Information Losses in Home Purchase Appraisals

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

Federal Reserve Bank of Philadelphia

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Abstract

Home appraisals are a standard feature of the mortgage underwriting process, yet since the 1990s it has been well-known that the vast majority of appraisals—typically about nine out of ten—are at or above the transaction price. It thus appears that appraisals are either biased or provide little informational value.

We construct a stylized model and exploit a unique data source to argue that the standard mortgage application review process–under which the loan-to-value ratio is calculated with a home value that is the minimum of the appraised value and the transaction price–creates an incentive for the appraiser to substitute the transaction price for the actual appraised value when the latter is below the transaction price. We demonstrate that the distribution of the ratio of appraised value to transaction price observed in the data can be simulated using our model.

Additional support for the model is obtained from an empirical analysis relating the frequency of reported negative appraisals to market conditions, policy changes, and transaction-specific characteristics that plausibly influence the tradeoff between reporting an inflated value that makes a transaction more likely to occur and increasing expected default costs. Greater information loss in appraisals appears, on balance, to increase the procyclicality of housing booms and busts.

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1. Introduction

Home appraisals are a standard feature of the mortgage underwriting process, yet since the 1990s it has been well-known that the vast majority of appraisals—typically about nine out of ten—are at or above the transaction price. It thus appears that appraisals are either biased or provide little informational value.

We construct a stylized model to argue that the standard mortgage application review process–under which the loan-to-value ratio is calculated with a home value that is the minimum of the appraised value and the transaction price–creates an incentive for the appraiser to substitute the transaction price for the actual appraised value if the latter is below the transaction price (a "negative appraisal"). This substitution, motivated by the potential cost of a lost lending opportunity due to the increase in required down payment accompanying a negative appraisal, we call information loss.

We demonstrate that the distribution of the ratio of appraised value to transaction price observed in the data can be simulated using our model. Additional support for the model is obtained from an empirical analysis in which we show that the frequency of reported negative appraisals can be predicted by variables that influence the decision of whether to substitute a sales price for an appraised value. This supporting evidence is developed using a unique database containing nationwide information on single-family home sale transactions and associated appraisals for the period 2007 through mid-2012. Moreover, the factors that contribute to greater information loss in appraisals appear, on balance, to increase the procyclicality of housing booms and busts.

To our knowledge, our study, together with a companion paper, Ding and Nakamura (2014), are the first to rely on a national sample of pre-sale, pre-mortgage transactions data that includes both reported appraised value and accepted offer price. Prior empirical studies on appraisals primarily have relied on the Fannie Mae appraisal database. That database is constructed from appraisals after the mortgage has been made; it does not have appraisals that result in failed mortgages. Thus the appraisals contained therein may show a bias due to selection. Cho and Megbolugbe (1996) pioneered in this area. Agarwal, Ben-David and Yao (forthcoming) use the Fannie Mae database to explore the bias of appraisals for refinances, where there is no accepted offer price to anchor on. Ding and Nakamura use the same database as our study, and focus on the impact of the 2009 Home Valuation Code of Conduct (HVCC), a regulatory change that sought to reduce appraisal bias.

The role of an appraisal is to provide an independent estimate of the underlying home value that constitutes the collateral for the mortgage loan. The appraisal is especially needed to identify instances where the accepted offer price may be too high due to fraud or too low due to a less-than-arm's-length relationship, such as a sale to a relative. The true underlying value of the home as collateral is difficult to know, due to uncertainty about the value of the land at the home's location or to idiosyncratic aspects of the property.[1] Recent transactions on nearby properties constitute valuable information about this underlying value and, hence, are a primary input into the appraisal process.

An independent appraisal estimate typically should not exactly equal the accepted offer price, as each may be affected by idiosyncratic factors. The accepted offer price may be affected by the parties' respective preferences, knowledge, and bargaining ability, while the appraisal may overlook non-standard features of the home that affect its market value.

Here, we examine information loss in the reporting of appraisals. The theoretical approach to appraisals typically follows Quan and Quigley (1991) and Lang and Nakamura (1993), assuming that 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.[2] Our theoretical approach builds upon this theory and assumes that appraisers determine the optimal appraised value but may choose to report a different value, often the transaction price itself. Appraisers and lenders are faced with a mortgage application review process in which the value of a property is taken to be the lower of the transaction price or the

[1] The dependence on recent neighboring transactions creates a dynamic information externality, as argued in Lang and Nakamura (1993). When the flow of transactions falters, the precision of appraisals falls and the loan becomes riskier. The empirical importance of this information externality has been explored in several papers, notably Blackburn and Vermilyea (2007), but also Calem (1996), Ling and Wachter (1998), Avery et al. (1999) and Ding (2013).

[2] Lang and Nakamura draw the explicit conclusion, which has been supported by considerable evidence, that the number of recent transactions increases the precision of appraisals. In our empirical analysis we apply this theory as a basis for the expectation that the variance of appraisals is negatively dependent on the number of recent transactions.

appraised value. As a consequence, an appraisal that is below the transaction price can result in denial of the mortgage and an unsuccessful transaction if the current owner is unwilling to reduce the accepted offer price, or the borrower is unwilling or unable to increase the down payment or otherwise accept less favorable terms.[3] The cost of the missed lending opportunity implies an incentive not to report appraisals that fall short of the transaction price, although there will be a tradeoff from the increased risk of default associated with ignoring the appraisal.[4]

This theoretical model of the appraisal process is consistent with the distribution of the ratio of reported appraised value to transaction price observed in our data, as demonstrated by comparison of simulated (using the model) and actual distributions. In particular, the model is consistent with the observed frequency with which reported appraised values align with accepted offer prices. Assuming, as seems likely, that the accepted offer price is on average equal to the true value of the property, then an unbiased appraisal should be below the accepted offer price roughly half the time. But empirically, only about ten percent or less of reported appraisals are below the accepted offer price. Some fifty percent of reported appraisals are at the accepted offer price or within 1 percent above it, while roughly forty percent are 1 percent or more above the accepted offer price.

According to our framework, the decision whether to report the actual appraised value or substitute the contract price reflects a tradeoff between mitigating default costs by relying on the actual appraisal, and the potential for a mortgage application and property transaction failing should a negative appraisal be revealed. Thus, factors that reduce the credit risk of the mortgage, should reduce the value of appraisal information with respect to default costs, and thereby strengthen the incentive for information loss.

Our empirical analysis yields evidence consistent with this implication of the model. In particular, we find that rising house prices and decreased foreclosure rates, which we interpret as indicators of lower expected default costs, are associated with increased information loss. We also find that having a high transaction price relative to the median price within the same ZIP code, which we view as increasing the perceived risk of default, appears to weaken the incentive for information loss.

[3] Provided the down payment was not already the minimum available, the buyer may be able to re-apply for a lower down payment or insured mortgage carrying a higher interest rate and/or mortgage insurance premiums.

[4] This missed lending opportunity is a cost borne directly by the lender and indirectly by the appraiser, who may be held responsible by the lender for failed transactions.

Our empirical analysis also examines relationships between institutional or regulatory factors and information loss. Appraisal management companies (AMCs), by acting as intermediaries between the lender and appraiser, may increase the objectivity of the appraiser by distancing the appraiser from the lender's incentive to complete the mortgage origination.[5] Similarly, the HVCC was, as discussed in Ding and Nakamura, an effort to insulate appraisers from bias. Consistent with these expectations, we find reduced information loss for appraisals conducted by AMCs and after the HVCC took effect.

The paper is organized as follows. Section 2 presents basic information about the institutional framework for appraisals. Section 3 presents the simple theoretical framework that formalizes the incentive for information loss in appraisals. Section 4 presents the data and outlines some basic empirical findings on the distribution of reported appraisals relative to accepted offers. We demonstrate that the model can be used to simulate the main features of the empirical distribution. In Sections 5 and 6 we analyze the determinants of information loss, and Section 7 offers conclusions.

