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What Is My Home Worth?*

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Abstract

Economic models often assume that agents always know the market value of their assets. We use residential property tax assessment as a laboratory to test this assumption for housing. We first show that assessed market value (AMV) is a noisy proxy for transaction-based market value (TMV). Innovations in AMV are less volatile than, are weakly correlated with, and lag innovations in TMV. An AMV-based, national-level house price index has shallower troughs and shorter peaks than its TMV-based counterpart. We merge in anonymized credit bureau data to test whether homeowners use AMVs, as signals of housing wealth, to make consumption decisions. Using local mass reassessments as an instrument, we find that AMV changes causally affect the likelihood that households take out a new home equity line of credit (HELOC) with a similar economic magnitude as TMV changes. A partial equilibrium calibration exercise suggests that innovations in AMV can explain approximately 1% of annual HELOC origination. Overall, our results suggest that homeowners do not fully know the value of their homes.

Keywords: Housing wealth, consumption, information frictions

JEL Classification: E2, G4, G5, R2

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1 Introduction

The full-information, rational framework that serves as the backbone of many important economic models often assumes that agents know the value of their assets. In macroeconomics, the permanent income hypothesis (PIH) (Modigliani and Brumberg, 1954; Friedman, 1957; Hall, 1978) assumes that households know their income and wealth levels and make consumption decisions based on shocks to these quantities. In microeconomics, standard models of insurance demand (Mossin, 1968; Einav et al., 2010) assume that households make optimal coverage decisions based on the prevailing insurance price, the value of the asset under consideration, and their private wealth level. Whether the asset value knowledge assumption holds has important implications for the validity of these models; that is, whether the introduction of information friction will change the models' main conclusions. Furthermore, if the main conclusions hold, then empiricists who wish to test these models in the real world would need to seriously consider the information friction that households in their datasets face.

This paper uses the administration of the residential property tax system in the United States as a laboratory to test the asset value knowledge assumption for housing, an asset that makes up a large part of households' net worth (Iacoviello, 2011). Every year, property owners receive a letter stating their homes' AMV and the amount of property tax that they owe. By law, local governments in the United States must, as accurately as possible, estimate the market value of real estate properties so that property taxes can be collected fairly within their jurisdictions. However, it is well known in the property tax literature that these estimated values, or AMVs, can substantially deviate from transaction-based market values (TMVs) (Sirmans et al., 2008). Therefore, AMV is an easy-to-observe but noisy estimate of households' housing wealth.

On the other hand, without putting their home on the market, it is difficult for homeowners to accurately know their homes' TMV. This is because, unlike publicly traded stocks, houses do not have readily available market prices and are heterogeneous assets that have many difficult-to-observe pricing characteristics, which, in sum, makes it difficult for market participants to accurately estimate the TMV (Black, 1977; Giacoletti, 2017; Amornsiripanitch, 2020). For example, in 2022, Zillow infamously lost $880 million (USD) from its real estate investment business because its house price estimates were not sufficiently accurate (Susarla et al., 2024). Hence, TMV is a difficult-to-observe but accurate measure of households' housing wealth. Exploiting this dichotomy, this paper, in short, uses AMV and TMV to test whether homeowners use the correct information set about their housing wealth to make relevant economic decisions.

The first part of the paper provides empirical evidence that AMV is a noisy signal of TMV. We begin our empirical analysis by documenting systematic differences between the two valuation measures. Using a near-nationally representative dataset of property tax assessments from CoreLogic, we do so by constructing county-level house price indices (HPIs) based on AMV changes and comparing them to the county-level transaction-based HPIs provided by the Federal Housing Finance Agency (FHFA). We document three facts. First, the assessment-based home price index (AHPI) is much less volatile than its transaction-based counterpart, the THPI. Second, AMV lags TMV – changes in AHPI are more correlated with lagged changes in THPI than with concurrent changes. Third, the correlation between the changes in AHPI and the changes in THPI is low. The R^2 value from a linear regression where we regress the change in county-level APHI onto the concurrent change in THPI is only 0.12. The R^2 values from specifications that include the lagged change in THPI hover around 0.2. Combined, the three facts make the aggregate house price dynamics, based on AMV, too smooth with shallower troughs and smaller peaks. Importantly, the stark differences between AMV and TMV imply that households that, due to information frictions, make economic decisions based on AMV and not TMV could end up behaving very differently from the counterfactual where they make decisions based on TMV.

The second part of the paper presents an indirect test of the asset value knowledge assumption. Adding in anonymized credit bureau data and following the literature that estimates the marginal propensity to consume (MPC) out of housing wealth, we test whether households' consumption decisions respond to changes in AMV, conditional on changes in estimated TMV, changes in property tax, and a set of control variables that capture the household's income and financial status. Our consumption measure of choice is whether the household takes out a new home equity line of credit, which is directly related to housing wealth. The consumption response regression is an indirect test of the asset value knowledge assumption because we do not directly observe the household's information set, i.e., how much the household knows about their housing wealth, but we can infer which set of information the household observes and uses if consumption responds to changes in AMV, TMV, or both.

It is well known in the MPC literature that one cannot get an unbiased estimate of the MPC out of housing wealth by regressing changes in consumption onto changes in housing wealth because the regression likely suffers from omitted variable bias (OVB). The same concern applies to our indirect test because unobservable homeowners' characteristics and actions (e.g., AMV appeals) can be correlated with both changes in consumption and changes in AMV. To overcome this endogeneity issue, we build an instrument that exploits scheduled and unscheduled local mass reassessment events as plausibly exogenous shocks to AMV. The instrument should be highly correlated with AMV changes because the majority of AMV changes are caused by reassessments done by local governments. More importantly, the instrument should satisfy the exclusion requirement because when and whether local mass reassessment events occur are beyond any homeowners' control. In our preferred specification, the instrumental variable regression results reveal that a one-standard-deviation increase in AMV raises the probability that the homeowner takes out a new HELOC by 0.027 percentage point (pp), which is a 1.7% increase relative to the sample mean. We interpret this result as telling us that homeowners do not always know the transaction-based market value of their homes and use the information in a way that the full-information, rational framework would predict. Importantly, the coefficients on current changes in AMV and current changes in TMV are similar in size (e.g., 0.34 versus 0.49), which implies that changes in TMV alone accounts only for approximately half of the concurrent marginal propensity to consume out of housing wealth through HELOCs.

We end the paper with a partial equilibrium calibration exercise that quantifies the contribution that AMV makes to aggregate HELOC demand. Using the coefficient estimates from our preferred IV regression specification, we find that, changes in AMVs account for approximately 1% of annual HELOC origination volume. Due to the fact that changes in AMV lag changes in TMV, elevated AMV values buoyed HELOC origination during the Great Recession. On the other hand, changes in AMV dragged HELOC origination during the post-GFC recovery period because AMV growth was sluggish compared with TMV growth. The macroeconomic implication of this finding is that the post-GFC recovery of the U.S. economy may have been significantly quicker if homeowners were able to fully observe their housing wealth because, as shown by the MPC literature, changes in housing wealth affect consumption through many channels, not just HELOCs. More generally, the key insight from this exercise is that frictions in households' ability to observe important economic variables (e.g., housing wealth) can have large economic consequences.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature and outlines our contribution. Section 3 discusses relevant institutional details. Section 4 describes the datasets that we use and the sample of analysis. Section 5.1 explains how we construct our house price indices. Section 5.2 explains and validates the identification strategy for our consumption response test. Section 6 presents the results and Section 7 concludes.

2 Literature Review and Contributions

This paper contributes to the large literature on the estimation of the marginal propensity to consume out of housing wealth and the theoretical implications of the estimated values (Muellbauer and Murphy, 1997; Case et al., 2005, 2013; Haurin and Rosenthal, 2006; Campbell and Cocco, 2007; Greenspan and Kennedy, 2008; Bostic et al., 2009; Carroll et al., 2011; Mian and Sufi, 2011; Mian et al., 2013; Aladangady, 2017). To estimate the MPC, the literature typically assumes that homeowners know the market value of their homes and, therefore, uses survey data on home prices or transaction-based estimated value of home prices as the regressor of interest. Our paper shows that homeowners use changes in assessed market values, a very noisy signal of changes in transaction-based market values, to make consumption decisions with respect to their housing wealth. This finding implies that previous estimates of the MPC out of housing wealth may be biased because the standard MPC regressions do not account for changes in AMV, which likely invalidates the exclusion restriction of conventional housing supply instruments (Saiz, 2010). More importantly, the finding implies that the standard assumption that many economic models make, which is that households know the market value of their assets, liquid or illiquid, is likely not valid.

This paper also contributes to the literature on the inaccuracy of property tax assessments relative to transaction-based market values. It is a well-known fact that assessed market values are regressive with respect to market prices; that is, inexpensive homes tend to be over-assessed relative to expensive homes (Smith et al., 2003; Eom, 2008; Weber and McMillen, 2010; Ross, 2012, 2013; McMillen, 2013; Hodge et al., 2017; Berry, 2021). Another well-established fact is that, due to infrequent reassessments, assessed market values tend to lag transaction-based market values (Kim and Hou, 2024). These features of the U.S. property tax system create systematic inequality in property tax burden across racial groups (Avenancio-León and Howard, 2022), income levels (Engle, 1975; Black, 1977), and any other characteristics that are strongly correlated with home prices (Amornsiripanitch, 2020).

With the motivation to use property tax assessments as a noisy signal of housing wealth, our paper contributes to this line of work by building national-level and county-level house price indices to document that assessed market values are less volatile than, slower to adjust to, and relatively uncorrelated with transaction-based market values. Together, the three differences make the aggregate house price dynamics, as presented by AMV, appear to have lower peaks and shallower troughs. Unlike previous works that use locality-specific datasets (e.g., city, county, or state level), we use a near-nationally representative dataset to document new facts about the local and aggregate movements of assessed market values. This part of our paper complements concurrent work by Chen and Cohen (2024), who use the ZTRAX data to document the last two facts and argue that these dynamics are partly caused by local governments' revenue-smoothing incentives.

Lastly, a recent work that uses similar data sources warrants some discussion. Using a high-frequency event study approach, Wong (2024) finds that property tax increases cause liquidity-constrained homeowners to consume less, fall into financial distress, and move. This work can be summarized as studying the impact that changes in property tax burden has on homeowners' consumption, financial health, and migration. On the other hand, while controlling for the channel that Wong (2024) studies, changes in tax burden, our paper studies how changes in assessed market values, determined for the purpose of taxation, serve as signals for changes in housing wealth and how these changes affect consumption decisions.

3 Institutional Details

In this section, we present relevant details of the U.S. property tax system that are required to understand the estimation method that we use below.

3.1 Determinants of Property Tax Burden

Residential property tax is an ad valorem tax; that is, the homeowner's property tax burden in a given year is calculated as a share of his or her property's taxable value:

$$T_{it} = \tau_{jt} \times Q_{it}. \tag{1}$$

T denotes the property tax amount in U.S. dollars (USD) for property i in year t. Q is the taxable value, which the taxing jurisdiction's (j) tax rate τ is applied to. We use the term taxing jurisdiction to refer to a small locality where all properties face the same property tax rate because they are taxed by the same set of local government entities (Amornsiripanitch, 2020; Berry, 2021; Avenancio-León and Howard, 2022). The jurisdiction tax rate τ_j is the sum of the tax rate imposed by each taxing local government entity in the taxing jurisdiction. Each "sub" tax rate is typically determined via a vote or as the choice variable that, given the local government's tax base, gives the local government its target property tax revenue (Amornsiripanitch, 2020; Avenancio-León and Howard, 2022). For the purpose of this paper, it is important to note that the change in a property's taxable value Q is not perfectly correlated with the change in its tax burden T because, in the case where the tax rate is a choice variable, how a change in Q translates to a change in T depends on the change in the property's relative weight in the tax base, the set of all taxable properties. For example, an increase in property i's taxable value may not translate to an increase in property i's tax burden because the taxable value of other properties in the tax base grew at a faster rate in the same time period.

