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Abstract

Home appraisals are produced for millions of residential mortgage transactions each year, but appraised values are rarely below the purchase contract price: Some 30% of appraisals in our sample are exactly at the home price (with less than 10% of them below it). We lay out a basic theoretical framework to explain how appraisers' incentives within the institutional framework that governs mortgage lending lead to information loss in appraisals (that is, appraisals set equal to the contract price). Consistent with the theory, we observe a higher frequency of appraisal equal to contract price and a higher incidence of mortgage default at loan-to-value boundaries (notches) above which mortgage insurance rates increase. Appraisals appear to be less informative for default risk measurement compared with automated valuation models.

Keywords: information, mortgage, regulation, appraisal, mortgage default, foreclosure

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

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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 market value of the property that constitutes the collateral for the mortgage loan.

The value of a home as collateral for a lender is its resale price if a default occurs; this in turn reflects an underlying valuation distribution. In general, the expected collateral value will differ from the original sale price, since the buyer and seller have idiosyncratic components to their valuations and act on imperfect information. Yet, it has long been observed that the vast majority of appraisals are at or above the purchase contract price (the accepted offer price).

The sizable literature on price determination in housing markets focuses on the roles of buyer and seller imperfect information and search costs in determining list and sale prices, abstracting from the role of appraisals and their potential role in disrupting the agreed-upon sale. Existing literature provides few models of the appraisal process. In this paper, we develop a model of appraisals that builds on the framework in Lang and Nakamura (1993). Our model, while taking the contract price as given, is broadly consistent with the price determination literature through its emphasis on the opportunity cost of a cancelled sale transaction.

The model represents the appraiser as internalizing trade-offs faced by the lender (this assumption can be generalized to allow additional influences), such that the appraiser may confirm the contract price to preserve the opportunity for a profitable mortgage transaction. In other words, the appraiser, who is commissioned by the lender, chooses whether to report the best estimate of market value when it is less than the contract price, versus biasing the appraisal upward toward confirming the contract price.

In making this decision as the agent of the lender, the appraiser faces a trade-off between a potentially cancelled mortgage transaction if the contract price is not confirmed and losing informational value from the appraisal if it is. One reason an appraised value below the contract price may imperil the transaction is that the lender is compelled to recalculate the loan-to-value ratio (LTV) using the appraised value when it is below the contract price, which could entail less desirable loan terms. In addition, appraising a home at a price lower than the contract price could compel renegotiation of the contract when there is an appraisal contingency clause, as there typically is.

On the one hand, cancellation of the sale transaction entails an opportunity cost for the mortgage originator and further search costs for the buyer, seller, and real estate agents. On the other hand, a biased appraisal implies increased credit risk (or underpricing of risk) tied to overvaluation of the property. Less informative appraisals entail costs to buyers as well, who may lose an opportunity to renegotiate a contract. Each of these costs may be reflected in reputational costs to the appraiser, whose income generally depends on repeat business from lenders. Often, the incentive to complete the transaction will prevail, leading the appraiser to confirm the contract price, or otherwise bias the appraisal upward.

Within this context, borrower behavior may be influenced by the existence of so-called LTV notches, above which underwriting and mortgage insurance requirements rise stepwise — most typically these are 80%, 90%, and 95%. The existence of LTV notches is reflected in various observable "notch effects," including the bunching of mortgage applicants at LTV notches. Indeed, notch applicants (relative to those not locating at notches) may more often be stretching their down payment to reach the notch and reduce their monthly payment obligation, leaving no bandwidth for a negative appraisal. In contrast, between notches, there is some leeway for negative appraisals not to impact the affordability of a mortgage, even for those who are stretching. Thus, the model suggests stronger incentive for appraisers to confirm the contract price at LTV notches.

We also present new empirical findings on appraisals in relation to contract prices using a national sample of home purchase mortgage appraisals from one of the the government-sponsored enterprises (GSEs), Fannie Mae or Freddie Mac. In addition to reported appraised values and contract prices, this rich new data set includes reported and preappraisal LTV measures. Selection bias is mitigated because the data set includes appraisals on mortgages that subsequently fail to originate, as well as those resulting in successful originations.

The data set also includes automated valuation model (AVM) estimates of market value that are concurrent with the appraisal estimates. The AVM estimates provide a useful benchmark for both contact prices and appraised values.

Consistent with prior studies, our data indicate that less than 10% of all appraisals in the data set are below the contract price, and approximately 30% of appraisals precisely equal the contract price. Moreover, as implied by the model, we find that the frequency of appraisals at or above the contract price is highest at LTV notches.

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 equal the contract price exactly, 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) should be comparatively informative that the buyer has overbid relative to the market value.

The loss of information in the appraisals implies less precise measurement and less efficient pricing of mortgage default risk. In aggregate, the cost of information loss may extend beyond the immediately impacted mortgage transaction to all potential, subsequent consumers of appraisal data, who could use it to evaluate lending decisions, property valuations, and default risk.

In addition, we explore a second GSE data set that provides appraisals and AVM estimates of originated loans along with performance outcomes (specifically, whether the loan became seriously delinquent). Supporting the view that reported appraisals frequently are biased upward, we find that appraisals are somewhat less predictive of default than AVM estimates. We also find that notch loans have an elevated likelihood of delinquency, consistent with the notion that applicants at LTV notches tend to be more liquidity constrained.

In the next section, we review the literature on appraisal bias and highlight the contributions of our paper in relation to this literature and to other aspects of housing and mortgage markets. In the subsequent sections, we develop our model of information loss in appraisals and present our empirical analysis and results.

1. Literature and Institutional Context

Our paper contributes to the theoretical and empirical understanding of the residential mortgage appraisal process and appraisal outcomes, a subject of long-standing interest that has recently received renewed attention. Our paper is also related to a broader literature on notch effects or "bunching" in home purchase and mortgage markets, which emphasize the role of search or transaction costs and institutional aspects.

1.1. Empirical studies of residential mortgage appraisals

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. The data for their study were limited to appraisals for completed home purchase mortgages.

Ding and Nakamura (2016) use a special sample of premortgage transactions from the vendor FNC, Inc. to study appraisal bias. Their study focuses on the impact of the 2009 Home Valuation Code of Conduct (HVCC), a regulatory change that sought to enhance the reliability of appraisals. While we also make limited use of the FNC sample, our empirical analysis primarily relies on a national sample of presale, premortgage transactions data from one of the GSEs (Freddie Mac or Fannie Mae). These detailed data include reported appraised values, contract prices (accepted offer prices), and preappraisal LTV measures. Thus, for instance, we are able to examine appraisal outcomes in relation to the LTV before any renegotiation has taken place.

Eriksen, Fout, Palim, and Rosenblatt (2016) use pairs of appraisals on postforeclosure properties, one just after the lender takes possession (which should be more neutral because 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 should be reported. The study emphasizes the adjustments made to the comparable sales used to appraise the property, which Mayer and Nothaft (2017) also find are at work.

All of these studies find that a large share of appraisals come in at values that are exactly identical or very close to the contract price, a phenomenon Eriksen et al. (2016) refer to as "confirmation bias," whereas negative appraisals are rare. Our empirical analysis expands on these prior studies primarily by demonstrating the existence of notch effects such that the negative appraisals are most infrequent and confirmation bias more pronounced at LTV boundaries.[1]

Fout and Yao (2016) conduct the first scholarly investigation of how negative appraisals affect home purchase transactions using the Uniform Appraisal Dataset, containing appraisals submitted to GSEs. They find that negative appraisals increase the probability from 8% to 51% that buyers and sellers renegotiate the price down. Negative appraisals 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.

The impact of appraisal bias on credit risk measurement has received little attention in the literature. The potential value of appraisals for assessing mortgage risk is vividly illustrated in Ben-David (2011), where it is shown that the means of evading LTV requirements using cash rebates and other techniques led to higher default rates. Carrillo, Doerner, and Larson (2018) show that home sale prices that exceed predicted prices (based on AVM estimates) are associated with elevated mortgage delinquencies and credit losses, underscoring the potential default cost associated with appraisal bias.[2] Our paper extends this line of research by providing a direct comparison of AVMs and appraisals in default prediction.

1.2. 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 — 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. This requirement has its

[1] Agarwal, Ben-David, and Yao (2015) use a Fannie Mae data set to explore collateral valuations for refinances, in which there is no contract price to anchor on, by comparing refinance valuations with subsequent sale prices, and find that the "valuation bias" of refinance transactions exceeds 5% on average. They also find that this bias tends to be larger at LTV notches.

[2] They find that "the difference between a -20% and +20% markup is a near doubling of the default rate of a mortgage, holding all other characteristics of the loan and borrower constant."

origin in FHA rules requiring that property valuations be based on independent appraisals, not on contract prices.

Historically, appraisals were simply required to be used as the LTV denominator. For many years, however, the requirement has been instead to equate the collateral value with the lesser of the sale price and the appraised value.[3] The requirement to value the collateral at the minimum of appraised value and sale price has significant implications because the LTV is a crucial indicator of the credit risk of the mortgage. Moreover, the LTV determines the interest rate and the terms the lender is willing to offer.

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 1, and mortgage interest rates typically increase across these notches as well. Those with sufficient liquidity to borrow at an LTV below 80 percent generally will qualify for the lowest possible interest rate for owner-occupied prime mortgages. In practice, borrowers have varying access to liquidity or the ability to provide a down payment, and cash constrained borrowers will locate at LTVs above 80 percent, requiring them to pay mortgage insurance premiums and higher interest rates.[4]

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, Bricker, Calem, and Wachter 2016). When prospective buyers make an offer on a home, they typically would have calculated their down payment and intended LTV, with some foreknowledge of the impact of their down payment on the

[3] 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 those insured by the FHA. For example, the table that gives the method for calculating the LTV 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).

[4] Mortgage costs also vary depending on borrower characteristics, such as credit score, but we are holding these other observable underwriting 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.

cost of the mortgage and its likelihood of being underwritten (Best, Cloyne, Ilzetzki, and Kleven 2015).

1.3. Notch and bunching literature

A discrete change in costs coinciding with a very small change in a variable provides a strong incentive for bunching behavior, whereby transactions tend to occur at notches.[5] In the U.S. mortgage context, bunching is characterized by borrowers concentrating at LTV notches. Bunching reflects the fact that most borrowers are not willing to incur the steeply higher monthly payment just above the notch, nor are most borrowers willing to locate in-between notches by putting down a larger down payment than required to achieve their targeted monthly payment.

In the U.K., mortgage insurance is not a factor in pricing of mortgages, but interest rate schedules are characterized by LTV notches and substantial bunching occurs (Best et al. 2015). The use of notches to price the increases in credit risk associated with higher LTV appears to be an administrative convenience that creates greater uniformity in the instruments, which in turn likely facilitates liquidity. Best et al. (2015) study bunching at the notches empirically in the British context in an effort to measure the intertemporal elasticity of substitution.

In our paper, we document bunching at LTV notches and consider effects when borrowers stretch to locate at an LTV notch at the cost of raising the likelihood of default. In particular, we examine appraised values relative to contract prices for notch applicants compared with nonnotch applicants, and assess default probabilities for borrowers at LTV notches relative to borrowers at neighboring LTVs.[6]

Notches are also important characteristics of buyer and seller search and transaction in residential real estate markets. Han and Strange (2016), building on the work of Chen and Rosenthal (1996), point out that asking bids commit the seller to sell at

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[5] Kleven (2016) provides a general discussion of notches and bunching.

[6] The more general relationship between LTVs and mortgage default rates is firmly established in the literature on mortgage repayment performance; more recent studies examining this relationship include Foote, Gerardi, and Willen (2008); Haughwout, Peach, and Tracy (2008); Elul, Souleles, Chomsisengphet, Glennon, and Hung (2010); and Palmer (2015). Bubb and Kaufman (2014) show localized increases in default risk associated with different credit score notches.

the asking price if there are no other simultaneous offers at or above the asking price. As such, the asking price becomes a notch in the sense of a conditional ceiling on bids. The purpose of this commitment device is to allow the potential buyer a reasonable probability of not having to pay his or her reservation price, thus providing an incentive to the buyer to engage in costly search.[7] Conceptually, buyer bids should tend to bunch at this notch to the extent that buyers have reservation prices greater than the asking price. Empirically, this bunching takes the form of contract prices frequently observed to coincide with seller list prices.

