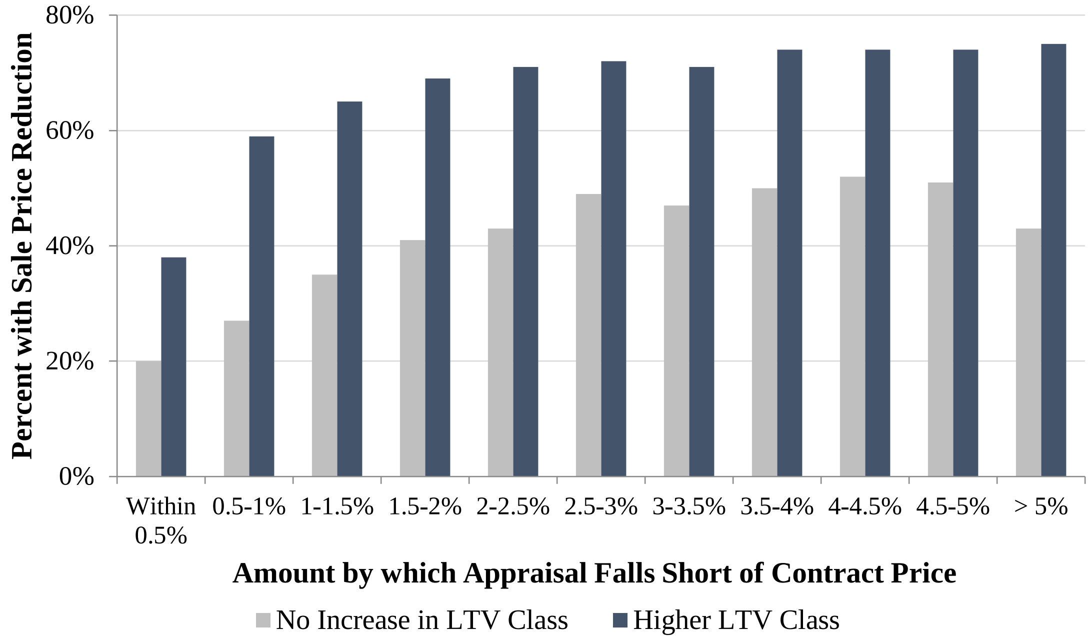
Source: Authors' tabulations of data from Goodmortgage.com's PMI Calculator for mortgage insurance payments required if the purchase price is $200,000. Calculations assume the borrower has a FICO score of 720 or higher. Data retrieved December 18, 2016.

Figure 5: Appraisal Outcomes by Applicant's Desired Loan-to-Value Ratio



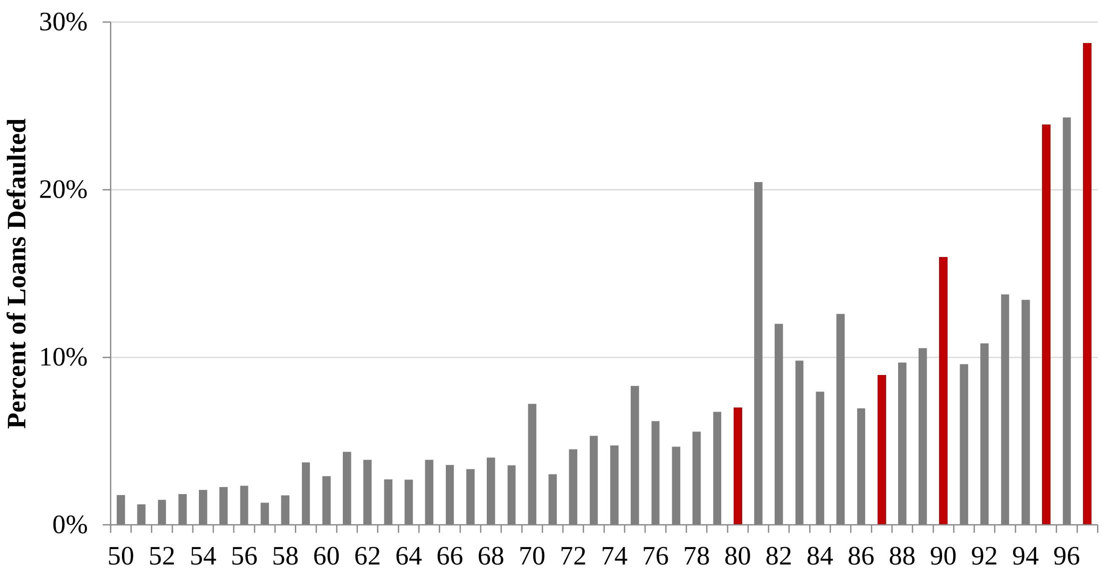
Source: Authors' calculations based on data from GSE

Figure 6: Incidence of Buyer-Seller Price Renegotiation Following Negative Appraisals, by Whether a Negative Appraisal Would Catapult Borrower to a Higher LTV Class



Source: Authors' calculations based on data from GSE

Figure 7: Percentage of 2007 Vintage Loans That Became 120+ Days Delinquent During Initial 3 Years after Origination, by Loan-to-Value Ratio



Source: Authors' calculations based on data from GSE. Note: The spike at 81% LTV is made up of only 44 mortgages in our dataset at this LTV, 9 of which defaulted. The next smallest group was 82% LTV, which had 125 observations.

Tables

Table 1: How Appraisals Vary Across Dataset and Sample Selection

Percentage of Values Falling Within Each Band of ln(Appraisal/Price)				
	Data Samples:			
ln(Appraisal/Price)	Full GSE Sample of Scored Applications (2013–2015)	Subsample Intended for Sale to GSE (2013–2015)	Historical GSE Sample of Originations (2003–2009)	Full Sample of FNC Applications (2007–2012)
< -0.1	1.1	0.5	0.2	3.1
< -0.05 and ≥ -0.1	1.8	1.4	0.4	2.7
< -0.01 and ≥ -0.05	3.9	3.8	1.1	3.6
< 0 and ≥ -0.01	0.7	0.7	0.5	0.5
Exactly = 0	28.8	29.5	44.8	27.9
> 0 and ≤ 0.0025	7.8	8.3	5.1	7.0
> 0.0025 and ≤ 0.005	6.2	6.7	4.2	4.5
> 0.005 and ≤ 0.0075	5.5	5.7	3.9	3.9
> 0.0075 and ≤ 0.01	4.7	4.9	3.3	3.5
> 0.01 and ≤ 0.05	30.5	30.8	24.1	26.3
> 0.05 and ≤ 0.1	6.4	5.7	7.0	9.5
> 0.1	2.5	2.0	5.5	7.5
Underlying Standard Deviation*	0.0469	0.0412	0.1020	0.0770

Source: Authors' calculations based on data from GSE. Note: The full sample of scored applications includes 3.6 million loans, for which the appraised value is compared to the final sale (transaction) price, as the contract price is not available. For the subsample intended for sale to the GSE (1.3 million loans), the contract price is available and is used in the calculation. The historical GSE sample covers 900,000 appraisals conducted in 2003–2009 and has only the final sale price. The FNC dataset includes 1.1 million mortgage applications.