The taxable value Q is a function of several objects:

$$Q_{it} = f(F_{it}, E_{ct}, R_{st}, X_{it}). \tag{2}$$

F denotes the property's fair market value, which is the local government's estimate of the property's market value in year t. This object can be produced by one of several valuation methods: the comparable sales approach, the cost approach, or the hedonic regression method (Amornsiripanitch, 2020). Local governments make various adjustments to the estimated fair market value to arrive at the final taxable value Q. E denotes the equalization ratio, often applied at the county level (c), which aims to make the distribution of property tax burden across the state more fair by accounting for differences in house price growth rates across counties.[1] R denotes the taxable ratio, often applied at the state level (s), which determines the share of the equalized assessed value that will be taxed. For example, Illinois uses a ratio of one-third.[2] Lastly, X denotes the property-year-specific exemptions that the homeowner may take to reduce the property's taxable value. A common exemption is the homestead exemption, which allows a homeowner to reduce his or her property tax amount if the property is used as his or her primary residence during the tax year. In summary, to arrive at the final taxable value Q, the local government (e.g., county) estimates the property's fair market value, makes various adjustments, and applies the appropriate exemptions.

3.2 Determinants of Assessed Market Value

The main object of interest in this paper is the assessed market value, denoted as A henceforth. Following from the discussion above, A is a function of the estimated fair market value, F, and the equalization ratio, E. F changes for two reasons. The first is when the local government conducts a mass reappraisal or reassessment, which occurs at different frequencies across jurisdictions. For example, the District of Columbia reappraises its properties every year, while properties in Cook County, Illinois, get reappraised once every three years. The second is when the homeowner successfully appeals his or her property value (McMillen, 2013). E changes every time the state conducts a sales ratio study and determines that the differences in house price growth rate across counties are sufficiently large that the existing distribution of estimated fair market values no longer reflects what the state determines to be a fair distribution of property tax burden. As an attempt to account for large year-to-year changes in house prices, equalization ratios are often used by jurisdictions that do not conduct frequent reappraisals. The instrumental variable presented below exploits changes in A that stem from mass reassessments and equalization ratio changes.

[1] See `https://tax.illinois.gov/content/dam/soi/en/web/tax/research/publications/pubs/documents/pub-136.pdf`.

[2] See `https://tax.illinois.gov/questionsandanswers/answer.318.html`.

4 Data

4.1 Data Sources

The first dataset that we use is the CoreLogic Tax data, which includes detailed property and tax characteristics for over 150 million properties across the U.S. Geographic coverage has increased over time from about 1,440 counties in 2005 to over 3,100 counties in 2023. Thus, for recent years, the data includes nearly the full universe of taxable parcels in the U.S. For most counties, we observe at least 15 years of historical data. In most jurisdictions, we observe the tax amount T, the taxable value Q and the assessed market value A. Since we are interested in how local governments' noisy estimates of properties' fair market values affect consumption decisions, we use the assessed market value for the analyses presented below.[3]

The second dataset we bring in is the CoreLogic Deeds data, which provides the public record information reported to the county recorder's offices whenever a sale or mortgage is completed. The recorded information can vary by county, however, it typically includes the transaction type, sale price, transaction date, and mortgage amount. We observe at least one mortgage transaction for about 90 million properties across 2,500 counties. Geographic coverage generally increases with time. Approximately half of the counties with mortgage and sale coverage in the CoreLogic Deeds data began coverage in 2005 or earlier.

The CoreLogic Tax and Deeds data can be easily linked using a CoreLogic-derived unique property identifier that is constant over time. The property identifier is based on several inputs, including the assessor parcel number (APN) and property address. CoreLogic also provides parcel-level coordinates for nearly all properties, enabling us to identify the property's Census Geographic Identifier by way of a geospatial join with Census shapefiles.[4]

The third dataset we use is the Equifax Credit Risk Insight Servicing and ICE McDash (CRISM) data, which contains anonymized credit bureau data on individual consumers' credit histories, matched to the ICE McDash mortgage servicing dataset (hereafter referred to as McDash). Equifax performs this

[3] All results are qualitatively and quantitatively similar when we use taxable value Q instead of assessed market value A.

[4] We use the R package *tigris* (`https://cran.r-project.org/web/packages/tigris/index.html`) to obtain Census shapefiles.

match using fields like original and current mortgage balance, origination date, ZIP Code, and payment history. The matches are given a confidence rating, which we use to filter out low-confidence matches.[5]

The CRISM data provides a rich set of consumer credit information, including tradeline-specific open line counts, balances and delinquency status. We also use Equifax Risk Score (Risk Score), an Equifax-derived score, which provides an overall measure of a consumer's credit worthiness, as well as an estimate of annual personal income, known as PIM. Additionally, we merge in a few fields from the full McDash dataset to aid in the match that we perform between the CRISM and CoreLogic datasets. The fields are property ZIP Code, occupancy status, property type, and transaction type. We also merge in the sale price and appraisal amount from McDash. The CRISM data begins in 2005. We observe consumer and mortgage information in CRISM on a monthly basis for as long as the loan is active and remains serviced by a McDash servicer. Overall, McDash servicing data covers approximately two-thirds of the U.S. mortgage market.

Lastly, we use the Federal Housing Finance Agency (FHFA) County and Five-Digit ZIP Code-Level Home Price Index (HPI) as our market-based measure of local home price growth.[6] We generate a census-tract-level version by using the December 2011 Department of Housing and Urban Development geographic crosswalk file to map five-digit ZIP Codes into 2000-vintage census tracts.[7]

4.2 Sample Construction

4.2.1 House Price Index Sample

The first part of the paper compares trends in transaction-based market values to those in assessed market values. For this portion of the analysis, we use a 20% random sample of the available property assessment history of single-family residences (SFRs) that appear in the CoreLogic Tax data. The CoreLogic Tax data begins significant coverage in 2004, so our sample spans 2004 to 2023 with geographic coverage increasing over time. States for which all necessary variables are populated are included in the analysis.[8]

[5]Following Equifax's recommendation for the data in our sample period, we drop any match with a confidence score below 0.8. This excludes roughly 10% of loans.

[6]The data can be accessed at `https://www.fhfa.gov/data/hpi/datasets?tab=additional-data`.

[7]The data can be accessed at `https://www.huduser.gov/portal/datasets/usps_crosswalk.html`.

[8]We exclude California, Vermont, Maine, Rhode Island, Connecticut, Nebraska, and Massachusetts due to missing assessed market value information. Very few observations from New Hampshire and Delaware make it into the sample for the same reason. All results are qualitatively and quantitatively similar if we instead use taxable value Q, which gives us

4.2.2 Consumption Response Sample

The second part of the paper examines the relationship between assessed market values and consumption. Thus, for this analysis we merge the CRISM data with the CoreLogic Tax and CoreLogic Deeds datasets. We link the datasets by mortgage origination attributes, which limits our sample to SFRs with a first-lien mortgage. We drop non-owner-occupied SFRs.

We first prepare the CoreLogic data for the match by reshaping the tax assessment data to a property-level dataset, which can then be merged with the Deeds data to create a loan-level dataset that includes the property's full tax history. We only keep mortgage origination attributes, sale price (if applicable), and tax history information from the CoreLogic datasets. We drop all personally identifiable information (PII) from CoreLogic to ensure that the resulting matched data set is anonymized.

In order to prepare the CRISM dataset for the merge, we apply the same lien status and property type filters. We then collapse the data to a loan-level dataset by selecting the record from the year-month that is one year after the year-month of origination. This ensures the loan and the consumer have been added to CRISM since the origination of the loan.

Our filtered CoreLogic and CRISM loan-level datasets consist of 138 million and 50 million loans, respectively, and span 2005 to 2023. We match first-lien mortgages in each dataset based on ZIP Code, loan amount at origination, origination year-month, and loan purpose (purchase or refinance). Among CRISM loans, we obtain a match in CoreLogic data for 67 percent of the loans. We would not expect every CRISM loan to match to a loan in CoreLogic because CoreLogic does not include data from all counties, and coverage in some areas begins after 2005. We only keep one-to-one matches, which slightly decreases the match rate to 60 percent of the CRISM loans.

Next, we transform the loan-level CRISM-CoreLogic matched data into a consumer-loan-year-level panel. First, we aggregate the CRISM data into a consumer-year-level dataset. Then we merge the CRISM-CoreLogic matched loans with the consumer-year-level CRISM dataset using the consumer identifier in CRISM. We drop any consumer-years that are not in the range of the origination year and termination year of the matched loan. This happens when a consumer has multiple non-overlapping loans in CRISM/McDash, but not all of them uniquely match to a loan record in CoreLogic. In order to

better coverage, instead of assessed market value A for the analyses.

estimate market values of properties for the entirety of the consumer-loan stint, we merge in the FHFA HPI data on census tract and year. We drop all observations with missing values of any of the covariates used in our consumption regression. Because one of the covariates in our main regression is a lagged change measure, we must observe at least three years of any consumer-loan stint (i.e., origination year plus two years) for the consumer-loan stint to be included in the sample. Finally, in order to minimize the influence of outliers, we drop all records with a sale or appraisal amounts greater than $10 million or less than $1,000. We end up with a final panel of 70.3 million records, including 17.1 million unique consumer-loan stints. Consequently, our final panel contains an average of roughly 4 years for each consumer-loan stint. Table 1 presents summary statistics of key variables for this sample.

4.3 Consumption Measure

We use new home equity line of credit (HELOC) origination as our consumption measure because home equity extraction, unlike changes in credit card balance, is directly associated with new consumption and HELOC availability is directly tied to home values via the collateral channel (Choi and Zhu, 2022). In the CRISM data, we observe the number of open HELOCs held by the consumer on a monthly basis. We generate an annual-level indicator for a new HELOC that is turned on if the maximum number of open HELOCs in year t is greater than the maximum number of open HELOCs observed in year $t-1$. Most commonly, this indicator is turned on when the consumer goes from zero to one HELOC in a given year.

5 Methodology

5.1 House Price Index

In the first portion of our analysis we investigate the degree to which changes in market values of homes align with changes in assessed market values of homes. To do so, we compare two home price indices: a transaction-based HPI (THPI) and an assessment-based home price index (AHPI). The THPI is the county-level FHFA All-Transactions HPI, which is constructed from transaction-level data on all SFR conventional mortgages (purchases and refinances) that are acquired or guaranteed by Fannie Mae or Freddie Mac (Bogin et al., 2019). The AHPI is constructed from property-level tax assessment history found in the CoreLogic Tax data. Using a 20% random sample of SFRs in the CoreLogic Tax data, we construct a county-level AHPI following the repeat-transaction methodology used in the FHFA HPI. We generate the AHPI by estimating the following regression equation:

$$\Delta V_{i,t-s} = \sum_{t=1}^{T} \beta_t \times D_{it} + \epsilon_{it}. \tag{3}$$

In Calhoun (1996), $\Delta V_{i,t-s}$ is the difference in log price for property i between the transaction period t and the previous transaction period s and, therefore, is defined only when we observe a pair of transactions. $\Delta V_{i,t-s}$ is regressed on a set of indicator variables D_{it} where time ranges from the first year of the sample, $t = 1$, to the last year of the sample, $t = T$. D_{it}, matching the year of the second transaction in the pair, equals one and D_{is}, matching the year of the first transaction in the pair, equals negative one. The other D_{it}s equal zero. The intercept is set to zero.

We modify this equation by using AMVs instead of sale prices. Thus, $\Delta V_{i,t-s}$ is the difference in log assessed market value on property i between year t and the previous year s. For most properties, we observe an assessed market value every year once the property first appears in the tax data, which makes s equal to $t - 1$. Note that this does not necessarily mean the property was reassessed every year. In areas where reassessments are done less frequently than annually, we observe consecutive assessment years where the assessed market value does not change. In this context, the vector of indicator variables D_{it} behaves as if the property were transacted every year.