Our model of appraisal outcomes bears some similarity to Han and Strange (2016), in that the potential for a failed bid or transaction put buyer and seller search costs at risk. In the case of seller asking price, the partial commitment serves to incentivize the borrower to undertake costly search. In the appraisal case, the commitment has already been made (the contract price), and the appraiser may have to weigh the opportunity cost of deal incompletion against increased credit risk.

1.4 Other determinants of overpaying

Linneman (1986) shows that there is a mean-reverting component of differences between transaction prices and hedonic-estimated values, which he interprets as transactor error. Harding, Rosenthal, and Sirmans (2003) show that buyer characteristics can affect transaction prices which they interpret as bargaining power. For example, women pay more for houses, which they interpret as having less bargaining power. This effect is stronger in thin markets, where less information is available. Another impact they find is that higher income borrowers exhibit less bargaining power, possibly due to diminishing marginal utility of income.

In our model, we disregard the complications of seller-asking prices and buyer bids, or of search costs, bargaining power, and transactor error. We acknowledge that an

[7] This commitment device resolves the so-called Diamond paradox, which is that if there are search costs and no price commitments, then identical competitors all charge the monopoly price, because once the shopper has arrived at a store, the store has a temporary monopoly. The market then collapses because the shopper has no incentive to shop, so no searching takes place.

extension of the model to explicitly incorporate buyer and seller search, transaction and bargaining potentially could shed further light on the role of appraisals.[8]

2. A Model of Appraisal Outcomes

In this section, we construct a theoretical representation in which the appraiser often chooses to substitute the contract price for the best estimate of market value when the appraised value is lower, in effect confirming the contract price. The model represents the appraiser as internalizing trade-offs faced by the lender (although, as discussed next, this assumption is more restrictive than required), and so the appraiser may confirm the contract price to preserve the opportunity for a profitable mortgage transaction.

2.1. The mortgage application and appraisal

Consider a property under contract such that the buyer and seller have agreed upon a contract price. The buyer applies for a mortgage loan of some amount, such that the terms of the mortgage are based on the desired LTV, in accordance with the lender's loan pricing schedule. The log-transformed LTV is denoted $\lambda_0 = L_0 - v_0$, where L_0 and v_0 denote natural log of loan amount and contract price, respectively. For now, we assume that this desired LTV is at a notch, where the effects represented in the model are apt to be the strongest and the majority of mortgages are, in fact, located. Next, we discuss the extension of the model to nonnotch LTVs.

The lender proceeds to evaluate the mortgage application and commissions an appraisal of the property. The appraised property value, the natural log of which we denote a, would be the appraiser's best estimate of the (log of the) underlying market value of the property, which we denote as V. The appraiser uses an efficient information collection process that takes into consideration the contract price together with information in recent comparable transactions, as in Quan and Quigley (1991) and Lang and Nakamura (1993).

This property valuation is assumed to move as a random walk in relation to a succession of comparable sales transactions, and, using the Kalman filter, there is an optimal

[8] Moreover, the microrelationship among list prices, bidding, and appraisals appears to be an empirical question that is subject to future research. Such a model could also consider how a bidder could increase his competitiveness by waiving an appraisal contingency clause when making an offer.

expected price $V_t^* = \gamma V^*_{t-1} + (1-\gamma)\ v_0$, where 1-γ is the updating parameter.[9] It follows that the best-estimate appraised value is:

$$(1) \quad a = v_0 + \gamma(V^*_{t-1} - v_0).$$

Recent transactions on nearby properties are a primary input into this process, as they are directly informative about the market value.[10]

2.2. The lender's trade-off

In the absence of a regulatory or institutional requirement to confirm the requested loan terms on the basis of the appraised value, the lender would only use the appraised value to recalculate the LTV for the purpose of assessing the credit risk of the mortgage. The recalculated LTV would not be binding on the lender's decision whether to approve the requested loan terms. We shall denote this recalculated LTV as $\lambda = L_0 - a$.

If the appraisal were nonbinding as such, a negative appraisal (less than or equal to the contract price) would not compel the lender to reject the requested loan terms, and there would be no incentive for the appraiser to bias the appraisal. In response to a negative appraisal, the lender might choose to approve the requested loan terms while accepting the increased credit risk implied by the negative appraisal. Alternatively, the lender may choose to request a larger down payment (reduce the loan amount) to restore the LTV to λ_0, or may offer a higher interest rate loan compatible with the increased credit risk implied by $\lambda > \lambda_0$.

In deciding among these options, the lender would weigh the increase in credit risk associated with an LTV greater than λ_0 against the cost implications of rejecting the application or offering revised loan terms which in turn the buyer may reject.[11] Note that the lender would have to bear the cost of this increased risk even if originating the mortgage for

[9] 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.

[10] 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, Beeson, and Sniderman (1999), and Ding (2014).

[11] A negative appraisal also raises the possibility that the buyer may exit the transaction (by exercising an appraisal contingency) even if the lender approves the originally requested loan terms. However, the lender's decision on the mortgage is independent of this possibility (as there would be no trade-off to consider in that case).

sale rather than for its own portfolio because the purchaser of the mortgage would observe the appraised value and require compensation for the higher risk.

The cost to the lender of rejecting the requested loan terms is the opportunity cost of the potentially lost mortgage origination, including the net present value of the mortgage servicing rights, plus the mortgage origination fee (if the lender is originating the mortgage for sale to an investor) or net present value of the mortgage as an asset (if the mortgage is to be retained in the lender's portfolio). Of course, losing the mortgage also imposes a cost on the seller (and the seller's real estate agent) due to the additional search cost and the delay incurred in finding a new buyer.

However, the requirement that the LTV associated with the mortgage application be confirmed by an appraisal nullifies the lender's optimization problem because the lender's decision on the loan application must be based on the postappraisal LTV. Postappraisal, the LTV is recalculated by applying the minimum value rule, which dictates that the property value is the lesser of a and v_0. If $a < v_0$, then the postappraisal LTV λ exceeds the originally requested LTV λ_0 and frequently will be incompatible with the requested loan terms according to the lender's pricing schedule.

In this case, the lender would be compelled to reject the requested loan terms but may offer a higher LTV loan with higher monthly payments.[12] The buyer would then have to decide whether to make a larger down payment and restore the original target LTV, accept a higher LTV loan (at a greater cost) if offered, renegotiate the contract price with the seller, pursue a combination of these, or withdraw from the transaction.

2.3. The appraiser's incentive to confirm the contract price

Our framework described previously represents an appraiser as internalizing the lender's cost trade-off. Thus, the appraiser would validate the contract price whenever it would be optimal for the lender to approve the originally requested loan terms. Similarly, the appraiser would have an incentive to bias the appraisal upward if it would be optimal for the lender to offer revised loan terms that associate with an LTV greater than λ_0 but less than λ. In other words, the appraiser internalizes the following optimization problem.

[12] Note that the same outcome prevails if the lender simply is required to use the appraised value and not the contract price (rather than the minimum of the two).

On the one hand, to the extent that the contract price v_0 exceeds the appraised value a, the property is overvalued at the contract price, implying increased credit risk. The increased credit risk associated with $a < v_0$ is represented as $g(v_0 - a)$, where $g(0) = 0$ and $g'(v_0 - a) > 0$. Alternatively, $g(v_0 - a)$ may be interpreted as the degree to which the mortgage is mispriced when the down payment (and pricing) is based on the contract price rather than the appraised value.

On the other hand, to the extent that v_0 exceeds a, there is an increasing likelihood that the transaction will not be completed because the lender would be compelled to reject the requested loan terms. The opportunity cost of potentially losing the mortgage origination when $v_o > a$ is represented as $f(v_o - a)$, where $f(0) = 0$ and $f'(v_o - a) > 0$. Putting together these two cost components, we have that the appraiser, when internalizing the lender's costs, rather than provide the market value estimate a calculated from (1), would report the appraised value $\tilde{a}$ that solves the cost minimization problem:

$$(2) \quad \min_{v} f(v_o - v) + g(v - a).$$

In the case of an interior solution, the reported appraised value will be biased upward relative to the market value best estimate but not so far as the contract price; that is, $v_o > \tilde{a} > a$. If the marginal cost of a potentially lost transaction $f'(v_o - v)$ exceeds the marginal credit loss $g'(v - a)$ over the entire interval between a and v_o, then the appraiser will report $\tilde{a} = v_o$.[13] Otherwise, $\tilde{a} = a$.

We illustrate the model with a linear-quadratic version of the cost minimization (2):[14]

$$(3) \quad g(\tilde{a} - a) = d(\tilde{a} - a)^2$$

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

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

$$(4\text{-i}) \quad \text{if } a \geq v_0, \text{ then } \tilde{a} = a$$

[13] 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.)

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

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

(4-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 market value best estimate is greater than the contract price, the reported appraisal is equal to the market value best estimate; 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.

The second statement holds that when the underlying market value best estimate is below but sufficiently near the contract price, the reported appraisal is identical to the contract price. Specifically, the market value best estimate must be within a distance of the contract price such that the potential cost of a cancelled transaction exceeds the credit loss impact of overvaluing the property.

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

Particularly noteworthy are the implications of the 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 true appraised values a relative to v_o in the region where $a < v_o$, with a piling up of probability mass at $\tilde{a} = v_o$. Thus, the model can serve to explain the frequent convergence of appraised value and contract price demonstrated by empirical studies.

2.4. Reported appraised value and information loss

Substitution of the contract price for the best estimate of market value from (1) entails information loss because the true appraised value of the property is lost in the process. Figure 2 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).

Although this may be a good outcome from the lender's perspective since it enables the cost-minimizing decision on the mortgage application, the result is socially inefficient. One important inefficiency from information loss is that borrowers are denied the opportunity to reevaluate their offers on the basis of the true appraised values. Another is that the information is also lost to all subsequent consumers of appraisal data, who could use it to evaluate lending decisions, property valuations, and credit risk.

In addition, the lender is not able to make fine-grained distinctions across properties. For example, as we show in Figure 2, there appears to be more information loss when property values have small underlying variance.

2.5. Nonnotches

Thus far, we have assumed that the applied-for LTV occurs at a notch. However, it is generally known (and we observe in our data as well) that not all mortgage applicants target a notch LTV. First, a substantial proportion of mortgages are at LTVs below 80; these are generally borrowers who are not down payment constrained. Second, there are nonnotch borrowers who are at LTVs above 80.

A question that naturally arises is why any borrower would *not* locate at a notch, given that there would appear to be little benefit to providing a larger down payment than is necessary to obtain the applied-for loan terms.[15] In the notch literature, there is generally a shadow area in which theory predicts no participants will locate; when some do show up there (which is typical), these are attributed to errors (either in participants' decisions or in the data). In the mortgage context, additional explanations are possible.

For instance, it is possible that some borrowers may end up between notches (above the notch they had targeted) because of agreeing to a higher price than they had anticipated. With the higher purchase price, the LTV could be raised to the next higher notch, instead of leaving it in between the old notch and the next higher one. But the borrower may not reduce the down payment, if this is the best use that the borrower has for the money. It also is possible that some borrowers may want to reduce their LTV as much as possible even if they

[15] In other words, the marginal benefit of an additional 1 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.

wind up short of the next lowest notch. They may do so to increase the likelihood of the loan being approved (such as in the case of borrowers with weak credit histories) or to reduce the loan amount to satisfy GSE (conforming loan size) requirements.

If λ_0 is not a notch LTV, then only if the appraisal is far enough below v_0 that the recalculated LTV increases to or beyond the next notch would the requested loan terms be rejected. An appraisal that falls below v_0 but remains sufficiently close would not trigger rejection of the requested loan terms, which suggests a discontinuity in $f(v_o - a)$ such that it equals zero within this "grace interval."

However, a negative appraisal may compel a renegotiation of the contract that may lead to its cancellation, irrespective of whether or not the applied-for LTV λ_0 is at a notch. Moreover, in the case of borrowers with marginal credit profiles, even if λ_0 is not a notch LTV, a negative appraisal could increase the likelihood of a rejected mortgage application. These considerations imply that in the case of a nonnotch LTV, $f(v_o - a)$ remains non-zero within the grace interval and the discontinuity is modest — the opportunity cost of a potentially foregone transaction is reduced but not eliminated.

Compared with nearby notches, however, there should be less appraisal bias and reduced frequency of appraised values equal to the contract price because of the presence of the grace interval. In other words, the model's distinction between notch and nonnotch applicants may entail an observable notch effect, such that we expect a greater frequency of information loss at LTV notches.