2. Institutional aspects of appraisals

In the U.S., mortgages whose credit is guaranteed by a government sponsored agency (Freddie Mac or Fannie Mae) or by the Federal Government (FHA or VA), and those originated by a federally insured commercial bank or savings-and-loan institution require that an appraisal be performed as part of the valuation of the collateral, for purposes of calculating the loan-to-value ratio. The collateral value in these cases is required to be equated to the lesser of the transaction price and the appraised value.[6] This requirement matters, because the loan-to-value ratio is a crucial indicator of the credit risk of the mortgage. A lowered home valuation due to an appraisal at or below the transaction price can thus result in cancellation of the transaction. The lender may reject the mortgage application if the home seller is unwilling to lower the sale price and the buyer is unable to provide a larger down payment. Alternatively, the borrower may

[5] By definition, appraisal management companies rely on a network of appraisers. This breaks the reliance of any individual appraiser on any particular lender for repeat business, in as much as individual appraisers work for various appraisal management companies or appraisal management companies serve multiple lenders.
[6] E.g., the table that gives the method for calculating the loan-to-value ratio in the Fannie Mae Selling Guide (2014), pp. 171-172, reads: "Divide the loan amount by the property value. (Property value is the lower of the sales price or the current appraised value.)"

reject the mortgage if unwilling to pay the mortgage insurance premium and/or higher interest rate associated with a low down payment loan.

The requirement to use the lesser of the appraisal and the accepted offer price as the valuation of the collateral implies that if both are unbiased estimates of the underlying home value, then the resulting valuation will be downwardly biased. This downward bias may be appreciable. Precisely, suppose that the appraisal (a) and the accepted offer (v_o) are distributed lognormally relative to the true market value. That is, ln a and ln v_o are distributed bivariate normally, with both means m equal to the underlying value, with variances σ_a^2 and σ_o^2, and correlation coefficient ρ. Then the expected value of

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

where ϕ is the pdf of a standard normal distribution, so that $\phi(0) = 1/\sqrt{2\pi} \approx 0.4$.[7] Thus, the effect of this rule is to bias low the expected value by 0.4 times the standard deviation of (ln a – ln v_o).

If $\rho = 0$ (that is, if the error in the accepted price is orthogonal to the error in the appraisal, conditional on the common mean), then the effect is to bias low the expected value by more than 0.4 times the standard deviation of the appraisal.

3. Model

We consider the problem faced by an appraiser who appraises a property which is under contract, so that the buyer and seller have agreed upon a price v_o, the accepted offer price (which the appraiser expects to be the transaction price). If the reported appraisal, a, is below the transaction price, the valuation of the property as financial collateral, v, will be equated to be the reported appraisal, otherwise the value is the transaction price. Thus $v = \min(v_o, a)$.

If the reported appraisal is below the accepted offer price, this increases the likelihood that the mortgage will not be made, either because the loan-to-value ratio becomes too large (the down payment is too small); or because the seller is unwilling to reduce the transaction price to the reported appraisal (permitting a smaller loan); or because the borrower is unwilling to bear the cost of the required insurance or risk premium associated with a low down payment loan. The expected cost to the appraiser due to the possibility that the loan will not be made is $f(v_o-a)$. If $v_o < a$ then $f(v_o-a) = 0$, as then the appraisal is not used in the loan-to-value calculation and so

[7] Nadarajah and Kotz (2008).

does not affect the mortgage application. If $v_o > a$ then $f'(v_o\text{-}a) > 0$, since the likelihood of the loan being rejected increases as the property valuation declines.

If the true appraisal, defined as the appraiser's unbiased estimate of the value of the property, is a^*, and the reported appraisal deviates above a^* (such that a^* cannot be precisely inferred from a), then this inaccuracy will reduce the information value of the appraisal and cause the lender to place more weight on contract prices as a signal of the underlying home value.[8] This will result in a reduced down payment and higher risk of default. We denote the cost of this information loss as $g(a^*\text{-}\ a)$ where $g(0) = 0$ and $g'(a^*\text{-}a) > 0$ if $a > a$.

Note that we opt not to complicate the model by introducing an agency problem. We shall assume that the appraiser fully internalizes the two costs faced by the lender and seeks to minimize the total cost. Thus, if $a^* \geq v_o$ then $a = a^*$, and if $a^* < v_o$ then the appraiser seeks to minimize:

$$\mathrm{E}[f(v_o\text{-}a) + g(a^*\text{-}a)].$$

An inaccurate appraisal impacts both the probability of default and the loss-given-default of the associated mortgage, which both increase with the degree of overvaluation of the property, with the impact on expected loss being multiplicative. Thus, it seems plausible to assume that the cost of an inaccurate appraisal rises more than proportionately to the gap between the reported and true appraisal. In contrast, the primary impact of an appraisal below the transaction price is on the probability that the loan will not be made. This distinction helps to motivate a highly simplified, linear-quadratic version of the model, as follows: [9]

$$g(a^*\text{-}a) = d(a^*\text{-}a)^2$$

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

where b and d are strictly positive constants.

Proposition: With these costs, the appraiser sets the appraisal as follows

i. If $a^* \geq v_o$, then $a = a^*$.

ii. If $a^* < v_o$ and $a^* > v_o - b/2d$, then $a = v_o$.

iii. If $a^* < v_o - b/2d$, then $a = a^* + b/2d$.

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[8] In particular, when the reported appraisal equals the transactions price, the lender will only be able to infer that the actual appraised value is at or below the transactions price.

[9] Implicitly, $g(a^*\text{-}a)$ incorporates the lender's beliefs about a^* conditional on the reported value a; that is, a conditional probability distribution over a^*. Our derivation of the Proposition below assumes the naive belief that $a^*=a$; however, it is not difficult to show that the outcome described in the Proposition is sustained under rational beliefs such that, in equilibrium, the lender infers that $a^* \leq v_o$ if $a = v_o$ and $a^* = a - b/2d$ if $a < v_o$.

The first statement is obvious. The other two are straightforward to derive and are proved in the Appendix.

We interpret this model as having three main implications. First, when the true appraisal is greater than the transaction price, then the reported appraisal is equal to the true underlying appraisal. There is no incentive for distortion. Second, when the true underlying appraisal is within a distance of the transaction price such that the incentive to disregard the appraisal is dominant, the reported appraisal is identical to the transaction price. The size of this range depends positively on the perceived cost of the loan application failing and negatively on the cost of inaccuracy. Third, if the true appraisal is sufficiently below the transaction price, the reported appraisal will be between the true appraisal and the transaction price and will exceed the true appraisal.

In sum, the distribution of appraisals should include an undistorted portion, the appraisals greater than the accepted offer price, which we can test. There should also be a substantial proportion of appraisals precisely at the accepted offer price. The proportion of appraisals precisely at the transaction price should be larger when the cost of the loan application failing is higher and smaller when the cost of inaccuracy is higher. Note that according to our model, negative appraisals are somewhat informative as long as they are interpreted as being biased upward by $b/2d$. However, substantial information is lost when appraisals are set equal to the offer price. These appraisals are biased upward by an uncertain amount up to $b/2d$. Moreover, as we show, the factor $b/2d$ varies depending on the location and the time period. Assuming, as seems likely, that a lender does not know all the factors affecting the amount of distortion (and so cannot infer the true appraisal), information loss occurs.

Accuracy of appraisals and transaction prices relative to underlying values.

This stylized framework implicitly holds constant the relative precision of the appraised value and the transaction price as indicators of the underlying value of the property. Factors that reduce the relative accuracy of the appraisal can be expected to provide further impetus toward reporting an appraised value equal to the transaction price. Thus we show below that in county-quarter data, less precise appraisals (where the implied precision is measured using the variance of the positive appraisals) lead to more information loss.

4. The Empirical Distribution of Appraised Values Relative to Transactions Prices

We explore the model's conclusions using a dataset of approximately 800,000 appraisals completed in 2007 through early 2012 on single-family homes across the United States. The data vendor, a real estate mortgage technology company called FNC, stores information on the date of each appraisal, the ZIP code of the property, the offer price in the sale contract rounded to the nearest $50,000, the ratio of the (precise) contract price to the reported appraised value, and a code signifying the lender requesting the appraisal. This lender code distinguishes between appraisals coordinated by an appraisal management company and those contracted directly by the lender.