*Underlying standard deviation calculated using the positive appraisals. Method takes the standard deviation of a synthetic dataset comprised of the positive appraisals plus the positive appraisals multiplied by -1.

Table 2: Appraisal Outcomes by Anticipated Loan-to-Value Ratio
(2013–2015)

Applied-for LTV	Total	% of Appraisals	% Negative	% Positive	% Equal	% Equal or within 1% positive
< 70	157,315	11.9	8.7	60.2	30.9	55.7
70	16,277	1.2	8.0	60.0	32.0	56.3
71	8,865	0.7	8.1	62.9	29.0	55.5
72	10,933	0.8	8.5	60.7	30.8	55.9
73	10,963	0.8	8.7	60.8	30.6	56.7
74	11,777	0.9	8.6	60.4	31.1	56.1
75	28,514	2.2	7.6	59.4	33.0	57.4
76	11,492	0.9	9.9	61.9	28.3	54.7
77	13,719	1.0	10.1	61.1	28.8	54.1
78	16,875	1.3	9.9	60.2	29.9	55.4
79	19,668	1.5	10.1	60.9	29.0	54.7
80	313,307	23.8	5.2	64.0	30.9	55.9
81	19,030	1.4	9.3	71.9	18.8	53.0
82	16,234	1.2	11.0	60.1	28.8	49.3
83	13,588	1.0	9.7	61.0	29.3	51.9
84	13,719	1.0	9.2	60.5	30.3	53.5
85	31,383	2.4	6.0	63.8	30.3	55.2
86	11,996	0.9	8.7	62.4	29.0	54.1
87	14,114	1.1	7.5	62.8	29.7	53.8
88	15,461	1.2	7.2	63.4	29.4	54.4
89	16,987	1.3	7.8	63.0	29.2	54.9
90	126,479	9.6	5.0	64.3	30.7	56.3
91	15,874	1.2	8.4	68.0	23.6	53.2
92	17,887	1.4	8.1	63.9	27.9	52.7
93	21,395	1.6	8.1	64.0	27.9	53.2
94	22,245	1.7	8.2	64.2	27.6	53.6
95	294,052	22.3	4.3	67.5	28.2	54.8
96	12,945	1.0	6.6	74.6	18.8	54.8
97	34,920	2.6	5.0	65.8	29.2	54.3
Total	1,318,704	100.0	6.4	64.1	29.5	55.2
Notches 80, 90, 95	733,838	55.7	4.8	65.4	29.8	55.9
All Notches	828,655	62.9	4.9	65.2	29.9	55.5
Non-Notches	489,419	37.1	8.8	62.3	28.9	54.6

Source: Authors' calculations based on data from GSE

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	30	62	100	391,458
2014	5	29	65	100	431,707
2015	6	29	65	100	494,909
Appraisal management company used?					
No	5	28	67	100	506,102
Yes	7	31	62	100	811,972
Regions:					
West Coast (CA, OR, WA)	9	46	46	100	207,233
Sand States (AZ, FL, NV)	12	27	61	100	134,762
Rust Belt (IN, MI, OH)	6	28	66	100	110,901
All	6	30	64	100	1,318,074

Panel B, Appraisals Less Than or Equal to Contract Price

	Percentage		
Appraisal management company used in transaction	65		
Loans 90+ days delinquent or in foreclosure:			
5–7%	17		
> 7%	18		
	Median	**Mean**	**Std. Dev.**
ln contract price	12.6	12.6	0.5
ln county median sale price	12.3	12.4	0.5
1-year lagged house price appreciation	4.3	5.5	7.1

Source: Authors' calculations based on data from GSE, McDash Analytics, CoreLogic, and Zillow. Note: 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, except for 8.4% of observations, in which it captures the state-level change, since county-level data are unavailable. 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.

Table 4: Likelihood That Appraisal Identically Matches Contract Price, 2013–2015 Sample

	(1) All Obs.	(2) No AMCs	(3) AMCs
Applied-for LTV			
74	0.0180**	0.0337***	0.0097
	(3.02)	(3.45)	(1.30)
75	0.0450***	0.0529***	0.0407***
	(10.72)	(7.59)	(7.76)
76	-0.0199***	-0.0220*	-0.0189*
	(-3.31)	(-2.28)	(-2.47)
79	-0.0246***	-0.0343***	-0.0195***
	(-5.07)	(-4.35)	(-3.17)
80	0.0909***	0.0945***	0.0890***
	(34.31)	(22.00)	(26.63)
81	-0.0942***	-0.0697***	-0.106***
	(-16.77)	(-7.57)	(-15.04)
84	0.0017	0.0143	-0.0051
	(0.29)	(1.57)	(-0.72)
85	0.0650***	0.0826***	0.0553***
	(15.34)	(12.07)	(10.29)
86	0.0028	0.0153	-0.0043
	(0.46)	(1.58)	(-0.55)
89	0.0231***	0.0212*	0.0240***
	(4.38)	(2.47)	(3.60)
90	0.0906***	0.0981***	0.0864***
	(30.39)	(20.34)	(22.84)
91	-0.0270***	-0.0285**	-0.0258***
	(-4.68)	(-3.09)	(-3.52)
94	0.0046	-0.0081	0.0126*
	(0.95)	(-1.06)	(2.04)
95	0.106***	0.104***	0.107***
	(38.69)	(23.57)	(30.73)
96	-0.0173*	-0.0194~	-0.0164~
	(-2.49)	(-1.76)	(-1.84)
97	0.0842***	0.0987***	0.0746***
	(19.77)	(15.03)	(13.40)
Appraisal management company (AMC) used	-0.0244***		
	(-21.03)		
County default/foreclosure rate 5–7%	-0.0181***	-0.0139***	-0.0214***
	(-9.34)	(-4.63)	(-8.42)
County default/foreclosure rate > 7%	-0.0326***	-0.0269***	-0.0364***
	(-12.98)	(-6.86)	(-11.17)
Constant	0.515***	0.575***	0.464***
	(18.49)	(12.53)	(13.20)
Other county and home characteristics	✓	✓	✓
State-by-year Controls	✓	✓	✓
Observations	472,960	166,060	306,900
R^2	0.0544	0.0576	0.0522

Source: Authors' calculations based on data from GSE, Zillow, CoreLogic, and McDash Analytics. Note: Coefficients displayed with t-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, and 92-93. Notch LTVs are shaded in gray. Sample includes appraisals conducted in 2013-2015. Other county and home characteristics include ln contract price, ln 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. Sample includes observations with appraisal and contract price. Model 2 (3) excludes (is restricted to) appraisals conducted by AMC.

