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Do Homeowners Mark to Market?

A Comparison of Self-reported and Market-based Home Value Estimates During the Housing Boom and Bust

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Do Homeowners Mark to Market? A Comparison of Self-reported and Estimated Market Home Values During the Housing Boom and Bust

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This paper examines homeowners' self-reported values in the American Housing Survey and the Health and Retirement Study from the start of the recent housing price run-ups through recent price declines. We compare zip code level market-based estimates of housing prices to those derived from homeowners' self-reported values. We show that there are systematic differences which vary with market conditions and the amount of equity owners hold in their homes. When prices have fallen, homeowners systematically state that their homes are worth more than market estimates suggest, and homeowners with little or no equity in their homes state values above the market estimates to a greater degree. Over time, homeowners appear to adjust their assessments to be more in line with past market trends, but only slowly. Our results suggest that underwater borrowers are likely to understate their losses and either may not be aware that their mortgages are underwater or underestimate the degree to which they are.

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1. Introduction

It has been widely reported that the value of homes in the United States fell by almost one-third between the middle of 2006 and the middle of 2009. Estimates suggest that the value of homeowners' equity in their homes fell by more than 50% over this period (Brown et al., 2010). Faced with such massive reductions in wealth, households may change their consumption, investment and labor supply decisions, and they may be more likely to walk away from their mortgages, as they find themselves owing more than their house is worth. However, behavioral responses to wealth changes and negative home equity positions, including strategic default, are likely triggered by a homeowner's individual perception of changes in her property value rather than by any externally estimated change in its market price. If homeowners overstate the value of their homes in declining markets, then we should observe less dramatic shifts in behavior than expected.

This paper examines homeowners' assessment of their home values and draws out implications for expected changes in behavior. We discuss possible mechanisms and behavioral biases that may drive differences between self-reports and market values, and our empirical analysis aims to demonstrate a reduced form effect. We build on the existing literature in several respects. First, we examine and compare homeowners' self-reported values in two national, longitudinal surveys: the American Housing Survey and the Health and Retirement Study. Second, we follow households from the start of the recent housing price run-ups through recent price declines and explore how the discrepancy between owners' reported values and market estimates varies across the market cycle and with levels of home equity. Third, in contrast to prior studies, we use restricted, geocoded versions of these datasets, which identify the neighborhood in which each household resides, allowing us to compare homeowners' self-reported values to the estimated market value of their homes, formed by inflating the reported original purchase price using a zip code level housing price index.

We show that there are systematic differences in market-based and self-reported values, which vary with market conditions and the amount of equity owners hold in their homes. When prices have fallen, homeowners systematically state that their homes are worth more than market estimates suggest, and homeowners with little or no equity in their homes state values above the market estimates to a greater degree. Over time, homeowners appear to adjust their assessments to be more in line with past market trends, but only slowly. In short, our results suggest that underwater borrowers are likely to understate their losses and either may not be aware that their mortgages are underwater or underestimate the degree to which they are.

2. Background: Theory and Literature Review

While this paper focuses on differences in household perceptions and market predictions, we are interested in these differences because of the important role of housing wealth in household behavior. For example, several papers explore how housing price changes shape household decisions about consumption. Using aggregate data, Case (1991) finds that the real estate price boom in the late 1980s in Massachusetts was associated with large increases in household consumption. Case et al. (2005) build on this work with an analysis of data from multiple countries and states, which also shows that increases in housing wealth are associated with large increases in consumption. Using household-level data from the Panel Study of Income Dynamics, Engelhardt (1996) finds that the marginal propensity to consume out of real capital gains in owner-occupied housing is 0.3 for the median household, but he finds that the savings behavior of households experiencing capital losses is much more sensitive to price changes than the behavior of those experiencing gains.

Why perceptions of home values might differ from market estimates

These papers demonstrate that changes in home values can shape household economic decisions and collectively have dramatic effects on the economy at large. We do not examine such behavioral responses here, but rather focus on whether homeowners accurately assess the value of their homes and the degree to which their homes have changed in value. Economists and psychologists have offered several useful theories for why homeowners might overstate the value of their homes relative to the market. If owners engage in self-serving bias, then they will choose the comparable sales that are most favorable and therefore overstate values in all market contexts (Babcock et al., 1996).

Earlier research offers theoretical justification for why the estimates of some owners might be further from the market value of their homes (Kain and Quigley 1972). Specifically, homeowners who have owned for longer may have outdated information.

The literature has focused less on why homeowners might particularly overstate the value of their homes during downturns, but there are theoretical reasons to expect such a pattern. Perhaps most obviously, homeowners might have outdated information about price levels. They might benchmark their estimates to market prices when they purchased their home and adjust them only slowly. Long-time owners are thus likely to have less up-to-date and accurate assessments of their home values, and so we might expect to see survivor bias. Case and Shiller (1988) also suggest that owners are backward-looking in their expectations about future house price growth and are slow to adjust their expectations. They tend to assume that market conditions at the time they purchased persist. Thus, owners who bought during boom times may be particularly optimistic about their home values, even as prices are falling.[1]

The problem may run deeper than delayed access to information, however. Homeowners may also hold some psychological biases that prevent them from accepting or acknowledging the magnitude of their losses. As Kahneman and Tversky (1979) have famously argued, individuals tend to assess gains and losses relative to a reference point, which for homeowners is likely to be their original purchase price, with the outstanding mortgage principal balance as another salient value. They further argue that the declines in utility individuals suffer from realizing losses are greater than the increases that they enjoy from realizing gains. As a result, people tend to be reluctant to realize losses, and prefer to delay selling an asset rather than accept a reduced price (Case and Shiller, 1988; Einio et al., 2007; Genesove and Mayer, 2001). Such loss aversion also suggests a potential asymmetry in acknowledgement of price changes, as it would lead homeowners to understate the degree to which their homes have fallen in value, but not lead them to over-estimate any gains in value. Some research suggests that consumers tend to update their price expectations when new information about prices is close to prior expectations (Kalwani and Yim, 1992).

These behavioral theories generally predict that owners will be particularly likely to overstate home values relative to the market during downturns. While different theories predict somewhat different outcomes in other contexts, our aim is not to adjudicate among these mechanisms; households may suffer from multiple biases. Rather, our aim is to demonstrate a reduced form, average effect that may be the combination of a number of these mechanisms.

[1] Of course this correlation may reflect selection instead, with optimistic buyers tending to purchase homes during booms.

Of course, it is possible that homeowners who report smaller losses in value than those suggested by market-based indices are correct, and that the market estimates are wrong. Market estimates, after all, are based only on the homes that sell in any time period, which may not be a random subsample of the stock. Specifically, there may be some adverse selection in the homes put on the market during downturns, with the owners who choose to sell during a downmarket owning homes that have experienced greater losses in value. In this case, market-based price indices would exaggerate the degree to which home prices have fallen overall.[2] Similarly, the "market" used to calculate the index (in our case zip codes) might differ from the relevant market for the respondent's home. For example, within many metropolitan areas, the bottom tier of homes, based on prices, experienced a more extreme boom and bust than their higher-priced counterparts in recent years. Our analysis uses zip code housing price indexes - the smallest geography for which estimated trends in housing prices are readily available - for neighborhood market trends. Because housing size, types, and quality vary even within zip codes, differential appreciation rates may have occurred within this geography as well, though likely to a lesser degree.

Finally, while few theoretical analyses directly address the question of how equity position might shape perception of house price changes, we expect that more highly leveraged borrowers may be even more likely to underestimate losses for several reasons. First, there may be some selection: borrowers who take out high loan-to-value mortgages at origination presumably have high expectations about future growth in prices. Second, because a highly leveraged household's equity position is more damaged by a given change in housing values, much of the psychology described above is more relevant for higher leverage borrowers.

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[2] Ihlanfeldt and Martinez-Vazquez (1986) find that selection bias does not significantly affect estimates of prices.

Borrowers may be less willing to acknowledge a loss in equity when it takes them across the negative equity threshold: a loss from 50 to 40 percent equity may be easier to accept than a loss from 10 percent equity to zero. And related to this, homeowners may benchmark their assessments of value to the outstanding balance of their mortgage and be less willing to acknowledge price reductions below this threshold.