Using these data, 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 reported appraised value to contract price and compare the distribution of these values to those we would expect to observe if reported appraised values never deviate from true appraised values ($a = a^*$) and the log appraisal-price ratio were normally distributed. Table 1 presents this comparison.

After winsorizing at 1% and 99%, this distribution has a mean of 0.02 and a standard deviation of 0.07. We display below it two lognormal distributions. The first is a theoretical lognormal distribution, assuming a mean of zero (indicating that the reported apprasial is unbiased relative to the contract price, consistent with both being unbiased in relation to underlying value) and the empirical standard deviation of 0.07. The second is a theoretical lognormal whose mean and standard deviation agree with the empirical distribution

The most striking aspect of the observed distribution relative to lognormal distributions is that there is a large mass point at exactly zero; approximately one-third of appraisals are identical to the offer price. Also striking is the degree of asymmetry. The right-hand portion of the distribution, where the ratio exceeds zero (reported appraisal exceeds transactions price), has a shape that roughly resembles a normal distribution (although somewhat thicker tailed, as discussed below), while only a small portion of the distribution falls on the left-hand side.

In comparison to the lognormal distributions, the tail of the empirical distribution on the right hand side, which according to our model should match the true distribution, is somewhat too thick. One plausible interpretation is that the empirical distribution is a mixture of appraisals with different standard deviations; indeed, a mixture distribution as such would generate thicker tails. Lang and Nakamura (1993) imply that different homes should have appraisals whose precision differs, potentially justifying the view that the empirical distribution is best represented as a mixture distribution.[10]

Accordingly, Table 1 also displays corresponding values from a theoretical mixture distribution (labeled "Mix"), with a mean of zero and with half the distribution having a standard deviation of 0.02, and half with 0.10. This fits the right-hand side of the observed distribution reasonably well, though there are still 5 percentage points too many observations falling just above zero (but less than 0.01). Almost all these excess observations, relative to the mixture, however, are quite small, between 0 and 0.005.[11]

Finally, the "Left Side" version of the distribution assumes that our model is exactly correct, with $b/2d$ = .08, and that the underlying distribution has the mixture normal we have just described. That is, it adds 0.08 to the part of the left side tail of the mixture distribution that falls below -0.08. Although 6 percentage points too many observations fall exactly at zero, the mass point, this distribution generally fits the data well, where the appraisal is less than or equal to the offer price. Moreover, this 6-percentage-point share of the appraisals is comparable to the excess five percent that, as noted, lie just above the offer pirce, and again may represent may represent appraisals subject to a small amount of added noise. The close fit between the simulated and observed distribution in this case suggests that for the most negative values (where offer prices most exceed appraisals), the appraisal-price ratio is biased upward by 0.08 or is set equal to zero, whichever adjustment is smaller. This simulation exercise also supports the theoretical model presented in Section 3 and suggests that, on average in this period, $b/2d$ is equal to 0.08.

5. Panel Regression Analysis of Factors Influencing the Degree of Information Loss

We test the model's implications concerning factors affecting degree of information loss using two empirical approaches, distinguished by their level of aggregation. In this section, we apply a panel regression analysis of degree of information loss by county and quarter. In the next section, we conduct a logit analysis of individual appraisal outcomes.

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[10] Alternatively, the mixture can arise because of differences in the *relative* precision of the appraisal compared to the transaction price as estimates of the property value under differing circumstances.

[11] Thus, the average difference is about $625 on a median accepted offer price of $250 thousand. Some appraisers (in the vicinity of one-sixth of our sample) may choose to produce an appraisal very slightly above the accepted offer price when our model would specify that the appraisal should be exactly at the accepted offer price

One advantage to aggregating by county and quarter is that we can directly test the relationship between information loss and underlying appraisal variance as indicted by the right hand side of the observed distribution of appraised value relative to contract price within each county and quarter. In addition, the panel regression approach allows inclusion of county and time fixed effects to control for unobservable factors. The individual outcomes analysis, however, can more fully exploit the variation in the circumstances of individual appraisals, particularly in regard to neighborhood characteristics.

Information loss measure. The dependent variable for our panel regression analysis is a summary measure of information loss by county and quarter in which the appraisal was conducted. The information loss to which we refer is the proportion of the underlying appraisals in a county-quarter whose value is set at the accepted offer price or very slightly above. On the assumption that half the underlying unbiased appraisals should be below the accepted offer price and half above, information loss is 0.5 less the proportion of all appraisals that are below the accepted offer price.

$$Information\ loss_{it} = 0.5 - \frac{number\ of\ negative\ appraisals_{it}}{number\ of\ total\ appraisals_{it}}$$

If the measured information loss is less than zero, it is set equal to zero (this restriction has no qualitative impact). For our panel regressions, the dependent variable is information loss, measured as a percentage by county and quarter.

Our theory implies that this summary measure of information loss is determined by the cost of losing the contract (represented above by f) relative to the increase in expected default costs resulting from a reported appraisal deviating above the underlying appraised value (represented by g). On this basis, we test the following factors in relation to information loss.

Expectations of house prices rising or falling. Brueckner et al. (2012, 2014) argue that because house price inflation is positively serially correlated, a rising house price reduces the expected default cost of a mortgage. Using the previous year's house price appreciation as a proxy for this year's expected appreciation, they find that as expected appreciation rises, the supply of subprime and alternative, riskier mortgage products expands, consistent with the hypothesized relation to expected default cost.

We likewise expect rising house prices to reduce expected default costs and, in turn, strengthen the incentive for information loss. Here, we use ZIP code-level Zillow house price appreciation rates, aggregated to the county level as a weighted average using the ZIP code share of the sample population of appraisals, to measure expected house price inflation. We specify this, as in Brueckner et al., as the four-quarter house price inflation rate, lagged four quarters.[12]

Foreclosure rates. A high rate of foreclosures in a neighborhood is likely to increase the perceived riskiness of mortgage lending for homes in that neighborhood, reducing the incentive for information loss. Proportion of mortgage loans in process of foreclosure by quarter are calculated using McDash mortgage data from Black Knight Financial Services at the ZIP code-level, again aggregated to the county level using the proportion of appraisals in each ZIP code.[13]

Mortgage practices and regulation. In response to the mortgage crisis and indications that reported appraisals had been biased upwards, the New York Attorney General's office investigated appraisals, and the outcome was an agreement with the GSEs (Fannie Mae and Freddie Mac) to the Home Valuation Code of Conduct in May 2009. Ding and Nakamura (2014) use a difference-in-differences methodology to show that in the wake of the HVCC, mortgages qualifying for GSE backing showed less bias relative to jumbo loans that were not subject to the HVCC.

We control for impact of the HVCC by including the proportion of appraisals that are not subject to the HVCC, interacted with a dummy variable for dates in or after the third quarter of 2009, when the HVCC took effect. Appraisals not subject to the HVCC are those associated with a loan amount above the GSE (conforming) limit. We can only identify these approximately, as observations where the contract price (reported in our data as rounded to the nearest 50,000 dollars) is more than 1.25 times the local conforming loan limit (on the assumption that a standard mortgage loan has an 80 percent loan to value ratio).

Appraisal management companies (AMCs). AMCs are intermediaries standing between lenders and appraisers, specializing in appraisal quality control and ensuring appraiser independence. As such, AMCs are expected to reduce information loss in appraisals. AMCs proliferated in the wake of the mortgage crisis to reduce the possibility that lenders or realtors might attempt to influence appraisal reports. In particular, many lenders have turned to AMCs to help ensure compliance with the appraiser independence rules in the Dodd-Frank Act and with

[12] For example, for an appraisal conducted in May 2007, we factor in the house price change between May 2005 and May 2006.
[13] The ZIP code foreclosure rate is the percentage of all loans 90 days or more past due, in foreclosure, or bank owned.

Interagency Guidelines on appraisal conduct.[14] We use the proportion of AMC appraisals in a given county-quarter as our measure of the influence of AMCs on information loss.