Table 5: Likelihood That Appraisal Identically Matches Contract Price, Appraiser and Lender Controls

	(1) No AMCs	(2) AMCs	(3) No AMCs	(4) AMCs	(5) No AMCs	(6) AMCs
Applied-for LTV						
74	0.0337***	0.0097	0.0372***	0.0089	0.0314**	0.0108
	(3.45)	(1.30)	(3.76)	(1.23)	(3.23)	(1.46)
75	0.0529***	0.0407***	0.0535***	0.0371***	0.0555***	0.0421***
	(7.59)	(7.76)	(7.61)	(7.22)	(7.98)	(8.04)
76	-0.0220*	-0.0189*	-0.0126	-0.0165*	-0.0246*	-0.0169*
	(-2.25)	(-2.43)	(-1.27)	(-2.16)	(-2.52)	(-2.18)
79	-0.0343***	-0.0195**	-0.0192*	-0.0120*	-0.0341***	-0.0184**
	(-4.35)	(-3.17)	(-2.40)	(-2.00)	(-4.32)	(-3.00)
80	0.0945***	0.0890***	0.0901***	0.0812***	0.0933***	0.0895***
	(22.00)	(26.63)	(20.69)	(24.47)	(21.71)	(26.79)
81	-0.0697***	-0.106***	-0.0463***	-0.0826***	-0.0686***	-0.104***
	(-7.57)	(-15.04)	(-4.98)	(-11.90)	(-7.47)	(-14.73)
84	0.0143	-0.0051	0.0322***	0.0042	0.0102	-0.0029
	(1.57)	(-0.72)	(3.51)	(0.60)	(1.12)	(-0.41)
85	0.0826***	0.0553***	0.0847***	0.0529***	0.0785***	0.0561***
	(12.07)	(10.29)	(12.26)	(10.05)	(11.47)	(10.47)
86	0.0153	-0.0043	0.0181~	0.0066	0.0115	-0.0028
	(1.58)	(-0.55)	(1.85)	(0.87)	(1.19)	(-0.36)
89	0.0212*	0.0240***	0.0256**	0.0280***	0.0196*	0.0250***
	(2.47)	(3.60)	(2.95)	(4.27)	(2.28)	(3.76)
90	0.0981***	0.0864***	0.0925***	0.0776***	0.0949***	0.0865***
	(20.34)	(22.84)	(18.96)	(20.90)	(19.64)	(22.87)
91	-0.0285**	-0.0258***	-0.0100	-0.0074	-0.0279**	-0.0232**
	(-3.109)	(-3.52)	(-1.07)	(-1.02)	(-3.01)	(-3.17)
94	-0.0081	0.0126*	-0.0081	0.0146*	-0.0123	0.0136*
	(-1.06)	(2.04)	(-1.05)	(2.39)	(-1.62)	(2.20)
95	0.104***	0.107***	0.0954***	0.0951***	0.101***	0.107***
	(23.57)	(30.73)	(21.23)	(27.72)	(22.69)	(30.62)
96	-0.0194~	-0.0164~	0.0046	0.0038	-0.0229*	-0.0157~
	(-1.76)	(-1.84)	(0.42)	(0.44)	(-2.09)	(-1.77)
97	0.0987***	0.0746***	0.0943***	0.0727***	0.0922***	0.0713***
	(15.05)	(13.44)	(14.11)	(13.19)	(13.95)	(12.80)
Constant	0.575***	0.464***	0.688***	0.457***	0.542***	0.373***
	(12.53)	(13.20)	(8.66)	(4.03)	(10.09)	(9.86)
Other county, home characteristics	✓	✓	✓	✓	✓	✓
State-by-year controls	✓	✓	✓	✓	✓	✓
Appraiser dummies	-	-	✓	✓	-	-
Lender dummies	-	-	-	-	✓	✓
Observations	166,060	306,900	164,355	305,269	166,060	306,900
R^2	0.0576	0.0522	0.3164	0.2777	0.0929	0.0739

Source: Authors' calculations based on data from GSE, Zillow, CoreLogic, and McDash Analytics. Note: Coefficients displayed with t-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, and 92-93. Notch LTVs are shaded in gray. Sample includes appraisals conducted in 2013-2015. Other county and home characteristics include ln contract price, ln 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. Models 1-3 include appraiser-level dummy variables, whereas Models 4-6 include lender-level dummy variables.

Table 6: Likelihood That Appraisal Identically Matches Contract Price, Geographic Robustness

	(1) West Coast	(2) Sand States	(3) Rust Belt	(4) Rural
Applied-for LTV				
74	0.0206*	-0.0170	0.0219	-0.0118
	(2.05)	(-0.77)	(0.85)	(-0.40)
75	0.0471***	0.0279~	0.0529**	0.0043
	(6.80)	(1.74)	(2.77)	(0.19)
76	-0.0076	-0.0286	-0.0015	0.0352
	(-0.70)	(-1.34)	(-0.06)	(1.10)
79	-0.0045	-0.0534**	-0.0071	-0.0401
	(-0.53)	(-3.01)	(-0.33)	(-1.55)
80	0.0853***	0.113***	0.110***	0.0779***
	(18.81)	(12.29)	(8.93)	(5.89)
81	-0.0547***	-0.106***	-0.0955***	-0.0333
	(-5.17)	(-5.26)	(-4.51)	(-1.12)
84	0.0113	-0.0343~	0.0238	0.0097
	(1.01)	(-1.72)	(1.18)	(0.35)
85	0.0648***	0.0684***	0.0924***	0.0685**
	(7.89)	(4.34)	(5.73)	(3.08)
86	0.0105	-0.0305	0.0378~	0.0453
	(0.88)	(-1.39)	(1.73)	(1.59)
89	0.0370***	0.0045	0.0178	0.0065
	(3.67)	(0.24)	(0.90)	(0.26)
90	0.0866***	0.111***	0.107***	0.0788***
	(15.99)	(10.40)	(8.19)	(5.16)
91	-0.0065	-0.0643**	-0.0156	0.0274
	(-0.54)	(-3.07)	(-0.75)	(0.96)
94	0.0226*	-0.0322~	0.0354*	0.0110
	(2.18)	(-1.87)	(2.00)	(0.48)
95	0.104***	0.147***	0.129***	0.0979***
	(19.87)	(15.73)	(10.52)	(7.34)
96	-0.0165	0.0244	0.0298	-0.0230
	(-1.02)	(1.00)	(1.26)	(-0.67)
97	0.0859***	0.0920***	0.103***	0.0842***
	(9.21)	(5.84)	(6.43)	(4.33)
Constant	0.0830~	0.731***	1.026***	0.549***
	(1.94)	(5.0+)	(8.88)	(4.02)
Controls				
Other county, home characteristics	✓	✓	✓	✓
State-by-year controls	✓	✓	✓	✓
Types of observations included				
States	CA, OR, WA	AZ, FL, NV	IN, MI, OH	All
Loan types	FRM 30	FRM 30	FRM 30	FRM 30
Null values on controls	No	No	No	No
Observations	112,407	52,707	37,669	17,824
R^2	0.0346	0.0390	0.0615	0.0540

Source: Authors' calculations based on data from GSE, Zillow, CoreLogic, and McDash Analytics. Note: Coefficients displayed with t-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, and 92-93. Notch LTVs are shaded in gray. Sample includes appraisals conducted in 2013-2015. Other county and home characteristics include ln contract price, ln 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. Models 1-3 estimate the main model on observations on the west coast, in the Sand States, and in the Rust Belt, respectively. Model 4 uses only appraisals in rural counties, that is, those outside metropolitan statistical areas.