Comparisons of market estimates and self-reported home values

Several empirical papers compare owners' assessment of home values to market values. A key challenge for these papers is identifying the true market value of a home. A few papers compare owners' estimates of values to appraised and assessed values, and most find that owners' estimates are higher (Kish and Lansing, 1956; Robins and West, 1977; Ihlanfeldt and Martinez-Vasquez, 1986). Given that appraisals and assessed values are often criticized as being poor measures of market value, other authors have tried to compare owners' estimates of their home values with their subsequent or previous reported sales prices, using longitudinal household surveys. Goodman and Ittner (1992), for example, analyze homes in the American Housing Survey (AHS) that sold between 1985 and 1987 to compare homeowners' assessment of their home value in 1985 to the sales price recorded in the 1987 survey. They find that the typical homeowner overvalued his or her home by roughly 6 percent.[3] DiPasquale and Somerville (1995) and Kiel and Zabel (1999) also use the AHS, but rather than comparing

[3] Notably, they find that future sellers value their homes more highly than non-sellers, suggesting that these results may understate the degree to which the typical homeowner overstates the value of his or her home. In contrast, Kiel and Zabel (1999) find no evidence that future sellers value their homes more highly.

owners' self-reported values to future sales prices, they compare the prices of homes that were purchased in the year *before* the survey interview to homeowners' subsequent assessment of value. Both studies find that owner-reported values are higher than sales prices, even for sales that occurred within one year of the survey. They estimate that on average owners overvalue their homes by roughly five percent.

More recently, Benitez-Silva et al. (2010) use the Health and Retirement Study to conduct an analysis very similar to Goodman and Ittner (1993), comparing owners' assessment of values to subsequent sales prices. Even though they use different datasets, the two studies find very similar results. Benitez-Silva et al. (2010) suggest an average overstatement of between 6 and 10 percent. Looking over multiple decades, they find that owners who purchased their homes during boom-times tend to be particularly optimistic about the value of their homes, consistent with the predictions of Case and Shiller (1988).

Our research builds on these existing papers but differs in several important respects. First, we use two different longitudinal, biannual data sets – the American Housing Survey and the Health and Retirement Study – and compare results across them. Second, we introduce external sources of data to arrive at estimates of the market value of each home. Specifically, we use geocoded versions of the two surveys that allow us to link in zip code level estimates of home price changes. Our estimate of "market value" is the reported original purchase price adjusted to the date of the survey response using the external, market-based housing price index. This approach allows us to use the full sample of homes to analyze owners' assessment of values and not just the relatively small set of homes that have recently sold or will sell shortly, as earlier papers have done. More than increasing our sample size, this allows us to observe how discrepancies between home value perceptions and market estimates vary with a broader set of household and market characteristics.

Third, we analyze a period of large and rapid changes in house prices, which allows us to examine whether the difference between owners' assessments and market estimates of values differs in boom and bust periods. Finally, we also consider the degree to which owners' assessment of market values varies with the amount of home equity, a question that has been left largely unexamined by earlier work. As noted above, there are theoretical reasons to think that owners will be less willing or able to accept losses when their home investments are highly leveraged.

Henriques (2013) uses the Survey of Consumer Finances (SCF) and takes an approach that is similar to ours in terms of matching self-reports with market indices, however her paper focuses on reconciling differences in *aggregate* housing wealth changes based on market indices versus self-reports and does not make use of any household level explanatory variables, except for LTV. Moreover, the SCF is a tri-annual survey, as opposed to our biannual panels, and the housing price indices used to match to the SCF are defined at the CBSA-level, a much larger geographic area than the zip codes that we use. As we discuss further below, there can be substantial intra-metropolitan variation in housing values that will be missed by using city wide indices.

3. Methods

We first calculate the degree to which owners' self-reported home values differ from the estimated market price of their homes. We obtain self-reported values from survey data, and we calculate estimated market price by inflating the reported original purchase price using a zip code level housing price index (HPI).[4] While this estimate relies on a homeowner's reported purchase price, it is independent of his or her assessment of house price appreciation since purchase. Specifically, our key measure is:

$$\%DISCREPANCY = 100 * \left(\frac{Reported\ Value - Estimated\ Market\ Value}{Estimated\ Market\ Value}\right)$$

which will take on positive values when a homeowner's self-report exceeds market estimates and negative values when a homeowner's report is less than the value of his or her home. We test whether the direction and degree of the discrepancy vary across homeowners and whether, in particular, they vary with market conditions and differ during housing busts and booms. Specifically, we examine how an owner's discrepancy changes with recent house price appreciation by estimating the following regression model:

$$\%DISCREPANCY_{ijt} = \alpha + \beta \Delta HPI_{jt} + \gamma X_{it} + \varepsilon_{it} \qquad [1]$$

where ΔHPI_{jt} represents a series of categorical variables indicating the extent of recent house price appreciation experienced in zip code j at time t, and X_{it} are individual controls for homeowner i. We also estimate a lagged dependent variable version of equation [1], adding $\%DISCREPANCY_{ij(t-1)}$ as a regressor. This model allows households' assessments of their home values to be "sticky" over time, with the magnitude of a current discrepancy linked to prior discrepancy, separate from recent price changes.

To explore whether the degree of discrepancy varies with the level of equity that owners have in their homes, we include a measure of the household's estimated lagged loan to value ratio (LTV), and in an alternate specification, an interaction between lagged LTV and recent

[4] For example, if the home was purchased three years ago for $100,000 and the zip code's HPI had increased by 30 percent over those three years, we would inflate the original home price by 30 percent to arrive at an estimated market value of $130,000.

local house price appreciation. In addition, we estimate regressions using LTV at origination to help address concerns about endogeneity of lagged LTV.

We experiment with several different model specifications including models that test whether the magnitude of discrepancies are larger in zip codes that have experienced an increase or decline in prices that is greater than the average in the surrounding metropolitan area. As a robustness test, we also re-estimate models using as our measure of market value the actual sales prices for the set of homes that sell to a new owner before the next wave of the survey, although we must rely on a much smaller sample for this analysis.

4. Data

We use geocoded versions of two longitudinal datasets, the American Housing Survey (AHS) and the Health and Retirement Study (HRS). In both cases, we can identify the metropolitan area (MSA), census tract and zip code in which each household resides. We use MSA identifiers to merge in MSA-level house price indices from the Federal Housing Finance Agency (FHFA).[5] The FHFA provides house price indices back to 1975 for most metropolitan areas.

The FHFA index of course only captures average price appreciation in a metropolitan area, and research suggests that there is significant variation in price appreciation within metropolitan areas. A recent example is Guerrieri et al. (2013), which uses FHFA metro level housing price indices and Case-Shiller zip code level price indices to show that "within-MSA variation during the 2000-2006 was about one half as large as the cross-MSA variation but was

[5] The FHFA HPI data reports indices for 2010 MSA definitions, while the AHS reports the 1983 SMSA. We use county codes to link AHS households to 2010 MSAs.

still substantial at 18 percentage points." In our AHS data, the median MSA includes 11 zip codes with an average of over 26 zip codes per MSA.[6] Thus, we also merge in zip code level house price indices which should more accurately reflect the price appreciation experienced by a given home.

We use indices from Zillow that are a monthly estimate of the value of the median home in a zip code based on public data on transactions, combined with a proprietary model that adjusts for housing and neighborhood attributes using a competing algorithms approach.[7] The Zillow indices have been shown to closely track other proprietary zip code level repeat-sales indices, such as those from S&P/Case-Shiller, particularly after accounting for differences in

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[6] We relate zip codes to census tract characteristics using the HUD USPS zip Code Crosswalk File available at http://www.huduser.org/portal/datasets/usps_crosswalk.html. The overlap suggested by this crosswalks indicates that on average, zip codes cover 4 census tracts, with a median of just under 3 tracts per zip code.

[7] To clarify, we do not have access to Zillow's house-level value predictions, but rather the publicly available zip code level indices that Zillow generates using house-level predictions. The more familiar repeat sales arithmetic mean housing price indices from S&P/Case-Shiller are intended as a prediction of price movements for housing as an asset class, rather than as a prediction model for a particular home. In contrast, Zillow indices are developed such that the individual predictions underlying the indices minimize median absolute error (recently at 8.4%) when compared to individual transaction prices. This feature makes Zillow indices particularly suited to our research question of comparing owner's stated values to the best available prediction of market value. In any case, S&P/Case-Shiller zip-code level indices have not been made available to researchers in recent years.

included geography and exclusion of distressed properties.[8] Guerrieri et al. (2010) find no significant difference in their results when substituting Case-Shiller zip code house price data with those from Zillow.

Zillow provides median house price estimates back to 1996 for over 10,000 metropolitan zip codes, or approximately one third of all zip codes in metropolitan areas across the country.[9] Some states are under-represented because they do not require disclosure of property transactions, but 39 states and the District of Columbia are included . For households in our sample who purchased their home prior to the start of the Zillow indices, we build a composite index by extending the Zillow indices back beyond 1996 using FHFA metropolitan area and state indices. Note that throughout, we restrict our analysis to households living in metropolitan areas covered by both FHFA and Zillow data.