Relative price. If a home has a high price relative to its neighbors, there is likely to be more risk that the buyer has overpaid for the house, or that fraud is occurring, reducing the incentive for information loss. Conversely, when a home has a relatively low price, there is less risk that the buyer has overpaid for the house and it is possible that the transaction is less-than-arm's-length. We measure relative price as the percent difference of an appraised home's accepted offer price (as reported in our data rounded to the nearest fifty thousand) from the average single-family home value in that ZIP code (as measured by Zillow). We use the mean for all appraisals in the county quarter, after winsorizing at the 1st and 99th percentiles.

Underlying appraisal precision. A final right-hand side variable is the underlying variance of the distribution of appraisal to accepted offer price (after applying log transformation to the ratio.) Our underlying theory suggests that there is no incentive for appraisers to misreport the underlying appraisal if it is above the accepted offer price. Under this theory, the true underlying appraisal variance can be recovered by measuring the observed variance of the distribution using the appraisals that are greater than the *accepted* offer price. This observed variance is equal to the mean squared plus the variance of the log-transformed ratio, a procedure that assumes that the underlying mean is zero, that is the mean of the appraisals is the mean of the accepted offer price.[15]

Note that higher variance of appraised values relative to transactions price suggests that property valuation is more uncertain, in which case the appraisal and potentially also the transactions price would be less precise measures of true underlying values. If under such circumstances transactions prices are viewed as more precise than appraisals, information loss should increase.[16]

Model specifications. County fixed effects are included in some specifications, along with quarter fixed effects or a time trend. In specifications where we control for the HVCC, we also include separately the proportion of jumbo loans as additional variables and, if time

[14] See, for example, http://www.realtor.org/appraisal/nar-issue-brief-appraisal-management-company-qa

[15] What is observed is $E(X-0)^2 = E(X^2)$. Since it is well-known that $Var(X) = E(X^2)-(E(X))^2$, then $E(X^2)= Var(X) +(E(X))^2$. See, e.g., Rice (2007) p. 133.

[16] Within the context of our model, reduced precision increases default costs. In particular, greater uncertainty around the home valuation may result in increased credit risk (increased likelihood of default and higher loss given default due to increased likelihood of zero equity) associated with the mortgage.

dummies are not present, a dummy variable for dates in or after the quarter when the HVCC took effect. The regressions are limited to county-quarters with 10 or more total appraisals, and we weight the regressions with frequency weights using the total number of appraisals. Means and standard deviations of the dependent and independent variables are provided in Table 2.

Regression results. The regression estimates are reported in Table 3. The first column in Table 3 shows the coefficient results from our regressions when we include only the year-over-year house price inflation rate lagged 4 quarters and the foreclosure frequency. As expected, the higher the expected house price inflation rate, the more information loss occurs. A one-standard-deviation increase in the house price inflation rate increases information loss by 3.0 percentage points; since the standard deviation of information loss is 6.7 percentage points, this is an economically significant amount. On the other hand, as the foreclosure rate rises, information loss decreases. A one-standard-deviation increase in the foreclosure rate reduces information loss by 1.6 percentage points. Note that these together result in an R-squared of 40 percent, so we are accounting for a large proportion of the movements in information loss with these two variables alone. Moreover, both factors are likely to increase information loss during housing booms, when home price inflation is high and foreclosures are low.

The second column provides the model estimates when we add in the underlying variance of appraisals and the proportion of appraisals conducted by AMCs. The coefficients on house price inflation and foreclosures show little change. The coefficient on the underlying variance of appraisals is positive. Thus, as underlying appraisals become less precise, appraisers tend to react by increasing information loss. This makes sense conceptually in that the appraisals are less reliable, but is worrisome in that it is precisely when information is scarce that the appraisal is most important. A one-standard-deviation increase in the underlying variance results in a 0.8-percentage-point increase in information loss.

A higher proportion of AMC appraisals appears to have the desired effect, that less information loss occurs A one-standard-deviation increase in AMC appraisals results in a 0.6-percentage-point decrease in information loss.

The third column presents results after incorporating the control for HVCC impact along with a time trend. These results suggest that once appraisals became subject to the HVCC, information loss decreased for loans under the GSE loan limit relative to jumbo loans. Thus the HVCC appears to have had the desired effect, consistent with Ding and Nakamura (2014). A one-standard-deviation increase in the difference-in-differences variable results in a 0.7-percentage-point decrease in information loss for the affected, non-jumbo loans, relative to the jumbo loans.

Also in this regression, there is a notable increase in the strength of the AMC effect, as a one-standard-deviation increase in AMCs now accounts for a one-percentage-point decrease in information loss. Other coefficients are largely unaffected. However, it is notable that the time trend shows a very significant erosion of these gains over time, with information loss trending back towards a higher level. Overall, in this regression our variables account for some 45 percent of the squared errors, as measured in R-squared. Thus we are able to account for a large proportion of the movement in information loss.

The fourth column shows the impact of adding state and time dummy variables into the simplest (column one) regression with expected house price inflation and foreclosures. The coefficient of the house price inflation rate drops by about one-third but remains highly significant, while the coefficient on foreclosures remains roughly the same and the R-squared rises to 57 percent.

In columns five and six we add to the (column three) HVCC difference-in-differences specification first a set of state dummies (column five) and then state and quarter dummies (column six). In the latter case, we drop the time trend and the HVCC period dummy, which are vitiated by the full set of time dummies. In our most complete regression, we are able to account for 60 percent of the variation in information loss across county-quarters, as measured by R squared. Adding state and time dummies does not change the signs of any of our coefficients of interest, so our qualitative conclusions remain intact.

6. Individual Appraisal Analysis

We now turn to an analysis at the appraisal level, focusing on the probability that the appraised value equals the offer price (the event of information loss), conditional on it being equal to or falling short of the offer price. We relate this outcome to factors viewed as determinants of information loss, and examine how these relationships may have changed over time. These factors are viewed as indicative of costs of inaccuracy (likelihood and cost of default) or the cost of a lost lending opportunity,.

As discussed above, appraisals exceeding the offer price are assumed to have $a = a^*$. In other words, the appraisal represents the appraiser's unbiased estimate of the value of the home, so there is no information loss experienced with those appraisals. The remaining appraisals may be subject to an appraiser's efforts to improve the chance that the mortgage application is successful. We note from the distribution of appraisal to price ratios in Table 1 that there is pile-up of values with appraisals just above the offer price. Because of this, we treat appraised values between 100 and 101 percent of the offer price as being identical.[17]

About half of all appraisals in our dataset matched the offer price agreed upon by the buyer and seller, which indicates that information loss was likely prevalent. As shown in Table 4, while negative appraisals approximately doubled from 5 percent in 2007 to 10-13 percent in 2009-2012, appraisals equal to the offer price hovered around 50 percent.

We specify a set of logit models to estimate the probability that a particular appraisal, i, "matches" the offer price:

$$prob(v_{oi} \leq a_i < 1.01\ v_{oi} \mid a < 1.01\ v_{oi}) = \frac{\exp(\beta' x_i)}{1+\exp(\beta' x_i)}.$$

We estimate the model five times, once for each appraisal year (2007-2011). x_i represents a vector of explanatory variables summarized in Table 4 that are likely to influence the cost of a default or the cost of a missed lending opportunity.

Factors migrated from the panel regressions. As in the county-quarter panel regressions, variables viewed as indicators of default costs include rate of house price appreciation, foreclosure rates, and relative home value. For the individual appraisal analysis, we measure these at the more granular, ZIP code level. We also include a dummy variable flagging appraisals coordinated by appraisal management companies.

In particular, we include a dummy variable indicating that the appraised property is located in a ZIP code with a foreclosure rate between 3 and 10 percent, and a dummy variable indicating location in a ZIP code with foreclosure rate in excess of 10 percent. We include dummy variables signifying that the price exceeded the ZIP code median single-family home value by at least 50 percent or fell short of it by at least 33 percent, but any additional variation in the relative price may be partly captured by a contract price variable.

[17] We present results in the appendix that show this distinction is not driving our results. Our results are similar when we require that appraisals strictly match the offer price to be considered equivalent.

Neighborhood and property-specific factors. The individual appraisal analysis is conducive to a more granular analysis of neighborhood or property-specific factors potentially impacting expected default costs or the cost of a missed lending opportunity. In particular, we control for low frequency of home sales in the neighborhood, which may imply greater uncertainty around the appraisal as an indicator of value of the property (as there will be fewer "comparables" available to the appraiser). Specifically, we include a dummy variable for less than 5 percent of ZIP code single-family homes sold in the year leading up to the appraisal.