Following the filters used in Bogin et al. (2019), we drop assessment records where the change from the previous assessment record was greater than +/- 30% in annual assessed market value change. This filter is applied because repeat-transaction-based HPIs rely on a "constant-quality" assumption. This assumption is necessary for β to estimate market appreciation as opposed to changes in quality of the property itself (e.g., significant renovation). Properties with greater than 30% price change, in absolute value, are more likely to have underwent a substantial improvement and therefore violate the constant-quality assumption. When considering the house price index analysis that we present below, it is important to note that the FHFA THPI that we use also excludes properties that experienced price changes larger than 30%. Therefore, any conclusions that we get from the comparison between our AHPI and the THPI are not mechanically driven by this data filter.[9]

We estimate equation 3 separately for each county, including all assessment years available for that county. We omit $D_{i,t=z}$, where z is the first year of observed tax records for the county in our data. Omitting $D_{i,t=z}$ ensures that the estimated β parameters are relative to the base year, z. Once we estimate equation 3 using ordinary least squares (OLS) regression, we transform the β coefficients into index value by exponentiating them and multiplying by 100.

The full FHFA HPI methodology incorporates additional steps to account for the fact that the error variance in equation 3 may be predictable based on the time between transactions (Bogin et al., 2019). This is a much smaller concern for assessment data because the time between observations is one year for nearly all property-year observations in our data.

5.2 Consumption Response Regression

5.2.1 Theoretical Framework

The test for whether homeowners know the value of their primary residence is motivated by the academic debate over whether markets are effectively complete (Cochrane, 1991) as this line work estimates regression equations that rely on the assumption that wealth information is fully observable by households (Mian et al., 2013). Consider the following equation:

$$\Delta log(C_{it}) = \alpha + \beta \times \Delta log(X_{it}) + \epsilon_{it}. \tag{4}$$

$\Delta log C_{it}$ is the log change in household i's consumption from time $t-1$ to time t and $\Delta log X_{it}$ is the concurrent log change in the household's wealth. In the benchmark model where markets are complete and, hence, consumers can insure each other against idiosyncratic wealth shocks, β, which can be interpreted as the representative agent's elasticity of consumption with respect to wealth, should be equal to zero. The same null relationship can also arise in models with incomplete insurance markets

[9] All results are quantitatively and qualitatively similar when we do not apply this filter in the AHPI construction. We cannot change how the THPI is constructed. Large changes in AHPIs can result from infrequent mass reassessments. Therefore, as a robustness check, we also present results for counties where mass reassessments occur.

and borrowing constraints because agents can still diversify consumption risk by trading in existing asset markets and endogenously sort into jobs that fit their risk preferences (Heaton and Lucas, 1992, 1996; Telmer, 1993; Constantinides and Duffie, 1996; Schulhofer-Wohl, 2011). When we replace the right-hand-side variable with the concurrent log change in household i's housing wealth, β can still be equal to zero because of the necessity to consume housing services, i.e., higher current wealth from house price appreciation is offset by higher cost of living in the future (Sinai and Souleles, 2005; Campbell and Cocco, 2007; Buiter, 2010).

Instead of adding one more estimate to this literature, we take as given that changes in households' housing wealth affect their consumption decisions ($\beta > 0$) and test whether households know and use the correct housing wealth information to make consumption decisions. Consider the following equation:

$$\Delta log(C_{it}) = \alpha + \gamma \times \Delta log(A_{it}) + \beta \times \Delta log(H_{it}) + \epsilon_{it}. \tag{5}$$

Equation 5 states that household i's log change in consumption is a function of the household's log change in the home's assessed market value A and log change in housing wealth H. Conditioning on changes in property tax payments that mechanically affect consumption (Wong, 2024), in a world where households can accurately observe their housing wealth in each period, β should be positive and γ should be equal to zero because a noisy signal of the object of interest cannot contribute to household's already perfect information set.

However, as stated in the introduction, housing wealth, which is based on TMV, can be very difficult to observe and estimate. Hence, in practice, γ may be positive because the change in a house's AMV is easy to observe and, more or less, contains some relevant information about the change in its fair market price, which is a useful signal of housing wealth when information frictions exist. A well-estimated equation 5, therefore, also serves as an indirect test for whether homeowners fully know the value of their own homes. This is an indirect test because we cannot directly observe homeowners' information set and, therefore, we assume that a positive γ implies that homeowners observe and use AMVs to make consumption decisions because they cannot fully observe their true housing wealth level.

5.2.2 Baseline Specification

To test whether changes in assessed market values affect homeowners' consumption decisions, we estimate variants of the following OLS regression equation:

$$HELOC_{it} = \alpha + \gamma \times \Delta \log(A_{it}) + \beta' \mathbf{x}_{it} + \theta_t + \psi_j + \epsilon_{it}. \quad (6)$$

i is the index for consumer, t is the index for year, and j is the index for census tract. $HELOC$ is an indicator variable that equals one if the consumer added a new home equity line of credit in year t and zero otherwise. A is the assessed market value on the consumer's home. We include year (θ_t) and census tract (ψ_j) fixed effects to absorb nation-wide macroeconomic shocks and static differences across census tracts.

$\mathbf{x}$ is a vector of control variables. First, we control for the annual change in property tax bills because this object is directly related to consumption (Wong, 2024) and financial distress. Importantly, we would like to separately estimate the impact that changes in AMV has on consumption via the housing wealth channel and not via the mechanical relationship between property tax burden and consumption – more property tax leads to more spending. For reasons explained in Section 3, changes in A are not colinear with changes in the tax amount T. We directly verify this statement. In Panel A of Table A3, we show that the correlation between the log changes of A and the log change in tax amount is only 0.36. Panel B of the same table presents the variance inflation factor (VIF) for each of the log change variables that we include in the consumption regression. We can see that the VIF values are all close to one, which suggests that multicollinearity is not a major concern among this set of variables (Neter et al., 1996; Sheather, 2009).[10]

Second, in light of the large literature on the MPC out of housing wealth, we control for concurrent and lagged changes in estimated home value. We estimate the market price of the home by growing the observed sale price or appraisal amount (for refinance mortgages) at the time of the mortgage's origination with the change in the tract-level FHFA HPI value. We include both the current and previous year's changes in market value of the home because there is uncertainty about when exactly the homeowner

[10] We use the Stata package `collin` to compute the VIF values.

receives signals about their home's transaction-based market value. Third, following Aladangady (2017), we control for age and age squared, which we construct based on year of birth. Importantly, age is also an important determinant of access to housing-related debt (Mayer and Moulton, 2020; Amornsiripanitch, 2023) and housing collateral value (Campbell and Cocco, 2007; Amornsiripanitch et al., 2025). Lastly, the literature on the MPC out of housing wealth has found that financial constraint is an important determinant of the MPC (Mian et al., 2013; Gross et al., 2020). Therefore, we control for changes in the consumer's financial situation by including proxies for credit score, income, bankruptcy status, and indebtedness. Refer to the appendix for the list of control variables and their definitions.

γ is the marginal impact that changes in assessed market values have on the consumer's probability of opening a new HELOC. The full-information null hypothesis is that $\widehat{\gamma}$ is not statistically different from zero because changes in assessed market values do not give the homeowner any additional information about their housing wealth above and beyond the concurrent and the lagged changes in transaction-based market values. If $\widehat{\gamma}$ is positive and statistically different from zero, then the null hypothesis is rejected and the result would suggest that homeowners rely on changes in assessed market values to make consumption decisions, possibly because of information frictions.

While we are able to control for a rich set of consumer characteristics, there may still be unobserved differences between houses experiencing small and large assessed market value changes that may bias our estimate of γ. One such source of omitted variable bias (OVB) is property tax assessment appeals, which we cannot account for (Weber and McMillen, 2010; Ross, 2017; Avenancio-León and Howard, 2022). Suppose that wealthier households that consume more are more likely to appeal for lower property assessments and are also more likely to succeed, then $\widehat{\gamma}$ would be biased. Another threat to identification is home renovation, which may increase both assessed market value and consumption. More generally, any sorting behavior that we cannot control for in the regression equation and is jointly correlated with innovations in assessed market value and consumption decision will bias the coefficient of interest.

5.2.3 Instrumental Variable

We use an instrumental variable identification strategy and a two-stage least squares (2SLS) estimator to address the OVB concerns. The instrument exploits mass reassessments, scheduled and unscheduled, and equalization ratio adjustments. For example, Colorado operates on a biennial schedule; that is, each property in the state needs to be reassessed once every two years. We treat these reassessment events as quasi-random shocks to properties' assessed market values. We operationalize these mass reassessment events in our data by defining our instrumental variable as an indicator variable based on the modal AMV change in each tract-year cell. To construct our instrument, we count the number of SFRs in each tract-year that has (1) an increase in their AMV, (2) a decrease in their AMV, or (3) no change. We then code the instrument, Z_{jt}, with the following values: zero if the count of properties in the tract-year with no change is the largest, negative one if the count of properties with a decrease in AMV in the tract-year is the largest, or positive one if the count of properties with an increase in AMV in the tract-year is the largest. The instrument is computed at the tract-year level because mass reassessments can occur at geographic units that are smaller than counties. For example, Cook County, Illinois, splits the county into three assessment districts and reassesses the properties in each district once every three years.[11]

Constructed this way, the instrument should be highly correlated with changes in assessed market values, the endogenous right-hand-side variable, because mass reassessments use methods such as the comparable sales approach, the hedonic regression method, and the cost approach, which capture average local (neighborhood) changes in home prices (Amornsiripanitch, 2020). Therefore, a group of houses located near each other usually experience directionally similar changes in assessed market values. The same intuition applies for equalization ratio changes, which, as mentioned in Section 3, vary at the county-year level. Appendix Table A4 presents the first stage regression results, which show that the correlation between the instrument Z and $\Delta log(A)$ is high. A one-unit increase in Z increases the $\Delta log(A)$ by 0.05 to 0.06 and the coefficient is statistically significant at the 1% level.

The instrument should overcome any homeowner-specific source of OVB because mass reassessments occur on a regular schedule that either is determined by the state or by the taxing jurisdiction (county, township, etc.) or is ordered by a judge as a result of a lawsuit.[12] In each case, these are decisions that are outside of the homeowner's control, which makes it exogenous to the regression equation that we wish to estimate. Of course, in response to the reassessment, homeowners can appeal to lower their assessed market values. To overcome this endogenous response, we code Z based on the modal value in the census tract, which mechanically ensures that variation in the instrument's value is orthogonal to the

[11] See `https://www.cookcountyassessor.com/cook-county-property-tax-system`.

[12] See an example for Pennsylvania at `https://www.delcotimes.com/2017/03/28/court-orders-new-countywide-reassessment/`.

focal homeowner's appeal action.[13] This feature of the instrument addresses sources of OVB that stem from the focal homeowner's actions (e.g., appeal, renovation, and sorting behavior).[14]

The exclusion restriction, which is that variation in Z should affect $HELOC$ only through $\Delta log(A)$, should hold because whether homeowner i is able to take out a HELOC only depends on the amount of his or her own home equity and his or her credit worthiness. Therefore, changes in homeowner i's neighbor's assessed market value should be orthogonal to homeowner i's consumption decision because, due to insights from the assessment error literature (Engle, 1975; Sirmans et al., 1995, 2008; Amornsiripanitch, 2020; Berry, 2021; Avenancio-León and Howard, 2022), homeowner i's neighbor's assessed market value is already a noisy signal of the neighbor's housing wealth, let alone homeowner i's housing wealth.[15]

5.2.4 Validation Exercises

This section presents some validation exercise results for our instrumental variable because it is meant to proxy for local mass updates in assessed market values, but it is constructed from observed annual changes in assessed market values in the CoreLogic Tax data. The validation exercises attempt to verify two things: (1) the CoreLogic Tax data correctly captures mass reassessment events and (2) our empirical approach can largely identify mass reassessments.

One way to verify that the CoreLogic Tax dataset can accurately capture mass reassessment events is to analyze how AMVs behave during reassessment years and non-reassessment years. To do so, we choose states where we can find county-year level information on reassessment schedules. These are Ohio and Tennessee.[16] For each state and year, we compute the average share of SFRs that experienced AMV changes among two groups of counties: those that have a scheduled mass reassessment in that year and those that do not. Panels A and B of Figure 1 present the result. We can clearly see that the share of

[13] One concern that the reader might have about the instrument is that, in some instances, it may be picking up local changes in assessed market values that are caused by clusters of homes concurrently receiving favorable appeal decisions. Although we cannot directly explore whether this behavior is a sample-wide concern because a nation-wide appeal dataset does not exist, works on property tax appeals that use data from Cook County, Illinois, suggest that the unconditional appeal success rates are low and appeal successes do not cluster spatially (Weber and McMillen, 2010; Ross, 2017).

