Underappraisal and Time Adjustments to Comparable Sales Prices in Mortgage Appraisals

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Accurate valuation is essential for well-functioning markets, yet real estate appraisals often fail to keep pace with changing prices, complicating lenders' risk assessments. We examine excess underappraisal—where appraised values fall below contract prices—due to insufficient time adjustments to comparable sales. Using a confidential nationwide dataset, we document that time adjustments typically occur in only 10% of cases and are often too small to reflect market trends. These shortfalls result in anomalous seasonal underappraisal patterns, and account for roughly half of valuation gaps across neighborhoods. These inefficiencies have spurred recent efforts to enhance appraisal standards and collateral evaluation tools. (*JEL* G21, J15, L85)

Mortgage appraisal accuracy became a major concern following the global financial crisis in the late 2000s. In the United States, legislation and industry guidance was implemented to reduce accidental and avoidable misvaluation of residential real estate. Stricter professional practices were established including appraiser independence requirements and new conflict of interest standards. Nonetheless, researchers continue to document discrepancies.

Recently, popular news stories have raised concerns over possible systematic inequities in residential mortgage appraisals.[1] Striking press reports have emerged of low appraised values for Black homeowners replaced with much higher ones after a re-appraisal conducted

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[1]Anecdotes have been covered by outlets like Bloomberg, The Boston Globe, Chicago Tribune, CNN, Los Angeles Times, New York Times, NPR, USA Today, Wall Street Journal, and the Washington Post.

with a White stand-in for a Black homeowner. Underappraisals can disrupt a home sale by requiring the buyer to renegotiate the purchase price, put more cash down, accept worse loan terms, or abandon the purchase. Economic research on the topic has started to appear (Ambrose et al., 2023). Racial neighborhood pricing differentials or failed transactions that keep specific groups out of certain areas can contribute to increased housing costs (Box-Couillard and Christensen, 2024), limited civic participation (Yoder, 2020), reduced educational opportunities (Chetty and Hendren, 2018), and limited wealth creation (Akbar et al., 2022; Beach et al., 2024; Derenoncourt et al., 2024). In short, it is important to arrive at accurate and consistent appraisal values that do not vary by borrower or neighborhood demographics.

This paper takes a new approach to studying appraisal valuations and racial differences. We focus on inadequate adjustments for rapid house price movements that result in valuation gaps between similar homes in different neighborhoods. Appraisers can adjust for price changes since a comparable property was sold, a process known as time adjustment.[2] However, previous research shows that appraisals often lag price changes, with values being too low when prices rise quickly. Studying this has been challenging due to limited data. Our paper takes advantage of a newly available appraisal database that details mortgage valuations across the United States. For the first time, we can document that appraisers rarely apply time adjustments, even when markups could substantially improve appraisal accuracy. The underuse may stem from technical challenges appraisers face, with limited information and heavy workloads. Appraisers have considerable flexibility over whether and how to adjust, which presents an opportunity for inconsistencies to arise.

Analyzing a nationwide historical database with a rich set of characteristics for single-family home appraisals, we document that these time adjustments are used too infrequently, are not large enough to correctly reflect current market conditions, and that these shortfalls result in underappraisal. The data are the largest and most representative source of appraisal information currently available.[3] Next, we examine whether time adjustments are made consistently across neighborhoods, and patterns of misvaluation that vary across neighborhoods. Time adjustments are underused disproportionately in majority Black and majority

[2]Formally, these are date of comparable sale and time adjustments, or market conditions adjustments.

[3]The database represents the majority of the mortgage market, including all loan applications sent to Fannie Mae and Freddie Mac, as well as a portion of Federal Housing Administration and other loans (e.g., private portfolio). It consists of more than 45 million records from "subject" single-family properties and 228 million records from "comparable" single-family properties.

Hispanic neighborhoods, especially when they are a potentially decisive factor determining underappraisal. We explore how these patterns are affected by price growth and how they relate to underappraisal. Our estimates suggest that appraisals are mainly time adjusted when a home would otherwise be underappraised. In addition, when local price growth is higher, raising the impact of time adjustments, underappraisal inconsistencies are more common as well. These findings suggest that differential usage of time adjustments is an important source of misvaluation in mortgage appraisals that is identifiable and correctable.

I. Literature Review

Research on real estate appraisal valuations and procedural challenges comprise an extensive academic literature.[4] Economists have uncovered many discrepancies, including overappraisal in service of a smooth loan transaction, underappraisal due to incomplete information, and an excess of appraisals anchored exactly at the sales price.

Appraisal anchoring is a well-documented tendency. Although an appraisal is meant to capture the fair market value of a subject property, studies have demonstrated that the appraisal value is often not only close, but exactly equal to a property's sales price (Ferguson, 1988; Cho and Megbolugbe, 1996; Eriksen et al., 2020; Calem et al., 2021). Appraisers review home purchase contracts for terms that impact valuation. These contracts disclose the sales price as well, leading skeptics to question the objectivity of many appraisals.

Appraisal steering is an institutional issue. Studies have noted that ethical conflicts led to a principal-agent problem where appraisers, who were hired and paid by lenders, were unduly influenced to return a valuation that would allow for a mortgage deal to take place (Shi and Zhang, 2015; Ding and Nakamura, 2016). After the Great Financial Crisis, the Home Valuation Code of Conduct of 2009 improved appraiser independence, resulting in better mortgage performance, lower default rates, and more suitable valuations at origination, but

[4]We focus on single-family residential home appraisals which are usually based on the comparable sales method. Real estate appraisals for multifamily and commercial property are typically based on construction costs or financial statements. Appraisals, often called assessments, are also performed for property taxation. They share procedural similarities such as the use of comparable sales but they have their own set of unique complications including homesteading discounts, evaluation cycles, property tax caps, valuation appeals, and policies that vary across tax jurisdictions.

higher loan application rejection rates (Shi and Zhang, 2015).[5] This relationship conflict has not disappeared but seems to no longer dominate conversations in the same way.

Appraisal smoothing caused by the lagged nature of appraisals and valuations that fail to keep up with dynamic market movements is another well-documented mismeasurement (Geltner, 1991; Geltner, MacGregor, and Schwann, 2003). Appraisers' tendency to undershoot price movements may be an efficient response to incomplete and noisy information, a process akin to Bayesian updating (Quan and Quigley, 1991). Undervaluation, or underappraisal, can also occur if a buyer is overly zealous in bidding and the appraisal has more accurate valuation. One recent study found that wealthier households are more likely to overpay, perhaps to minimize on search costs (Aiello, Kotter, and Schubert, 2024). If the seller lists the property above the current market price, it is possible that a low appraisal can result in a downward revision of the contract price (Shui and Murthy, 2019; Fout, Mota, and Rosenblatt, 2022).

The academic literature on racial gaps in underappraisal is fairly sparse. LaCour-Little and Green (1998) found that underappraisal is related to borrower race, but not neighborhood racial composition. Grodzicki et al. (2024) found that that neighborhood racial composition is associated with low appraisals of purchase-only loans, but the effect diminishes in thicker markets or with appraisers' local experience. Recently, Ambrose et al. (2023) found systematic underappraisal of refinance loans for Black and Hispanic borrowers at a large subprime lender, but not for home purchase loans. A larger literature has examined racial and ethnic differences in housing outcomes (for example, Bayer, Ferreira, and Ross, 2016; Kermani and Wong, 2024) and mortgage pricing (for example, Bhutta and Hizmo, 2021).

Finally, increased attention in appraisal valuation practices from the policy world has launched a large volume of analysis from research institutes, government agencies, and industry. In 2021, following striking press reports, the federal government launched an interagency task force to address appraisal practices. Soon after, the American Enterprise Institute (AEI) kicked off the discourse by studying the frequency of appraiser racial differences (Pinto and

[5]The reform initially affected only loans being purchased or securitized by Fannie Mae and Freddie Mac, but was soon extended to the rest of the mortgage industry in the Dodd-Frank Act. This is not the first time a financial crisis spurred appraisal improvements. The Savings and Loan Crisis in the 1980s was followed by legislation like the Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA) of 1989 governing the licensing and regulation of appraisers.

Peter, 2021*b*), Freddie Mac joined with results on racial and ethnic valuation gaps (Narragon et al., 2021), the Federal Housing Finance Agency (FHFA) examined appraisal free-form text fields (Broadnax and Wylie, 2021), Fannie Mae chimed in about gaps in refinance mortgages (Williamson and Palim, 2022), the Urban Institute discussed the role of AVMs (Zhu, Neal, and Young, 2022), Freddie Mac updated their analysis with additional modeling (Narragon et al., 2022), FHFA showcased a new data source for exploring appraisal valuation differences in minority neighborhoods (Liles, 2022), Brookings argued that differential treatment has lead to devaluation in minority neighborhoods (Rothwell and Perry, 2022), and AEI rounded out the series of recent debates by proposing alternative explanations (Pinto and Peter, 2023). FHFA posted two blogs in early 2024 on the underutilization of time adjustment (Susin, 2024*b*) and their role in driving appraisal valuation differences across neighborhoods (Susin, 2024*a*) that serve as precursors to this paper.

II. Preparing an Appraisal Dataset for Analysis

The data in this paper are based on single-family real estate valuations in the Uniform Appraisal Dataset (UAD) that are collected by Fannie Mae and Freddie Mac ("the Enterprises"). During the period of 2015 thru the third quarter of 2023, the UAD contains approximately 45 million subject property records.[6] The FHFA releases quarterly aggregate statistics and an appraisal-level public use file (PUF) based on a five percent nationally representative random sample of those appraisals.[7] Those files provide information on several dozen of the data fields found on the standardized Uniform Residential Appraisal Report (URAR) form and are updated on a quarterly basis. We obtain access to the confidential UAD which contains geographic location and additional variables not in the PUF, including ZIP Code™ and time adjustments.

A. Creating the Analysis File

We extract a five percent random sample of subject properties from 2015 through the third quarter of 2023. For each subject property, data is also available for the characteristics and sales price of the comparable properties ("comparables" or "comps") that were used in its appraisal. After limiting the sample to home purchase transactions and the other filters described in Appendix A, the final sample includes approximately one million subject

[6] Following Narragon et al. (2022), we omit the first two years of data (2013-2014) due to quality concerns.

[7] A full description of the UAD, the aggregate statistics, and the PUF can be found at https://www.fhfa.gov/data/uniform-appraisal-dataset-aggregate-statistics and https://www.fhfa.gov/data/uad-appraisal-level-public-use-file-puf.

properties and four million comparables. The database focuses on single-family residential properties, which means they exclude condominiums, manufactured housing, housing with two or more units, single-family investment properties, and appraisals without a property inspection. This dataset contains all information from a standardized form submitted by appraisers, but not photos nor attachments. The sample data are geocoded and merged with census tract neighborhood demographics from the 2019 American Community Survey five-year file, and monthly ZIP Code single-family price estimates from Zillow.

The UAD data cover all appraisals submitted to the Enterprises, including those for loans ultimately originated through other channels, such as portfolio and Federal Housing Administration loans, as well as applications eventually denied or withdrawn. Many appraisals are submitted to the UAD by lenders who do not plan to sell them to the Enterprises but want to make use of their collateral valuation and underwriting software. While the data do not identify the ultimate disposition of the applications, we do know that approximately 45% of the appraisals are associated with Enterprise-backed loans.[8] Thus, the data cover the majority of appraisals but are not completely representative of the whole market.