American Housing Survey (AHS)

The AHS is a nationally-representative, longitudinal survey of housing units in the United States. It surveys between 60,000 and 70,000 housing units every two years.[10] It

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[8] Zillow estimates tend to be somewhat lower than S&P/Case-Shiller after 2007 due to the inclusion of foreclosure sales in the Case-Shiller indices. A recent Urban Institute webinar by Zillow and CoreLogic (which now includes the Case-Shiller indices) Chief Economists at http://www.urban.org/events/Home-Price-Indices-Webcast.cfm provides an overview and comparison of the variety of housing price indices.

[9] Estimates are provided for more than 95 percent of these zip codes in all months, and we fill in missing values using MSA-level FHFA indices. In the few cases where MSA-level FHFA indices are missing, we fill in values using state-level FHFA indices.

[10] The 2011 interview wave includes over 186,000 housing units due to the integration of the national and metropolitan area surveys.

provides detailed information about structures and housing costs and also about the occupants living in the unit at the time of the survey. The current national panel started in 1985 and has been periodically replenished with new housing units. We link housing units across survey years from 1997 through 2011. We use census tract identifiers in the geocoded version of the survey to match households to the zip code in which they are located, which allows us to merge in zip code level HPIs.[11]

Many housing units in the survey were occupied by more than one household during this period. Thus, we link households across survey years to separate our data into housing spells in which the same household is present in the housing unit.[12] Given our questions of interest, we restrict our sample to owner-occupants of 1-4 unit homes. We also trim the data in several ways to remove outliers and missing values related to our key variables of self-reported home value,

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[11] The AHS geocodes residence based on the 2000 census tract definitions while Zillow reports by the most recent zip code designation (2010). We use a correspondence file to link 2000 census tracts to 2010 census tracts, which we then use to link the geocoded AHS households to 2010 zip codes.

[12] We classify a household as a 'stayer' household across two waves if they are coded as such by the AHS SAMEHH variable (and SAMEHH2 variable starting in 2005). We also categorize a few households as stayers because the age and gender of household members are consistent across waves and respondents in later wave do not report moving into the unit during the previous two years.

purchase price, and key household characteristics.[13] Our final sample includes approximately 47,000 survey responses.[14]

With regard to self-reported value, the AHS asks respondents explicitly about the value of their home: "How much do you think your house, lot/apartment/mobile home/property would sell for on today's market?"

We construct estimated market price by inflating a household's reported purchase price (using the value reported in the first wave that it is reported) by the local HPI over the months between the purchase year and the survey month. We estimate outstanding mortgage balance for first and second mortgages by using the AHS-provided formula, which relies on purchase data, original loan amount, interest rate, and term.[15] We calculate contemporaneous loan-to-value (LTV) by dividing the total outstanding principal on the mortgage by the estimated market price. In order to avoid a mechanical correlation between our LTV measure and our measure of discrepancy, we lag LTV by one wave. For households who purchased or refinanced their homes in the past two years and thus do not have a lagged value of LTV, we construct the LTV

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[13] We exclude observations with missing or topcoded self-reported values and then trim the top and bottom one percent of the remaining self-reported values in each wave. We further trim any household that reports a change in self-reported home value across waves that falls into the top or bottom one percent in that wave. We also exclude households that do not have a valid purchase year or purchase price in any wave of the survey, as we cannot assign them a predicted home price. Finally, we drop any housing units that are not in metropolitan areas due to a lack of HPI data.

[14] The number of observations is rounded to the nearest thousand, as required by Census for use of the geocoded AHS.

[15] 486 households report having more than two mortgages in a given wave, but the information provided for these additional mortgages is very limited.

measure based on LTV at the time of mortgage origination. As noted, we also estimate models using LTV at origination, based on reported purchase price and mortgage amount, as LTV at origination is even more clearly uncorrelated with recent appreciation.

Table 1 shows basic demographics of our sample. Given the timing of survey waves, we have more household-wave observations during times of positive appreciation than negative, but both are represented. About 40 percent of the sample have lagged LTV ratios above 80 percent. We consider these high LTV borrowers, especially given that lagged LTV will likely understate contemporaneous LTV in downmarkets. About three quarters of the observations report that their properties have undergone a home improvement or remodeling that amounts to at least two percent of the estimated price of the home at any time since purchase.

As for demographics, the majority of householders are aged between 40 and 60, but about a third are under 40 and 17 percent are above 60. [16] Over 40 percent have lived in their homes for over 10 years and over one third are female. The sample is fairly educated, perhaps not surprising given the focus on homeowners, with over 70 percent having attended some college or having college degrees. The breakdown of the sample by race and ethnicity looks close to the national distribution, with 70 percent describing themselves as white, 11 percent black, 12 percent Hispanic, and 6 percent Asian and other race.

[16] The AHS defines the householder as the first household member listed on the questionnaire who is an owner or renter of the sample unit (e.g., is listed on lease) and is 18 years or older. When more than one household member could qualify as householder, the first listed eligible person is considered the householder.

Health and Retirement Study (HRS)

The HRS is a nationally representative longitudinal survey of people aged 50 and over that collects in-depth information about assets, housing, and a variety of other characteristics and behaviors every two years.[17] The panel started in 1992 and has been periodically replenished with new households. The sample birth years range from 1924 to 1954.[18] Geocodes identify each household's zip code in each wave.[19] Unlike the AHS, there is no issue with linking households across waves as the HRS follows individuals and not housing units.

The HRS sampling design chose individuals who were in the appropriate birth year range, and then also interviewed their spouse or partner regardless of age. In couple households, survey questions regarding housing and finances were answered by the self-designated "financial respondent". We include all households in our analyses regardless of whether the financial respondent is the sampled individual, or the partner. The HRS asks the financial respondent a series of questions about their home, including: "What is its present value? I mean, what would it bring if it were sold today?"

Because our zip code level housing price indices begin in 1996, we track households from the 1998 wave (or later, if they enter the HRS later), every two years, until the 2010 wave.

[17] The HRS over-samples Hispanics, blacks, and residents of Florida.

[18] We use all four HRS cohorts: (i) the original HRS cohort (born 1931-1941) who were first interviewed in 1992, (ii) the War Babies cohort (born 1942-1947) who were first interviewed in 1998, (iii) the Children of Depression cohort (born 1924 to 1930), also first interviewed in 1998, and (iv) the Early Baby Boomers cohort (born 1948-1953) who were first interviewed in 2004. This gives us an unbalanced panel with ages spanning 57 to 86 in 2010.

[19] We do not have access to geocodes for 2010 so we only include respondents in 2010 wave if they did not move between 2008 and 2010.

However, we also use earlier waves for some variables including self-reported home purchase price, as well as to create lagged values for the 1998 wave. We restrict the sample to households residing in owner-occupied one or two family homes and drop those that did not match to the zip code level house price indices. We further perform the same data cleaning steps to remove outliers as used for the AHS.[20] Our final sample consists of 12,875 household-waves, representing 3,365 unique households (new partnerships or separations are defined as new households) and 4,077 housing spells (defined as a unique household in a specific housing unit).

The second column of Table 1 displays some key sample characteristics. A few notable differences from the AHS sample jump out. First, the sample is considerably older, with two thirds over the age of 60, and 70 percent have owned their homes for more than 10 years. Not surprisingly then, far fewer households have high levels of housing debt: almost one third of the observations have no mortgage and only 9 percent have a lagged LTV of above 80 percent.[21] Almost 18 percent of the observations were reported after a one year period of local house price declines of greater than 5 percent. Similar to the AHS sample, a large share (68 percent) report a

[20] Specifically, we drop from our sample any housing spells in which the household does not report a purchase price or purchase date, or when the housing price index does not extend as far back as the purchase date. We set to missing the top and bottom one percent of self-reported home values in each wave, as well as values that implied a wave-to-wave change in self-reported value that was in the top or bottom one percent for each wave. The top and bottom one percent trim was also applied to the original purchase price, and the *%DISCREPANCY*.

[21] Unlike the AHS, the mortgage balance is directly self-reported in each wave and the loan-to-value ratios displayed in the table represent the sum of all mortgage balances.

major renovation in their home since purchase. [22] Demographic characteristics are similar across the two samples, though the HRS has fewer Hispanic respondents and somewhat fewer respondents with college degrees. Because income is a less meaningful measure of resources for households that may be drawing down accumulated retirement savings, we construct a dummy variable indicating whether the household has both income and assets below the sample's median levels, by wave. Almost one third of the household-waves are in this category.