[14] All consumption response regression results hold if we instead define Z using the leave-one-out modal value because, in our sample, changes in the focal homeowner's assessed market value are never marginal such that they change the value of Z.

[15] All consumption response regression results hold when we control for the change in the leave-one-out average tract assessed market value.

[16] For Ohio, see `https://tax.ohio.gov/government/real-state/reappraisal-and-triennial-update`. For Tennessee, see `https://comptroller.tn.gov/office-functions/pa/tax-resources/assessment-information-for-each-county/reappraisal-schedule.html`.

SFRs that experience AMV changes is much larger in counties that have a scheduled mass reassessment than that of counties that do not.[17] This exercise gives us confidence that the CoreLogic Tax dataset can accurately capture mass reassessment events.

To verify that we can empirically identify mass reassessment events in the data, we first identify, for each year, census tracts where the majority (greater than 50 percent) of SFRs experience a change in AMV and the rest. We then compute the average share of SFRs that experience a change in AMV for each group of tracts and plot the two averages for each year. Figure 2 presents the result. Among tracts in which the majority of SFRs change assessed market value, over 95 percent of the SFRs in those tracts underwent a change in assessed market value; conversely, among tracts where a majority of SFRs did not change assessed market value, roughly 10 percent of SFRs underwent a change in assessed market value. This pattern is consistent across the sample period. It is important to note that this pattern is not mechanical. If our classification were uninformative, then the yellow bars would be slightly taller than the 50 percent mark and the black bars would be slightly shorter than the 50 percent mark. The stark difference between the yellow and black bars aligns with what we would expect given local assessment regimes and serves as evidence that our classification is doing a good job of capturing local reassessment cycles and, hence, our instrumental variable should be able to do the same. Reassuringly, the criterion that we use to identify mass reassessment events replicates the mass reassessment schedules for Ohio and Tennessee.

6 Results

6.1 House Price Index

In this section, we document stylized facts on the systematic differences between the assessment-based home price index (AHPI) and transaction-based home price index (THPI). It is important to note that, through the lens of the literature on consumption out of housing wealth, our goal for this section is to document systematic differences between AHPI and THPI and not to explain the sources of these

[17]Appeal is a driver of AMV changes during non-reassessment years. The shares of SFRs that experienced AMV changes in counties that do not have a scheduled mass reassessment are roughly consistent with the shares of SFRs that enjoy successful assessed market value appeals (Weber and McMillen, 2010; Ross, 2017; Avenancio-León and Howard, 2022).

differences. We begin by exploring how the two indices behave differently on an annual basis. Table 2 presents the average annual percent change in THPI and AHPI. For this exercise, in each year, we include only counties where we can compute changes in both indices. Due to the nature of CoreLogic's geographic coverage, the number of counties included in the exercise grows over time.

The annual percent changes tell us a few things. First, qualitatively, the two indices appear to be positively correlated; that is, average annual changes tend to agree directionally. This finding is consistent with the idea that AMVs, broadly, capture some information about the local housing market. Second, however, the average percent changes are mostly statistically different from each other, as the two-tailed t-test on the two means shows that the differences are mostly statistically significant. The systematic differences come from AHPI's low variance; that is, the average annual changes in AHPI tend to be, in absolute value, much closer to zero. For example, compared to the THPI, the AHPI grew slower leading up to the Global Financial Crisis (GFC), fell slower during the Great Recession, and, again, grew slower during the recovery period and the COVID-19 pandemic. AHPI's suppressed volatility is not surprising, given that it has been well documented that, in many jurisdictions, AMVs do not get updated every year (Engle, 1975; Kim and Hou, 2024).

However, long reassessment cycles are not the main driver of the low volatility result. On the right side of the table, we present the same statistics for the sample of counties where, in each year, the majority of SFRs in the county experienced a change in AMV, which is our proxy for identifying mass reassessment events. For this set of counties, we see the same low-volatility pattern, which means that the muted movements are also driven by factors unrelated to infrequent reassessments. Likely candidates are local assessment growth limit laws and the assessment methods (e.g., the comparable sales approach, the cost approach, and the hedonic pricing method) that assessors use, which can be summarized as computing local conditional means of house prices (Amornsiripanitch, 2020). Intuitively, transformations (e.g., computing HPIs) of conditional means (AMVs) yield statistics that have lower variance than statistics that result from transformations of the raw data (e.g., transaction prices).

To show that assessment growth limit laws are not the sole contributor to the low-variance nature of AHPI, we exclude states that have assessment growth limit laws and repeat the analysis. We obtain the list of states that have such laws from Walczak (2018). The results presented in Table A1 are qualitatively and quantitatively similar to that of the baseline analysis. The similarity suggests that the inaccuracy of assessment methods is an important driver of these systematic patterns.

Next, we, more formally, consider the correlation between AHPI and THPI. Table 3 presents various correlation statistics for the two indices' annual changes. The Pearson correlation coefficients confirm the general notion that the two indices are positively correlated. More interestingly, we compare the correlation between the concurrent changes in AHPI and THPI and the correlation between the current change in AHPI and the one-year lagged change in THPI. Using the Steiger test for differences in correlation, we find that changes in AHPI are more correlated with the lagged changes in THPI than with the current changes in THPI. This finding implies that the house price information that AMVs capture is relatively stale, which is not surprising since local assessors use data from year t or earlier to compute AMVs that are given to homeowners in the year $t+1$. The conclusions are robust to using the sample of county-years that likely experienced mass reassessments and excluding states that have assessment growth limit laws (see Table A2).

We can show that the conclusions above hold when we instead use a multivariate regression approach. Following Chen and Cohen (2024), we regress the county-level AHPI growth on various measures of the county-level THPI growth. Table 4 presents the results. In line with the results from Chen and Cohen (2024), we find that the amount of variation in current AHPI growth that can be explained by the variation in current THPI growth is small as indicated by the small positive slope coefficient and the low R^2 value of 0.12 (column 1). A 1 percentage point (pp) increase in THPI growth is associated with only a 35 basis point (bps) increase in AHPI growth. Replacing current THPI growth with lagged THPI growth to the regression highlights the notion that current changes in AHPI are more correlated with lagged changes than with current changes in THPI (column 2). The slope coefficient and the R^2 value are slightly larger, 0.42 and 0.16, respectively. These conclusions are robust to the inclusion of year and county fixed effects (columns 3 through 6) and to dropping states that have assessment growth limit laws (see Table A5).

The aforementioned patterns become clear when we plot national-level versions of the AHPI and THPI. The national-level series are constructed by assigning 2004 as the base year and using the average annual percentage change in each year for available counties as the growth factor.[18] The average is a

[18]We use this method to ensure we are comparing the same set of counties. In Figure A2, we show an alternative version of the national series where we use the national-level FHFA HPI as the THPI and construct a "true" national-level AHPI using a nationwide sample of SFRs. There is little discernible difference between Figures A1a and A2, which suggests that the set of counties being analyzed matters little.

weighted average where the weight is the number of SFRs in the county. The national series are plotted for both samples in Figure 3.

In Figure A1a, we can see the impact of infrequent reassessment, as the flatness of the AHPI line leads to a growing gap between the AHPI and the THPI lines in later years when there is substantial price growth. In the restricted sample shown in Figure A1b, we see that assessed market value growth does a better job of keeping up with market value growth when reassessments are being performed. However, there is still a remaining gap that grows toward the end of the period. Moreover, we see that, in the pre-2015 period, there were significant gaps between the two series that appear consistent with assessed market values lagging transaction-based market values as well as assessed market values being downwardly constrained – the AHPI experiences a 13% drop in its downturn years (2008-2013) compared to a 20% drop in the THPI in its downturn years (2007-2012). The upturn years following the Great Recession also suggest increases in assessed market values are also constrained – the AHPI increases by 56% during its upturn years (2013-2023), while the THPI increases by 101% during its upturn years (2012-2023). The same conclusions hold when we exclude states that have assessment growth limit laws (see Figure A1).

Overall, the key takeaway from the results presented in this section is that changes in assessed market values are very different from changes in transaction-based market values. Therefore, agents that use changes in assessed market values as signals of changes in house price or housing wealth can potentially make very different economic decisions than if they were able to fully observe changes in transaction-based market values.

6.2 Consumption Response

In this section we present our regression results on households' consumption response to changes in AMV. Our consumption response outcome, new HELOC origination, is relatively infrequent. Across the entire sample, our outcome is turned on for 1.6% of consumer-year observations. Figure A3 illustrates the time trend in the outcome measure as well as the number of consumers in the sample. We draw on data starting in 2005, but due to the need for lagged changes in some control variables in our regression, the first year with fully populated variable values is 2007. New HELOC origination is at its highest at the beginning of the sample period in 2007 and falls sharply through the Great Recession. New origination gradually picks back up after 2013 and remains relatively steady between 1.5% and 2% after 2015. Additionally, our matched sample does not meaningfully differ from the full CRISM sample in terms of the observed new HELOC origination rate over time. This reassures us that the matched sample is generally representative of the original credit bureau data.

We proceed with the regressions described in Section 5.2. Columns 1 and 2 in Table 5 show OLS regression results using no control variables and the full set of control variables, respectively. In both columns, we find that the probability of taking out a new HELOC is positively associated with the changes in AMV. The control variables added in column 2 cut the coefficient of interest nearly in half, but the coefficient remains positive and statistically significant. Interestingly, the coefficient on AMV changes is as large as the coefficient on concurrent changes in estimated home price, which suggests that, in the current period, AMV and TMV have similar marginal effects on consumption decisions. In addition, the coefficient on the lagged changes in log estimated home value is about ten times as large as the coefficient on the current changes in AMV and TMV. This suggests that, for HELOCs, lagged changes in housing wealth matter more than current changes.

As mentioned above, the OLS regressions likely suffer from OVB. Columns 3 and 4 present the 2SLS regression results where we use the proposed instrument to address potential OVB concerns. The results are qualitatively and quantitatively similar to the OLS results. We interpret the results as showing that changes in AMV causally increase the probability that the homeowner takes out a new HELOC. In terms of magnitude, the 0.34 value of the coefficient of interest in our preferred specification (column 4) implies that a one-standard-deviation increase in assessed market value causes a 0.027 pp increase in the likelihood of opening a new HELOC, which is a 1.7% increase relative to the sample mean. Lastly, the Kleibergen and Paap F-statistics suggest that the instrument is sufficiently strong such that the resulting standard errors do not need to be adjusted (Lee et al., 2022).[19]

The consumption results hold when we limit the sample to including only non-disclosure states, which do not have commercially-available home price estimates such as Zillow's Zestimate.[20] This exercise addresses the concern that the exclusion restriction may not hold if property tax assessments feed into

[19]Appendix Table A6 presents regression results for the sample where we include only consumers in states that have assessment growth limit laws. We find that the results are quantitatively and qualitatively similar to the baseline results.

[20]See `https://www.zillow.com/c/why-doesnt-my-house-have-a-zestimate/`.

commercially-available home price estimates and homeowners also use these estimates to make consumption decisions. Taken at face value, the result also suggests that the existence of commercially-available house price estimates does not alleviate the information friction that homeowners face.

Overall, the results imply that homeowners face information frictions with respect to knowing the level of their housing wealth in each time period and, hence, rely on a highly imperfect proxy to make related consumption decisions. The results also imply that previous estimates of the MPC out of housing wealth are likely to be biased upward because changes in AMV are positively correlated with consumption and changes in house prices. In addition, the exclusion restriction for the class of instrumental variables that exploits geographic variation in housing supply restrictions (Saiz, 2010) may not hold because the instrument would also affect consumption through the omitted AMV. Lastly, to get a more complete view of how homeowners make consumption decisions out of housing wealth, researchers need to account for the consumption response to both AMV and TMV changes.

