2333 North Broadway, Suite 350
Santa Ana, California 92706 USA

714 415 6300 | Fax 714 425 6360

August 17, 2023

Re: Quality Control Standards for Automated Valuation Models 2023

Dear Interagency Review Panel:

Veros Real Estate Solutions (Veros) appreciates the opportunity to respond to the agencies' questions within the *Quality Control Standards for Automated Valuation Models* proposal. Veros is a well-established industry leader with more than two decades of excellence in real estate valuation data, systems, and analytics. Veros developed one of the first lending-grade Automated Valuation Models (AVMs) in 2001. Since that time, Veros has been a leader in the AVM and related real estate data and analytics marketplace.

Lending-grade AVMs have received more widespread use in recent years due to their growing access to copious amounts of data, greater model accuracy, and rapid computing. Veros commends the agencies for identifying their proposed rules for the use of AVMs and fully agrees with the non-prescriptive, flexible approach. Rules set around the use of AVMs in determinations of collateral value, along with credit decisions or securitization determinations, make logical sense. The approach allows for important guidelines of reasonable quality control standards to be put in place. These sound rules may be easily adopted to ensure that all AVMs provide accurate and fair results when risk decisions are made.

Today, it is crucial that AVMs are not only accurate but also fair. Veros is leading in the areas of AVM racial bias research and AVM redlining impacts through the publication of its research reports:

- "AVM Performance. Is there evidence of racial bias?" and
- "Does historical redlining influence today's AVM estimates?"

Veros welcomes any comments or questions the agencies or industry stakeholders may have regarding the need for and ability to provide accurate and fair property valuations. Veros believes the housing finance system can significantly benefit from the greater application and use of nondiscriminatory AVMs and other forms of non-biased alternative and traditional valuation approaches. With the ongoing focus from the agencies, continued transparency from AVM providers, and the safe and controlled use of AVMs by industry stakeholders, AVMs, along with other alternative valuation approaches, have the potential to provide an even greater benefit to the industry and consumers.

Sincerely,

Darius Bozorgi
CEO & President
Veros Real Estate Solutions

Response To Quality Control Standards for Automated Valuation Models Proposal

PREPARED BY

VEROS REAL ESTATE SOLUTIONS

2023

Contents

Response to *Quality Control Standards for Automated Valuation Models* Proposal 2023

Home Equity Line of Credit (HELOC) Reductions or Suspensions

QUESTION 2.
Part II.B of this SUPPLEMENTARY INFORMATION discusses the proposed definitions of mortgage originator and secondary market issuer. To what extent do financial institutions purchase or service HELOCs without engaging in mortgage originator or secondary market issuer activities as defined by the proposed rule?

Lending-grade AVMs are viable tools that fit nicely in the HELOC origination process. It makes sense that the AVM rules would apply to the HELOC originators. There is a secondary market for HELOCs. With the ease of access, the speed of valuation, the high accuracy, and the minimal costs associated with AVMs, there is clear value being added when a purchaser or servicer of HELOCs quickly identifies the values and risks of the properties using the same lending-grade AVMs as originators.

QUESTION 3.
How might a rule covering only AVM usage by mortgage originators and secondary market issuers disadvantage those entities vis-à-vis their competitors?

AVM rules provide advantages to the sound and effective use of these analytic tools. AVM testing and individual AVM model performance detail may be readily available through a firm's internal testing group or numerous third-party, independent testing organizations. Firms that choose not to employ AVMs or are not compelled to follow AVM guidelines do so at their peril, as the AVM guidelines constitute best practices. Firms that do NOT use AVMs are disadvantaged vis-à-vis their competitors. The accuracy and efficiency lending-grade AVMs provide should not be overlooked or disregarded. Guidelines and applicable uses of lending-grade AVMs should be set in a slow, deliberate, safe, and continual expansion. Flexible, principles-based approaches to AVM guidelines are not costly or time-consuming to incorporate, but they provide significant gains in efficiency, safety, and fairness.

QUESTION 5.
Please address the feasibility of mortgage originators performing quality control reviews of the AVMs that secondary market issuers use to evaluate appraisal waiver requests. What, if any, consequences would such an approach have for mortgage originators' use of appraisal waiver programs?

It is not financially feasible for an originator to perform quality checks on the AVMs used to evaluate appraisal waiver requests. However, it is feasible for secondary market participants to provide greater transparency into how the AVM(s) are tested, measured, and applied in the appraisal waiver process. Secondary market participants should actively test all the market, lending-grade AVMs and determine the best AVMs or AVM rule sets to determine appraisal waivers.

Other Uses by Secondary Market Issuers

QUESTION 6.
The agencies are proposing to include securitizations within the scope of the proposed rule where the AVM is being used to determine the collateral value for loans being considered for inclusion in pools collateralizing mortgage-backed securities. To what extent do secondary market issuers use AVMs to determine collateral value in securitizations?

Historically, the GSEs have kept their data, analytics, and testing to themselves and have not shared information with the industry. Having the AVM rules apply to them will be very different than what has been done in the past, but good for the entire industry. It seems clear that prudent compliance and safeguards must be applied for a resurgence of the private secondary market to regain any real market share. Lending-grade AVMs are tools that should be used to immediately identify values and risks associated with the pools of loans. Transparency in how AVMs are tested, measured, and applied will allow for better valuations and more informed risk decision-making. Rating agencies may want to devote time and energy to this endeavor again.

QUESTION 7.
Would covering uses of AVMs for securitizations hinder small entities' access to secondary market liquidity and, if so, how might such impacts be mitigated?

AVM testing is a small expenditure. It can be done easily by large or small entities. AVM testing and the granular performance results can be provided in a straightforward and transparent manner. Cascading rule sets and platforms utilizing multiple lending grade AVMs from quality providers are readily available. Therefore, AVM usage has no impact that would disadvantage small entities.

QUESTION 9.
Are the compliance obligations of lenders and securitizers clear under this proposed rule?

Yes, rules set around using AVMs in determinations of collateral value, along with credit decisions or securitization determinations, make logical sense. Industry stakeholders, from originators to the secondary market along with property valuation vendors, have already established straightforward, transparent, and fair AVM testing and rule set development. Applying these rules, continual testing, and ongoing, scheduled rule set updates are an important part of using AVMs. Flexible, transparent, principles-based approaches to AVM guidelines are relatively inexpensive and not time-consuming to incorporate and apply. AVMs provide significant efficiency, safety, and fairness gains to the consumer and all parties involved.

Uses of AVMs by Appraisers

QUESTION 10.
How often are AVMs used by certified or licensed appraisers to develop appraisals?

Generally, appraisers do not use lending-grade AVMs to develop full, traditional appraisals. Some appraisers may use consumer AVMs found on free sites to gauge a starting point for the appraisal, but appraisers have limited access to lending-grade AVMs, although there are advantages to having access to lender-grade AVMs. See question 11.

Desktop appraisals and other alternative valuation approaches are natural fits for appraisers to use lending-grade AVMs and additional data risk analytic products.

QUESTION 11.
What would be the advantages and disadvantages of excluding AVMs used by certified or licensed appraisers in developing appraisal valuations?

The disadvantages of excluding lending-grade AVMs for certified or licensed appraisers in developing traditional appraisal valuations include missing or excluding relevant sales data in the lending-grade AVM not available to the appraiser, limited ability to apply advanced analytics and metrics when making adjustments to comparables, and lack of access to an alternative value opinion not influenced by local area demographics.

The advantages of using lending-grade AVMs include access to more potential market data and reliable and consistent analytics to support comparable selection and market-based property adjustments. Also, since AVMs do not know the racial composition of the borrower or neighborhood, an AVM may help an appraiser's ability to provide a fair and unbiased estimate of value.