Table 7: Multinomial Logit Information Loss Model

Applied-for LTV	Marginal Effects	z-statistic
74	0.0070	1.57
75	0.0142***	4.51
76	-0.0109*	-2.37
79	-0.0073*	-1.97
80	0.0184***	9.32
81	-0.1105***	-26.52
84	0.0223***	5.32
85	0.0175***	5.67
86	0.0088*	1.97
89	0.0108**	1.97
90	0.0220***	9.96
91	-0.0401***	-9.56
94	0.0061~	1.73
95	0.0214***	10.53
96	-0.0878***	-17.93
97	0.0312***	10.21
County and home characteristics	✓	
State-by-year controls	✓	
Observations	1,318,074	
Pseudo R^2	0.0461	

Source: Authors' calculations based on data from GSE, CoreLogic, McDash Analytics, and Zillow. Note: Sample includes appraisals that equal, exceed, and fall short of the contract price. Average marginal effects and z-statistics reported for LTV dummies. ~ 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, and 92-93. Notch LTVs are shaded in gray. Sample includes appraisals conducted in 2013-2015. Other county and home characteristics include ln contract price, ln 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.

Table 8: Likelihood That Appraisal Identically Matches Contract Price, GSE vs. FNC Data

	GSE Data: 2013–2015 Applications			**FNC Data: 2007–2012 Applications**		
	(1)	(2)	(3)	(4)	(5)	(6)
	All Obs.	Not AMCs	AMCs	All Obs.	Not AMCs	AMCs
ln(contract price)	-0.0208***	-0.0193***	-0.0216***	-0.0191***	-0.0215***	0.00004
	(-15.13)	(-8.83)	(-12.24)	(-15.58)	(-16.37)	(0.01)
ln(county median)	0.0294***	0.0250***	0.0312***	0.0813***	0.0819***	0.0721***
	(13.72)	(7.12)	(11.52)	(33.84)	(31.33)	(11.54)
Appraisal management company (AMC) used	-0.0242***			-0.0421***		
	(-20.71)			(-19.34)		
County house price change	-0.0003*	-0.0004	-0.0003~	0.0049***	0.0050***	0.0043***
	(-2.35)	(-1.47)	(-1.83)	(34.07)	(32.70)	(10.03)
County default/foreclosure rate 5–7%	-0.0180***	-0.0139***	-0.0210***	-0.0007	-0.0009	-0.0024
	(-9.17)	(-4.62)	(-8.22)	(-0.26)	(-0.33)	(-0.36)
County default/foreclosure rate > 7%	-0.0320***	-0.0265***	-0.0357***	-0.0292***	-0.0273***	-0.0395***
	(-12.64)	(-6.69)	(-10.85)	(-10.89)	(-9.46)	(-5.38)
Constant	0.769***	0.808***	0.731***	0.0224	0.026	-0.0825
	(28.00)	(17.82)	(21.12)	(0.56)	(0.58)	(-0.89)
State-by-year controls	✓	✓	✓	✓	✓	✓
Observations	472,960	166,060	306,900	403,322	344,322	59,000
R^2	0.0392	0.0411	0.0374	0.07	0.07	0.07

Source: Authors' calculations based on data from GSE, FNC Analytics, Zillow, CoreLogic, and McDash Analytics. Note: Coefficients displayed with t-statistics in parentheses. ~ denotes 0.10 level of significance, * 0.5, ** 0.01, *** 0.001. † House price change captures the change in the Zillow county-level home value index from 24 to 12 months before the appraisal. Models 1-3 estimate the main model.

Table 9: Percentage of Negative-Appraisal, Closed Loans with Renegotiated Contract Prices

Amount by which Appraisal Falls Short of Price	No Increase in LTV Class			Higher LTV Class		
	All	Hot Market	Price Growth < 10%	All	Hot Market	Price Growth < 10%
Within 0.5%	20%	19%	21%	38%	36%	39%
0.5–1%	27%	24%	27%	59%	52%	62%
1–1.5%	35%	32%	36%	65%	57%	68%
1.5–2%	41%	35%	43%	69%	61%	72%
2–2.5%	43%	39%	45%	71%	65%	74%
2.5–3%	49%	45%	51%	72%	64%	75%
3–3.5%	47%	40%	51%	71%	62%	75%
3.5–4%	50%	45%	53%	74%	69%	76%
4–4.5%	52%	48%	55%	74%	68%	77%
4.5–5%	51%	48%	53%	74%	72%	75%
Greater than 5%	43%	39%	47%	75%	72%	77%
All Negative	**40%**	**37%**	**42%**	**71%**	**66%**	**73%**

Source: Authors' calculations based on data from GSE and Zillow. Note: "Hot Market" is defined as a county having year-over-year house price appreciation greater than 10%, captured at the time of the appraisal. The remainder counties appear in the columns to the right, "Price Growth < 10%." Differences between hot markets and others are statistically signficant both for the group of loans that would have no increase in the LTV class (difference = 4.8%, $p < 0.0001$) and the group of loans that would be bumped to a higher LTV class by the negative appraisal (difference = 7.0%, $p < 0.0001$).

Table 10: Appraisal Outcomes and Characteristics of 2003–2009 Vintage Loans

	All Loans (n = 919,408)			No Default (n = 877,843; 95%)			Default (n = 41,565; 5%)		
	Median	Mean	SD	Median	Mean	SD	Median	Mean	SD
FICO	736	723	64	739	727	61	645	649	71
Back-end DTI	39	40	12	39	39	12	46	46	11
House price change (%) †	-2.0	3.1	25.1	-1.4	3.8	25.0	-12.6	-11.9	22.7
House price trough (%) †	-3.6	-8.0	10.5	-3.2	-7.6	10.1	-13.2	-16.6	15.1
Reserves (months of mortgage payments)									
< 3 months		11%			11%			19%	
3–11 months		30%			30%			37%	
12+ months		51%			51%			31%	
Co-borrower		50%			52%			27%	
New construction		1%			1%			1%	
Appraisal < Price		2%			2%			1%	
Appraisal = Price		44%			44%			44%	
Appraisal > Price		53%			53%			54%	

Source: Authors' calculations based on data from GSE and Zillow. Note: Percentages at times do not sum to 100% due to rounding. †For 13% of observations, county house price indices were not available for the study period. For these, we assigned the state-level house price index. "Default" is defined as becoming 120+ days delinquent in the first three years after the loan was originated.