We also include the natural log of the rounded contract price, though we are agnostic about how it impacts information loss. A larger contract price, all else equal, indicates a larger mortgage and more fee revenue. Because of this, one could expect contract price to be positively associated with the cost of a lost lending opportunity, leading to reported appraised values that are inflated. However, a larger contract price also means greater potential loss to the lender if the borrower defaults, and appraisers may be more skeptical about high contract prices, particularly if a home is priced higher than others in the area.

We additionally incorporate several neighborhood (ZIP code) level variables derived from Home Mortgage Discosure Act (HMDA) data. These include the share of home purchase loan applications that are for government (FHA or VA) insured mortgages; share of applications that are associated with an application for a "piggyback" second lien, and share of home purchase loan applications that will involve the use of private mortgage insurance (PMI) if origintated. The expected relationship to information loss for these variables is ambiguous a priori. While the higher loan-to-value ratios of loans in these categories imply higher default risk, they also imply higher likelihood of loan approval (and thus greater likelihood of a lost lending opportunity) should the property appraise low. Thus, the a priori relationship to information loss is ambiguous.

An additional HMDA-derived variable included in the analysis is the percentage of home purchase loan applications in the ZIP code that were filed with local (in-market) depository institutions, defined as institutions with a branch in the county where the sought-after property is located. We also interact this variable with an indicator variable for ZIP codes experiencing substantial house price depreciation (annualized rate of price decline in excess of 10 percent.) In-market institutions are expected to have ongoing relationships with appraisers, which in general should increase the cost of a lost lending opportunity resulting from a low appraisal, due to potential disruption of such a relationship. Thus, we expect a larger share of applications going to in-market lenders to be postively related to likelihood of information loss. However, in a declining-price market, lenders may be more concerned with default risk than with lending opportunities, weakening or reversing this expected relationship.

Another HMDA-derived variable included in the analysis is the percentage of home purchase loan applications in the ZIP code that are for properties located in low- or moderate-income Census tracts. Loans originated in low- and moderate-income neighborhoods may have elevated default risk; thus, we expect a lower likelihood of information loss in ZIP codes where low- or moderate-income borrowers are more predominant. Also, where applications for home purchases in low- or moderate-income borrowers are more plentiful, it is easier for banks to comply with Community Reinvestment Act requirements, mitigating the cost of lost lending opportunities, and thus reinforcing the expected, inverse relationship to information loss.

Finally, we include a set of state dummies. Separate models are estimated by year of the appraisal. In each of our logit models, standard errors are clustered by ZIP code. Means and standard deviations of the dependent and independent variables are provided in Table 4.

Estimation results. Table 5 displays the estimated odds ratios and z-statistics from the logit models. The results are consistent with the implications of our theoretical model and our hypothesized relationships for the explanatory variables. Specifically, ZIP code house price inflation, measured as the four-quarter lagged year-over-year rate of change in Zillow median home values, is positively associated with the the likelihood that a reported appraised value equals the transaction price. Figure 1 displays fitted probabilities of a reported appraisal matching the offer price that are associated with different values of the qustion variables, calculated using the median values for the continuous predictors and modal categories for the other controls. The top left panel of the figure displays the fitted probabilities under three scenarios: house prices rising by 5 percent anually, remaining stable, or falling by 10 percent. The relationship between prices and appraisal outcomes was strongest in 2009 and 2010, years in which there was more variation among the appraisal observations in the degree of house price appreciation.

Having greater foreclosure activity in a neighborhood makes it more likely that a reported appraisal will come in short of the contract price. Appraisals in areas with foreclosure rates of 3 to 10 percent of mortgages are 69 to 85 percent as likely to have an appraisal match the contract price. In areas with foreclosure rates over 10 percent, appraised values are 48 to 76 percent as likely to be equivalent to the offer price. As shown in the top panel of Figure 1, the relationship was strong and fairly consistent in magnitude overtime, even though the effect, when represented in odds, varied over the sample period. This also provides evidence of a monotonic relationship between higher area foreclosure rates and less information loss in the appraisals. Interestingly, information loss is prevalent even in areas with high foreclosure rates; for no year does our fitted estimate of information loss fall below 83 percent of non-positive appraisals.

As expected, appraisals conducted through an appraisal management company were associated with a reduced likelihood that the reported appraised value matched the transaction price.   In 2009, AMC appraised values were about 77 percent as likely to be identical to the contract price as appraised values submitted by appraisers who were hired directly by the lender. However, this gap narrowed over time, as shown in the lower left panel of Figure 1.

We find only a very small positive relationship between having few sales in a ZIP code (< 5 percent of properties sold in past year) and greater incidence of the appraisal matching the contract price. This relationship is statistically significant only in 2010 and 2011. As we note above, fewer sales means greater uncertainty about values, which could increase concern about credit risk and make negative appraisals more likely. However, this same uncertainty could push some appraisers to depend more heavily on the contract price when deciding what appraised value to report.[18] We believe these competing effects explain the relatively small effect of having few transactions.

Having a high relative price (the contract price exceeding the ZIP code single-family median value by 50% or more) consistently means an appraisal was more likely to come in short of the contract price (in other words, there was reduced information loss). Having a higher contract price was also associated with more negative appraisals.

Finally, considering the HMDA-derived variables, we observe the expected relationships to information loss for the share of in-market lenders and its interaction with the indicator for declining house prices. A larger share of loan applications associated with in-market lenders implies increased information loss, except where prices were declining (and in 2007, when the market was about to decline). However, we note that these effects are not economically large.

[18] Table A-1 in the Appendix shows a much stronger positive relationship when we consider $a = v_0$ only when the two are perfectly identical. This supports the argument that appraisers rely heavily on the precise contract price in areas with a low volume of sales to use as comparables.

We also observe the expected, inverse relationship between share of applications for properties in low- and moderate-income areas and likelihood of information loss. Finally, we note that appraisals carried out in ZIP codes with a large share of loan applications for the FHA and VA programs are less likely to suffer from information loss. In contrast, other types of high-LTV lending in a ZIP code are, in most years, positively correlated with information loss. This finding could indicate that FHA and VA appraisals are higher quality or subject to greater scrutiny, though this topic deserves further exploration, ideally using mortgage-level (rather than ZIP code-level) indicators of FHA and VA status.