Finally, the HRS includes a measure of numeracy, which is intended to capture an individual's facilty with numbers, including a basic understanding of probability and rates of change. The measure is based on a respondent's ability to correctly perform three numerical problems.[23] As can be seen from the data in Table 1, our sample found these numeracy questions challenging: only 14 percent answered all three questions correctly (labeled 'high numeracy score' in the table), while 45 percent had only one or no correct answers (labeled 'low numeracy score'). Prior research suggests that numeracy skills are not fully explained by

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[22] The HRS measure is built from responses to the question "Did you make any major additions or home improvements to a primary residence that you owned? Do not count general maintenance or upkeep."

[23] (1) "If the chance of getting a disease is 10 percent, how many people out of 1,000 would be expected to get the disease?" (2) "If 5 people all have the winning numbers in the lottery and the prize is two million dollars, how much will each of them get?" (3) "Let's say you have $200 in a savings account, the account earns ten percent interest per year. How much would you have in the account at the end of two years?" These questions were asked only from 2002 onwards and we filled in missing values for earlier waves with an individual's observation from a later wave when possible. The numbers in the table do not include the 20 percent of the sample that still had missing values and in our analyses below, we include an indicator variable for these individuals. Following prior research, a refusal to answer or an answer of "don't know" was coded as a zero.

education and that even highly educated individuals have difficulty with relatively simple numeracy questions (see for example, Lipkus et al., 2001).

5. Results

Our key dependent variable is *%DISCREPANCY*, or the percentage difference between an owner's self-reported value and our estimated market price of the home. Figure 1 shows density functions of *%DISCREPANCY* for the AHS and the HRS for the wave immediately preceding 2006 when prices were generally rising, and the post-2006 years when prices were generally falling. The area under these density functions each sum to 100 percent. Positive values of *%DISCREPANCY* imply that a household's reported value is greater than the market estimate. Across all waves, the mean household in the AHS reports that her home is worth 3.2 percent more than the estimated market price, while the mean household in the HRS reports that her home is worth 3.7 percent more than the estimated market price, but there is clearly substantial variation. These optimistic appraisals are consistent with most earlier studies, though the degree of discrepancy is somewhat smaller, especially in the AHS. The figures show that patterns shift as market conditions change: as prices fell in most areas, the densities shift to the right, reflecting a greater incidence of reporting higher values than the zip code level market indices would predict.

Our regressions explicitly correlate *%DISCREPANCY* to recent local housing price movements after controlling for other factors. Table 2 show baseline regression results for the AHS (columns 1A - 6A) and HRS (columns 1B - 6B). The dependent variable is *%DISCREPANCY*. The model in columns 1A and 1B includes the *ΔHPI* categorical variables (without a constant), which indicate whether local house price appreciation in the previous year fell into the specified range of positive and negative appreciation levels.

The results show that households tend to report that the value of their home is higher than that suggested by market estimates when prices have fallen in their local market, and tend to report lower values relative to the market when house prices have risen considerably. For example, the HRS coefficients suggest that households in markets that have seen a fall in value of over 10 percent in the past year report home values that are at least 10 percentage points above the market estimate (coefficients on ΔHPI below -10% between 10.15 and 12.44 across models), whereas households in markets with modest appreciation have no discrepancy (coefficients on ΔHPI from +5 to +10 percent set to zero or estimated between 0.35 and 2.87). In fact, the coefficient magnitudes for each of the negative levels of ΔHPI is roughly proportional to the ΔHPI level. In rapidly appreciating local markets, discrepancies between household reported values and market estimated values are on the order of 5 percentage points (coefficients for ΔHPI above 20% between -4.22 and -6.35 across models). In other words, households appear to be understating large price swings in both directions, perhaps as a result of delayed information, or because they anchor their perception of house prices to their purchase price and adjust expectations only slowly. Homeowners in markets experiencing modest house price appreciation appear to report home values that are fairly similar to those estimated by the market price indices. The results are strikingly consistent across the two datasets. We also re-estimated the AHS models restricting the sample to householders within the HRS range of 50 and above, and the coefficients are even closer in magnitude.

The next columns adds a dummy variable to indicate a homeowner with a lagged LTV ratio greater than 80 percent. Households with higher LTV ratios report above-market values to a much greater degree (the coefficient on Lag LTV > 80% indicates 19 percentage points in the AHS and 25 in the HRS) than similar households with more equity in their homes. While we cannot tell whether this association is the result of selection – borrowers who take out high LTV loans may simply be more optimistic about house prices – or whether it reflects a more causal relationship, the association is strong in both datasets and suggests that in the current market, where large shares of owners have little or no equity in their homes, a larger than usual share of homeowners are likely to think their homes are worth substantially more than market indices suggest. Columns 3A and 3B adds interactions between recent changes in house prices and high lagged LTV. These coefficients show that the tendency of high LTV borrowers to overstate values relative to other borrowers holds in all market conditions.

We have explored many alternative ways of capturing the non-linear effect of LTV and its interactions, including adding more categories of lagged LTV and using a series of spline functions. These alternate specifications all told a similar story: higher lagged LTVs are associated with a greater discrepancy regardless of recent house price movements. The presented results show an average effect; for both the AHS and HRS, successively higher lagged LTVs are associated with greater discrepancies.

Columns 4 to 6 of Table 2 are analogous to columns 1 to 3, but adds an additional set of controls. For ease of interpretation, we included a constant in these regressions and set the reference category of HPI changes to +5 to +10%. Adding these controls does little to change the magnitude of the *ΔHPI* effects in either sample, although the coefficients themselves change because of the added constant. Furthermore, the results in columns 5 and 6 show that the LTV associations are robust to controlling for household demographic characteristics, with virtually no change in the lagged LTV coefficient.

The coefficients on the other controls are again quite consistent across the two samples, especially for the variables for which we have strong theoretical predictions. For example, households that have undertaken previous home improvements report values that are on average about 4 percentage points (coeffients range from 3.89 to 4.15) higher than the value that the market index would predict. Of course, the market index would not capture any value increase due to the renovation, so we would expect owners to report a higher value if they believe that the prior home improvement increased the market value of their home. The coefficients on this variable indicate that homeowners report values that capitalize approximately 60 percent of the cost of the prior improvements.[24]

As expected, older owners report values that are relatively higher than the market, as do homeowners who have lived in their homes for a longer period of time. In the HRS, the coefficients for these variables together indicate that elderly homeowners with the longest tenure understate the value of their home relative to market estimates by over 20 percentage points. These results are consistent with delayed information, anchoring to purchase price, or owner awareness of accumulated deferred maintenance. More educated homeowners are less likely to report higher values than the market compared with those who are less educated, with coefficients for college graduates between -6.1 and -8.4, perhaps because more educated

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[24] This calculation is based on an average reported major improvement cost of approximately 7 percent of reported value (among improvements that exceed 2 percent of value). All of our results are essentially unchanged if we drop all observations that have experienced a previous home improvement.

homeowners provide more conservative assessments of their home's value.[25] Similarly, the HRS results suggest that respondents who obtain higher scores on a numeracy test are less likely to report values above the market than those who receive lower scores. Finally, the results provide modest evidence that higher income households report values above the market to a greater degree than lower income households (but this association is not economically or statistically significant in the HRS sample).

We have less clear expectations about the coefficients on the race and gender variables, and they differ somewhat across the two samples. Neither dataset reveals any economically or statistically significant differences across gender. The coefficient on black race in the HRS is positive and marginally significant in one model, suggesting black households appear to report higher relative values compared to whites, but this pattern is reversed in the AHS results. The AHS results meanwhile provide some evidence that Hispanic homeowners and those of Asian and other race report values above the market to a lesser degree than whites, but the HRS results do not. It is possible that where significant, the coefficients may reflect genuine within-zip code variation in home price appreciation experienced by homeowners of different racial and ethnic backgrounds.

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[25] This empirical finding has a number of interpretations. More educated owners might track their home values more astutely, and provide lower estimates that are closer to actual market estimates. Alternatively, such borrowers may consider the higher-priced market in their MSA as their reference point for assessing their home values. Conservative reports may be in line with these areas experiencing slower appreciation during the boom and smaller declines during the bust. Finally, more educated homeowners may be more likely to hold other assets in addition to their home. This may lead them to think of their home value as their "safe" asset which does not fluctuate as much, resulting in lower reported gains and losses.

