Loss Aversion and Focal Point Bias: Empirical Evidence from Housing Markets

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Abstract

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Keywords: housing sales, loss aversion, anchoring, mortgage, behavioral bias, round numbers, focal point bias, house prices, sale likelihood

JEL Codes: D91, G12, G41, R21, R31

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1. Introduction

Several recent studies have examined the within individual correlation between behavioral biases (e.g., Chapman et al., 2018a; Dean and Ortoleva, 2019; Stango and Zinman 2022).[1] However, these studies use survey or experimental data, so we have little information about whether behavioral biases operate together when individuals are making higher stakes decisions and so influence market outcomes. To our knowledge, the only empirical evidence involving high-stakes is provided by Fraser-Mackenzie et al. (2015) who show that focal point bias is more pronounced when stock trades involve losses. This paper uses housing market transactions data to provide new evidence on whether the influence of behavioral biases on market outcomes interact with each other in a high-stakes setting.

We focus on two biases that have been extensively studied in housing markets: loss aversion (Genesove and Mayer 2001; Anenberg 2011; Bokhari and Geltner 2011; Clapp and Zhou 2020; Bracke and Tenreyro 2021; Anderson et al. 2022) and focal point bias (Pope et al. 2015, Chava and Yao, 2017; Repetto and Solís 2020; Lieb et al. 2021; Wiltermuth et al., 2022; Meng, 2023). While these biases belong to different families, prospect theory (Barberis, 2013; Kahneman and Tversky, 1979) and bounded rationality (e.g., Lacetera et al. 2012) respectively, "framing" can lead to systematic biases like loss aversion (Kahneman and Tversky, 1979; Tversky and Kahneman, 1981), and also strategies to reduce cognitive effort (Simon, 1955) such as simplifying heuristics or rules of thumb (Tversky and Kahneman 1974; Gilovich et al. 2002) that in turn lead to focal

[1] Dean and Ortoleva (2019) evaluate a variety of measures of attitudes to risk and uncertainty and find strong positive correlations between most measures, even though they find that cognitive and personality measures are weak predictors of behavior. Stango and Zinman (2022) organize biases into present-biased discounting, inconsistent/dominated choices, risk, overconfidence, math, and limited attention/memory and find that behavioral biases are positively correlated within individuals, especially within theoretically-related groups. Chapman et al. (2018a) also find strong correlations between different measures of risk attitudes, as well as strong correlations between different measures of overconfidence.

point responses (Hurd, 2009; Gan et al. 2005).[2] Alternatively, Gabaix (2018) illustrates how many behavioral biases could be driven by anchoring, e.g. to the previous price in the case of loss aversion and to salient left-side digits for focal point bias.[3]

Since none of the papers above provide *direct* evidence on the within individual correlation between loss aversion and focal point behaviors, we first utilize data that contains both a measure of loss aversion and a survey question that creates the opportunity for rounding. As part of a broader experiment, Karle et al. (2015) conducted experimental lotteries to create measures of loss and risk aversion, and based on their design also asked participants how much they typically spend for lunch. The purpose of this exercise is to provide *direct* evidence on the relationship between loss aversion and a tendency to select round numbers. We find that individuals that reported integer numbers when asked about past spending were measured as having substantially higher loss aversion, even after conditioning on risk aversion and spending levels, i.e., 29% of a standard deviation higher loss aversion parameter estimate than those who do not. Balancing tests do not find systematic correlations between subject observables and reporting a round number, and estimates are relatively stable as controls are added and as we restrict the sample to subsamples with better support over past spending.

With low stakes evidence in hand, we examine the effects of loss aversion on the housing sales prices, a high-stakes context, and then condition on whether the initial buyer selected a round mortgage amount, another high-stakes decision. Using single-family, repeat sales housing transactions in Connecticut from 1994 to 2017, we identify focal point biased sellers as those who

[2] Round reporting is consistent with heuristic decision making given a tendency of respondents to insufficiently refine their answers (Hurd, 2009). Also, many studies examine correlations between cognitive ability and behavioral biases. Benjamin et al. (2013), Dohmen et al. (2010), Casari at al. (2007), Oechssler et al. (2009), Hoppe and Kusterer (2011) and Bergman et al. (2010) find a negative correlation for many biases, while Stango and Zinman (2022) and Chapman et al. (2018b) find a positive correlation for loss aversion.

[3] In related work, Pagel (2018) proposes a model where investors are negatively affected by bad news and aversion to news of such losses leads to inattention.

did not appear downpayment-constrained at the time of purchase and yet coordinated on round numbers in their purchase mortgage amount. Specifically, we restrict the sample based on the first transaction in each repeat sale by (1) dropping homebuyers who appear credit-constrained based on selecting critical loan to value ratios or use of subordinate debt since mortgage amount could be affected by downpayment constraints,[4] and (2) dropping homebuyers who purchased the house for cash and so did not have a mortgage.

We focus on a round mortgage amount because both parties involved in a transaction likely influence sales price, while lenders typically focus on loan to value and income ratios, not mortgage amount. By focusing on round mortgage amounts that are not at critical LTV values, our sample of borrowers effectively did not face substantive financial constraints or incentives when selecting their mortgage amount beyond each individual's own allocation of resources between home equity and liquidity. Therefore, the selection of round mortgage within this non-downpayment constrained population is unlikely to correlate with financial factors that might influence time on market or reservation price. Further, while round mortgage amounts might arise to meet a specific loan to value ratio, constraints on housing or debt payment to income ratios should not create clusters of mortgage amounts at round numbers.

Assuming smoothness on other economic factors over mortgage amount, we test for discontinuities in the response to potential losses at round mortgage amounts to detect behavioral differences between individuals who selected a round amount and those who did not. This empirical strategy is similar to Backus et al. (2019) and Repetto and Solís (2020) who examine the impact of selecting round list prices on eventual sales prices.[5] For non-downpayment constrained

[4] See Appendix B, Identifying Critical LTV Thresholds.
[5] Repetto and Solís (2020) attribute the observed discontinuities to inattention, while Backus et al. (2019) suggest that round number list prices provide a signal concerning the seller's confidence in their assessment of value. However, in our case, selecting a round number mortgage during the initial purchase is unlikely to have meaningful signal value.

borrowers, a thousand dollars smaller or larger mortgage should not reflect a discrete difference in economic circumstances, but rather capture unobserved differences between individuals that contribute to a tendency for selecting round numbers – what Stango and Zinman (2022) might refer to as behaviorally distinct attributes. Therefore, round number departures from the smooth evolution of the relationship between sales price and expected loss as mortgage amount changes provides evidence that loss aversion is disproportionately concentrated among our focal point borrowers. We center the data by setting the running variable to zero if the mortgage amount is a multiple of $5,000, and we select a bandwidth of $2,500 on either side to create non-overlapping mortgage amount bins.

We first assess persistence in our mortgage amount-based indicator for focal point bias given the stability of behavioral biases within individuals over time, see Stango and Zinman (2020) and Chapman et al. (2018a). We regress selecting a round mortgage amount for a second home purchase on our initial round mortgage amount dummy conditional on the running variable and mortgage amount bin fixed effects. Having an initial round mortgage amount raises the likelihood that the next mortgage is round by 11 percentage points relative to a 16% sample share.

Then, we test whether loss aversion effects on housing sales prices are larger among individuals who exhibit focal point bias. We estimate reduced-form models of loss aversion on housing sales prices as in Genesove and Mayer (2001), Anenberg (2011), Bokhari and Geltner (2011), and Bracke and Tenreyro (2021). We regress housing sales price in the second sale on an estimate of expected losses interacting both expected loss and standard controls from Genesove and Mayer's (2001) model with a dummy variable for whether the borrower had a round initial mortgage amount, controlling for mortgage amount (the running variable) and mortgage amount bin fixed effects.

The estimate on the interaction of expected loss and round number mortgage is sizable at 0.11, or 11% more of the loss is recaptured in higher sales price, as compared to the effect of loss for the continuous mortgage amount subsample of 17%. Focal point borrowers also see a lower likelihood of a sale when facing losses. A one standard deviation increase in expected loss implies a 0.5 to 0.8 percentage point larger reduction in sale likelihood for focal point borrowers, compared to a mean likelihood of 3.8%. Differential sales price effects for our focal point sample are larger for shorter holding periods, consistent with greater loss aversion when the anchoring price is more salient (DellaVigna et al. 2017; Ben-David and Hirshleifer 2012), and larger for buyers of more expensive houses, consistent with more loss aversion for wealthier home buyers (e.g. Chapman et al., 2018).

The primary threat to identification arises from unobserved socio-economic attributes that correlate with selecting a round mortgage amount. First, we conduct and pass balancing tests on housing, neighborhood, and mortgage attributes and show that these controls have minimal impact on our estimates. The inclusion of these attributes, as well as interactions with round mortgage, decreases the focal point buyer interaction estimate by less than 4%, while the additional inclusion of census tract-by-round mortgage fixed effects increases the estimate by 11% yielding a final estimate of 0.12. On the other hand, the estimate for the continuous mortgage amount subsample falls by 39% from 0.17 to 0.10 with the inclusion of these controls.[6] Second, we conduct falsification tests moving our estimated housing price levels back in time for calculating expected

[6] Traditional models yield an estimate 30% for the continuous amount subsample, similar to Anenberg (2011), Bokhari and Geltner (2011), and Bracke and Tenreyro (2021), but three times larger than the 10% estimate above. After including additional controls, our 10% estimates fall between Genesove and Mayer's (2001) estimates of 3% to 18% for their homogenous sample of Boston condominiums. Conditional on sale date, homeowners only face losses if they purchased near the market peak, while unobserved quality increases in "for sale" housing during periods of price appreciation (Shen and Ross 2021; Nowak and Smith 2020; Zhou et al. 2022) and buyer composition also changes over the cycle (Bayer et al. 2016).

loss. Although direct estimates on false expected loss are sizable, falsification estimates on the interaction with round mortgage are statistically insignificant and near zero.

Our paper contributes to the growing literature on within individual correlations between behavioral biases (Stango and Zinman 2022; Dean and Ortoleva 2019; Chapman et al. 2018a). We provide new evidence of impact of behavioral biases being observed together in market outcomes for a high-stakes setting, while almost all existing evidence is based on experimental or survey data. Further, existing evidence tends to focus on related biases like risk preferences (Dean and Ortoleva 2019; Chapman et al. 2018a) or overconfidence (Chapman et al. 2018a), while we find a strong association between loss aversion and focal point tendencies, which traditionally belong to different families. These findings support the view that biases may be driven by the same underlying behaviors, such as anchoring (Gabaix 2018), "ostrich effect" (Galai and Sade, 2006), or the effect of bounded rationality on loss/gain framing (Niu et al. 2022).[7]

Second, our study contributes to the literature on focal points and loss aversion in housing markets. Several studies document persistent differences related to round number purchase prices (Chava and Yao, 2017; Wiltermuth et al., 2022; Meng, 2023).[8] However, Wiltermuth et al. (2022) and Meng's (2023) estimated effects on future sales price may arise either because an original purchase price at or above a round number reveals information about the seller/original buyer, e.g., a seller for whom left digits are more or less important, or because all sellers respond more strongly to the left most digits.[9] By focusing on mortgage amount, we isolate behavioral differences

[7] The "ostrich effect" states that people pay more attention to things that please them and avoid things that hurt them (Galai and Sade, 2006). Niu et al. (2022) found that improved cognitive control reduced the disposition effect of selling winners rather than losers.

[8] See Pope et al. (2015) for evidence of clustering of home sales prices at round numbers.

[9] Several studies show that round number listing prices lead to lower sales prices, Lieb et al. (2021) and Repetto and Solís (2020) in housing and Backus et al. (2019) in on-line markets because round list prices signal to buyers that the seller has poor information on value. Similarly, Hukkanen and Keloharju (2018) find that round number offers in mergers/acquisitions lead to higher acquisition prices. Busse et al. (2013) and Lacetera (2012) find that used car buyers

between sellers who tend to coordinate on round numbers and those that do not without confounding information associated with whether the original sales price was round. Finally, the widely used, loss aversion test introduced by Genesove and Mayer (2001) may be biased upwards in more heterogeneous housing markets due to the correlation between the quality of housing for sale and the housing market cycle (Shen and Ross 2021; Nowak and Smith 2020). We estimate loss aversion effects on housing prices (based on focal point bias effects) that are far less sensitive to the inclusion of observables by differencing out market circumstances between borrowers at round mortgage amounts and at nearby continuous amounts.

