House Price Markups and Mortgage Defaults

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Abstract

(97 words) The transaction price of identical housing units can vary widely due to heterogeneity in buyer and seller preferences, matching, and search costs, generating "markups" above or below the average market price. These markups are mean reverting upon subsequent transactions, suggesting dynamics that are unrelated to market fundamentals. Markups are an important driver of mortgage defaults and credit losses conditional on default even after accounting for collateral coverage (loan-to-value ratio) and a comprehensive set of other covariates. The findings suggest standard collateral coverage estimation may be inaccurate, with implications for credit portfolio risk assessment.

Keywords: mortgage · house price · credit risk · collateral risk · automated valuation model · appraisal bias

JEL Classification: C4 · G2 · R1 · E3

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1. Introduction

For publicly traded stocks, transactions occur at either the bid or the ask price, but never at the midpoint of the spread. Accordingly, each transaction has either a positive *price markup*, where a transaction price exceeds the average market price, or a negative price markup. Markups defined in such a manner exist in every market—even those without explicit bid-ask spreads—as long as there is variation in the transaction price around some known or unknown average market price. For assets traded in markets characterized by high liquidity and low transaction costs, markups are likely small and of little concern. But in markets where markups tend to be large, there may be important implications for loan performance when such assets serve as collateral.

The housing market is characterized by major information asymmetries, heterogeneous preferences, and high transaction costs. Accordingly, the effective spread for housing is large, and the prices at which buyers and sellers are willing to trade vary widely relative to an average market price, even after controlling for location, observable house and borrower characteristics, and unobservable fixed effects.[1] Housing is also highly leveraged, making individual mortgage performance sensitive to variation in the value of the collateral on the loan and the market susceptible to leveraged bubbles (Óscar Jordà et al., 2015). These attributes make housing the ideal market to explore issues related to markups, leverage, and loan performance.

In this paper, large markups and high leverage introduce a major source of unaccounted-

[1] Case and Shiller (1989) estimate a property-specific appreciation standard deviation of 15% around the market average using repeat-sales regressions, suggesting large spreads for transactions of identical homes. These regularities are explained and predicted by a long and growing literature that employs search-and-matching models to study the microstructure of housing transactions. Han and Strange (2015) present a comprehensive survey of this topic; examples of recent studies in the housing literature include Carrillo (2012), Merlo et al. (2015), and Adelino et al. (2019). For an excellent survey of search and matching models in labor markets, see Mortensen and Pissarides (1999). Nominal loss aversion may also play a role (Genesove and Mayer, 2001). House price expectations may also play a role in markups; see Glaeser and Nathanson (2017) for a recent paper on the subject.

for-risk in loan performance using information on over 100 million home transactions and 40 million mortgages in the United States between 1975 and 2018. The findings have important consequences for modeling mortgage defaults, credit losses conditional on default, and cash flows and pricing of mortgage-backed securities. Because these findings are driven by the fundamental attributes of the housing market, they are generalizable to markets with similar characteristics, including land, auto loans, collectibles, insurance pools, and any other market with heterogeneous assets, high transaction costs, and/or information asymmetries.

A simple conceptual framework can show that a transaction price and its deviation from the expected price mechanically determine *future* equity value and, thus, is a key determinant of mortgage performance. Loans with higher (lower) price markups at origination should be, all other things equal, more (less) risky.

A price markup might be measured in two ways, both of which are common but competing approaches used in the mortgage industry. The measurement challenge lies in isolating the unobserved component of the transaction price that is idiosyncratic to the buyer-seller match rather than unobserved characteristics of the unit. The first approach, which draws the main focus of this paper, exploits repeat-sales to predict the transaction price of a unit in a manner similar to Anenberg (2016). The method is simple: take an initial transaction price and project it forward using a house price index. The markup is then computed as the percentage difference between the observed and predicted transaction price. Intuitively, the markup resembles (but it is not identical to) a residual from a repeat-sales regression. This measurement is termed a *house price index AVM* because it is an automated method of valuing a home. The second approach uses the unit's appraisal as an estimate of the predicted price to compute the markup. The markup, here, represents a buyer's deviation from what an industry professional judges to be a market value.

AVM markups are computed using a comprehensive dataset of house price transactions in the United States. Combining house price data from mortgages purchased or securitized by Fannie Mae, Freddie Mac, and the Federal Housing Administration with property values from sales and transfer documents that are filed at county recorder offices, more than 100 million transactions are amassed involving single-family housing units since the mid-1970s.[2] The richness of these data allows the AVM to estimate markups for any house that sells more than once in the sample. Empirical tests suggest that AVM markups are partially mean reverting, suggesting markups do not solely reflect unobserved changes in economic fundamentals of a housing unit's quality or location; rather, because markups are mean reverting, they contain a transitory, transaction-specific component.

In order to measure the effects of markups on various aspects of mortgage outcomes, the house price data are merged with loan-level mortgage origination and performance information. Two public sources are combined for single-family loan-level data using a proprietary process to track nearly 40 million loans from origination to termination. The loan performance sample begins in the early 2000s, which allows us to capture rising and falling markets and, most importantly, provide takeaways about both the Great Recession and the recovery environment. The mortgage origination data provide other important details such as a loan's terms (amount, length, and interest rate), purpose (purchase-money or refinance), and other underwriting characteristics.[3] The mortgage performance data track outstanding loan balances, loan maturity, delinquency status, and details about termination. The combined data are used to estimate traditional mortgage performance models. To begin, the exclusive focus is on purchase mortgages. Results from a wide set of specifications and samples pro-

[2] The county recorder data have been licensed from CoreLogic.

[3] A purchase-money mortgage is one used to purchase a house. A rate/term refinance mortgage involves executing the prepayment option by prepaying an old loan and then issuing a new loan with more favorable borrower terms. A cash-out refinance is a refinance that may also include extracting equity from the house by issuing a new loan for more than the loan balance of the prior note. The share of purchase-money mortgages fluctuated from between 9% to 74% (with a mean of 32%) of conventional loan originations each year between 2001 and 2012. The sample of refinance mortgages might have issues related to sample selection (take-ups may be likelier for properties with greater appreciation) or censoring (only certain loans are eligible for conventional refinancing). Such influences are tested via a series of subsample stratifications and controlling for refinances in models of all loans.

vide convincing evidence that AVM markups can predict future mortgage default. In the baseline specification for purchase mortgages, default rates are 3.4% for a +20% markup but approximately 1.9% at a -20% markup, conditional on origination LTV and other covariates, between 2001 and 2012.

These price and mortgage data also allow us to comment on the relation between markups and credit losses when a loan defaults. Conditional on default, markups are associated with greater credit losses for the holder of the mortgage. Assuming a downpayment-constrained borrower, markups are entirely financed through a higher initial loan balance, which translates directly to a higher loan-to-value (LTV) at origination. For example, a 10% markup on a 97 LTV loan could result in an underwater mortgage at origination, with the loan's actual LTV being at 108. On the other hand, a -10% markup on the same loan would give an actual LTV at origination of 88. These scenarios illustrate that mis-pricing can result in substantially more less (or more) collateral for the lender at a loan's inception. Overall, a 20% markup is associated with an additional 3.5% in eventual credit losses. Importantly, unlike variation in LTV, which has mechanical interactions with mortgage insurance (MI) coverage and depth and is thus insured, variation in the markup translates to credit risk regardless of MI incidence.[4]

The mechanism for the association is explored after establishing the existence of a relation between markups, defaults, and credit losses conditional on default. The key question is why markups predict credit risk even after collateral coverage (or the amount of LTV) is taken into account. Besides loan amount, LTV depends, by definition, on both the sale price and the appraisal.[5] But neither the sale price nor the appraisal capture the "true" average value of a home. The sale price captures conditions that are *idiosyncratic* to each transaction and that may not reflect *average* market conditions. Average rather than idiosyncratic

[4]Lenders often require credit enhancements that require mortgage insurance depending on the LTV of the loan. MI is in force until enough collateral is accumulated through principal payments.

[5]LTV is defined as $LTV = \frac{Loan}{\min\{Price, Appraisal\}}$ in seller and servicer guides.

conditions should be stronger driving factors for determining collateral value. Moreover, manually performed (human) appraisals may be subject to bias as reported by a growing set of studies in this area (see Nakamura, 2010; Agarwal et al., 2013; Calem et al., 2015; Ding and Nakamura, 2016). To confirm the existence of appraisal bias in the sample, the following is shown: a) the distribution of appraisal based markup computed as the difference between the sale price and the appraisal has excess mass at zero (in nearly 50% of cases the sale price is within 0.5% of the appraisal); and b) the there is almost no relation between appraisal based markups and default, except when the appraisal is nearly equal to the transaction price which itself is a default determinant. The previous evidence and discussion allows us to conclude that collateral coverage may be substantially mismeasured, and this is likely the reason why AVM markups are correlated with default risk.

To further hone in on this mechanism, markups are calculated using the AVM approach, and estimate default models for refinance mortgages. Refinance mortgages are different than purchase mortgages because the LTVs on refinances are based solely on appraisals of the units as there is no transaction price. The data indicate that markups for refinance mortgages are much more likely to be positive than for purchase mortgages. For example, in 2003 and 2004, over 70% of all cash-out refinances in the dataset had positive markups, indicating the presence of appraisals that are higher than predicted by market fundamentals. When the markup is included in default models for refinance mortgages for all periods, the markup is highly predictive of defaults.

This paper contributes to a growing literature concerned with how the mis-pricing of assets affects immediate valuations and subsequent performance outcomes. A large number of studies have documented that collateral value relative to the outstanding balance is an important determinant of payment default, highlighting the role of accurately assessing current equity when estimating runoffs and default risks (Campbell and Dietrich, 1983; Deng et al., 2000; Foote et al., 2008; Mayer et al., 2009; Piskorski et al., 2010, among many others).

This study makes an important point: due to factors idiosyncratic to each trade, transaction values should not be expected to always reflect average market conditions. Units that have been sold or refinanced at an above (below) average price have, other things equal, less (more) equity and are exposed to more (less) mortgage default risk.[6] Hence, heterogeneity in prices at the time of transaction can point to an additional source of asset default risk that may not be apparent with certain underwriting valuation (appraisal) techniques.

More broadly, these findings could be applicable to other assets that are characterized by both large spreads and highly leveraged transactions where the asset purchased serves as the collateral on the loan. This includes the market for auto loans, collectibles such as art, wine, or trading cards, heavy machinery, and insurance policies. When these assets are highly leveraged and markups are large and positive, incentives to default are higher than for loans with small and/or negative markups, holding leverage constant.

2. Conceptual framework

A simple conceptual framework can illustrate why price markups exist in the housing market, and the relation between markups and future default rates. Allow for a stylized one-sided, partial equilibrium, two-period model where potential home buyers search for a house in period $t = 0$. To keep things simple and tractable, assume that each buyer is able to find exactly one seller. Homes are identical in their observed characteristics but a buyer obtains a random utility component B that is idiosyncratic to each home-buyer combination. From a buyer's point of view, the seller's reservation value and potential trading price P_0 is random as it depends on the seller's characteristics and valuation of the house. Assume that the house price is an independently and identically distributed realization drawn from a pre-determined continuous distribution F_0; that is, $P_0 \sim F_0$. A buyer has access to credit

[6] Ben-David (2011) and Carrillo (2013) show that house prices that are *artificially* high at origination due to fraudulent practices can be associated with future default rates. Bian et al. (2018) explores the relation between transaction prices and collateral values, with a particular focus on loan attributes.

and can purchase the house after paying a downpayment of δP_0, where $1-\delta \in [0,1]$ measures the loan-to-value ratio (LTV). In period $t=1$, a home buyer can become a seller and put a house on the market. A random price offer $P_1 \sim F_1$ is expected. Let F_1 be exogenously determined. If selling the house is not profitable, a seller has the option to default on the loan. In what follows, the model is formally set up while denoting random variables and their realizations with upper- and lower-case letters, respectively.

After a buyer has inspected a house and negotiated with the seller, a realization of B and P_0 is revealed. From the buyer's perspective, the value of having an opportunity to buy such house V_0^b in period $t=0$ is equal to

$$V_0^b(p_0) = \max\{b - \delta p_0 + E[V_1^s(P_1, p_0)], 0\} \tag{1}$$

where the match value b denotes the increased utility from housing consumption relative to the outside option (renting), and $E[V_1^s(P_1, p_0)]$ is the expected value of having an opportunity to sell this house next period. In period $t=1$, a home owner has the option to sell the house and repay the loan or default

$$V_1^s(P_1, p_0) = \max\{P_1 - b - (1+r)(1-\delta)p_0, -D\} \tag{2}$$

where r is the loan interest rate and D captures both pecuniary and non-pecuniary default costs. A simple examination of Equation 2 allows us to conclude that, conditional on b and p_0, a seller would default as long as the realization of $P_1 \leq \gamma$, where $\gamma = b+(1+r)(1-\delta)p_0 - D$. Note that the probability of default (given realizations b and p_0) is equal to

$$\Pr[P_1 \leq \gamma \mid b, p_0] = F_1(b + (1+r)(1-\delta)p_0 - D) \tag{3}$$

Let

$$P_R^S(b, p_0) = \gamma \tag{4}$$

be the seller's reservation price: the minimum price at which she is willing to sell his/her house. Now compute

$$E[V_1^s(P_1, p_0)] = \int_\gamma^\infty (P_1 - b - (1+r)(1-\delta)p_0)dF_1(P_1) - F_1(\gamma)D \tag{5}$$

After simple differentiation, one can show that

$$\frac{\partial E[V_1^s(P_1, p_0)]}{\partial p_0} \leq 0$$

and

$$\frac{\partial V_0^b(p_0)}{\partial p_0} \leq 0$$

Hence, in period 0 it is also optimal for a home buyer to follow a reservation strategy such that a house is purchased if the realization of P_0 is smaller than a reservation price P_0^R. After inspecting Equation 1, it is clear that P_0^R is implicitly defined by

$$\int [V_1^s(P_1, P_0^R)]dF(P_1) = \delta P_0^R - b \tag{6}$$

As shown in Figure 1, the solution to this equation exists and it is unique.