Reviews of completed collateral valuation determinations (page 25-26)

QUESTION 12.
What would be the advantages and disadvantages of including AVMs that are used in reviews of completed determinations within the scope of the proposed rule? To what extent do institutions use AVMs in reviewing completed determinations?

There are many advantages to using lending-grade AVMs for review purposes. Some include having an unbiased second value opinion based purely on data and analytics and access to additional sales and market data that may not be available to the reviewer due to limited resources. AVMs can be used for Reconsiderations of Value (ROVs) or to identify potential undervaluation and overvaluation. Understanding lender-grade AVM reports, the data and analytics that are immediately available will provide immediate efficiency, safety, and fairness to the final value. Some institutions use lending-grade AVMs in a limited capacity due to a lack of understanding of the value conclusions. With more awareness, education, and testing validation, Veros believes lending-grade AVM usage should and will safely increase.

Quality Control Standards

1. Proposed requirements for the first four quality control factors

QUESTION 30.
Is additional guidance needed on how to implement the quality control standards to protect the safety and soundness of financial institutions and protect consumers beyond the existing supervisory guidance described in part I.A of this SUPPLEMENTARY INFORMATION? Should such additional guidance explain how a regulated entity would implement quality control for an AVM used or provided by a third party?

Veros does not feel that this is necessary. Today, financial institutions that use Veros AVMs already require Veros to fill out numerous questionnaires (usually once to twice per year) to address large numbers of compliance and best practices (this is in addition to AVM developer, lender, and third-party testing). This also requires explanations and testing detail that documents how Veros' AVMs work, their accuracy, their multiple models, and the Veros infrastructure. The number of questions per questionnaire can easily range into the hundreds. The predominant theme of the questionnaire is to address concerns that the financial institution has and is following a process to protect its safety and soundness as well as those of its customers. As a result, Veros does not feel that additional guidance over and above what these financial institutions already do is necessary. Still, Veros supports more quality standard testing by truly independent and unbiased third parties.

QUESTION 31.
In what ways, if any, would a more prescriptive approach to quality control for AVMs be a more effective means of carrying out the purposes of section 1125 relative to allowing institutions to develop tailored policies, practices, procedures, and control systems designed to satisfy the requirement for quality control standards? If so, what would be the key elements of such an alternative approach?

Veros recommends a non-prescriptive approach that demonstrates the requirements for quality control standards. As all AVMs differ as well as the vast diversity in lender, investor, guarantor and related stakeholder uses of AVMs differ, a prescriptive approach would need to recognize all these potential differences and uses which would most likely lead to unintended consequences.

2. Specifying a nondiscrimination quality control factor (page 36-42)

QUESTION 32.
What are the advantages and disadvantages of specifying a fifth quality control factor on nondiscrimination? What, if any, alternative approaches should the agencies consider?

While AVMs are completely blind to racial, gender, or related data regarding the parties to a real estate transaction as well as the comparable properties and surrounding neighborhoods, some AVMs could potentially reflect algorithmic or inherent bias in any underlying data sources (just as with any property valuation product, service or tool). The advantage of an AVM or similar automated tool is that it is completely blind to the participants to the transaction. Veros recognizes the importance of identifying and, ideally, eliminating racial bias from all forms of property valuation. AVMs can be a very effective tool in helping to identify potential bias across the property valuation spectrum of tools. Veros has studied racial bias in the use of its AVM, and the findings have shown no empirical evidence that its valuations are influenced by race or other variables related to disadvantaged communities. Enclosed are two studies carried out by Veros. The first study, entitled *"AVM Performance. Is there evidence of racial bias?"* includes the findings of this research. The findings of this research reveal no evidence of systemic undervaluation from the VeroVALUE AVM as the percentage of the minority population increases and no evidence of systemic overvaluation from the VeroVALUE AVM as the percentage of the white population increases. The second study, entitled "Does historical redlining influence today's AVM estimates?" reveals that the VeroVALUE AVM has no indications of algorithmic bias due to historical redlining practices. As a result of these findings, Veros suggests a close examination of the report's findings and the various ways in which AVMs may be validated to be free from any disparate impact in minority or disadvantaged communities. While arguably already addressed or covered under other fair lending requirements (see response to Question 33), the advantages of specifying a fifth quality control factor are that it will emphasize the safe and effective use of AVMs that have been validated using a fifth quality control factor and encourage expanded use of AVMs as a valuation tool in the industry, both on a stand-alone or independent basis where appropriate, as well as in concert with and as additional support for traditional, hybrid and alternative approaches to value. Thus, providing the necessary aspect of fairness in all property valuation approaches.

QUESTION 33.
To what extent is compliance with nondiscrimination laws with respect to covered AVMs already encompassed by the statutory quality control factors requiring a high level of confidence in the estimates produced by covered AVMs, protection against the manipulation of data, and random sampling and reviews? Should the agencies incorporate nondiscrimination into those factors rather than adopt the fifth factor as proposed? Would specifying a nondiscrimination quality control factor in the rule be useful in preventing market distorting discrimination in the use of AVMs?

While compliance with nondiscrimination laws with respect to covered AVMs ensures that AVMs do not incorporate any protected class data or any related data or proxies, some AVMs could potentially exhibit algorithmic or inherent bias (see response to Question 32). Hence, specifying a nondiscrimination quality control factor in the rule will be useful in emphasizing the importance of proving support for nondiscrimination or disparate impact in the use of AVMs.

QUESTION 34.
What are the advantages and disadvantages of a flexible versus prescriptive approach to the nondiscrimination quality control factor?

Veros supports a more flexible approach to any guidance or regulatory framework related to AVM usage and believes it is important to avoid the temptation of being overly prescriptive. As opposed to hard-coded rules that may set forth only one method or path to properly determine property value and identify valuation risk, Veros encourages focusing instead on the ultimate question of safety, soundness and fairness. Guidelines regarding the use of AVMs (and any property valuation product or service) should consider whether a stakeholder is appropriately utilizing an approach, strategy, or process given the risk of its intended use, that is supported by statistically significant data, has appropriate operational controls, is independently driven or derived, has been properly validated, implemented, executed, and is regularly tested or validated. Veros encourages a principle-based framework focused on those segments of the mortgage process that pose the highest risk to consumers. While best practices certainly exist and will continue to evolve, different stakeholders across the U.S. housing finance industry will (and should) have different strategies, processes, and risk tolerances for the use of AVMs – this should not be a one-size-fits-all approach that will most certainly lead to a host of unintended consequences.

QUESTION 35.

Are lenders' existing compliance management systems and fair lending monitoring programs able to assess whether a covered AVM, including the AVM's underlying artificial intelligence or machine learning, applies different standards or produces disparate valuations on a prohibited basis? If not, what additional guidance or resources would be useful or necessary for compliance?

Lenders and related stakeholder existing compliance management systems, due diligence and testing/validation processes should be able to assess whether an AVM applies different standards or produces disparate valuations on a prohibited basis. Veros would caution against strict limitations prohibiting or regulating the use of artificial intelligence or machine learning (AI/ML) within an AVM. The responsible use of AI/ML throughout the entire housing finance industry (and across all industries for that matter) is rapidly becoming an important part of effective risk management. But it must be approached in a careful and thoughtful manner. Property valuation in housing finance in no exception. This is yet another reason that a prescriptive approach is ill-advised as technology is continuously evolving at an increasing pace. The regulatory focus should be on the results and outcomes produced by these proven tools and the expected support to demonstrate both accuracy and fairness in their results. As part of this support, AVMs (and any model or tool that incorporated AI/ML) should also be expected to provide transparency into how and where any of their models implement AI/ML. In general, AVM developers should be expected to effectively describe and support how their models are built and managed without having to disclose anything that is truly proprietary (a legitimate concern of any technology provider). Ultimately, it is the results, outcome and supporting data from an AVM that can be tested and validated through existing compliance, due diligence and validation processes.