6.3 Partial Equilibrium Calibration

To summarize the results presented in the previous two sections, we estimate the impact of consumers' responsiveness to assessed market value changes on the aggregate number of new HELOCs originated during the sample period. We do so by using a partial equilibrium calibration method where we estimate the counterfactual number of new HELOCs in each year if consumers do not respond to AMV changes and compare this estimate to the case where consumers respond to AMV changes as in the IV estimate that we present earlier. The difference between the two estimates gives us the share of aggregate HELOC origination that can be explained by consumers' response to changes in AMV.

The calculation largely follows the approach from Chodorow-Reich (2014) and Amornsiripanitch (2022). We use the coefficients from the full-control 2SLS regression (column 4 in Table 5) to calculate the predicted likelihood that consumer i takes out a new HELOC in year t. The predicted value is denoted as $\widehat{HELOC}_{it}$. As shown in equation 7, we then calculate the counterfactual likelihood of a new HELOC if consumers did not respond to changes in AMV, in which case $\gamma = 0$.

$$HELOC_{it}(\gamma = 0) = \widehat{HELOC}_{it} - \widehat{\gamma} \times \Delta \log(A_{it}) \tag{7}$$

$\widehat{\gamma}$ is the 2SLS regression coefficient on the change in log AMV from column 4 of Table 5. We sum the counterfactual likelihood and the predicted likelihood by year and present the results in Table 6. The numbers in each column represent the predicted and counterfactual numbers of new HELOCs opened in each year, respectively. Throughout the series, we find that, in absolute value term, changes in AMV account for approximately 1% of aggregate annual HELOC origination. Not surprisingly, the pattern follows the stylized facts about AMV that we document in the earlier sections. For the time period spanning 2007 and 2011, the no-response counterfactual number of new HELOCs is smaller because assessed market values were not decreasing at the same pace as transaction-based market values. Once transaction-based market values swung back upward, we find that, on average, annual HELOC origination was dragged down by the AMV channel because AMV growth lagged TMV growth. The estimates imply that the post-GFC recovery may have been quicker if consumers were able to fully observe the market value of their homes because changes in housing wealth affect consumption through many channels (Mian and Sufi, 2011; Mian et al., 2013), not just HELOCs. Overall, because AMVs behave very differently from market values and homeowners use changes in AMV to make consumption decisions, actual aggregate consumption in the macroeconomy can be very different from its full-information counterfactual.

7 Conclusion and Discussion

The first part of this paper uses a large sample of single family homes to document systematic differences between assessed market values (AMVs) and transaction-based market values (TMVs). We find that AMVs and TMVs are positively correlated. However, the correlation is low. Furthermore, AMVs tend to be less volatile than TMVs such that, in periods of growth, AMVs grow slower and, in periods of contraction, AMVs fall slower. Lastly, AMV changes lag concurrent TMV changes as they are more correlated with lagged changes in TMV.

The second part of the paper uses an instrumental variable approach to show that changes in AMVs matter for homeowners' consumption decisions. Specifically, we exploit local mass reassessment events to show that increases in AMVs raise the probability that homeowners take out a new HELOC. The economic magnitude of this effect is comparable to that of TMV changes. A partial equilibrium calibration exercise suggests that changes in AMV can explain approximately 1% of aggregate annual

HELOC origination volume. Importantly, the results are consistent with the idea that homeowners are not fully aware of the transaction-based value of their own homes and hence they use a noisy proxy of their housing wealth to make consumption decisions.

This paper's findings have several important implications. From an academic perspective, the causal effect that changes in AMV have on consumption decisions implies that homeowners face information frictions in learning about their housing wealth and rely on a highly imperfect proxy of housing wealth to make related consumption decisions. The finding disagrees with the idea that economic agents know the value of the assets that they own, which is a standard assumption in many models. Therefore, information frictions should be introduced into these models and empirical tests of these models should take seriously the information frictions that agents in observational data may have faced. Furthermore, the HELOC result also implies that previous estimates of the marginal propensity to consume out of housing wealth is likely to be biased upward due to omitted variable bias. Finally, a homeowner's marginal propensity to consume out of housing wealth is also driven by changes in AMV and not just by the changes in market value of homes, which means that the literature's prior focus on changes in market values alone underestimates the total size of the MPC.

For policymakers, the results suggest that macroeconomic shocks and policies (e.g., the transmission of monetary policy) that operate through the housing wealth channel are distorted because of the information friction that homeowners face. For example, the impact of loose monetary policy would be relatively muted in localities where properties are not set to be concurrently reassessed because homeowners in these areas would be less aware of the positive effect that the policy may have on their housing wealth. Furthermore, this type of information friction may also cause homeowners to make suboptimal financial decisions such as not buying sufficient homeowners and flood insurance against potential climate-related physical risk (Wylie et al., 2025; Amornsiripanitch et al., 2025). Through these lens, local property tax administration (e.g., choice of assessment methods and reassessment frequency) not only affects the equity of property tax burden, but also how homeowners make important economic decisions.

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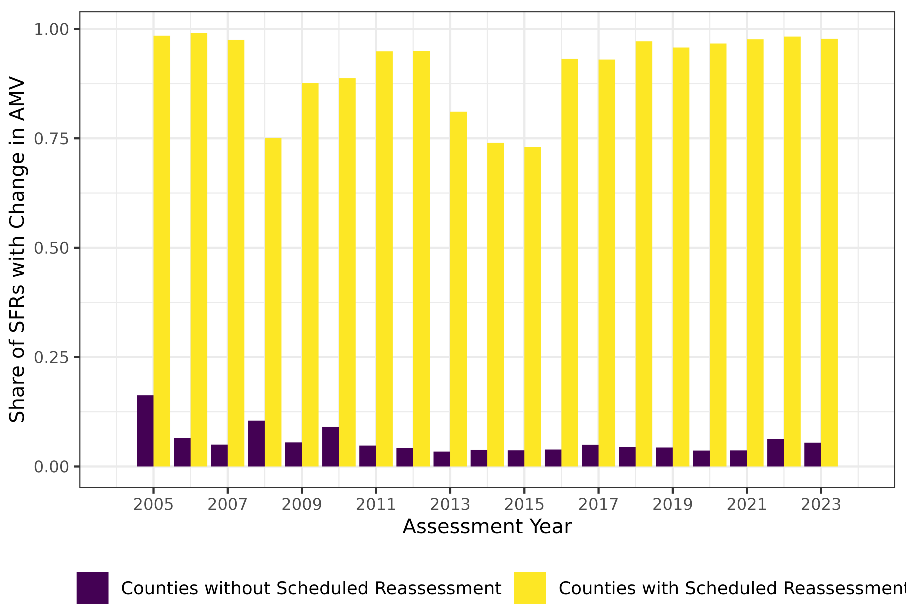
Figure 1: Identification of Local Mass Reassessments – Ohio and Tennessee

This figure shows the share of SFRs that experienced a change in assessed market value (AMV) in counties that were and were not scheduled for reassessment per the state's schedule. In each state, a county-based reassessment schedule is used. In Ohio, each property is reappraised every 6 years and the assessed market value is updated every 3 years based on sales transactions. In Tennessee, properties are reappraised every 4-6 years depending on the county. Data source: CoreLogic Tax, Tennessee Comptroller of the Treasury Reappraisal Schedule, Department of Taxation Property Value Reappraisal and Update Schedule.

(a) Ohio



(b) Tennessee

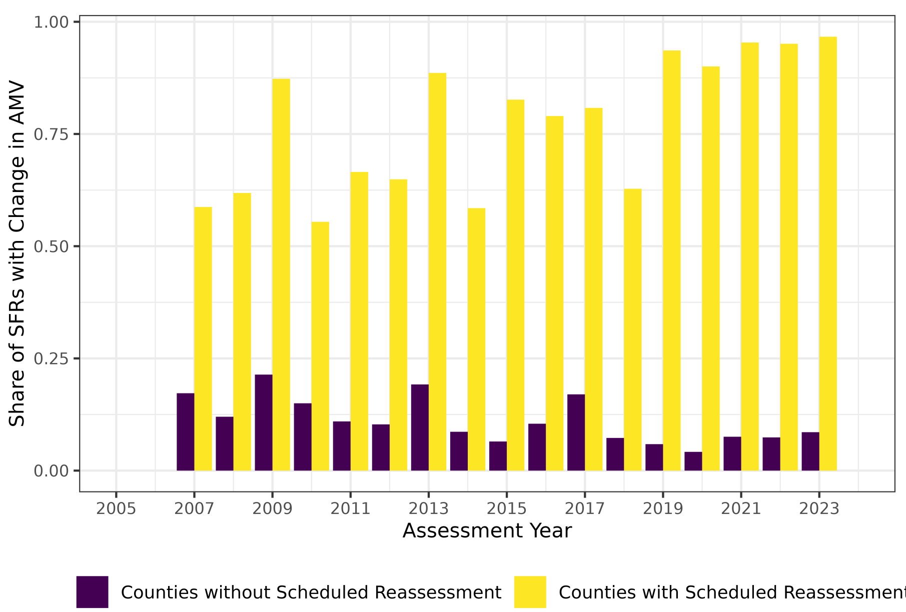


Figure 2: Identification of Local Mass Reassessments

This figure shows the share of SFRs in our regression sample that undergo a change in assessed market value (AMV) for tracts where we identify a reassessment and tracts where we do not identify a reassessment. A tract is defined as undergoing a reassessment if we observe the majority (> 50%) of SFRs changing AMV from the previous assessment year. Data source: CoreLogic Tax.

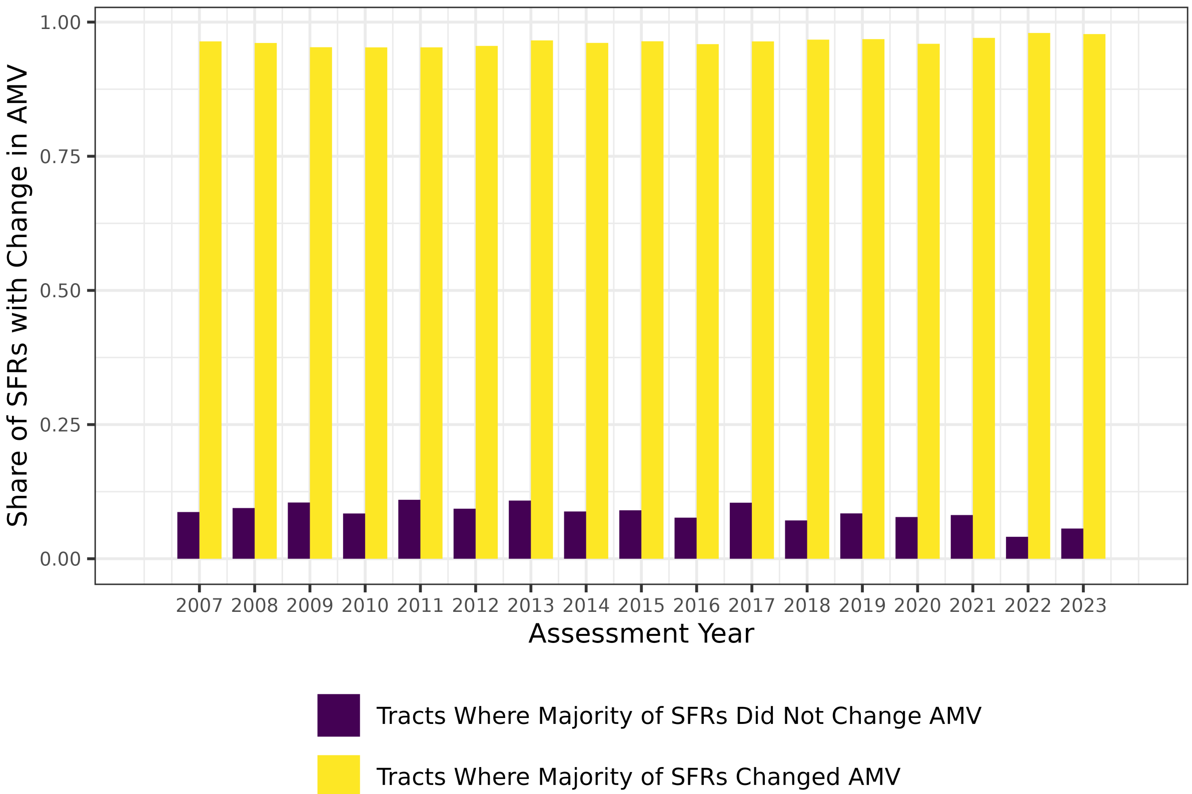
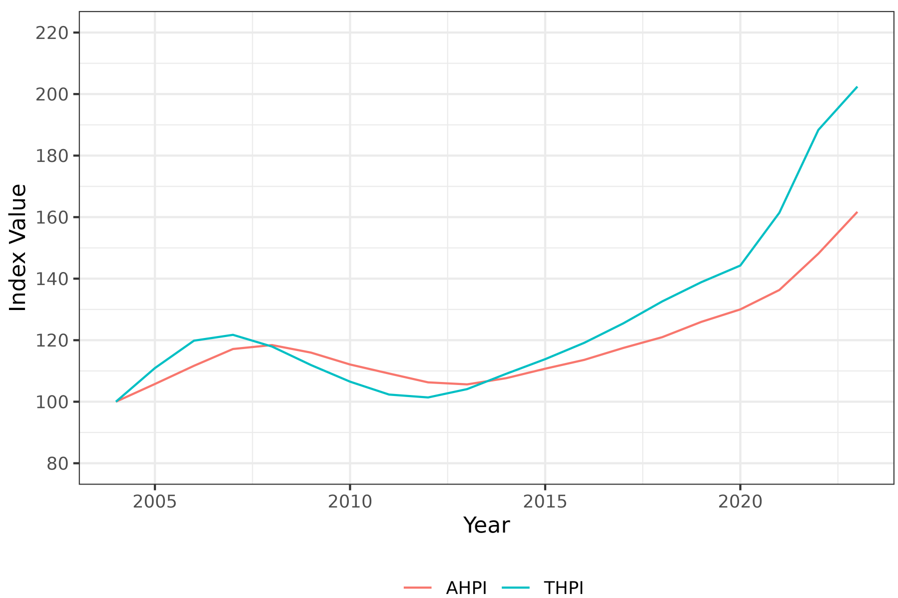