This simple model allows us to make two important conjectures that will later guide the empirical analysis. First, the model predicts that households pay different prices for identical housing. Some households pay a positive price markup (sale price above the average), while others pay less. What is important to remark here is that the price markup is *not* a consequence of unobserved housing heterogeneity but rather it is due to random matching and heterogeneity in buyer and seller tastes. This is an important observation that is considered when estimating the price markups empirically.

Second, the model clearly shows that there is a negative relationship between price markups and default rates: higher markups (higher p_0) increase the probability of future default (see Equation 3). In the empirical section, this hypothesis is tested and the implications are investigated.[7]

3. Measurement of markups and descriptive statistics

This section introduces the primary method of measuring house price markups, a *house price index AVM*. This method uses two transaction prices of the same housing unit, along with a house price index, to calculate the difference between the actual price and a predicted price. After outlining this method along with its strengths and weaknesses, a description is provided for the data used to calculate the measures found in the empirical sections. Finally, some basic descriptive statistics of the markups are presented for origination cohorts, loan outcomes, distributions, and same-unit dynamics.

3.1 Markup measurement

The first step in the analysis is to identify the *house price markup* for a transaction, defined as the log-difference between the actual transaction price (P) and a predicted price ($\hat{P}$) of a unit. This predicted price could potentially come from an in-home appraisal, an automated valuation model (AVM), or some other source. In this section, a method is proposed to estimate markups using an AVM which will be used to estimate the relationship between markups and default. The markup is estimated with appraisals in a later section.

Markups are measured using a house price index AVM by taking the previous transaction

[7] Partial equilibrium solutions have been analyzed where it has been assumed that F_0 and F_1 are exogenous to the model. This may not be a reasonable assumption since sale prices are typically determined after a (sometimes complex) negotiating and bargaining process between buyers and sellers. Moreover, a home buyer can become a home seller in the future. This complication is avoided for the sake of clarity and simplicity.

price of unit i in area j at time t, and multiplying this price by the change in a local house price index (HPI) between the time of the first *anchor* transaction in time t , and a second *subject* transaction at $t+1$.[8] This method requires two transactions of the same unit in order to calculate a markup (m). The average markup will be nearly zero and resemble an un-differenced residual from a repeat-sales regression, though by focusing on housing units with two or more transactions, the mean markup within an area may be non-zero.[9] Conceptually, the two transactions in the markup calculation can come from any combination of cash transactions, purchase mortgages, or a refinance mortgages. When a refinance mortgage is used, the house value is implied by the LTV and the original loan balance.[10] In the empirical sections, the anchor transaction is allowed to be of any type, but focus exclusively on purchase mortgage subject transactions.[11]

$$m_{i,j,t+h} \equiv \ln P_{i,j,t+h} - \ln \hat{P}_{i,j,t+h}; \quad \hat{P}_{i,j,t+h} = \frac{HPI_{j,t+h}}{HPI_{j,t}} P_{i,j,t} \tag{7}$$

An example of the calculation of the price markups for a particular housing unit is shown in Figure 2. This house transacted four times between 1998 and 2015, with transaction prices denoted by solid circles. Each predicted price, based on the previous anchor transaction and the change in the house price index, is denoted by a hollow diamond. The markup is shown in the lower panel with the bar height representing the percent difference between the actual and predicted subject transaction prices. The 2002 transaction was about 6% lower than the predicted transaction price, indicating a -6% markup that is denoted with a solid red

[8]This price estimation approach is also used by Anenberg (2016) and Molloy and Nielsen (2018) in other contexts.

[9]There are two important things to note about this particular method. First, the markup calculated using the house price index AVM inherently includes estimation error in the index construction. Second, repeat sales indices incorporate information from later periods to estimate the value at a particular point in time. This does not affect the interpretation of the main findings, as the estimates are intended to be *ex post* predictive and not real time or *ex ante*.

[10]While most of the analysis focuses on cases where the second transaction is a GSE purchase mortgage, cases are also considered where both transactions are purchase transactions, the second transaction is a refinance mortgage, or other permutations.

[11]Estimates are also provided for exclusively purchase-purchase pairs in some applications.

circle.[12] Then, based on this second transaction price, the predicted price in 2009 was about 10% lower than the actual, giving a +10% markup as depicted with a solid green circle. Finally, the fourth transaction indicates a -10% markup relative to the third transaction, and is depicted with another red circle because of the negative markup.

This particular method of constructing a markup potentially includes at least three different factors. First, markups could reflect fundamental value changes to the housing unit. For instance, if a large renovation took place between the anchor and subject transactions, the value of the home presumably increased and the markup is likely to be positive. Second, markups include measurement error. This includes both the possibility of a non-zero markup in the anchor transaction and house price index estimation error which would result in area- and time-period-specific bias in the markup calculation. Third, there is the portion of the markup that is due to buyer and seller heterogeneity, transaction heterogeneity (e.g. cash vs mortgage financing), and search costs (e.g. forced or distressed sales). These factors are grouped together because they are likely to be mean-reverting upon subsequent transactions and correlated with default in the manner the conceptual framework predicts. In this paper, no attempt is made to disentangle these components. Instead, this approach is to first demonstrate the existence of mean reversion in the markup and then to take the raw markup measure to the data to measure the associations with mortgage performance, leaving further decompositions of this precise markup calculation method to future research.

3.2 Data

To calculate markups for a large set of houses and estimate their association with various mortgage outcome measures, a database is assembled with information on three main items for each housing unit: a time series of transactions, a relevant house price index, and mortgage attributes and performance.

[12]Throughout the paper, log-differences and percent changes are used interchangeably. This is a reasonable approximation for small ($< |.3|$) log-differences, but becomes increasingly inaccurate as differences increases.

3.2.1 Transaction record

The base dataset is a nearly complete coverage of real property and refinance transactions for single-family housing in the United States. This record is based on two main sources and is identical to the data used by the Federal Housing Finance Agency (FHFA) to produce its suite of house price indices. These sources combine to include more than 100 million transactions involving single-family housing units since the mid-1970s.

The first source is administrative data from Fannie Mae, Freddie Mac, and the Federal Housing Administration. These include transaction and appraised values of homes from both purchase-money and refinance mortgages purchased, securitized, or guaranteed by any of these three entities.

Appended to this dataset is a county recorder transaction file from CoreLogic consisting of transaction values from sales and transfer documents that are filed with county recorder offices. These include information that the administrative data misses, including cash purchases or purchases with loans that are held in portfolios or private label securities.

3.2.2 House price indices

A panel of local HPIs is merged onto the transaction records. To account for local variation in house prices, a ZIP code level file is obtained from the FHFA as described in Bogin et al. (2019a).[13] After combining these indices with the transactions record, markups are calculated for all transactions on a property except for the first recorded transaction.

3.2.3 Loan performance data

Finally, mortgage origination and performance information are gathered at the loan-level to measure the effects of price markups on specific payment outcomes. This information is

[13] These indices are produced at an annual frequency for ZIP codes with at least 25 "half-pairs" (a count of the paired transactions where either the first or the second transaction occurs in the respective year) in each year. The out-of-sample standard deviation of prediction errors for these indices is approximately 10% for a 1-year holding period, rising to about 15% for 8 years (see Figure 1a in Bogin, Doerner, and Larson, 2019b).

from Fannie Mae and Freddie Mac's publicly available single-family performance files.[14]

The mortgages represent fully amortizing fixed-rate loans that have been purchased or securitized between 2001 and 2012. These are "full documentation" loans, which means loan application information has been verified or waived. A typical loan is underwritten for 30-years but the data also contain 15-, 20-, and 40-year terms, although loan data with these other lengths are not available for originations before 2005. Mortgages are excluded if they are adjustable-rate, interest-only, balloon, step-rate, or non-first liens. The sample also usually excludes mortgages that have credit enhancements which go beyond primary mortgage insurance. Government-issued mortgages, such as from FHA or VA, are not present in this performance dataset, though they are present in the transactions records used in the creation of the markups measures. Loans are also excluded if they participated in the Home Affordable Refinance Program (HARP) or if they have been flagged for other non-standard attributes such as LTVs above 97 percent, immediate liquidations, bi-weekly payment due dates, reduced documentation, streamlined processing, or had been part of a lender recourse or third-party credit-sharing arrangement.

The origination data provide details about a loan's terms (amount, length, and rate), purpose (purchase or refinance), mortgage insurance coverage, origination channel, and general location. The ongoing performance files track monthly outstanding loan balance, maturity (age and remaining months), loan modification, delinquency status, and outcomes upon termination (actual loss revenues and expenses, covered chargeoffs, or repurchased workouts). A "default" is defined as a negative loan termination, including foreclosure, foreclosure alternative, or lender repurchase. For robustness where appropriate, default may also consider delinquency.

[14]Data are obtained from Freddie Mac and Fannie Mae from their websites and a database of proprietary identifiers via a regulatory oversight agreement. Freddie Mac data are at `http://www.freddiemac.com/news/finance/sf_loanlevel_dataset.html`. Fannie Mae data can be found at `http://www.fanniemae.com/portal/funding-the-market/data/loan-performance-data.html`.

3.3 Loan counts

The analysis begins with the 17.5 million loans in the loan performance file used to finance properties where multiple transactions are observed for the same housing unit and are able to calculate a markup. About 15.6 million loans pass several basic data quality filters.[15] Of these, the primary focus of the paper is on the 4.2 million purchase mortgages. Table 1 outlines some basic counts of loan originations and outcomes by origination cohort.[16] For some applications, the scope of the analysis is limited to purchase loans with markups originated in 2006 and 2007 (the "crisis sample") in order to focus on a period with heightened levels of variation in outcomes.[17]

The number of purchase originations in the sample is highest in 2001 through 2003 at around 450,000 loans per year, then remains roughly constant at between 290,000 and 370,000 loans per year for the remainder of the sample. For loans originated prior to 2009, about 90% or more of each vintage of loans has resolved in either default or prepayment. Defaults are low in 2001 at 1.0%, rising to 6.6% in 2007, and falling to 0.1% in 2012, though with each successive vintage past 2007, an increasing share of loans is current. Loan modifications follow a similar pattern as defaults.

Direct defaults are tracked as a measure of strategic default. A direct default happens when a borrower makes no payments after becoming delinquent, instead choosing to "simply walk away from the home" (Foote et al., 2010). Direct defaults follow Foote et al. (2010) by applying three criteria: 1) the borrower must be current for three consecutive months, then register a 90 day delinquency three months later; 2) the borrower must never have been

[15] Drops include 600,000 observations with markups greater than +/-50% calculated using the HPI AVM, 150,000 observations with markups calculated using appraisals, and 1,100,000 observations with a loan term less than 10 years.

[16] Outcomes are as of March 2018.

[17] In other sections, other samples of data are used. Some of these include: (1) loans with both a prior and successive markup (requiring a minimum of 4 transactions, (2) the sample of all loans with performance data, including refinances, (3) loans with a prior GSE purchase markup, or (4) loans with a prior GSE purchase markup that is approximately zero.

seriously delinquent (90 days) before triggering (1); and 3) the borrower must never become current again before defaulting. Across the sample, about 54% of defaults are direct, with loans in 2005 and 2006 averaging about 56%.

Over the entire sample, about 51.5% of purchase loans have positive markups.[18] Table 1 also presents default rates by markup sign. In every year, negative markups have at least as low default rates than positive markups. The magnitudes are often remarkably dissimilar, indicating a large unconditional correlation between markups and defaults. For instance, in 2007, the default rate for loans with negative markups is 6.0%; for positive markups it is 7.2%. This relationship between negative and positive markups and default rates persists in non-crisis periods; even with default rates dropping to less than 1% in post 2009 cohorts, positive markups still have (weakly) greater default rates than negative markups. Overall there is a clear, bivariate, reduced-form relationship between the sign of the markup at origination and eventual default. This relationship is remarkably robust and economically relevant, especially in periods of heightened default risk.