2. Evidence from an Earlier Experiment

To provide low-stakes evidence of a correlation between loss aversion and focal point tendencies, we regress reporting round numbers on a survey question and an estimated measure of loss aversion. Karle et al. (2015) conducted an experiment with University of Mannheim students in the fall of 2010.[10] In this study, individuals participate in a series of lotteries and sure pay-offs, and they used these responses to estimate the loss aversion parameter from Tversky and Kahneman's (1992) exponential utility function and a measure of risk aversion.[11]

In addition, individuals reported how much they typically spend on lunch in Euros. The distribution of price responses is shown in Figure 1. Responses range between 0 and 15 Euros, but are concentrated between 1.8 and 8 Euros. We drop zero Euro responses as not representing actual purchases, and also create two subsamples: first dropping the two outlier observations with responses of 10 and 15 Euros (the next highest response was 8 Euros), and second restricting our

ignore left digits in vehicle mileage, and in Kuo et al. (2015) investors who trade at integer values have worse performance.

[10] The data is provided by Karle et al. (2019) and downloaded from https://www.openicpsr.org/openicpsr/project/114322/version/V1/view (accessed Nov 2020).

[11] Karle et al. (2015) only calculate these measures for individuals who gave consistent responses to the lottery questions, and so like them we drop individuals who gave inconsistent responses.

sample to between 1.8 and 6 Euros dropping values of 7 and 8 that were not adjacent to any fractional responses. We focus on integer Euros because the vast majority of focal point bias studies focus on the left most digit. While some respondents might view 0.5 Euro increments as round, the distribution suggests substantial clustering at one Euro increments relative to the reported fractional amounts.

{*Insert Figure 1 Here*}

Table 1 Panel A presents a model that regresses the estimated loss aversion parameter on whether the self-reported amount typically spent on lunch was an integer or not plus an additional control for the respondents' estimated risk aversion.[12] Panel B presents results controlling for respondent demographics in the first column for each sample and in the second column also controlling for the amount spent on lunch and the self-reported number of times eating lunch out each week, capturing any correlation between consumption levels and loss aversion. In panel A, reporting a round number implies 34% of a standard deviation increase in the estimated loss aversion parameter for the full sample, a 27% increase dropping the extreme outliers, and a 29% increase for our preferred sample that had more concentrated support over the amount spent on lunch.

Turning to panel B, the coefficients on all control variables are insignificant, but the estimates are somewhat unstable as controls are added. The estimated effects increase by 7%, 8%, and 10% across the three columns as demographic controls are added, but the standard errors also increase. The addition of the controls for spending level and the number of times eating out cause further increases in parameter instability and in the standard errors with the estimate for the first sample falling by 20% and the estimates for the last two samples rising by 40%. Still, for our two

[12] We include the control for risk aversion due to previous evidence of a strong correlation between risk and loss aversion (e.g., Dean and Ortoleva, 2019), but results are robust to omitting this control.

preferred samples that drop outliers, our estimated effects are larger and continue to be statistically significant, in spite of the standard errors having increased by 70%.[13] These results provide low stakes support for a within individual correlation between loss aversion and a tendency to focus on round numbers. Appendix Table A1 presents balancing tests for whether the subject reported a round number for spending and all tests are statistically insignificant.

{Insert Table 1 Here}

3. Loss Aversion in Housing Sales Prices and Focal Point Bias

3.1 Model Specifications

Genesove and Mayer (2001) use a repeat sale framework to test for loss aversion in housing sales prices. Following their approach, sales price for seller *i* in the quarter of purchase *s*, the quarter of sale *t*, and labor market area *c* is

$$P_{icst} = \beta Loss_{icst} + \boldsymbol{\delta X}_{icst} + \theta_{ct} + \varepsilon_{icst} \quad (1)$$

where expected loss ($Loss_{icst}$) is defined as the maximum of log of nominal purchase price minus log of the expected market value of the second sale and zero. i.e., $Loss_{icst} = Max\left(0, logPrice_{ics} - log\widehat{Price}_{ict}\right)$.[14] $\boldsymbol{X}_{icst}$ includes standard controls in the Genesove and Mayer model, including the expected market value of the second sale, residual from the first stage hedonic model of the initial sales price (proxy for unobserved housing unit quality),[15] months since purchase, and equity position at the second sale. For equity position or current loan to value ratios (LTV), we follow Anenberg (2011) and Abel (2018) using an estimated remaining mortgage

[13] Oster's (2019) bounding exercises are relatively uninformative given the low explanatory power of control variables and increasing standard errors with controls.

[14] We follow the literature using nominal purchase price, but sellers could update their purchase price based on inflation. We examine this possibility using McCrary tests for mass points at a discontinuity and break point tests. All evidence points towards discontinuities at the nominal price.

[15] Genesove and Mayer (2001) observe that inclusion of this residual can create an errors-in-variables bias. We investigate this issue later in the paper.

balance amortized using the 30-year FHFA mortgage rate observed at purchase. θ_{ct} is the labor market area (LMA)-by-year-by-quarter fixed effects and absorbs time-varying local market conditions at the time of the second sale. Like all reduced form papers in this literature, loss aversion is identified based on variation in the timing of initial purchase prior to a housing market downturn.[16] We use two-way clustered standard errors by census tract and by LMA-by-year-by-quarter (Bertrand, Duflo, and Mullainathan, 2004).

Bokhari and Geltner (2011) find that sellers with an expected gain are willing to accept a lower price. For completeness, we next include the expected gain in equation (1) and consider the following model.

$$P_{icst} = \beta_1 Loss_{icst} + \beta_2 Gain_{icst} + \boldsymbol{\delta X}_{icst} + \theta_{ct} + \varepsilon_{icst} \qquad (2)$$

where expected gain ($Gain_{icst}$) is the maximum of log purchase price minus the log of expected market value of the second sale and zero.

Following Backus et al. (2019), we extend equations (1) and (2) to estimate a model where discontinuities occur at round numbers. Our model and theirs are fundamentally different from standard regression discontinuity (RD), which relies an exogenous cut-off for assignment to treatment so that treatment is quasi-random in a small neighborhood of the threshold conditional on a running variable. Instead, this model exploits endogenous selection into round listing prices in Backus et al. (2019) or round mortgage amounts in our case. Like many focal point papers, we attribute these differences to behavioral biases under the assumption that economic factors evolve smoothly over the mortgage amount and so do not contribute to clustering at round mortgages.

However, a round sales price might lead to round mortgage amounts if borrowers are targeting a specific loan to value ratio. Therefore, we delete apparently downpayment constrained

[16] Clapp and Ross (2004) find that town housing prices within the same LMA tend to move together. Results are similar using town-by-year fixed effects.

borrowers who selected critical loan to value ratios or used a second or third subordinate mortgage in the home purchase. On the other hand, credit constraints arising from payment to income ratios ould not be expected to create clusters at round mortgage amounts due to variation in expenses from closing costs, interest rates, and mortgage insurance.

We specify round-number thresholds x for each bin *b*, and define the operator $rnd(x, y)$ to be the value of x rounded to the nearest positive multiple of y. We then define *Run* as

$$Run_{icsb} = Amount_{ics} - rnd(Amount_{ics}, y). \tag{3}$$

We also define an indicator variable *Above* that is one for *Run* greater than zero and zero otherwise, and our *Round* number mortgage dummy is one when *Run=0*. We interact $Round_{ics}$ with $Loss_{icst}$ and additional controls $\boldsymbol{X}_{icst}$ from equation (1), and the resulting interactive discontinuity specification is

$$P_{icst} = \beta_1 Loss_{icst} + \beta_2 Loss_{icst} * Round_{ics} + \gamma_1 Run_{icsb} + \gamma_2 Loss_{icst} * Run_{icsb}$$
$$+\gamma_3 Run_{icsb} * Above_{icsb} + \gamma_4 Loss_{icst} * Run_{icsb} * Above_{icsb}$$
$$+\gamma_5 Above_{icsb} + \boldsymbol{\delta_R X}_{icst} + \varphi_b + \theta_{ct} + \varepsilon_{icst} \tag{4}$$

The variable *Run* represents the running variable, and the interaction with *Above* allows the effect of *Run* to differ on either side of the threshold. The running variable allows for a smooth evolution of the effect of loss on sales price with small changes in the mortgage amount. φ_b and θ_{ct} represent initial mortgage amount bin fixed effects and labor market area by year by quarter fixed effects (based on the second sale), respectively. Similar to equation (1), we use multi-way clustering of standard errors by mortgage bin, by LMA by year by quarter, and by census tract.

Prior to estimating equation (4), we test whether having selected a round initial mortgage amount captures something that is persistent about the individual by showing that those individuals are more likely to select round mortgages in the future. We create a dummy variable, $NextRnd_{icst}$, for whether the next observed, home purchase mortgage amount is round in quarter *t* for buyer *i* in labor market area *c*, and regress this upon whether the first mortgage amount was round.

$$NextRnd_{icst} = \beta Round_{ics} + \gamma_{1R} Run_{icsb} + \gamma_{2R} Above_{icsb} + \gamma_{3R} Run_{icsb} * Above_{icsb} + \boldsymbol{\delta_R X}_{icst} + \theta_{ct} + \varphi_b + \varepsilon_{icst} \quad (5)$$

where $\boldsymbol{X}_{icst}$ follows equation (1) including expected market value, residual from first purchase, months since purchase, and equity position at second purchase.

We also model sale hazard in a panel framework to capture the likelihood of sale each year. The hazard function for homeowner *i*, year of purchase *s*, calendar year *t*, and labor market area *c* is

$$\Pr(Sale)_{icst} = \beta_1 Loss_{icst} + \beta_2 Loss_{icst} * Round_{ics} + \gamma_1 Run_{icsb} + \gamma_2 Loss_{icst} * Run_{icsb} + \gamma_3 Run_{icsb} * Above_{icsb} + \gamma_4 Loss_{icst} * Run_{icsb} * Above_{icsb} + \gamma_5 Above_{icsb} + \boldsymbol{\delta_R X}_{icst} + \theta_{ct} + \varphi_b + \varepsilon_{icst} \quad (6)$$

We estimate linear probability models with the dependent variable taking a zero every year following the initial sale until the sample ends or a sale occurs in which case the variable is set to one and future years are dropped for a given sale spell. The expected loss and gain variables vary over time *t* as LMA housing prices change. $\boldsymbol{X}_{icst}$ also includes time-varying equity position, again calculated using the estimated remaining mortgage balance divided by the expected sales price at time *t*, and years since purchase. θ_{ct} is the LMA-by-year fixed effects. We cluster standard errors at the mortgage bin, LMA-year and census tract levels.

3.2 Housing Sales Data and Sample Construction

Our housing assessors' data contains 548,568 single-family residential transactions between January 1994 and December 2017 in 9 labor market areas (LMAs) across 169 towns in

Connecticut.[17] This sample excludes non-single-family units, non-Arm's length transactions, and records with apparent data quality problems based on Clapp and Salavei (2010), see Appendix Table A2 Panel A.1. Our sample spans 24 years compared to 18 years for Anenberg (2011), 13 years for Bracke and Tenreyro (2021), and less than 10 years for most other studies. Our sample like all other studies contains one major period of price decline.[18] Appendix Figure A1 presents housing price levels by labor market area. The peak varies between the first quarter of 2006 and the middle of 2007. Markets also vary substantially in the size of the peak and the extent of price recovery by 2018.

Unlike many assessors' data sets, our data contains property characteristics recorded at the time of each sale. We mitigate concerns about large unobservable quality changes over time by deleting observations with changes in interior size greater than 5% between sales, and directly control for smaller changes by calculating predicted price using hedonic attributes at the time of sale. We use the names of buyers and sellers and a fuzzy name match to ensure that the seller in the second transaction was the buyer in the first, as required to assign the initial mortgage amount to seller and estimate an expected loss (or gain). We also identify future home purchase mortgages originated by these same homeowners to test for persistence in selecting a round mortgage.[19]

With a fixed starting point, the number of repeat sales tends to increase as one moves forward in time through the sample. As a result, we require that the second sale occurs after 1999, a point at which the ratio of repeat sales to all sales has stabilized. Otherwise, the sample will over-

[17] Assessors' data is utilized through a license with the Warren Group (accessed July 2018). Our data does not reliably report the identity of the mortgage lender.

[18] Our data contains one and one half housing cycles from the bottom of the market in the mid-nineties, through the boom and great recession, and the following recovery. Andersen et al. (2022) and Genesove and Mayer (2011) contain the second half of a price decline followed by recovery, Bokhari and Geltner (2011) observe a recovery and part of the decline that follows, and Bracke and Tenreyro (2021) and Anenberg (2011) include one housing cycle from peak to peak.

[19] We perform a fuzzy match using Matchit in STATA. We include matches where the seller or buyer in the second transaction was the buyer in the first transaction for our repeat sales and purchase mortgage samples, respectively.

represent homes that sell rapidly. Our repeat sales sample includes 139,674 sale pairs. Appendix Table A2 Panel A.2 shows the filters that yield this sample. We also create a repeat home purchase mortgage sample for every individual involved in an initial home purchase that includes instances where one or more of the initial buyers use a mortgage for a second home purchase, Appendix Table A2 Panel B.