2.6 Some comments and caveats on the model

As developed previously, the model assumes that an appraiser would act as agent of the lender and act to minimize the lender's costs. Since appraisers are hired by the lenders, it is plausible that the appraiser would have a strong incentive to act on behalf of the lender so that the lender will be incentivized to maintain a continuing relationship.

It is not necessary, however, to assume that the appraiser acts solely in the interest of the lender — the assumption can be relaxed without fundamentally changing the model. For instance, relationships with real estate agents also may be important to appraisers, so that costs of a lost transaction $f(v_o - v)$ might be interpreted more broadly as reflecting costs to real estate agents as well. Likewise, the increased credit risk $g(v - a)$ attributed to information loss can be augmented to include the cost to borrowers or potential harm to an appraiser's reputation for professionalism and independence.[16]

Our model suggests that it is socially inefficient to require confirmation of the requested loan terms (in relation to the lender's pricing and mortgage insurance requirement schedule) on the basis of the appraised value, using the minimum value rule to recalculate the LTV. In our model, this requirement underlies the appraiser's incentive to report a biased appraised value that may often equal the contract price, implying information loss.

Moreover, even in the case of an appraiser who maintains full independence and reports the true (best estimate) value, the minimum value rule appears to be inefficient, in that it would generate a statistically biased valuation. The minimum value rule implies that if both the true (best-estimate) appraisal (1) and the contract price each are unbiased estimates of the market value, then valuation based on the lesser of the two will be biased downward.[17]

An important caveat is that the institutional and regulatory requirements around appraisals might have evolved to address market inefficiencies that are outside the scope of our model. The model is intended to offer a plausible explanation for appraiser behavior and appraisal outcomes; it is not our objective to evaluate the efficiency of this requirement or of the minimum value rule.

A more general caveat is that the model employs a fairly simple framework highlighting one plausible mechanism that might explain the phenomenon of appraised values frequently equaling contract prices, and we recognize that this need not be the only such mechanism. The model leaves the search and contract negotiation processes of buyers and sellers in the background, focusing on the lender's decision on the postcontract

[16] If our representation of the appraiser as internalizing the lender's optimization problem is valid, then there would be no reason for the lender to be concerned about the upward bias and adjust the LTV threshold. If, however, the upward bias in appraisals is greater than implied by the lender's optimization problem, reflecting the influence of other parties such as real estate agents, then lenders might respond via pricing the increased default risk or by offsetting it through stricter underwriting.

[17] For example, suppose that the appraiser's best-estimate valuation a and the contract price v_0, measured in logs, are distributed bivariate normally relative to the true market value, 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 min(ln a, ln v_o) equals $\bar{v} - \sqrt{\sigma_a^2 + \sigma_o^2 - 2\rho\sigma_a\sigma_o}\,\phi(0)$, where ϕ is the pdf of a standard normal distribution (Nadarajah and Kotz 2008), so that $\phi(0) = 1/\sqrt{2\pi} \approx 0.4$, implying a downward bias of about 0.4 times the standard deviation of a – v_0.

mortgage application. Thus, for example, a more complex representation might view buyers and sellers as seeking to anticipate the decision on the mortgage application, which might yield additional insights into the role of the appraiser.

3. Data

We explore the model's conclusions using two data sets of appraisals acquired from a GSE. The data sets are the same in that they focus on 30-year, fixed-rate, single-family, owner-occupied purchase mortgages. They are all fully amortizing mortgages with full documentation at underwriting and no prepayment penalties. Home Affordable Refinance Program (HARP) loans, loans with streamlined processing, and loans with other types of credit variances are excluded. The data sets cover different time periods.

The first data set includes 1.3 million mortgage applications made in 2013–2015, taken from the GSE's underwriting software, and includes the contract price and appraised value associated with the loan application, and an AVM estimate captured at the time of the application. The data set 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. 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.

We compare the contract price with the appraised value and the AVM estimate. These data also include the applied-for loan amount and the initial contract price on the home, from which the preappraisal 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.[18]

The second data set we use includes 900,000 completed mortgages originated in 2003–2009 and ultimately guaranteed by the GSE. Since these loans are well-seasoned, we can use them to study how appraisal loss relates to mortgages' ultimate outcomes. Because the initial (i.e., preappraisal) contract price is not available, we must compare the appraised value with the final sale price.

[18] These fields are displayed on typical appraisal order forms, which are publicly accessible online.

Both data sets 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 data sets with Black Knight McDash data on area default and foreclosure rates, CoreLogic Solutions public records data on area home sale characteristics, and Zillow home value indices.[19]

3.1 The empirical distribution of appraised values relative to contract prices

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, depending on the data set in question).

Table 1 summarizes the distribution of these values (the appraised value relative to the price) for each of the two samples (2003–2009 mortgage originations and 2013–2015 mortgage applications), and Figure 3 displays this distribution for the 2013–2015 sample. Consistent with our model's predictions, negative appraisals are infrequent, unlike positive appraisals, and we observe significant bunching at $a = v_o$.

In our 2013–2015 data set of 1.3 million appraisals for 30-year fixed rate mortgages, only 6% were reported below the contract price. Only 5% of notch mortgages have negative appraisals compared with 9% of nonnotch mortgages. Close to 30% of the loan applications in 2013–2015 had appraised value equal to the contract price.

Table 1 also reports the distribution of AVM estimate relative to contract price for the 2013–2015 sample of mortgage applications. Not surprisingly, the AVM-to-price distribution is much different from the appraisal-to-price distribution. The AVM-to-price distribution is skewed to the left, with relatively few AVM estimates at or close to the contract price, and it may be characterized as noisier, with greater shares of observations falling in the tails of the distribution.

The 2003–2009 data set comprises originated loans sold to the GSE, whereas the 2013–2015 data set comprises loan applications. A longer history of appraisal outcomes associated with loan applicatons can be obtained by combining the 2013–2015 data set used

[19] Zillow data were acquired from zillow.com/data. Aggregated data on this page is made freely available by Zillow for noncommercial use.

here with the data used in Ding and Nakamura (2016) from the vendor FNC, covering 2007–2012.[20] Figure 4 shows the appraisal-to-price distribution by loan application year from these combined data sets. In each year from 2007–2015, 25% to 30% of mortgage applications had an appraised value that was exactly identical to the contract price.

While consistent with our model's predictions, this observed bunching of 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, the comparison shown in Table 1 between the appraisal-to-price and AVM-to-price distributions within the 2013-2015 sample suggests that appraisers make sizable upward adjustments to match contract prices. For over 40% of observations in our sample, the GSE's AVM indicated that the property's value was more than 5% below the contract price.

Also, note the asymmetry in the Figure 3 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% (the part of the distribution just above $\tilde{a} = v_o$ looks relatively smooth), but only 0.7% of appraised values fell below the contract price, although within 1%. Thus, 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.[21]

[20] This data set includes 1.1 million single-family purchase mortgage applications made in 2007–2012, 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 bankrupt during the recent mortgage crisis. See Ding and Nakamura (2016) for more information on the FNC data.[21] If anything, slightly more records reside just above $\tilde{a} = v_o$ than one might expect in a log-normal distribution. 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). Appraisers may even report $\tilde{a}$ slightly > v_o when $a = v_o$, if they view this as a way to strengthen the credibility of their assessment that the appraised value is not less than the contract price. For example, Kartik (2009) presents a model in which upwardly biased communication is employed as an influence mechanism.

[21] If anything, slightly more records reside just above $\tilde{a} = v_o$ than one might expect in a log-normal distribution. 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). Appraisers may even report $\tilde{a}$ slightly > v_o when $a = v_o$, if they view this as a way to strengthen the credibility of their assessment that the appraised value is not less than the contract price. For example, Kartik (2009) presents a model in which upwardly biased communication is employed as an influence mechanism.

4. Information Loss at LTV Notches

The preceding discussion highlights consistency of the observed appraisal-to-price distribution with the implications of our model that appraised values will tend to confirm the contract price and more often exceed the contract price than be below it. As noted, our model also suggests that, compared with nearby notches, at nonnotch LTVs there should be less appraisal bias and reduced frequency of appraised values equal to the contract price because of the presence of the grace interval. We now examine the appraisal-to-price ratio by LTV range for evidence of consistency with this aspect of model.

4.1. Notch effects

Table 2 shows application counts and appraisal-to-price outcomes by applied-for (anticipated) LTV. Specifically, the table shows the percent of applications associated with a negative appraisal for each LTV, percent with a positive appraisal, and percent with appraised value equal to contract price. In addition, for each LTV, the table reports the percent of applications with appraised value equal to or no more than 1 percent larger than the contract price, which represents a fuzzy equality between appraised value and contract price.

As expected, consistent with our earlier discussion regarding the incentive for buyers to target an LTV notch, mortgage applications concentrate at LTV notches. Specifically, from Table 2, 63% of 2013–2015 mortgage applications fell at one of six notches, with 56% at the three major notches of 80%, 90%, and 95% LTV.[22]

Table 2 also indicates that appraisals 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 contract price as well as when we examine appraisals that are equal or within 1 percent above the contract price. Further, negative appraisals are more likely just above and below each notch. The five lowest values of the "percent negative" outcome are all at notch LTVs.

[22] Although our discussion has focused on notches associated with mortgage insurance pricing in the LTV range of 80% or higher, there are various reasons why notches are observed at LTVs below 80%; for instance, 75% LTV typically is a threshold for pricing of special mortgage products such as loans on investment properties and low-documentation loans.

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. Arguably, this conditional metric is preferable, as the positive side of the distribution (where appraisal > price) is represented by our model to have little or no appraisal bias.[23]

At each notch in Figure 5, we observe a pronounced uptick in the dotted line, indicating elevated 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.

Thus, we conclude from the data in Table 2 and Figure 5 that there is more information loss for notch mortgages.[24] This observed notch effect is consistent with the distinction between notch and nonnotch LTVs implied by our model.

4.2. Stretching and bidding for homes

Our model can explain the observed dip in frequency of negative appraisals at LTV notches, which hence may be viewed as evidence supporting the model. However, a competing explanation for this observed pattern is that notch borrowers, because of the constraint implied by the increase in monthly payment associated with crossing the LTV boundary, may be at a disadvantage when bidding against other bidders for the same property. Similarly, they may be more inclined to continue searching rather than negotiate with a seller for a property with an idiosyncratically high list price. Thus, a dip in the frequency of negative appraisals at LTV notches could simply reflect higher average prices of properties sold to nonnotch borrowers.

[23] 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.

[24] Again invoking AVMs as a benchmark, we find that in contrast to appraised values, the frequency of negative AVM estimates exhibits no noticeable relation to LTV notches. For example, appraisals are 52% less likely to fall short of the transaction price when LTV is 90% than when LTV is < 70%. In contrast, AVMs are only 2% less likely to fall short of the transaction price at 90% LTV than at LTV < 70%. See Appendix Figure A1 for a comparison of appraisals and AVMs across LTVs.

In fact, if two buyers have the same valuation for a property, but different financial constraints, then in a sealed first bid auction (equivalent to a second bid auction), the more constrained bidder is likely to lose the auction (Che and Gale 1998). The less-constrained bidders are more likely to win and pay prices that are greater than expectations.[25] In other words, as argued by Harding et al. (2003), borrowers who are less liquidity constrained, for whom the marginal utility of income is lower, are willing to bid more for homes.

Although an in-depth examination of buyer bids and contract prices in relation to applied-for LTV is outside the scope of our study, an initial examination using AVM values suggests that constrained buyers tend to bid less aggressively for homes. First, we find that notch borrowers are less often found winning bids for homes in counties that have had a rapid price increase. Notch borrowers represent 66.7% of sales contracts when county prices inflation is 2.5% or less, and 60% of contracts when inflation is 8% or greater (data are presented in the Online Appendix A1). We interpret this along the lines of Harding et al. (2003), whereby higher bids are elicited from buyers who are less liquidity constrained.

Because market valuations based on the GSE's automated valuation model suffers from regression lag,[26] we create an augmented measure, denoted AVM*, based on a regression of contract price on the AVM valuation and recent county house price growth. We then compare contract price with AVM* across three liquidity-related groupings: buyers targeting an LTV of 80% or less, buyers targeting a nonnotch LTV above 80%, and buyers targeting a notch LTV above 80%. We expect the lower-LTV group to be least liquidity constrained and most likely to overbid (as reflected in contract price exceeding AVM*), and

[25] It is also possible that less-constrained bidders may be favored by sellers in auctions, if the seller is concerned that the deal will fall through with the more constrained bidder. Thus, it is possible that less-constrained bidders may win an auction despite not having the best bid.