B. Key Variables

The unit of analysis is the appraised subject property. Underappraisal, the main outcome studied here, is defined as an appraised value below contract price, without any adjustment for seller concessions. Seller concessions occur in about one-third of purchases and are about 2% of the price on average. We acknowledge the price net of concessions is a relevant metric for certain studies, but the gross price is more salient to appraisers, probably because concessions below a threshold, most commonly 3%, play no role in underwriting or pricing mortgages. For example, it is common for the appraisal to exactly equal the gross contract price (34% of cases when rounding to the nearest $1,000), but rare for it to equal the net price (2% of cases). In addition, time adjustment usage shows a very sharp increase when appraised value is below the gross contract price before an adjustment is made. No sharp increase happens for net contract price.

Important here are time adjustments, which occur when at least one comparable sales price is updated to a current fair market value. Time adjustments are entered by appraisers

[8]This percentage is based on an appraisal-to-loan matching for 2019Q2 to 2023Q4.

in the "Date of Sale/Time" line on the second page of the standard appraisal form.[9] For our purposes, time adjustments are calculated at the subject property level by averaging together the comparable properties' time adjustments, including zeros where no adjustment was made, and then dividing by the appraised value to obtain the percentage adjustment.

As a benchmark, we construct a predicted time adjustment to ascertain if a comparable sales price needs updating. To do so, both a high time frequency and geographic precision are needed. We choose a source that meets those criteria and is freely available: the monthly ZIP code-level, non-seasonally-adjusted, price indexes from Zillow. For each comparable sale, monthly price growth is applied to bring the comparable sale's age to match the subject property under consideration, using the older of the contract or settlement date (i.e., usually the contract date). The calculations exclude the appraisal month, so as not to use information that might not have been available to the appraiser. For example, if a comparable goes under contract in July and a subject property is appraised in December of the same year, the predicted time adjustment is price growth from June to November.[10]

Finally, we construct two measures of "distributional unusualness," to capture unusual properties are harder to appraise, because fewer comparables are available. To construct the measures, hedonic regressions are estimated for each market, defined as a metropolitan area, metropolitan division, or non-metropolitan portion of a state.[11] The first measure, like a first-order moment, is the difference between the predicted house value and the average predicted house value (both measured in logarithms) in the ZIP Code. We call this the hedonic difference. The second measure, like a second-order moment, is the predicted standard deviation of house price, estimated as the square root of the predictions from a second-stage regression of the first-stage squared residuals on all the explanatory variables, similar to the method used in Jiang and Zhang (2022) and Buchak et al. (2022). We call it the hedonic standard deviation.

[9]For yet-unsold comparables that are currently listed, the line records the expected discount from the offer price rather than an adjustment for changing market prices. Only comparables that have settled and have a final sales price are used to calculate the time adjustment variable.

[10]For comparable sales older than one year, linear interpolation of annual price growth is used.

[11]The regression specification is the same as used later for the underappraisal regressions. The dependent variable is the natural logarithm of the sale price. Markets must have at least 500 house sales over the nine years of appraisals covered by our data.

III. Background

In the United States, several financial regulatory agencies belong to the Appraisal Subcommittee (ASC) that oversees state appraiser regulators and the Appraisal Foundation, which is a group authorized by Congress to set the Uniform Standards of Professional Appraisal Practice (USPAP).[12] The national framework sets certain educational courses and work experience requirements, but each state has its own licensing rules. Secondary market underwriting guidelines, such as those of Fannie Mae, Freddie Mac, and the Federal Housing Administration, are crucial in shaping appraisal practices and they promulgate the URAR form used in most appraisals. This section covers appraisal methods for time adjustments and presents initial evidence of flaws in current practices with making these adjustments.

A mortgage appraisal is meant to capture the market value of a subject property. Market value is defined on the standard URAR appraisal form as "the most probable price which a property should bring in a competitive and open market under all conditions requisite to a fair sale, the buyer and seller, each acting prudently, knowledgeably and assuming the price is not affected by undue stimulus." This definition appears in secondary market underwriting guidelines and USPAP and is the standard for all mortgages funded by banks and credit unions.[13] In addition, the form asks for a value as of the "date of inspection." Thus, appraisers are not asked to forecast home prices, to provide a backward-looking value, or to identify bubbles or other deviations from fundamental values.

Appraisals feed into underwriting decisions in the form of a loan-to-value (LTV) ratio, where "value" is defined as the minimum of the contract price or appraised value. Thus, appraisals below contract price lower the LTV, potentially worsening the loan terms, but appraisals above contract price cannot improve the terms. Sales concessions, side payments from the seller that benefit the buyer, do not affect the LTV if they are customary or below certain limits. The limits range from 3% to 9%, depending on the LTV, except for investor properties

[12]More information about the ASC can be found at https://www.asc.gov/ while the USPAP and the Appraisal Foundation are online at https://www.appraisalfoundation.org. The ASC is a subcommittee of the Federal Financial Institutions Examination Council (FFIEC) whose membership includes the Consumer Financial Protection Bureau (CFPB), the Federal Deposit Insurance Corporation (FDIC), the Federal Housing Finance Agency (FHFA), U.S. Department of Housing and Urban Development (HUD), Board of Governors of the Federal Reserve System (FRB), the National Credit Union Administration (NCUA), and the Office of the Comptroller of the Currency (OCC).

[13]See *Interagency Appraisal and Evaluation Guidelines* (December 2, 2010).

which have a 2% limit.[14]

A. Appraisal Methods

Single-family homes are commonly valued by comparing a subject property to recent sales of comparable homes, called the sales comparison approach.[15] Appraisers adjust the price of comparable properties for any remaining differences in features such as size, condition, or amenities. In addition, where market conditions have been changing, appraisers are expected to estimate the price change over the time since the comparable sale and appropriately adjust its value. Hence, these market conditions adjustments are often called "time adjustments."

To make a time adjustment, appraisers typically collect information on comparable properties from a multiple listing service (MLS), public records, or other sources. There is no specific mandated method, but three strategies appear to be common.[16] First appraisers use grouped data, typically median sales prices for a year or quarter. After specifying a particular market segment or area, appraisers can retrieve median annual or quarterly sales prices from an MLS, and then calculate the average monthly growth in house prices.[17] Second, appraisers can use paired sales (also called repeat sales), calculating the price growth between the most recent and prior sale.[18] This adjustment is often based on a single set of paired sales. For example, The Appraisal of Real Estate textbook gives an example where the sale and resale of one comparable is used to adjust the price of another. Finally, MLS data on individual sales can be retrieved, and the appraiser can regress sales price on a time trend as well as plot the data to look for nonlinearities. However, as discussed below, the most common method is not making any time adjustment, implicitly assuming that no price growth has occurred.

B. Underutilization of Time Adjustments

The frequency of time adjustment by predicted adjustment is presented in Table 1. Generally, when the data suggest a larger predicted adjustment is needed, adjustments happen more often and are larger in size. However, the size of the actual adjustment tends to increase

[14]For example, see Fannie Mae, *Selling Guide*, B3-4.1-02, Interested Party Contributions (IPCs).

[15]Other property types may rely on the cost or income approaches.

[16]These methods are discussed in chapters 21 and 22 of Appraisal Institute (2020).

[17]This technique is encouraged by the data reported on the Market Conditions Addendum, Form 1004MC. While this form has not been required by the Enterprises since 2018, it remains in widespread use. The use of grouped data is endorsed in Andersen (2016), but critiqued in Dell (2013).

[18]This approach is suggested by Federal Housing Administration (FHA) underwriting guidelines in their Handbook 4000.1, Section II.D.4.c.iii (F) which describes a sale and resale comparison when determining property value trends. The paired sales method is critiqued in Wolff (2010) and Diaz (1994).

Table 1 – Time Adjustment Frequency by Predicted Adjustment

Max. Predicted Adjustment (PA)	Frequency of Adjustment (%)	Appraisals (column %)	Size of Adj., if made
PA $<$ -2	9.9	5.7	-1.4
-2 $\leq$ PA $<$ 0	4.8	3.2	1.6
0 $\leq$ PA $<$ 1	5.2	2.0	2.1
1 $\leq$ PA $<$ 2	6.2	6.0	2.3
2 $\leq$ PA $<$ 3	7.7	8.9	2.6
3 $\leq$ PA $<$ 4	9.2	10.4	2.9
4 $\leq$ PA $<$ 5	10.9	10.5	3.2
5 $\leq$ PA $<$ 10	17.4	34.0	4.0
PA $\geq$ 10	36.9	19.3	6.4
Total	17.0	100.0	4.7

Notes: Table shows figures for the each subject property's comparable with the largest predicted time adjustment in absolute value. Size of predicted adjustment (PA) is calculated with the age of each comparable and Zillow price growth data. Ties are broken by choosing the largest actual time adjustment. "Adj." is adjustment.

Sources: Uniform Appraisal Dataset, Zillow

more slowly than the predicted ones, and the difference becomes increasingly consequential. For example, when predicted adjustments are between four and five percent, appraisers time adjust only 11 percent of the time, with the adjustments averaging 3.2 percent.

When comparable sales are recent or house price growth is de minimis, there may be no need for a time adjustment. Thus, to determine whether time adjustments are underutilized, it is insufficient to note that adjustment rates are well below 100 percent. However, Table 1 shows that the size of the required adjustment is large enough to warrant a time adjustment far more often than actually occurs. The maximum predicted adjustment is two percentage points or less in absolute value for only 11% of comparables. Appraisers time adjust only 5% to 6% of these properties, perhaps because the magnitudes of changes are too small to have much impact. Even for these small price changes, it is worth noting that making no time adjustment amounts to an assumed adjustment of zero, which is unlikely to be accurate. That observation is not a statistical critique made blindly without considering what does or should happen in practice—a leading appraisal textbook discusses examples featuring time adjustments close to one percent, or even less (Appraisal Institute, 2020). If we take a narrow stance that a predicted adjustment is not necessary between -2% and 2%, then

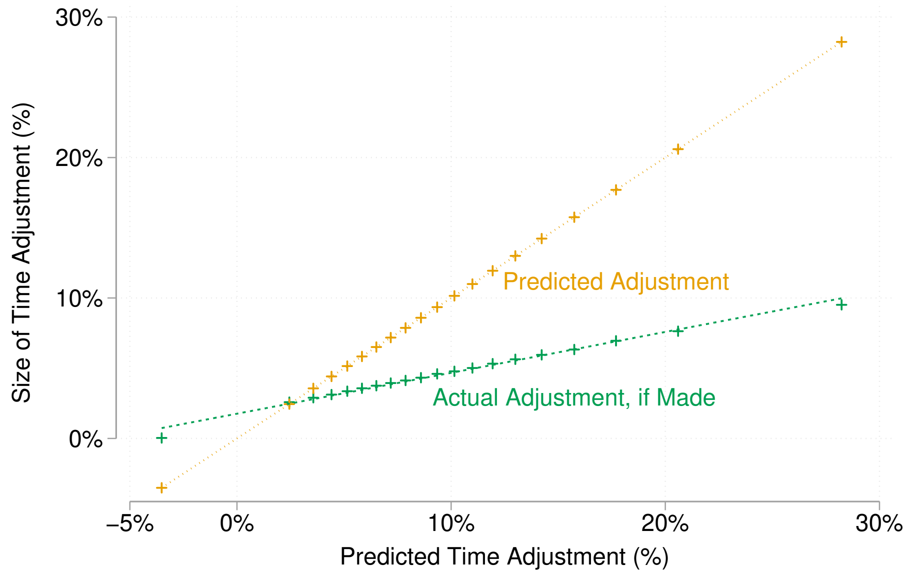


Figure 1. Actual Time Adjustment vs. Predicted

Notes: The sample is restricted to appraisals where a time adjustment was applied. Actual adjustment shows the average of each subject property's largest time adjustment within each of 20 ventiles of predicted time adjustment. Predicted adjustment is a 45° line.

appraisers should time adjust at least one comparable for 89% of properties. If we expand the exemption from 2% to 5%, then 53% of properties need updates.[19] Both far exceed the 17% of properties actually adjusted.