When analyzing sale probability, we assume that the relevant population of houses are those ever sold during our full sample period, 1994-2017. We then construct a sample of 4,058,238 house-year observations based on 366,557 unique properties, Appendix Table A2 Panel C. This sample consists of 500,579 sale spells, which start from the year after the sale of a property and end in the year of the next sale or the end of our sample period if no sale is made. Similar to our sale price analysis, we analyze sale probability using second sales that occur in 2000 or later to ensure the representativeness of our repeat sale sample, i.e., dropping observations associated with a second sale prior to 2000.

Appendix Table A3 defines the variables used in our analyses. Appendix Table A4 compares the variable means for the clean single-family sample to the means for the seasoned repeats sales and the dropped (early resale) repeat sales transactions. The repeat sales subsample contains older houses on somewhat smaller lots, as has been found in previous studies. Notably, housing sales prices also differ between the samples. Some of these differences arise because the samples are concentrated in different time periods. Once we adjust sales prices to a constant-year price using LMA housing price indices, the sales price mean for the seasoned repeat sales sample moves closer to the full sample mean, while the dropped repeat sales sample has substantially higher sales prices than the seasoned repeat sales sample. Finally, the full and seasoned repeat sales samples have very similar LTV, while the dropped repeat sales sample has substantially lower LTVs.

In Appendix Table A5, we present the descriptive statistics separately for the expected loss and the expected gain subsamples. The comparison of "months since purchase" reveals that loss is positively correlated with the holding period between sales, consistent with loss aversion. In terms of housing attributes, houses in the loss sample are larger and older. In terms of mortgage attributes, sellers with an expected loss have lower initial LTV ratios and are less likely to have a second mortgage at purchase. Turning to neighborhood attributes (measured using the 1990 census prior to our sample period), sellers with expected loss are in census block groups with a higher percent of males, whites, and individuals with a college degree. Sellers with an expected loss also reside in neighborhoods with higher household income, lower poverty, and lower unemployment. These differences suggest that the sample is not balanced between home sellers with expected losses and those with expected gains. We will present formal balancing tests below.

We also classify the buyers in the first sale (i.e., the sellers of the second sale) into four purchase types: LTV-focused (presumably credit constrained), cash purchases, focal point/round number mortgage, and all other purchases (continuous mortgage amount). The LTV-focused group includes likely downpayment constrained buyers who either select one of the key LTV thresholds (i.e., an LTV ratio of 0.80, 0.90, 0.95, 0.97, and 1.00) suggesting that the buyer targeted an important LTV ratio at purchase or took out a second mortgage at the time of purchase (subordinate debt). Appendix B summarizes details on identifying critical LTV ratios for all sample periods. The cash purchase group includes any home purchase that did not involve a mortgage origination. The round number mortgage group includes buyers with mortgage amounts ending with 5,000 or 10,000 excluding buyers in the LTV-focused group. The last group includes all other sellers whose initial purchase involved a mortgage. Appendix Figure A2 provides a visualization of the clumping of mortgage amounts at round numbers that are multiples of $5,000 illustrating substantial excess mass at round number mortgages. Referring back to Appendix Table A5, we find that sellers with an expected loss are more likely to be in our round number mortgage subsample. Sellers facing an expected loss also appear to have been more likely to focus on a critical LTV ratio, suggesting that they were more financially constrained at the time of their initial purchase. Our regression sample drops the LTV-focused/potentially downpayment constrained individuals and those without a mortgage, but results are similar when including these the downpayment constrained individuals.

3.3 Empirical Results

To first illustrate our results, we plot the stacked discontinuity in Figure 2 by creating a $2,500 bandwidth on either side of each round mortgage amount where the running variable takes a value of zero at the round mortgage amount. Each $2,500 window on the left- or right-hand side is further divided into 10 bins of $250, and we have the 21st bin at zero containing the individuals with round mortgage amounts. For each bin, we calculate the unconditional correlation between expected loss and the difference between the sale price and the expected sale price. The gray dots show a consistently positive correlation between the excess sale price and expected loss. The gray lines are fitted to the correlation estimates. There is a clear discontinuity in the pattern of estimates with the correlation at zero being 10 to 15 percentage points above the grey lines at the nearest bins.

{*Insert Figure 2 Here*}

As a comparison, we also plot the correlation between expected loss and selected housing, mortgage, and census attributes. For ease of presentation, we show tests for a limited number of attributes in Figure 3. Unlike Figure 2, all correlation estimates when the running variable is zero are generally within the scatterplot of correlations for the non-round mortgage amount bins.

{Insert Figure 3 Here}

3.3.1 Balance Tests

Table 2 provides formal balancing tests where we estimate equation (4) replacing housing price one at a time with housing attributes, the mortgage loan to value ratio, and census block group attributes. Consistent with Figure 3, only one out of 18 estimates on expected loss interacted with the round mortgage amount dummy are significant at the 95 percent level of confidence and none are significant at the 90 percent level. Notably, given our focus on round mortgage amounts, the coefficient on the round mortgage interaction for loan to value ratio balancing test is small and insignificant. On the other hand, virtually every coefficient on the expected loss itself for our continuous mortgage amount sample is significant, consistent with sample imbalance between housing units facing expected losses and those that do not. Similarly, if we estimate models nearly identical to Genesove and Mayer (2001) using the full repeat sales sample and dropping the round number dummy interactions and mortgage amount bin fixed effects, virtually every balancing test coefficient on expected loss is large and statistically significant.

{Insert Table 2 Here}

3.3.2 Main Results

Next, we examine whether selecting a round mortgage during the first transaction explains whether the same buyer selects a round number for their next home purchase mortgage. These results are shown in column 1 of Table 3. Panel A reports the model including the standard controls described above, while panels B and C show results first adding the balancing test variables and then also including census tract fixed effects. Having an initial mortgage that is a round number raises the likelihood that the next mortgage is a round number by 11-12 percentage points, relative to the sample mean of 16%.

{Insert Table 3 Here}

Column 2 presents the estimates of the effect of expected losses on sales price using the standard controls and column 3 adds additional controls for expected gain and its interaction with round mortgage. The coefficient estimate on the interaction of round mortgage with expected loss in column 2 panel A is 0.114 or 11% more of the expected loss is captured in higher sales prices for the subsample that selected a round mortgage amount, as compared to the level effect for the continuous mortgage amount subsample of 16%. Column 3 estimates conditional on gains are similar.

Columns 4 and 5 present results for the likelihood of sale. The estimates for the interaction with round mortgage range between a 2 and 3 percentage point decline in the likelihood of sale, consistent with a lower likelihood of sale as loss aversion increases the owner's reservation price. The standard deviation of expected loss in log terms for the experiencing a loss at sale subsample is 0.28, and a one standard deviation increase in loss is associated with between a 0.5 and 0.8 percentage point decrease in the likelihood of sale in any year, relative to a mean likelihood of sale of 3.8%. While sales price and sale likelihood effects might move together because selecting a round number mortgage is correlated with patience (rather than loss aversion), patience alone cannot explain why this pattern arises for expected losses, but not for gains, as shown in Appendix Table A6.

Panels B and C add controls for balancing test variables interacted with whether the mortgage was round and then these variables plus census tract by round mortgage fixed effects, respectively. The differential effect estimates for the round mortgage subsample in Table 3 are quite stable as additional controls are added. Starting with selecting a round new mortgage (column 1), the estimate barely moves when adding the balancing test controls, and increases by about 10% when we add census tract fixed effects. Using Oster's (2019) test for omitted variables with a maximum R-squared of one, we compare the changes in the estimate as controls are added to the fraction of the residual variance explained by those controls, and conclude that unobservables must be three times more influential as the observables and operate in the opposite direction to eliminate these effects.

Now turning to the effect of expected losses on sales price in column 2, the addition of balancing test controls and their interactions with the round mortgage dummy in Panel B reduces the estimate by less than 5% to 0.109. Based on the Oster criteria, the remaining unobservables would need to be four times more important than the observables to explain these effects. The addition of census tract by round mortgage fixed effects in Panel C increases the estimate from 0.109 to 0.121 or an 11% increase. While modest and an increase in the estimate, given the only moderate improvement in the R-squared with the addition of the tract fixed effects, unobservables could erode these effects if they were one and a half times more influential than the tract fixed effects and that influence was in the opposite direction. Results for the model after including controls for gains are very similar.

On the other hand, the conditional correlation between expected loss and housing sales price for our continuous mortgage amount subsample is substantially less stable and exhibits substantial declines in effect size, consistent with the balancing test failures discussed above. Focusing on column 2 of Table 3, the coefficient estimate on expected loss is 16% of the amount of the loss. The addition of the balancing test controls plus interactions and the census tract by round mortgage fixed effects reduces the estimates on expected loss to only 10%. In comparison,

Appendix Table A7 shows estimates based on Genesove and Mayer's (2001) model specification for our pooled sample of round and continuous mortgage amount borrowers with round mortgage amount interactions. The estimate for the continuous mortgage subsample is 30% in models that do not include balancing test variables, or census tract and mortgage amount bin fixed effects, three times the final estimate in Table 3. Estimates are also unstable using the full repeat sales sample with estimates falling from 39% to 25% as balancing test controls and census tract fixed effects are added. The Oster (2019) statistic for the full sample is 0.87, or unobservables need only be 87% as important as observables to explain the entire estimated effect.

Next, we conduct falsification tests basing expected loss on housing price declines that occur in the future. Specifically, when calculating expected loss, we use the housing price index from five years later in time to calculate expected loss, rather than the index from the current quarter. We drop all repeat sales transactions where the second transaction happens in the first quarter of 2007 or later once significant price declines have begun. Alternatively, we select a sample excluding initial purchase and repeat sale years in which expected losses are experienced and purchases prior to 2004. Although house prices started to fall in 2007, we can include transactions as late as the end of 2008 in this alternative sample.

Table 4 columns 1 and 2 present results for the sample through the end of 2006 and columns 3 and 4 presents results for the 2004 to 2008 sample. While the estimates on expected loss are sizable for both samples, the estimates on the interaction between expected loss and round mortgage are small and statistically insignificant whether or not the balancing test controls are included in the model. We repeat this exercise for the loss/gain model and using different lead lengths for the false housing price, and the estimates on the round mortgage interaction are always small, as shown in Appendix Figure A3.

{Insert Table 4 Here}

3.3.3 Robustness Tests

We also show that our results are robust to several alternative specifications: (1) an alternative measure of LTV ratio, (2) removing transactions involving flippers, i.e., transactions involving short-holding period investors, (3) using a housing price index based only on transactions of unconstrained borrowers with continuous mortgage amounts (avoid sales affected by loss aversion or credit constraints), (4) expanded sample of 965,934 transactions including condos, 2-4 family units, and observations with extreme values on hedonic attributes, and finally (5) using a triple transaction sample to address an errors-in-variables problem arising when using an earlier sale to control for housing unit quality.

The first four tests are in Appendix Table A8, and all models build off Table 3 Panel C. First, we follow Genesove and Mayer (1997, 2001), Engelhardt (2003), and Anenberg (2011) re-examining our results using an equity control based on whether the current LTV is above the key threshold of 0.8, i.e., the equity variable is the minimum of zero and the estimated current LTV minus 0.8. Results shown in Panel A are similar to Table 3. Next, we follow Bayer et al. (2020) using the names of buyers and sellers to identify flippers as individuals engaged in buying and selling at least two different properties while holding them for less than two years.[20] Panel B shows that results are robust to dropping transactions involving a flipper as either the seller or buyer. Panels C and D present results where the housing price index is based only on purchases where the initial buyer did not have either a downpayment constraint or round mortgage amount and for the expanded sample, respectively. Again, the results are robust.

[20] We observe a smaller proportion of flippers, as compared to Bayer et al. (2020) in Los Angeles, because single-family housing in Connecticut is less subject to speculative activities. Results are highly similar when we delete only buyers or only sellers who are identified as flippers.

Finally, we show that results are robust to addressing an errors-in-variables problem identified by Genesove and Mayer (2011). This bias arises because one factor contributing to expected losses is if the first buyer paid too much for the house, and paying too much also creates measurement error when the initial sales price is used as an indicator for unobserved housing quality. We follow Anenberg (2011) and use a sample of housing units that sold three times so that the first transaction can be used to proxy for unobserved quality without contaminating estimates of losses between the second and third sale. This restriction yields a much smaller sample of only 12,000 triple sales transactions.

These results are presented in Appendix Table A9. In Columns 1 and 3, we present results using our discontinuity model from Table 3 and the triple transaction sample, but just using the second and third transactions. In Columns 2 and 4, we use the sales price from the first sale to provide information on housing unit unobserved quality (sales price residual), and the second sales price is used to calculate expected losses for the third transaction and identify borrower type. While estimates on expected loss are larger in Columns 2 and 4 due to addressing the errors-in-variables bias, our key discontinuity results for the differences between focal point and non-focal point borrowers are robust. Considering that standard errors almost double, the estimates are quite stable at 0.09.