[26] Regression lag occurs in real-time AVM estimation based on hedonic models. While the statistical models are generated by cross-section regressions, the AVM estimate must rely on past transactions that have been completed and recorded, and thus are not completely timely. We use regressions of the AVM estimate and the county home price inflation rate from CoreLogic Solutions on current contract prices to correct this lag problem. The regressions have no constant to minimize the errors-in-variables problem that would otherwise tend to reduce the coefficient estimates. The coefficients on the home price inflation rate are around one-quarter, suggesting a reasonable regression lag. In the Online Appendix, Table A2 shows the relationships of AVM and AVM* to contract price. As seen in the overall totals, the average of ln(Price/AVM) is 3.9%, evidence of considerable regression lag, while ln(Price/AVM*) has an average of 0.06%, so that the corrected AVM* has nearly no bias, despite the absence of the constant term.

the buyers with a notch LTV above 80% to be most liquidity constrained and least likely to overbid.

Table 3 summarizes these comparisons. As expected, the log of the ratio of house price-to-predicted house value AVM* is inversely related to LTV and is further reduced at LTV notches (column 3). Similarly, the proportion of buyers with AVM* less than price increases as LTV rises and is lower at LTV notches (column 4). This is evidence of credit-constrained bidding at notches. Although not reported for the sake of brevity, a more granular breakdown by LTV indicates that the relationship to LTV is essentially monotonic and that notch effects are evident at each LTV notch greater than or equal to 80% (Online Appendix Table A3).

These effects appear too small, however, to account for the sizable reduction in frequency of negative appraisals at LTV notches. For example, there is a 4.3 percentage point gap in the frequency of between higher-LTV (above 80%) nonnotches and LTV notches with respect to frequency of negative appraisal (9.1% - 4.8%). Yet there is only a 2.7 percentage point gap between these categories with respect to frequency of contract price exceeding AVM* (51.7% - 49.0%). (Online Appendix Table A3 has more complete data on biases by applied for LTV.) The proportion of contract prices that are less than the AVM is essentially monotonic in the LTV whether we consider the notches or the nonnotches, and notch effects are substantial. Thus, while these stretching effects on bidding are important, they do not fully account for the appraisal impacts at notches.

4.3. Multivariate analysis of LTV notch effects

To confirm that elevated information loss is an inherent characteristic of the LTV notches because of 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 preferred 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). However, the results are robust to considering three possible outcomes (appraisal exceeding, falling short of, or equaling the contract price) in a multinomial framework.

We employ a full set of dummy variables for LTVs 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 whether the loan amount is within $5,000 of the conforming loan limit.

We also include a dummy variable indicating the use of an Appraisal Management Company (AMC) to facilitate the appraisal. 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.[27]

We display summary statistics for these variables in Table 4. The baseline regression results are shown in column 1 of Table 5.[28] Columns 2 and 3 of Table 5 provide the results from performing regressions separately for appraisals conducted by AMCs and other appraisals, while columns 4 and 5 incorporate appraiser- and lender-specific dummy variables, respectively.

Table 5 confirms that notch mortgages have a sharply higher incidence of information loss relative to mortgages with 1 percentage point higher or lower LTV. On average, notch mortgages are about 9 percentage points more likely than nonnotch mortgages to have the appraisal equal the contract price, conditional on not exceeding it.

We also find that higher county default and foreclosure rates 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 are indicated to have less information loss, consistent with Ding and Nakamura (2016).

The results are robust to splitting the sample by AMC status (columns 2 and 3), controlling for the identity of the appraiser (column 4) or for the individual lender (column 5). In particular, the practice of reporting appraisals identical to contract price holds even

[27] In the wake of the mortgage crisis, many lenders have turned to AMCs to help ensure compliance with the Home Valuation Code of Conduct (HVCC), the appraiser independence rules in the Dodd–Frank Wall Street Reform and Consumer Protection Act, and the Interagency Appraisal and Evaluation Guidelines. See, for example, National Association of Realtors (2013).

[28] Table 5 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 2, which are nonpositive. Results for all the control variables can be found in Online Appendix Table A4.

within appraiser.[29] Interestingly, controlling for the identity of the appraiser also dramatically increases the model fit, as evidenced by the adjusted R^2, suggesting strong between-appraiser differences in the tendency to report equal appraisals.

In additional robustness checks available in an online appendix, we confirm that information loss is present across geographic regions (Table A5). The first three columns in Table A5 presents results from estimating separate equations for the West Coast, which over the sample period had rapid and accelerating appreciation in home values; the Sand States, which had rapid, steady growth, and the Rust Belt, which had slower but accelerating growth. The fourth column presents results from estimating a separate equation for rural counties, which are likely to be thinner markets. Statistically significant notch effects are observed consistently across the differing contexts, supporting the view that information loss occurs in varying market environments.

Further, in Table A6 we investigate effects across hot and cold markets by considering the median price-to-list ratio and time-on-market in each appraisal's county, using multiple listing service data provided by CoreLogic solutions.[30] We find that in hot markets (those where price-to-list is at the 90th percentile or higher, > 99%, and time-on-market is in the 10th percentile or lower, < 60 days), information loss is less common, while in cooler-market areas (those with county median price-to-list < 94%, the 10th percentile), information loss is more common. Notch effects persist in both cold and hot markets.

We also confirm that the results hold for adjustable-rate mortgages and loans with a term of less than 30 years, and results are similar when we drop various control variables or add the ratio of AVM predicted price to actual price (Table A7). Finally, we should note that information loss is greater at LTV notches when we specify the model as a multinomial logit with outcomes as appraisal exceeding, falling short of, or equaling to the contract price, rather than using OLS (Table A8).

5. Information Value of Appraisals versus AVMs

While we have argued that many appraisals suffer from information loss, they

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

[30] Price-to-list measures the ratio between the sale price and the asking price for listings that result in a sale.

sometimes contain information that can help a lender assess a loan's default risk. How do appraisals compare in informational value with relatively inexpensive results from an AVM? Are appraisals of substantial value despite their bias?

To address this question, we turn to the sample of mortgages originated in 2003–2009 and evaluate the relationship between the original LTV and the likelihood that a loan defaults. To simplify the analysis with respect to LTV, we exclude loans with a second-lien mortgage at origination (that is, a piggyback mortgage). We also limit the sample to loans with LTVs of 50–97% and to 30-year, fixed-rate mortgages for purchasing primary residences.

In our 2003–2009 data set, 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 are unable to use a hazard modeling approach.

Another limitation is that 2003–2009 data set lacks information on the applied-for LTV or the initial contract price, and, as a result, the estimation 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 data set may be different from the group that had a negative appraisal and subsequently walked away from the transaction.[31] These limitations make it impossible to know the overall contribution of appraisals in helping predict (and prevent) defaults.

We estimate a set of linear probability models in which the dependent variable is the probability of becoming 120 or more days past due ("defaulting") within the first three years after origination. Our primary explanatory variables of interest are, respectively, the

[31] 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-versus-contract-price measure. Table 1 compares the 2013–2015 data set with the 2003–2009 data set, 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) were not available.

appraised value and AVM valuation relative to the contract price, ln(appraisal/sale price) and ln(AVM/sale price), and a dummy that equals one if the appraisal was reported exactly equal to the sale price.

We expect the informational value of appraisals and AVMs to be reflected in the degree to which a higher-property value estimate (whether appraisal or AVM) relative to contract price is reflected in reduced likelihood of default. We expect that an appraised value equal to contract price indicates potential appraisal bias, implying higher likelihood of default compared with an otherwise similar loan (in particular, the same reported LTV) for which appraised value diverges from the contract price.

Other explanatory variables include a linear spline specification for the LTV and measures of postorigination house price trends at the county level (or state level, if county-level data are unavailable). These variables are included to capture the well-established relationship between mortgage performance and borrower equity in the home. Also included are several other well-established default risk indicators available in the data, specifically, the borrower FICO score, debt payment-to-income ratio, and number of months of saving "reserves" the borrower has on hand as of when the mortgage was originated. In addition, we include indicators for notch LTVs; indicators for near-notch LTVs; an indicator for the presence of a coborrower; an indicator for new construction; and a set of vintage, state, and lender dummy variables. Finally, we include the natural log of the original loan amount, and an indicator for loan amount close to the conforming limit that defines eligibility for sale to the GSEs.

Descriptive statistics in Table 6 show the characteristics of the sample overall and broken down by whether the mortgage is observed to default. About 45% of all borrowers, regardless of default outcome, had an appraisal that exactly equaled their sale price. Overall, 4.5% of the loans are observed to default, and as expected, these loans' borrowers had lower mean-credit scores, higher debt-to-income ratios, and less saving reserves, and they experienced worse area house price change after origination than their counterparts who did not default.

Appraisals should offer the most informational value (in this case, being the most effective in predicting mortgage default) in cases in which the appraisal is reported with the least amount of bias. Our stylized model and the empirical evidence presented thus far suggest that appraisal bias should be least common when the appraisal is positive. Therefore, in addition to estimating the linear probability model using the full sample, we estimate it separately for the case of positive appraisals and for the case of appraised value less than or equal to contract price.

The estimation results are reported in Table 7. We find that appraised values relative to the transaction price are negatively correlated with default, above and beyond controlling for the AVM value. But importantly, the appraisal offers informational value only when the appraisal is greater than the sale price (Model 3). In other words, for this subsample, the higher the appraisal was relative to what the borrower paid, the lower the borrower's risk of default — consistent with the implication of our model that appraisals are unbiased measures of default risk when they exceed the contract price. For other loans (Model 2), there is no relationship between ln(appraisal/price) and default risk.

Interestingly, ln(AVM/price) is negatively correlated with default risk, across all three sample definitions. Furthermore, in each case, the AVM measure is more economically and statistically significant in predicting default, suggesting that AVMs offer more predictive power than appraisals. This gap is particularly wide for the case that we expect information loss in the appraisal: those in which the appraisal was reported less than or equal to the sale price.

Additionally, as expected, we find that mortgages with appraisal equal to the transaction price are at significantly elevated default risk. These loans have default rates 73 to 78 basis points higher than other mortgages, which is a material increase, given that the overall default rate in this sample is 4.5%. 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.

Not only is appraisal bias more common at notches, but as shown in Table 7, we find that default frequencies are higher at high LTV notches (above 80%) compared with neighboring observations. There are several plausible explanations why defaults are higher at notches, most notably that borrowers at notches may be more financially stretched than those just below the notch. But there may also be some small role of the appraisal itself increasing probability of default, since biased appraisals allow borrowers to take on more debt and achieve higher effective LTVs.

As indirect evidence that borrowers at notches tend to be more financially constrained, the finding that notch mortgages default at higher rates complements our stylized model. After all, if borrowers were financially unconstrained, there would be much less risk of a negative appraisal killing a transaction. A borrower may walk away from a transaction with a negative appraisal for fear of overpaying, but he would not walk away because he is unable to afford the down payment.

6. 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 residential mortgage industry, in which $6.0 trillion in 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: less than 1 out of 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 trade-off between the cost of potentially losing the mortgage transaction and the cost of losing informational value from the appraisal. This trade-off, in turn, arises because of institutional factors, including the requirement that mortgage lenders base the LTV for their lending decision on the lower of the contract price and appraised value. Appraisers may bias the appraisal upward even so far as setting it equal to the contract price to mitigate the risk of a lost transaction.

The model suggests stronger incentive for appraisers to confirm the contract price at LTV notches, across which underwriting and mortgage insurance requirements differ — most typically these are 80%, 90%, and 95%. In particular, notch applicants (relative to those not locating at notches) may more often be stretching their down payment to reach the notch and reduce their monthly payment obligation, leaving no bandwidth for a negative appraisal. In contrast, between notches, there is some leeway for negative appraisals to not have an impact on the affordability of a mortgage, even for those who are stretching.

We also present new empirical findings on appraised values in relation to contract prices and AVM estimates, and in relation to measured default risk. As implied by the model, we find that the frequency of appraisals at or above the contract price is highest at LTV notches. We also find that some of this effect is due to borrowers at notches bidding less than nonnotch borrowers, evidence that they are in fact constrained borrowers. Supporting the view that reported appraisals are frequently characterized by upward bias or information loss, we find that appraisals are somewhat less predictive of default than AVM estimates. We also find that notch loans have an elevated likelihood of default, consistent with the notion that applicants at LTV notches tend to be more liquidity constrained.