As it relates specifically to AI/ML, Veros offers two potential and different examples of how AI/ML could be implemented in an AVM. The first scenario is that an AVM's sub-model (such as a hedonic or time model) uses AI/ML directly. That is to say, if all the sales prices, dates, and property characteristics are input to an AI/ML model, the model will look at trends and predict a value for the subject. If there are input variables that are correlated (even complex multivariate correlation) with an unused protected class variable, the sub-model itself could have bias and be unknown to the modeler. So, it is important that AI/ML either (a) not be used for the various sub-models that produce estimates of value for the subject or (b) be tested to ensure that such biases are not present.

In a second scenario the AVM may be asked what to do with numerous sub-model estimates of value. Suppose that models M1, …, Mn produce estimates of value for a subject of V1, …, Vn. How is the final estimate of value for the subject determined from V1, …, Vn? Simple statistics such as the mean or median of the V1, …, Vn values could be taken. Likewise, these could be input to an AI/ML model, which determines patterns among the valuations to determine the best value. For example, the AI/ML might determine that V1 is always the most accurate value for the subject if it is the largest value and should therefore be used as the valuation for the subject. This is a pattern that may never be detected without AI/ML. This type of use of AI/ML does not rely on variables such as square footage or zip code to determine the value of the subject. Rather, it is simply trying to determine which estimated values are most likely correct based on patterns among valuations. The use of AI/ML in this scenario is very low risk and should be viewed very differently from the first scenario.

Nevertheless, in either of these two (or many other) scenarios the AVM developer, lender, and related stakeholder should be able to provide reasonable support that the results and outcomes of the model do not produce disparate valuations on a prohibited basis (where or not said model incorporates AI/ML). This concept should apply to any property valuation product, service or tool.

QUESTION 36.
What, if any, other approaches should the agencies consider for incorporating nondiscrimination requirements in this proposed rule?

Veros believes the methodologies documented in its two research reports, *"AVM Performance. Is there evidence of racial bias?"* and *"Does historical redlining influence today's AVM estimates?"* would make a solid baseline approach for incorporating nondiscrimination requirements in the proposed rule.

QUESTION 39.
Is the number of hours estimated to establish policies, procedures, and control systems to comply with the rule realistic for small institutions. If not, what number is hours would be more appropriate?

AVM testing is a small expenditure. Industry stakeholders, from the secondary market to originators to vendors, have already established straightforward, transparent, and fair AVM testing and rule set development. Applying these rules, continual testing, and ongoing, scheduled rule set updates are an important part of using AVMs. Flexible, transparent, principles-based approaches to AVM guidelines are not costly or time-consuming to incorporate and apply.

AVM PERFORMANCE

Is there Evidence of Racial Bias?

2022

Reena Agrawal and Eric Fox

www.veros.com communications@veros.com

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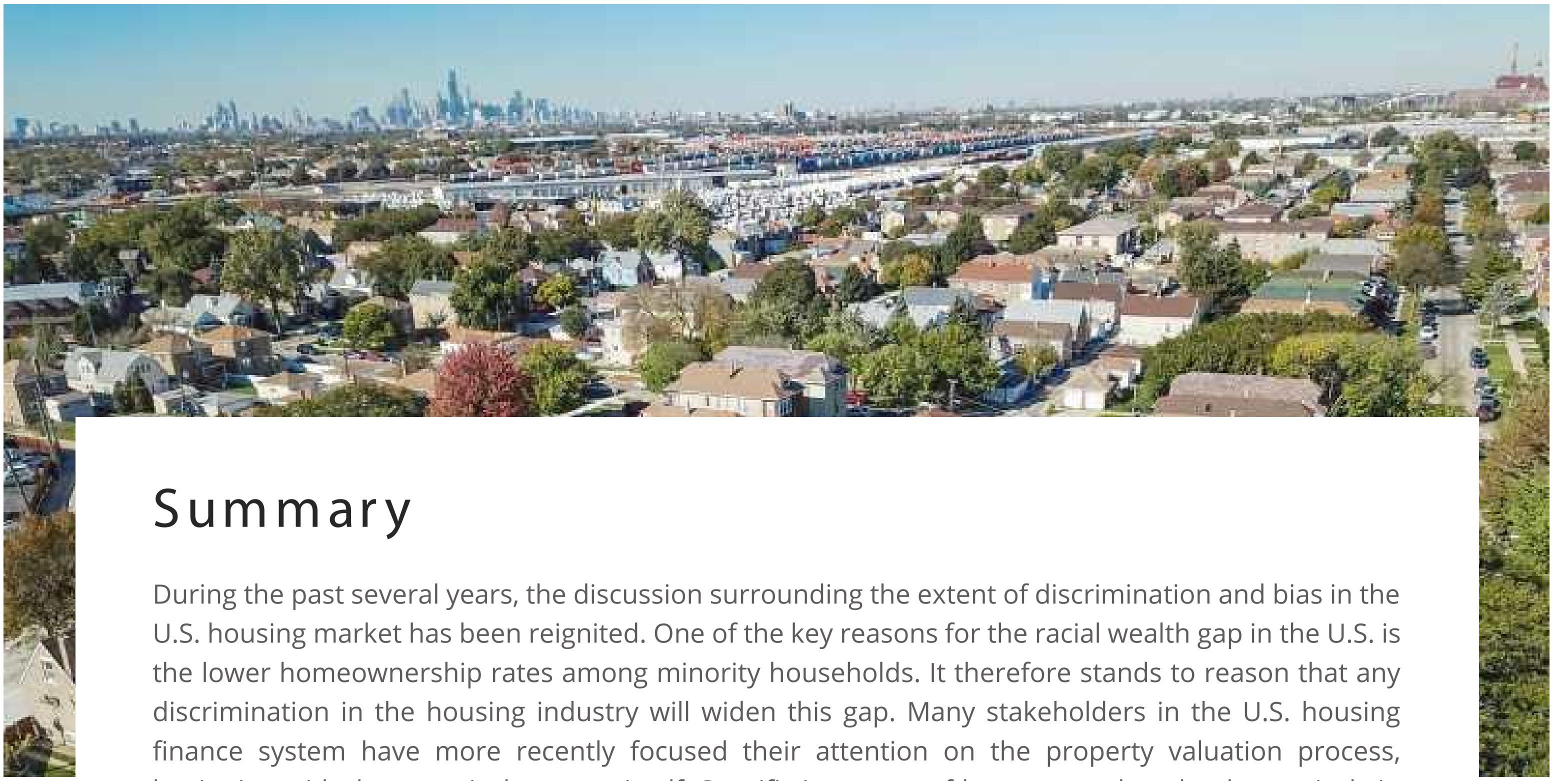


Summary

During the past several years, the discussion surrounding the extent of discrimination and bias in the U.S. housing market has been reignited. One of the key reasons for the racial wealth gap in the U.S. is the lower homeownership rates among minority households. It therefore stands to reason that any discrimination in the housing industry will widen this gap. Many stakeholders in the U.S. housing finance system have more recently focused their attention on the property valuation process, beginning with the appraisal process itself. Specific instances of lower or undervalued appraisals in minority or disadvantaged communities have been cited as evidence of potential systemic issues. Several articles and studies have been conducted, often reaching different conclusions concerning the existence or extent of any bias in the appraisal process. The discussion has expanded to other property valuation products and services, including appraisal hybrids and alternatives, automated valuation models (AVMs), and broker-price opinions (BPOs).

This report will focus on the question of whether an AVM exhibits evidence of racial bias in its results. With appraisals coming under increasing scrutiny due to allegations of racial bias, AVMs have a unique advantage, as they are blind to the demographic characteristics of the parties involved in real estate transactions, including the surrounding properties and neighborhoods that are used in the determination of the AVM results. AVMs can estimate the value of a home without any human assessment in an objective and cost and time-effective manner. Further, many AVMs utilize numerous valuation methodologies that are independently analyzed and aggregated to produce a final estimate of value, which helps ensure more accurate results. Therefore, AVMs may be used as an objective and more efficient tool for home valuations in certain situations.