Turning to parameter stability, Appendix Table A10 re-estimates the errors-in-variables corrected model for the full sample of transactions. We continue to see substantial parameter instability in these corrected estimates as additional controls are added, i.e., the estimate falls 38% yielding an Oster statistic of 0.759. Admittedly, the estimated effect of expected loss for a sample including all borrower types is 69%, as compared to a 55% estimate from the traditional repeat sales model using the triple transaction sample. However, this estimate is still well below the estimate of 105% that arises in models that exclude the sales price residual. This evidence supports the standard focus in the literature on models that include the sales price residual from the first sale.

3.3.4 Holding Period and Loss Aversion

DellaVigna et al. (2017) on length of the unemployment spell and Ben-David and Hirshleifer (2012) on house holding period show that loss aversion weakens over time. To test this proposition, we create a dummy variable based on the median months (or years for sale likelihood) since the initial purchase, and interact the dummy variable with expected loss and the expected loss/round mortgage amount interaction. Table 5 presents results based on models in Table 3 panel C. In column 1 for whether the next mortgage is round, we add the interaction of whether the number of months between the first purchase and the owner's next home purchase mortgage is below median (43 months). In columns 2 and 3 for sales price, we add the interactions of below-median months between the first and second sale (56 months). Finally, in columns 4 and 5 for the likelihood of a sale, we interact whether the years between the initial purchase and the current observation year is below median (5 years).

{*Insert Table 5 Here}*

In column 1, the interaction estimate for below median and round mortgage is small and insignificant, and round number bias in the mortgage context appears very persistent. However, turning to columns 2 and 3, the additional effect of loss aversion on sales price for the round number subsample is larger for transactions with shorter holding periods, similar to Ben-David and Hirshleifer (2012). In columns 4 and 5 on sale likelihood, we obtain small and statistically insignificant estimates on sale for below-median holding period interaction.

3.3.5 Housing Demand and Loss Aversion

Many studies have examined the relationship between behavioral biases and cognitive skills or proxies for skills like income or education (see DellaVigna (2009) for a survey). While we do not observe income, we can use the amount of housing purchased as a proxy for wealth or permanent income. We create a dummy variable based on whether an initial sales price is above the median sales price within the labor market. We base median price on the quarter and year of the purchase, to avoid confounding changes in housing price levels and "quantity/quality" of housing purchased. Table 6 presents results based on models in Table 3 panel C.

{*Insert Table 6 Here*}

In column 1, the estimate on the interaction between above median and round mortgage is positive and significant. This result suggests that round number bias in the mortgage context is larger/more persistent for those who are buying more housing, either in terms of quantity or quality. Then, turning to columns 2 and 3, we also find differences in the round mortgage effect on loss aversion. Specifically, we find strong positive interactions implying that our robust estimates of loss aversion on the round mortgage interactions are larger among households exhibiting higher housing demand, potentially wealthier or higher permanent income households. The same initial buyers for whom likelihood of selecting a round number mortgage is more persistent and so likely a stronger indicator of focal point bias. However, for sale likelihood, we obtain small and statistically insignificant interaction estimates.

4**. Conclusions**

While most evidence of correlations between behavioral biases arises from survey and experimental data (Stango and Zinman 2022; Dean and Ortoleva 2019; Chapman et al. 2018a), we provide empirical evidence that the effect of loss aversion on market outcomes is stronger among individuals who exhibited focal point bias by reporting or selecting round numbers in the high stakes setting of the housing and mortgage market. We test for a discontinuity in the relationship between expected loss and sales prices for home sellers who selected a round mortgage amount during their initial purchase, as compared to sellers who selected nearby, non-round mortgage amounts. We first document that selecting round mortgage amounts is persistent within borrowers over time, and then show that the effect of facing an expected loss on sales price is substantially larger for sellers at round, initial mortgage amounts compared to sellers with similar, but non-round, initial amounts. We also find that the likelihood of sale falls more for the focal point sample relative to the continuous mortgage amount sample when the owner faces expected losses. Further, the correlation documented in this paper is between loss aversion and focal point, behavioral biases that have traditionally been classified into different families, consistent with Gabaix's (2018) view that many biases may be driven by the same underlying behaviors. On the other hand, most studies document correlations between related biases, like biases related to risk preferences (Dean and Ortoleva 2019; Chapman et al. 2018a) or overconfidence (Chapman et al. 2018a).

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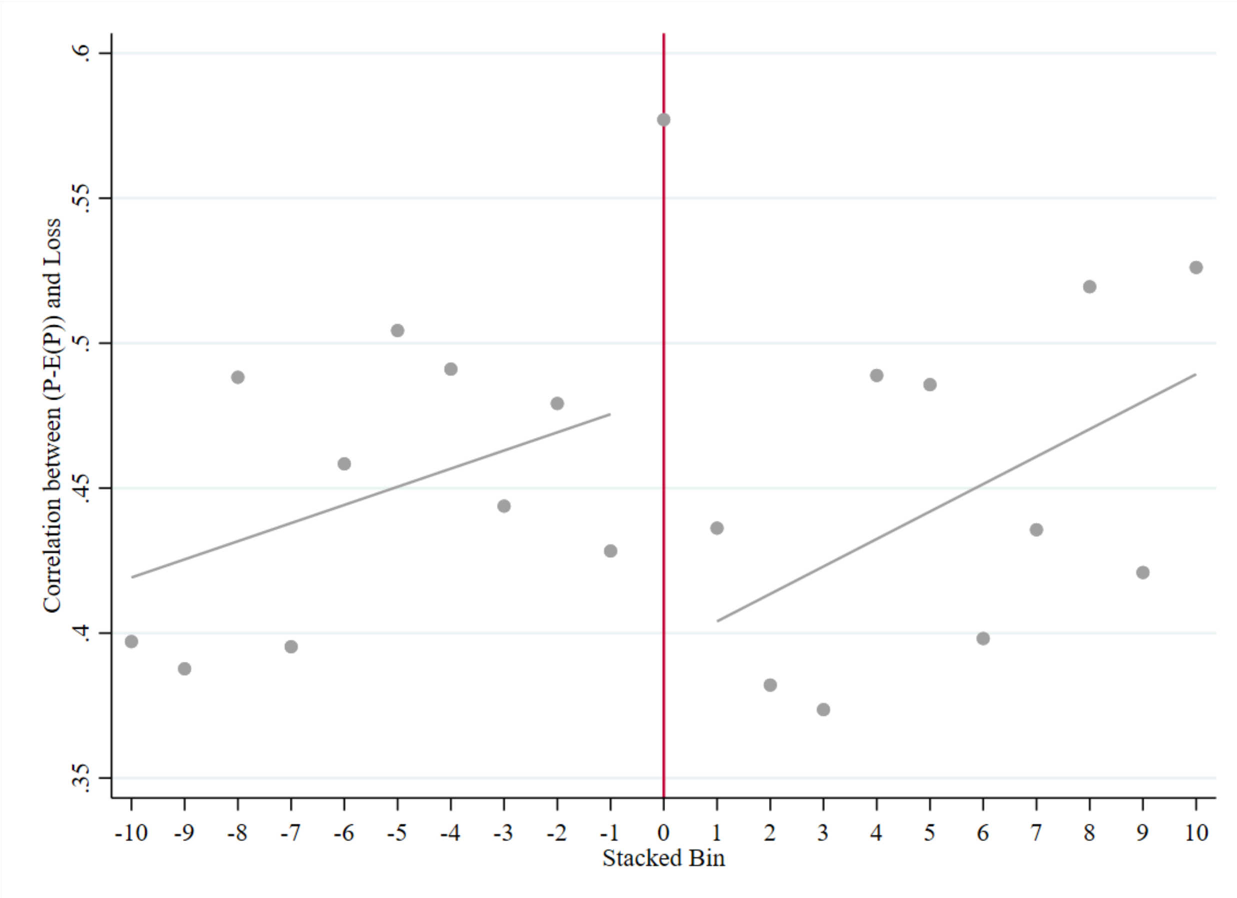
Figure 1. Distribution of Average Price Spent on Lunch

Price (Euros)	Number	Histogram
0.00	2	**
1.80	1	*
2.00	4	****
2.50	11	***********
2.80	1	*
3.00	39	***************************************
3.50	11	***********
4.00	30	******************************
5.00	27	***************************
5.50	4	****
6.00	10	**********
7.00	3	***
8.00	5	*****
10.00	1	*
15.00	1	*
Total	150	

Notes. This table shows the distribution of the average price spent on lunch.

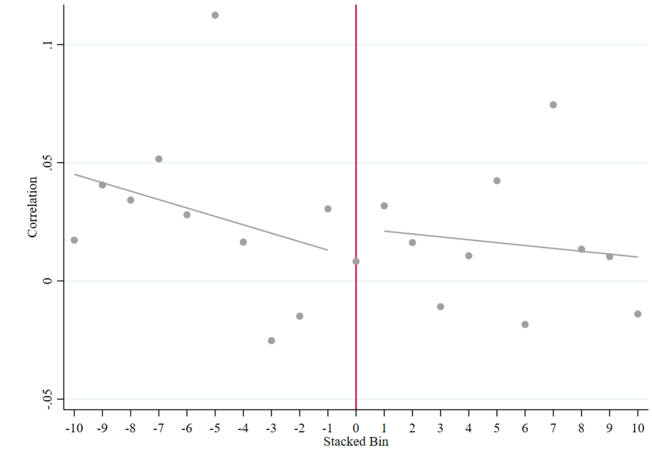
Figure 2: Correlation between Sales Price Premium and Expected Loss at Round Numbers



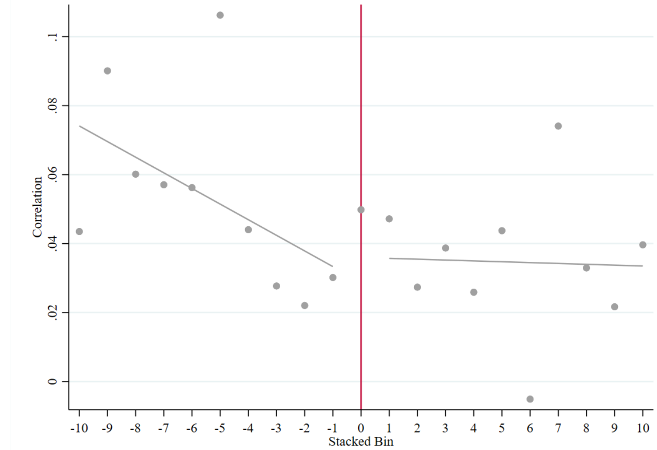
Notes. A stacked discontinuity sample is created with a \$2,500 bandwidth on either side of \$5,000 mortgage amount increments. Each \$2,500 bin is further divided on either side into 10 bins, and has an 11^{th} bin for the \$5,000 increments. The observations of credit-constrained borrowers and cash purchases are dropped. The gray dots are unconditional correlations between expected loss and the difference between sale price and expected sale price. The gray lines are fitted lines for the 10 points below 0 and separately for the 10 points above 0. The vertical line in the center of the graph highlights the clear discontinuity at the zero value of the running variable.