3.4 Kernel densities

Kernel density functions in Figure 3 reveal several facts in the data related to markups, their distributions, covariates, and dynamics. Before beginning, it is necessary to introduce some notation which will be used throughout the paper. Analysis focuses on the markup where loan performance data are available at time t. The prior markup on the same property, is denoted as time $t-1$, and the next markup is denoted as $t+1$. The mortgages in

[18]The average markup is positive, indicating a difference in the selection mechanism into the sample versus the house price index. By construction, the house price index AVM should give markups that are, on average, equal to zero if the samples are identical and markups are symmetric. The combination of price index and property selection has isolated a subset of houses that have transacted for prices that are higher than the area average. This is likely due to two main reasons. First, the price indices are based on conforming, conventional GSE loans. If an initial transaction were cash or non-GSE foreclosure sale and therefore depressed in price, the markup calculated for the second transaction may be artificially inflated. Second, houses that have transacted multiple times in sequence may have undergone a renovation or "flip" causing, again, a positive markup. Ultimately, the analysis is continued but acknowledges this potential threat to the external validity.

these figures are the sample of properties for which three consecutive markups are observed, necessitating four transactions. The markup at time t is a GSE purchase-money mortgage. Markups at $t-1$ and $t+1$ can be refinances, cash-only transactions, or GSE or non-GSE purchase mortgages. This allows us to focus on the primary objective, purchase-money mortgages, while also maximizing the number of markups to be considered.[19]

The first thing to note in these figures is the large variance of the markups across all panels. This is attributed to the presence of error in the markup measurement and quality changes across transactions. Both of these factors attenuate any estimated relation between markups and outcome variables in empirical work. However, as will be shown, the markup is highly predictive across a battery of loan outcomes, model specifications, and samples, despite the potentially high degree of noise in the particular measure.[20]

Panel (a) shows the distribution of markups is slightly more positive, on average, than for loans that eventually prepay, suggesting positive markups may be associated with higher rates of default. In panel (b), there is a clear correlation between the current markup and the next markup on the same property if the current loan defaults. The distributions are both roughly symmetric, but when the current loan prepays, the distribution is centered on 0, whereas if the loan defaulted, the distribution is centered at about -20%. This difference captures the negative foreclosure premium Campbell, Giglio, and Pathak (2011), who estimate this premium to be -27%, though a portion of the differences may be due to other factors.

Panel (c) shows the dynamics of consecutive markups when the transaction that generated the first markup resulted in default. When the initial markup is positive—indicating the property was purchased at too high of a price—the markup conditional on default is, on

[19] The implications of different financing types on markups are considered later in this section.

[20] In Panel (a), 12.4% of all loans have markups greater than 0.25 or less than -0.25. This compares to the 20 to 26% of "markups" falling outside of this range when using Zillow's Home Value Index, according to Molloy and Nielsen (2018).

average, much less than if the property was purchased for too low of a price. This indicates there may be some mean reversion in markups when default occurs, and potentially the -20% reduced-form premium shown in panel (a) consists of both the foreclosure premium and some mean reversion of the prior markup. The relation between current markups and defaults is echoed in panel (d) for the *prior* markup, indicating that positive markups may persist between transactions.

3.5 Same-unit dynamics

One last set of stylized facts relates to the dynamics of markups in consecutive transactions involving the same housing unit. These facts allow us to establish the extent to which markups contain information reflecting transitory microstructure dynamics versus permanent changes in unit-specific fundamentals: if markups are mean reverting—that is, positive markups turn negative in later transactions and negative markups turn positive—then it may be inferred that markups do not reflect changes to the fundamental value of the housing unit; if markups are persistent, then they may reflect a change in underlying value. The sample of loans is the same as in the kernel densities presented previously, and consists of all GSE purchase-money mortgages that have a measured previous and next markup.

To model the same-unit dynamics of markups, a future markup is expressed as a function of the current markup, the prior markup, and other covariates, as shown below. This equation is an adapted version of the simple mean-reversion specification found in Davis and Weinstein (2002). A variable is also included for default due to the well-documented foreclosure premium, as well as the financing type (versus a GSE purchase-money mortgage), and in some specifications, the time between transactions, $h(t, t+1)$. To control for the possibility that markups are non-zero on average, time period and state fixed effects are included. To account for the possibility that the residual variance in the model varies by the state and year in question, standard errors are clustered at the level of the state interacted with the year.

$$m_{i,t+1} = \beta_0 + \beta_1 m_{i,t-1} + \beta_2 m_{i,t} + X'\gamma + u_{i,t+1} \tag{8}$$

If $\beta_1 + \beta_2 = -1$, then an initial markup is fully transitory after two transactions. On the other hand, if $\beta_1 + \beta_2 h = 0$ then some amount of the initial markup is maintained and persisted fully to into two successive transactions. Values between -1 and 0 indicate partial mean reversion.

Table 2 shows estimates of same-unit markup dynamics across transactions. There are four models, with each corresponding to a different conditioning set or subsample. Column 1 presents estimates using the full set of purchase mortgages. The current markup parameter is -0.30 and the previous markup parameter is -0.12.[21]

Summing these two parameters gives about -0.42, indicating that about 42% of a markup has mean-reverted after two further transactions. In terms of other covariates, the foreclosure premium is estimated to be about -16%. Financing appears to have little effect beyond cash-out refinances, which have a positive association of about 5% with the markup.

Column 2 presents results from a model with covariates for the time-between-transactions and interactions with the markup. This result suggests the markup increasingly mean-reverts the longer the holding period. At these parameter values, for a +20% markup on a loan that did not default, the next expected markup is is -2% if a transaction occurs for the same unit one year later. This indicates about 1/10th of the initial markup reverts in the subsequent

[21] Genesove and Mayer (2001) estimate the residual from the previous sale hedonic to have a partial effect of 0.16 on the next sale, and a "months since last sale" parameter of -0.0004, or about -0.005 per year. This hedonic residual is an alternative calculation of a markup. This specification is remarkably close to ours but is not adapted to the task of estimating markup dynamics, making the task of comparison somewhat difficult. If they had estimated an interacted variable parameter relating the residual $\times$ months since last sale along with a vector of controls, then the parameters would be comparable. As it stands, the estimate of 0.16 for the residual on the next sale corresponds to a -0.84 estimate (about 2.5x the estimate) on the following markup in the specification. The -0.005 per year is about 1/3 of the estimate of 0.17. Though by assumption, they are restricting the interacted coefficient to 0, while ours is -0.002. Accordingly, the findings are broadly consistent with the signs and significance levels found in Genesove and Mayer (2001) though they are fairly far apart in magnitude.

transaction. Similarly, the predicted markup is -9% after five years, for a mean-reversion of about one half. If the loan defaulted, the predicted next markup is -17%, suggesting 85% mean reversion in the subsequent transaction; after 5 years, the predicted markup is -24%, indicating some overshooting may have occurred.

Columns 3 and 4 show that positive markups exhibit lower levels of mean reversion than negative markups, consistent with Figure 3. While loans with higher markups may end more often in default, it appears it is default and the passage of time that causes the reversion in the transaction price. Negative markups, however, are mean reverting more quickly.

In sum, markups are mean reverting, especially when the loan defaults. Financing plays a minimal role in markup dynamics, with the exception of cash-out refinance valuations, which on average, are 4% to 5% above market average valuations. These results indicate markups are driven by transaction-level pricing that is, in part, transitory. Because this component is not tied to the fundamental value of the housing unit, it is likely that markups are associated with variation in collateral risk for mortgages. The analysis now turns to an examination of the relationship between markups, mortgage defaults, survival lengths, losses conditional on default, and comparisons with markups calculated using mortgage financing appraisals.

4. Predicting eventual defaults

Conceptually, it is clear that lower collateral, holding the loan balance and other variables constant, should be associated with a higher risk of default. This directly applies to markups for reasons best illustrated by the following simple illustration. Suppose a mortgage with a stated 97 LTV that is used to purchase a house, but the sales price contains a +10% pricing error. This loan would immediately be underwater with a current LTV of about 108 because the collateral is worth less than the the initial valuation going into the calculation of the LTV. Similarly, if the housing unit is underpriced by 10%, the 97 LTV mortgage would immediately have a current LTV of 88, making it substantially less risky.[22] In either case, the standard LTV is not based on an accurate collateral valuation. This is especially dangerous in the case of a positive markup, because it potentially indicates an appraisal failure. One of the primary purposes of an appraisal is to help assess the risk of default for both the lender and the borrower. With a positive markup, the LTV understates the default risk. For these reasons, emphasis is placed on assessing how price markups affect default risk *conditional* on the origination LTV.

The bivariate relationship between the markup and default is shown in the first panel of Figure 4 for the 2001 through 2012 sample. At a -20% markup, the default probability is 1.9%, whereas at +20%, the default probability is about 3.4%, nearly double. The relation is monotonic and of the predicted sign, giving a strong indication that markups can be used to predict eventual defaults in a meaningful way. While +/-20% may seem to be a wide range, recall that 1), the particular markups estimate likely includes substantial idiosyncratic noise, and 2) the range between these values includes about 80% of the markups; i.e. over 20% of values are outside this range.

4.1 Methods

To examine empirically the link between markups and default in a more rigorous fashion, a standard competing options default model is constructed. The dependent variable d for loan i is set equal to 1 if the mortgage terminates in default, defined as a foreclosure, foreclosure alternative such as a short sale, or a lender repurchase, 2 if the loan prepaid, and 0 if it is current as of March 2018. The variable of interest is the markup, calculated for the origination period, and the partial correlation of this variable is hypothesized to be positive on all forms of default. Note that this models requires complete *ex post* information and cannot be used to model causal lender or borrower behavior or answer the questions

[22] The LTV math is as follows: $\frac{97}{90} = 1.077$; $\frac{97}{110} = 0.881$.

regarding whether lenders or borrowers account for markups in their choices to issue/take out a mortgage. Additionally, the markup calculation in a repeat-sales framework benefits from sales subsequent to the origination period. These limitations notwithstanding, the model here is illustrative of partial relations between the variables in question.

The functional form of the specification is a logit equation, with control variables in the vector X, coefficients for controls in the vector γ, and e as a generalized extreme value IID random variable.[23] Normalization requires all $d = 0$ parameters set equal to zero, or $\{\beta_{0,0}, \beta_{1,0}, \gamma_0\} = \{0, 0, \mathbf{0}\}$.

$$Pr(d_i = j) = \frac{\exp\left(\beta_{0,j} + \beta_{1,j} m_i + X_i' \gamma_j + e_{i,j}\right)}{\sum_{\tau=j}^{J} \exp\left(\beta_{0\tau} + \beta_{1,\tau} m_i + X_i' \gamma_\tau + e_{i,j}\right)} \tag{9}$$

The choice of controls are standard in the literature, but in particular, are motivated by Ghent and Kudlyak (2011). First, variables are included for both the combined LTV (all liens on the property), the LTV on the particular mortgage, and a dummy variable set equal to 1 if the LTV is within 0.5 percentage points of 80, as each of these LTV variables may include unique and relevant explanatory power.[24] The debt service payment to income ratio (DTI) at origination is a standard default indicator, as a high debt fraction of household income makes a household particularly susceptible to income shocks in terms of ability to repay. Credit score at origination is also a common indicator, representing a household's willingness and ability to repay debt in the past. Multiple borrowers can mitigate the income risk of default,

[23] This is not the precise functional form as presented in Section 2. In the conceptual framework (and in other models, e.g. Hatchondo, Martinez, and Sanchez, 2015; Bailey, Davila, Kuchler, and Stroebel, 2017), the interaction between interest rates and the LTV determines the equilibrium outcome. The markup is layered onto this expression, which if properly specified, would necessitate a triple interaction and multiple double interactions, with default increasing in each of the arguments both through direct and interacted effects. These complex interactions are omitted in order to focus on the total partial effects using a parsimonious specification, acknowledging the possibility of omitted variable bias at extreme values.

[24] Subsequent second mortgages cannot be measured, which would affect the current CLTV on the loan. Insofar as subsequent seconds are correlated with observed controls, this unmodeled variation will bias control estimates. Any other variation that is correlated with markups, conditional on the controls, will bias the markups estimate. Because of the number and predictive power of the controls included, this bias should be very small.

as the risk of a default-inducing income shock falls. First-time home buyers may be more or less risky because they often have less wealth, yet also often receive preferable treatment in the tax code, have acquired mortgages during a period of their lives when incomes tend to be accelerating, and may be held to stricter lending standards than repeat borrowers, all else equal. Investment properties and second houses are also risk indicators because debt on these sorts of luxury assets are the first to be defaulted upon in times of stress for the borrower, who presumably has multiple mortgages simultaneously.[25] The origination channel controls for associations between different types of mortgage originators and loan outcomes. The amortization period is covered by dummy variables for 20-, 30-, and 40-year terms (vs 15-year term).

A prepayment option control is included by way of the interest rate at origination. Combined with a time period fixed effect, the interest rate variable turns into a spread-at-origination variable, which is a prepayment risk indicator.[26] A default option variable is included as the cumulative change in the house price index between origination and the next transaction. This variable captures the Deng et al. (2000) concept of an underwater mortgage without explicitly calculating the probability.[27] In addition, the positive markup variable itself is an underwater indicator, as it serves to increase or decrease the fundamental property value relative to the mortgage balance. The seasoning of the loan is included as a vector of amortization year fixed effects to account for amortization.

[25] Chinco and Mayer (2016) show that such buyers are more prone to mis-pricing home purchases. This can be taken a step further by analyzing whether such borrowers also perform worse on loans and if the mispricing exacerbates credit losses.

[26] Agarwal et al. (2017) show that mortgage points are correlated with prepayment speeds, but less so than would be implied by the cost of the points. These points may be associated with markups as well, as a buyer who has a positive preference for a particular home may be both willing to overpay for a house and also purchase points on the mortgage. Unfortunately, a variable representing mortgage points is not available in the data. The (relative) interest rate acts as a control for a latent preference to remain in a home.