This report analyzes how Veros' AVM, VeroVALUE®, performs in ZIP codes with different racial compositions by analyzing the following commonly accepted AVM performance metrics:

1) The proportion of properties the AVM undervalues by more than 15% (P15L),

2) The proportion of properties the AVM overvalues by more than 15% (P15H), and

3) Median Absolute Error (MAE) of the AVM.

We investigate the correlations of P15L and P15H with the racial composition of ZIP codes and which variables, including race, determine the size of MAE.

This report finds no empirical evidence of racial bias in the VeroVALUE AVM results. More specifically, P15L is not significantly correlated with the racial composition of ZIP codes. Hence, there is no

evidence of systemic undervaluation from the VeroVALUE AVM as the percentage of minority population increases. Further, there is no evidence of systemic overvaluation (P15H) from the VeroVALUE AVM as the percentage of White population increases. Additionally, MAE is not significantly explained by the racial compositions of communities. That is to say, the AVM does not exhibit racial bias and is no less accurate in minority communities. This report concludes that the VeroVALUE AVM is a tool that should be leveraged in the property valuation process as an independent determination of value in support of or in concert with other determinations of value and may be effectively used to identify potential bias or discrimination in all valuation products and services.

Introduction

Existing Research on Appraisal Bias in the Housing Industry

There have been several, recent media reports on racial bias in home appraisals, claiming that homes were undervalued because of the race of the homeowner (e.g., Kamin, 2020; Johns et al., 2021). In June 2021, President Biden announced the creation of an Interagency Task Force on Property Appraisal and Valuation Equity (PAVE) to remove racial and ethnic bias in home valuations by developing a transformative set of actions. This action plan, released in March 2022, seeks to ensure that all Americans have an equal opportunity to build wealth through homeownership (PAVE Action plan, 2022).

Recent research articles have also pointed to bias in home appraisals (Howell & Korver-Glen, 2018; National Fair Housing Alliance, 2022). Howell and Korver-Glen (2018) conclude that after controlling for various physical, socioeconomic and demand characteristics, the price of an average house in a White neighborhood was higher compared to a similar house in a Black or Hispanic neighborhood, due to the unconscious racialized assumptions of appraisers. In another study, a group of researchers from Freddie Mac found that 15.4% of properties in Latino tracts and 12.5% in Black tracts received an appraisal value lower than the contract price compared to just 7.4% of properties in White tracts that received appraisals lower than the contract price (Narragon, Wiley, McManus, Li, Li, Wu, & Karamon, 2021). However, they do not reach a conclusion as to why properties in minority tracts receive appraisals lower than the contract price. Brookings researchers, Perry, Rothwell, & Harshbarger (2018), concluded that “bias is likely to be a large part of the unexplained devaluation of Black neighborhoods” (p.19). More recently, researchers from Fannie Mae (2022) analyzed refinance applications and compared appraised values to two internal Fannie Mae AVMs and found that the median difference between the appraisal and Fannie Mae’s AVMs was negative for Black homeowners, but positive for White homeowners.

In comparison, other studies do not find the presence of bias in appraisals. For example, research on refinance appraisals conducted by Ambrose, Conklin, Coulson, Diop & Lopez (2021) finds “no evidence that Black homeowners suffered lower appraisals from appraisers of either race” (p.23). Further, Pinto & Peter (2021) also conclude that any racial bias by appraisers on refinance loans is uncommon and not systemic.

Given the concerns regarding the appraisal process, industry stakeholders have begun to raise questions as to whether any similar real or perceived bias exists in other property valuation products and services, including appraisal alternatives, hybrids, AVMs or BPOs. AVMs have a unique advantage over other property valuation tools because they are blind to demographic and socioeconomic characteristics of the parties (and the surrounding dependent data) involved in real estate transactions; however, there is a legitimate question as to whether an AVM that relies upon data (e.g., sales prices) that may be inherently biased will produce biased AVM results.

AVMs and Appraisals

APPRAISALS

An appraisal is an independent method for lenders and homeowners to assess the collateral risk and market value of a property. Appraisals are especially important in markets with few or distant sales (like rural areas) or properties with significant non-homogeneous characteristics (like renovations, views, additions, etc.). Due to an appraiser's exposure to the homeowner and neighborhood demographics, there is the potential for conscious and unconscious bias. Also, appraisers rely heavily on local comparable sales data sources and make negative or positive adjustments to account for any market differences to the borrower's home. The selection of comparable sales and the market adjustments applied to those sales can be subjective and based on limited access to more extensive databases and fewer quantitative modeling options.

AVMs

AVMs rely on hundreds of recent and historical sales and thousands of related data points to derive a final valuation estimate. The comparable sales data and market adjustments are determined by a variety of objective models and statistical information from large databases that the typical appraiser may not have access to when completing an appraisal report. Because an AVM does not involve a property inspection and does not have access to racial, gender or related data, it is "blind" to any borrower and neighborhood demographics and therefore offers an objective value determination. An AVM can be used in conjunction with a traditional appraisal and serve as a tool to help identify, substantiate, and mitigate any potential bias issues by the appraiser performing the personal inspection.

Professional-grade AVMs (also known as commercial-grade or lending-grade AVMs) are rigorously tested on a large scale, so their performance, consistency, and risk are well known and documented by lenders, investors, and third-party stakeholders throughout the mortgage industry. Professional-grade AVMs provide added metrics, such as confidence scores, that identify levels of risk in the performance of the AVM output. Professional-grade AVMs are relied upon for mortgage lending and portfolio, review, and quality-control purposes throughout the mortgage value-chain. They differ from consumer facing AVMs, which are generally found on realtor-related sites and provided to users free of charge. All references to AVMs in this paper are to professional-grade AVMs.

VeroVALUE AVM

VeroVALUE has been developed and is maintained by Veros' in-house team of modelers, statisticians, economists, data operators, and industry experts with a proven track-record of excellent performance for over two decades. VeroVALUE utilizes data from multiple data sources, including public records (county assessors and recorders), multiple listing services (MLS), and related property databases, that are refreshed daily on over 100 million properties. VeroVALUE is one of several professional-grade AVMs in the market today. VeroVALUE is the source of the AVM findings within this report; this report does not provide results with respect to other professional-grade AVMs in the market, which will need to be tested for any potential bias in a similar manner.

The VeroVALUE AVM is based on a "blended" approach that uses multiple and intentionally different methods in each of the following modeling categories:

(1) **Comparative assessment models:**

These models are based on hundreds of recent sales so that the impact of a few incorrectly valued properties is greatly reduced or eliminated. The vast set of data used in the generation of VeroVALUE does not include any data on demographics such as race, gender or socioeconomic status of any party involved in the real estate transaction, or any protected class data as identified by the Equal Employment Opportunity Commission and the Fair Housing Act.

(2) Index models:

Index models incorporate time trends of thousands of home prices in geographical areas such as ZIP codes, counties, and metropolitan areas. These models take a previous sales price of a subject property and update that value to current pricing by utilizing measured changes in prices in that area between the previous known sale date and the current time-period.

(3) **Hedonic models**:

These are valuation models based on the physical attributes (such as square footage, number of bedrooms, number of bathrooms, year built, lot size, and many other features) of thousands of properties. These models estimate the influence that various physical attributes of a property can have on its price. However, this data does not include the physical condition of the property.

Each valuation method is backed by many predictive technologies, including linear and non-linear regression models, econometric and statistical time trend models, probabilistic analyses, and optimization approaches.