Table 11: Linear Probability Models for Default Risk at and Near LTV Notches, 2003–2009 Originations

	(1) All	(2) Negative Appraisal	(3) Equal Appraisal	(4) Positive Appraisal
Dummies for LTVs at or Near a Notch				
78.5-79.5	0.0008	-0.0052	0.0012	-0.0004
	(0.44)	(-0.70)	(0.49)	(-0.17)
80.0	0.0001	-0.0002	-0.0006	-0.0006
	(0.16)	(-0.05)	(-0.45)	(-0.52)
80.5–81.5	0.0166~	0.0188	0.0068	0.0223
	(1.77)	(1.01)	(0.44)	(1.60)
83.5–84.5	-0.0012	-0.0164	-0.0088~	0.0058
	(-0.34)	(-1.02)	(-1.68)	(1.17)
85.0	0.0069***	-0.0295*	0.0050~	0.0082**
	(3.41)	(-2.15)	(1.76)	(2.85)
85.5–86.5	-0.0074*	-0.0028	-0.0157**	-0.0010
	(-2.24)	(-0.15)	(-3.22)	(-0.21)
88.5-89.5	0.0006	-0.0163	0.0006	0.0008
	(0.24)	(-1.10)	(0.17)	(0.24)
90.0	0.0108***	0.0135	0.0136***	0.0076***
	(7.88)	(1.56)	(6.30)	(4.16)
90.5–91.5	-0.0011	0.0410**	-0.0008	-0.0031
	(-0.35)	(2.75)	(-0.15)	(-0.78)
93.5–94.5	-0.0071**	-0.0218~	-0.0084*	-0.0067*
	(-2.99)	(-1.76)	(-2.15)	(-2.18)
95.0	0.0165***	-0.0140*	0.0221***	0.0118***
	(17.70)	(-1.99)	(13.64)	(10.06)
95.5–96.5	0.0036	-0.0171	0.0033	0.0031
	(0.80)	(-0.79)	(0.45)	(0.53)
97.0	0.0091***	-0.0281*	0.0107***	0.0069***
	(5.93)	(-2.24)	(4.19)	(3.48)
House price change†	-0.0003***	-0.0001	-0.0003***	-0.0003***
	(-15.88)	(-1.54)	(-10.33)	(-12.41)
House price trough†	-0.0029***	-0.0015***	-0.0032***	-0.0027***
	(-68.94)	(-6.70)	(-52.64)	(-44.42)
Constant	1.1216***	0.7832***	1.1849***	1.0845***
	(141.11)	(18.05)	(102.03)	(95.82)
Vintage, state, and lender dummies	✓	✓	✓	✓
Borrower, loan, and house traits	✓	✓	✓	✓
Observations	919,408	19,669	411,724	488,015
R^2	0.1414	0.0980	0.1514	0.1364

Source: Authors' calculations based on data from GSE and Zillow. Note: Coefficients displayed with t-statistics in parentheses. ~ denotes 0.10 level of significance, * 0.5, ** 0.01, *** 0.001. "Default" is defined as becoming 120+ days delinquent in the first three years after the loan was originated. Borrower, loan, and house traits include: 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 that might be used for mortgage payments, a linear spline of LTV (with knots at 70%, 80%, and 90%), a linear spline of the minimum FICO score of borrower/co-borrower (captured at origination) with knots at 680 and 720, 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 3 years post-origination..

Table 12: Linear Probability Models for Default Risk at and Near LTV Notches, Vintage Groups

	(1) Main	(2) 2003-2005	(3) 2006-2007	(4) 2008-2009
Dummies for LTVs at or Near a Notch				
78.5–79.5	0.0008	0.0006	-0.0029	0.0038
	(0.44)	(0.30)	(-0.63)	(1.24)
80.0	0.0001	0.0009	0.0020	-0.0012
	(0.16)	(0.92)	(0.84)	(-0.72)
80.5–81.5	0.0166$^{\sim}$	0.0099	0.0257	0.0151
	(1.77)	(1.02)	(1.11)	(0.74)
83.5–84.5	-0.0012	0.0063$^{\sim}$	-0.0079	-0.0033
	(-0.34)	(1.65)	(-0.87)	(-0.48)
85.0	0.0069***	0.0038	0.0175***	0.0057$^{\sim}$
	(3.41)	(1.57)	(3.40)	(1.73)
85.5–86.5	-0.0074*	-0.0043	-0.0006	-0.0134*
	(-2.24)	(-1.16)	(-0.07)	(-2.21)
88.5–89.5	0.0006	0.0008	0.0105	-0.0045
	(0.24)	(0.27)	(1.55)	(-1.00)
90.0	0.0108***	0.0071***	0.0266***	0.0047*
	(7.88)	(4.53)	(7.14)	(2.00)
90.5–91.5	-0.0011	0.0093**	-0.0085	-0.0135*
	(-0.35)	(2.70)	(-1.07)	(-2.32)
93.5–94.5	-0.0071**	-0.0064**	-0.0249***	-0.0077
	(-2.99)	(-2.56)	(-4.09)	(-1.59)
95.0	0.0165***	0.0022*	0.0199***	0.0162***
	(17.70)	(2.39)	(7.33)	(8.51)
95.5–96.5	0.0036	0.0009	-0.0247**	-0.0009
	(0.80)	(0.17)	(-2.65)	(-0.08)
97.0	0.0091***	0.0072***	0.0139***	0.0080*
	(5.93)	(4.90)	(2.95)	(2.38)
House price change†	-0.0003***	-0.0002***	0.0006***	0.0006***
	(-15.88)	(-9.91)	(3.56)	(3.81)
House price trough†	-0.0029***	-0.0011***	-0.0043***	-0.0037***
	(-68.94)	(-16.36)	(-21.30)	(-18.75)
Constant	1.1216***	0.7108***	1.5983***	1.8405***
	(141.11)	(84.17)	(84.96)	(87.44)
Vintage, state, and lender dummies	✓	✓	✓	✓
Borrower, loan, and house traits	✓	✓	✓	✓
Observations	919,408	402,966	220,856	295,586
R^2	0.1414	0.0666	0.2107	0.1424

Source: Authors' calculations based on data from GSE and Zillow. Note: Coefficients displayed with t-statistics in parentheses. $^{\sim}$ denotes 0.10 level of significance, * 0.5, ** 0.01, *** 0.001. "Default" is defined as becoming 120+ days delinquent in the first three years after the loan was originated. Borrower, loan, and house traits include: 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 that might be used for mortgage payments, a linear spline of LTV (with knots at 70%, 80%, and 90%), a linear spline of the minimum FICO score of borrower/co-borrower (captured at origination) with knots at 680 and 720, 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 3 years post origination.