Figure 1 plots the relationship between predicted and actual adjustments, among appraisals with a time adjustment.[20] It shows that for the smallest 5% (first ventile) of predicted adjustments, the predicted adjustment averages -3.5% while the actual adjustment averages 0%. For the second and third ventiles (fifth through fifteenth percentiles), predicted and actual adjustments are fairly close, differing by less than one percentage point. After that, the numbers diverge and we see the two colored lines cross then begin separating. By the sixth ventile, the difference is more than two percentage points (5.8% predicted versus 3.6% actual). For the median (averaging ventiles 10 and 11), the average actual adjustment is about 4.5%, about half the size of the 9% predicted adjustment.

[19]We refrain from taking a policy stance on the appropriate level of time adjustment buc clearly, some usage is merited and the optimal level is non-zero.

[20]Figure 1 is restricted to appraisals with a time adjustment, and thus is weighted towards appraisals with larger predicted adjustments, while Table 1 includes the full sample.

The large divergence when the predicted adjustment is negative is noteworthy as well, suggesting that appraisers are reluctant to time adjust prices downwards. Breaking down the figures further shows that when the predicted adjustment is negative, only 3.6% of properties have negative time adjustments made, with 5% having positive adjustments. In contrast, when the predicted adjustment is positive, 18% of properties have positive adjustments and 0.2% have negative ones.

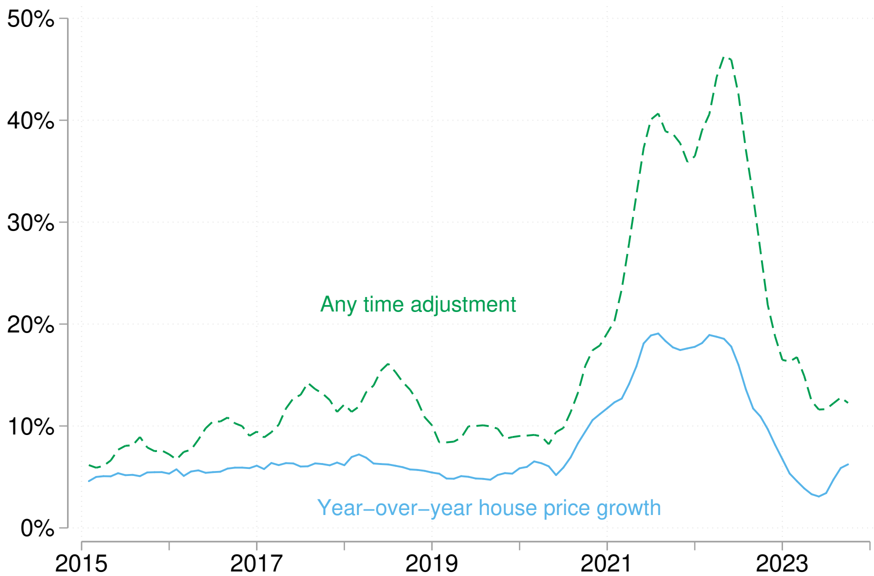
C. Time Series and Seasonality

From 2015-2020, time adjustment rates have averaged about 10% of appraised properties, never rising above 15% of homes. As price growth accelerated in 2021 and 2022, to nearly 18% annual growth rates, time adjustments rose, but always remained below 50% of appraisals as shown by trends in Figure 2's top graphic in panel (a).

The bottom graphic in panel (b) of Figure 2 documents the relationship between house price growth and underappraisal at both annual and monthly frequencies. For much of the analysis period, monthly underappraisal rates mostly fluctuated between 7% and 9%. However, during the (nominal) house price boom of 2021 and 2022, underappraisal rates were often above 15% and briefly touched as high as 22%. Thus, underappraisal varies with price growth, which suggests an insufficient usage of time adjustments. Because appraisals rely on past sales of comparable properties, valuations will be too low when prices are rising rapidly. This phenomenon has been widely noted by appraisal experts (for an example, read Reuter, 2021). As discussed in the literature review section above, academics have also documented this phenomena in the appraisal smoothing literature, and proposed theoretical explanations such as the optimal downweighting of noisy new information. While house price appreciation is often included as a control in the sparse literature on underappraisal, its coefficient has rarely been reported. Fout and Yao (2016) are an exception, finding that faster price growth predicts underappraisal.

The seasonal pattern is even more striking. Both underappraisal and house price growth are highest in the summer and lowest in the winter, aligning with seasonal patterns in sales volume. Underappraisal rates typically have an annual peak-to-trough range of two to three percentage points, tracking quarterly price growth, but made a wild swing of around 10 percentage points in 2021 and 2022, again coinciding with short-run price growth. The annual pattern could reflect Quan and Quigley (1991) style discounting of new information, or appropriate caution. However, the predictable seasonal pattern of underappraisal is much

(a) Frequency of Time Adjustments and House Price Growth



(b) Underappraisal Rates and House Price Growth

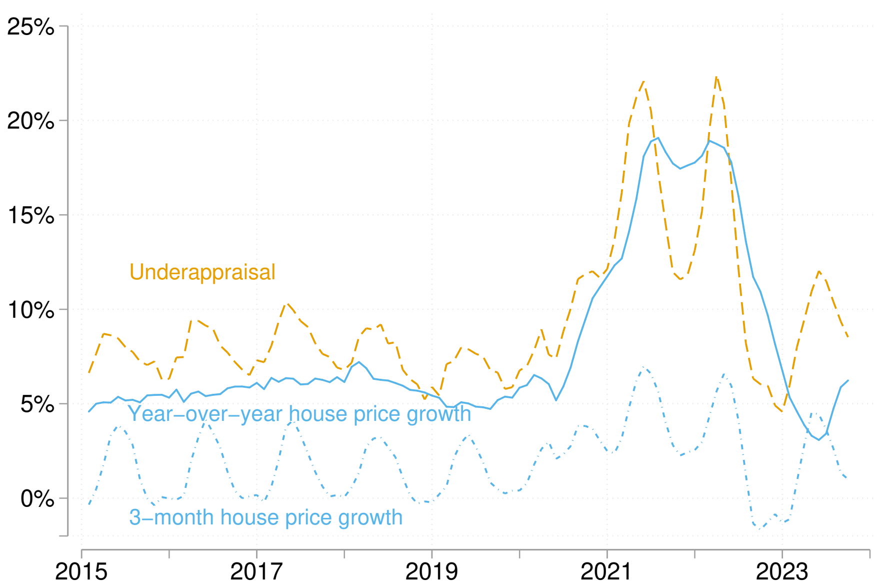


Figure 2. Appraisals and Housing Trends

Notes: Figures use appraisals for mortgage loans to demonstrate how time adjustments (panel a) and underappraisal (panel b) relate to house price growth. All rates are based on author calculations from the Uniform Appraisal Dataset (UAD). Time adjustments reflect the percentage of properties where at least one comparable was time adjusted. Underappraisals compare appraisal values and contract prices as reported on standardized appraisal forms. House price growth is computed with the monthly, purchase-only Federal Housing Finance Agency House Price Index (FHFA HPI®).

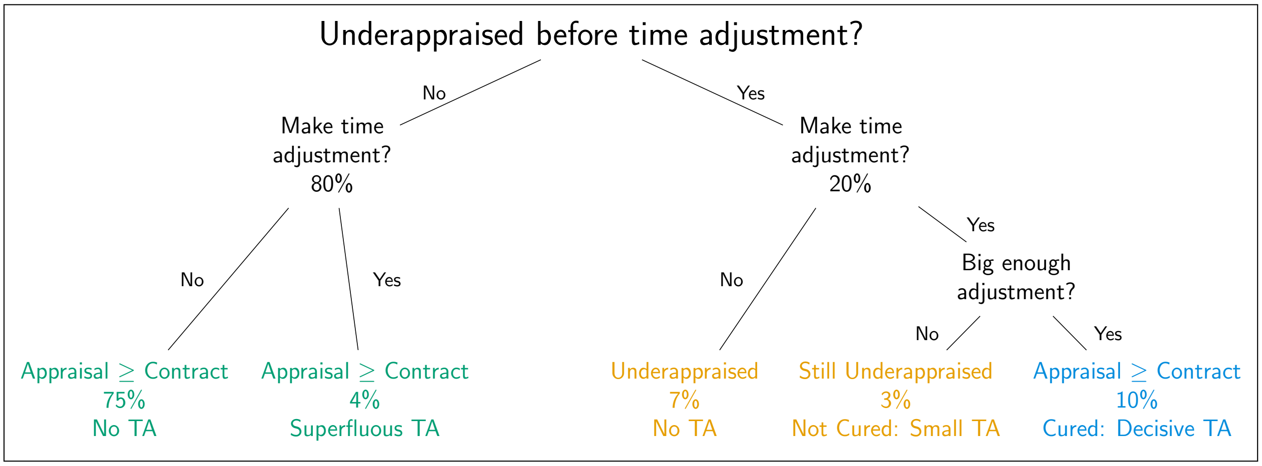


FIGURE 3. TIME ADJUSTMENT AND UNDERAPPRAISAL WITH HYPOTHETICAL APPRAISAL WORKFLOW

harder to rationalize, and suggests that better procedures could lead to welfare gains.

D. Appraisal Workflow

In order for mortgages to be acquired by several major purchasers (e.g., Fannie Mae, Freddie Mac, and the Federal Housing Administration), originators must ensure their loans comply with delivery guidance. An important requirement is that appraisers must adjust for evolving market conditions. However, time adjustments almost exclusively happen for properties that initially appraise below contract price. The role of time adjustments becomes clear when comparing appraised values before they have been made. Figure 3 shows a cross-tabulation of UAD data arranged in a classification tree, illustrating the assumption that time adjustments occur at the end of the appraisal process. In the left branch, before time adjustment, 80% of properties initially appraise above contract price, and appraisers only adjust 5% (4 out of 80) of cases. In the right branch, the remaining 20% of properties initially appraise below contract. For these properties, time adjustments can substantially affect whether the final appraised value will end up below contract, so appraisers make the changes more frequently—65% (13 of 20) of the time. These patterns suggest appraisers usually apply time adjustments as one of the last steps in the appraisal process, and only make such changes for initial underappraisals.

This pattern bears some similarities to that documented in Eriksen et al. (2019), who argued that appraisers increase (decrease) the appraised value of initially underappraised (overappraised) properties by adjusting the weights they use to average the comparables sales prices.