Further, as a "blended" AVM, VeroVALUE only returns property valuations when there is strong agreement among the multiple valuation models using the many different modeling approaches. Estimates from the various models are reconciled through a separate process or model that weighs each model and how likely it is to produce an accurate valuation. When all models are in high agreement, the AVM produces very accurate property valuations at high levels of confidence. When all models exhibit large disagreement, the AVM is unable to produce an accurate valuation. In the latter scenario, a "no hit" is declared and an estimated value is not returned by the AVM (or the value is returned with a low confidence score).

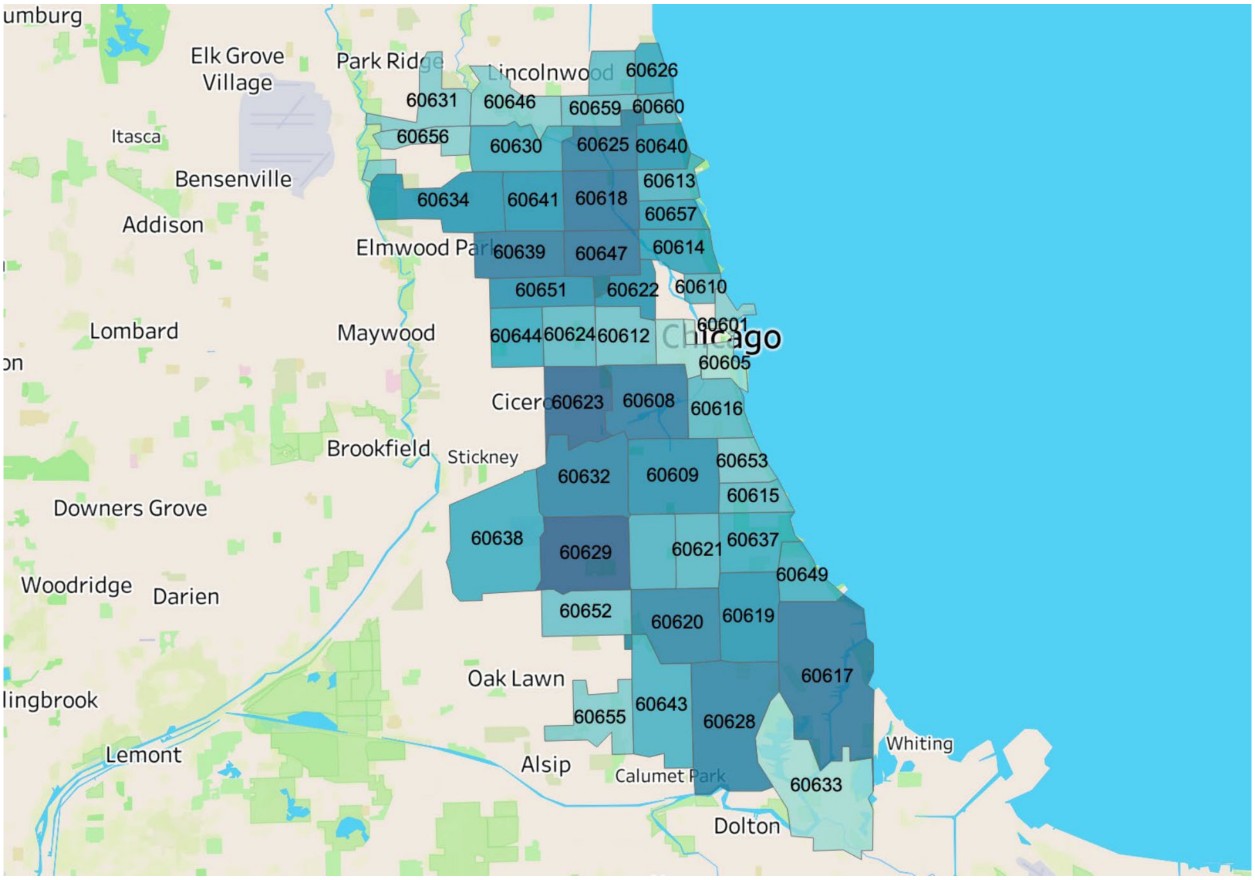
Unlike any other property valuation product or service, an AVM confidence score provides excellent insight into the quality of an AVM's determination of value. The Veros Confidence Score (VCS) is specifically designed to be a predictive measurement of the accuracy of the subject property's estimated market value. The Veros AVM provides correlation between confidence scores and the accuracy of the value estimate. High values of the VCS, such as those between 90 and 99 correlate to high levels of P10. P10 is the percent of total observations in which an AVM rendered a value within +/-10% of the known benchmark value. As levels of VCS go down, the average value of P10 also declines.

The objective of this report is to determine whether the VeroVALUE AVM produces biased results in minority or disadvantaged communities despite being blind to any demographic data. To accomplish this objective, this report examines the performance of the VeroVALUE AVM using racial composition data from fifty ZIP codes in the city of Chicago. Specifically, the report analyzes whether the percent of undervalued properties (P15L) and percent of overvalued properties (P15H) are related to the racial composition of the ZIP code. Further, the MAE is analyzed to determine if VeroVALUE is less accurate on average in minority ZIP codes. Finally, based on the findings, we propose recommendations on the use of AVMs to potentially mitigate these issues.

Research Methodology and Data

For our analysis, we utilize data from the city of Chicago because of its ethnically diverse population, comprised of 33.3% non-Hispanic or non-Latino White, 29.6% Black or African American, 28.8% Hispanic or Latino, 6.6% Asian, and 1.7% other (U.S. Census Bureau, 2021, Quick Facts).[1] We use data at the ZIP code level for our analyses. The ZIP codes not included are either industrial areas populated with many factories (and few homes) or urban business areas with several business high-rises and retail establishments (and few homes). A map of the Chicago area showing the fifty ZIP codes used in the analyses is provided in Figure 1.

Figure 1. Map of Chicago city ZIP codes by Population Size



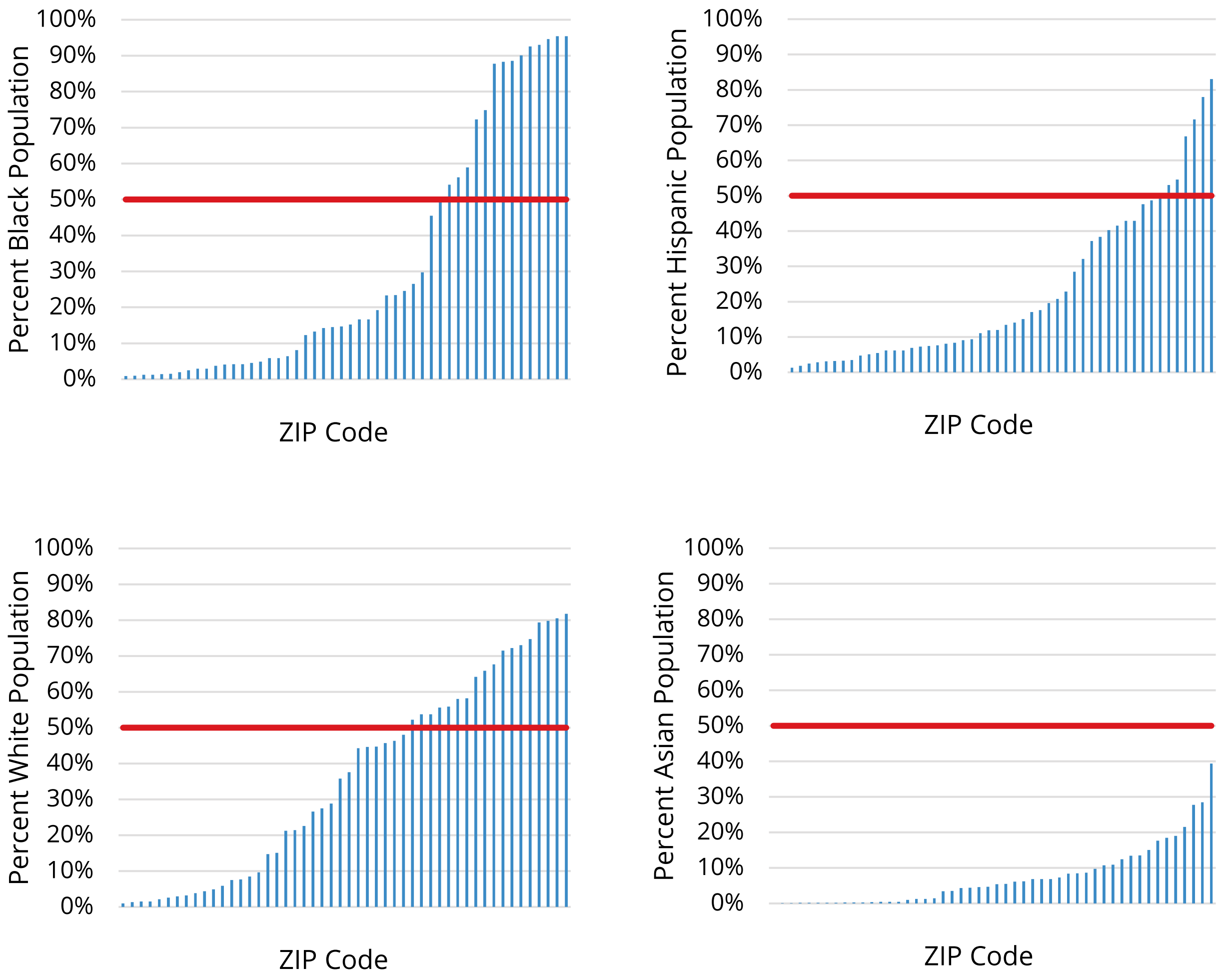
Note: This map was made using Tableau software with darker shades showing larger populations.