Figure 3: Correlation between Transaction Attributes and Expected Loss at Round Numbers

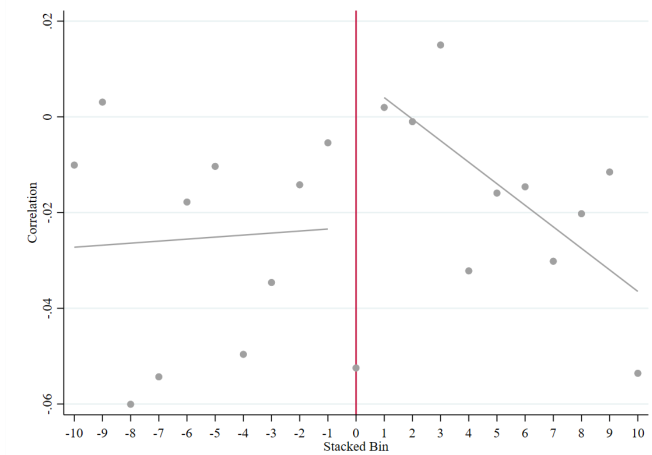
Panel A: House Attribute - Interior Size



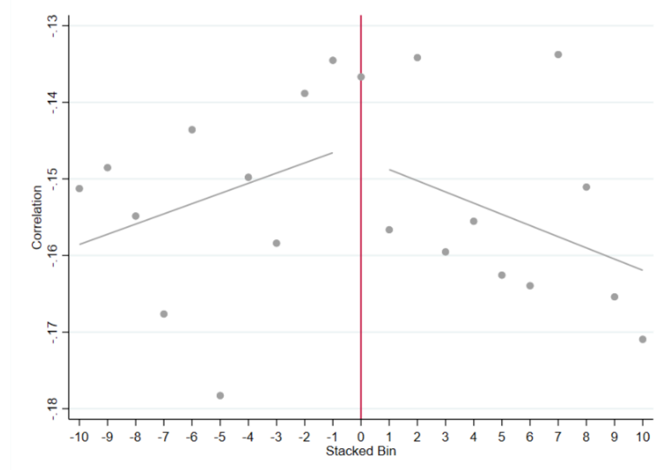
Panel B: House Attribute – Age



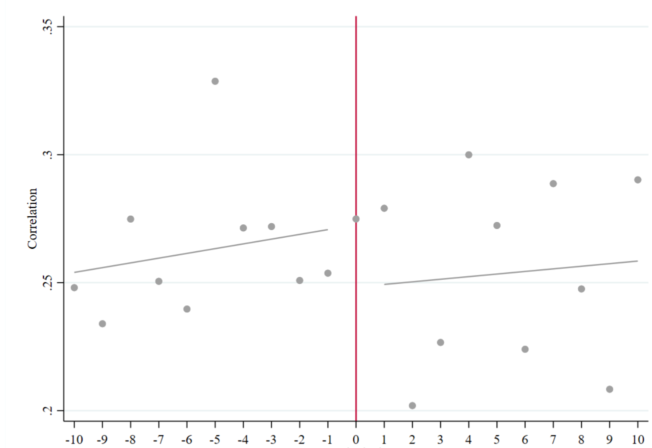
Panel C: Mortgage Attribute – LTV



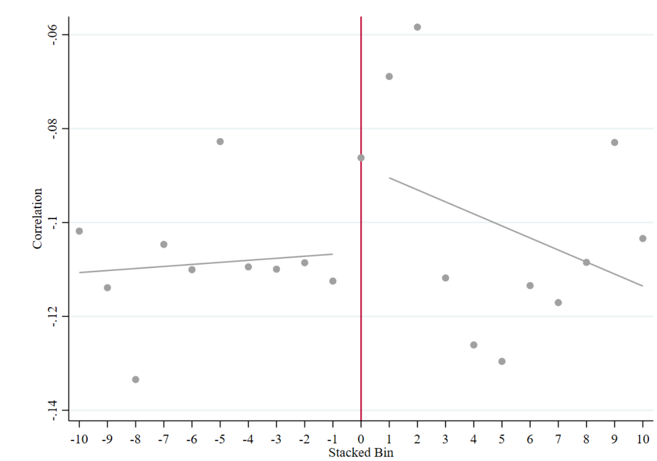
Panel D: Census Attribute - % Black Alone



Panel E: Census Attribute - % College Education



Panel F: Census Attribute – Unemployment Rate



Notes. A stacked discontinuity sample is created with a $2,500 bandwidth on either side of the $5,000 mortgage amount increments. Each $2,500 bin is further divided on either side into 10 bins, and has an 11th bin for the $5,000 increments. The observations of credit-constrained borrowers and cash purchases are dropped. The gray dots are unconditional correlations between expected loss and house, mortgage, and census attributes. The gray lines are fitted lines for the 10 points below 0 and separately for the 10 points above 0. The vertical line in the center of each graph indicates the correlation at zero.

Table 1: Loss Aversion and Self-Reported Round Numbers

	Full Sample	Drop 10 & 15	Drop >=7
A. No Controls	(1)	(2)	(3)
Rounded Reporting	1.786**	1.447**	1.530**
	(0.783)	(0.688)	(0.724)
Risk Aversion Estimate	7.270***	5.891***	6.222***
	(2.544)	(2.216)	(2.346)
R-squared	0.146	0.131	0.139
Observations	124	122	118

B. With Controls	(4)	(5)	(6)	(7)	(8)	(9)
Rounded Reporting	1.907**	1.541	1.559*	2.175*	1.693*	2.200*
	(0.924)	(1.192)	(0.849)	(1.223)	(0.901)	(1.258)
Risk Aversion Estimate	7.410***	7.113***	5.948**	5.997**	6.421**	6.242**
	(2.778)	(2.653)	(2.429)	(2.383)	(2.614)	(2.451)
Age	-0.047	-0.061	-0.011	-0.014	-0.024	-0.018
	(0.066)	(0.075)	(0.054)	(0.054)	(0.054)	(0.057)
Gender (Male=1)	-0.400	-0.185	-0.908	-0.712	-1.111	-0.857
	(1.057)	(1.043)	(0.945)	(0.858)	(0.983)	(0.858)
Semester	0.036	0.038	0.025	0.055	0.028	0.056
	(0.030)	(0.045)	(0.028)	(0.046)	(0.029)	(0.048)
Work Income (log)	0.020	0.001	-0.071	-0.067	-0.071	-0.079
	(0.184)	(0.174)	(0.158)	(0.161)	(0.163)	(0.167)
Number of Lunches Out per Week		-0.298		-0.596		-0.574
		(0.458)		(0.447)		(0.460)
Self-Reported Cost of Lunch		0.252		-0.670		-0.656
		(0.676)		(0.510)		(0.587)
R-squared	0.142	0.151	0.130	0.165	0.142	0.169
Observations	119	119	117	117	114	114

Notes. This table shows results from regressions of loss aversion on rounded reporting dummy and control variables using the experimental data in Karle et al. (2015). The loss aversion parameter is estimated from an experiment of choices between lotteries and sure payment. Panel A (B) shows the result without (with) controls. Column (1), (2), and (3) in Panel A (Column (1)-(2), (3)-(4), and (5)-(6) in Panel B) shows results using the full sample deleting reported costs of lunch equal to zero, this sample deleting reported costs equal to 10 or 15 euros, and this sample deleting reported costs greater than 7, respectively. * significant at 90%, ** significant at 95% and *** significant at 99% confidence level.

Table 2: Balancing Tests Continuous and Round Mortgage Amount Subsamples

	OLS	Discontinuity Model	
	Loss	Loss	Loss * Round Mortgage
	(1)	(2)	(3)
Hedonic Characteristics			
Interior Size	328.157***	276.134***	-86.910
	(29.721)	(58.459)	(58.633)
Lot Size	-971.027	1129.616	1049.404
	(2343.364)	(2435.469)	(2438.738)
Number of bathrooms	0.241***	0.396***	0.042
	(0.024)	(0.071)	(0.057)
Number of bedrooms	0.589***	0.094**	0.051
	(0.059)	(0.037)	(0.033)
Age	27.470***	0.236***	0.007
	(1.754)	(0.047)	(0.042)
Mortgage Attributes			
First Mortgage Amount	0.244***		
	(0.029)		
Combined Mortgage Amount	0.243***		
	(0.029)		
Loan to Value Ratio	-0.201***	-0.683***	0.033
	(0.020)	(0.032)	(0.028)
Combined LTV Ratio	-0.202***		
	(0.020)		
Census block characteristics (Census 1990)			
Percent Female	0.006***	0.003*	-0.002
	(0.001)	(0.002)	(0.002)
Percent black	0.046***	0.030***	-0.006
	(0.009)	(0.006)	(0.005)
Percent white	-0.067***	-0.043***	0.002
	(0.011)	(0.007)	(0.005)
Log Median Household income	-0.026	-0.050**	0.024
	(0.024)	(0.023)	(0.022)
Percent with college education	0.062***	0.047***	-0.001
	(0.009)	(0.011)	(0.011)
Average household size	-0.025***	-0.017**	-0.000
	(0.006)	(0.007)	(0.007)
Percent below poverty	0.004***	0.023***	-0.001
	(0.001)	(0.003)	(0.002)
Percent of owner-occupants w/ mortgage	-0.026***	0.006	-0.011
	(0.008)	(0.009)	(0.010)

Unemployment rate	0.012***	0.010***	-0.003
	(0.002)	(0.002)	(0.002)
Vacancy rate	0.043***	0.016***	0.016**
	(0.008)	(0.005)	(0.006)
Median value of owner-occupied housing	0.108***	-0.002	0.026
	(0.027)	(0.028)	(0.023)
Percent of 65 and over	0.008**	0.001	-0.003
	(0.004)	(0.005)	(0.005)

Notes. This table summarizes the results of balancing tests using the sample deleting cash-only purchases and LTV-focused purchases. Mortgage Amount in the "Mortgage Attributes" block is dropped due to collinearity with mortgage amount bins, and Combined Mortgage Amount and combined LTV are dropped because this sample omits all borrowers who took out a second mortgage at purchase.

Table 3: Discontinuity Analysis

	Round Next Mortgage	Sale Price	Sale Price	Sale Hazard	Sale Hazard
		Loss	w/ Gain	Loss	w/ Gain
	(1)	(2)	(3)	(4)	(5)
A. Baseline					
Round Mortgage (Previous)	0.112***				
	(0.036)				
Loss		0.166***	0.142***	0.001	-0.016
		(0.036)	(0.040)	(0.009)	(0.012)
Loss*Round Mortgage (Previous)		0.114***	0.106***	-0.020***	-0.024***
		(0.032)	(0.035)	(0.007)	(0.008)
R-squared	0.278	0.830	0.830	0.0042	0.0050
B. Baseline + balance control (and interactions)					
Round Mortgage (Previous)	0.111***				
	(0.036)				
Loss		0.134***	0.158***	0.001	-0.015
		(0.028)	(0.031)	(0.009)	(0.012)
Loss*Round Mortgage (Previous)		0.109***	0.102***	-0.021***	-0.026***
		(0.027)	(0.030)	(0.007)	(0.008)
R-squared	0.287	0.860	0.860	0.0045	0.0052
C. Baseline + balance control (and interactions) + tract (or tract-by-type) FEs					
Round Mortgage (Previous)	0.121***				
	(0.039)				
Loss		0.102***	0.119***	0.002	-0.015
		(0.023)	(0.026)	(0.010)	(0.013)
Loss*Round Mortgage (Previous)		0.121***	0.112***	-0.028***	-0.032***
		(0.026)	(0.027)	(0.008)	(0.009)
R-squared	0.459	0.883	0.884	0.0109	0.0116
Observations	14,413	50,959	50,959	312,559	312,559

Notes. This table presents the discontinuity analysis using the sample deleting cash-only purchases and LTV-focused purchases. Column (1) shows regressions of whether the next mortgage amount is round on round mortgage dummy in equation (1). Columns (2) and (3) show regression of sale price on loss, loss*round mortgage, and controls described in equation (4). Columns (4) and (5) show regression of sale probability on loss, loss*round mortgage, and controls described in equation (6). Panel A shows the baseline results, Panel B adds all the balance controls for the hedonic, mortgage, and census characteristics and for columns 2-5 interact with the round mortgage dummy, and Panel C adds both these controls and census tract or for columns 2-5 tract by purchase type fixed effects. Standard errors are clustered at mortgage bin, labor-market-area-by-quarter, and tract level. * significant at 90%, ** significant at 95% and *** significant at 99% confidence level.

Table 4: Falsification Analysis

	Drop >2007	Drop >2007	2004-2008	2004-2008
	Sale Price	Sale Price	Sale Price	Sale Price
	Loss	w/ Gain	Loss	w/ Gain
	(1)	(2)	(3)	(4)
A. Baseline				
Loss	0.257***	0.618***	0.297***	0.553***
	(0.058)	(0.065)	(0.060)	(0.069)
Loss*Round Mortgage (Previous)	-0.052	-0.003	0.026	0.057
	(0.052)	(0.057)	(0.057)	(0.062)
B. Baseline + balance control (and interactions)				
Loss	0.185***	0.510***	0.208***	0.435***
	(0.048)	(0.055)	(0.052)	(0.062)
Loss*Round Mortgage (Previous)	-0.040	0.008	0.027	0.057
	(0.045)	(0.048)	(0.051)	(0.054)
C. Baseline + balance control (and interactions) + tract-by-type FEs				
Loss	0.152***	0.428***	0.178***	0.348***
	(0.040)	(0.049)	(0.045)	(0.055)
Loss*Round Mortgage (Previous)	-0.009	0.034	0.033	0.058
	(0.044)	(0.047)	(0.047)	(0.050)
Observations	19,712	19,712	15,193	15,193

Notes. This table summarizes the falsification analysis in which expected loss is calculated using the housing price fixed effect estimates from five years later in time, rather than the fixed effects from the current quarter. In columns 1 and 2, we drop all repeat sales transactions where the second transaction happens in the first quarter of 2007. In columns 3 and 4, we keep 2004-2008 in which the differences between the actual HPI and the HPI five years ahead were the largest. Panel A shows the baseline results. Panel B adds all the balance controls for the hedonic, mortgage, and census characteristics, Panel C adds both these controls and tract by purchase type fixed effects. Standard errors are clustered at mortgage bin, labor-market-area-by-quarter, and tract level. * significant at 90%, ** significant at 95% and *** significant at 99% confidence level.