Figure 3: National AHPI and THPI

This figure shows the AHPI and THPI calculated using (a) all counties for which both measures can be calculated and (b) all common counties where we observe the majority of SFRs changing assessed market value from the previous year, our proxy for mass reassessment. The national-level series are generated by aggregating the county-level AHPIs and THPIs using the number of SFRs in each county as the weight. Data source: CoreLogic Tax, CoreLogic Deeds, and FHFA All-Transaction HPI.

(a) Common Counties



(b) Common Counties with Mass Reassessments

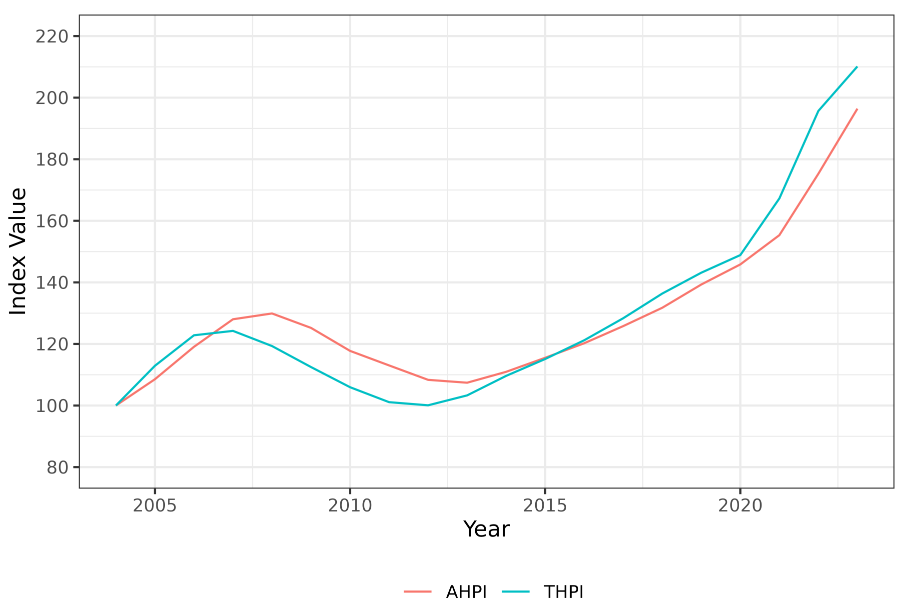


Table 1: Regression Sample Summary Statistics

This table presents the summary statistics for key variables in the regression sample. PIM is an Equifax-derived consumer income estimate, presented in thousands of dollars. Riskscore is an Equifax-derived measure of consumer credit worthiness, ranging from 280-850. Dollar amounts are not adjusted for inflation. HELOC stands for home equity line of credit. Data source: CRISM, CoreLogic Tax, CoreLogic Deeds, and FHFA All-Transaction Home Price Index.

	N	Mean	S.D.	Min	Max
Indicator for new HELOC	70,313,645	0.016	0.125	0	1
Assessed market value	70,313,645	240,807	171,491	37,760	1,000,800
Change in log assessed market value	70,313,645	0.030	0.079	-0.21	0.262
Tax amount	70,313,645	3,588	3,031	325	16,929
Change in log tax amount	70,313,645	0.024	0.094	-0.37	0.441
Estimated home value	70,313,645	289,245	207,311	56,234	1,225,000
Change in log estimated home value	70,313,645	0.044	0.067	-0.166	0.211
Riskscore	70,313,645	753	79	509	833
Change in log Riskscore	70,313,645	0.003	0.042	-0.18	0.122
PIM	70,313,645	63.3	25.4	26.0	146.0
Change in log PIM	70,313,645	0.025	0.096	-0.316	0.363
Consumer credit balances (excluding mortgages)	70,313,645	30,843	31,141	0	162,258
Change in log consumer credit balances (excluding mortgages)	70,313,645	0.011	0.682	-2.305	2.628
Indicator for non-HELOC delinquency	70,313,645	0.223	0.417	0	1
Indicator for bankruptcy	70,313,645	0.022	0.147	0	1
Age	70,313,645	49.5	12.7	20.0	80.0

Table 2: Annual Changes in County-Level AHPI and THPI

This table presents the average percent change and the differences therein for two county-level home price indices: (1) the assessment-based home price index (AHPI) and (2) the transaction-based home price index (THPI), which is the FHFA All-Transactions HPI. Only counties for which both measures are available are included in the sample for a given year. Results for the subset of counties where the majority (> 50%) of single-family residences (SFRs) underwent a change in assessed value in the year are also shown. p-values from two-tailed t-test for difference of means are presented. *** p<0.01, ** p<0.05, * p<0.1. Data source: CoreLogic Tax, CoreLogic Deeds, and FHFA All-Transactions HPI.

	Common Counties				Counties with Mass Reassessments			
Year	AHPI Avg Annual % Change	THPI Avg Annual % Change	Average Difference	Number of Counties	AHPI Avg Annual % Change	THPI Avg Annual % Change	Average Difference	Number of Counties
2005	5.4	10.0	-4.6***	334	7.5	11.6	-4.1***	225
2006	5.4	7.6	-2.2***	499	8.7	8.4	0.4	294
2007	4.4	2.9	1.5***	731	7.2	2.7	4.5***	420
2008	1.7	-1.1	2.8***	750	2.8	-1.6	4.4***	388
2009	-0.2	-3.8	3.5***	853	-0.6	-4.4	3.8***	438
2010	-1.7	-4.3	2.6***	1,040	-3.3	-4.9	1.7***	499
2011	-1.8	-3.0	1.2***	1,153	-3.0	-3.5	0.5***	640
2012	-1.5	-1.2	-0.4***	1,221	-2.9	-1.4	-1.5***	606
2013	-0.5	1.6	-2.1***	1,414	-0.8	1.9	-2.7***	809
2014	0.9	3.1	-2.1***	1,802	1.8	3.7	-1.9***	869
2015	1.6	3.2	-1.7***	1,979	2.5	3.8	-1.3***	1,145
2016	1.5	3.5	-2.0***	2,060	2.7	3.8	-1.2***	1,063
2017	2.3	4.0	-1.7***	2,138	3.5	4.5	-1.0***	1,347
2018	1.9	5.0	-3.1***	2,141	3.4	5.4	-2.0***	1,116
2019	3.0	4.5	-1.6***	2,151	4.7	4.9	-0.2	1,295
2020	2.4	3.6	-1.2***	2,173	4.2	3.7	0.5***	1,155
2021	4.1	11.0	-6.9***	2,209	6.0	11.4	-5.4***	1,447
2022	6.7	16.1	-9.4***	2,163	11.1	16.1	-5.0***	1,277
2023	7.9	7.9	0.0	1,608	11.2	7.8	3.5***	1,102

Table 3: Correlation Between AHPI and THPI

This table presents the correlation between the annual percent changes in two county-level home price indices: (1) the assessment-based home price index (AHPI) and (2) the transaction-based home price index (THPI), which is the FHFA All-Transactions HPI. The table also presents Steiger test p-values to test whether the correlation between the current AHPI percent change and the current THPI percent change is statistically different from the correlation between the current AHPI percent change and the one-year lagged THPI percent change. Only counties for which both measures were available are included in the sample for a given year. Results for the subset of counties where the majority (> 50%) of single-family residences (SFRs) underwent a change in assessed value in the year are also shown. *** p<0.01, ** p<0.05, * p<0.1. Data source: CoreLogic Tax, CoreLogic Deeds, and FHFA All-Transactions HPI.

	Common Counties				Counties with Mass Reassessments			
Year	Correlation of AHPI % Change and THPI % Change	Correlation of AHPI % Change and Lagged THPI % Change	p-value of Steiger Test of Difference in Correlation	Number of Counties	Correlation of AHPI % Change and THPI % Change	Correlation of AHPI % Change and Lagged THPI % Change	p-value of Steiger Test of Difference in Correlation	Number of Counties
2005	0.49	0.46	0.52	334	0.43	0.44	0.98	225
2006	0.48	0.60	0.00***	499	0.57	0.69	0.00***	294
2007	0.14	0.34	0.00***	731	0.27	0.42	0.01***	420
2008	0.40	0.35	0.15	750	0.56	0.50	0.14	388
2009	0.51	0.61	0.00***	853	0.62	0.69	0.01**	438
2010	0.54	0.65	0.00***	1,040	0.65	0.72	0.01***	499
2011	0.53	0.58	0.02**	1,153	0.61	0.61	0.93	640
2012	0.33	0.48	0.00***	1,221	0.42	0.56	0.00***	606
2013	0.20	0.31	0.00***	1,414	0.27	0.37	0.02**	809
2014	0.36	0.34	0.41	1,802	0.43	0.43	0.90	869
2015	0.31	0.43	0.00***	1,979	0.32	0.47	0.00***	1,145
2016	0.27	0.25	0.55	2,060	0.36	0.33	0.35	1,063
2017	0.35	0.28	0.01***	2,138	0.39	0.33	0.07*	1,347
2018	0.25	0.26	0.66	2,141	0.33	0.40	0.03**	1,116
2019	0.26	0.29	0.28	2,151	0.29	0.32	0.39	1,295
2020	0.15	0.19	0.31	2,173	0.23	0.24	0.79	1,155
2021	0.33	0.13	0.00***	2,209	0.38	0.20	0.00***	1,447
2022	0.20	0.28	0.00***	2,163	0.40	0.44	0.11	1,277
2023	0.03	0.14	0.00***	1,608	0.10	0.21	0.01**	1,102

Table 4: AHPI on THPI Regression Results – Excluding Assessment Growth Limit States

This table presents OLS regression results where the annual growth in the county-level assessment-based home price index (AHPI) is regressed onto the current and lagged annual growth in the county-level transaction-based home price index (THPI), which is the FHFA All-Transactions HPI. Heteroskedasticity-robust standard errors are clustered at the county level. t-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data source: CoreLogic Tax, CoreLogic Deeds, and FHFA All-Transactions HPI.