[27] Deng et al. (2000) calculate the probability a mortgage is underwater by taking the cumulative standard normal distribution of the log-difference in the current loan balance (u) and the current house value (i.e. the log-approximation of the current LTV) divided by the estimated residual standard deviation of the house price index value, or $\Phi[(\ln u_{i,t+h} - \ln V_{i,t+h})/\sqrt{\omega^2}]$. Rather than using a probabilistic measure, the origination LTV and the change in the house price index are included as separate covariates.

Time period and state fixed effects serve as important controls as well. In addition to the previously mentioned transformation of the interpretation of the interest rate variable, period fixed effects control for other macroeconomy-related conditions, including housing market liquidity, national unemployment rate changes, and other factors. State effects capture state-level variation in recourse vs not-recourse laws, elasticity of housing supply, propensity to overbuild, fraud, and other factors throughout the crisis and its aftermath. Overall, these controls jointly and sufficiently eliminate any omitted variable bias in the treatment parameter, allowing us to capture unbiased and consistent estimates of a predictive relation between markups and defaults.

4.2 Results

Results of several different default models are shown in Table 3. The first model is a multinomial logit specification, with "current" as the baseline outcome, and defaults and prepayments as competing options. Markups have a consistently positive and statistically significant effect on the probability of default. The effect of markups on prepayments is negative and also statistically significant. These estimates are also economically relevant, as going from a -20% markup to a 20% markup increases the default probability from 1.9% to 3.3% for a mortgage with average characteristics in 2005.[28]

Control variables give estimates as predicted. The default option control variable—the cumulative level of ZIP code-level house price appreciation—reduces the probability of default. The mortgage interest rate, the LTVs, longer loan terms, Broker and TPO originators, and the DTI are each associated with increased default probabilities. The credit score, the presence of multiple borrowers, status as a first-time home buyer, and intended

[28]Note that a mortgage with mean characteristics does not give the portfolio average default rate because of the convexity of the default function. Categorical variables are chosen to represent a 30-year, fixed rate, cash-out refinance mortgage in Florida in 2005, with one first-time borrower, issued through a retail channel, which terminates after three years.

status as an owner-occupier are all factors that reduce the probability of default.[29]

Model 2 expands the default indicator in three separate outcomes: foreclosure alternatives, repurchases, and foreclosure/REO sales. Estimates for the markup variable are remarkably robust except for mortgage repurchases, which is attributable to the fact there are only about 8,000 repurchases in the sample to go alongside state-by-year fixed effects and other controls.[30] Due to this robustness, repurchases notwithstanding, the omnibus default indicator in model 1 is the preferred default metric.

Models 3 through 6, shown in Table 3, consider four other outcomes of interest. The first is direct defaults. Markups are hypothesized to have a positive effect on the incidence of direct default, conditional on default. Borrowers are continually gathering information and updating their beliefs of property values. This is aided, in part, by companies such as Zillow and Redfin, which produce real-time estimates of house values. As shown in models 1 and 2, a borrower who faces a large, positive markup is more likely to default. This type of borrower is also more likely to be underwater and, upon receiving information on the true price of their previously overpriced unit, may choose to direct default. Evidence for this hypothesis exists as the parameter estimate is positive and statistically significant.

Model 4 estimates the effects of markups at origination on propensity to seek and acquire a loan modification from a lender. Because markups are a default indicator, they are also likely an indicator of modifications for the same reasons. Results show markups are highly significant predictors of loan modifications. Controls are also of anticipated sign and significance, and are the same as models 1 and 2 with some exceptions. In particular, mortgages on investment properties and second homes are substantially less likely to receive loan mod-

[29]This finding on first-time homebuyers may seem surprising. Should such borrowers be expected to perform worse because they lack experience? Not if outcomes can be influenced by markups, or the lack thereof. Given that these younger and poorer buyers have a more leveraged portfolio (see Cocco (2005)), it seems that they may more carefully select their housing investment, intentionally avoid areas with higher price volatility, and subsequently perform better.

[30]Also note the lack of robustness of other standard controls such as the change in the house price index, the DTI, and the credit score.

ifications versus owner-occupied homes. Models 5 and 6 estimate the effects of markups on delinquency using both D90 and D180 definitions. The signs and significance levels for these two models are nearly identical to models 1 and 2.[31]

Model 7 presents estimates from a simple Cox (1972) proportional hazard model to estimate reduced-form relations between a price markup and a mortgage's survival length.[32] This model is estimated for the crisis sample of originations (the 2006/2007 cohort) because these loans have mostly resolved. Results from the default hazard model are consistent with the other variables and methods considered. Markups are highly predictive of default.

This set of models demonstrates that house price markups provide a simple, robust mortgage stress indicator, conditional on standard controls. Markups at origination, calculated using a house price index AVM, are predictive of delinquencies, defaults, loan modifications, and a loan's default path.

4.3 Markups in hot and cold national housing markets

Estimates thus far are based on the pooled sample of transactions between 2001 and 2012. Another interest is the extent to which parameters vary over time when estimated on a year-by-year basis. In doing so, a link may be established between the association of markups with defaults and prepayments in hot versus cold national housing markets.

Table 4 shows the results of 12 models, each with the same specification as Table 3, model 1. The markups log-odds parameter is presented and all other covariates are estimated but

[31] More robustness tests are also available in appendix table A.1 concerning subsamples around certain LTV values, as it is possible that markups in certain ranges may reflect alternative constraints and incentives for the borrower as well as endogenous sorting, and table A.2, which considers interactions and several other subsamples, including markups that are nearly zero for the previous markup. Models reinforce the robustness of the markups sign, significance, and magnitudes.

[32] Prepayment and default hazards, from a borrower's perspective, are competing options: in each period, a borrower must decide to remain current, prepay the balance of the mortgage, or default. In a proportional hazard model, competing options can be treated as censored, facilitating a substantial reduction in the computation burden necessary to estimate unbiased and consistent reduced-form parameters, but removing causal interpretation from the resulting estimates. For a recent example of this approach, see Foote et al. (2010), who model the prepayment and default hazards for prime and subprime loans.

not reported. Default parameters are between 0.7 and 1.9, with no discernable pattern in terms of parameters over time. This is evidence that the relation between markups and defaults is relatively stable over time, with variation due to chance. It is remarkable that even as absolute default rates rise and fall, the parameter estimate stays reasonably similar.

5. Credit losses conditional on default

This section considers the intensive margin of defaults—the credit losses suffered by mortgage holders, conditional on default. As with the extensive margin, it is clear how markups could affect losses conditional on default based on the difference between perceived and actual collateral value. When there is a positive markup at origination, the collateral is less valuable than that which is indicated by the LTV at origination, and this may persist to an eventual REO sale, reducing recoveries.

The accounting of credit losses is based on accounting present in the GSE performance data. Credit losses are defined as the net proceeds from the final REO sale, including additions from gross sale proceeds and mortgage insurance payments, and subtractions from unpaid principal balance (UPB), legal fees, taxes, insurance, homeowners' association fees, and maintenance. To simplify the accounting and the notation in this section, the net loss (L) realized is expressed at the time of the REO sale ($t + 1$) as the sum of the gross sale proceeds (P), mortgage insurance claims (I), UPB (u), and an omnibus "other expenses" category (e):

$$L_{t+1} = u_{t+1} + e_{t+1} - P_{t+1} - I_{t+1} \tag{10}$$

Let us define the loss fraction of the final unpaid principal balance as $\mathcal{L}_{t+1} = L_{t+1}/u_{t+1}$ and i_{t+1} as the mortgage insurance coverage ratio at the time of default. Additionally, recall that LTV is the origination (time t) loan-to-value ratio, u_t/P_t, ΔHPI is the change in the house price index over the time period, and m_t is the markup at origination. After some manipulation, equation 10 becomes the following:

$$\mathcal{L}_{t+1} = 1 + \underbrace{\frac{e_{t+1}}{u_{t+1}}}_{\text{Expense Ratio}} - \underbrace{\frac{1 + \%\Delta P_{t+1}}{LTV_t + \Delta u_{t+1}/P_t}}_{\text{Current Equity}} - \underbrace{i_{t+1}}_{\text{MI Payment Ratio}} \tag{11}$$

Within "Current Equity," the term $(1 + \%\Delta P_{t+1})$ represents the change in the sale price between the initial and REO sale, including the markup. This term includes the markup, the change in the average market value, and variation in the REO sale price from the market average. The term $\Delta u_{t+1}/P_t$ represents the contribution of principal payments to equity. Because this is typically positive on a standard amortization loan, this term usually represents decreases in losses in the case of default. Accordingly, higher LTVs, negative house price appreciation, higher origination markups, and slower amortization increase losses. Expenses and MI payments are expressed as fractions of the initial balance, with expenses adding to credit losses and mortgage insurance reducing losses.

5.1 Empirical model

A reduced-form expression is linearized and stochastically specified for the loss fraction $\mathcal{L}_{t+1}$ below. The markup is the treatment variable, and the addition of the remaining variables is to ensure there is no omitted variable bias. In this model, as with the default model, only partial correlations are captured and these parameter estimates should not be interpreted as causal relations between the variables.

In place of the loan payoff fraction, the mortgage interest rate, r_t, is included and negatively affects amortization. In place of the house appreciation, which includes the markup and the appreciation of the particular house, three terms are included: the change in the local house price index, $\Delta \ln HPI_t$, the markup, and allow any other random variation in the REO sale price to be absorbed within the residual. In specifications where loans have mortgage insurance, the depth of coverage at the time of REO sale, i_{t+1}, is tracked. Additional controls include GSE, state, and origination month fixed effects to account for different Enterprise strategies for REO properties, recourse vs non-recourse states and other legal issues, as well as macroeconomic factors related to the housing and mortgage finance system. The expenditure share is taken as a constant fraction, and is therefore subsumed within the fixed effects. Other factors affecting the amortization period and small factors due to linearization are subsumed within the error term.

$$\mathcal{L}_{t+1} = \alpha_{it} + \beta_1 m_t + \beta_2 r_t + \beta_3 LTV_t + \beta_4 \Delta \ln HPI_{t+1} + \beta_5 i_{t+1} + e_t \tag{12}$$

A higher interest rate causes the average principal payment each period to decline in the early years of the amortization schedule, so the effect of the interest rate r_t on the loss fraction is predicted to be positive. Variation in foreclosure premiums and the time until foreclosure that varies by state is captured by the fixed effects. A term for the mortgage insurance depth of coverage is added in samples where coverage is present. While this is correlated with LTV, it typically increases in a stepwise fashion. Both conditional and unconditional on LTV, the coverage depth is predicted to be negative and between zero and one on the basis that some non-zero fraction of the losses will be made up by the coverage payment, but this payment will not exceed the total losses.

5.2 Results

Estimates of this model are shown in Table 5, calculated over samples of purchase loans originated in the 2006 through 2007 period that eventually defaulted. Model 1 covers the sample of loans without mortgage insurance, and model 2 considers loans with mortgage insurance in effect. The sample is split into two subsamples based on the incidence of mortgage insurance because it is possible that mortgage insurance protects the creditor from losses on the loan associated with markups.

In model 1, the markup coefficient is about 0.16, indicating that about 1/6th of the markup at origination is predictive of credit losses for loans without mortgage insurance. For instance, suppose a 10% markup on a \$600,000 house (\$60,000). This coefficient suggests credit losses for the holder of the mortgage are about \$10,000 higher than for an equivalent loan with no markup. Other control coefficients are consistent with comparative statics from equation 11, with LTV and the interest rate contributing positively to losses and house price appreciation contributing negatively.

Model 2 presents a similar story. The markup coefficient is a bit smaller at about 0.13, indicating that in loans with mortgage insurance, the markup is still predictive of losses, but with a weaker relationship. This suggests mortgage insurance may alleviate some of the risk posed by markups to creditors. Highlighting the role of mortgage insurance is the LTV parameter which is now negative, implying that higher LTVs are associated with more-than-compensating mortgage insurance depth with *lower* overall credit risk.

When considering both models together, the markup coefficient is remarkably robust across different samples and control variables, indicating the markup calculated using the HPI AVM is strongly associated with credit losses conditional on default. Mortgage insurance may protect against some credit losses associated with markups, but this effect is estimated to be small.

6. Mechanisms

While this paper is the first to formally estimate the effect of price markups at origination on mortgage performance, the industry has been consistently using an approach that is similar in spirit. Note that the sale price (P_0) and the appraised value (P_{app}) mechanically determine a loan's LTV at origination

$$LTV = 100 \times \frac{L}{\min\{P_{app}, P_0\}}$$

If the "true" average value of a home were correctly captured by P_0 and/or P_{app}, the correlation between positive markups and future defaults should be partially (or completely) captured by the coefficient(s) on LTV in a default model. However, both the transaction price and the appraisal may be inadequate measures of the housing unit's valuation for the following reasons. First, as it was discussed in the conceptual framework, P_0 captures conditions that are *idiosyncratic* to each transaction and that may not reflect *average* market conditions. Obviously, a lender cares about the average and not the idiosyncratic component of collateral's value. Second, the appraisal P_{app} may be subject to appraisal bias (see Nakamura, 2010; Agarwal et al., 2013; Calem et al., 2015; Ding and Nakamura, 2016; Shui and Murthy, 2018). These factors suggest a mechanism for the predictability of markups: a failure of the average appraisal to accurately estimate the value of the mortgage collateral at origination.