[1] Throughout our analyses, we use the census definition of White alone, Black alone, Asian alone or Hispanic to determine the percent of population belonging to a particular race.

ZIP codes in the analysis from the city of Chicago include those that span the full spectrum of racial composition – from less than 1% of Black population to over 95% of Black population, 1% to 82% White population, and 1% to 83% Hispanic population.

Figure 2 shows that, of the fifty ZIP codes analyzed, 15 ZIP codes are majority Black neighborhoods with a Black population of 50% or more; 18 ZIP codes are majority White, with a White population of 50% or more; seven ZIP codes have a majority Hispanic population; and none of the ZIP codes has a majority Asian population. Data on racial composition is derived from the ZIP code level data of the American Community Survey (ACS) 5-year estimates for 2019.[2]

Figure 2. Racial Composition by ZIP Code



[2] The American Community Survey (ACS) is an ongoing survey conducted by the Census Bureau that provides data every year. The 5-year estimates from the ACS are "period" estimates that represent data collected over a period of time. The primary advantage of using multiyear estimates is the increased statistical reliability of the data for less populated areas and small population subgroups. These estimates are based on data collected over a 5-year period of time and therefore they describe the average characteristics for that 5-year time period. For 2015-2019 ACS 5-year estimates, data was collected between: January 1, 2015, and December 31, 2019.

To evaluate the performance of VeroVALUE, we analyze three measurements: the proportion of properties undervalued by the AVM by more than 15% (P15L), the proportion of properties overvalued by more than 15% (P15H), and the MAE. These measurements were taken from December 2021 sales data for the same Chicago ZIP codes highlighted in Figure 1 and VeroVALUE's estimate of value for those properties immediately before their sale. The differences in these values, or errors, are used for the analyses. All discussions in this report on AVM performance relate solely to the Veros AVM, VeroVALUE.

First, we analyze P15L, the percentage of properties for which the AVM undervalues by 15% or more compared to the sale price. We use simple regression analysis to determine the relationship between P15L and the racial composition of a ZIP code.[3] Specifically, we analyze four different models:

- Model L1: Response variable is P15L, and predictor variable is percent Black population.
- Model L2: Response variable is P15L, and predictor variable is percent Hispanic population.
- Model L3: Response variable is P15L, and predictor variable is percent Asian population.
- Model L4: Response variable is P15L, and predictor variable is percent White population.

Each model will determine the relationship between P15L and the proportion of racial population that is used as the predictor; for example, model L1 will determine the relationship between P15L and percent Black population.

Second, we use simple regression analysis again to analyze the performance of P15H, the percentage of properties for which the AVM overvalues by 15% or more as compared to the sale price. It is possible that while the AVM does not undervalue properties in minority neighborhoods, it may overvalue properties in majority White neighborhoods. This scenario could be evidence of racial bias and pose issues of wealth creation for minority communities. The four simple regression models to analyze the performance of P15H are:

- Model H1: Response variable is P15H, and predictor variable is percent Black population.
- Model H2: Response variable is P15H, and predictor variable is percent Hispanic population.
- Model H3: Response variable is P15H, and predictor variable is percent Asian population.
- Model H4: Response variable is P15H, and predictor variable is percent White population.

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[3] Simple linear regression is a statistical technique that is used to determine the relationship between a response variable and a predictor variable. We also need some measure to show how strongly the independent variable is associated with the dependent variable. To determine this, p-values are used. P-value measures how likely it is that any observed difference is due to chance. Values close to 0 indicate that the observed difference is unlikely due to chance, while values closer to 1 suggest no difference other than due to chance. To quantify the strength of evidence, a standard level of 5% is used, so that if $p<0.05$, we say that the variable is significant in explaining the variation in the dependent variable. Further, how well a linear regression model "fits" a dataset is determined by R-squared. Also commonly called the coefficient of determination, R-squared is the proportion of the variance in the response variable that can be explained by the predictor variable – it is the fraction of the variation in the dependent variable, Y, that is accounted for by or predicted by the independent variable.

Third, we utilize multiple regression analysis to examine which variables determine the size of the MAE.[4] MAE calculates the median deviation (in absolute value terms) between AVM predictions and actual sales prices. For example, a value of 5% means that 50% of the absolute value of errors are greater than 5% and 50% of the errors are smaller. Unlike mean absolute error which may easily be skewed by one large outlier, median absolute error is more representative of central tendency and performance.

In our analysis, we want to assess the impact of racial composition of a ZIP code on MAE while accounting for other factors such as quality of housing stock and percent of homes sold. Table 1 shows the descriptive statistics (minimum, 50th percentile, and maximum values) of P15L, P15H, and MAE for the sample.

Table 1. P15L, P15H, and Median Absolute Error

	DEFINITION	MIN	50TH PERCENTILE	MAX
P15L	Proportion of properties undervalued by 15% or more	1.11%	2.46%	11.58%
P15H	Proportion of properties overvalued by 15% or more	3.24%	6.71%	11.59%
Median Absolute Error	Median deviation between predictions and actual values	1.71%	2.38%	3.96%

Racial composition in each ZIP code is defined as follows: the proportion of people that identified as Hispanic is the percent Hispanic population, proportion of non-Hispanic Black are used as percent Black population, non-Hispanic White as White population, non-Hispanic Asian as Asian, and the remaining are termed as Other.

[4] Multiple linear regression is a statistical technique that uses several explanatory variables to predict the outcome of a response variable. It is used to determine the relationship between a response variable and a predictor variable while simultaneously considering the effects of other predictor variables. By accounting for the effects of these other variables, we can isolate and measure the relationship between the response variable and predictor variable of interest. Any multiple regression analysis should ensure the following: (1) there are no influential observations, that is, the data does not include any single observation that is substantially different from all other observations that can make a large difference in the results (use Cook's distance test or studentized residuals to test the presence of unusual and influential data), (2) residuals are normally distributed (use Shapiro-Wilk test to test for normality), and (3) multicollinearity is absent, that is, the predictor variables should not be linearly related (use variance inflation factors to determine presence of multicollinearity).