Table 13: 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 Linear Spline									
< 680	-0.0016***	-0.0016***	-0.0016***	-0.0017***	-0.0017***	-0.0017***	-0.0013***	-0.0013***	-0.0013***
	(-127.92)	(-127.92)	(-128.03)	(-129.07)	(-129.09)	(-128.26)	(-59.44)	(-59.44)	(-59.38)
680–720	-0.0002***	-0.0002***	-0.0002***	-0.0001***	-0.0001***	-0.0001***	0.0001**	0.0001**	0.0001**
	(-8.66)	(-8.73)	(-8.74)	(-3.14)	(-3.15)	(-3.08)	(3.15)	(3.14)	(3.16)
> 720	-0.0002***	-0.0002***	-0.0002***	-0.0003***	-0.0003***	-0.0003***	-0.0001***	-0.0001***	-0.0001***
	(-18.12)	(-18.27)	(-18.44)	(-22.61)	(-22.59)	(-22.68)	(-7.70)	(-7.70)	(-7.71)
DTI	0.0008***	0.0008***	0.0008***	0.0005***	0.0005***	0.0005***	0.0002***	0.0002***	0.0002***
	(33.75)	(33.58)	(33.50)	(20.08)	(20.10)	(19.76)	(5.86)	(5.86)	(5.81)
3–11 months of reserves	-0.0087***	-0.0088***	-0.0088***	-0.0091***	-0.0091***	-0.0090***	-0.0087***	-0.0087***	-0.0087***
	(-10.79)	(-10.86)	(-10.82)	(-10.65)	(-10.64)	(-10.58)	(-6.08)	(-6.08)	(-6.07)
12+ months of reserves	-0.0157***	-0.0157***	-0.0156***	-0.0163***	-0.0162***	-0.0160***	-0.0136***	-0.0136***	-0.0136***
	(-20.16)	(-20.19)	(-20.13)	(-20.16)	(-20.11)	(-19.90)	(-10.89)	(-10.90)	(-10.90)
House price change†	-0.0003***	-0.0003***	-0.0004***	-0.0002***	-0.0002***	-0.0003***	< 0.0001	< 0.0001	<0.0001
	(-12.29)	(-12.34)	(-13.33)	(-9.95)	(-9.96)	(-11.97)	(-0.96)	(-0.96)	(-1.20)
House price trough†	-0.0027***	-0.0027***	-0.0027***	-0.0032***	-0.0032***	-0.0032***	-0.0010***	-0.0010***	-0.0010***
	(-44.65)	(-44.90)	(-44.94)	(-53.81)	(-53.75)	(-53.86)	(-12.66)	(-12.65)	(-12.69)
LTV linear spline									
< 70% LTV	0.0003*	0.0003*	0.0003*	0.0003**	0.0003**	0.0003***	0.0004***	0.0004***	0.0004***
	(2.39)	(2.42)	(2.51)	(2.60)	(2.60)	(2.86)	(5.91)	(5.91)	(6.01)
70–80% LTV	0.0005***	0.0006***	0.0006***	0.0005***	0.0005***	0.0006***	0.0002	0.0002	0.0001
	(4.59)	(4.68)	(4.99)	(4.78)	(4.67)	(5.33)	(0.41)	(0.41)	(0.37)
80–90% LTV	0.0018***	0.0018***	0.0018***	0.0019***	0.0019***	0.0019***			
	(19.80)	(19.71)	(19.92)	(19.72)	(19.70)	(19.97)			
> 90% LTV	0.0036***	0.0036***	0.0036***	0.0039***	0.0039***	0.0038***			
	(20.54)	(20.64)	(20.88)	(20.20)	(20.20)	(19.77)			
ln(appraisal/sale price)		-0.0228***			-0.0253			-0.0211	
		(-7.40)			(-0.84)			(-0.70)	
Appraisal = sale price					0.0054**			0.0015	
					(3.03)			(0.72)	
ln(AVM/sale price)			-0.0207***			-0.0415***			-0.0087***
			(-19.11)			(-33.62)			(-5.06)
Constant	1.0851***	1.0866***	1.0848***	1.1694***	1.1643***	1.1586***	0.8644***	0.8630***	0.8628***
	(96.38)	(96.50)	(96.38)	(104.72)	(103.06)	(103.85)	(55.96)	(55.50)	(55.86)
Vintage, state, and lender dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
New construction and co-borrower dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	488,015	488,015	488,015	431,393	431,393	431,393	90,269	90,269	90,269
R^2	0.1361	0.1362	0.1367	0.1487	0.1487	0.1509	0.0872	0.0872	0.0875

Source: Authors' calculations based on data from GSE and Zillow. Note: Linear probability model coefficients displayed with t-statistics in parentheses. $^{\sim}$ denotes 0.10 level of significance, * 0.5, ** 0.01, *** 0.001. "Default" is defined as becoming 120+ days delinquent in the first three years after the loan was originated.

Appendix

Proof of the proposition.

The goal is to minimize the total cost (C):

$$C = d(\tilde{a} - a)^2 + max(b(v_o - a), 0).$$

If $a \geq v_o$, then C is minimized with $\tilde{a} = a$, where $C = 0$, establishing (i).

Now note that in regions where $v_o > a$, C is strictly positive, with:

$$C = d(\tilde{a} - a)^2 + b(v_o - \tilde{a})$$

and

$$\frac{dC}{d\tilde{a}} = 2d(\tilde{a} - a) - b = 0$$

implies $\tilde{a} = a + b/2d$, is a local minimum as:

$$\frac{d^2C}{d\tilde{a}^2} = 2d > 0.$$

If $a < v_o$, then if the appraiser reports (ii), $\tilde{a} = a + b/2d$, total cost is:

$$C = \frac{b^2}{4d} + b(v_o - a - b/2d) = b(v_o - a) - b^2/4d$$

On the other hand, if the appraiser reports (iii), $\tilde{a} = v_o$, then:

$$C = d(v_o - a)^2$$

The minimum cost of these two is then (ii) when:

$$d(a - v_o)^2 > b(v_o - a) - b^2/4d$$

$$(a - v_o)^2 - \frac{b}{d(v_o - a)} + \frac{b^2}{4d^2} > 0$$

$$(v_o - a - b/2d)^2 > 0$$

$$v_o - a > b/2d$$

And conversely, (iii) is the minimum cost of the two when this does not hold.

Table A1: Full Results for Main Information Loss Model

Applied-for LTV		**Controls**	
74	0.0180**	ln(contract price)	-0.00192
	(3.02)		(-1.34)
75	0.0450***	ln(county median)	0.0262***
	(10.72)		(12.30)
76	-0.0199***	Appraisal management company (AMC) used	-0.0244***
	(-3.26)		(-21.03)
79	-0.0246***	County house price change	-0.0004**
	(-5.07)		(-2.84)
80	0.0909***	County default/foreclosure rate 5–7%	-0.0181***
	(34.41)		(-9.34)
81	-0.0942***	County default/foreclosure rate > 7%	-0.0326***
	(-16.77)		(-12.98)
84	0.0017	Constant	0.515***
	(0.29)		(18.49)
85	0.0650***		
	(15.34)		
86	0.0028		
	(0.46)		
89	0.0231***		
	(4.38)		
90	0.0903***		
	(30.39)		
91	-0.0270***		
	(-4.68)		
94	0.0046		
	(0.95)		
95	0.106***		
	(38.69)		
96	-0.0173*		
	(-2.49)		
97	0.0842***		
	(19.81)		
State-by-year controls	✓		
Observations	472,960		
R^2	0.0544		

Source: Authors' calculations based on data from GSE, CoreLogic, and Zillow. Note: Coefficients displayed with t-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, and 92-93. Notch LTVs are shaded in gray. Sample includes appraisals conducted in 2013–2015. House price change is captured as the change in the Zillow county-level home value index from 24 to 12 months before the appraisal.