Adjustments Over Time

Given that we are examining associations between discrepancies in assessment and price appreciation over the past year, one obvious question is whether households adjust their assessments over time to match more closely to the market. In other words, do these results simply reflect a short-term 'mistake' or delay in receiving information about market conditions? To test this, we estimate the same set of regression models, but with lagged dependent variables on the right-hand side. Table 3 show results for the AHS and HRS respectively. The coefficient on the lagged dependent variable hovers consistently around 0.7, suggesting some persistent stickiness in perceptions of value. In other words, to the extent that households adjust their assessments of value to match more closely to the market, those adjustments take place slowly over time.[26]

Metropolitan Area vs. Neighborhood House Price Appreciation

One of the unique aspects of this analysis is our use of geocoded data that allow us to use zip code level house price indices. But it is an empirical question whether households tend to benchmark their house price assessments to price appreciation in their local community or in the broader metropolitan area. To examine whether households pay attention to metropolitan area trends, we estimate versions of our regressions where we interact the zip code level ΔHPI with a set of dummy variable indicating whether (i) ΔHPI_{zip} is less than ΔHPI_{MSA} by at least 2

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[26] Further, we also estimated models that included not only price appreciation in the past year but also price appreciation between year t-1 and year t-2 and found that households were more likely to overstate values relative to the market when prices had declined in both periods.

percentage points; (ii) ΔHPI_{zip} is within 2 percentage points of ΔHPI_{MSA}; or (iii) ΔHPI_{zip} is greater than ΔHPI_{MSA} by at least 2 percentage points. Results are shown in Table 4.

In the AHS, we find that in zip codes where house prices fared worse than in the larger metropolitan area (the first set of rows in the table), the discrepancies between individual assessments and predicted prices are more positive than in zip codes where house price appreciation was similar to or better than the MSA (the second and third sets of rows). This suggests that households are more bullish about the value of their homes when the surrounding MSA is doing better than their neighborhood, and they are paying more attention to the MSA trends under these conditions. However, the effect is asymmetric as they are not more bearish when the surrounding MSA is faring worse than their neighborhood.

In the HRS, clear differences among the three possibilities are less evident. The only consistent difference is in strongly appreciating markets (ΔHPI above +20 percent) where we find that households tend to report lower values relative to the market when the zip code is appreciating by more than the MSA (the third set of rows) compared to when zip code appreciation is similar to or worse than the MSA (the first and second sets of rows). This is consistent with households focusing more on MSA trends when prices are rising rapidly.

Robustness Tests

To address the concern that lagged LTV>80 is endogenous due to the use of estimated market price to calculate both *%DISCREPANCY* and loan to value, we re-estimated regressions using loan to value at origination > 90 instead of lagged LTV > 80. Note that we can only do this for the AHS as we do not have data on the original mortgage in the HRS. While the coefficient on original LTV > 90 in this robustness check model and lagged LTV > 80 in our reported model are not directly comparable, the original LTV > 90 coefficient implies the same order of magnitude greater discrepancy for more leveraged borrowers.

Finally, we use the AHS to estimate a model where a subsequent rather than prior sales price is used to calculate discrepancy. This model explores the possibility that borrowers may be accurate about the value of their particular home despite deviation from the zip code level house price indices. Using the much smaller sample of homes that sell during our time period, we measure *%DISCREPANCY* as the difference between the sales price (as reported by the next household who moves into the home) and the reported value of the home in the immediately preceding wave. This proximate, subsequent sale provides a second market opinion on the property's value. We observe a similar pattern among coefficients, with households reporting higher values relative to the market in down markets and lower values relative to the market in boom markets. If anything, coefficients are larger. (Results are available upon request.)

6. Conclusion

Our results provide robust evidence, across two different data sets, that households tend to report higher home values relative to the market during downturns than they do in other market conditions. In the wake of the housing bust, this means that many homeowners do not fully understand (or have not fully accepted) the degree to which the market suggests that their homes have lost value. Whether due to loss aversion or slow adjustment to market conditions, these skewed perceptions help to explain the correlation between sales volume and market conditions highlighted by Genoseve and Mayer (2001), as sellers during downturns hold out for prices that are far above the market.

The gap between owner assessments and market estimates of value is particularly pronounced for the many homeowners with low or negative levels of equity. Indeed, our estimates suggest that in the most recent survey waves, nearly 40 percent of the AHS homeowners that are underwater according to our market estimates (that is, they have estimated loan balances that exceed the estimated market price of their home by more than five percent) report home values that were at least five percent above their outstanding loan balance. In other words, nearly half of the borrowers deemed to be underwater by market price estimates do not perceive themselves to be underwater. These findings suggest that some of the behavioral responses we might fear from reduced house values – including strategic default – may not be as extreme as predicted because homeowners underestimate their equity loss relative to market measures.

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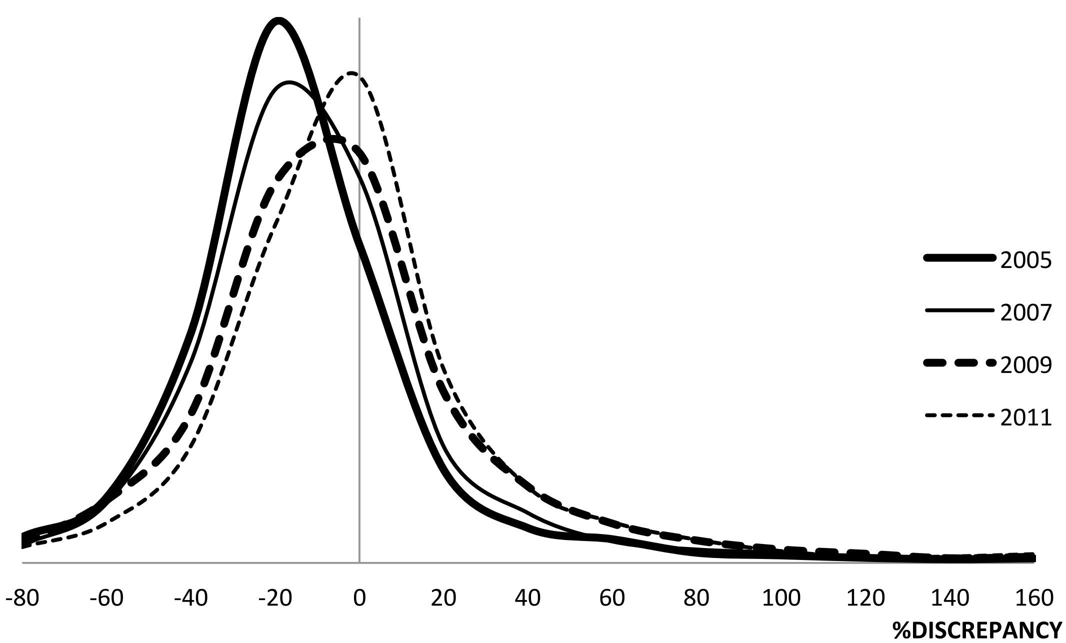
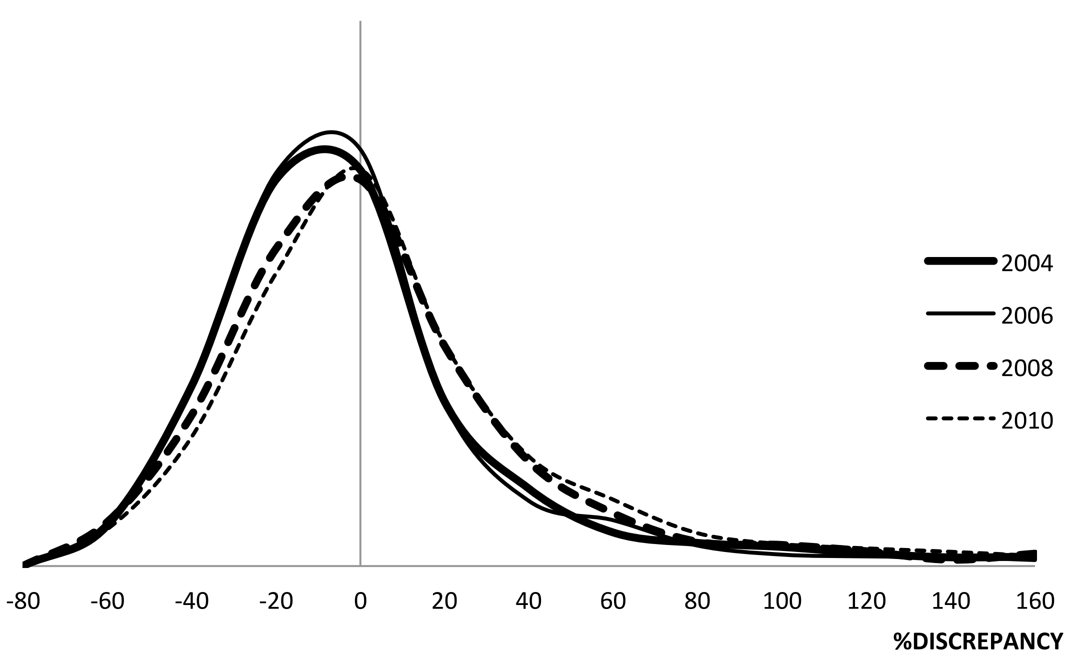
Figure 1. %DISCREPANCY density function

American Housing Survey:



Health and Retirement Study:



%DISCREPANCY = 100*(Reported home value - Estimated market value) / (Estimated market value)
The area under each graph sums to 1.