7. Summary and Conclusion

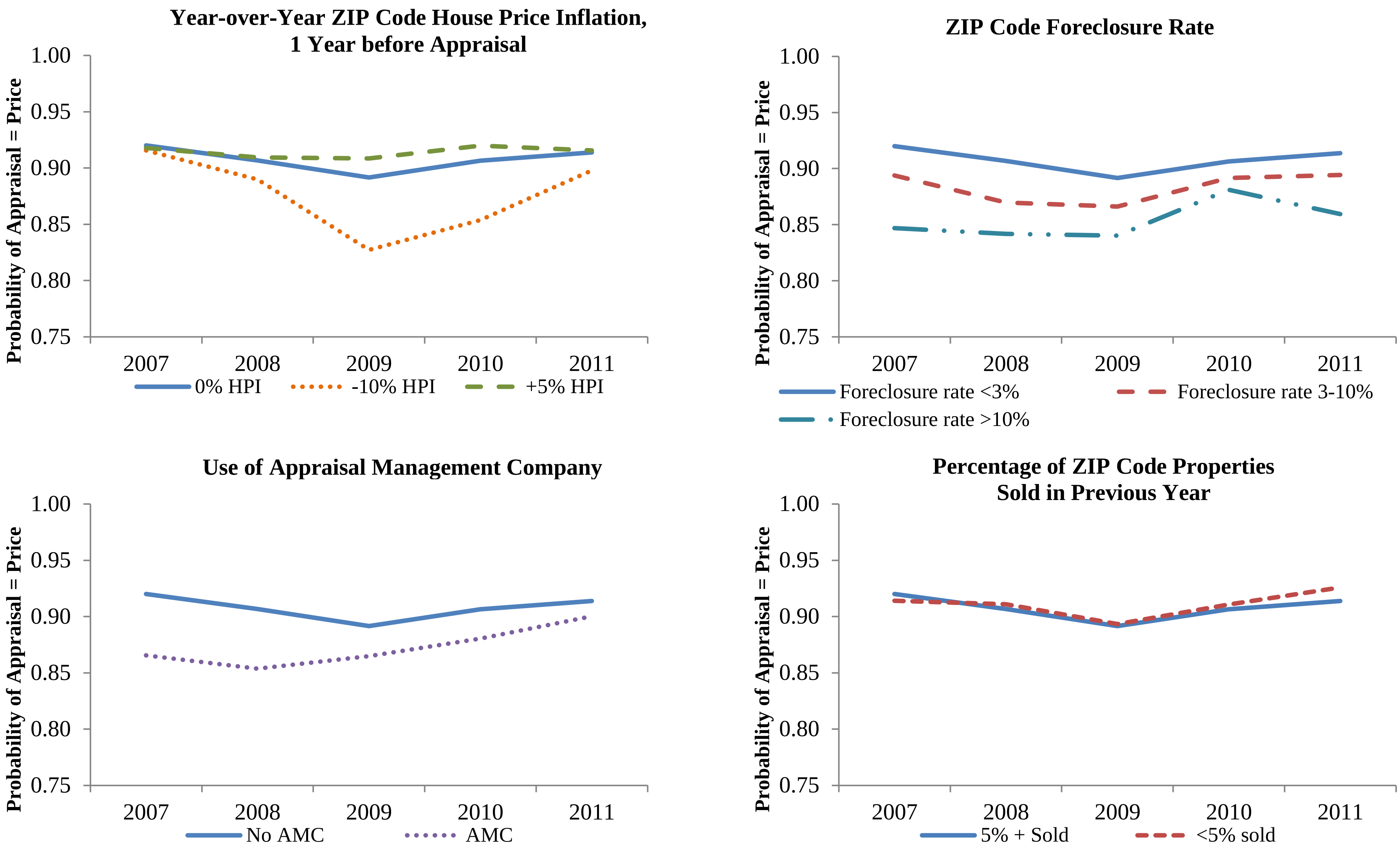
We have demonstrated that the current mortgage practice of setting the property valuation to the lesser of the transaction price and the appraised value provides incentives for substantial information loss. While this information loss was somewhat reduced by the implementation of the Home Valuation Code of Conduct and by the advent of appraisal management companies intermediating between lenders and appraisers, information loss continues to be prevalent.

Moreover, information loss is greater during boom times in the housing market, when prices are rising, and smaller during weak markets. These effects were exacerbated by the Home Valuation Code of Conduct. A likely consequence was that the home price boom was extended by these practices and that the home price bust was similarly worsened. Thus, appraisals can be added to the list of practices that tend to exaggerate the natural home price cycle and tend to therefore lead to what are ex-post perceived as bubbles and to economic crises.

We have not set up our framework so as to be able to determine the optimal contract. However, we believe we have created a strong argument that the current arrangements are far from optimal. It might thus be valuable for securitizers and regulators to re-evaluate the method for property valuation and perhaps engage in experimentation. For example, suppose the property valuation were to be set to equal to transaction price, with the appraisal reported as an additional characteristic of the property. This would likely reduce somewhat the tendency of appraisals to be reported as exactly the transaction price. Over time, this might lead to more accurate, and less biased, appraisals.

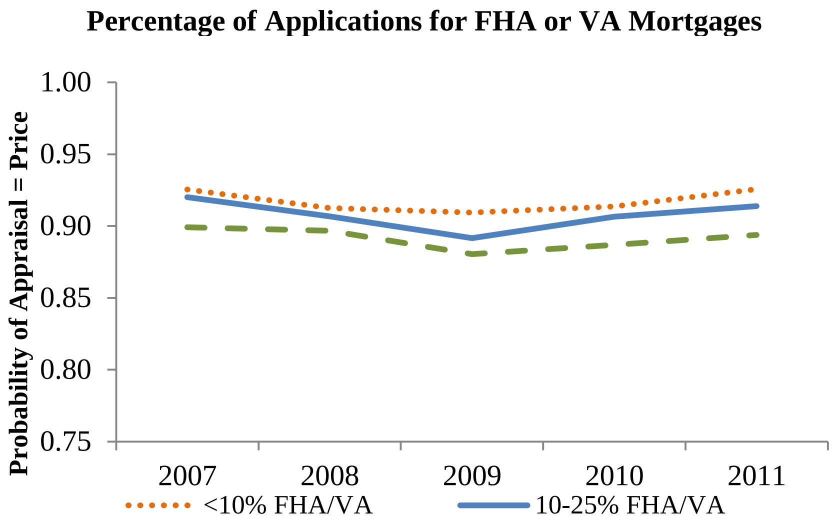
Figures

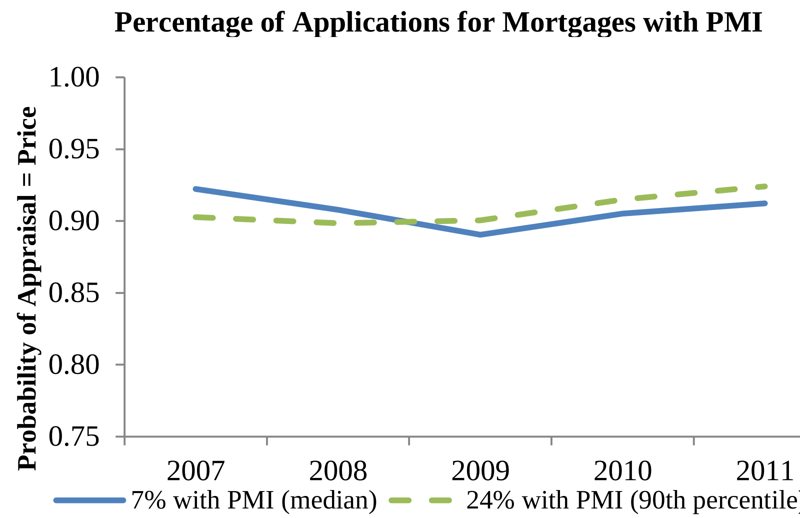
Figure 1: Investigating How Appraisal Chracteristics Influence the Prevalence of Information Loss
Outcomes Conditional on Appraisal ≤ 1.01 Transaction Price