Table A2: Robustness of Information Loss Results to Alternative Specifications and Samples

	(1)	(2)	(3)	(4)
Applied-for LTV				
74	0.0180**	0.0170**	0.0173**	0.0151**
	(3.02)	(2.82)	(2.86)	(2.75)
75	0.0450***	0.0464***	0.0470***	0.0495***
	(10.72)	(10.85)	(11.05)	(12.99)
76	-0.0199**	-0.0249***	-0.0249***	-0.0260***
	(-3.26)	(-4.01)	(-4.04)	(-4.60)
79	-0.0246***	-0.0251***	-0.0242***	-0.0208***
	(-5.07)	(-5.06)	(-4.93)	(-4.62)
80	0.0909***	0.0893***	0.0902***	0.0904***
	(34.41)	(33.38)	(33.90)	(40.05)
81	-0.0942***	-0.0962***	-0.0959***	-0.0993***
	(-16.77)	(-16.82)	(-16.88)	(-18.97)
84	0.0017	0.0018	0.0009	0.0018
	(0.29)	(0.03)	(0.15)	(0.34)
85	0.0650***	0.0696***	0.0707***	0.0707***
	(15.34)	(16.19)	(16.54)	(17.94)
86	0.0028	0.0034	0.0010	0.0006
	(0.46)	(0.56)	(0.16)	(0.10)
89	0.0231***	0.0227***	0.0232***	0.0251***
	(4.38)	(4.24)	(4.36)	(5.02)
90	0.0906***	0.0932***	0.0940***	0.0961***
	(30.39)	(30.97)	(31.40)	(36.45)
91	-0.0270***	-0.0286***	-0.0283***	-0.0246***
	(-4.68)	(-4.90)	(-4.89)	(-4.49)
94	0.0046	0.0058	0.0064	0.0096*
	(0.95)	(1.18)	(1.32)	(2.09)
95	0.106***	0.103***	0.103***	0.105***
	(38.69)	(37.81)	(38.28)	(45.22)
96	-0.0173*	-0.0256***	-0.0257***	-0.0221***
	(-2.49)	(-3.64)	(-3.68)	(-3.30)
97	0.0842***	0.0874***	0.0885***	0.0892***
	(19.81)	(20.65)	(21.08)	(22.53)
Constant	0.515***	0.766***	0.763***	0.761***
	(18.49)	(315.92)	(316.39)	(380.65)
Controls				
Other county, home characteristics	✓	-	-	-
State-by-year controls	✓	-	-	-
Types of observations included				
States	All	All	All	All
Loan types	FRM 30	FRM 30	FRM 30	All
Null values on controls	No	No	Yes	Yes
Observations	472,960	472,960	484,622	552,461
R^2	0.0544	0.0158	0.0158	0.0161

Source: Authors' calculations based on data from GSE, CoreLogic, and Zillow. Note: Coefficients displayed with t-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, and 92-93. Notch LTVs are shaded in gray. Sample includes appraisals conducted in 2013–2015. Other county and home characteristics include ln contract price, ln 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. Model 1 is the main model. Model 2 uses the same sample but excludes control variables, and Model 3 extends Model 2 to observations with null values on those control variables. Model 4 extends the analysis to adjustable-rate mortgages and those with terms less than 30 years.

Table A3: Robustness of Information Loss Results to Flexible Definition of "Identical" Appraisal

	(1) All Obs.	(2) No AMCs	(3) AMCs
Applied-for LTV			
74	0.0109**	0.0216***	0.0048
	(2.92)	(3.80)	(0.98)
75	0.0279***	0.0303***	0.0265***
	(10.49)	(7.38)	(7.67)
76	-0.0091*	-0.0104~	-0.0086~
	(-2.41)	(-1.84)	(-1.71)
79	-0.0130***	-0.0184***	-0.0098*
	(-4.27)	(-3.99)	(-2.44)
80	0.0589***	0.0559***	0.0606***
	(35.43)	(22.22)	(27.73)
81	-0.0086**	-0.0018	-0.0144***
	(-2.74)	(-0.38)	(-3.49)
84	-0.0063~	0.0038	-0.0121**
	(-1.76)	(0.70)	(-2.58)
85	0.0412***	0.0485***	0.0367***
	(15.62)	(12.20)	(10.55)
86	0.0025	0.0085	-0.0011
	(0.67)	(1.50)	(-0.23)
89	0.0161***	0.0136**	0.0176***
	(4.92)	(2.76)	(4.08)
90	0.0588***	0.0578***	0.0593***
	(31.55)	(20.55)	(24.14)
91	0.0032	-0.0003	0.0057
	(0.95)	(-0.06)	(1.26)
94	0.0062*	-0.0020	0.0116**
	(2.07)	(-0.46)	(2.93)
95	0.0688***	0.0621***	0.0728***
	(40.28)	(24.16)	(32.29)
96	0.0352***	0.0303***	0.0381***
	(9.52)	(5.52)	(7.74)
97	0.0530***	0.0576***	0.0494***
	(20.19)	(15.15)	(13.88)
Appraisal management company (AMC) used	-0.0202***		
	(-28.81)		
County default/foreclosure rate 5–7%	-0.0149***	-0.0111***	-0.0178***
	(-12.77)	(-6.51)	(-11.23)
County default/foreclosure rate > 7%	-0.0300***	-0.0234***	-0.0340***
	(-19.65)	(-10.34)	(-16.58)
Constant	0.791***	0.809***	0.76***
	(46.29)	(30.47)	(34.13)
Other county and home characteristics	✓	✓	✓
State-by-year controls	✓	✓	✓
Observations	810,821	304,345	506,476
R^2	0.0384	0.0349	0.0384

Source: Authors' calculations based on data from GSE, Zillow, CoreLogic, and McDash Analytics. Note: Coefficients displayed with t-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, and 92-93. Notch LTVs are shaded in gray. Sample includes appraisals conducted in 2013–2015. Other county and home characteristics include ln contract price, ln 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. Sample includes observations with appraisal and contract price. Model 2 (3) excludes (is restricted to) appraisals conducted by AMC.

Table A4: Full Results for Default Model

Dummies for LTVs at or Near a Notch		**Controls**	
78.5–79.5	0.0008	Linear FICO Spline	
	(0.44)	< 680	-0.0017^{***}
80	0.0001		(-180.87)
	(0.16)	680–720	-0.0002^{***}
80.5–81.5	$0.0166^{\sim}$		(-8.78)
	(1.77)	> 720	-0.0003^{***}
83.5–84.5	-0.0012		(-28.26)
	(-0.34)	DTI	0.0006^{***}
85	0.0069^{***}		(38.28)
	(3.41)	3–11 months of reserves	-0.0092^{***}
85.5–86.5	-0.0074^{*}		(-15.65)
	(-2.24)	12+ months of reserves	-0.0164^{***}
88.5–89.5	0.0006		(-29.18)
	(0.24)	Co-borrower	-0.0275^{***}
90	0.0108^{***}		(-67.13)
	(7.88)	New construction	0.0096^{***}
90.5–91.5	-0.0011		(5.32)
	(-0.35)	House price change†	-0.0003^{***}
93.5–94.5	-0.0071^{**}		(-15.88)
	(-2.99)	House price trough†	-0.0029^{***}
95	0.0165^{***}		(-68.94)
	(17.70)	LTV linear spline	
95.5–96.5	0.0036	< 70% LTV	0.0003^{***}
	(0.80)		(3.40)
97	0.0091^{***}	70-80% LTV	0.0005^{***}
	(5.93)		(4.19)
		80–90% LTV	0.0010^{***}
			(6.91)
		> 90% LTV	0.0032^{***}
			(12.06)

Constant	1.1216^{***}
	(141.11)
Vintage, state, and lender dummies	✓
Observations	919,408
R^2	0.1414

Source: Authors' calculations based on data from GSE and Zillow. Note: Coefficients displayed with t-statistics in parentheses. $^{\sim}$ denotes 0.10 level of significance, * 0.5, ** 0.01, *** 0.001. Controls include vintage dummies (coefficients not displayed), 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 that might be used for mortgage payments, a linear spline of LTV (with knots at 70%, 80%, and 90%), a linear spline of the minimum FICO score of borrower/co-borrower (captured at origination) with knots at 680 and 720, 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 3 years post origination.