While other mechanisms cannot be ruled out, there is substantial evidence reinforcing this claim by performing four simple exercises. First, a new version of the markup is calculated using appraisals and show that this variable is highly right-censored at zero and does not appear to be associated with defaults. Second, competing options default models are run with both the appraisal and HPI AVM markups variables; the appraisal markup contributes almost no information and the HPI AVM maintains its magnitude, sign, and significance.

Third, similar default models are estimated using the HPI AVM markups variable but with a sample of refinance mortgages. Refinance mortgage LTVs are calculated using only appraisals because there is no bilaterally negotiated purchase price. Accordingly, appraisal bias is likely to be more apparent in refinance mortgages than purchase mortgages, whose appraisals are anchored by a contract price, with similar effects on markups. Markups for refinance mortgages are, on average, more likely to be positive than for purchase mortgages and are also highly predictive of defaults.

As a final exercise, a portfolio-level counterfactual is constructed and suggests substantial collateral-risk-based defaults may have been avoidable in the Great Recession if AVMs had been available and used in place of appraisals. In total, these findings suggest that appraisals are missing important variation in the fundamental value of a home based on their failure to predict defaults, with potentially serious consequences.

6.1 Appraisals and defaults

Appraisal markups are calculated as the difference between the sale price P_0 and the appraisal P_{app}. Because mortgage appraisals are used to estimate the collateral on a loan, an appraisal that is substantially lower than a transaction price will often cause a loan application to be rejected. If loan rejection were the only cause of a lack of mass in the right half of the distributon, it could be said that appraisers are fulfilling one of their primary objectives: to prevent a buyer from overpaying on a home, which from the lender's perspective, would reflect lower relative collateral. However, excess mass exists at zero in the second panel of Figure 4 suggesting censoring rather than truncation in the distribution, reflecting substantial appraisal bias. For purchase mortgages, 37% of all appraisals are exactly equal to the transaction price and 49% are within 0.5% of the transaction price. Previous research has shown an appraisal nearly equal to the contract price is an indicator of heightened risk (see Nakamura, 2010; Agarwal et al., 2013; Calem et al., 2015; Ding and Nakamura, 2016). Across the distribution of markups, it appears as though markups have little or no correlation with defaults on a reduced-form basis.

It is possible, however, that appraisal markups are predictive conditional on other observables. This may occur due to the mechanical interaction of the appraisal with the LTV: a negative appraisal markup results in a lower LTV, all else equal. On the other hand, as with AVM markups, endogenous sorting into different markup values may occur and drive partial correlations within the data.

As before, the relation between appraisal markups and default is analyzed using a competing-options default model. Estimates are reported for three models in Table 6, each with the same baseline specification and sample as model 1 in Table 3. These models estimate default and prepayment log-odds parameters as a function of the markup and covariates. Model 1 uses AVM markups, and is identical to the earlier model. Model 2 uses appraisal markups instead, and model 3 includes both. Because of the heavy censoring at zero, a fixed effect is added for when the appraisal is within 0.5% of the contract price to indicate a potentially censored appraisal.

In the first two models, the log-odds parameter estimate is 0.11 for appraisal markups versus 1.40 for house price AVM markups, indicating that both capture a statistically significant and potentially useful risk factor, but the AVM markups capture much more variation in default rates. The strongest markup predictor in the appraisal equation is the Appraisal=Sale Price fixed effect, which is a positive default indicator that is two orders of magnitude larger than the continuous markup variable parameter when multiplied by a typical markup (e.g. -0.1). The overall fit of the model is lower using appraisal markups, with a pseudo-R^2 of 0.718 and a log-likelihood of -659,048 versus 0.719 and -657,392 for house price index AVM markups. In the third model, when both appraisal and AVM markups are included the continuous markup parameters are mostly unchanged, and the log-likelihood is almost identical to model 1. The one exception is the Appraisal=Sale Price fixed effect, which falls from 2.08 to 0.64, implying that a substantial fraction of the explanatory power has been subsumed within the AVM markup variable. Overall, these findings confirm that appraisals contain limited information beyond the observed LTV, and that there is still collateral-related information that is predictive of defaults.

In the next two models, the same model is estimated as shown in model 1, but with rate/term and cash-out refinances. Thus far exploration of markups on refinance mortgages has been omitted because these are not home purchases. Because the LTV is defined exclusively by the appraisal, the LTV is not based on a transaction price for the property and is particularly susceptible to appraisal error. Also, because there is no transaction price for the housing unit in a refinance mortgage, the markup instead is based on the difference between the AVM and the appraisal rather than the difference between the AVM and the transaction price.

As shown in appendix table A.3, 56% of all rate/term refinances and 67% of all cash-out refinances have positive markups, as opposed to the 52% for purchase mortgages, indicating refinances are more likely to have positive markups across the sample. In 2003 and 2004, the fraction of cash-out refinances with positive markups exceeded 70%, and in no period in the sample was it less than 62%. This indicates substantial overestimation of collateral values on refinance mortgages.

Additionally, there are large gaps in the average default rates for positive versus negative markups, and the gaps are larger for refinances than for purchase mortgages. For instance, in 2007, the gap between average default rates for positive versus negative markup purchase mortgages is 1.21 percentage points (7.25% versus 6.04%, a difference of 20.0%). For rate/term refinances, the gap is 5.06 percentage points (13.15% vs. 8.09%; 62.5%) and for cash-out refinances, the gap is 2.0 percentage points (10.19% vs. 8.11%; 25.5%).

Results for the competing options models for rate/term and cash-out refinance mortgages are shown in models 4 and 5. The parameters on the markups confirm the importance of markups in mortgage defaults, as both log-odds parameters are larger than for purchase mortgages.

6.2 Stress portfolio counterfactual

The evidence suggests collateral coverage (LTV) is not adequately measured by appraisals for individual loans. To investigate how LTV mismeasurement can affect estimates of mortgage performance risk on a portfolio of loans, a simple, stylized, counterfactual exercise is run. Suppose instead the LTV is calculated using the HPI AVM by replacing the appraisal value with the estimated value from the AVM, P_{AVM}.

$$LTV^* = 100 \times \frac{L}{\min\{P_{AVM}, P_0\}}$$

The HPI AVM is unbiased by construction allowing us to correctly assess LTVs. Figure 5 shows LTVs calculated using both methods across the purchase loan sample. Several characteristics of both figures become immediately apparent. First, for the classic AVM calculation, there are spikes in the distribution at increments of 5, especially at 70, 80, 90 and 95. These are maintained in the AVM LTV calculation, but they are less pronounced. Second, there are far greater number of loans that are underwater (LTV $>$ 100) at origination when the LTV is calculated using the AVM (about 6%) versus appraisals (less than 0.1%). LTV is one of the most important determinants of default. Hence, the strong relationship between markups and mortgage performance is suspected to be, in part, due to LTV mismeasurement produced by appraisal bias.

A standard competing-options default model is estimated for the 2007 origination cohort which is identical in specification and sample to those in Table 4, but without the markup variable. Predicted portfolio-level default rates are calculated using LTV and then LTV^* while keeping all other variables constant. The predicted default rates are then compared in both models.[33] Predicted portfolio default rates are calculated as the average of the predicted loan-level default rates of the 300,000 loans in the 2007 cohort sample. The portfolio-level default rate in the data is 6.6%, as is the posterior default rate estimated using the model. When LTV^* is used in place of the LTV, the posterior default rate is 8.9%. This is remarkable in that it suggests the classic LTV calculation may have led to an understatement of

[33]Of course, this exercise has many limitations including: a) the model has been estimated with the reported LTV based on the appraisal; if the model would have been estimated with the "correct" LTV the coefficients would have been different (in particular, the coefficient on markup); and b), many of the underwater loans would not have been originated with LTVs as high as the ones indicated by the house price index AVM.

not just loan-level risk, but risk to the U.S. mortgage portfolio as a whole.

The key reason LTV miscalculation can affect economy-wide estimates of defaults is because of the convex relationship between the LTV and loan-level default. As a consequence of this convexity, a mean-preserving spread of the LTV results in a greater number of defaults.[34] Markups create variation in collateral represented by the LTV calculated using appraisals. Accordingly, markups—even if they are offsetting in magnitude across the economy—are associated with portfolio-level default probabilities.

7. Concluding discussion

House price markups—calculated as the difference between a transaction price and a predicted price—are associated with mortgage delinquencies, defaults, prepayments, losses conditional on default, and loan modifications. Moreover, these associations are economically relevant—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. Because appraisals are biased towards the contract price, and the LTVs calculated using these appraisals give measures of expected defaults, appraisal bias may be an important factor of credit risk mismeasurement. The analysis has the dual strengths of being based on a set of modeling approaches rooted firmly in the literature and being estimated with a near-universe of house sales from a large pool of mortgages.

Markups are related to loan performance for fundamental reasons related to the microstructure of the housing and mortgage markets. As shown in the conceptual framework, markups do not *cause* default. Rather, the price paid for an asset is chosen simultaneously with the expected probability of default because housing is highly leveraged relative to

[34] Suppose two loans have 80 LTV ratios at origination. Under a +15% markup, both have a true LTV of 95 and neither borrower is underwater. Instead, suppose one loan has an origination LTV of 70 and the other has an LTV of 90. The mean LTV is the same, but with a 15% markup, one borrower is underwater (and therefore more likely to default) and the other is not.

expected house price appreciation, and the house itself serves as the collateral on the loan.

Although the estimates are specific to the market for residential real estate, a similar mechanism emerges in many settings: any market with both large spreads and high leverage, where the collateral on the loan is the purchased asset, likely exhibits a similar type of relation between markups and loan performance. Of particular similarity is the market for auto loan debt, but this relation could also extend to collectibles or insurance pools.

References

Adelino, M., Gerardi, K., Hartman-Glaser, B., 2019. Are lemons sold first? dynamic signaling in the mortgage market. Journal of Financial Economics 132, 1–25.

Agarwal, S., Ben-David, I., Yao, V., 2013. Collateral Valuation and Borrower Financial Constraints: Evidence from the Residential Real Estate Market. Working Paper 19606. National Bureau of Economic Research.

Agarwal, S., Ben-David, I., Yao, V., 2017. Systematic mistakes in the mortgage market and lack of financial sophistication. Journal of Financial Economics 123, 42–58.

Anenberg, E., 2016. Information frictions and housing market dynamics. International Economic Review 57, 1449–1479.

Bailey, M., Davila, E., Kuchler, T., Stroebel, J., 2017. House price beliefs and mortgage leverage choice. National Bureau of Economic Research Working Paper Series .

Ben-David, I., 2011. Financial constraints and inflated home prices during the real estate boom. American Economic Journal: Applied Economics 3, 55–87.

Bian, X., Lin, Z., Liu, Y., 2018. House price, loan-to-value ratio and credit risk. Journal of Banking & Finance , 1–40 (forthcoming).

Bogin, A.N., Doerner, W.M., Larson, W.D., 2019a. Local house price dynamics: New indices and stylized facts. Real Estate Economics 47, 365–398.

Bogin, A.N., Doerner, W.M., Larson, W.D., 2019b. Missing the mark: Mortgage valuation accuracy and credit modeling. Financial Analysts Journal 75, 32–47.

Calem, P.S., Lambie-Hanson, L., Nakamura, L.I., 2015. Information losses in home purchase appraisals. Working Paper 15-11. Federal Reserve Bank of Philadelphia.

Campbell, J.Y., Giglio, S., Pathak, P., 2011. Forced sales and house prices. American Economic Review 101, 2108–2131.

Campbell, T.S., Dietrich, J.K., 1983. The determinants of default on insured conventional residential mortgage loans. The Journal of Finance 38, 1569–1581.

Carrillo, P., 2013. Testing for fraud in the residential mortgage market: How much did early-payment-defaults overpay for housing? The Journal of Real Estate Finance and Economics 47, 36–64.

Carrillo, P.E., 2012. An empirical stationary equilibrium search model of the housing market. International Economic Review 53, 203–234.

Case, K.E., Shiller, R.J., 1989. The efficiency of the market for single-family homes. American Economic Review 79, 125–137.

Chinco, A., Mayer, C., 2016. Misinformed speculators and mispricing in the housing market. Review of Financial Studies 29, 486–522.

Cocco, J.F., 2005. Portfolio choice in the presence of housing. Review of Financial Studies 18, 535–567.

Cox, D., 1972. Regression models and life-tables. Journal of the Royal Statistical Society. Series B (Methodological) 34, 187–220.

Davis, D.R., Weinstein, D.E., 2002. Bones, bombs, and break points: The geography of economic activity. American Economic Review 92, 1269–1289.

Deng, Y., Quigley, J.M., Van Order, R., 2000. Mortgage terminations, heterogeneity and the exercise of mortgage options. Econometrica 68, 275–307.

Ding, L., Nakamura, L., 2016. The impact of the home valuation code of conduct on appraisal and mortgage outcomes. Real Estate Economics 44, 658–690.

Foote, C., Gerardi, K., Goette, L., Willen, P., 2010. Reducing foreclosures: No easy answers. NBER Macroeconomics Annual 24, 89–138.

Foote, C.L., Gerardi, K., Willen, P.S., 2008. Negative equity and foreclosure: Theory and evidence. Journal of Urban Economics 64, 234–245.

Genesove, D., Mayer, C., 2001. Loss aversion and seller behavior: Evidence from the housing market. The quarterly journal of economics 116, 1233–1260.

Ghent, A.C., Kudlyak, M., 2011. Recourse and residential mortgage default: Evidence from US states. Review of Financial Studies 24, 3139–3186.