Table 5: Heterogeneity by Holding Period

	Round Next Mortgage	Sale Price	Sale Price	Sale Hazard	Sale Hazard
		Loss	w/ Gain	Loss	w/ Gain
	(1)	(2)	(3)	(4)	(5)
A. Estimates for Above Median					
Round Mortgage (Previous)	0.135***				
	(0.044)				
Loss		0.156***	0.203***	0.002	-0.011
		(0.029)	(0.032)	(0.012)	(0.014)
Loss*Round Mortgage (Previous)		0.086***	0.069**	-0.036***	-0.024***
		(0.030)	(0.032)	(0.008)	(0.008)
B. Interactions with below Median					
Below*Round Mortgage	-0.007				
	(0.034)				
Below*Loss		-0.067***	-0.047*	-0.018***	-0.019***
		(0.026)	(0.028)	(0.005)	(0.005)
Below*Loss*Round Mortgage		0.080**	0.093**	0.006	0.008
		(0.033)	(0.037)	(0.006)	(0.006)

Notes. This table summarizes results of discontinuity analysis using the sample deleting cash-only purchases and LTV-focused purchases following the specification of Table 2, Panel C. Panel A presents the estimates for the omitted category: above median holding period, and Panel B presents estimates for the interaction of variables with a dummy for below median holding period. The interaction of below-median and the round mortgage dummy in columns (2)-(5) are included in the models for generalizability, but not presented to keep the table parsimonious. Column (1) shows regressions of whether the next mortgage amount is round on round mortgage dummy and the interaction of whether the number of months between the first purchase and the owner's next home purchase mortgage is below the sample median (43 months). Columns (2) and (3) show regression of sale price on loss, loss*round mortgage, and their interaction with whether months between first and second sale is below the median (56 months). Columns (4) and (5) show regression of sale probability on loss, loss*round mortgage, and the interactions of whether the years between the initial purchase and the observation year is below the sample median (5 years). Standard errors are clustered at mortgage bin, labor-market-area-by-quarter, and tract level. * significant at 90%, ** significant at 95% and *** significant at 99% confidence level.

Table 6: Heterogeneity by Real Housing Price

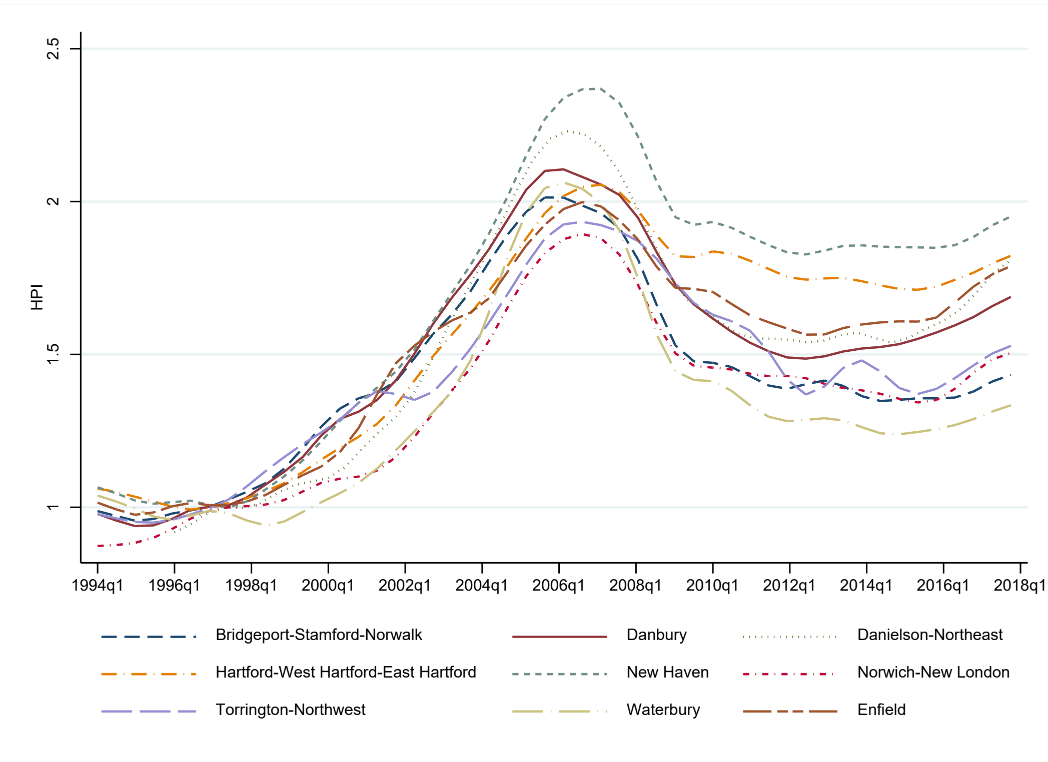
	Round Next Mortgage	Sale Price	Sale Price	Sale Hazard	Sale Hazard
		Loss	w/ Gain	Loss	w/ Gain
	(1)	(2)	(3)	(4)	(5)
A. Estimates for Below Median					
Round Mortgage (Previous)	0.079***				
	(0.019)				
Loss		0.015	0.072***	0.036**	0.017
		(0.027)	(0.027)	(0.015)	(0.017)
Loss*Round Mortgage (Previous)		0.051*	0.018	-0.029***	-0.028**
		(0.029)	(0.029)	(0.011)	(0.011)
B. Interactions with Above Median					
Above*Round Mortgage	0.036**				
	(0.018)				
Above *Loss		0.096***	0.014	-0.059***	-0.047***
		(0.024)	(0.027)	(0.009)	(0.010)
Above *Loss*Round Mortgage		0.084***	0.133***	0.008	-0.001
		(0.031)	(0.034)	(0.009)	(0.010)

Notes. This table summarizes results of discontinuity analysis using the sample deleting cash-only purchases and LTV-focused purchases following the specification of Table 2, Panel C. Panel A presents the estimates for the omitted category: below median sales price, and Panel B presents estimates for the interaction of variables with a dummy for above median sales price. Median sales price is calculated by labor market area by quarter so that sales prices are measured at the current housing price level for each market. The interaction of above-median and round in columns (2)-(5) are included in the models for generalizability, but not presented to keep the table parsimonious. Column (1) shows regressions of whether the next mortgage amount is round on round mortgage dummy and the interaction of whether the initial purchase price is above the median for a given LMA-quarter. Columns (2) and (3) show regression of sale price on loss, loss*round mortgage, and their interaction with whether the initial purchase price is above the median for a given LMA-quarter. Columns (4) and (5) show regression of sale probability on loss, loss*round mortgage, and the interactions of whether the initial purchase price is above the median for a given LMA-year. Standard errors are clustered at mortgage bin, labor-market-area-by-quarter, and tract level. * significant at 90%, ** significant at 95% and *** significant at 99% confidence level.

Appendix (On-line Publication Only)

Appendix A: Figures and Tables

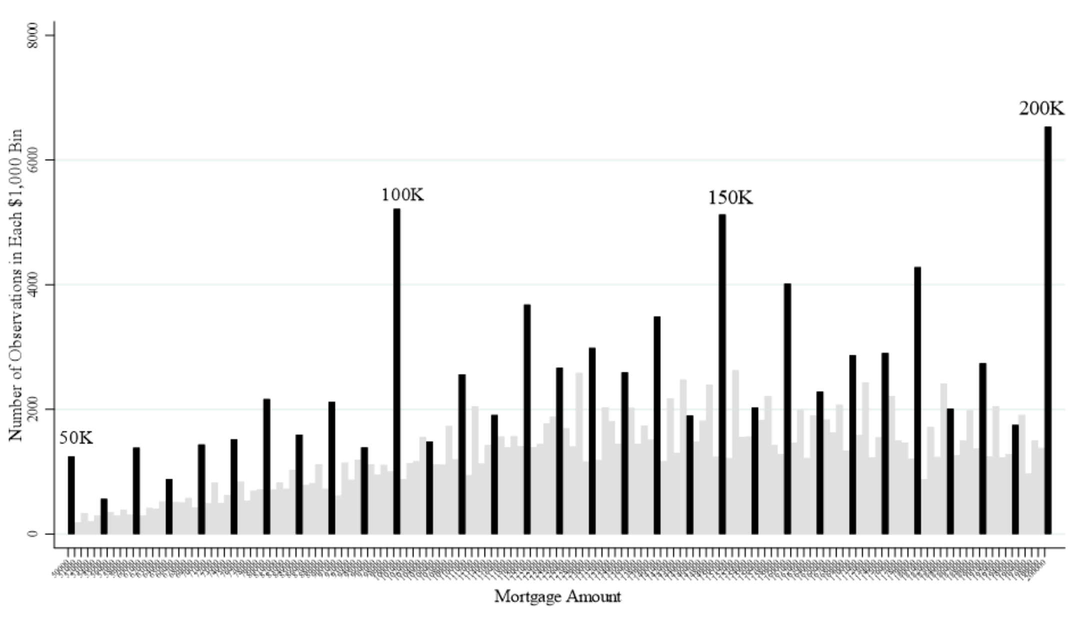
Figure A1: Housing Price Indices



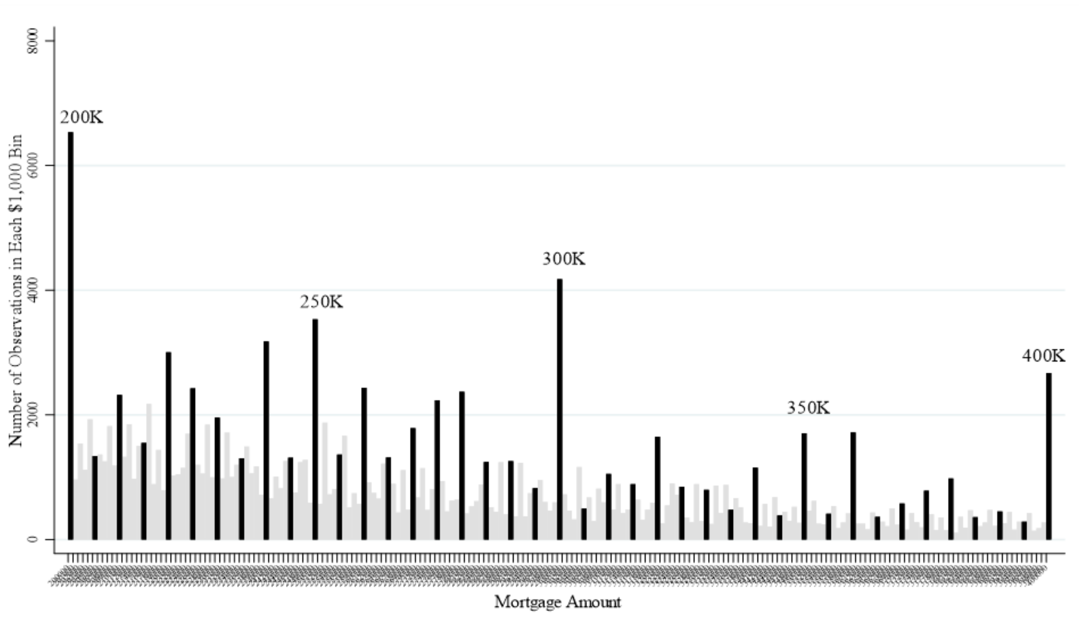
Notes. This figure shows the house price indices by the nine labor market areas in our sample from 1994Q1 to 2017Q4. 1997Q1 is the base year. Indices are plotted using a local polynomial smooth with the triangle kernel function.