Although 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 benefits 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 is largely a consequence of 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 the LTV, with the 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.

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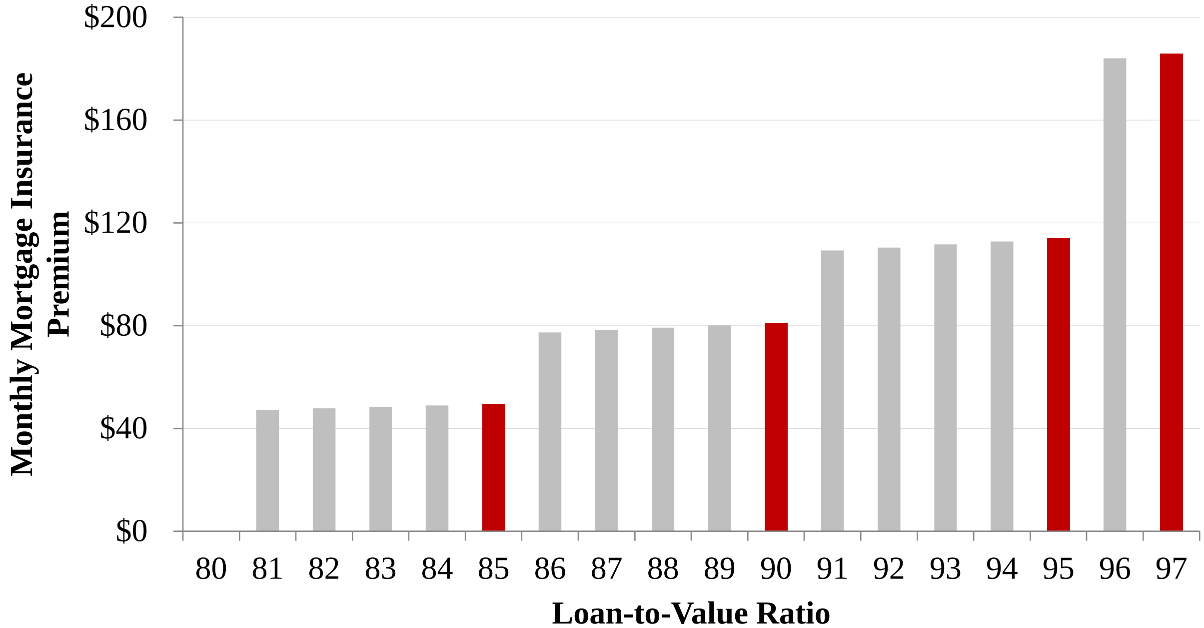
Figures

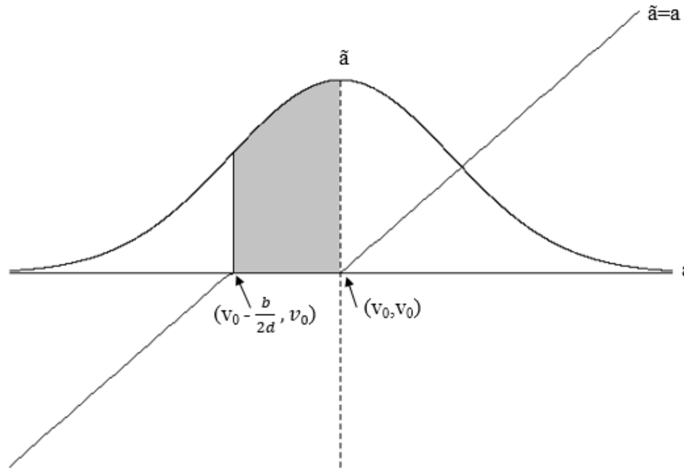
Figure 1: Monthly Mortgage Insurance Premium Costs by LTV
for a Borrower Purchasing a $200,000 Home



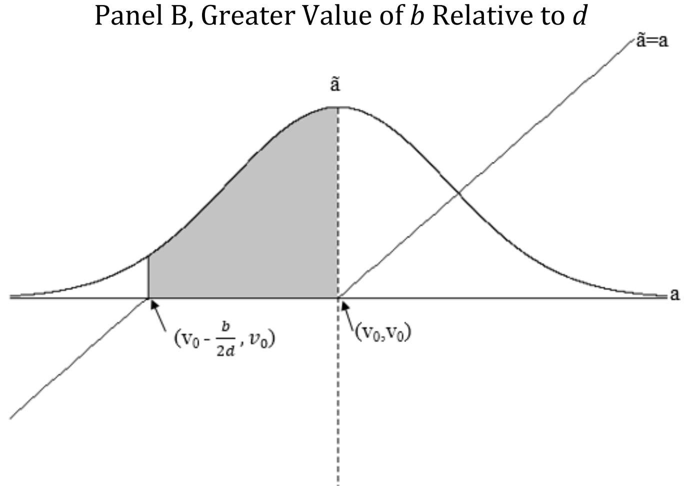
Source: Authors' tabulations of data from Goodmortgage.com's PMI Calculator for mortgage insurance payments required if the purchase price is $200,000. Calculations assume the borrower has a FICO score of 720 or higher. Data retrieved on December 18, 2016.

Figure 2: Biased Appraisals under Different Model Assumptions

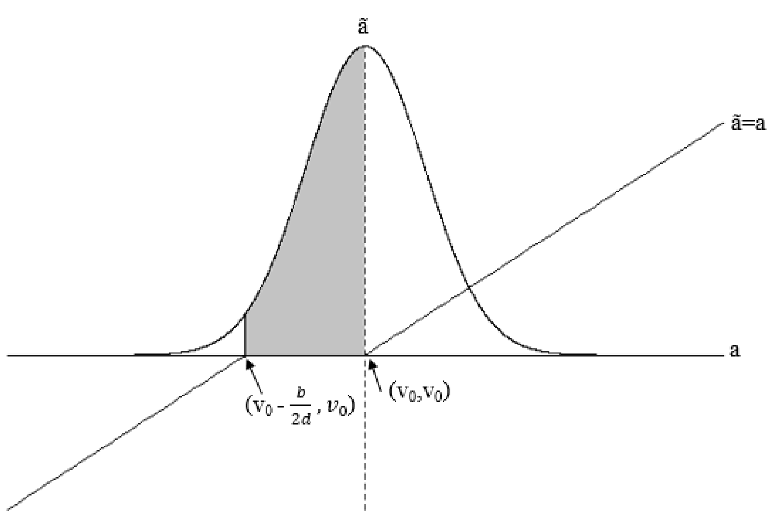
Panel A, Baseline



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

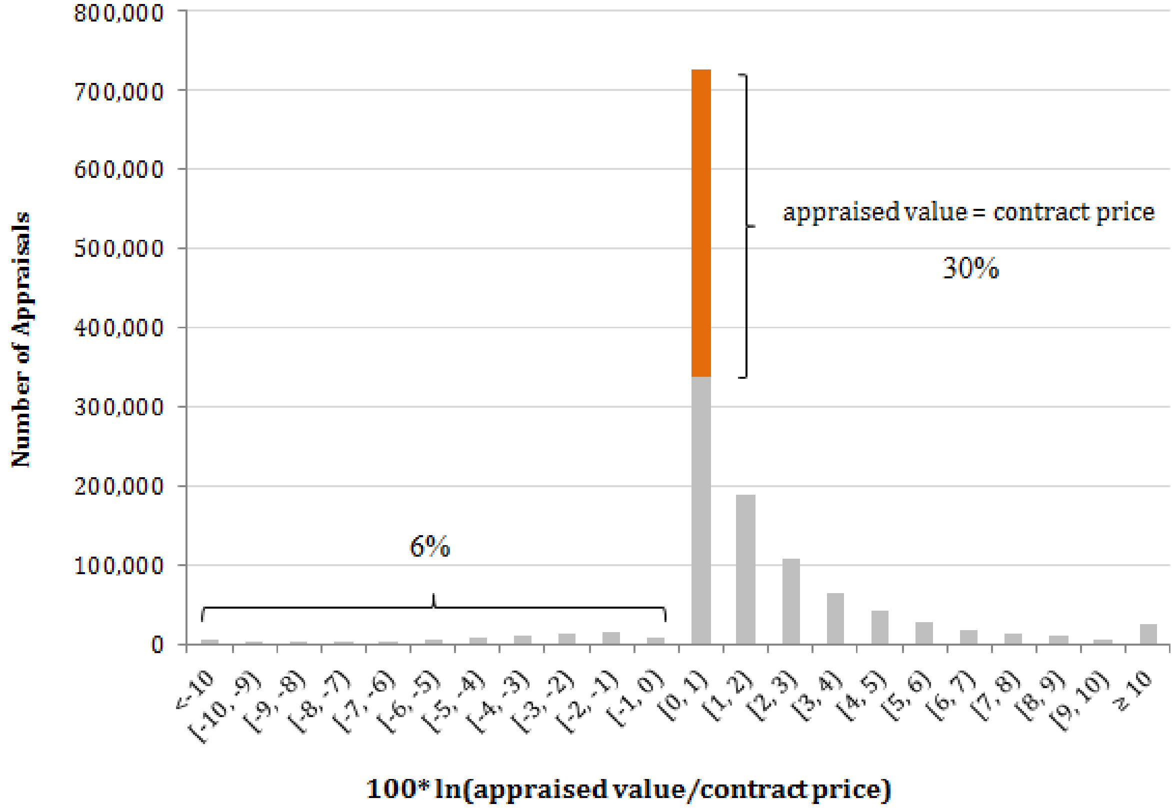


Panel C, Smaller Variance



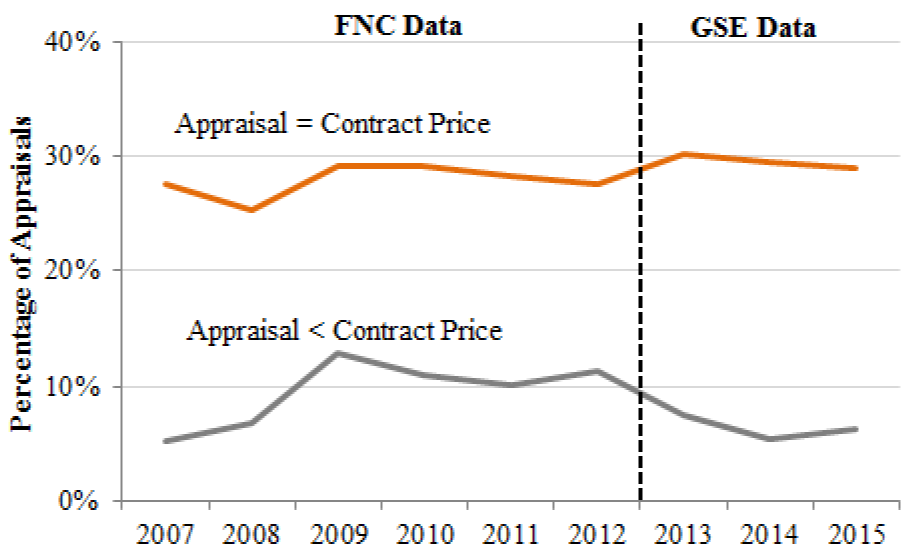
Note: The authors thank Paul Goldsmith-Pinkham for creating an initial version of this figure.