	$\%\Delta AHPI_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\%\Delta THPI_t$	0.35***		0.22***	0.22***	0.22***	0.21***
	(35.43)		(31.79)	(23.80)	(32.22)	(20.93)
$\%\Delta THPI_{t-1}$		0.42***	0.32***	0.29***	0.31***	0.26***
		(40.52)	(41.08)	(26.73)	(39.08)	(22.61)
Year FE				X		X
County FE					X	X
N	29,475	29,475	29,475	29,475	29,475	29,475
Adjusted R^2	0.123	0.161	0.199	0.203	0.201	0.207

Table 5: Consumption Response Regression Result

This table presents the coefficients estimates from OLS and 2SLS regressions where a new HELOC indicator variable, multiplied by 100, is regressed onto the annual change in log assessed market value (A). T is the household's property tax bill. M is the estimated transaction-based market price for the home. The full list of control variables are detailed in Appendix A.1. Heteroskedasticity-robust standard errors are clustered at the tract level. t-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data source: CRISM, CoreLogic Tax, CoreLogic Deeds, and FHFA All-Transaction HPI.

	HELOC			
	OLS		2SLS	
	(1)	(2)	(3)	(4)
$\Delta log(A_{it})$	0.98***	0.33***	1.49***	0.34***
	(38.28)	(11.72)	(27.89)	(5.07)
$\Delta log(T_{it})$		0.02		0.02
		(0.98)		(0.67)
$\Delta log(M_{it})$		0.49***		0.49***
		(10.36)		(9.82)
$\Delta log(M_{i,t-1})$		3.22***		3.22***
		(64.22)		(57.99)
Control Variables		X		X
Year FE	X	X	X	X
Tract FE	X	X	X	X
Kleibergen Paap F-statistic	-	-	58,750	40,025
N	70,313,645	70,313,645	70,313,645	70,313,645
R^2	0.01	0.01	-	-

Table 6: Partial Equilibrium Calibration Exercise

This table presents the results from a partial equilibrium calibration exercise where we estimate the counterfactual number of new HELOCs in each year in our regression sample if consumers did not respond to assessment market value (AMV). Data source: CRISM, CoreLogic Tax, CoreLogic Deeds, and FHFA All-Transaction HPI.

	Predicted Number of New HELOCs in Sample		
Year	*Main Specification*	*Assuming No Response to AMV Growth*	**Percent Difference**
2007	56,440	56,264	-0.31%
2008	41,341	41,349	0.02%
2009	23,643	23,942	1.27%
2010	17,901	18,295	2.20%
2011	24,228	24,572	1.42%
2012	36,179	36,554	1.04%
2013	38,240	38,277	0.10%
2014	62,110	61,618	-0.79%
2015	89,479	88,802	-0.76%
2016	91,581	90,963	-0.68%
2017	97,171	96,326	-0.87%
2018	124,501	123,718	-0.63%
2019	112,638	111,664	-0.87%
2020	83,790	83,126	-0.79%
2021	64,931	63,967	-1.49%
2022	96,068	94,742	-1.38%
2023	60,513	59,588	-1.53%

A Appendix

A.1 Control Variables in Consumption Response Regression

The following variables are used as additional control variables in the consumption response regression. All the variables are sourced from CRISM and McDash.

1. **Change in log Risk Score**. Risk Score is an Equifax-generated measure that indicates the likelihood of a consumer becoming seriously delinquent (90+ days past due). The scores range from 280 (highest risk) to 850 (lowest risk). The consumer's maximum Risk Score value observed during the year is used.

2. **Change in log PIM**. PIM is the estimated annual personal income in thousands of dollars. The estimate is Equifax-generated and is based on credit file attributes and behavior. The consumer's maximum PIM value observed during the year is used.

3. **Non-HELOC delinquency indicator**. Indicator variable of whether, at any point during the year, the consumer was more than 30 days past due on any consumer credit account other than HELOCs.

4. **Bankruptcy indicator**. Indicator of whether the consumer was ever in bankruptcy during the year.

5. **Change in non-mortgage consumer credit balances**. Non-mortgage consumer credit balances excluding HELOC and first-lien mortgage balances. Student loan balances are also excluded. Remaining credit products are credit card, auto, and other retail debt. The maximum observed monthly balance is used for the year. The changes are grouped into one of the following buckets:

    - 50% or greater decrease in balance compared to previous year
    - 20-50% decrease in balance compared to previous year
    - 0-20% decrease in balance compared to previous year
    - 0-20% increase in balance compared to previous year
    - 20-50% increase in balance compared to previous year

- 50% or greater increase in balance compared to previous year
- No balance in previous year and positive balance this year
- No balance in previous year and in current year.

6. **Refinance indicator**. Indicator of whether the active mortgage is a refinance.

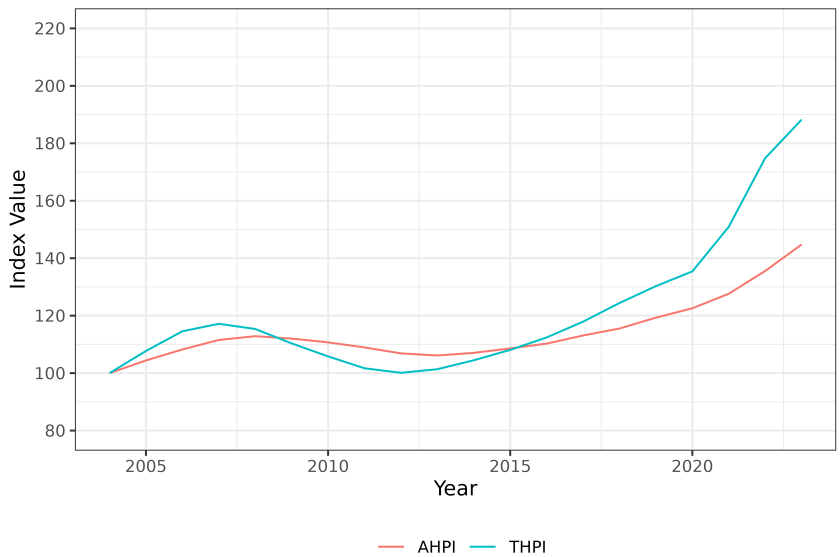
7. **Number of years since origination**. The number of years since the active mortgage was originated. This variable enters the regression equation as a set of indicator variables that ranges from zero to eight. The value is top-coded at 8 years.

A.2 Appendix Figures

Figure A1: National AHPI and THPI – Excluding Assessment Growth Limit States

This table presents the AHPI and THPI time series reported in Figure 3, excluding states with assessment growth limit laws, following Walczak (2018). Data source: CoreLogic Tax, CoreLogic Deeds, and FHFA All-Transaction HPI.

(a) Common Counties



(b) Common Counties with Mass Reassessments

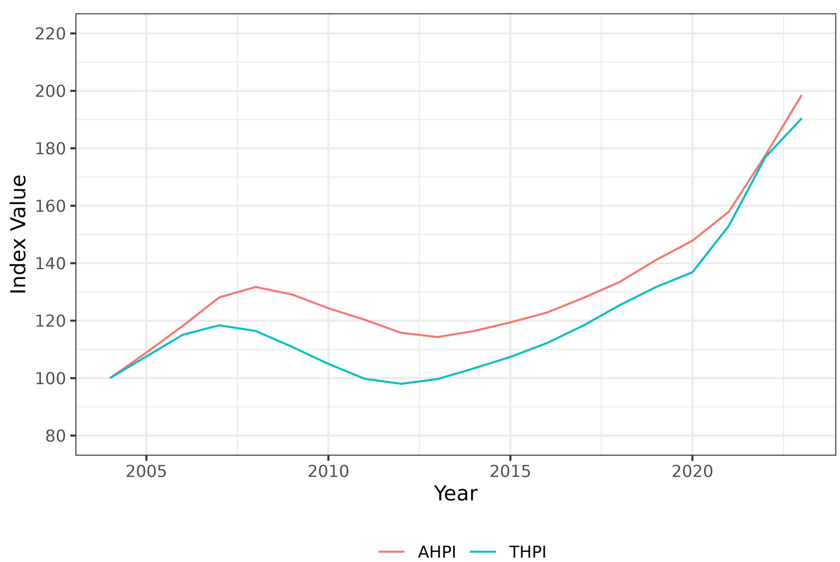


Figure A2: National AHPI and THPI – All Possible Counties

This figure shows alternative national-level AHPI and THPI that are not constrained to using a common set of counties, like in Figure A1a. The AHPI is constructed from a national sample of SFRs. The THPI is the national FHFA All-Transactions HPI rebased to 2004. Data source: CoreLogic Tax and FHFA All-Transactions HPI.

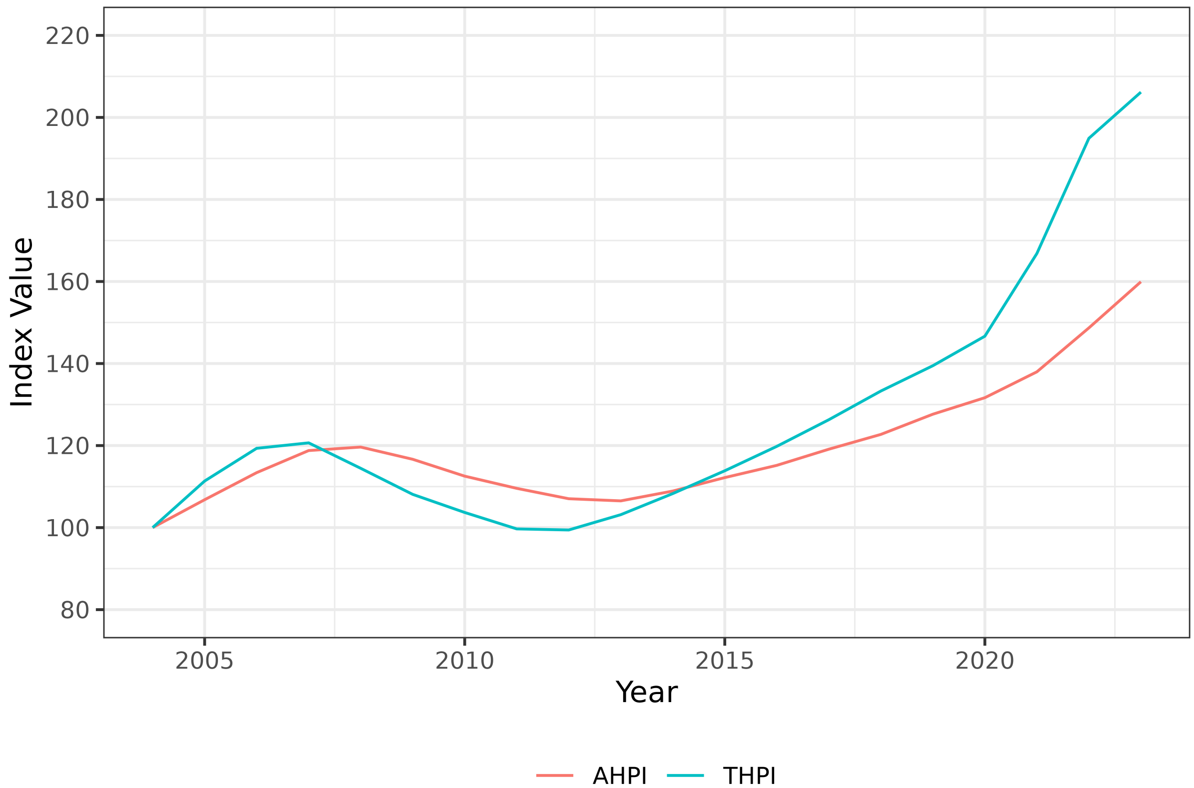
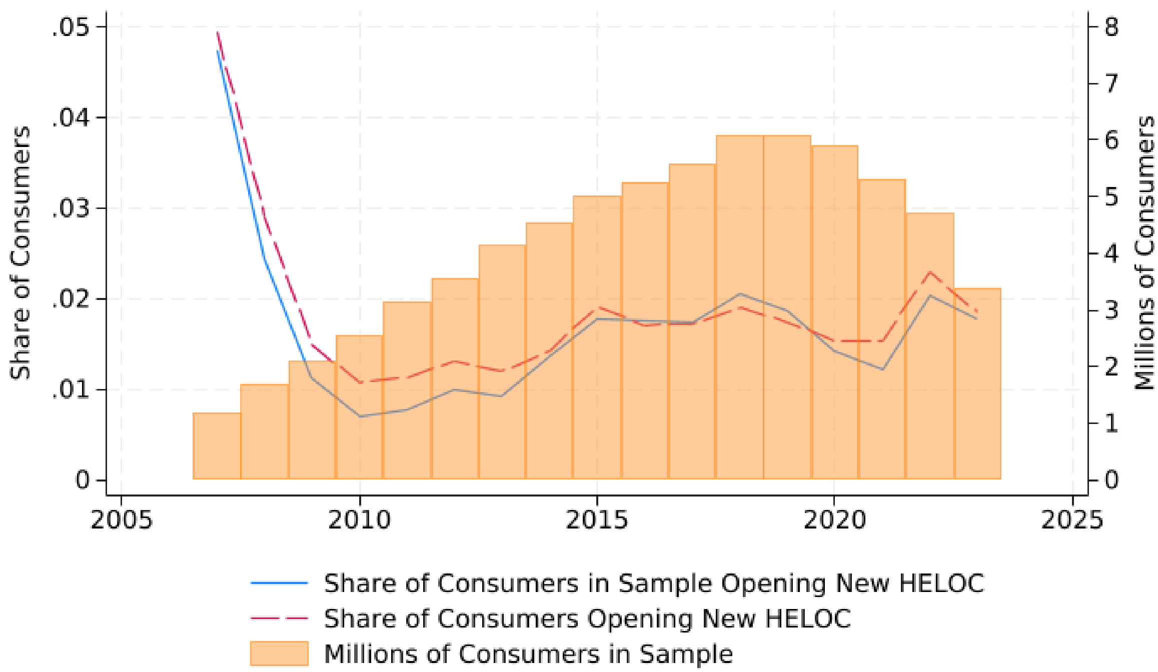