Figure A2: Mortgage Amount Histograms

Panel A: Mortgage Amount $50,000–$200,000

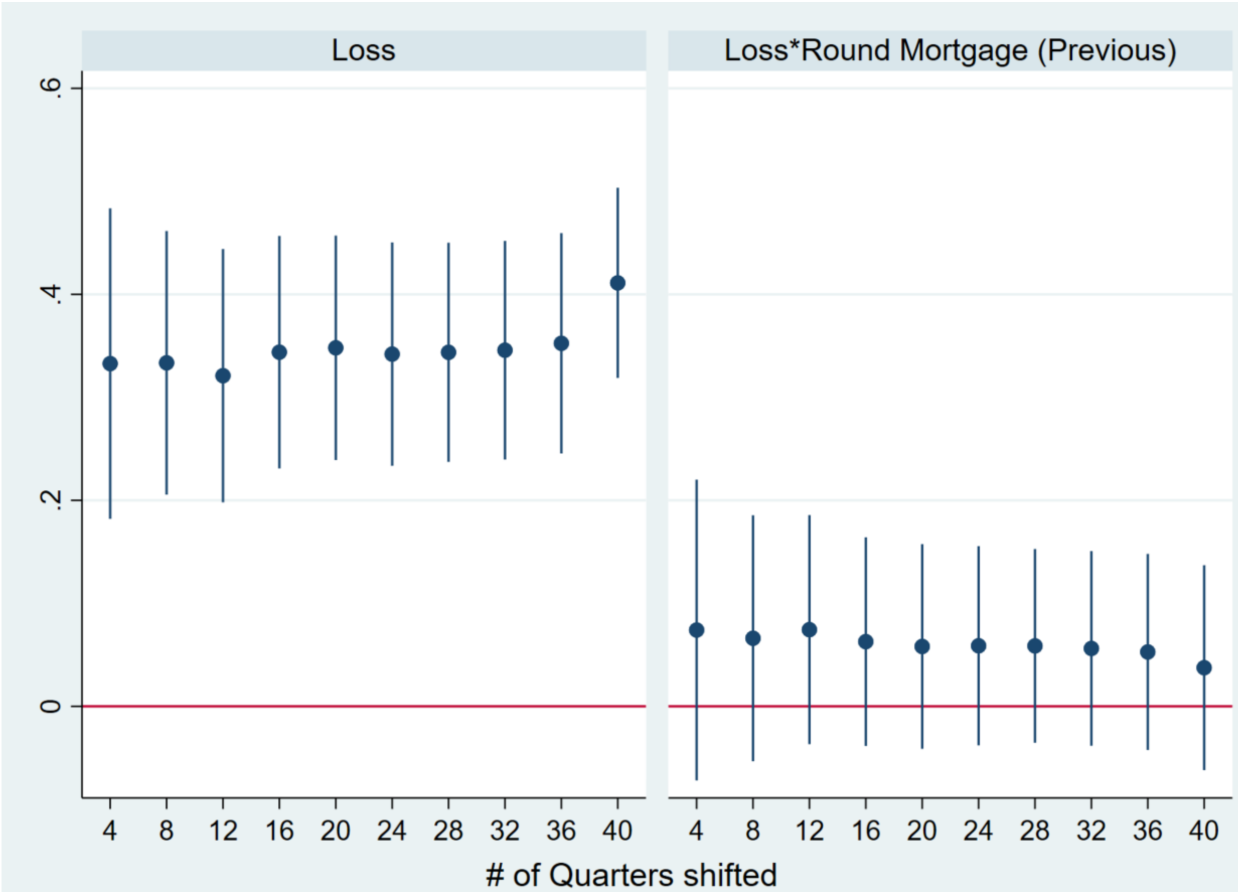


Panel B: Mortgage Amount $200,000–$400,000



Notes. This figure shows histograms for houses whose mortgage amounts were between $50,000 and $200,000 ($200,000 and $400,000) in Panel A (B). The histogram groups mortgages into $1,000 bins (rounded down). Dark bars indicate multiples of $5,000.

Figure A3: Falsification Tests with Different Lead Periods



Notes. This figure plots coefficient estimates of Loss (in the left-hand side panel) and Loss*Round Mortgage (Previous) (in the right-hand side panel) using the model specification and sample of column 2 Panel C in Table 4. The horizontal axis corresponds to different lead lengths for the falsification housing price used for calculating expected losses.

Table A1: Balancing Test for Self-Reported Round Numbers

	Drop 10 & 15		Drop >=7	
	(1)	(2)	(3)	(4)
Age	0.003	0.001	0.004	-0.000
	(0.009)	(0.009)	(0.009)	(0.009)
Gender (Male=1)	0.085	0.086	0.094	0.083
	(0.077)	(0.074)	(0.079)	(0.076)
Semester	-0.007*	-0.009**	-0.007*	-0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Work Income (log)	0.000	-0.002	-0.000	-0.001
	(0.014)	(0.013)	(0.014)	(0.014)
Number of Lunches Out		0.012		0.015
per Week		(0.028)		(0.028)
F-Test (Attributes)	1.14	1.44	1.19	1.50
p-value	[0.340]	[0.217]	[0.312]	[0.196]
R-squared	0.040	0.147	0.043	0.150
Observations	117	117	114	114

Notes. This table shows results from regressions of the rounded reporting dummy on control variables using the experimental data in Karle et al. (2015). All models also include the loss aversion parameter is estimated from an experiment of choices between lotteries and sure payment, and models 2 and 3 with number of lunches out per week also include a control for the average price of lunch. Column (1) and (2) present estimates after dropping the outlier amounts of 10 and 15 Euros, and (3) and (4) further restrict the sample of amounts by deleting reported costs greater than 7, respectively. The F-Test and associated p-values test the null hypothesis that all estimates presented in the column of this table are zero. * significant at 90%, ** significant at 95% and *** significant at 99% confidence level.

Table A2: Sample Construction

Panel A: Sample Construction - Sales Price Results

	Observations
Individual residential transactions between 1994 and 2017	1,409,127
Transactions with property types that are not single-family residential	(552,111)
Transactions without warranty deeds	(127,065)
Transactions with less than one bedroom	(77,623)
Transactions with less than 0.5 bathrooms	(7,462)
Transactions with interior footage less than 300 square feet	(29,566)
Transactions with lot size more than 500,000 square feet	(4,882)
Transactions with sale price less than $40,000	(10,323)
Transactions with structures built earlier than 1799 or after 2018	(45,019)
Transactions with missing dates or bought and sold on the same date	(5,986)
Transactions with year built later than year sold	(522)
A.1 Final Sample used in the hedonic estimation	548,568
Non-repeat Sale	(383,561)
Repeat sales before 2000	(4,033)
Repeat sales with non-matched buyer and seller and missing controls	(21,300)
A.2 Sample of repeat sales (baseline results in Appendix A6)	139,674
LTV-focused & cash-financed	(88,715)
A.3 Final Sample of repeat sales (baseline discontinuity results)	50,959

Panel B: Sample Construction – Repeat Purchase Results

	Observations
A.1 Final Sample used in the hedonic estimation (transaction level)	548,568
Add additional observations for transactions with multiple buyers	295,518
B.1 Individual by transaction observations	844,086
Non-repeat purchases	(804,150)
Observations with missing controls	(616)
B.2 Sample of repeat purchases	39,295
LTV-focused & cash-financed	(24,882)
B.3 Final Sample (baseline discontinuity results)	14,413

Panel C: Sample Construction - Sale Probability Results

	Observations
A.1 Final Sample used in the hedonic estimation (transaction level)	548,568
Add additional observations for every year prior to repeat sale	3,718,420
Number of houses by year observations	4,266,988
Observations before 2000	(208,750)
C.1 House by year observations	4,058,238
Non-repeat sale	(3,245,211)
C.2 Sample of repeat sale	813,027
LTV-focused & cash-financed	(500,468)
C.3 Final Sample (baseline discontinuity results)	312,559

Table A3: Variable Definitions

Variable	Definition
Sale price	Log of sale price of the second sale.
Sale probability	An indicator variable if house *i* was sold in year *t.*
Round mortgage	An indicator variable if 1st mortgage amount at purchase with 0 or 5 on 000' and LTV focused dummy equals zero.
LTV focused	An indicator variable if the LTV ratio at purchase equals one of the critical ratios, e.g., 0.80, 0.90, 0.95, 0.97, and 1.00, that suggest that the buyer targeted an important LTV ratio in the market) or took out a second mortgage at the time of purchase (subordinate debt). Appendix 2 summarizes details on identifying critical LTV ratios.
Cash financed	An indicator variable for all cash purchase.
Loss	Difference between the first sale price and the expected price truncated above at zero. It is measured at the time of the second sale (year t within a sale spell) in repeat sale analysis (panel data analysis) for sale price (sale probability) as the outcome variable.
Gain	Difference between the first sale price and the expected price truncated below at zero. It is measured at the time of the second sale (year t within a sale spell) in repeat sale analysis (panel data analysis) for sale price (sale probability) as the outcome variable.
Equity Position	Equity position of the loan assuming a 30-year mortgage amortized using the 30-year mortgage interest rate at purchase. It is measured at the time of the second sale (year t within a sale spell) in repeat sale analysis (panel data analysis) for sale price (sale probability) as the outcome variable. An alternative equity position is measured as an equity position truncated at above 0.8.
Expected price	Predicted value estimated by the hedonic model
First residual	The residual from the hedonic regression for the first sale
Month	Number of months between the first and second sale used in repeat sale analysis for sale price as the outcome variable
Years since last sale	Number of years since purchase used in panel data analysis for sale probability as the outcome variable
Housing Characteristic	
Interior size	Interior size (sq. ft.) of the house
Lot size	Lot size (sq. ft.) of the house
2-3 bathrooms	An indicator variable if 2-3 bathrooms
> 3 bathrooms	An indicator variable if > 3 bathrooms
Age	Age of the house
Mortgage attributes	
Mortgage amount	Log of 1st mortgage amount (taken from the first sale)
Combined mortgage amount	Log of combined mortgage amount (taken from the first sale)
LTV ratio	Loan-to-value ratio (taken from the first sale)
CLTV ratio	Combined loan-to-value ratio (taken from the first sale)
Presence of second mortgage	An indicator variable if there is a second mortgage in the first sale
Census block characteristics (Census 1990)	
Percent female	Percent of female population
Percent white	Percent of white population
Median income	Median Household Income (in 2000 Dollars)
Percent with college education	Percent of population with college degree
Percent of households with kids	Percent of married-couple families
Average household size	Average household size
Percent below poverty	Percent of households below poverty level

Percent of owner-occupied housing with mortgage	Percent of owner-occupied houses with mortgage
Unemployment rate	Unemployment rate
Vacancy rate	Percentage of vacant housing units
Median value of owner-occupied housing	Median value of owner-occupied housing (in 2000 Dollars)
Percent of 65 and over	Percent of age 65 and over

Table A4: Summary Statistics by Sample Filters

	Hedonic Estimation (incl. one-only and repeat sales)		Repeat Sales (2nd sale after 2000)		Repeat Sales (dropped – 2nd sale prior to 2000)	
	N = 548,568		N = 139,674		N = 25,333	
	Mean	Median	Mean	Median	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)
Sales Price	355,027	237,000	413,130	259,000	393,114	232,000
Sales Price (constant year prices)	284,156	169,947	317,723	173,329	327,924	170,813
Hedonic Characteristics						
Interior Size	1,892	1,630	1,887	1,598	1,976	1,661
Lot Size	33,047	15,855	29,998	14,810	32,160	15,246
Number of bathrooms	2.03	2.00	2.07	2.00	2.12	2.00
Number of bedrooms	3.31	3.00	3.34	3.00	3.36	3.00
Age	52.37	49.00	56.69	54.00	54.03	51.00
Mortgage Attributes						
First Mortgage Amount	229,856	179,450	266,714	200,000	222,194	160,714
First Mortgage Amount (adj.)	182,380	128,463	201,858	132,209	184,567	117,176
Combined Mortgage Amount	230,311	179,685	266,824	200,000	222,745	161,000
Combined Mortgage Amount (adj.)	182,882	128,676	201,964	132,238	185,186	117,575
Loan to Value Ratio	0.73	0.80	0.74	0.80	0.65	0.80
Combined LTV Ratio	0.73	0.80	0.74	0.80	0.65	0.80
1990 block group characteristics						
% Female	0.51	0.51	0.52	0.51	0.51	0.51
% white	0.94	0.98	0.94	0.98	0.94	0.98
Median Household Income (log)	11.07	11.05	11.07	11.05	11.09	11.07
% with college education	0.31	0.28	0.31	0.28	0.32	0.29
Average household size	1.31	1.31	1.31	1.30	1.31	1.31
% below poverty	0.03	0.02	0.03	0.02	0.03	0.02
% of owner-occupants w/ mortgage	0.69	0.70	0.69	0.70	0.69	0.71
Unemployment rate	0.05	0.04	0.05	0.04	0.05	0.04
Vacancy rate	0.06	0.04	0.05	0.04	0.05	0.04
Median value of owner-occupied housing (log)	12.40	12.33	12.41	12.33	12.44	12.34
% of 65 and over	0.14	0.13	0.14	0.13	0.14	0.13

Table A5: Summary Statistics by Treatment Status

	Loss > 0		Loss < 0	
	Mean	Std Dev	Mean	Std Dev
	(1)	(2)	(3)	(4)
Log of Sale Price	12.77	0.81	12.43	0.67
Dummy Round Number Mortgage	0.21	0.41	0.15	0.36
Dummy LTV Focused	0.47	0.50	0.44	0.50
Loss	0.32	0.28	0.00	0.00
Gain	0.00	0.00	0.46	0.37
Market Price (log)	12.49	0.58	12.52	0.59
1st Residual	0.28	0.34	-0.22	0.41
Equity Position (current LTV)	0.69	0.34	0.56	0.39
Equity Position (current LTV Truncated)	0.07	0.14	0.05	0.21
Months since the Previous Sale	68.27	43.75	64.83	55.09
Hedonic Characteristics				
Interior Size (sf.)	1,922	1,005	1,863	990
Lot Size (sf.)	30,965	41,555	29,293	41,125
2-3 bathrooms	0.51	0.50	0.49	0.50
>3 bathrooms	0.10	0.30	0.09	0.29
Age	57.77	32.00	55.94	31.62
Mortgage Attributes				
Mortgage Amount (First Mortgage, log)	12.52	0.63	11.95	0.61
Combined Mortgage Amount (log)	12.52	0.63	11.96	0.61
Loan to Value Ratio (initial LTV)	0.70	0.53	0.73	0.96
Combined Loan to Value Ratio (initial CLTV)	0.70	0.53	0.73	0.96
Presence of Second Mortgage	0.01	0.07	0.03	0.18
Census block characteristics (Census 1990)				
Percent Female	0.52	0.02	0.52	0.02
Percent white	0.96	0.07	0.92	0.15
Median Household income	77,744	32,108	65,353	26,143
Percent with college education	0.37	0.18	0.28	0.16
Percent households with kids	0.34	0.09	0.35	0.09
Average household size	2.76	4.35	2.75	2.60
Percent below poverty	0.02	0.03	0.04	0.07
Percent of owner-occupied housing with mortgage	0.69	0.13	0.68	0.15
Unemployment rate	0.04	0.03	0.05	0.04
Vacancy rate	0.06	0.07	0.05	0.05
Median value of owner-occupied housing	302,372	138,101	243,731	105,497
Percent of 65 and over	0.14	0.07	0.14	0.07

Notes. This table shows means and standard deviations for repeat-sale transactions with expected loss and expected gain.