It is conceivable that weights are used as backdoor time adjustments as well. However, while we find that the weighted average does increase in areas with faster price growth, it does so only slightly, an order of magnitude less than the increase in the explicit time adjustment.[21]

Figure 3 also suggests that time adjustments may play an important role in resolving underappraisal. Appraisers make changes for only 17% of properties, but these adjustments are often the decisive factor in determining underappraisal (10 of 17 properties as shown in blue). The non-decisive 7% of properties are split between appraisals for which the value is above contract even without the adjustment (4% in green), and those where adjustments are not large enough to increase the appraisal above the contract price (3% in orange). Another way to convey the importance of time adjustments is to look at how they affect appraisal outcomes. Initially, 20% of properties are underappraised before time adjustments (represented by the three right-most leaves). After making the adjustments, underappraisal drops to just 10% (shown by the two orange leaves). While these tabulations do not demonstrate causality, they suggest a potential link. The close association between time adjustments and initial underappraisal highlights that, despite their infrequent use, time adjustments are potentially important in addressing underappraisal issues.

E. Univariate Analysis

Figure 4 displays binscatter diagrams of underappraisal rates and key predictors. These diagrams partition the data into 20 equal-sized ventiles of each predictor, and plot the means within each bin. As we saw in the time series graphs, the size of the predicted time adjustment is a strong driver of underappraisal. The predicted adjustment is formed from ZIP-code price growth, also a strong predictor, and the age of comparables. The age of comparables is a strong predictor in the opposite direction, but is apparently offset by price growth when combined into the predicted adjustment. The next three variables are all measures of appraisal difficulty and uncertainty. The hedonic standard deviation is the strongest predictor of underappraisal. Perhaps surprisingly, the relationship is negative, indicating that atypical properties are less likely to be underappraised. The other measures also show the same relationship, with greater appraisal difficulty predicting less underappraisal, although the relationship is much weaker. A possible explanation is that underappraisals may face resis-

[21] The ratio of the appraised value to the average adjusted comparable price presumably reflects the weights used to produce the appraised value. Regressing this ratio on annual ZIP price growth yields a coefficient of 0.01, meaning that 1% price growth yields a 0.01% adjustment to the appraised value, compared to a coefficient of 0.1 for a similar regression of time adjustment percentage on price growth.

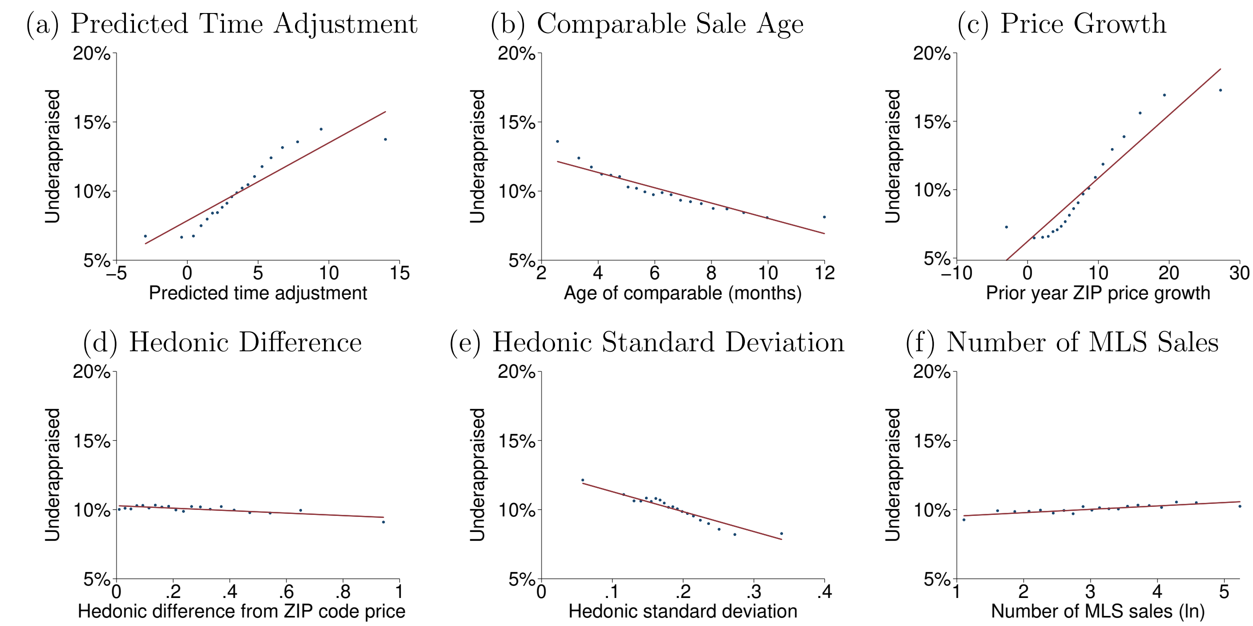


FIGURE 4. BINSCATTER GRAPHS OF UNDERAPPRAISAL RATES VERSUS KEY VARIABLES

Notes: Each figure shows underappraisal rates within 20 equal-sized bins in order to demonstrate the relationship between underappraisal and covariates that are used in regression estimations.

tance from borrowers or lenders, making appraisers less likely to undervalue properties unless they can provide clear documentation—something that is difficult for atypical properties.

F. Summary Statistics by Neighborhood Type

We have established that underappraisal exists and it might be reduced through time adjustments. However, we have not identified if certain places are affected differently by current practice. To do so, we examine valuation differences by defining census tract neighborhoods into four groups: majority white, majority Black, majority Hispanic, and no majority.[22] Table 2 displays simple averages of key variables that are stratified by the neighborhood groupings.[23] Underappraisal rates are lowest at 8.8% in white neighborhoods, compared to 14.5% in Black neighborhoods, 16.6% in Hispanic neighborhoods, and 13.0% in no major-

[22] A substantial share of the Asian population (45%) lives in no majority neighborhoods even though whites make up the largest group in these areas, with Asians being the fourth-largest. A majority Asian category is not included because only a small share of the Asian population (11%) lives in majority Asian tracts.

[23] Our focus is on neighborhood demographics because that information is accessible to appraisers through a site visit. Appraisers might learn the race and ethnicity of the seller as well, but that information is not available to us. Demographics of the buyer are available to us, but only for mortgages that were acquired by the Enterprises, and appraisers do not typically meet the buyer.

Table 2 – Mean Statistics of Key Variables

		Racial Majority Neighborhoods			
	Full Sample	White	Black	Hispanic	No Majority
		Outcomes			
Underappraised	0.100	0.088	0.145	0.166	0.130
Any Comparable with Time Adjustment (TA)	0.173	0.170	0.136	0.197	0.191
		Explanatory Variables			
Underappraisal before TA	0.203	0.190	0.218	0.277	0.240
Predicted TA	3.9	3.9	4.8	3.9	3.7
Age of Comparable (months)	6.4	6.5	6.4	5.6	5.7
Prior Year ZIP Code Price Growth	8.3	7.9	10.3	9.7	8.8
Hedonic Diff. from ZIP Code Price	0.279	0.289	0.280	0.232	0.246
Hedonic Standard Deviation	0.187	0.193	0.185	0.161	0.169
Number of MLS Sales (ln)	3.05	2.97	3.12	3.31	3.36
Number of MLS Sales (#)	38	35	41	44	48
		Figure 3 final leaves			
No TA, Not Underappraised	0.754	0.767	0.749	0.681	0.717
Superfluous TA	0.043	0.043	0.034	0.042	0.043
No TA, Underappraised	0.073	0.063	0.115	0.122	0.092
Small TA, Underappraised	0.027	0.024	0.029	0.044	0.038
Cure: TA, Not Underappraised	0.103	0.102	0.073	0.112	0.111
Number of Appraisals	987,797	752,881	35,399	57,662	141,855

Notes: The abbreviation "TA" stands for time adjustment, "Diff." for difference, and "MLS" for multiple listing service. The main data source is a five percent sample of the Uniform Appraisal Dataset (UAD) from 2015–2023.

Source: Uniform Appraisal Dataset

ity neighborhoods. Time adjustment rates are lower in Black neighborhoods (13.6%) than in white neighborhoods (17.0%), but higher in Hispanic (19.7%) and no-majority (19.1%) neighborhoods.

The next panel contrasts explanatory variables across neighborhood types. The first row shows underappraisal rates before time adjustment, which we also refer to as initial underappraisal. To compute this, we first compute the appraised value net of any time adjustment by subtracting from the appraised value the average time adjustment across each property's comparables (including zeroes). Initial underappraisal rates are lowest in white neighborhoods (19%) compared to neighborhoods that are majority Black (22%), Hispanic (28%), or have no majority (24%). As was shown in Section D, the use of time adjustments is strongly associated with initial underappraisal.

Another driver of time adjustments is the size of predicted time adjustment (based on local house price growth and the age of comparables), as seen above. During this period, house price growth was lowest in white neighborhoods at 7.9%, compared to 10.3% in Black neighborhoods, 9.7% in Hispanic neighborhoods, and 8.8% in areas with no majority. Although the age of comparables was similar in white and Black neighborhoods, it was lower in Hispanic and no majority areas. Consequently, predicted time adjustments are of roughly equal size in white, Hispanic, and no majority neighborhoods, but about one percentage point higher in Black neighborhoods, at 4.8%. Thus, in Black neighborhoods, the drivers of time adjustments are higher than in white neighborhoods, but time adjustments are lower. In Hispanic and no majority neighborhoods, time adjustment rates are higher than in majority-white neighborhoods, but the drivers are about the same (the predicted size of the adjustment) or higher (initial underappraisal), suggesting that there may be more to the story.

The two rows regarding "hedonics" measure how unusual the subject property is compared to the local distribution of homes. Both measures indicate that properties in white neighborhoods are the most atypical compared to local properties, while those in Hispanic neighborhoods are the most typical. Another measure of the difficulty and uncertainty of appraisals is the number of MLS sales, which is a count of comparable properties reported by the appraiser on the 1004 appraisal form. MLS sales are lowest in majority-white neighborhoods. On all three measures, appraisals in white neighborhoods seem to present the most challenges. As shown in the previous subsection, uncertainty tends to lower underappaisal rates.

Summing up, underappraisal rates are lowest in majority-white neighborhoods. However, these differences are potentially explained by the fact that some key predictors of underappraisal are also lower, in the form of lower price growth and lower uncertainty. Thus, in the next section we turn to multivariate analysis to sort this out.

The final panel, as noted by the italicized label in the gray colored row, presents data for the five terminal leaves from Figure 3. Borrowers in Black tracts are the least likely to have an initial underappraisal corrected by a time adjustment, with a rate of 7.3%, compared to 10.2% in white tracts. Time adjustments that completely cure underappraisal are about one percentage point more common in Hispanic and no majority neighborhoods than in white ones. As discussed below, these slightly higher adjustment rates in Hispanic and no majority tracts fall short of offsetting their greater initial underappraisal rates.

IV. Empirical Analysis

The next several subsections estimate various underappraisal models to assess time adjustments. We start with a baseline model similar to that estimated by other authors. The basic idea is that underappraisal is due to errors made by appraisers, homebuyers, or both. Generally, we apply a "short" model that includes the most critical covariates or a "long" model that incorporates a comprehensive set of variables captured in standardized appraisals. These variables are broadly categorized into "appraisal difficulty" and "housing quality." Models may also include tract-level demographics and state/metro fixed effects.