Figure 3: Distribution of Appraised Values Relative to Contract Price, 2013–2015 First-Lien Mortgage Applications



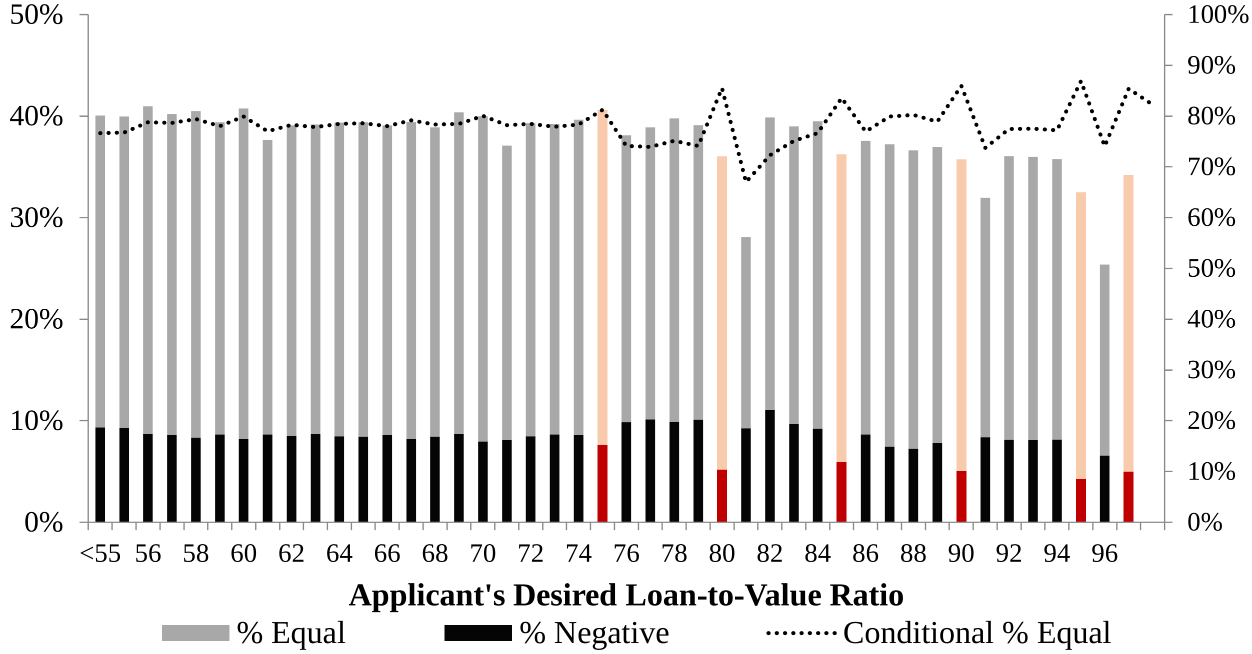
Source: Authors' calculations based on data from GSE

Figure 4: Appraisal Outcomes by Year, 2007–2015 First-Lien Mortgage Applications



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

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



Source: Authors' calculations based on data from GSE

Tables

Table 1: Distribution of Appraisals and AVMs Relative to Price

ln(valuation/price)	Percentage of 2003–2009 Originations	Percentage of 2013–2015 Applications	
	where valuation = appraisal	where valuation = appraisal	where valuation = AVM
< -0.1	0.2	0.5	19.9
< -0.05 and ≥ -0.1	0.4	1.4	20.7
< -0.01 and ≥ -0.05	1.1	3.8	20.8
< 0 and ≥ -0.01	0.5	0.7	5.0
Exactly = 0	44.8	29.5	0.0
> 0 and ≤ 0.0025	5.1	8.3	1.3
> 0.0025 and ≤ 0.005	4.2	6.7	1.2
> 0.005 and ≤ 0.0075	3.9	5.7	1.1
> 0.0075 and ≤ 0.01	3.3	4.9	1.1
> 0.01 and ≤ 0.05	24.1	30.8	14.4
> 0.05 and ≤ 0.1	7	5.7	9.1
> 0.1	5.5	2	5.5
Underlying Standard Deviation*	0.102	0.0412	NA

Source: Authors' calculations are based on data from GSE. Note: The full sample of scored applications includes 3.6 million loans, for which the appraised value is compared with the final sale (transaction) price because 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.

*Underlying standard deviation calculated using the positive appraisals. Method takes the standard deviation of a synthetic data set comprising the positive appraisals plus the positive appraisals multiplied by -1. Not applicable (NA) for AVMs.

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

Applied-for LTV	Total	% of Observations	% Negative	% Positive	% Equal	% Equal or Within 1% Positive
< 70	157,315	11.9	8.9	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	30.8	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	28.9	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	1,318,074	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
Nonnotches	489,419	37.1	8.8	62.3	28.9	54.6

Source: Authors' calculations based on data from GSE

Table 3: Appraisals and AVM Outcomes by Notch

(2013–2015)

LTV at Application	Number of Loans	% with Price < AVM*	ln(Price/ AVM*)	% with Negative Appraisal
Total	492,452	51.05%	0.06%	6.35%
All notches (≥ 80 LTV)	314,232	51.72%	-0.24%	4.78%
Nonnotches > 80 LTV	72,647	51.09%	0.07%	9.12%
All nonnotches	178,220	49.87%	0.60%	9.11%
Nonnotches < 80 LTV	105,573	49.03%	0.96%	9.11%
80% LTV notch	118,582	51.74%	-0.12%	5.13%
85% LTV notch	11,984	51.96%	-0.13%	5.79%
90% LTV notch	50,714	51.61%	-0.10%	4.86%
95% LTV notch	116,609	51.88%	-0.42%	4.27%
97% LTV notch	16,343	50.59%	-0.31%	4.97%

Source: Authors' calculations based on data from GSE

Table 4: 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
Near conforming loan limit?					
No	6	29	64	100	1,264,889
Yes	7	32	61	100	53,185
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		
Desired loan amount near conforming loan limit	4		
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 are based on data from GSE, Black Knight McDash, CoreLogic Solutions, 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 Solutions). Rural counties are considered to be those not located within a metropolitan statistical area.

Table 5: Likelihood That Appraisal Identically Matches Contract Price, 2013–2015 Sample

	(1)	(2)	(3)	(4)	(5)
Applied-for LTV					
74	0.0113~	0.0043	0.0250*	0.0145*	0.0115~
	(1.90)	(0.57)	(2.55)	(2.50)	(1.95)
75	0.0421***	0.0383***	0.0492***	0.0415***	0.0439***
	(10.02)	(7.29)	(7.06)	(10.17)	(10.48)
76	-0.0259***	-0.0241**	-0.0290**	-0.0183**	-0.0250***
	(-4.25)	(-3.10)	(-2.97)	(-3.07)	(-4.10)
79	-0.0291***	-0.0235***	-0.0391***	-0.0185***	-0.0279***
	(-5.97)	(-3.81)	(-4.95)	(-3.90)	(-5.75)
80	0.0901***	0.0882***	0.0939***	0.0843***	0.0900***
	(34.11)	(26.39)	(21.88)	(32.74)	(34.11)
81	-0.0960***	-0.108***	-0.0716***	-0.0706***	-0.0942***
	(-17.09)	(-15.26)	(-7.78)	(-12.93)	(-16.82)
84	-0.0008	-0.0074	0.0119	0.0107~	-0.0007
	(-0.14)	(-1.04)	(1.31)	(1.96)	(-0.13)
85	0.0633***	0.0537***	0.0812***	0.0646***	0.0626***
	(14.93)	(9.98)	(11.86)	(15.70)	(14.81)
86	-0.0003	-0.0071	0.0122	0.0085	-0.0004
	(-0.05)	(-0.92)	(1.26)	(1.44)	(-0.06)
89	0.0198***	0.0210**	0.0177*	0.0261***	0.0197***
	(3.76)	(3.15)	(2.06)	(5.09)	(3.74)
90	0.0893***	0.0851***	0.0986***	0.0827***	0.0882***
	(29.93)	(22.49)	(20.07)	(28.47)	(29.61)
91	-0.0293***	-0.0279***	-0.0311***	-0.0077	-0.0272***
	(-5.09)	(-3.81)	(-3.37)	(-1.37)	(-4.73)
94	0.0020	0.0103~	-0.0108	0.0059	0.0019
	(0.40)	(1.65)	(-1.42)	(1.25)	(0.39)
95	0.1040***	0.1050***	0.1020***	0.0944***	0.1030***
	(37.99)	(30.21)	(23.17)	(35.24)	(37.49)
96	-0.0195**	-0.0183*	-0.0221*	0.0011	-0.0201**
	(-2.81)	(-2.05)	(-2.01)	(0.17)	(-2.90)
97	0.0814***	0.0722***	0.0955***	0.0810***	0.0774***
	(19.13)	(12.99)	(14.55)	(19.44)	(18.13)
Appraisal management company (AMC) used	-0.0243***				
	(-20.97)				
County default/foreclosure rate 5–7%	-0.0183***	-0.0215***	-0.0142***	-0.0050*	-0.0161***
	(-9.41)	(-8.45)	(-4.74)	(-2.27)	(-8.15)
County default/foreclosure rate > 7%	-0.0326***	-0.0363***	-0.0272***	-0.0059~	-0.0254***
	(-12.98)	(-11.14)	(-6.94)	(-1.82)	(-9.66)
Near conforming loan limit	0.0441***	0.0354***	0.0610***	0.0340***	0.0408***
	(15.28)	(9.82)	(12.66)	(12.10)	(14.12)
Constant	0.574***	0.513***	0.654***	0.652***	0.481***
	(20.41)	(14.43)	(14.12)	(7.35)	(15.56)
Other county and home characteristics	✓	✓	✓	✓	✓
State-by-year controls	✓	✓	✓	✓	✓
Appraiser dummies				✓	
Lender dummies					✓
Observations	472,960	306,900	166,060	469,624	472,960
Adjusted R^2	0.0545	0.0519	0.0573	0.1893	0.0688

Source: Authors' calculations are based on data from GSE, Zillow, CoreLogic Solutions, and Black Knight McDash. Note: Coefficients displayed with t-statistics in parentheses. ~ denotes 0.10 level of significance, * 0.05, ** 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 and ln county median sale price that quarter. Lagged house price appreciation (HPA) captures 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. Model 2 (3) is restricted to (excludes) appraisals conducted by AMC.

Table 6: 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	39	12	39	39	12	46	46	11
House price change (%) †	-1.9	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
ln origination amount	12	12	0.5	12	12	0.5	12	12	0.6
Reserves (months of mortgage payments)									
< 3 months		11%			11%			19%	
3–11 months		30%			30%			37%	
12+ months		50%			51%			31%	
Coborrower		50%			52%			27%	
New construction		1%			1%			1%	
Near conforming loan limit		3%			3%			2%	
Appraisal < Price		2%			2%			1%	
Appraisal = Price		45%			45%			44%	
Appraisal > Price		53%			53%			55%	

Source: Authors' calculations are 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 7: Incidence of 120+ Day Default, 2003–2009 Vintages

	(1) All Appraisals	(2) Appraisal ≤ Price	(3) Appraisal > Price
Dummies for LTVs at or Near a Notch			
78.5–79.5	-0.0005	0.0001	-0.0011
	(-0.26)	(0.02)	(-0.43)
80	0.0004	0.0004	0.0003
	(0.49)	(0.31)	(0.26)
80.5–81.5	0.0168~	0.0119	0.0225
	(1.79)	(0.95)	(1.62)
83.5-84.5	-0.0015	-0.0092~	0.0061
	(-0.42)	(-1.85)	-1.23
85	0.0064**	0.0045	0.0085**
	(3.17)	(1.61)	(2.94)
85.5–86.5	-0.0078*	-0.0158***	-0.0005
	(-2.35)	(-3.34)	(-0.11)
88.5–-89.5	0.0000	-0.0006	0.0009
	0.00	(-0.17)	(0.26)
90	0.0107***	0.0140***	0.0081***
	(7.76)	(6.65)	(4.46)
90.5–-91.5	-0.0011	0.002	-0.0029
	(-0.34)	(0.40)	(-0.72)
93.5–-94.5	-0.0079***	-0.0093*	-0.0068*
	(-3.33)	(-2.47)	(-2.20)
95	0.0158***	0.0214***	0.0122***
	(16.99)	(13.55)	(10.40)
95.5–-96.5	0.0024	0.001	0.0034
	(0.54)	(0.15)	(0.58)
97	0.0080***	0.0100***	0.0075***
	(5.21)	(4.01)	(3.79)
House price change†	-0.0003***	-0.0003***	-0.0004***
	(-17.78)	(-12.38)	(-12.91)
House price trough†	-0.0029***	-0.0032***	-0.0027***
	(-69.69)	(-53.47)	(-44.78)
ln(appraisal/sale price)	-0.0056~	0.0124	-0.0078*
	(-1.84)	(0.41)	72.00
Appraisal = sale price	0.0078***	0.0073***	
	(18.01)	(4.07)	
ln(AVM/sale price)	-0.0288***	-0.0426***	-0.0184***
	(-34.41)	(-33.87)	(-16.30)
Constant	1.1021***	1.1737***	1.0392***
	(116.75)	(86.55)	(77.90)
Vintage, state, and lender dummies	✓	✓	✓
Borrower, loan, and house traits	✓	✓	✓
Observations	918,585	430,964	487,621
Adjusted R^2	0.143	0.1515	0.137

Source: Authors' calculations are based on data from GSE and Zillow. Note: Linear probability model coefficients displayed with t-statistics in parentheses. ~ denotes 0.10 level of significance, * 0.05, ** 0.01, *** 0.001. "Default" is defined as becoming 120+ days delinquent in the first three years after the loan was originated. †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 postorigination. 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.