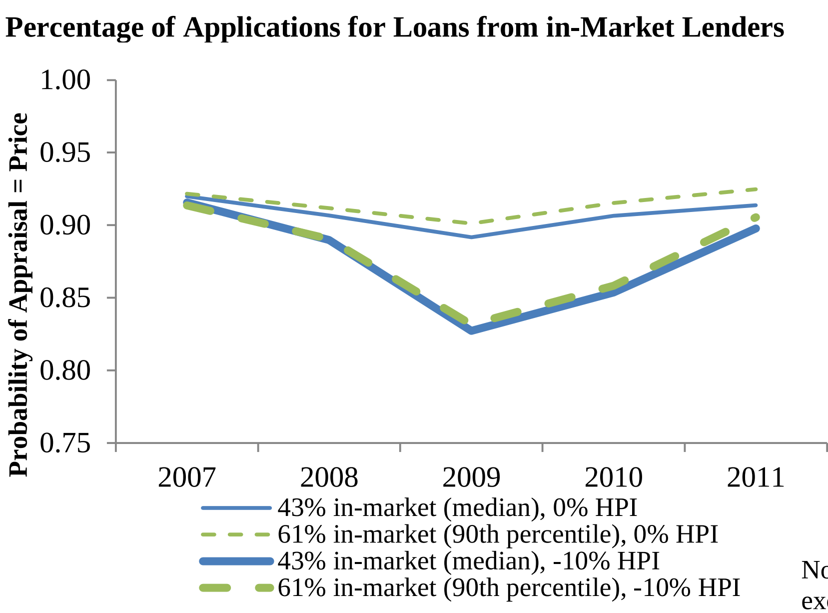


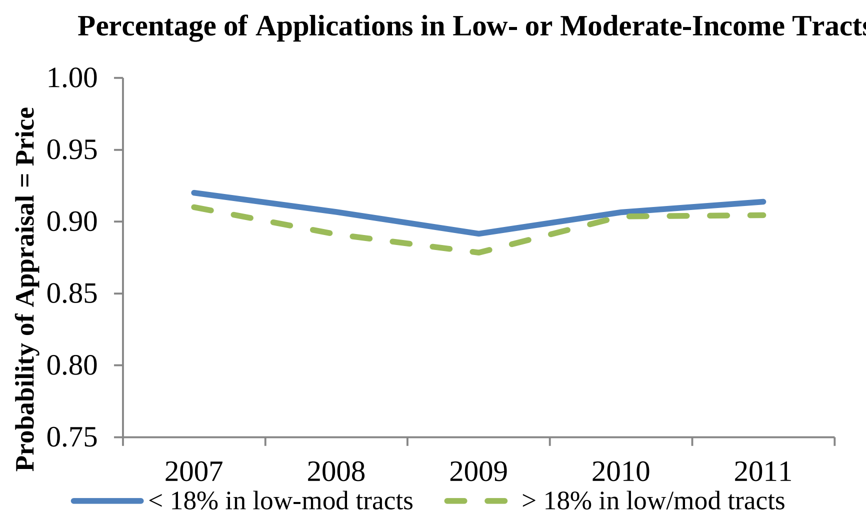
Note: Information loss is defined as an appraisal value matching the contract price (or exceeding it by no more than 1%), conditional on the appraisal falling below 101% of the transaction price. Fitted values are calculated using median values of covariates, unless indicated otherwise. Source: Authors' calculations, based on data from FNC, Zillow, Federal Financial Institutions Examination Council (Home Mortgage Disclosure Act), and Black Knight Financial Services.

Figure 2: Investigating How ZIP Code Chracteristics Influence the Prevalence of Information Loss
Outcomes Conditional on Appraisal ≤ 1.01 Transaction Price









Note: Information loss is defined as an appraisal value matching the contract price (or exceeding it by no more than 1%), conditional on the appraisal falling below 101% of the transaction price. Fitted values are calculated using median values of covariates, unless indicated otherwise. Source: Authors' calculations, based on data from FNC, Zillow, Federal Financial Institutions Examination Council (Home Mortgage Disclosure Act), and Black Knight Financial Services.

Tables

Table 1: Distribution of the Natural Log of Appraisals to Price Ratio

	Percent of Values Falling within Each Band of ln (Appraisal/Offer Price)								
	< -0.1	< -.05 and ≥ -0.1	< -.01 and ≥ -.05	< 0 and ≥ -0.01	Exactly equal to 0	> 0 and ≤ 0.01	> 0.01 and ≤ 0.05	> .05 and ≤ 0.10	> 0.10
Year									
2007	1.2	1.1	1.8	0.4	32.7	19.5	25.7	9.0	8.5
2008	2.1	1.7	2.0	0.3	31.1	16.5	24.6	10.3	11.3
2009	4.3	3.5	3.9	0.4	33.2	15.9	22.7	8.5	7.6
2010	2.9	2.9	3.8	0.5	34.6	17.0	23.4	8.1	6.8
2011	2.5	2.4	3.4	0.5	37.0	16.0	23.4	8.0	6.8
2012	2.6	2.9	4.0	0.6	36.4	16.4	23.3	7.4	6.4
Total	2.7	2.5	3.2	0.4	34.0	16.9	23.8	8.6	7.9
Theoretical									
Normal(0,.07)	7.7	16.1	20.6	5.7	0	5.7	20.6	16.1	7.7
Normal(.02,.07)	4.3	11.5	17.5	5.3	0	5.6	22.3	20.8	12.7
Mix	7.9	7.8	22.7	11.6	0	11.8	22.7	7.8	7.9
Left Side	1.8	3.0	4.3	1.4	39.4				

Source: Authors' calculations, based on data from FNC.

Table 2: County-quarter data summary statistics, weighted by number of appraisals

	mean	**Standard deviation**	**Number of County-Quarter Observations**	**Number of Appraisals Included**
Information loss, percent	40.91	6.65	6,645	573,028
House Price Inflation Rate, Previous year, percent	-5.52	10.20	6,645	573,028
Foreclosure Rate	15.60	15.16	6,645	573,028
Underlying variance of appraisals	.0054	.0034	6,642	572,993
AMC proportion	.1284	.1845	6,645	573,028
Proportion over GSE limit	.1048	.1285	6,645	573,028
Post HVCC dummy * Proportion over GSE limit	.0527	.0807	6,645	573,028

Source: Authors’ calculations, based on data from FNC, Zillow, and Black Knight Financial Services.

Table 3: Estimating information loss by county and quarter as function of risk, return, and regulation, with observations weighted by number of appraisals in given county-quarter and robust standard errors in parentheses. Information loss is defined to be .5 minus the proportion of appraisals below the accepted offer price.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
House Price Inflation Rate,	0.293***	.292***	.292***	.142***	.255***	.156***
Previous year	(.0009)	(.0009)	(.0010)	(.0012)	(.0012)	(.0012)
Foreclosure Rate	-.108***	-.122***	-.119***	-.133***	-.054***	-.105***
	(.0008)	(.0008)	(.0008)	(.0009)	(.0008)	(.0008)
Underlying variance of appraisals		237.5***	215.2***		205.9***	123.8***
		(2.78)	(2.79)		(3.155)	(2.691)
Price relative to zip code		-.0225***	-.0236***		-.0438***	-.0420***
		(.0004)	(.0004)		(.0005)	(.0005)
AMC proportion		-3.423***	-5.672***		-4.597***	-4.597***
		(.0941)	(.0607)		(.0947)	(.0947)
Proportion over GSE limit			-.1656***		3.527***	3.111***
			(.0454)		(.0475)	(.0496)
HVCC dummy			-3.514***		-3.425**	
			(.0291)		(.0291)	
HVCC dummy * Proportion over GSE limit			8.843***		8.885***	8.062***
			(.1075)		(.1149)	(.1149)
Time trend			.2300***			
			(.0026)			
Constant	44.21***	44,30***	.6321		10.09***	48.92***
	(.0103)	(.0220)	(.4999)		(.4732)	(.0969)
State dummy variables				✓	✓	✓
Time dummy variables				✓		✓
N	573028	572993	572993	572993	572993	572993
R-square	.3956	.4260	.4481	.5747	.5390	.6002

Source: Authors' calculations, based on data from FNC, Zillow, and Black Knight Financial Services. *** coefficients are significant at the .001 percent level.

Table 4: Appraisal-level data summary statistics. Percentages of observations each year are reported, unless otherwise noted.

	2007	2008	2009	2010	2011	Total
*Outcomes**						
Negative appraisal (A < P)	5	7	13	11	10	10
Appraisal approx. equal to price (P < A ≤ 1.01P)	52	46	49	50	49	49
Equal, conditional on A ≤ 1.01P	91	87	79	82	83	83
Positive appraisal (A ≥ 1.01P)	43	47	38	39	40	41
Controls						
High relative price (P > 50% above ZIP SF median)	23	22	22	24	27	23
Offer price similar to ZIP SF median $^{+}$	71	69	70	69	66	70
Low relative price (P > 33% below ZIP SF median)	6	9	8	7	7	7
< 5% of ZIP homes sold in last year	16	37	55	50	54	45
≥ 5% of ZIP homes sold in last year $^{+}$	84	63	45	50	46	55
< 3% of ZIP foreclosure rate $^{+}$	83	51	35	32	29	43
3-10% of ZIP foreclosure rate	16	37	47	55	58	45
> 10% of ZIP foreclosure rate	1	12	18	13	13	12
Appraisal management company	6	6	5	9	28	14
Appraisal requested directly by lender $^{+}$	94	94	95	91	72	86
Median ln (contract price, rounded to nearest $50k)	12.6	12.4	12.4	12.4	12.4	12.4
Observations	121,352	105,627	182,946	171,674	146,982	796,171

Source: Authors' calculations, based on data from FNC, Zillow, and Black Knight Financial Services. ZIP foreclosure rate is the percentage of all loans 90 days or more past due, in foreclosure, or bank owned. $^{+}$ indicates categories treated as base cases in the regression models (the output of which can be found in Tables 2-4). *Note, due to rounding, percentages for 2010 do not sum to 100.