Glaeser, E.L., Nathanson, C.G., 2017. An extrapolative model of house price dynamics. Journal of Financial Economics 126, 147–170.

Han, L., Strange, W.C., 2015. Chapter 13 - The microstructure of housing markets: Search, bargaining, and brokerage, in: Gilles Duranton, J.V.H., Strange, W.C. (Eds.), Handbook of Regional and Urban Economics. Elsevier. volume 5 of *Handbook of Regional and Urban Economics*, pp. 813–886.

Hatchondo, J.C., Martinez, L., Sanchez, J.M., 2015. Mortgage defaults. Journal of Monetary Economics 76, 173–190.

Óscar Jordà, Schularick, M., Taylor, A.M., 2015. Leveraged bubbles. Journal of Monetary Economics 76, S1–S20.

Mayer, C., Pence, K., Sherlund, S.M., 2009. The rise in mortgage defaults. Journal of Economic Perspectives 23, 27–50.

Merlo, A., Ortalo-Magne, F., Rust, J., 2015. The home selling problem: Theory and evidence. International Economic Review 56, 457–484.

Molloy, R., Nielsen, E., 2018. How can we measure the value of a home? Comparing model-based estimates with owner-occupant estimates. FEDS Notes, Board of Governors of the Federal Reserve System .

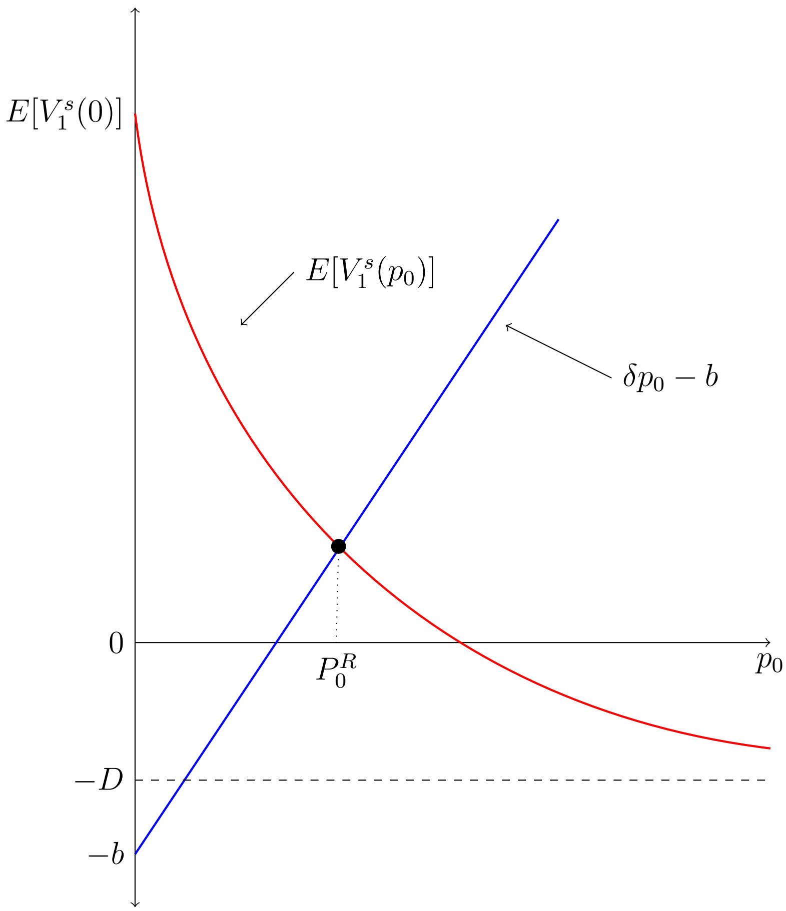
Mortensen, D.T., Pissarides, C.A., 1999. Chapter 39 New developments in models of search in the labor market, Elsevier. volume 3 of *Handbook of Labor Economics*, pp. 2567–2627.

Nakamura, L.I., 2010. How much is that home really worth? Appraisal bias and house-price uncertainty. Business Review , 11–22.

Piskorski, T., Seru, A., Vig, V., 2010. Securitization and distressed loan renegotiation: Evidence from the subprime mortgage crisis. Journal of Financial Economics 97, 369–397.

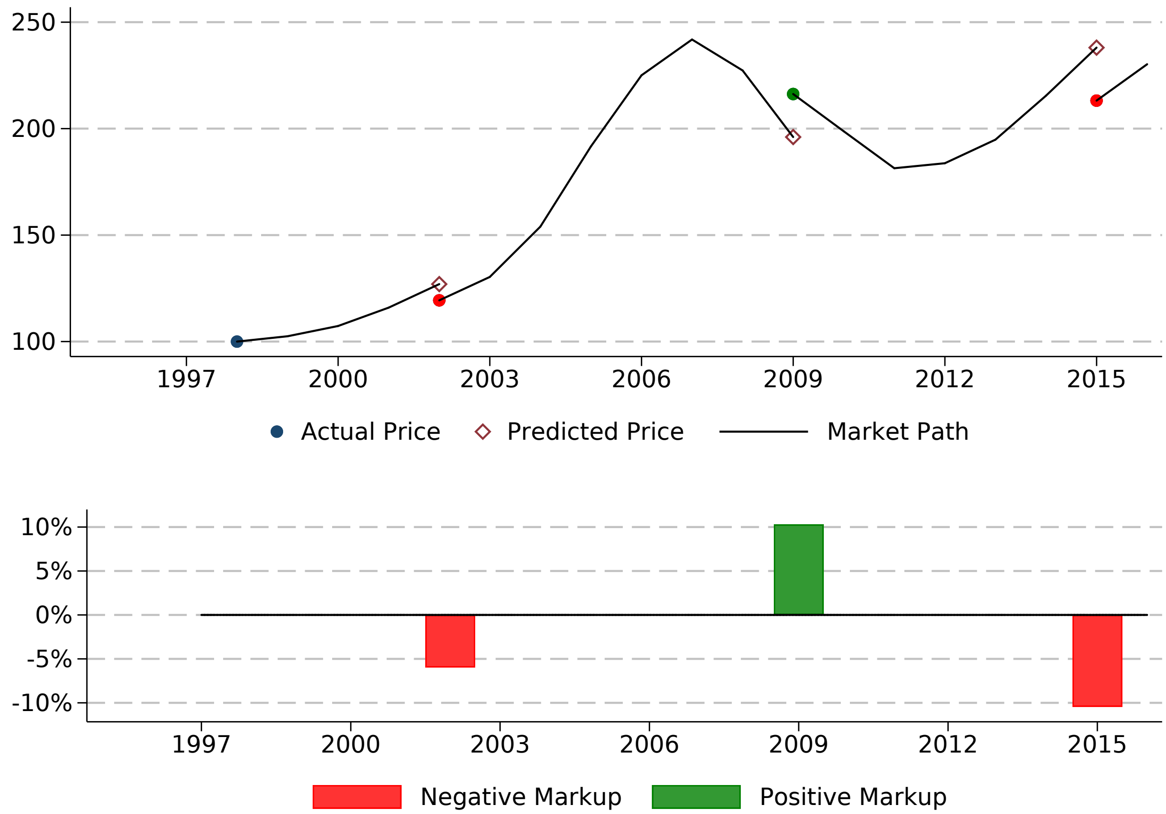
Shui, J., Murthy, S., 2018. Are Appraisal Management Companies Value-Adding? Stylized Facts from AMC and Non-AMC Appraisals. Working Paper 18-01. Federal Housing Finance Agency.

Fig. 1. Home buyer's optimal reservation price



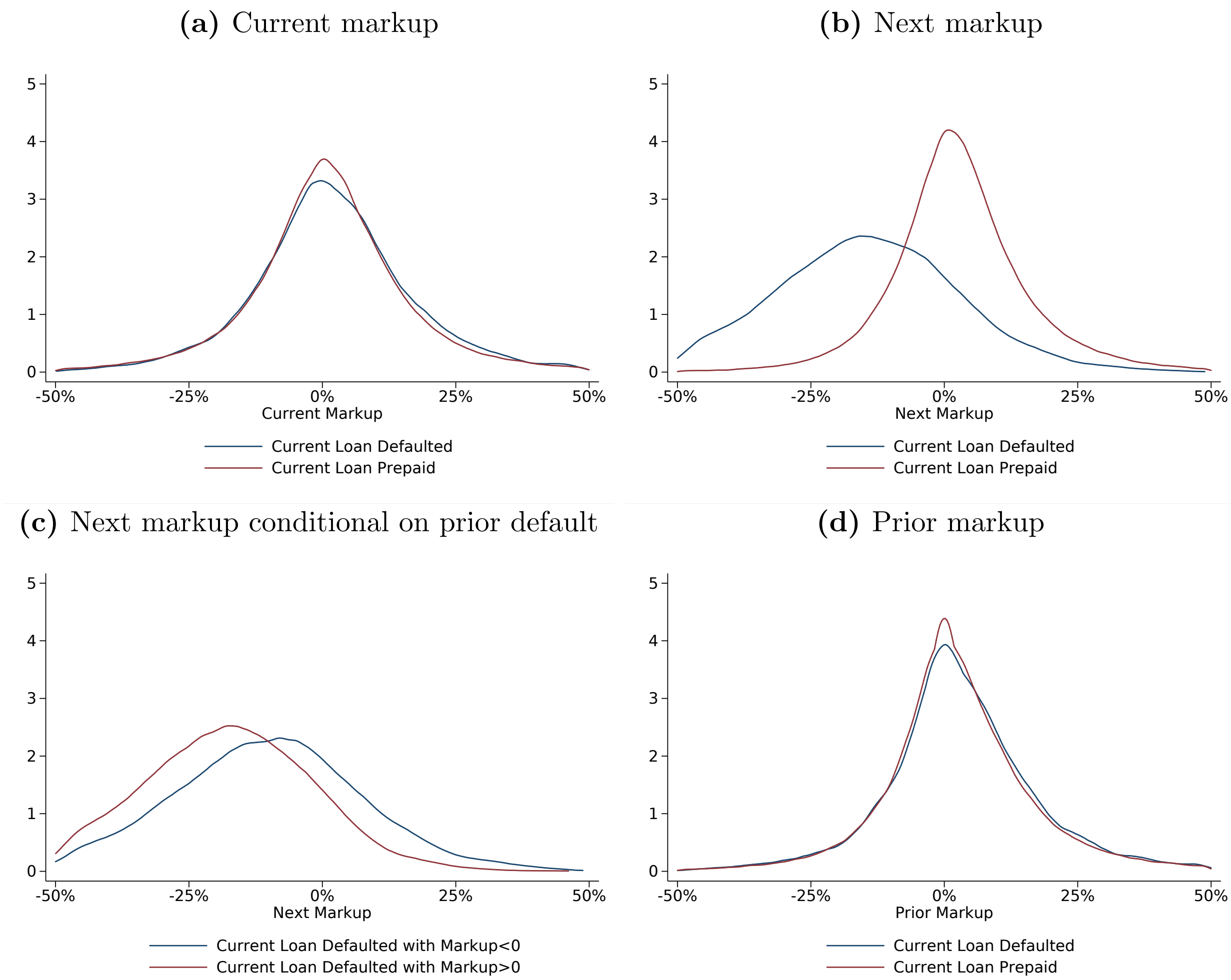
Notes: This figure illustrates the solution to the home buyer's reservation problem defined in equation 6. The buyer would buy a house if, and only if, the transaction price is below P_0^R. The left-hand side of equation 6 is non-increasing, convex, and converges to $-D$ as p_0 approaches infinity. The right-hand side is an increasing linear function of p_0. Hence, a unique solution exists. Any shift of the distribution F_1 to the right (that is, an increase in expected future appreciation rates) will increase current buyers' reservation values.

Fig. 2. An illustration of the calculation of a markup



Notes: This figure is calculated using GSEs' data on mortgages and county recorder data on transactions from an actual sequence of four transactions of a single housing unit in Washington, D.C.