Table 1. Descriptive statistics

Percent of sample, unless otherwise noted	American Housing Survey (1997 - 2011)	Health and Retirement Study (1998 - 2010)
	(1)	(2)
Recent Δ HPI:		
below -10%	12	10.7
-10% to -5%	14	7.2
-5% to +5%	35	35.3
+5% to +10%	*17*	*21.1*
+10% to +20%	17	20.1
above +20%	4	5.6
Lag LTV >80%	40	8.7
Lag LTV >80% and recent Δ HPI:		
below -10%	5	0.6
-10% to -5%	6	0.6
-5% to +5%	15	3.4
+5% to +10%	7	2.1
+10% to +20%	6	1.6
above +20%	1	0.5
Prior home improvement	74	68.0
Age:		
less than 40	*34*	
41-60	53	
60+	14	
50-60		*31.9*
61-70		43.8
70-80		21.3
80+		3.0
Tenure:		
Less than 1 year	*5*	*1.4*
1 year	9	3.2
2 years	10	3.1
3 years	6	3.4
4 years	6	3.2
5-10 years	25	15.4
10-20 years	26	33.5
20 years or more	13	36.8
Married	68	70.1
Female	38	46.7
Education:		
Less than high school	*7*	*14.0*
High school graduate	21	25.8
Some college	29	26.4
College graduate	43	33.7
Race/ethnicity:		
White	*77*	*78.7*
Black	9	12.0
Asian and other race	5	4.8
Hispanic	9	6.7
Average household income	$ 90,000	
Below median assets and income		30.9
Numeracy score:		
Low		*44.9*
Moderate		41.2
High		14.0
Number of household-wave observations	47,000	12,875

Except for household income, all variables are binary and the table shows the percent of observations with that variable = 1.
Samples as described in the text. Italics indicate the left-out category in the models in tables 2-4.
Recent Δ HPI denotes the change in the home price index for the homeowner's zip code over the past year.
Lag LTV is the homeowner's loan-to-value in the previous observation wave.
Prior home improvement indicates a reported home improvement costing at least 2 percent of reported property value.
American Housing Survey numbers were rounded to the nearest one digit for disclosure purposes.

Table 2. Baseline models

Dependent variable=	American Housing Survey (1997 - 2011)						Health and Retirement Study (1998 - 2010)					
%DISCREPANCY	(1A)	(2A)	(3A)	(4A)	(5A)	(6A)	(1B)	(2B)	(3B)	(4B)	(5B)	(6B)
Recent Δ HPI:												
below -10%	16.11**	8.469**	5.538**	17.27**	16.08**	12.40**	12.436**	11.021**	10.353**	10.414**	11.220**	10.146**
	(0.640)	(0.615)	(0.673)	(0.749)	(0.731)	(0.792)	(1.330)	(1.300)	(1.291)	(1.431)	(1.415)	(1.416)
-10% to -5%	9.626**	1.476**	1.373*	11.04**	9.291**	8.576**	9.800**	7.713**	7.768**	7.159**	7.388**	6.918**
	(0.481)	(0.478)	(0.540)	(0.622)	(0.611)	(0.690)	(1.556)	(1.529)	(1.544)	(1.642)	(1.624)	(1.661)
-5% to +5%	4.328**	-3.574**	-3.419**	4.769**	4.024**	3.438**	6.305**	3.891**	3.809**	3.359**	3.403**	2.724**
	(0.280)	(0.292)	(0.311)	(0.479)	(0.469)	(0.521)	(0.867)	(0.835)	(0.844)	(0.946)	(0.934)	(0.963)
+5% to +10%	0.223	-7.419**	-6.588**	**omitted**	**omitted**	**omitted**	2.868**	0.353	0.943	**omitted**	**omitted**	**omitted**
	(0.393)	(0.393)	(0.418)				(0.884)	(0.870)	(0.893)			
+10% to +20%	-3.171**	-9.434**	-8.731**	-2.884**	-1.840**	-1.853**	-0.004	-2.015*	-2.251**	-2.346*	-1.974+	-2.791**
	(0.396)	(0.389)	(0.402)	(0.554)	(0.543)	(0.578)	(0.894)	(0.866)	(0.861)	(1.057)	(1.043)	(1.071)
above +20%	-5.363**	-11.45**	-10.70**	-5.328**	-3.956**	-4.038**	-4.219**	-6.349**	-5.934**	-6.216**	-6.020**	-6.080**
	(0.794)	(0.775)	(0.775)	(0.883)	(0.863)	(0.870)	(1.409)	(1.397)	(1.404)	(1.493)	(1.481)	(1.512)
Lag LTV >80%		18.63**			18.79**			25.309**			24.184**	
		(0.370)			(0.453)			(2.265)			(2.334)	
Lag LTV >80% and recent Δ HPI:												
below -10%			25.78**			25.95**			37.257**			33.505**
			(1.334)			(1.352)			(6.577)			(6.790)
-10% to -5%			18.86**			18.73**			24.641**			23.364**
			(0.976)			(1.002)			(6.819)			(6.799)
-5% to +5%			18.26**			18.41**			26.163**			25.501**
			(0.571)			(0.628)			(3.378)			(3.460)
+5% to +10%			16.60**			16.97**			19.376**			18.463**
			(0.827)			(0.868)			(3.114)			(3.168)
+10% to +20%			16.54**			16.62**			28.275**			27.267**
			(0.921)			(0.952)			(3.918)			(3.947)
above +20%			16.34**			16.75**			20.377**			17.988**
			(1.918)			(1.938)			(5.967)			(5.795)
Prior home improvement				4.068**	3.886**	3.932**				4.100**	4.147**	4.151**
				(0.413)	(0.404)	(0.404)				(1.267)	(1.241)	(1.241)
Age:												
41-60				-1.594**	0.554	0.533						
				(0.412)	(0.409)	(0.408)						
60+				-3.418**	0.265	0.312						
				(0.687)	(0.680)	(0.680)						
60-70										-1.136	-0.059	-0.076
										(1.076)	(1.048)	(1.048)
70-80										-5.477**	-3.376*	-3.373*
										(1.513)	(1.481)	(1.479)
80+										-9.464**	-6.965*	-6.821*
										(2.958)	(2.888)	(2.891)