Online Appendix, Not for Publication

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:

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

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

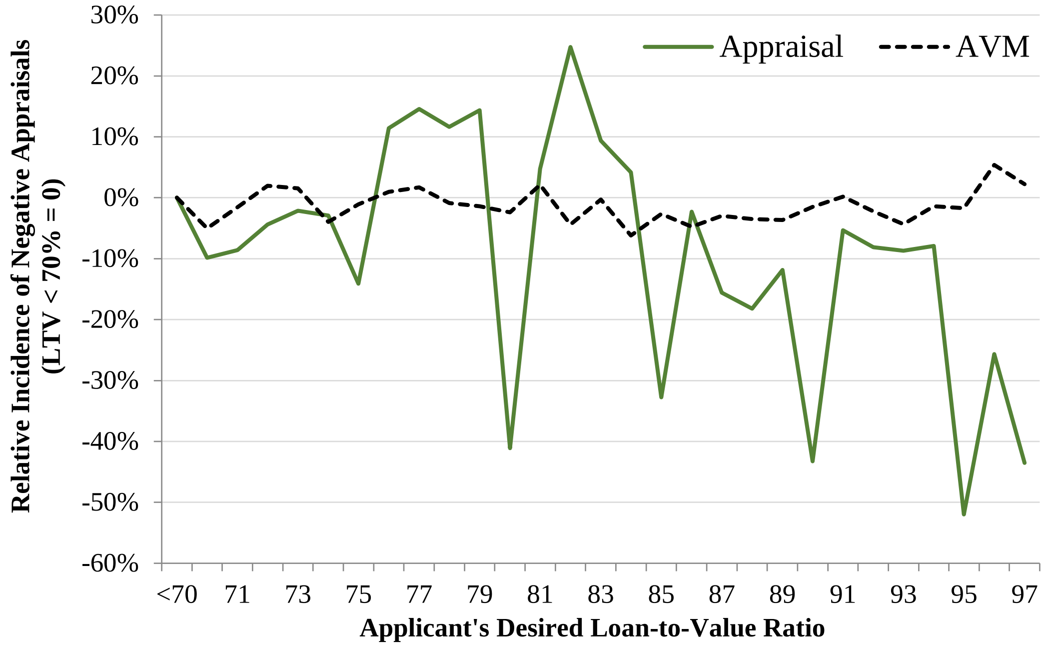
$$(v_o - a - b/2d)^2 > 0$$

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

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

Appendix Figures

Figure A1: Incidence of Negative Appraisals and AVMs by LTV
(Calculated Relative to LTV < 70%)



Note: Values displayed indicate the prevalence of negative appraisals (AVMs) at each LTV, relative to LTV < 70%. For example, appraisals are 52% less likely to fall short of the transaction price when LTV is 90% than when LTV is < 70%. In contrast, AVMs are only 2% less likely to fall short of the transaction price at 90% LTV than at LTV < 70%. Source: Authors' calculations based on data from GSE

Appendix Tables

Table A1: Proportion of Notch and Nonnotch Borrowers by County House Price Appreciation

	Rate of increase in country house price inflation over previous 12 months			
	8 % or Greater	**8 % to 5 %**	**5 % to 2.5 %**	**2.5 % or Less**
Notch	60.0 %	63.7 %	65.4 %	66.7 %
Nonnotch	40.0 %	36.3 %	34.6 %	33.3 %
Nonnotch < 80 LTV	26.1 %	21.2 %	19.4 %	18.4 %
Nonnotch > 80 LTV	13.9 %	15.1 %	15.2 %	15.0 %

Source: Authors' calculations based on data from GSE. Notches are defined as those with applied for LTVs of 80, 85, 90, 95 and 97. All others are nonnotches.

Table A2: AVM versus Price in Low LTV and Nonnotch Borrowers

Applied-for LTV	**Total**	**ln(Price/AVM)**	**ln(Price /AVM)***
<61	31,540	5.55%	1.49%
61	1,517	5.53%	1.48%
62	1,901	5.56%	1.52%
63	2,046	5.12%	1.11%
64	2,224	4.55%	0.47%
65	2,767	4.98%	0.94%
66	2,499	5.30%	1.21%
67	2,898	5.33%	1.30%
68	2,759	5.13%	1.13%
69	2,939	5.24%	1.20%
70	5,907	4.19%	0.12%
71	3,052	4.79%	0.74%
72	3,800	5.36%	1.37%
73	3,789	4.95%	0.94%
74	4,143	4.97%	0.92%
75	10,833	4.42%	0.34%
76	3,817	4.92%	0.91%
77	4,625	4.49%	0.51%
78	5,807	4.40%	0.41%
79	6,710	4.31%	0.35%
80	118,582	3.76%	-0.12%
81	6,305	4.51%	0.61%
82	5,491	3.90%	0.04%
83	4,408	3.95%	0.12%
84	4,558	3.95%	0.15%
85	11,984	3.67%	-0.13%
86	3,944	3.81%	0.00%
87	4,763	3.84%	0.02%
88	5,305	3.96%	0.16%
89	5,862	3.61%	-0.19%
90	50,714	3.72%	-0.10%
91	5,329	4.07%	0.31%
92	6,324	3.64%	-0.10%
93	7,672	3.66%	-0.06%
94	8,162	3.55%	-0.16%
95	116,609	3.28%	-0.42%
96	4,524	3.78%	0.16%
97	16,343	3.21%	-0.31%
Total	492,452	3.90%	0.06%
Notches	314,232	3.54%	-0.24%
Nonnotches > 80 LTV	72,647	3.85%	0.07%
All Nonnotches	178,220	4.53%	0.60%
Nonnotches < 80 LTV	105,573	5.00%	0.96%

Source: Authors' calculations are based on data from GSE. Notches are defined as those with applied for LTVs of 80, 85, 90, 95 and 97. Nonnotches are all others. AVM estimates are real-time. AVM* estimates are augmented by ex post using county inflation rates derived from CoreLogic Solutions data. These estimates include only the best three appraisal accuracy categories of the GSE that supplied the data.

Table A3: Proportion of Contract Prices Relative to Appraisal and AVM Outcomes by Applied-for LTV

Applied-for LTV	(1) % Negative	(2) % Equal	(3) % Positive	(4) % with Price < AVM*	(5) Nonnegative Bias	(6) Positive Bias
<61	9.32%	33.29%	57.39%	47.92%	42.77%	9.48%
61	7.78%	33.88%	58.34%	48.71%	43.51%	9.62%
62	9.21%	32.04%	58.76%	48.34%	42.45%	10.42%
63	9.48%	32.11%	58.41%	49.80%	40.71%	8.60%
64	8.99%	33.54%	57.46%	50.22%	40.78%	7.24%
65	8.28%	33.21%	58.51%	48.75%	42.97%	9.76%
66	8.56%	31.61%	59.82%	50.18%	41.26%	9.64%
67	8.42%	33.33%	58.25%	47.24%	44.34%	11.01%
68	8.70%	31.82%	59.48%	48.86%	42.44%	10.62%
69	8.78%	32.22%	59.00%	47.64%	43.59%	11.36%
70	7.99%	33.60%	58.41%	51.58%	40.43%	6.82%
71	7.93%	30.70%	61.37%	49.57%	42.50%	11.80%
72	8.82%	33.82%	57.37%	47.68%	43.50%	9.68%
73	8.47%	32.57%	58.96%	48.22%	43.31%	10.74%
74	8.95%	33.04%	58.00%	50.04%	41.01%	7.97%
75	7.51%	35.10%	57.39%	50.77%	41.72%	6.62%
76	10.61%	30.05%	59.34%	48.73%	40.66%	10.61%
77	10.70%	30.34%	58.96%	49.21%	40.09%	9.75%
78	10.85%	32.00%	57.16%	49.44%	39.71%	7.71%
79	10.75%	31.24%	58.02%	50.06%	39.20%	7.96%
80	5.13%	32.87%	62.00%	51.74%	43.14%	10.27%
81	10.47%	20.40%	69.14%	49.52%	40.02%	19.62%
82	11.38%	30.34%	58.28%	51.70%	36.91%	6.57%
83	10.07%	30.58%	59.35%	51.23%	38.70%	8.12%
84	9.68%	32.03%	58.29%	51.01%	39.32%	7.28%

85	5.79%	31.37%	62.84%	51.96%	42.25%	10.88%
86	9.31%	29.97%	60.73%	51.32%	39.38%	9.41%
87	7.60%	30.93%	61.47%	51.69%	40.71%	9.78%
88	7.62%	31.97%	60.41%	51.97%	40.41%	8.44%
89	7.64%	30.01%	62.35%	51.94%	40.41%	10.41%
90	4.86%	32.51%	62.63%	51.61%	43.52%	11.02%
91	9.38%	25.26%	65.36%	49.99%	40.63%	15.37%
92	9.31%	28.97%	61.72%	51.58%	39.10%	10.14%
93	9.36%	28.94%	61.70%	51.55%	39.09%	10.15%
94	8.70%	28.94%	62.36%	51.52%	39.78%	10.84%
95	4.27%	29.58%	66.15%	51.88%	43.84%	14.26%
96	7.89%	20.23%	71.88%	48.63%	43.48%	23.25%
97	4.97%	30.38%	64.65%	50.59%	44.43%	14.05%
Total	6.35%	31.25%	62.40%	51.05%	42.60%	11.35%
Nonnotch	9.11%	30.97%	59.92%	49.87%	41.01%	10.05%
Notch	4.78%	31.40%	63.81%	51.72%	43.49%	12.09%
Nonnotches < 80 LTV	9.11%	32.81%	58.08%	49.03%	41.86%	9.05%
Nonnotches > 80 LTV	9.12%	28.28%	62.60%	51.09%	39.79%	11.51%

Source: Authors' calculations ae based on data from GSE. Notches are defined as those with applied for LTVs of 80, 85, 90, 95 and 97. All others are nonnotches. AVM* estimates are augmented by ex post using county inflation rates derived from CoreLogic Solutions data. These estimates include only the best three appraisal accuracy categories of the GSE that supplied the data. Note: Columns 1, 2, and 3 are appraisals relative to contract prices. Column 4 shows the proportion of contract prices that are lower than augmented AVM* estimates. Column 5 is the sum of columns (2) and (3) less column (4), that is the proportion of appraisals that are greater than or equal to contract price relative to the proportion of AVM* estimates that are greater than contract price. Column 6 is column (3) less column (4), that is, the proportion of appraisals that are greater than contract price relative to the proportion of AVM* estimates that are greater than contract price. Since we did not round AVM* estimates, there are no AVM* estimates exactly equal to contract price.