In the multiple linear regression model used to analyze the performance of the MAE, we include only the following race variables as explanatory variables, where percent White population is used as the reference group:

- percent Black population,
- percent Hispanic population, and
- percent Asian population.

Therefore, the regression parameter estimates on the racial variables should be thought of as the impact of the racial variable compared to the White population on MAE. We exclude the "Other" population because it comprises on average only 2.3% of the population in a ZIP code and had little influence on the results.

The housing stock variables, also derived from the ZIP code level data of the American Community Survey (ACS) 5-year estimates for 2019 are:

- median year properties were built in a ZIP code,
- the median number of rooms, and
- vacant units in the ZIP code (units where no one is living as a proportion of all units).

Additionally, the percent of homes sold as a proportion of total housing units is also used as an explanatory variable. A larger proportion of comparable homes sold would provide more accurate valuations of the AVM. Variables used in these analyses, their definitions, sources, means, standard errors, and maximum and minimum values are provided in Appendix A.

Results

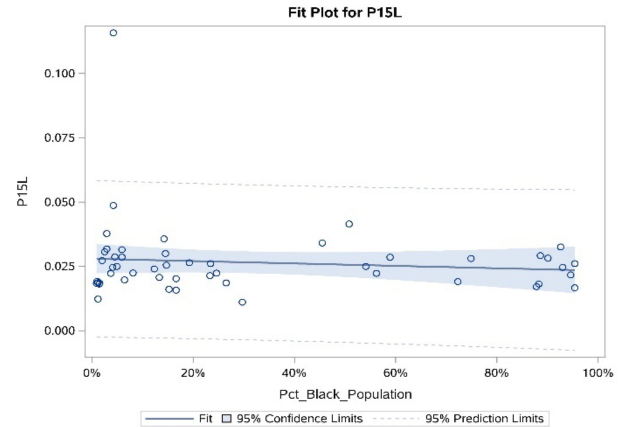
Performance of P15L

The performance of P15L is crucial to the analysis of racial bias in property valuations, as it addresses concerns about undervaluations of minority owned properties. Valuation differences of 10% or less are usually considered acceptable in most circumstances due to nuances of a property's condition, quality, characteristics, and features. For this reason, two different real estate appraisers or professional-grade automated valuation models may arrive at slightly different property value estimates and neither value would be considered inaccurate. However, we believe valuation estimates that vary by 15% or more represent a more significant valuation concern that is beyond the typical subjective differences.

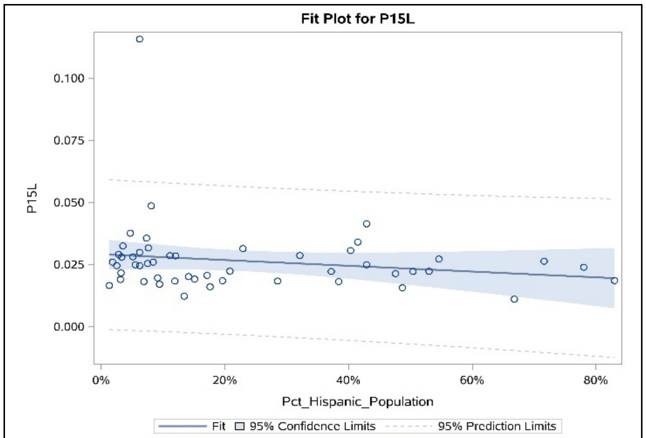
We find that P15L, the proportion of properties that are undervalued by 15% or more, is not correlated with the proportion of Black, Hispanic, Asian, or White populations in a ZIP code using the VeroVALUE AVM. Linear regressions show that the coefficient of percent Black, Hispanic, White, and Asian populations are all statistically insignificant at the 5% level with p-values > 0.05. The percent White population is borderline insignificant with a p-value = 0.09, with the P15L value increasing by only 0.6%, from 2.2% for 0% White population to 2.8% for 50% White population.[5]

Figure 3 shows the fit plots of P15L with respect to the different racial compositions and the corresponding coefficients and p-values. The results show that, from the perspective of minority communities, there is no evidence of systemic undervaluation from the VeroVALUE AVM as the percentage of minority population increases.

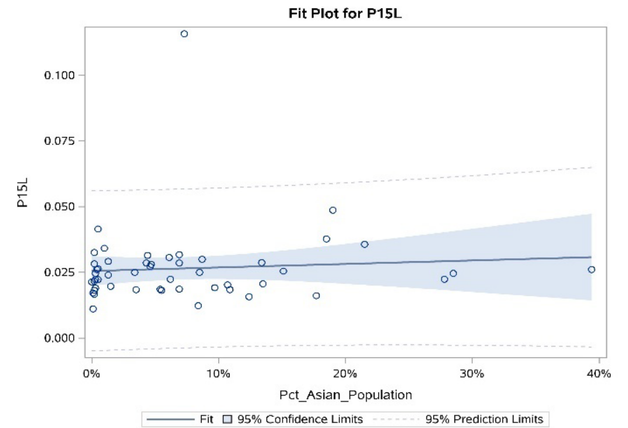
FIGURE 3. P15L AND RACIAL COMPOSITION OF ZIP CODES



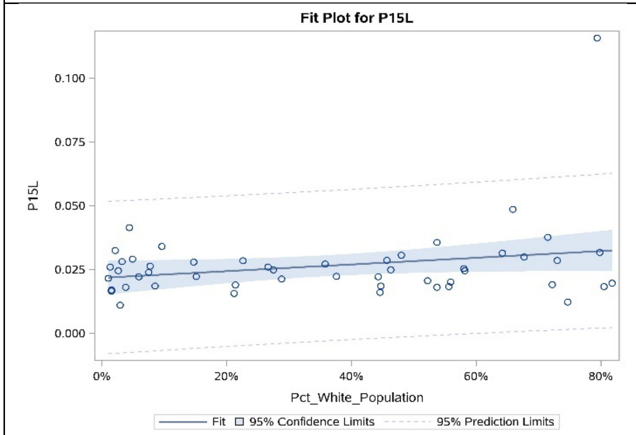
Model L1: P15L and Percent of Black Population
Coefficient = -0.005, p-value = 0.46



Model L2: P15L and Percent of Hispanic Population
Coefficient = -0.012, p-value = 0.22



Model L3: P15L and Percent of Asian Population
Coefficient = 0.013, p-value = 0.59



Model L4: P15L and Percent of White Population
Coefficient = 0.013, p-value = 0.09

[5]A closer analysis of the data used in the regression for the percent White population shows that there is one outlier in the data (ZIP code 60614, P15L = 11.58%, Percent White population = 79.4%, Percent Black population = 4.2%, Percent Hispanic population = 6.2%), that is, a data point that is far from the regression fit line. We use the Cook's Distance statistic to find influential outliers, that is, any point for which the Cook's Distance is higher than 4/n, where n is the number of observations. The Cook's Distance value for this observation is 1.37, much higher than 0.08 (4/n, where n=50). Removing the outlier observation from the regression (for percent White population) results in a coefficient value of 0.003 and a p-value of 0.51.

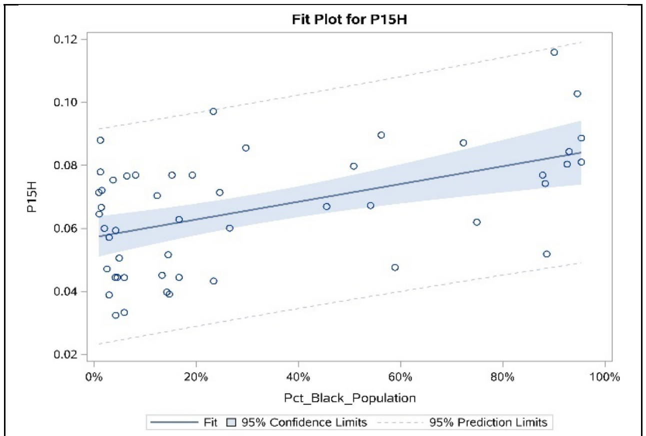
Performance of P15H

We analyze P15H to check if the VeroVALUE AVM overvalues properties in non-minority ZIP codes. The overvaluation of properties in non-minority neighborhoods can lead to the disparate creation of wealth, just as the undervaluation of properties owned by minority populations can lead to the disparate creation of wealth.