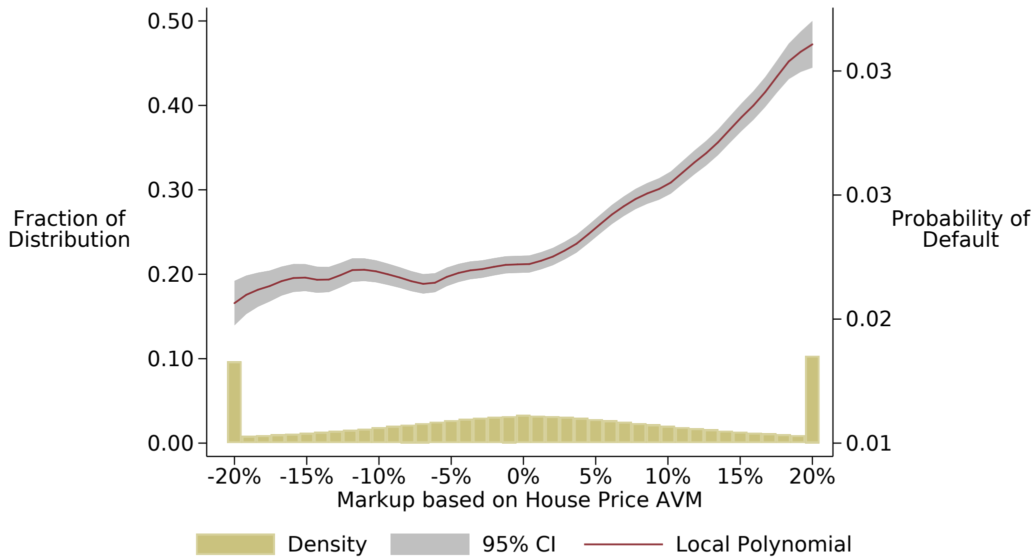
Fig. 3. Kernel densities of pricing markups



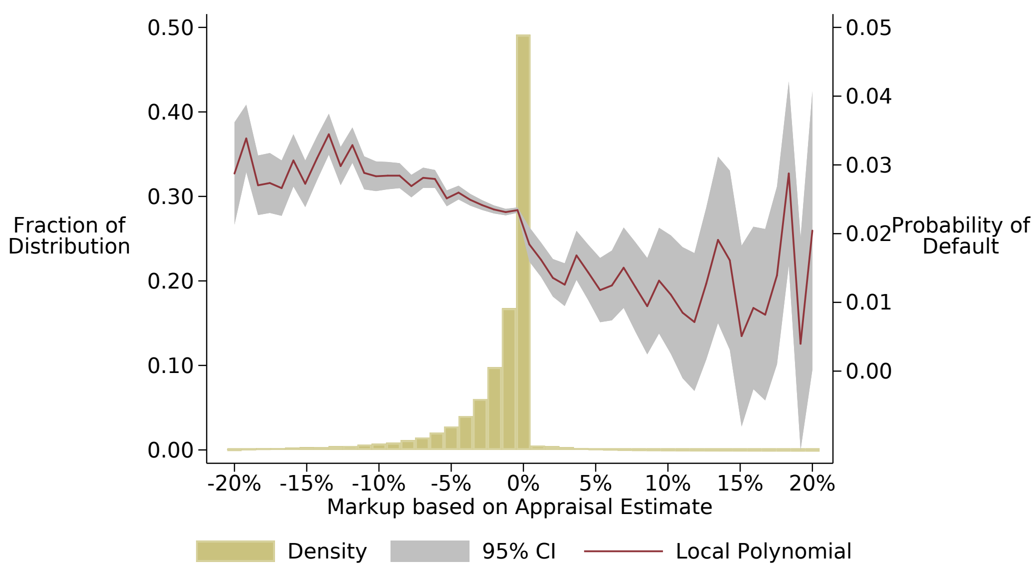
Notes: The sample includes GSE purchase mortgages originated in 2001 through 2012 with both an earlier $(t-1)$ and later $(t+1)$ calculated markup, necessitating a sequence of four transactions.

Fig. 4. Distributions of markups and defaults for house price AVMs and appraisals

(a) Based on house price AVM



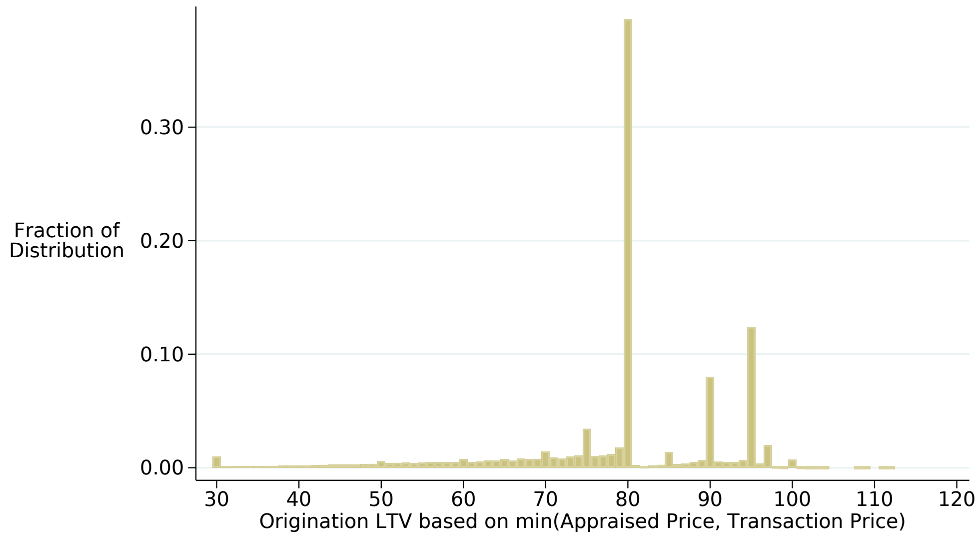
(b) Based on appraisal estimate



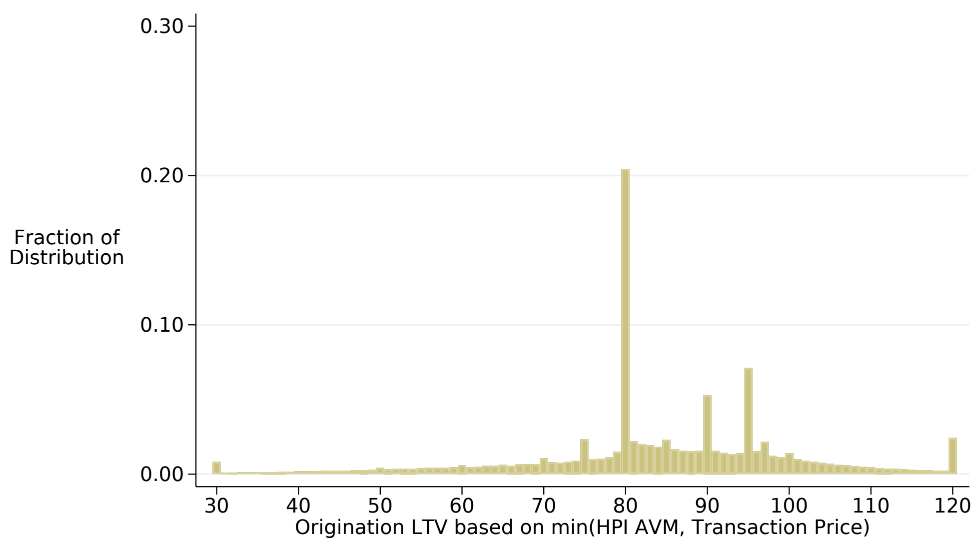
Notes: The sample includes loans originated in 2001 through 2012, with a calculated markup, subject to filters noted in the text. Histogram bins at the edges of the respective figures censor values at the extremes for visual reasons, but the default curves are not based on censored values.

Fig. 5. LTVs calculated using appraisals versus a house price AVM

(a) Appraisals



(b) House price AVM



Notes: The sample includes loans originated in 2001 through 2012, with a calculated markup, subject to filters noted in the text. The groupings at 30 and 120 include values less than 30 or greater than 120, respectively.

Table 1

Purchase loan counts and outcomes

Year	Loans	Current	Prepay	Default	Direct Default	Modification	Positive Markup	Neg. markup Default rate	Pos. markup Default rate
2001	469,580	1.5%	97.4%	1.0%	0.3%	0.5%	52.6%	0.9%	1.1%
2002	429,767	3.0%	95.6%	1.3%	0.5%	0.8%	54.9%	1.2%	1.4%
2003	446,183	7.8%	90.0%	2.2%	1.1%	1.6%	62.5%	2.2%	2.3%
2004	321,470	8.6%	88.2%	3.2%	1.8%	2.2%	60.1%	2.9%	3.3%
2005	350,626	9.9%	85.0%	5.1%	3.2%	3.0%	56.7%	4.1%	5.9%
2006	302,575	7.2%	87.0%	5.8%	3.5%	3.4%	52.4%	5.2%	6.3%
2007	300,213	8.4%	84.9%	6.6%	3.5%	4.3%	47.6%	6.0%	7.2%
2008	316,902	8.3%	87.8%	4.0%	1.8%	3.5%	39.2%	3.3%	5.0%
2009	322,812	20.1%	79.2%	0.7%	0.3%	0.5%	41.0%	0.6%	0.8%
2010	290,433	29.6%	70.1%	0.3%	0.1%	0.4%	46.3%	0.2%	0.4%
2011	274,074	37.8%	62.0%	0.2%	0.1%	0.3%	45.2%	0.2%	0.2%
2012	363,973	67.8%	32.1%	0.1%	$< 0.1\%$	0.2%	51.7%	0.1%	0.1%
Total (all)	4,188,608	16.5%	81.0%	2.4%	1.3%	1.6%	51.5%	2.1%	2.7%
Total (2006-2007)	602,788	7.8%	86.0%	6.2%	3.5%	3.9%	50.0%	5.6%	6.8%

Notes: The sample includes all purchase loans with a calculated markup subject to filters noted in the text as of March 2018. A direct default is defined following Foote et al. (2010): 1) the borrower must be current for three consecutive months, then register a 90 day delinquency three months later; 2) The borrower must never have been seriously delinquent (90 days) before triggering (1); and 3), the borrower must never become current again before defaulting.

Table 2

Same-unit markup dynamics

	Dependent variable: Next markup (Markup[t+1])			
Sample	All	All	Positive Markup	Negative Markup
Model:	[1]	[2]	[3]	[4]
Markup[t]	-0.297***	-0.236***	-0.0868***	-0.372***
	[0.00689]	[0.00755]	[0.00546]	[0.00846]
h[t,t+1]		-0.0172***	-0.0184***	-0.0202***
		[0.000843]	[0.000837]	[0.00177]
Markup[t] x h[t,t+1]		-0.00211***	-0.00211***	-0.00222***
		[0.000164]	[0.000182]	[0.000220]
Markup[t-1]	-0.121***	-0.121***	-0.101***	-0.131***
	[0.00349]	[0.00347]	[0.00297]	[0.00462]
Default[t]	-0.158***	-0.154***	-0.157***	-0.152***
	[0.00342]	[0.00336]	[0.00310]	[0.00485]
GSE Cash-Out Refinance[t-1]	-0.00358***	-0.00399***	-0.00597***	-0.00469***
	[0.000633]	[0.000633]	[0.000901]	[0.000475]
GSE Rate/Term Refinance[t-1]	-0.00371***	-0.00413***	-0.00280***	-0.00848***
	[0.000483]	[0.000484]	[0.000640]	[0.000467]
Cash Purchase[t-1]	0.00765***	0.00788***	0.00260**	0.00297
	[0.00157]	[0.00158]	[0.00117]	[0.00227]
non-GSE Purchase Mortgage[t-1]	0.0208***	0.0214***	0.0124***	0.0300***
	[0.000884]	[0.000863]	[0.00108]	[0.00120]
GSE Cash-Out Refinance[t+1]	0.0468***	0.0459***	0.0397***	0.0494***
	[0.00154]	[0.00161]	[0.00181]	[0.00156]
GSE Rate/Term Refinance[t+1]	-0.00941***	-0.0100***	-0.00769***	-0.0120***
	[0.00144]	[0.00147]	[0.00142]	[0.00164]
Cash Purchase[t+1]	-0.00839***	-0.00987***	-0.00780***	-0.0134***
	[0.00117]	[0.00117]	[0.00123]	[0.00146]
non-GSE Purchase Mortgage[t+1]	-0.00635***	-0.00476***	-0.00591***	-0.00264*
	[0.00114]	[0.00115]	[0.00131]	[0.00144]
Constant	0.0366***	0.0457***	0.0277***	0.0368***
	[0.00105]	[0.00130]	[0.00132]	[0.00148]
Observations	1,736,845	1,736,845	887,247	847,558
R-squared	0.219	0.224	0.136	0.222
	E[Next Markup | t+1, Markup[t]=20%, Markup[t-1]=0%]			
1 year (no default)	-2%	-2%	-1%	-6%
5 years (no default)	-2%	-9%	-8%	-14%
1 year (default)	-18%	-17%	-17%	-21%
5 years (default)	-18%	-24%	-24%	-29%

Notes: Robust standard errors in brackets and clustered by State × Year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Fixed effects by State × Year are absorbed prior to estimation, with standard errors reflecting true degrees of freedom. The sample includes GSE purchase mortgages originated in 2001 through 2012 with both an earlier $(t-1)$ and later $(t+1)$ markup, necessitating at least 4 sequential purchase or refinance transactions on the same housing unit.