Throughout estimations, our primary focus is on whether we continue to find statistically significant results related to the indicators for a census tract's majority population belonging to a racial minority group, which represent unexplained differences across neighborhoods.[24] Subsequent subsections will test the underappraisal findings to determine if they are influenced by localized house price growth and separate out the time adjustment effect on underappraisal gaps. We decompose the regression estimates to evaluate whether wider use of time adjustments could resolve differences across neighborhoods.[25]

A. Empirical Approach

Let the appraised value equal $P^a_{it} = X_{it}\beta^a + e^a_{it}$, where X_{it} are observed factors that enter the appraisal for property i at time t, β^a is the coefficient vector, and e^a is the appraisal error. Similarly, the contract price is $P^c_{it} = X_{it}\beta^c + e^c_{it}$, where e^c is the buyer error. Then the underappraisal amount is

$$\Delta P = P^a - P^c = X(\beta^a - \beta^c) + e^a_{it} - e^c_{it}, \tag{1}$$

and the property is underappraised if $P^a < P^c$. For exposition ease, we assume the appraisal value and contract price are established in the same period, information is freely available such that the same set of X is known to both parties, and we omit subscripts. This suggests

[24] We do not attempt to determine whether these effects stem from intentional or accidental practices. Our goal is to identify whether differences exist and persist after accounting for various controls.

[25] The appendix contains additional results. Appendix B focuses on time adjustment usage. **??** has the full set of estimations. Appendix C turns to machine learning to analyze the selection, functional form, and covariate contributions to studying how time adjustments affect underappraisal.

the regression specification,

$$\Delta P = X\beta + W\gamma + D + u, \tag{2}$$

where we partition the errors into an unobserved part u, an observed part $W\gamma$, and add D as indicators for neighborhood race/ethnicity.[26] Because equality between the appraised value and the contract price is such a salient cutoff, we estimate this specification throughout this paper using an underappraisal indicator as the dependent variable,

$$I(\Delta P < 0) = X\beta + W\gamma + D + u, \tag{3}$$

where $I(\cdot)$ is the indicator function. Equation 3 is estimated by regressing the underappraisal indicator on variables used in the appraisal or that predict appraiser and buyer errors. We estimate a short model which includes a small set of the most influential variables, a longer model that adds many controls taken off the appraisal report, and a model that also uses census tract measures.

As displayed in Table 3, the short model consists of variables measuring circumstances associated with appraisal difficulty and appraisal errors. The two hedonic measures of distributional unusualness, the difference between the hedonic prediction and the average ZIP Code predicted price as well as the hedonic standard deviation, capture properties that are more difficult to appraise. The comparable age and predicted time adjustment variables are related to the time adjustment size, and appraisal errors are larger when greater time adjustments are required. Finally, appraisals are less reliable in market areas with fewer comparable sales.

Unfortunately, our data do not include buyer characteristics that could indicate overbidding, such as credit scores and first-time homebuyer status, which have been considered in previous studies (Shui and Murthy, 2019; Fout, Mota, and Rosenblatt, 2022). Typically, incorporating buyer-level variables is feasible only when appraisals can be linked to approved loans. We prefer to avoid this restriction due to the relationship between underappraisal and loan approval. Instead, we will discuss an alternative empirical strategy below that aims to address this limitation by focusing on the impact of appraiser actions.

[26]Implicitly, $\beta \equiv \beta^a - \beta^c$ and $W\gamma + D + u = e^a - e^c$. Standard assumptions apply for the error term, u, as normally distributed and independent of X, W, and D.

Table 3 – Regressions Defined by Sets of Variables

	Long Model		
Short Model	*Column 1*	*Column 2*	Census tract
Comp age (months)	Condition	Basement GLA (ln)	Homeownership (%)
Predicted time adjust.	Quality	Finished bsmt. GLA (ln)	Median family income
Diff. from ZIP price (ln)	Location	Lot size (ln)	Median age
Hedonic standard deviation	View	Effective age	Children (%)
Num. of MLS sales (ln)	Water location	Effective age missing	60 or older (%)
	Water view	Any half baths	Emp./pop. ratio
	Gross lvg. area (ln)	Basement	
	Fireplace	Finished basement	
	Pool	Urban	
	Garage	Neigh. built up	
	House age	Neigh. growth	
	Baths	Demand/supply	
	Bedrooms	Marketing time	
	2+ Stories		

Notes: Table lists various sets of covariates that are used to define different models. The "Short Model" is meant to capture an initial set of characteristics that are important for predicting the likelihood for a time adjustment or underappraisal. The "Long Model" includes a more extensive set of covariates that are available from the industry-standardized appraisal form and that have been used in prior studies or reports. The variables are split across two columns only for visual presentation in this table, but all listed variables are used in estimations (i.e., Column 1 and Column 2 are appended). The "short" and "long" lists of covariates are complemented by either "tract" or "state/metro" controls. The "Census tract" column lists the tract-level covariates. When included, the label "Tract" appears in a column header and is synonymous for neighborhood. Some models have state/metro fixed effects as denoted with "SM" in a column header. A column header of "LongSMTract" would indicate the "Long Model" with both tract-specific controls and state/metro fixed effects. All models have year/month controls.

Sources: Uniform Appraisal Dataset, Zillow

We focus on regressions that incorporate a comprehensive set of factors influencing house prices, as detailed in Table 3 under the Long Model. These variables primarily reflect characteristics of the home but also include some neighborhood factors reported by the appraiser, similar to the model in Narragon et al. (2022).

Finally, we run models that add census tract characteristics, as included in other studies (Grodzicki et al., 2024; Narragon et al., 2022; Pinto and Peter, 2021*a*; LaCour-Little and Green, 1998). However, in legal proceedings, the inclusion of such variables could be controversial. Many researchers have argued that variables correlated with race but lacking strong theoretical justifications are "tainted" and should be excluded. Basing appraisals on census tract demographics such as age or the presence of children, which are commonly used in property appraisal research, might be considered illegal under the Equal Credit Opportunity Act or Fair Housing Act. Similarly, using income or employment measures in appraisals could unintentionally lead to what lawyers refer to as disparate impact discrimination. Although there may be theoretical interest in these variables, our goal is to identify neighborhood differences that lack legitimate explanations. Thus, our preferred specification is the long model with state and metro effects without census tract controls, but we still report a model with tract characteristics for comparability with other studies.[27]

Some of these authors have included appraiser fixed effects as well, with Narragon et al. (2022) finding that the adding metro and appraiser effects together reduce estimated gaps by roughly one half, while results reported here show that metro effects alone reduce gaps by roughly one third. However, we do not include appraiser effects because of tainted variable concerns.[28] Including appraiser effects would mask any systematic differences due to the types of appraisers working in different neighborhoods. For example, racial gaps might arise if appraisers working in Black neighborhoods are less experienced, or in short supply. While such gaps would not be due to intentional discrimination by appraisers, they might constitute disparate impact discrimination, or otherwise point to a problem that could be addressed.

Table 4 displays the neighborhood type coefficients from OLS underappraisal regressions, including the variables listed in Table 3. Model 1 features only a limited set of variables along with year/month effects. In this model, the coefficient for Black neighborhoods is 0.052, which is substantial compared to the 0.088 base underappraisal rate in majority white neighborhoods. Including additional variables in Models 2 and 3 has only a minor impact in Black tracts, with the coefficient decreasing slightly, but a larger effect in Hispanic tracts. Incorporating state/metro effects in Model 5, which is the long model without tract measures, reduces the coefficient to 0.036. In other words, Model 5 estimates that underappraisal rates are 3.6 percentage points higher in Black tracts than for comparable appraisals in white tracts. In this model, the coefficient for majority Hispanic neighborhoods is approximately 0.039, and for no majority tracts, it is 0.021. Adding the census tract variables, in Model 6, modestly reduces the coefficients.

[27]It is uncertain whether such measures would be accepted by courts as justifications for such gaps. Guidance has been provided by the Federal Judicial Center (2011) and the danger that illegitimately included variables might mask disparate impact has been emphasized by Ross and Yinger (2002, Section 10.5.2) and Ayres (2005).

[28]In addition, an accurate appraiser ID is not simple to construct, since each state issues its own professional identifiers.

TABLE 4 – UNDERAPPRAISAL REGRESSIONS

	(1) Short	(2) Long	(3) LongTract	(4) ShortSM	(5) LongSM	(6) LongSMTract
Majority Black	0.0515***	0.0511***	0.0476***	0.0420***	0.0362***	0.0292***
	(6.67)	(7.46)	(6.61)	(8.90)	(7.88)	(6.24)
Majority Hispanic	0.0719***	0.0618***	0.0546***	0.0470***	0.0392***	0.0279***
	(6.00)	(5.65)	(4.80)	(13.55)	(12.05)	(8.24)
No Majority	0.0385***	0.0323***	0.0292***	0.0240***	0.0206***	0.0148***
	(9.10)	(10.23)	(8.66)	(15.27)	(15.36)	(9.78)
Appraisal Difficulty	×	×	×	×	×	×
Housing Quality		×	×		×	×
Census Tract			×			×
State/Metro Effects				×	×	×
N	987,797	987,797	987,797	987,797	987,797	987,797
adj. R^2	0.029	0.042	0.042	0.042	0.052	0.053

Notes: Table entries are OLS regression coefficients with t statistics in parentheses and. The dependent variable is underappraisal. Standard errors are adjusted for clustering at the state/metro level. The bottom part of the table as well as the column headers ("short", "long", etc.) clarify the groups of covariates used in each specification and specifically listed in Table 3. All columns have year/month fixed effects. Statistical significance levels are denoted as * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Source: Uniform Appraisal Dataset (2015–2023)

B. *Empirical Results — House Price Growth Interactions*

A goal in this paper is to assess how much time adjustments contribute to differences in underappraisal across neighborhoods. It might seem straightforward to test this question by including a time adjustment indicator in the regression, or by interacting it with race/ethnicity coefficients. However, time adjustments are likely endogenous because they are more common when homes are at risk of being underappraised. Although time adjustments can help correct underappraisal, they are not sufficiently frequent to counteract the contributions of other factors. Consequently, homes subject to time adjustments are more likely to be underappraised. For instance, Figure 3 shows that 16% of homes with time adjustments are underappraised (3 out of 17 properties), compared to 7% of those without time adjustments (7 out of 83 properties). This is unlikely to be a causal effect of time adjustments. Instead, it is more probable that both time adjustments and underappraisal arise from the same underlying factors, such as high house price growth or buyer overbidding. These factors may lead appraisers to apply time adjustments, which sometimes correct underappraisal.