Table A5: Linear Probability Models for Default Risk at and Near LTV Notches, 2003–2009 Originations
Default Definition: 180 Days Delinquent in First 5 Years after Loan Was Originated

	(1) All	(2) Negative Appraisal	(3) Equal Appraisal	(4) Positive Appraisal
Dummies for LTVs at or Near a Notch				
78.5–79.5	0.0004	-0.0053	0.0016	-0.0015
	(0.22)	(-0.61)	(0.57)	(-0.52)
80.0	0.0006	0.0026	-0.0001	-0.0004
	(0.58)	(0.48)	(-0.08)	(-0.31)
80.5–81.5	0.0169	0.0429~	0.0046	0.0166
	(1.60)	(1.95)	(0.26)	(1.07)
83.5-84.5	-0.0035	-0.0016	-0.0113~	0.0028
	(-0.88)	(-0.08)	(-1.92)	(0.50)
85.0	0.0054*	-0.0099	0.0029	0.0071*
	(2.39)	(-0.61)	(0.89)	(2.19)
85.5–86.5	-0.0068~	-0.0010	-0.0136*	-0.0018
	(-1.83)	(-0.05)	(-2.46)	(-0.35)
88.5–-89.5	0.0000	-0.0313~	0.0055	-0.0038
	(0.02)	(-1.78)	(1.26)	(-0.95)
90.0	0.0100***	-0.0018	0.0124***	0.0075***
	(6.49)	(-0.17)	(5.06)	(3.67)
90.5–-91.5	-0.0054	0.0314~	-0.0038	-0.0079~
	(-1.54)	(1.78)	(-0.64)	(-1.76)
93.5–-94.5	-0.0074**	-0.0252~	-0.0041	-0.0093**
	(-3.15)	(-0.78)	(-1.33)	(-2.94)
95.0	0.0151***	-0.0198*	0.0244***	0.0089***
	(14.42)	(-2.39)	(13.31)	(6.76)
95.5–-96.5	0.0197***	-0.0291	0.0139~	0.0246***
	(3.92)	(-1.13)	(1.67)	(3.76)
97.0	0.0091***	-0.0151	0.0156***	0.0047*
	(5.29)	(-1.02)	(5.41)	(2.09)
House price change†	-0.0003***	-0.0002~	-0.0002***	-0.0004***
	(-12.19)	(-1.75)	(-5.97)	(-11.48)
House price trough†	-0.0033***	-0.0021***	-0.0035***	-0.0031***
	(-80.57)	(-9.27)	(-59.89)	(-52.88)
Constant	1.0662***	0.7707***	1.1351***	1.0248***
	(119.33)	(15.03)	(86.60)	(80.91)
Vintage, state, and lender dummies	✓	✓	✓	✓
Borrower, loan, and house traits	✓	✓	✓	✓
Observations	919,408	19,699	411,724	488,015
R^2	0.1490	0.1074	0.1576	0.1447

Source: Authors' calculations based on data from GSE and Zillow. Note: 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 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 that might be used for mortgage payments, a linear spline of LTV (with knots at 70%, 80%, and 90%), a linear spline of the minimum FICO score of borrower/co-borrower (captured at origination) with knots at 680 and 720, 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 A6: Linear Probability Models for Default Risk at and Near LTV Notches, 2003–2009 Originations
Default Definition: 90 Days Delinquent in First 2 Years after Loan Was Originated

	(1) All	(2) Negative Appraisal	(3) Equal Appraisal	(4) Positive Appraisal
Dummies for LTVs at or Near a Notch				
78.5–79.5	0.0012	-0.0015	0.0013	0.0005
	(0.79)	(-0.22)	(0.57)	(0.22)
80.0	-0.0001	-0.0018	-0.0001	-0.0011
	(-0.12)	(-0.44)	(-0.12)	(-1.02)
80.5–81.5	0.0108	0.0076	-0.0042	0.0222~
	(1.29)	(0.46)	(-0.31)	(1.81)
83.5–84.5	-0.0023	-0.0137	-0.0101*	0.0045
	(-0.74)	(-0.95)	(-2.17)	(1.01)
85.0	0.0078***	-0.0308*	0.0065*	0.0086***
	(4.35)	(-2.51)	(2.55)	(3.38)
85.5–86.5	-0.0047	-0.0123	-0.0123**	0.0015
	(-1.58)	(-0.75)	(-2.81)	(0.37)
88.5–89.5	0.0018	-0.0030	-0.0006	0.0033
	(0.79)	(-0.23)	(-0.17)	(1.04)
90.0	0.0105***	0.0093	0.0121***	0.0081***
	(8.53)	(1.19)	(6.22)	(4.98)
90.5–91.5	-0.0032	0.0227~	-0.0054	-0.0032
	(-1.14)	(1.70)	(-1.15)	(-0.89)
93.5–94.5	-0.0050*	-0.0142	-0.0048	-0.0054~
	(-2.34)	(-1.28)	(-1.38)	(-1.95)
95.0	0.0152***	-0.0034	0.0212***	0.0103***
	(18.33)	(-0.54)	(14.62)	(9.87)
95.5–96.5	-0.0033	-0.0075	-0.0024	-0.0046
	(-0.83)	(-0.38)	(-0.36)	(-0.89)
97.0	0.0093***	-0.0080	0.0109***	0.0073***
	(6.83)	(-0.71)	(4.75)	(4.10)
House price change†	-0.0001***	-0.0000	-0.0001***	-0.0002***
	(-6.63)	(-0.39)	(-4.42)	(-5.12)
House price trough†	-0.0029***	-0.0015***	-0.0033***	-0.0026***
	(-62.51)	(-5.97)	(-48.63)	(-40.05)
Constant	1.0843***	0.8093***	1.1484***	1.0437***
	(153.09)	(20.85)	(110.48)	(103.90)
Vintage, state, and lender dummies	✓	✓	✓	✓
Borrower, loan, and house traits	✓	✓	✓	✓
Observations	919,408	19,669	411,724	488,015
R^2	0.1218	0.0809	0.1326	0.1160

Source: Authors' calculations based on data from GSE and Zillow. Note: 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 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 that might be used for mortgage payments, a linear spline of LTV (with knots at 70%, 80%, and 90%), a linear spline of the minimum FICO score of borrower/co-borrower (captured at origination) with knots at 680 and 720, 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 2 years post origination.