Figure A3: Sample Size and New HELOC Measure Over Sample Period

This figure shows the share of consumers opening a new HELOC in each year in the regression sample (solid line) as well as in the full CRISM dataset (dotted line). The figure also displays the number of consumers in the sample for each year in the sample period. Data source: CRISM, CoreLogic Tax, CoreLogic Deeds, and FHFA All-Transaction HPI.



A.3 Appendix Tables

Table A1: Annual Changes in County-Level AHPI and THPI – Excluding Assessment Growth Limit States

This table presents the results from a robustness check exercise for results presented in Table 2 where we exclude states with assessment growth limit laws, following Walczak (2018). p-values from two-tailed t-test for difference of means are presented. *** p<0.01, ** p<0.05, * p<0.1. Data source: CoreLogic Tax and Deeds and FHFA All-Transactions HPI.

	Common Counties				Counties with Mass Reassessments			
Year	AHPI Avg Annual % Change	THPI Avg Annual % Change	Average Difference	Number of Counties	AHPI Avg Annual % Change	THPI Avg Annual % Change	Average Difference	Number of Counties
2005	4.1	7.2	-3.1***	138	7.0	7.5	-0.5	73
2006	3.6	6.4	-2.8***	226	7.0	6.7	0.3	109
2007	3.1	2.9	0.2	357	7.0	2.9	4.1***	149
2008	1.9	-0.4	2.3***	367	4.2	-0.4	4.5***	156
2009	0.4	-3.0	3.4***	407	0.7	-3.0	3.8***	170
2010	-0.7	-3.7	3.0***	491	-1.7	-4.1	2.4***	200
2011	-1.2	-2.9	1.7***	494	-2.3	-3.2	0.9***	248
2012	-1.2	-1.2	0.0	551	-2.6	-1.2	-1.4***	260
2013	-0.4	1.1	-1.5***	745	-0.8	1.2	-2.0***	395
2014	0.8	2.5	-1.7***	887	1.5	2.9	-1.3***	430
2015	1.0	2.9	-1.9***	1,000	1.8	3.3	-1.4***	504
2016	1.3	3.3	-2.0***	1,065	2.3	3.6	-1.3***	540
2017	1.8	3.8	-2.0***	1,119	3.1	4.2	-1.1***	592
2018	1.8	4.9	-3.1***	1,109	3.5	5.3	-1.8***	515
2019	2.4	4.5	-2.1***	1,145	4.6	5.0	-0.4	572
2020	2.3	3.7	-1.3***	1,149	4.3	3.5	0.8***	577
2021	3.4	10.8	-7.5***	1,156	5.9	11.3	-5.4***	624
2022	6.2	15.8	-9.6***	1,133	12.0	15.6	-3.6***	576
2023	5.5	8.0	-2.5***	767	10.3	7.6	2.7***	391

Table A2: Correlation Between AHPI and THPI – Excluding Assessment Growth Limit States

This table presents the results from a robustness check exercise for results reported in Table 3 where we exclude states with assessment growth limit laws, following Walczak (2018). *** p<0.01, ** p<0.05, * p<0.1. Data source: CoreLogic Tax, CoreLogic Deeds and FHFA All-Transactions HPI.

	Common Counties				Counties with Mass Reassessments			
Year	Correlation of AHPI % Change and THPI % Change	Correlation of AHPI % Change and Lagged THPI % Change	p-value of Steiger Test of Difference in Correlation	Number of Counties	Correlation of AHPI % Change and THPI % Change	Correlation of AHPI % Change and Lagged THPI % Change	p-value of Steiger Test of Difference in Correlation	Number of Counties
2005	0.19	0.20	0.96	138	0.19	0.19	0.98	73
2006	0.24	0.35	0.07*	226	0.32	0.49	0.07*	109
2007	0.12	0.14	0.70	357	0.20	0.21	0.89	149
2008	0.18	0.24	0.37	367	0.28	0.35	0.45	156
2009	0.32	0.30	0.70	407	0.45	0.41	0.53	170
2010	0.47	0.49	0.66	491	0.63	0.64	0.73	200
2011	0.41	0.47	0.12	494	0.51	0.53	0.69	248
2012	0.23	0.44	0.00***	551	0.36	0.57	0.00***	260
2013	0.19	0.31	0.02**	745	0.28	0.42	0.03**	395
2014	0.31	0.35	0.39	887	0.38	0.44	0.29	430
2015	0.24	0.41	0.00***	1,000	0.27	0.47	0.00***	504
2016	0.20	0.21	0.83	1,065	0.25	0.28	0.61	540
2017	0.29	0.22	0.08*	1,119	0.37	0.31	0.27	592
2018	0.26	0.25	0.76	1,109	0.39	0.40	0.71	515
2019	0.28	0.30	0.47	1,145	0.34	0.37	0.49	572
2020	0.08	0.19	0.01**	1,149	0.24	0.23	0.94	577
2021	0.32	0.15	0.00***	1,156	0.43	0.31	0.01***	624
2022	0.12	0.24	0.00***	1,133	0.38	0.44	0.14	576
2023	0.00	0.10	0.06*	767	0.09	0.24	0.06*	391

Table A3: Regressor Correlation Matrix and Variance Inflation Factor

This table presents the correlation matrix (Panel a) and the variance inflation factors (Panel b) for selected regressors that appear in the consumption response regression. PIM is an Equifax-derived consumer income estimate. Riskscore is an Equifax-derived measure of consumer credit worthiness ranging from 280 to 850. Data source: CRISM, CoreLogic Tax, CoreLogic Deeds, and FHFA All-Transaction HPI.

(a) Correlation Matrix

	$\Delta log(A_t)$	$\Delta log(T_t)$	$\Delta log(M_t)$	$\Delta log(M_{t-1})$	$\Delta log(Riskscore_t)$	$\Delta log(PIM_t)$
$\Delta log(A_t)$	1.00					
$\Delta log(T_t)$	0.36	1.00				
$\Delta log(M_t)$	0.47	0.12	1.00			
$\Delta log(M_{t-1})$	0.52	0.12	0.60	1.00		
$\Delta log(Riskscore_t)$	0.04	0.01	0.07	0.05	1.00	
$\Delta log(PIM_t)$	0.04	0.01	0.06	0.07	0.29	1.00

(b) Variance Inflation Factor (VIF)

	VIF
$\Delta log(A_t)$	1.63
$\Delta log(T_t)$	1.15
$\Delta log(M_t)$	1.67
$\Delta log(M_{t-1})$	1.77
$\Delta log(Riskscore_t)$	1.10
$\Delta log(PIM_t)$	1.10

Table A4: First Stage Regression Results

This table presents the first stage the first stage regression results for the 2SLS regressions reported in Table 5. The instrument, Z, indicates whether the modal assessed market value change in the tract (j) where the focal SFR (i) is located decreased (Z = -1), increased (Z = 1), or remained unchanged (Z = 0). The full list of control variables are detailed in Appendix A.1. t-statistics are reported in parentheses. Heteroskedasticity-robust standard errors are clustered at the tract level. *** p<0.01, ** p<0.05, * p<0.1. Data source: CRISM, CoreLogic Tax, CoreLogic Deeds, and FHFA All-Transaction HPI.

	$\Delta log(A_{it})$	
	(1)	(2)
Z_{jt}	0.0607***	0.0498***
	(242.38)	(200.06)
$\Delta log(T_{it})$		0.2073***
		(124.82)
$\Delta log(M_{it})$		0.1563***
		(63.92)
$\Delta log(M_{i,t-1})$		0.2220***
		(94.78)
Control Variables		X
Year FE	X	X
Tract FE	X	X
N	70,313,645	70,313,645

Table A5: AHPI on THPI Regression Results – Excluding Assessment Growth Limit States

This table presents OLS regression results where the annual growth in the county-level assessment-based home price index (AHPI) is regressed onto the current and lagged annual growth in the county-level transaction-based home price index (THPI), which is the FHFA All-Transactions HPI. We exclude states with assessment growth limit laws, following Walczak (2018). Heteroskedasticity-robust standard errors are clustered at the county level. t-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data source: CoreLogic Tax, CoreLogic Deeds and FHFA All-Transactions HPI.

	$\%\Delta AHPI_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\%\Delta THPI_t$	0.28***		0.18***	0.18***	0.19***	0.15***
	(19.56)		(16.90)	(11.83)	(18.43)	(9.84)
$\%\Delta THPI_{t-1}$		0.33***	0.24***	0.24***	0.23***	0.19***
		(20.22)	(18.72)	(12.69)	(17.18)	(9.16)
Year FE				X		X
County FE					X	X
N	14,772	14,772	14,772	14,772	14,772	14,772
Adjusted R^2	0.052	0.062	0.079	0.081	0.075	0.078

Table A6: Consumption Response Regression Result – Excluding Assessment Growth Limit States

This table presents results from a robustness exercise for the consumption response regression results where we exclude states with assessment growth limit laws, following Walczak (2018). The full list of control variables is detailed in Appendix A.1. Heteroskedasticity-robust standard errors are clustered at the tract level. t-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Data source: CRISM, CoreLogic Tax, CoreLogic Deeds, and FHFA All-Transaction HPI.

	HELOC			
	OLS		2SLS	
	(1)	(2)	(3)	(4)
$\Delta log(A_{it})$	1.39***	0.75***	2.02***	0.99***
	(30.17)	(15.66)	(23.42)	(10.31)
$\Delta log(T_{it})$		0.10***		0.03
		(2.89)		(0.77)
$\Delta log(M_{it})$		1.50***		1.45***
		(19.17)		(17.98)
$\Delta log(M_{i,t-1})$		3.66***		3.59***
		(41.09)		(38.90)
Control Variables		X		X
Year FE	X	X	X	X
Tract FE	X	X	X	X
Kleibergen Paap F-statistic	-	-	28,732	24,624
N	34,448,691	34,448,691	34,448,691	34,448,691
R^2	0.01	0.01	-	-