Instead of examining the direct impact of time adjustments on underappraisal, we focus on

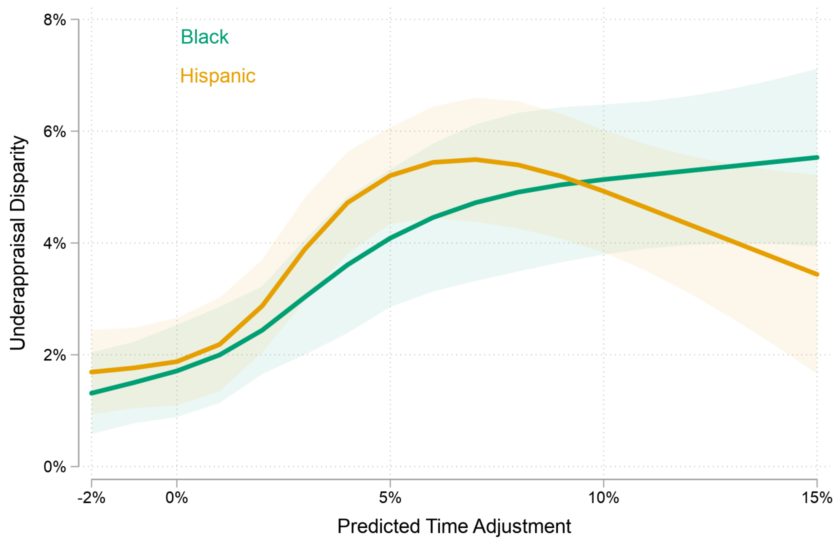


Figure 5. Neighborhood Underappraisal Gap Varies with Predicted Time Adjustment

Notes: Figure shows the interaction between the majority Black and majority Hispanic neighborhood coefficients with a restricted cubic spline of predicted time adjustment, in a regression model including all the controls from Model 5 of Table 4. Shading shows the 95% confidence interval.

factors that drive time adjustments. A crucial test for the significance of time adjustments is to see if racial and ethnic neighborhood gaps vary with house price growth, which we measure as the predicted time adjustment. This test is especially clean because house price growth is clearly exogenous and not influenced by the actions of any specific appraiser or home buyer. Therefore, we proceed by estimating the model to analyze this relationship as

$$I(\Delta P < 0) = X\beta + W\gamma + Df(g) + u, \tag{4}$$

where $f(g)$ is a flexible function of the predicted time adjustment, implemented with a restricted cubic spline.[29]

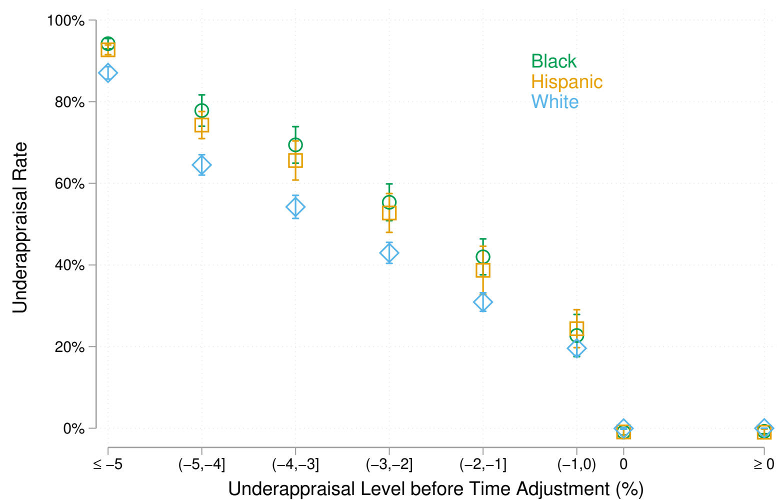
Figure 5 visualizes the effects of including interactions in Model 5 from Table 4, which features the Long list of variables and state/metro effects.[30] The racial neighborhood gap ranges from 2% at zero predicted time adjustment—either due to no house price growth or

[29]The restricted cubic spline has five knot points, chosen by the Stata software, but only four parameters because of the restrictions that the first and second derivatives match at the knot points.

[30]Full results are provided in Table **??** in the Appendix.

very recent comparables—to approximately 5% when the predicted time adjustment reaches 5%. This pattern is consistent across both types of minority neighborhoods, indicating that time adjustments account for a significant portion of the difference. The coefficients of 3.6% and 3.9% in Table 4 would decrease to around 2% without the need for time adjustments.

(a) Rates



(b) Gaps

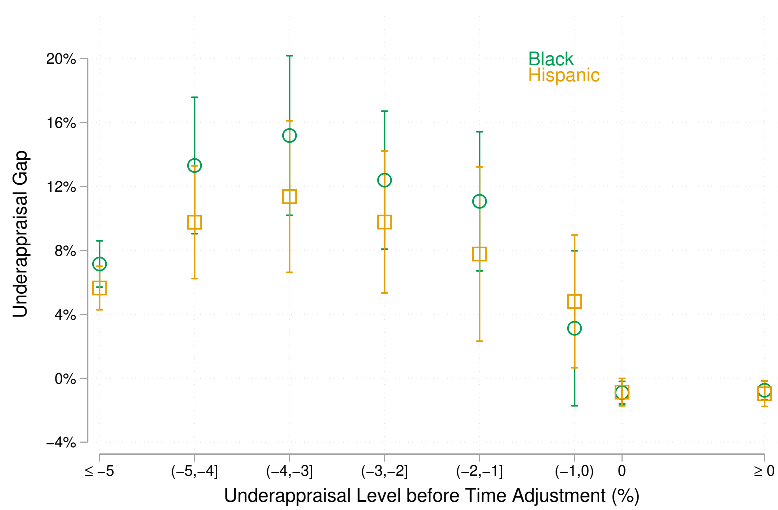


Figure 6. Underappraisal by Underappraisal Level Before Time Adjustment

Notes: Figure shows race/underappraisal level interactions from the Model 5 of Table 4 long regression specification with state/metro effects.

C. *Empirical Results — Appraisals before Time Adjustment*

The second method for investigating the impact of time adjustment on underappraisal is to condition on the underappraisal level prior to time adjustment, in order to isolate the effect. To fix ideas, Figure 6 displays regression-adjusted underappraisal estimates for white, Black, and Hispanic tracts, categorized by the size of the underappraisal before time adjustment. To obtain the appraised value before time adjustment, we subtract the average time adjustment of the comparables from the appraised value.

A notable observation is that when the initial appraisal is at or above the contract price, underappraisal almost disappears after time adjustment, as seen in panel (a). For the 23% of the data where the appraisal exactly matches the contract price before adjustment, underappraisal rates are zero across all tracts. Among the 57% with initial appraised values higher than the contract price, final underappraisal rates average just 0.03% across all racial and ethnic neighborhood groups. This low rate of underappraisal is not necessarily expected, but occurs because negative time adjustments are rare (0.5% of appraisals), and those leading to underappraisal extremely rare (0.02% of appraisals). When there is an initial appraisal gap, underappraisal can be substantial. Even for initial underappraisal of less than one percent, 20% to 25% are not cured by time adjustment, and result in underappraisal. Turning to panel (b), neighborhood underappraisal differences generally widen with increasing underappraisal levels. Gaps range from about 3% to 15% in Black tracts and from 5% to 12% in Hispanic tracts, with a peak when initial underappraisal levels are 3% to 4%.

Figure 6 illustrates the potential importance of time adjustments in determining underappraisal. However, these conditional gaps cannot be directly compared to the unconditional underappraisal gaps in Table 4, so they do not show how much is attributable to time adjustments. As a rough estimate, the gap averages about 8% for the 20% of borrowers initially underappraised. Multiplying these figures provides an average neighborhood divergence attributable to time adjustments of 1.6%, which is substantial relative to the underappraisal gaps in Table 4. In the remainder of this section, we directly measure the portion of underappraisal difference due to time adjustments.

Table 5 estimates models with an additional indicator for initial underappraisal included as an explanatory variable. We call this the "cured by time adjustment" specification because, given initial underappraisal, a property will remain underappraised unless it is cured by time

Table 5 – Cured by Time Adjustment Regressions

	(1) Short	(2) Long	(3) LongTract	(4) ShortSM	(5) LongSM	(6) LongSMTract
Majority Black	0.0503***	0.0414***	0.0397***	0.0295***	0.0235***	0.0188***
	(11.03)	(10.06)	(9.06)	(11.47)	(9.64)	(7.57)
Majority Hispanic	0.0375***	0.0326***	0.0298***	0.0234***	0.0192***	0.0131***
	(4.85)	(4.92)	(4.30)	(11.19)	(9.34)	(5.87)
No Majority	0.0191***	0.0190***	0.0185***	0.0124***	0.0114***	0.00835***
	(5.97)	(7.26)	(6.56)	(12.07)	(12.68)	(8.48)
Initial Underappraisal	0.505***	0.514***	0.514***	0.511***	0.516***	0.516***
	(34.40)	(35.73)	(35.76)	(36.53)	(36.79)	(36.78)
Appraisal Difficulty	×	×	×	×	×	×
Housing Quality		×	×		×	×
Census Tract			×			×
State/Metro Effects				×	×	×
N	987,797	987,797	987,797	987,797	987,797	987,797
adj. R^2	0.447	0.455	0.455	0.457	0.463	0.463

Notes: Table entries are OLS regression coefficients with t statistics in parentheses. The dependent variable is underappraisal. Standard errors are adjusted for clustering at the state/metro level. The bottom part of the table as well as the column headers ("short", "long", etc.) clarify the groups of covariates used in each specification and specifically listed in Table 3. All columns have year/month fixed effects. Statistical significance levels are denoted as * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Source: Uniform Appraisal Dataset (2015–2023)

adjustment. This does not address the possibility that negative time adjustments will cause underappraisal, but this is so uncommon it can be neglected. The initial underappraisal indicator captures the fact that time adjustments are typically made when a property is underappraised before the adjustment, as these adjustments can rectify the issue. Conversely, time adjustments are rarely applied if the initial appraisal exceeds the contract price. The regression equation is

$$I(\Delta P < 0) = X\beta + W\gamma + D + I(P^b < P^c) + u. \tag{5}$$

where P^b is the initial appraised value before time adjustment, and P^c is the contract price. By conditioning on underappraisal caused by all other factors, Equation 5 isolates differences attributable solely to time adjustments.

This indicator also captures unobservable factors influencing the appraised value and contract price, as it is derived from them. This specification focuses on the appraisal process element that is entirely within the appraiser's control: the determination of the time adjustment.

We have excellent controls for this process, including the age of comparables and local house price growth, which are used to predict time adjustments. Buyer decisions are less directly accounted for but are embodied in the contract price and potentially included in the initial underappraisal indicator.

Another interpretation of equation 5 is that the initial underappraisal indicator identifies marginal borrowers for whom time adjustments can have the most significant impact. These borrowers, initially underappraised, are similar to marginal borrowers analyzed in fair lending underwriting examinations and regulatory compliance (Cosans, 2019; Office of Comptroller of the Currency, 2023). This concept is akin to the "thick folder" legal theory of discrimination, where loan officers have the discretion to put in extra effort to help borrowers submit additional documentation to address any issues in their application (Ladd, 1998). Similarly, borrowers at risk of underappraisal before a time adjustment may find their loan approval dependent on whether the appraiser chooses to make the effort to calculate the adjustment.

The Model 5 coefficients in Table 5 are 0.024 and 0.019 in Black and Hispanic tracts, respectively. These gaps, which reflect only whether a large enough time adjustment was made or neglected, are substantial compared to the simple underappraisal gaps in Table 4. There, the comparable coefficients are 0.036 and 0.039 in Black and Hispanic tracts, respectively.

D. Decomposition of Underappraisal Differences

The previous sections offer two methods for decomposing underappraisal differences into those attributable to time adjustments and those due to other factors. Table 6 summarizes these results. The first column displays the full underappraisal difference across neighborhoods from the model that controls for a comprehensive set of explanatory factors and state/metro effects. The second column reports the differences conditioned on a predicted time adjustment of zero, derived from a model that includes interactions between neighborhood indicators and a flexible function of the predicted time adjustment. These estimates do not use potentially endogenous information about actual time adjustments. For Black tracts, the difference when predicted time adjustments of zero indicate that no time adjustment is needed, is 0.017, compared to a full underappraisal gap of 0.036. The difference between these values, shown in the next column, is 0.019. This indicates that 53% of the gap is due to time adjustments, while 47% is attributed to other factors.