Table A6: Estimates on Expected Gains

	Sale Price	Sale Hazard
	(1)	(2)
A. Baseline		
Gain	0.024	0.034***
	(0.027)	(0.009)
Gain*Round Mortgage	0.022	0.013
	(0.021)	(0.008)
R-squared	0.830	0.0050
B. Baseline + balance control interactions		
Gain	-0.051**	0.032***
	(0.021)	(0.009)
Gain*Round Mortgage	-0.002	0.015*
	(0.017)	(0.008)
R-squared	0.860	0.0052
C. Baseline + balance control interactions + tract by type FEs		
Gain	-0.031*	0.036***
	(0.018)	(0.009)
Gain*Round Mortgage	-0.017	0.014
	(0.016)	(0.009)
R-squared	0.884	0.0116
Observations	50,959	312,559

Notes. This table summarizes results for the gain estimates from regressions of sale price on expected loss and gain and these variables interacted with round mortgage, and controls. Column 1 presents results for sales price, and column 2 presents results for likelihood of sale. Panel A follows a standard model in Genesove and Mayer (2001). Panel B adds the full list of controls (shown in the balancing tests in Table 1) and in the case of columns 2 and 4 interacted with round mortgage amount. Panel C adds both these controls and census tract or census tract by purchase type fixed effects. * significant at 90%, ** significant at 95% and *** significant at 99% confidence level.

Table A7: Traditional Linear Models using All Housing Transactions

	G&M	Round	w/ Gains	Round w/ Gains
	(1)	(2)	(3)	(4)
A. Baseline				
Loss	0.389***	0.299***	0.386***	0.317***
	(0.017)	(0.028)	(0.018)	(0.029)
Loss*Round Mortgage		0.150***		0.148***
		(0.027)		(0.026)
R-squared	0.812	0.822	0.812	0.823
B. Baseline + balance control interactions				
Loss	0.319***	0.222***	0.306***	0.230***
	(0.013)	(0.022)	(0.015)	(0.023)
Loss*Round Mortgage		0.127***		0.127***
		(0.025)		(0.024)
R-squared	0.839	0.845	0.839	0.846
C. Baseline + balance control interactions + tract by type FEs				
Loss	0.254***	0.171***	0.245***	0.175***
	(0.012)	(0.017)	(0.012)	(0.018)
Loss*Round Mortgage		0.113***		0.113***
		(0.021)		(0.021)
R-squared	0.869	0.872	0.869	0.872
Observations	139,674	139,674	139,674	139,674

Notes. This table summarizes results from regressions of sale price on expected loss and loss*round mortgage, and controls. Standard errors are clustered at the labor-market-area-by-quarter and tract level. Column 1 replicates the Genesove and Mayer (2001) model. Column 2 compares non-credit constrained borrowers with continuous mortgage amounts to those with round mortgage amounts adding interactions of a round mortgage amount dummy variable with expected loss, as well as with all other controls. Column 3 adds expected gain to the Genesove and Mayer model in column 1. Column 4 repeats column 2 adding expected gain and the interactions with round mortgage amount. Panel A follows a standard model in Genesove and Mayer (2001). Panel B adds the full list of controls (shown in the balancing tests in Table 1) and in the case of columns 2 and 4 interacted with round mortgage amount. Panel C adds both these controls and census tract or census tract by purchase type fixed effects. * significant at 90%, ** significant at 95% and *** significant at 99% confidence level.

Table A8: Robustness Tests

	Round Next Mortgage	Sale Price	Sale Price	Sale Hazard	Sale Hazard
		Loss	w/ Gain	Loss	w/ Gain
	(1)	(2)	(3)	(4)	(5)
A. Alternative Equity Measure					
Round Mortgage (Previous)	0.119***				
	(0.039)				
Loss		0.081***	0.095***	0.003	-0.014
		(0.023)	(0.027)	(0.010)	(0.013)
Loss*Round Mortgage (Previous)		0.135***	0.120***	-0.028***	-0.032***
		(0.026)	(0.027)	(0.008)	(0.009)
R-squared	0.461	0.883	0.884	0.0109	0.0117
B. Deleting Transactions Involving Flippers					
Round Mortgage (Previous)	0.130***				
	(0.037)				
Loss		0.110***	0.128***	-0.001	-0.017
		(0.024)	(0.027)	(0.011)	(0.013)
Loss*Round Mortgage (Previous)		0.114***	0.106***	-0.027***	-0.031***
		(0.026)	(0.028)	(0.009)	(0.010)
R-squared	0.487	0.885	0.885	0.0107	0.0115
C. Using Non-Round Mortgage Amount Buyers for Price Index Estimation					
Loss		0.110***	0.119***	0.002	-0.013
		(0.023)	(0.025)	(0.010)	(0.013)
Loss*Round Mortgage (Previous)		0.119***	0.110***	-0.027***	-0.031***
		(0.025)	(0.026)	(0.008)	(0.009)
R-squared		0.884	0.884	0.0108	0.0116
D. Using An Expanded Sample of Housing Transactions					
Round Mortgage (Previous)	0.096***				
	(0.011)				
Loss		0.162***	0.203***	-0.002	-0.010*
		(0.022)	(0.025)	(0.005)	(0.006)
Loss*Round Mortgage (Previous)		0.087***	0.103***	-0.025***	-0.025***
		(0.023)	(0.026)	(0.005)	(0.005)
R-squared	0.182	0.868	0.868	0.010184	0.010834

Notes. This table summarizes results based on the models in Panel C of Table 2. Panel A present results replacing the LTV with the minimum of zero and LTV minus 0.8. Panel B presents the results dropping any transactions where either the seller or the buyer was defined as a flipper. Panel C calculates expected loss based on a price index that only uses a subsample of sales where borrowers had mortgages that were not at round numbers and were not LTV-focused. Panel D increases the sample to 965,934 transactions (as compared with 548,568 observations in Table A2, Panel A.1) by including condos, 2-4 family housing units, and units that were dropped due to extreme outliers on hedonic attributes. In Panel D models, controls are expanded to add dummy variables for type of housing unit and for whether each hedonic attribute was an extreme value. Standard errors are clustered at mortgage bin, labor-market-area-by-quarter, and tract level. * significant at 90%, ** significant at 95% and *** significant at 99% confidence level.

Table A9. Triple Transaction Sample to Address Errors in Variables

	Expected Loss		w/ Gains	
	Repeat Sales	Triple Sales	Repeat Sales	Triple Sales
Loss	0.156***	0.198***	0.171***	0.236***
	(0.040)	(0.036)	(0.044)	(0.040)
Loss*Round Mortgage (Previous)	0.095*	0.089**	0.092*	0.081*
	(0.049)	(0.043)	(0.050)	(0.048)
R-squared	0.908	0.909	0.908	0.910
Observations	11,857	11,857	11,857	11,857

Notes. This table presents results based on the models in Panel C of Table 2 except for using a triple sales sample. Columns 1 and 3 use the second and third sale to estimate the model specifications of columns 2 and 3 of Table 2, respectively. For columns 2 and 4, the first observed sale is used to calculate the sales price residual, the second observed sale is used as the initial purchase in the repeat sales and the associated mortgage determines whether the buyer is a round number borrower, and the third sale is used to characterize whether this second buyer experiences an expected loss. Standard errors are clustered at mortgage bin, labor-market-area-by-quarter, and tract level. * significant at 90%, ** significant at 95% and *** significant at 99% confidence level.

Table A10: Errors in Variables Bias created by Controls for Unobserved Quality

	G&M	Unbiased	G&M w/ Gains	Unbiased w/ Gains
	(1)	(2)	(3)	(4)
A. Baseline				
Loss	0.551***	0.694***	0.539***	0.641***
	(0.025)	(0.016)	(0.027)	(0.018)
R-squared	0.828	0.838	0.828	0.842
B. Baseline + balance controls				
Loss	0.442***	0.547***	0.417***	0.520***
	(0.020)	(0.016)	(0.021)	(0.017)
R-squared	0.855	0.859	0.856	0.860
C. Baseline + balance controls + tract FEs				
Loss	0.340***	0.393***	0.319***	0.384***
	(0.017)	(0.015)	(0.018)	(0.015)
R-squared	0.878	0.880	0.878	0.880

Notes. This table summarizes results from regressions of sale price on loss using a subsample of housing units that sold three times. Columns 1 and 3 replicate the standard model using the last two transactions for each housing unit in the sample. For columns 2 and 4, the first observed sale is used to calculate the sales price residual, the second observed sale is used as the initial purchase in the repeat sales, and the third sale is used to characterize whether this second buyer experiences an expected loss. Panel A follows a standard model in Genesove and Mayer (2001). Panel B adds the full list of controls (shown in the balancing tests in Table 1). Panel C adds both these controls and census tract fixed effects. Standard errors are clustered at the labor-market-area-by-quarter and tract level. * significant at 90%, ** significant at 95% and *** significant at 99% confidence level.

Appendix B: Identifying Critical LTV Thresholds

Given the complexities of the mortgage market, we use a data-driven approach to establishing LTV ratios associated with borrowers attempting to hit critical thresholds within the mortgage market. We start with the standard critical LTVs, including 0.8, 0.9, 0.95, 0.97, 1.00. As one never gets exactly 0.8. The exact LTV is something like 0.800001. We follow Pope et al. (2015), round down LTVs into 3-digit bins, and define the critical LTV thresholds using these bins. For example, 0.7912 will be round to 0.791.

In addition to the standard LTVs, we run histograms of the number of loans at different LTV percentage points (e.g., 0.80<=LTV<0.81) to check actual spikes. For example, we observe huge spikes at 0.95 due to conforming loan limit with PMI and at 0.97 due to the FHA limit. Specifically, we perform checks for (A) every 0.001 from 0.780 to 0.820, from 0.880 to 0.920 and 0.930 to 0.960 for the entire sample; (B) every 0.001 from 0.960 to 1.010 by splitting the sample into three parts: (1) start to Q32008, (2) Q42008 to Q42014, and (3) Q12015 to the end of the sample.

After checking the spikes in the histogram (unreported), we identify the following critical LTVs:

- 0.799, 0.800, 0.899, 0.900, 0.949, 0.950 for the entire sample,
- 0.969, 0.970, 0.983, 0.984, 0.991, 0.992, 0.999, 1.000 before 2009,
- 0.974, 0.981, 0.986, 1.000 from 2009 to 2014, and
- 0.970, 0.981, 1.000 from 2015 to the end of the sample.

Although these spikes vary over the sample period and some do not fall right at integers, these critical LTVs can be justified. For example, Fannie Mae had a smaller Flex 97 program launched after 2008. The fact that post-2008 FHFA increased their loan requirements from 3 to 3.5 percent explains the mortgage spike at 0.974. The 0.986 might be some additional mortgages that were made at 0.97 – there were some exceptions to the 0.965. We justify spikes at 0.981 and 0.984 (just over 0.98) as the borrowers could roll the upfront mortgage insurance premium into the mortgage amount. Spikes at 0.991 are because prior to 2008 there were quite a few non-governmental mortgages right at 0.99.

We defined constrained borrowers based on LTV thresholds, instead of CLTV thresholds. This is because having a second mortgage usually involves a credit constraint, we lump people who have a second mortgage together with people who hit a specific LTV threshold. Nevertheless, our results do not change if we use CLTV because there are only a small fraction of borrowers with a second mortgage.