Table 3

Markups and loan outcomes, part 1

Estimator:	M. Logit (vs Current)		Multinomial Logit (vs Current)			
Sample:	All Loans		All Loans			
Outcome:			Default Type			
	Default	Prepay	Forec. Alt.	Repurchase	REO	Prepay
Model	[1]		[2]			
Markup	1.404***	0.0120	0.997***	0.0862	1.283***	0.0258
Δ House Price Index	-3.866***	0.649***	-5.302***	-0.759	-5.310***	-1.248***
Mortgage interest rate	0.630***	0.153***	0.289***	0.169	0.455***	0.0122
Combined LTV	0.0478***	0.0110***	0.0353***	-0.00578	0.0258***	0.00796***
LTV	1.630***	-0.947***	-0.891***	-0.218	1.583***	-0.809***
LTV = 80	-0.0899***	0.0100	-0.0398	-0.148***	-0.276***	0.0500***
DTI	0.0144***	-0.00113***	0.00682***	-0.00317	0.00848***	-0.00207***
Credit Score	-0.00907***	0.00221***	-0.00306***	0.000762	-0.00925***	0.00243***
Multiple Borrowers	-0.590***	0.170***	-0.236***	-0.213***	-0.650***	0.156***
First-time homebuyer	-0.140***	-0.0782***	-0.142***	0.00581	-0.0780***	-0.0546***
Channel (vs Retail)						
Broker	0.0624**	-0.109***	-0.0941***	0.0182	0.0995***	-0.0251**
Correspondent	-0.0862***	-0.114***	-0.132***	-0.185***	-0.0801***	-0.0381***
Third-Party Originator	0.573***	0.434***	0.367***	-0.00182	0.368***	0.196***
Occupancy Type (vs Owner)						
Investment Property	0.230***	-0.162***	-0.167***	-0.127	0.447***	-0.0498***
Second Home	0.201***	-0.0277**	-0.128***	-0.185***	0.251***	-0.0490***
Amortization Period (vs 15yr)						
20 Years	-0.00663	-0.0220	-0.446***	-0.132	-0.335***	0.0331*
30 Years	0.635***	0.0640***	0.293***	0.487***	0.196***	0.188***
40 Years	0.637***	-2.402***	0.899***	3.409***	1.983***	-0.945***
Observations	4,188,608		4,188,608			
Pseudo R-Squared	0.719		0.428			

Notes: Values presented are the marginal log-odds estimates. Robust standard errors are clustered by State × Year, but are intentionally omitted for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample includes purchase loans originated in 2001 through 2012, with a calculated markup, subject to filters noted in the text. Cohort year, state, seasoning, and GSE fixed effects are included in all specifications, but omitted from the table.

Table 3

Markups and loan outcomes, part 2

Estimator:	Logit	Logit	Logit	Logit	Cox
Sample:	Defaults	All	All	All	2006-2007
	Direct	Ever	Ever	Ever	
Outcome:	Default	Modified	D90	D180	Default
Model	[3]	[4]	[5]	[6]	[7]
Markup	0.144***	0.393***	0.753***	0.888***	0.766***
%Δ House Price Index	-0.863***	-0.616***	-2.420***	-2.896***	-3.426***
Mortgage interest rate	-0.238***	0.606***	0.583***	0.553***	0.575***
Combined LTV	0.0129***	0.0208***	0.0244***	0.0276***	0.0372***
LTV	-0.785***	1.429***	1.051***	1.164***	1.088***
LTV = 80	0.0143	-0.0751***	-0.132***	-0.109***	-0.0236*
DTI	-0.00389***	0.0282***	0.0182***	0.0169***	0.0120***
Credit Score	0.00630***	-0.0118***	-0.0129***	-0.0119***	-0.00671***
Multiple Borrowers	0.142***	-0.235***	-0.662***	-0.674***	-0.445***
First-time homebuyer	-0.0472***	-0.118***	-0.0886***	-0.0893***	-0.178***
Channel (vs Retail)					
Broker	-0.0699**	0.337***	0.216***	0.229***	0.208***
Correspondent	-0.0306	0.275***	0.0814***	0.0778***	0.111***
Not Specified	-0.0691***	0.170***	0.174***	0.178***	0.0617***
Occupancy Type (vs Owner)					
Investment Property	0.226***	-1.724***	-0.147***	-0.0645	-0.0625***
Second Home	0.113***	-0.902***	-0.0404*	-0.00408	0.0302
Amortization Period (vs 15yr)					
20 Years	-0.0867	0.147	0.0542	-0.00404	0.237
30 Years	0.178	0.842***	0.538***	0.644***	0.700***
40 Years	-0.531***	9.387***	6.584***	4.309***	0.0395
Observations	100,372	4,188,608	4,188,608	4,188,608	602,788
Pseudo R-Squared	0.0916	0.541	0.322	0.312	0.0586

Notes: Values presented are the marginal log-odds estimates for the logit models, and partial effects for the Cox hazard model. Robust standard errors are clustered by State $\times$ Year, but are intentionally omitted for brevity. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample includes purchase loans originated in 2001 through 2012, with a calculated markup, subject to filters noted in the text. Cohort year, state, seasoning, and GSE fixed effects are included in all specifications, but omitted from the table.

Table 4

Markups and loan outcomes by origination cohort

Estimator: Multinomial Logit (vs Current)
Sample: Column header

Year	2001	2002	2003	2004	2005	2006
Markup	1.453***	1.680***	1.342***	1.030***	1.242***	0.826***
	[0.183]	[0.206]	[0.166]	[0.152]	[0.138]	[0.114]
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	469,580	429,767	446,183	321,470	350,626	302,575
Pseudo R-Squared	0.596	0.666	0.686	0.655	0.624	0.591
Year	2007	2008	2009	2010	2011	2012
Markup	0.975***	1.789***	1.867***	1.483***	1.394***	0.702***
	[0.100]	[0.151]	[0.128]	[0.187]	[0.106]	[0.265]
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	300,213	316,902	322,812	290,433	274,074	363,973
Pseudo R-Squared	0.597	0.628	0.778	0.807	0.661	0.759

Notes: Robust standard errors in brackets, clustered by State $\times$ Year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample includes purchase loans originated in the relevant column year, with a calculated markup, subject to filters noted in the text. The models include all covariates in Table 3 but each except the markup coefficient is omitted from the table text for brevity. The prepay equation is also omitted for brevity.

Table 5

Losses, markups, and mortgage insurance

Dependent variable: Loss fraction of final UPB

Sample:	No MI coverage	MI coverage
Model:	[1]	[2]
Markup	0.162***	0.133***
	[0.0125]	[0.0133]
LTV	0.535***	-0.185**
	[0.0360]	[0.0725]
%Δ House Price Index	-0.418***	-0.403***
	[0.0179]	[0.0249]
Mortgage Insurance Coverage Depth		-0.441***
		[0.0501]
Mortgage Interest Rate	0.104***	0.0710***
	[0.00603]	[0.00503]
Constant	-0.697***	0.085
	[0.0464]	[0.0608]
Observations	35,537	38,650
R-squared	0.272	0.226

Notes: Robust standard errors in brackets, clustered by State × Year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample includes purchase loans originated in 2006 or 2007, with a calculated markup, subject to filters noted in the text. The loss fraction is calculated as the proceeds net of expenses from property sale divided by the final unpaid principal balance on the mortgage. The MI coverage depth is defined as the percent of the UPB covered by mortgage insurance. GSE fixed effects are included in all specifications but omitted from the table.

Table 6

Markups and mortgage defaults, appraisals, and house price AVMs

Estimator:	Multinomial Logit (vs Current)				
Sample:	Purchase	Purchase	Purchase	Rate/Term Refinance	Cash-out Refinance
Markup variable(s)	HPI AVM	Appraisal	Both	HPI AVM	HPI AVM
Model	[1]	[2]	[3]	[4]	[5]
Markup (HPI AVM)	1.404***		1.345***	2.098***	1.581***
	[0.0745]		[0.0774]	[0.0931]	[0.0673]
Appraisal = Sale Price		2.079***	0.648***		
		[0.196]	[0.209]		
Markup (Appraisal)		0.112***	0.115***		
		[0.0140]	[0.0138]		
Other Covariates	Yes	Yes	Yes	Yes	Yes
Observations	4,188,608	4,188,608	4,188,608	5,928,099	5,540,831
Pseudo R-Squared	.719	.718	.719	0.751	0.693
Log-Likelihood	-657392.4	-659048.7	-657215.7	-841608	-1008597

Notes: Values presented are the marginal log-odds estimates. Robust standard errors in brackets, clustered by State × Year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The sample includes loans originated in 2001 through 2012, with a calculated markup, subject to filters noted in the text. The models include all covariates in Table 3 but each except the markup coefficients are omitted from the table text for brevity. The Prepay equation is also omitted. Model [1] is the same as in Table 3, model [1].

Table A.1

Markups and loan outcomes, robustness 1

Sample	Baseline	*Appraisal* = *Price*	*Appraisal* > *Price*	
Markup	1.404***	1.486***	1.224***	
	[0.0745]	[0.0943]	[0.0707]	
Observations	4,188,608	2,057,499	2,037,468	
Pseudo R-Squared	0.719	0.715	0.720	
Fraction positive markup	51.5%	57.1%	45.1%	
Sample	$LTV = 80$	$LTV = 90$	$LTV = 95$	$LTV = 97$
Markup	1.445***	1.845***	1.215***	1.024***
	[0.0936]	[0.109]	[0.0756]	[0.182]
Observations	1,655,548	335,528	519,555	83,779
Pseudo R-Squared	0.730	0.679	0.650	0.645
Fraction positive markup	51.2%	48.9%	51.7%	54.5%
Sample	$LTV < 60$	$LTV \geq 60$ & $LTV < 80$	$LTV \geq 80$ & $LTV < 95$	$LTV \geq 95$
Markup	1.043***	1.458***	1.424***	0.930***
	[0.234]	[0.0970]	[0.0718]	[0.111]
Observations	414,556	2,521,873	1,117,782	134,397
Pseudo R-Squared	0.804	0.741	0.668	0.590
Fraction positive markup	55.2%	51.1%	50.7%	52.2%

Notes: Robust standard errors in brackets, clustered by State × Year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Samples where conditions involve strict equality (i.e. $LTV = 80$) include some tolerance and represent values that are within 0.5% of the target value. The sample includes purchase loans originated in the relevant column year, with a calculated markup, subject to filters noted in the text. The models include all covariates in Table 3 but each except the markup coefficient is omitted from the table text for brevity.

Table A.2

Markups and loan outcomes, robustness 2

Description	Baseline	HPI Interaction	> 2 years Between trans.	
Markup	1.404***	1.124***	1.301***	
	[0.0745]	[0.0466]	[0.0699]	
Markup $\times \% \Delta HPI$		-0.563		
		[0.433]		
Observations	4,188,608	4,188,608	3,165,111	
Pseudo R-Squared	0.719	0.719	0.702	
Sample	**Prior Markup Exists**	**Prior Trans. Purchase**	**Prior Markup Small $\|m\| < 5\%$**	**Prior Trans. Purchase and Prior Markup Small $\|m\| < 5\%$**
Markup	1.505***	1.415***	1.576***	1.847***
	[0.0917]	[0.0764]	[0.0831]	[0.131]
Observations	2,625,140	1,147,514	1,586,597	344,233
Pseudo R-Squared	0.73	0.719	0.735	0.734

Notes: Robust standard errors in brackets, clustered by State $\times$ Year. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The models include all covariates in Table 3 but each except the markup coefficient is omitted from the table text for brevity. The "Prior Markup Sample" is the sample of all loans with a previously calculated markup. The "> 2 Years Between Transactions" sample includes all loans with a prior holding period greater than 2 years. The "Prior Markup Small" sample includes all loans with a prior markup that is less than abs(5%).

Table A.3

Loan outcomes by purpose and markup

	Share				Positive Markup			
Year	Purchase	Rate/Term	Cash-out		Purchase	Rate/Term	Cash-out	All
2001	31%	39%	31%		53%	51%	66%	56%
2002	26%	40%	34%		55%	53%	67%	58%
2003	18%	50%	33%		62%	49%	71%	58%
2004	35%	30%	35%		60%	45%	70%	59%
2005	31%	20%	49%		57%	47%	67%	60%
2006	38%	14%	48%		52%	57%	68%	60%
2007	35%	18%	47%		48%	62%	67%	59%
2008	33%	27%	40%		39%	65%	67%	57%
2009	18%	46%	37%		41%	63%	62%	59%
2010	26%	40%	34%		46%	63%	64%	59%
2011	30%	41%	29%		45%	63%	65%	58%
2012	25%	51%	24%		52%	63%	65%	61%
Total (All)	27%	38%	35%		52%	56%	67%	59%
Total (2006-2007)	37%	16%	47%		50%	60%	68%	60%
	Negative Markup Default Rate				Positive Markup Default Rate			
Year	Purchase	Rate/Term	Cash-out	All	Purchase	Rate/Term	Cash-out	All
2001	0.93%	0.79%	0.63%	0.80%	1.14%	1.61%	1.18%	1.32%
2002	1.24%	0.88%	0.69%	0.93%	1.43%	1.67%	1.33%	1.48%
2003	2.17%	1.20%	1.18%	1.35%	2.26%	2.05%	1.86%	2.02%
2004	2.90%	2.56%	2.54%	2.67%	3.33%	4.36%	3.91%	3.81%
2005	4.07%	3.91%	4.39%	4.16%	5.90%	6.76%	6.29%	6.25%
2006	5.18%	6.72%	7.25%	6.21%	6.32%	10.57%	9.31%	8.47%
2007	6.04%	8.09%	8.11%	7.17%	7.25%	13.15%	10.18%	9.90%
2008	3.34%	3.02%	3.81%	3.41%	4.96%	6.09%	6.21%	5.89%
2009	0.56%	0.44%	0.64%	0.54%	0.78%	0.88%	1.03%	0.92%
2010	0.24%	0.21%	0.42%	0.28%	0.35%	0.37%	0.53%	0.43%
2011	0.15%	0.15%	0.25%	0.17%	0.20%	0.23%	0.32%	0.25%
2012	0.11%	0.07%	0.10%	0.09%	0.10%	0.10%	0.15%	0.11%
Total (All)	2.13%	1.31%	2.29%	1.85%	2.74%	2.16%	3.37%	2.78%
Total (2006-2007)	5.63%	7.47%	7.70%	6.72%	6.76%	12.12%	9.76%	9.21%

Notes: The sample includes all loans with a calculated markup subject to filters noted in the text, as of March 2018.