An alternative decomposition includes "underappraised before time adjustment" as an ex-

TABLE 6 – DECOMPOSITION OF UNDERAPPRAISAL DIFFERENCES

		Predicted TA Model			Cured by TA Model		
	(1) Underappraisal Difference	(2) Other Factors	(1) - (2) Due to TA	$\frac{(1)-(2)}{(1)}$ % Due to TA	(3) Due to TA	(1) - (3) Other Factors	$\frac{(3)}{(1)}$ % Due to TA
Majority Black	0.036***	0.017***	0.019	53%	0.024***	0.012	67%
	(7.9)	(3.9)			(9.6)		
Majority Hispanic	0.039***	0.018***	0.021	54%	0.019***	0.020	49%
	(12.1)	(4.5)			(9.3)		
No Majority	0.021***	0.009***	0.012	57%	0.011***	0.010	52%
	(15.4)	(5.2)			(12.7)		
Appraisal Difficulty	×	×			×		
Housing Quality	×	×			×		
Census Tract							
State/Metro Effects	×	×			×		
N	987,797	987,797			987,797		
adj. R^2	0.036	0.053			0.453		

Notes: Table entries are OLS regression coefficients with t statistics in parentheses. The dependent variable is underappraisal. Standard errors are adjusted for clustering at the state/metro level. All regressions use the LongSM specification (Model 5 in Table 4). TA stands for time adjustment. The bottom part of the table clarifies the groups of covariates used in each specification and specifically listed in Table 3. A full set of coefficients is shown in **??**. All columns have year/month fixed effects. Labeled Column (1) corresponds to Model 5 of Table 4. Labeled Column (2) reflects the specification used in Figure 5 which is Model 5 of Table 4 with the addition of interactions of race/ethnicity indicators and a restricted cubic spline of predicted time adjustment. Values reported in the table are the race/ethnicity differences evaluated at zero predicted time adjustment. Labeled Column (3) corresponds to Model 5 of Table 5 that includes a control for whether underappraised before time adjustment. Statistical significance levels are denoted as * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Source: Uniform Appraisal Dataset (2015–2023)

planatory variable, effectively creating a "cured by time adjustment" regression. This approach estimates the difference attributable to time adjustments. For Black tracts, the full gap is 0.036, the divergence in appraisals cured by time adjustment is 0.024 in the column labeled (3), and their difference is 0.012. This suggests that 67% of the inconsistency across neighborhoods is due to time adjustments, with 33% attributable to other factors.

For Hispanic tracts, time adjustments account for 49% to 54% of the 3.9% gap, depending on the method used. In no majority tracts, time adjustments account for 52% to 57% of the 2.1% difference. Both methods yield fairly similar conclusions, despite one relying on actual data about time adjustments and the other on their predictors. Overall, these findings suggest that time adjustments account for approximately half of the racial and ethnic neighborhood difference in underappraisal, and possibly more in Black tracts.

V. Conclusion

A mortgage appraisal provides important information for financial institutions to grant a loan. An inflated estimate increases the lender's risk of default, while an undervaluation can limit access to credit. Hence, improvements in appraisal accuracy are worth pursuing.

This paper documents shortfalls in an understudied element of appraisal: using a time adjustment to update the value of comparable sales from their prior date of sale to current conditions. Except in periods of exceptional house price growth they were applied to only about 10% of properties. If used, these adjustments are often too small when benchmarked against house price indexes. Despite their infrequent use, time adjustments resolve about half of initial underappraisals. Their underuse likely explains the seasonal patterns in underappraisal that are hard to rationalize as economically efficient. Underappraisal can have substantial impacts on home purchases, necessitating price renegotiation, increasing down payment requirements, or even causing transactions to fall through.

Time adjustments are a key driver of appraisal inconsistencies across similar homes in different geographic areas. Our preferred model estimates these gaps as 3.6% in Black neighborhoods and 3.9% in Hispanic neighborhoods, compared to a baseline rate of 8.8% in white neighborhoods. The underuse of time adjustments accounts for 53% of the excess underappraisal in Black neighborhoods and 54% in Hispanic neighborhoods, according to one set of regression estimates. Another, quite different, method yields estimates of 67% in Black neighborhoods and 49% in Hispanic ones. These consistent results, as well as generally supportive results from machine learning causal forests estimates, bolster the findings.

As a result of concerns about the underuse of time adjustments, potentially leading to misvaluation, secondary market institutions have been revising their policies and processes. An undervaluation warning triggered by comparisons to automated valuation models was added to Fannie Mae and Freddie Mac's collateral evaluation software in mid-2022, complementing the overvaluation warning that had long been in use. Freddie Mac's appraisal guidelines were rewritten to further encourage time adjustment and explicitly allow the use of home price indexes in late 2023, with Fannie Mae following suit a year later. In early 2025, both agencies imposed additional requirements on appraisers to report the underlying data and analysis supporting time adjustments.

While making these adjustments may pose technical challenges for appraisers with limited data or training, automated valuation models and other resources are increasingly available to assist practitioners. Automation has proven effective in reducing errors and ensuring fair outcomes in various financial processes. For instance, automation in unemployment insurance claims reduced underpayment for non-white recipients (Compton et al., 2023). Similarly, minority-owned firms received small business loans during the pandemic primarily through fintech lenders, and traditional bank lending increased once loan processing was automated (Howell et al., 2024; Chernenko and Scharfstein, 2024). Even when human discretion is necessary, improvements are possible; for example, randomized appraiser assignments could help mitigate unintentional misvaluation. Given real estate's reliance on personal relationships, mitigating any systematic patterns of misvaluation is crucial.

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Appendix A. Analysis Sample

Table A1 – Selection of Analysis Sample

	Dropped		Remaining Properties	
	Number	Percent	Comparables	Subject
5% sample of subject properties		5%	11,410,945	2,238,819
Drop comparables out of scope (36.8% of initial cases dropped)				
Non-arm's length, REO, short sale	400,555	3.5%	11,010,403	2,158,761
Comparable not a settled sale	2,399,448	21.0%	8,610,955	2,158,733
Not a home purchase loan	4,201,792	36.8%	4,409,163	1,104,034
Drop comparables with missing, zero, or negative values (6.4% of universe dropped)				
MSA or state field	170,941	3.9%	4,238,222	1,061,862
ZIP price index (SA or NSA)	53,675	1.2%	4,184,547	1,048,323
Age of comparable negative or >36 months	4,886	0.1%	4,179,661	1,048,254
Predicted time adjustment 0.01% trim (SA or NSA)	1,125	0.0%	4,178,536	1,048,233
Tract race or median income	14,553	0.3%	4,163,983	1,044,532
Subject gross living area (GLA), baths, age, lot size	5,103	0.1%	4,158,880	1,043,254
Number of MLS sales	33,545	0.8%	4,125,335	1,034,350
Drop outlier properties (4.5% of subject properties dropped)				
GLA 0.01% trim	206	0.05%	4,124,447	1,034,144
Underappraisal %, 0.1% trim	2,152	0.2%	4,115,775	1,031,992
Less than 500 homes in market area (MSA/State)	44,195	4.3%	3,941,138	987,797

Notes: Table describes filters and conditional statements used to create a reliable set of subject properties and comparable sale properties ("comparables" or "comps") for analyzing time adjustments. Variables refer to the subject property, except where noted. The primary data source is an internal version of the Uniform Appraisal Dataset (UAD), which is a nationally representative database of appraisals associated with single-family mortgages acquired by Fannie Mae and Freddie Mac. The UAD includes information collected by appraisers using the Uniform Residential Appraisal Report (URAR), labeled as Form 1004 for Fannie Mae and Form 70 for Freddie Mac.

As outlined in Table A1, data cleaning is done in several groups of filters, with italicized rows describing the overall goal while columns show the number and percentage of dropped or remaining observations. The sample is restricted to home purchase transactions conducted at arm's length. We ensure the comparables are settled sales, eliminating comparables listed for sale but not yet sold, since time adjustments are not relevant for these properties and because appraisers give them much less weight in their valuation. We exclude a smaller number of properties under contract but not yet sold, which appraisers downweight. This initial cut of comparable sales that are out of scope trims 37% and leads us to 1,104,034 appraisals of subject site properties and 4,409,163 comparable sale properties. After dropping properties with missing information or invalid values, another 6% of the sample, we have 1,034,350 subject sites and 4,125,335 comparable sales. We apply several more filters, eliminating 4% more based on outlier values or small market size, providing a sample ready for auxiliary hedonic regression. The analysis sample has 987,797 appraisals of subject properties and the final number is listed in the last row of Table A1. An industry rule-of-thumb is three to five comparable sales for each subject site and we land at a ratio around 4-to-1.

Appendix B. Time Adjustment Models

The body of the paper focuses on the impact of time adjustment on underappraisal differences across neighborhood types. However, the question naturally arises whether there are differences in the use time adjustment as well. Table B1 displays regression with time adjustment as the dependent variable. The results are split into two parts. The top panel of the table shows estimations based on the full sample as used in prior tables. The bottom panel shows results from the same model with the sample restricted to properties underappraised before time adjustment.

In the top panel with the full sample estimation, Model 5 shows results for the long regression with state/metro effects emphasized here. In this model, time adjustments are 1.1% less common in Black tracts than in white tracts. However, in Hispanic tracts, time adjustments are 0.9% more common, which seems to contradict the conclusion that time adjustments are an important source of underappraisal differences in these neighborhoods. A potential resolution of this paradox is to note that underappraisal before time adjustment is much more common in Hispanic tracts, and this initial underappraisal is strongly associated with ultimate underappraisal. To be clear, we do not make claims about reasons for that initial underappraisal. As we have seen in Table 2, 19% of borrowers in white tracts are initially underappraised compared to 28% in Hispanic tracts. Initial underappraisal is higher in Black and no majority tracts as well, at 22% and 24%, respectively.

The bottom panel provides a straightforward way to adjust: restrict the sample to those initially underappraised. The Model 5R results show that, in this restricted sample, time adjustment is 7.2% less common in Black tracts than in white tracts, 4.5% less common in Hispanic tracts, and 2.7% less common in no majority tracts. We do not attempt to formally calculate how much of the underappraisal gap these results might explain. Such a calculation would be quite complex because we would have to account for the fact that time adjustments can cure underappraisal, be too small to cure underappraisal, or be superfluous when performed for loans not initially underappraised. However, it is worth noting that these effects are substantial when compared to the underappraisal differences in the restricted sample, as displayed in Figure 6. Thus the time adjustment differences are roughly in line with what we would expect to see if they were major drivers of underappraisal gaps.