Table A4: Full Results for Main Information Loss Model

Applied-for LTV		Controls	
74	0.0113~	ln(contract price)	-0.0093***
	(1.90)		(-6.18)
75	0.0421***	ln(county median)	0.0289***
	(10.02)		(13.52)
76	-0.0259***	Appraisal management company (AMC) used	-0.0243***
	(-4.25)		(-20.97)
79	-0.0291***	County house price change	-0.0004**
	(-5.97)		(-2.96)
80	0.0901***	County default/foreclosure rate 5–7%	-0.0183***
	(34.11)		(-9.41)
81	-0.0960***	County default/foreclosure rate > 7%	-0.0326***
	(34.11)		(-12.98)
84	-0.0008	Near conforming loan limit	0.0441***
	(-0.14)		(15.28)
85	0.0633***	Constant	0.574***
	(14.93)		(20.41)
86	-0.0003		
	(-0.05)		
89	-0.0198***		
	(3.76)		
90	0.0893***		
	(29.93)		
91	-0.0293***		
	(-5.09)		
94	0.0020		
	(0.40)		
95	0.1040***		
	(37.99)		
96	-0.0195**		
	(-2.81)		
97	0.0814***		
	(19.13)		
State-by-year controls	✓		
Observations	472,960		
Adjusted R^2	0.0545		

Source: Authors' calculations are based on data from GSE, CoreLogic Solutions, and Zillow. Note: Coefficients displayed with t-statistics in parentheses. ~ denotes 0.10 level of significance, * 0.05, ** 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 A5: Likelihood That Appraisal Identically Matches Contract Price, Geographic Robustness

	(1) West Coast	(2) Sand States	(3) Rust Belt	(4) Rural
Applied-for LTV				
74	0.0131	-0.0213	0.0209	-0.0124
	(1.30)	(-0.97)	(0.81)	(-0.42)
75	0.0435***	0.0255	0.0524**	0.0039
	(6.27)	(1.59)	(2.74)	(0.17)
76	-0.0136	-0.0330	-0.0030	0.0340
	(-1.23)	(-1.54)	(-0.12)	(1.06)
79	-0.0104	-0.0558**	-0.0078	-0.0404
	(-1.23)	(-3.14)	(-0.37)	(-1.56)
80	0.0834***	0.1120***	0.1110***	0.0778***
	(18.36)	(12.25)	(8.96)	(5.88)
81	-0.0574***	-0.1070***	-0.0954***	-0.0337
	(-5.42)	(-5.33)	(-4.51)	(-1.13)
84	0.0071	-0.0361~	0.0237	0.00919
	(0.64)	(-1.81)	(1.17)	(0.33)
85	0.0613***	0.0673***	0.0943***	0.0656**
	(7.45)	(4.27)	(5.74)	(3.07)
86	0.0060	-0.0331	0.0369~	0.0445
	(0.50)	(-1.51)	(1.68)	(1.56)
89	0.0321**	-0.0019	0.0177	0.0055
	(3.18)	(0.10)	(0.89)	(0.22)
90	0.0840***	0.1100***	0.1070***	0.0786***
	(15.46)	(10.30)	(8.21)	(5.15)
91	-0.0103	-0.0658**	-0.0155	0.0271
	(-0.85)	(-3.19)	(-0.74)	(0.94)
94	0.0182~	-0.0345*	-0.0354*	0.0106
	(1.76)	(-2.00)	(2.00)	(0.46)
95	0.1000***	0.1460***	0.0129***	0.0106
	(19.08)	(15.61)	(10.53)	(0.46)
96	-0.0205	-0.0228	0.0301	-0.0236
	(-1.27)	(0.94)	(1.28)	(-0.69)
97	0.0815***	0.0901***	0.1030***	0.0837***
	(8.72)	(5.72)	(6.43)	(4.30)
Constant	0.1440***	0.7930***	1.050***	0.567***
	(3.30)	(5.49)	(9.03)	(4.12)
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
Adjusted R^2	0.0345	0.0382	0.0601	0.0439

Source: Authors' calculations are based on data from GSE, Zillow, CoreLogic Solutions, and Black Knight McDash. Note: Coefficients displayed with t-statistics in parentheses. ~ denotes 0.10 level of significance, * 0.05, ** 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, county foreclosure rate, an indicator for AMC use, an indicator for loan near conforming loan limit, 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 A6: Likelihood That Appraisal Identically Matches Contract Price, Hot and Cold Markets Based on County Median Price-to-List (PTL) and Time-on-Market (TOM) in Multiple Listing Service (MLS) Data

	(1) With MLS Data	(2) PTL Controls	(3) PTL > 99%	(4) PTL < 94%	(5) TOM Controls	(6) TOM < 60 Days	(7) TOM > 117
Applied-for LTV							
74	0.013~	0.013~	0.040*	0.008	0.013~	0.046*	0.010
	(1.93)	(1.95)	(2.46)	(0.36)	(1.93)	(2.43)	(0.49)
75	0.043***	0.043***	0.038**	0.025	0.043***	0.051***	0.047***
	(9.36)	(9.39)	(3.29)	(1.52)	(9.38)	(3.86)	(3.60)
76	-0.027***	-0.026***	-0.002	0.008	-0.026***	-0.021	0.003
	(-3.96)	(-3.92)	(-0.09)	(0.35)	(-3.95)	(-1.06)	(0.15)
79	-0.025***	-0.025***	0.013	-0.002	-0.025***	0.008	0.004
	(-4.74)	(-4.67)	(0.95)	(-0.11)	(-4.75)	(0.47)	(0.28)
80	0.093***	0.093***	0.082***	0.114***	0.093***	0.092***	0.099***
	(32.11)	(32.20)	(10.50)	(11.75)	(32.10)	(10.25)	(12.51)
81	-0.103***	-0.102***	-0.026	-0.116***	-0.103***	-0.105***	-0.135***
	(-16.63)	(-16.56)	(-1.48)	(-5.54)	(-16.64)	(-5.62)	(-6.78)
84	-0.005	-0.005	0.046*	0.015	-0.005	0.008	-0.007
	(-0.82)	(-0.76)	(2.54)	(0.72)	(-0.83)	(0.39)	(-0.36)
85	0.064***	0.065***	0.055***	0.087***	0.064***	0.074***	0.068***
	(13.72)	(13.81)	(3.94)	(5.63)	(13.70)	(4.93)	(5.00)
86	0.000	0.000	0.022	0.038~	0.000	-0.031	0.018
	(-0.04)	0.00	(1.19)	(1.81)	(-0.03)	(-1.45)	(0.84)
89	0.020***	0.021***	0.056***	0.054**	0.020***	0.043*	0.040*
	(3.45)	(3.53)	(3.37)	(2.83)	(3.43)	(2.24)	(2.17)
90	0.093***	0.094***	0.083***	0.111***	0.093***	0.101***	0.094***
	(28.49)	(28.62)	(8.89)	(10.19)	(28.44)	(9.57)	(10.23)
91	-0.030***	-0.030***	0.034	-0.025	-0.030***	-0.02	-0.052*
	(-4.67)	(-4.59)	(1.63)	(-1.22)	(-4.68)	(-0.94)	(-2.51)
94	0.001	0.001	0.022	0.021	0.001	0.024	0.000
	(0.14)	(0.23)	(1.25)	(1.22)	(0.12)	(1.31)	(-0.02)
95	0.109***	0.110***	0.102***	0.133***	0.109***	0.111***	0.103***
	(36.19)	(36.41)	(11.00)	(13.44)	(36.15)	(11.14)	(11.83)
96	-0.021**	-0.020*	0.008	0.035	-0.021**	-0.092**	0.035
	(-2.67)	(-2.57)	(0.29)	(1.41)	(-2.68)	(-3.27)	(1.26)
97	0.082***	0.083***	0.079***	0.116***	0.082***	0.099***	0.068***
	(16.93)	(17.05)	(5.10)	(7.83)	(16.93)	(5.78)	(4.41)
County Median Price-to-List < 94%		0.025***					
		(10.79)					
County Median Price-to-List > 99%		-0.009***					
		(-3.49)					
County Median Time-on-Market < 60 days					-0.013***		
					(-4.52)		
County Median Time-on-Market > 117 days					-0.004		
					(-1.29)		
Intercept	0.488***	0.392***	-0.028	0.874***	0.452***	-0.682***	0.990***
	(17.03)	(13.06)	(-0.34)	(8.73)	(15.18)	(-4.53)	(11.10)
County and home characteristics	✓	✓	✓	✓	✓	✓	✓
State-by-year controls	✓	✓	✓	✓	✓	✓	✓
Observations	390,886	390,886	39,374	38,584	390,886	38,761	37,562
Adjusted R^2	0.059	0.059	0.039	0.072	0.059	0.047	0.039

Source: Authors' calculations are based on data from GSE, Zillow, CoreLogic Solutions, and Black Knight McDash. Note: Coefficients displayed with t-statistics in parentheses. ~ denotes 0.10 level of significance, * 0.05, ** 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. County and home characteristics include ln contract price, ln county median sale price that quarter, county foreclosure rate, an indicator for AMC use, an indicator for loan near conforming loan limit, 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. MLS = Multiple Listing Service. PTL = Price-to-List ratio. TOM = Time-on-Market, measured in days. Model 1 is the paper's main specification, restricted to appraisals with county MLS data available through CoreLogic Solutions.

Table A7: Robustness of Information Loss Results to Alternative Specifications and Samples

	(1)	(2)	(3)	(4)	(5)
Applied-for LTV					
74	0.0113~	0.0170**	0.0173**	0.0151**	-0.0049
	(1.90)	(2.82)	(2.86)	(2.75)	(-0.58)
75	0.0421***	0.0464***	0.0470***	0.0495***	0.0395***
	(10.02)	(10.85)	(11.05)	(12.99)	(6.68)
76	-0.0259***	-0.0249***	-0.0249***	-0.0260***	-0.0428***
	(-4.25)	(-4.01)	(-4.04)	(-4.60)	(-4.79)
79	-0.0291***	-0.0251***	-0.0242***	-0.0208***	-0.0417***
	(-5.71)	(-5.06)	(-4.93)	(-4.62)	(-5.92)
80	0.0901***	0.0893***	0.0902***	0.0904***	0.0849***
	(34.11)	(33.38)	(33.90)	(40.05)	(22.40)
81	-0.0960***	-0.0962***	-0.0959***	-0.0993***	-0.116***
	(-17.09)	(-16.82)	(-16.88)	(-18.97)	(-14.00)
84	-0.0008	0.0002	0.0009	0.0018	-0.0091
	(-0.14)	(0.03)	(0.15)	(0.34)	(-1.10)
85	0.0633***	0.0696***	0.0707***	0.0707***	0.0585***
	(14.93)	(16.19)	(16.54)	(17.94)	(9.73)
86	-0.0003	0.0034	0.0010	0.0006	-0.0268**
	(-0.05)	(0.56)	(0.16)	(0.10)	(-2.98)
89	0.0198***	0.0227***	0.0232***	0.0251***	0.0021
	(3.76)	(4.24)	(4.36)	(5.02)	(0.28)
90	0.0893***	0.0932***	0.0940***	0.0961***	0.0857***
	(3.76)	(30.97)	(31.40)	(36.45)	(20.30)
91	-0.0293***	-0.0286***	-0.0283***	-0.0246***	-0.0466***
	(-5.09)	(-4.90)	(-4.89)	(-4.49)	(-5.56)
94	0.0020	0.0058	0.0064	0.0096*	-0.0128~
	(0.40)	(1.18)	(1.32)	(2.09)	(-1.86)
95	0.1040***	0.103***	0.103***	0.105***	0.0969***
	(37.99)	(37.81)	(38.28)	(45.22)	(24.75)
96	-0.0195**	-0.0256***	-0.0257***	-0.0221***	-0.0468***
	(-2.81)	(-3.64)	(-3.68)	(-3.30)	(-4.72)
97	0.0814***	0.0874***	0.0885***	0.0892***	0.0809***
	(19.13)	(20.65)	(21.08)	(22.53)	(14.32)
Constant	0.574***	0.766***	0.763***	0.761***	0.561***
	(20.41)	(315.92)	(316.39)	(380.65)	(14.15)
Controls					
Other county, home characteristics	✓	-	-	-	✓
State-by-year controls	✓	-	-	-	✓
Types of observations included					
States	All	All	All	All	All
Loan types	FRM 30	FRM 30	FRM 30	All	FRM 30
Null values on controls	No	No	Yes	Yes	No
Observations	472,960	472,960	484,622	552,461	228,133
Adjusted R^2	0.0545	0.0157	0.0157	0.0160	0.2075

Source: Authors' calculations are based on data from GSE, CoreLogic Solutions, and Zillow. Note: Coefficients displayed with t-statistics in parentheses. ~ denotes 0.10 level of significance, * 0.05, ** 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, county foreclosure rate, an indicator for AMC use, an indicator for loan near conforming loan limit, 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. Model 5 is identical to Model 1 but also includes ln(AVM-contract price) as a control. The sample size falls because the AVM is not universally available in the data set.

Table A8: Multinomial Logit Information Loss Model

Applied-for LTV	Marginal Effects	z-statistic
74	0.0077~	1.73
75	0.0145***	4.61
76	-0.0102*	--2.21
79	-0.0069~	-1.86
80	0.0184***	9.28
81	-0.1104***	-26.51
84	0.0224***	5.35
85	0.0175***	5.67
86	0.0090*	2.01
89	0.0110**	2.82
90	0.0220***	9.95
91	-0.0400***	-9.53
94	0.0063~	1.78
95	0.0214***	10.52
96	-0.0878***	-17.92
97	0.0313***	10.25
County and home characteristics	✓	
State-by-year controls	✓	
Observations	1,318,074	
Pseudo R^2	0.0463	

Source: Authors' calculations are based on data from GSE, CoreLogic Solutions, Black Knight McDash, 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, * 0.05, ** 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, county foreclosure rate, an indicator for AMC use, an indicator for loan near conforming loan limit, and lagged house price captured as the change in the Zillow county-level home value index from 24 to 12 months before the appraisal.