continued

Table 2 continued

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Tenure:												
1 year				0.978	1.364+	1.352+				-5.807+	-4.531	-4.539
				(0.699)	(0.712)	(0.711)				(3.278)	(3.332)	(3.340)
2 years				(0.267)	0.131	0.065				-6.911*	-8.624**	-8.709**
				(0.720)	(0.729)	(0.729)				(3.072)	(3.129)	(3.140)
3 years				(0.194)	1.789*	1.564+				-12.124**	-14.742**	-14.430**
				(0.833)	(0.838)	(0.837)				(3.332)	(3.416)	(3.416)
4 years				-1.857*	1.754*	1.540+				-13.309**	-14.785**	-14.701**
				(0.847)	(0.852)	(0.852)				(3.260)	(3.328)	(3.333)
5-10 years				-3.701**	2.481**	2.323**				-14.349**	-14.516**	-14.511**
				(0.648)	(0.680)	(0.682)				(3.169)	(3.207)	(3.214)
10-20 years				-5.606**	2.889**	2.770**				-16.458**	-15.527**	-15.498**
				(0.706)	(0.751)	(0.752)				(3.125)	(3.171)	(3.178)
20 years or more				-13.52**	-3.670**	-3.726**				-19.008**	-17.540**	-17.497**
				(0.864)	(0.903)	(0.904)				(3.199)	(3.238)	(3.244)
Married				0.463	0.541	0.590				-1.115	-1.419	-1.414
				(0.416)	(0.409)	(0.409)				(1.452)	(1.417)	(1.419)
Female				-0.353	-0.163	-0.121				-1.549	-1.787	-1.747
				(0.374)	(0.365)	(0.365)				(1.415)	(1.374)	(1.372)
Education:												
High school graduate				-3.496**	-2.507**	-2.513**				-3.599	-3.362	-3.418
				(0.928)	(0.907)	(0.906)				(2.406)	(2.320)	(2.323)
Some college				-3.840**	-2.806**	-2.841**				-5.271*	-5.043*	-5.075*
				(0.908)	(0.888)	(0.886)				(2.278)	(2.205)	(2.209)
College graduate				-8.399**	-6.104**	-6.165**				-6.992**	-6.722**	-6.773**
				(0.897)	(0.877)	(0.876)				(2.336)	(2.255)	(2.260)
Race/ethnicity:												
Black				0.643	-1.455*	-1.495*				3.903+	2.724	2.768
				(0.733)	(0.717)	(0.716)				(2.297)	(2.243)	(2.247)
Asian and other race				-5.522**	-4.833**	-4.845**				-1.138	-1.511	-1.488
				(0.667)	(0.660)	(0.659)				(2.441)	(2.333)	(2.334)
Hispanic				-0.969	-1.889**	-1.846**				-3.190	-2.987	-2.989
				(0.687)	(0.674)	(0.674)				(2.313)	(2.267)	(2.265)
Household income ('$0,000)				0.0785*	0.103**	0.103**						
				(0.031)	(0.032)	(0.032)						
Below median assets and income										-0.471	-1.336	-1.315
										(1.182)	(1.152)	(1.152)
Numeracy score:												
Moderate										-1.346	-1.432	-1.413
										(1.323)	(1.300)	(1.301)
High										-3.474*	-3.562*	-3.531*
										(1.763)	(1.711)	(1.711)
Constant				6.783**	-8.883**	-8.061**				24.008**	20.671**	21.208**
				(1.081)	(1.120)	(1.136)				(4.123)	(4.134)	(4.139)
Number of observations	47,000	47,000	47,000	47,000	47,000	47,000	12,875	12,875	12,875	12,875	12,875	12,875
Adjusted R-squared	0.036	0.092	0.093	0.046	0.091	0.092	0.024	0.056	0.056	0.028	0.056	0.057

OLS regression coefficients with robust standard errors in parentheses. ** p<0.01, * p<0.05, + p<0.1.

%DISCREPANCY = 100*(Reported home value - Estimated market value) / (Estimated market value). All explanatory variables are indicator variables, except for household income.

Recent Δ HPI denotes the change in the home price index for the homeowner's zip code over the past year. Lag LTV is the homeowner's loan-to-value in the previous observation wave.

Table 3. Lagged dependent variable models

Dependent variable=	American Housing Survey (1997 - 2011)							Health and Retirement Study (1998 - 2010)						
%DISCREPANCY	(1A)	(2A)	(3A)	(4A)	(5A)	(6A)	(7A)	(1B)	(2B)	(3B)	(4B)	(5B)	(6B)	(7B)
Lag %Discrepancy	0.715**	0.708**	0.684**	0.684**	0.700**	0.678**	0.678**	0.742**	0.742**	0.737**	0.737**	0.741**	0.736**	0.736**
	-0.012	-0.012	-0.012	-0.012	-0.012	-0.012	-0.012	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Recent Δ HPI:														
below -10%		10.44**	8.600**	8.479**	12.21**	12.13**	11.86**		13.884**	13.653**	13.677**	18.047**	18.145**	17.977**
		(0.614)	(0.613)	(0.635)	(0.742)	(0.739)	(0.760)		(0.975)	(0.974)	(0.982)	(1.150)	(1.152)	(1.160)
-10% to -5%		5.083**	3.046**	3.387**	6.912**	6.573**	6.823**		5.858**	5.654**	5.814**	10.023**	10.131**	10.092**
		(0.490)	(0.511)	(0.544)	(0.632)	(0.631)	(0.686)		(0.941)	(0.945)	(0.978)	(1.118)	(1.119)	(1.151)
-5% to +5%		1.936**	(0.180)	-0.588+	3.471**	3.271**	2.739**		2.157**	1.841**	1.623**	5.246**	5.269**	4.865**
		(0.289)	(0.313)	(0.315)	(0.486)	(0.484)	(0.515)		(0.413)	(0.421)	(0.427)	(0.652)	(0.651)	(0.670)
+5% to +10%		-1.305**	-3.428**	-3.268**	**omitted**	**omitted**	**omitted**		-2.680**	-3.017**	-2.837**	**omitted**	**omitted**	**omitted**
		(0.387)	(0.412)	(0.431)					(0.456)	(0.468)	(0.483)			
+10% to +20%		-3.478**	-5.278**	-5.007**	-2.116**	-1.844**	-1.690**		-2.974**	-3.244**	-3.315**	-0.265	-0.212	-0.454
		(0.409)	(0.419)	(0.410)	(0.563)	(0.562)	(0.579)		(0.528)	(0.530)	(0.538)	(0.740)	(0.740)	(0.761)
above +20%		-4.781**	-6.408**	-5.697**	-3.450**	-2.981**	-2.381**		-6.241**	-6.468**	-6.005**	-3.644**	-3.542**	-3.222**
		(0.773)	(0.780)	(0.778)	(0.867)	(0.866)	(0.878)		(1.040)	(1.048)	(1.069)	(1.166)	(1.164)	(1.194)
Lag LTV >80%			6.141**			6.345**				3.493**			3.480**	
			(0.454)			(0.497)				(1.062)			(1.097)	
Lag LTV >80% and recent Δ HPI:														
below -10%				6.530**			6.805**				3.140			3.355
				(1.554)			(1.557)				(4.589)			(4.732)
-10% to -5%				5.160**			5.262**				0.952			1.170
				(1.147)			(1.157)				(3.736)			(3.664)
-5% to +5%				7.305**			7.501**				5.786**			5.811**
				(0.707)			(0.732)				(1.720)			(1.752)
+5% to +10%				5.679**			5.973**				1.750			1.711
				(0.908)			(0.936)				(1.751)			(1.771)
+10% to +20%				5.207**			5.369**				4.371			4.250
				(1.081)			(1.107)				(2.824)			(2.814)
above +20%				3.410			3.548+				-3.559			-4.011
				(2.110)			(2.124)				(4.245)			(4.203)
Additional controls	No	No	No	No	Yes	Yes	Yes	No	No	No	No	Yes	Yes	Yes
Constant					0.504	-4.882**	-4.691**					17.950**	17.533**	17.815**
					(1.266)	(1.339)	(1.358)					(5.420)	(5.399)	(5.399)
Number of Observations	27,000	27,000	27,000	27,000	27,000	27,000	27,000	10,488	10,488	10,488	10,488	10,488	10,488	10,488
Adjusted R-squared	0.421	0.437	0.441	0.442	0.437	0.441	0.442	0.516	0.537	0.537	0.537	0.537	0.538	0.538

OLS regression coefficients with robust standard errors in parentheses. ** p<0.01, * p<0.05, + p<0.1. Additional controls are those displayed in Table 2.
%DISCREPANCY = 100*(Reported home value - Estimated market value) / (Estimated market value). All displayed explanatory variables are indicator variables.
Recent Δ HPI denotes the change in the home price index for the homeowner's zip code over the past year. Lag LTV is the homeowner's loan-to-value in the previous observation wave.

Table 4. Models that control for the difference between MSA- and zipcode-level ΔHPI.