Table B1 – Time Adjustment Regressions

	Full Sample					
	(1) Short	(2) Long	(3) LongTract	(4) ShortSM	(5) LongSM	(6) LongTractSM
Majority Black	-0.0675***	-0.0397***	-0.0429***	-0.0201***	-0.0113***	-0.0104***
	(-6.39)	(-5.81)	(-5.60)	(-5.36)	(-4.40)	(-3.78)
Majority Hispanic	0.00498	0.00142	-0.00464	0.00909	0.00882*	0.00660
	(0.43)	(0.17)	(-0.54)	(1.85)	(2.10)	(1.76)
No Majority	0.00599	-0.00385	-0.00792	0.00394	0.00192	0.000719
	(0.69)	(-0.64)	(-1.22)	(1.79)	(1.01)	(0.39)
N	987,797	987,797	987,797	987,797	987,797	987,797
adj. R^2	0.119	0.178	0.178	0.166	0.204	0.204
	Restricted Sample to Properties Initially Underappraised					
	(1R) Short	(2R) Long	(3R) LongTract	(4R) ShortSM	(5R) LongSM	(6R) LongTractSM
Majority Black	-0.216***	-0.157***	-0.151***	-0.0979***	-0.0724***	-0.0586***
	(-11.37)	(-11.25)	(-9.79)	(-10.43)	(-9.98)	(-7.89)
Majority Hispanic	-0.107***	-0.0822***	-0.0757***	-0.0559***	-0.0452***	-0.0282***
	(-3.99)	(-4.36)	(-3.79)	(-7.54)	(-6.59)	(-3.88)
No Majority	-0.0514**	-0.0502***	-0.0518***	-0.0289***	-0.0270***	-0.0195***
	(-3.32)	(-4.47)	(-4.41)	(-8.03)	(-8.54)	(-5.64)
N	200,686	200,686	200,686	200,686	200,686	200,686
adj. R^2	0.122	0.207	0.208	0.209	0.260	0.261
	Covariates Used in Each Specification					
Appraisal Difficulty	×	×	×	×	×	×
Housing Quality		×	×		×	×
Census Tract			×			×
State/Metro Effects				×	×	×

Notes: Table entries are OLS regression coefficients with t statistics in parentheses. The dependent variable is the use of a time adjustment to correct valuations of one or more comparable sales. Standard errors are adjusted for clustering at the state/metro level. The table is grouped vertically into two samples as described in the gray colored rows. The top panel presents estimates using the full sample (in Models 1–6) while the bottom panel has estimates using a restricted sample of only properties that are underappraised before time adjustment (Models 1R–6R where "R" stands for "restricted"). The bottom part of the table as well as the column headers ("short", "long", etc.) clarify the groups of covariates used in each specification and specifically listed in Table 3. Statistical significance levels are denoted as * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Source: Uniform Appraisal Dataset (2015–2023)

Appendix C. Contrasting with Machine Learning

The empirical analysis builds on existing research about underappraisals, which has not considered the role of time adjustments. While we use many of the same variables as previous studies and achieve similar qualitative results, one might wonder whether the variable selection is optimal or if alternative functional forms should be explored. Existing literature often relies on theoretical reasoning tied to appraisal practices, while machine learning lets the computer choose the most predictive set of variables and interactions.

We use a causal forests model, a generalization of machine learning random forest models developed by Wager and Athey (2018). Like random forests, it estimates an ensemble model of many decision trees (2,000 here). While random forests optimize predictiveness, causal forests also maximize treatment effect variance—in this case, the racial neighborhood difference. In the body of paper, we interact the treatment effect with one variable, the predicted time adjustment, but the causal forest model selects the best from many possible interactions. Unlike many machine learning methods, causal forests produce statistical tests and their metaparameter choice is largely automated.

Incorporating fixed effects into causal forests is not straightforward. We use a method from Suk and Kang (2023), which includes fixed effects to estimate a propensity score (the probability that a tract is majority Black or majority Hispanic) along with other explanatory variables. Suk and Kang demonstrate that using this propensity score in a causal forests model yields better predictions than directly including fixed effects. Table C1 displays treatment effects from causal forest estimations, which are slightly larger in magnitude (by one percentage point) than earlier tables but lead to the same conclusions.[31]

Table C2 lists the top ten variables for two neighborhood minority types.[32] The most important covariate in both sets is the hedonic standard deviation, using a metric based on

[31]Future work could explore why OLS and causal forest estimates have minor differences. For example, OLS assumes the effects are the same across tracts, but the treatment effect in majority minority neighborhoods might be larger due to a higher baseline underappraisal rate. The treatment effect might be multiplicative rather than additive. Also, OLS estimates have larger standard errors (likely due to robust estimators).

[32]The table reflects 3%/97% propensity score trim levels. We tried 10%/90% and the results are fairly similar. A larger trim avoids potential critique that high-propensity Black and Hispanic tracts may not have many good matches to white tracts. Any issues should show up in the standard errors and since they are small with the smaller trim, we chose that option.

Table C1 – Causal Forest: Treatment on Treated Estimates

	Long	LongSM	LongSMTract
Majority Black	0.0424***	0.0423***	0.0388***
	(17.4)	(17.6)	(16.3)
Majority Hispanic	0.0540***	0.0494***	0.0373***
	(21.9)	(18.1)	(14.7)
No Majority	0.0282***	0.0249***	0.0214***
	(19.7)	(15.9)	(13.4)

Notes: Table entries are causal forest treatment on treated estimates with t statistics in parentheses. Models include the same variables as in the equivalent Table 4 models and propensity scores with all the same variables plus year/month and state/metro fixed effects. Statistical significance levels are denoted as * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Source: Uniform Appraisal Dataset (2015–2023)

the frequency with which algorithm chooses the covariate to form a decision tree split. The top six variables in both types of neighborhoods are identical, though ordered differently. Two findings are noteworthy. First, the variables reflecting appraisal difficulty, such as the two hedonic uncertaintly meaures, rank high. Among the large set of house quality variables, gross living area ranks as highly as the difficulty variables. Second, predicted time adjustment is highly ranked, placing second in Black tracts and fifth in Hispanic tracts. This finding confirms the importance of house price growth and time adjustment in driving underappraisal.

Figure C1 further explores how underappraisal differences relate to the main drivers of heterogeneity. Of particular interest are the predicted time adjustment graphs which, for Black tracts, resemble the regression estimates in Figure 5 and reiterate their robustness. The time adjustment effect is minor in Hispanic tracts. However, we approach these findings cautiously since we do not have estimates of their confidence interval that would account for uncertainty in the gap estimates.

Overall, the machine learning analysis highlights factors that influence the variability of neighborhood difference estimates. Differences increase with appraisal difficulty, except for the hedonic standard deviation in Black neighborhoods. Notably, predicted time adjustment is a key variable affecting racial and ethnic neighborhood differences.

Table C2 – Causal Forest Variable Importance Metric

	Majority Hispanic Neighborhoods		Majority Black Neighborhoods	
1	Hedonic Standard Deviation	0.201	Hedonic Standard Deviation	0.310
2	Number of MLS Sales (ln)	0.183	Predicted Time Adjustment	0.231
3	Hedonic Diff. from ZIP Code Price (ln)	0.142	Gross Living Area (ln)	0.084
4	Gross Living Area (GLA) (ln)	0.070	Hedonic Diff. from ZIP Code Price (ln)	0.069
5	Predicted Time Adjustment	0.065	Comparable Sale Age (months)	0.058
6	Comparable Sale Age (months)	0.059	Number of MLS Sales (ln)	0.053
7	Basement Gross Living Area (ln)	0.048	Condition Rating	0.031
8	Neighborhood Location	0.047	Basement Gross Living Area (ln)	0.028
9	Effective House Age	0.044	Marketing Time	0.021
10	House Age	0.041	House Age	0.021

Notes: Causal forest model includes 32 variables and a Black/Hispanic neighborhood propensity score that includes year/month and state/metro fixed effects. "MLS" stands for multiple listing service. The main data source is a five percent sample of majority Black and Hispanic neighborhood tracts, and a one percent sample of majority white neighborhood tracts.

Source: Uniform Appraisal Dataset (2015–2023)

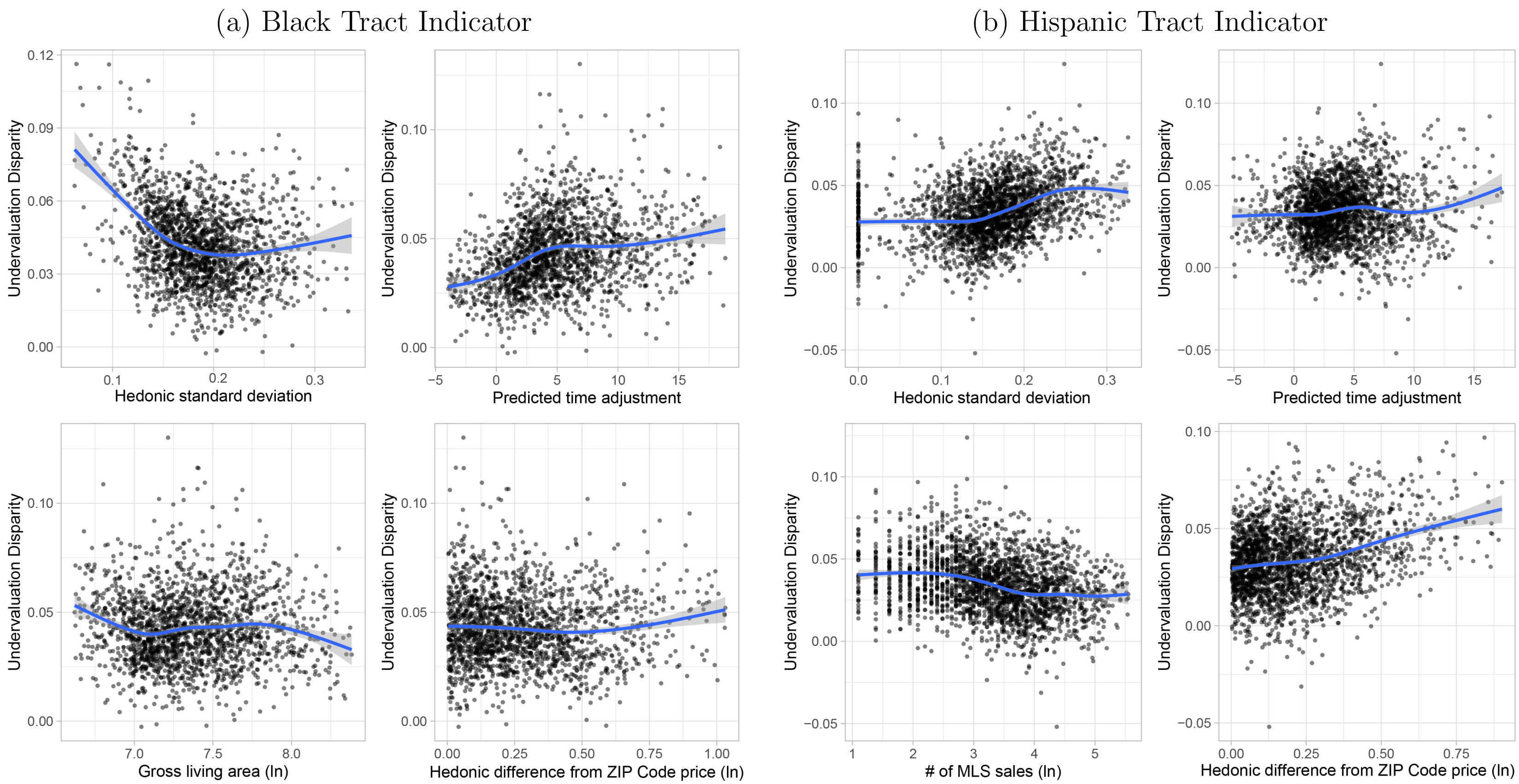

Figure C1. Most Important Interactions with Neighborhoods Variables

Notes: Figures compare the variables with the top four importance scores listed in Table C2, except that predicted time adjustment (ranked fifth) replaces gross living area (ranked fourth) in panel [b]. Each point consists of the the values of the specified predictor and the estimated gaps for a borrower in a Black (panel [a]) or Hispanic (panel [b]) neighborhood. In order to keep the figures legible, 5,000 borrowers were chosen at random for each plot. Confidence intervals take the data as given, and do not account for the uncertainty of the estimates. The main data source is a five percent sample of Black and Hispanic tracts, and a one percent sample of white tracts, in the Uniform Appraisal Dataset (UAD) from 2015–2023.