Table 5: Estimating the prevalence of information loss, defined as the probability of that an appraisal equals the offer price (or is within 1 % above it), conditional on not exceeding the offer price (or being within 1 % above it).

	2007	**2008**	**2009**	**2010**	**2011**
House price inflation (percentage)	0.994*	1.006*	1.038***	1.035***	1.005*
	(-2.43)	(2.13)	(19.78)	(21.99)	(2.24)
3-10% foreclosure rate in ZIP	0.733***	0.686***	0.787***	0.849***	0.799***
	(-6.50)	(-8.88)	(-8.60)	(-5.81)	(-6.93)
10% + foreclosure rate in ZIP	0.481***	0.547***	0.639***	0.765***	0.577***
	(-4.71)	(-9.59)	(-10.76)	(-5.06)	(-8.43)
Appraisal management co.	0.560***	0.600***	0.777***	0.760***	0.851***
	(-10.28)	(-9.25)	(-6.18)	(-8.73)	(-7.09)
< 5% of ZIP homes sold	0.924	1.051	1.017	1.053*	1.177***
	(-1.64)	(1.32)	(0.67)	(2.13)	(5.89)
ln contract price	0.760***	0.732***	0.775***	0.775***	0.836***
	(-12.91)	(-13.27)	(-23.04)	(-18.25)	(-16.56)
High relative price	0.883***	0.735***	0.850***	0.797***	0.801***
	(-3.33)	(-8.88)	(-7.54)	(-9.77)	(-9.18)
Low relative price	1.061	1.097	0.992	0.891*	0.891*
	(0.63)	(1.30)	(-0.20)	(-2.46)	(-2.56)
<u>HMDA ZIP Code Characteristics</u>					
< 10% FHA/VA	1.078$^{\sim}$	1.072	1.220***	1.091	1.174**
	(1.88)	(1.37)	(3.49)	(1.46)	(2.86)
> 25% FHA/VA	0.775**	0.892**	0.895***	0.809***	0.794***
	(-2.98)	(-2.92)	(-3.38)	(-5.82)	(-6.74)
ln % with PMI	0.820***	0.915***	1.091***	1.102***	1.135***
	(-6.94)	(-3.46)	(6.43)	(7.02)	(8.57)
ln % with piggyback mortgage	1.254***	1.082**	1.073**	1.082**	1.160***
	(8.96)	(3.25)	(3.22)	(2.94)	(5.00)
% with in-market lender	1.001	1.003*	1.006***	1.006***	1.008***
	(0.70)	(2.15)	(5.43)	(6.05)	(7.34)
% in-market lender interacted	0.997$^{\sim}$	0.997**	0.996***	0.996***	0.997***
prices falling by 10% +	(-1.83)	(-3.27)	(-8.34)	(-4.92)	(-4.49)
% of applications in low/mod tracts	0.879***	0.843***	0.878***	0.969	0.894***
	(-3.50)	(-4.89)	(-5.33)	(-1.19)	(-3.94)
State dummy variables	✓	✓	✓	✓	✓
N	68,055	55,702	111,939	104,322	86,914
Log likelihood	-19,326.7	-20,407.7	-54,290.1	-46,094.0	-37,420.7

Source: Authors' calculations, based on data from FNC, Zillow, the Federal Financial Institutions Examination Council (Home Mortgage Disclosure Act), and Black Knight Financial Services. Odds ratios are displayed, along with z-statistics in parentheses. Standard errors are clustered by ZIP code. ~, *, **, and *** represent statistical significance at the 10, 5, 1, and 0.1 percent levels, respectively. Appraisals that exceed the offer price by less than one percent are treated as equivalent to the offer price. See Table 4 for control variable descriptions and summary statistics.

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Appendix.

Proof of the proposition.

The goal is to minimum the total cost (C)

$$C = d(a^* - a)^2 + max(b(v_o - a), 0)$$

If $a^* \geq v_o$, then (i) if a = a*, where C=0. Any other value of a results in a strictly positive value of C.

Now note that in regions where $v_o > a$

$$C = d(a^* - a)^2 + b(v_o - a)$$

$$\frac{dC}{da} = -2d(a^* - a) - b = 0$$

implies $a = a^* + b/2d$, is a local minimum as

$$\frac{d^2C}{da^2} = 2da > 0$$

If $a^* < v_o$, then if the appraiser reports (ii) $a = a^* + b/2d$, total cost

$$C = b(v_o - a^*) - b^2/4d$$

On the other if the appraiser reports (iii) $a = v_o$ then

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

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

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

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

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

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

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

Table A-1: Estimating the prevalence of information loss, defined as the probability of that an appraisal exactly equals the offer price, conditional on not exceeding the offer price.

	2007	**2008**	**2009**	**2010**	**2011**
House price inflation (percentage)	0.998	1.006$^{\sim}$	1.033***	1.030***	1.004*
	(-0.67)	(1.83)	(15.93)	(18.43)	(2.04)
3-10% distressed in ZIP	0.815***	0.747***	0.835***	0.906**	0.870***
	(-4.15)	(-6.45)	(-6.04)	(-3.24)	(-4.17)
10% + distressed in ZIP	0.719*	0.654***	0.701***	0.888*	0.717***
	(-2.36)	(-6.44)	(-7.98)	(-2.07)	(-4.92)
Appraisal management co.	0.570***	0.622***	0.793***	0.765***	0.871***
	(-9.39)	(-7.91)	(-5.34)	(-8.11)	(-5.83)
< 5% of ZIP homes sold	1.024	1.173***	1.116***	1.131***	1.242***
	(0.48)	(4.03)	(4.22)	(4.80)	(7.55)
ln contract price	0.725***	0.729***	0.764***	0.770***	0.816***
	(-14.35)	(-15.74)	(-26.56)	(-21.41)	(-19.31)
High relative price	0.857***	0.690***	0.802***	0.734***	0.729***
	(-4.01)	(-10.22)	(-10.04)	(-13.34)	(-12.57)
Low relative price	1.222*	1.225**	1.122**	1.021	1.007
	(2.18)	(2.77)	(2.82)	(0.43)	(0.15)
<u>HMDA ZIP Code Characteristics</u>					
< 10% FHA/VA	1.203***	1.106$^{\sim}$	1.319***	1.175*	1.256***
	(4.38)	(1.83)	(4.70)	(2.56)	(3.94)
> 25% FHA/VA	0.750**	0.826***	0.846***	0.758***	0.749***
	(-3.14)	(-4.65)	(-4.75)	(-7.52)	(-8.26)
ln % with PMI	0.740***	0.890***	1.100***	1.100***	1.126***
	(-10.05)	(-4.32)	(6.72)	(6.51)	(7.71)
ln % with piggyback mortgage	1.319***	1.043	1.075**	1.096**	1.169***
	(10.66)	(1.64)	(3.16)	(3.22)	(5.02)
% with in-market lender	1.004*	1.008***	1.007***	1.006***	1.010***
	(2.43)	(4.91)	(6.66)	(6.12)	(8.89)
% with in-market lender X	0.996**	0.998*	0.997***	0.996***	0.997***
prices falling by 10% +	(-2.82)	(-2.16)	(-6.45)	(-4.29)	(-3.90)
% of applications in low/mod tracts	0.974	0.874***	0.928**	0.997	0.941*
	(-0.68)	(-3.55)	(-2.91)	(-0.10)	(-2.10)
State dummy variables	✓	✓	✓	✓	✓
N	42,613	37,381	82,442	73,678	60,388
Log likelihood	-16,031.2	-16,867.9	-45,901.7	-38,621.4	-311,42.9

Source: Authors' calculations, based on data from FNC, Zillow, the Federal Financial Institutions Examination Council (Home Mortgage Disclosure Act), and Black Knight Financial Services. Odds ratios are displayed, along with z-statistics in parentheses. * ~, *, **, and *** represent statistical significance at the 10, 5, 1, and 0.1 percent levels, respectively.