Dependent variable=		American Housing Survey (1997 - 2011)						Health and Retirement Study (1998 - 2010)					
%DISCREPANCY		(1A)	(2A)	(3A)	(4A)	(5A)	(6A)	(1B)	(2B)	(3B)	(4B)	(5B)	(6B)
MSA ΔHPI is above zipcode, and													
zipcode ΔHPI is	below -10%	14.32**	9.493**	9.471**	11.96**	11.34**	5.342+	14.581**	13.069**	11.893**	14.508**	14.963**	11.817**
		(2.550)	(2.523)	(2.943)	(2.567)	(2.559)	(2.962)	(1.668)	(1.624)	(1.645)	(1.703)	(1.685)	(1.727)
	-10% to -5%	14.18**	8.639**	6.904**	11.02**	10.46**	2.42	7.389**	5.336**	5.616**	6.737**	6.797**	5.084**
		(1.654)	(1.615)	(1.520)	(1.696)	(1.657)	(1.566)	(1.679)	(1.659)	(1.698)	(1.745)	(1.735)	(1.765)
	-5% to +5%	9.492**	3.301**	2.622**	5.928**	5.240**	-1.674*	4.588**	2.205+	2.085+	4.516**	4.327**	2.056+
		(0.635)	(0.630)	(0.725)	(0.734)	(0.721)	(0.824)	(1.175)	(1.126)	(1.119)	(1.275)	(1.250)	(1.234)
	+5% to +10%	6.412**	0.838	0.264	**omitted**	**omitted**	**omitted**	-0.703	-2.623	-1.998	**omitted**	**omitted**	**omitted**
		(0.626)	(0.617)	(0.667)				(1.819)	(1.785)	(1.864)			
	+10% to +20%	4.821**	-0.0293	1.016	1.277	2.340**	-2.906**	-7.521**	-8.573**	-8.664**	-6.399**	-5.507**	-7.691**
		(0.767)	(0.762)	(0.822)	(0.846)	(0.835)	(0.896)	(1.841)	(1.805)	(1.815)	(1.945)	(1.916)	(1.926)
	above +20%	6.012**	0.506	3.438	2.243	2.726	-0.76	-3.889	-7.202	-2.821	-3.366	-4.117	-2.547
		(1.659)	(1.667)	(2.119)	(1.689)	(1.686)	(2.127)	(11.719)	(12.053)	(13.505)	(11.980)	(12.073)	(13.659)
MSA ΔHPI is equal to zipcode, and													
zipcode ΔHPI is	below -10%	7.057**	2.734	2.127	4.295+	4.728*	-2.016	10.722*	9.902**	9.376**	12.107**	13.168**	10.626**
		(2.172)	(2.133)	(2.147)	(2.194)	(2.159)	(2.188)	(2.553)	(2.509)	(2.529)	(2.636)	(2.611)	(2.624)
	-10% to -5%	7.350**	1.825+	0.921	4.425**	3.804**	-3.212**	8.120*	6.249*	5.537*	8.406**	8.393**	5.744*
		(0.997)	(0.978)	(1.079)	(1.066)	(1.043)	(1.154)	(2.914)	(2.848)	(2.811)	(2.924)	(2.876)	(2.884)
	-5% to +5%	5.645**	-0.5	0.371	2.221**	1.647**	-3.797**	3.917*	1.752+	1.880+	3.575**	3.574**	1.572
		(0.358)	(0.376)	(0.424)	(0.519)	(0.511)	(0.581)	(1.059)	(1.028)	(1.033)	(1.116)	(1.103)	(1.123)
	+5% to +10%	1.560**	-4.677**	-3.992**				0.682	-1.642	-1.017			
		(0.548)	(0.550)	(0.607)				(1.100)	(1.083)	(1.109)			
	+10% to +20%	1.18	-3.451**	-2.631**	-2.291*	-1.172	-6.703**	-0.292	-2.033	-2.112	0.275	0.543	-1.504
		(0.808)	(0.800)	(0.846)	(0.890)	(0.876)	(0.932)	(1.386)	(1.359)	(1.352)	(1.417)	(1.401)	(1.409)
	above +20%	0.624	-4.083**	-4.703**	-2.530+	-1.66	-8.444**	-5.830+	-7.486*	-6.279+	-4.649	-4.448	-5.350
		(1.465)	(1.413)	(1.412)	(1.500)	(1.440)	(1.437)	(3.160)	(3.197)	(3.313)	(3.270)	(3.273)	(3.395)
MSA ΔHPI is below zipcode, and													
zipcode ΔHPI is	below -10%	6.108**	1.629	2.026	3.049*	3.585**	-2.341+	12.087**	10.840**	10.367**	13.890**	14.618**	12.205**
		(1.160)	(1.149)	(1.268)	(1.218)	(1.204)	(1.326)	(2.667)	(2.627)	(2.658)	(2.664)	(2.641)	(2.673)
	-10% to -5%	7.048**	1.287	0.429	4.183**	3.195**	-3.923**	9.255**	7.446*	8.486**	7.173*	7.497*	6.615*
		(0.806)	(0.793)	(0.883)	(0.893)	(0.876)	(0.980)	(3.186)	(3.198)	(3.235)	(3.301)	(3.316)	(3.344)
	-5% to +5%	5.863**	-0.427	-1.038*	2.595**	1.439*	-5.323**	6.345**	3.768**	3.973**	4.427*	4.100*	2.270
		(0.426)	(0.430)	(0.479)	(0.571)	(0.561)	(0.630)	(1.478)	(1.442)	(1.458)	(1.787)	(1.755)	(1.765)
	+5% to +10%	2.993**	-3.240**	-4.492**				1.270	-1.053	-0.721			
		(0.887)	(0.866)	(0.900)				(1.279)	(1.261)	(1.295)			
	+10% to +20%	0.969	-3.666**	-3.562**	-2.331*	-1.461	-7.556**	-2.315*	-4.327**	-4.752**	-2.740*	-2.532*	-5.133**
		(1.077)	(1.057)	(1.056)	(1.131)	(1.107)	(1.130)	(1.074)	(1.050)	(1.060)	(1.192)	(1.174)	(1.193)
	above +20%	1.088	-2.064	-1.184	-1.413	0.659	-4.727*	-9.355**	-11.315**	-11.450**	-9.089**	-8.956**	-11.120**
		(1.961)	(1.950)	(2.215)	(1.971)	(1.951)	(2.218)	(1.603)	(1.545)	(1.516)	(1.675)	(1.636)	(1.612)
Lag LTV >80%			14.40**			16.26**			24.842**			23.326**	
			(0.379)			(0.465)			(2.237)			(2.320)	

continued

Table 4 continued

		(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Lag LTV>80%, MSA ΔHPI is above zipcode, and													
zipcode ΔHPI is	below -10%			14.46**			15.47**			44.179**			40.810**
				(5.586)			(5.616)			(7.719)			(8.039)
	-10% to -5%			18.91**			20.32**			21.460**			18.968**
				(3.757)			(3.755)			(6.746)			(7.068)
	-5% to +5%			15.98**			16.94**			26.094**			24.888**
				(1.304)			(1.321)			(5.367)			(5.498)
	+5% to +10%			15.88**						16.748*			
				(1.356)						(8.096)			
	+10% to +20%			11.29**			11.93**			26.986*			24.530*
				(1.770)			(1.772)			(11.586)			(12.357)
	above +20%			6.731*			7.700*			-8.016			-5.101
				(3.385)			(3.385)			(13.572)			(13.921)
Lag LTV>80%, MSA ΔHPI is equal to zipcode, and													
zipcode ΔHPI is	below -10%			16.42**			17.45**			40.768*			36.317*
				(5.487)			(5.435)			(16.471)			(16.457)
	-10% to -5%			16.75**			17.73**			34.304*			31.821*
				(2.150)			(2.165)			(15.328)			(14.871)
	-5% to +5%			12.35**			13.45**			23.380**			22.229**
				(0.732)			(0.776)			(4.339)			(4.395)
	+5% to +10%			12.81**						18.169**			
				(1.131)						(4.263)			
	+10% to +20%			11.85**			12.81**			25.977**			22.607**
				(1.917)			(1.917)			(6.313)			(6.342)
	above +20%			16.29**			16.82**			6.737			5.178
				(3.485)			(3.471)			(10.171)			(10.669)
Lag LTV>80%, MSA ΔHPI is below zipcode, and													
zipcode ΔHPI is	below -10%			13.12**			14.49**			34.266*			28.718+
				(2.708)			(2.719)			(14.726)			(14.975)
	-10% to -5%			16.54**			17.96**			10.560			7.870
				(1.708)			(1.727)			(14.948)			-15.091
	-5% to +5%			15.79**			16.78**			22.866**			21.265**
				(0.872)			(0.902)			(5.898)			(5.936)
	+5% to +10%			17.29**						21.299**			
				(1.842)						(4.864)			
	+10% to +20%			14.07**			14.81**			30.094**			29.204**
				(2.638)			(2.588)			(4.892)			(4.862)
	above +20%			10.38*			11.38*			26.552**			23.481**
				(4.634)			(4.543)			(7.446)			(7.109)
Additional controls		No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Constant					7.773**	-5.806**	2.902**				21.141**	18.058**	20.054**
					(1.089)	(1.136)	(1.097)				(3.912)	(3.915)	(3.941)
Number of Observations		43,000	43,000	43,000	43,000	43,000	43,000	12,640	12,640	12,640	12,640	12,640	12,640
Adjusted R-squared		0.027	0.062	0.063	0.015	0.050	0.042	0.024	0.056	0.057	0.042	0.068	0.065

OLS regression coefficients with robust standard errors in parentheses. ** p<0.01, * p<0.05, + p<0.1. Additional controls are those displayed in Table 2.
%Discrepancy = 100*(Reported home value - Estimated market value) / (Estimated market value). All displayed explanatory variables are indicator variables.
MSA Δ HPI and zip code Δ HPI denote the change in the home price index for the homeowner's MSA and zip code over the past year, respectively.
Lag LTV is the homeowner's loan-to-value in the previous observation wave.