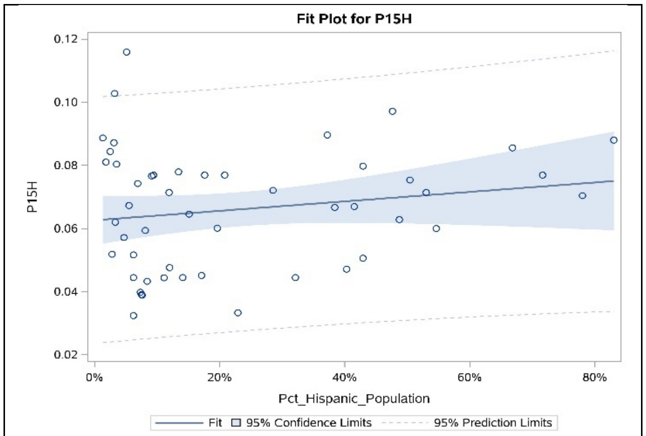
We find that a slightly statistically significant higher percentage of properties were overvalued by the AVM as the proportion of Black population increased, but that the percentage of overvalued properties decreased as the percent of White or Asian population increased. The fit plots for the regression, coefficients and p-values are in Figure 4. We find that the coefficients for percent Black population, White population, and Asian population are all significant. The coefficient for percent Hispanic population is not significant. Though the findings for Black, White, and Asian populations have significant regression coefficients, it should be noted that the magnitude of the overprediction changes are small in all cases. For example, as the Black population increases from 0% to 50%, the percentage of properties overvalued by the AVM by 15% or more compared to the sales price, increases from 5.7% to 7.1%. With respect to the White population, as it increases from 0% to 50%, the percentage of properties overvalued by 15% or more, declines from 8% to 6%. For the Asian population, the percentage of properties overvalued by 15% or more declines from 7.4% to 5.3% as the Asian population increases from 0% to 20%.

So, from the perspective of majority White communities, there is no evidence of systemic overvaluation from the VeroVALUE AVM as the percentage of White population increases.

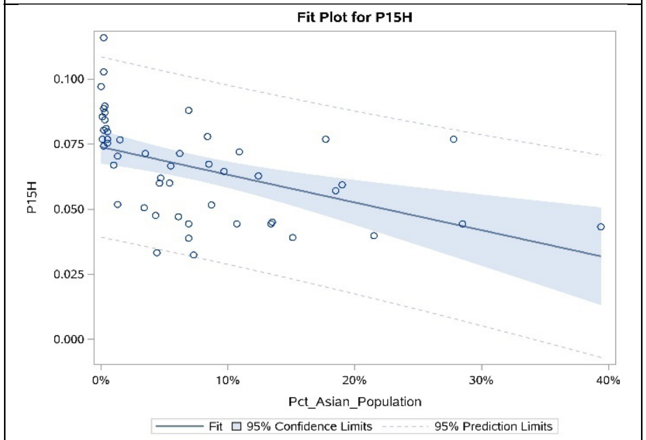
FIGURE 4. P15H AND RACIAL COMPOSITION OF ZIP CODES



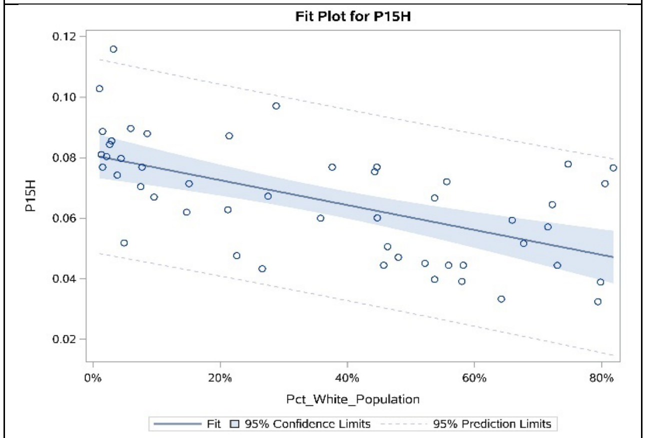
Model H1: P15H and Percent of Black Population
Coefficient = 0.028, p-value < 0.001



Model H2: P15H and Percent of Hispanic Population
Coefficient = 0.015, p-value = 0.22



Model H3: P15H and Percent of Asian Population
Coefficient = -0.107, p-value < 0.001



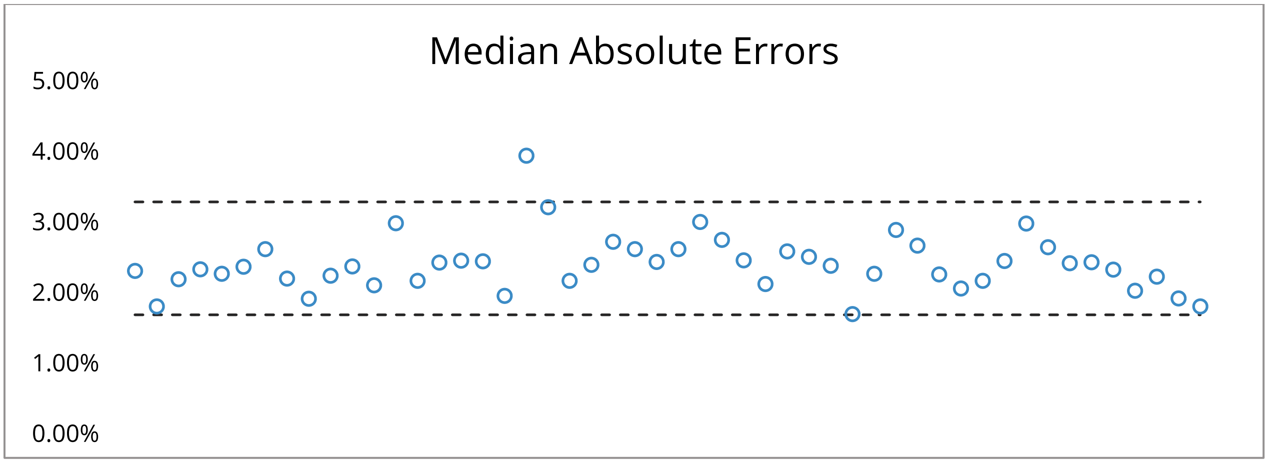
Model H4: P15H and Percent of White Population
Coefficient = -0.041, p-value < 0.001

Performance of Median Absolute Error

MAE is another measure of an AVM's precision and allows analysts to determine the "typical" error that occurs between an AVM's estimate of value and the corresponding sales price benchmarks. The median is less sensitive to outliers than the mean. A scatter plot of the MAE (Figure 5) shows that the minimum value for the MAE among all ZIP codes analyzed was 1.71%. There is one ZIP code for which the MAE is 3.96%; for the remaining the range is between 1.71% and 3.23%, a narrow range.[6]

[6] The MAE is 3.96% for ZIP code 60623, with 67% Hispanic population, 30% Black population, and 3% White population. The median home sales price for this ZIP code was $212,500 during August-October 2021 (2nd quintile), with 66% of the housing units built in 1939 or earlier.

FIGURE 5. SCATTER PLOT OF MEDIAN ABSOLUTE ERRORS



We also examine if the variation in MAE is explained by the racial compositions of communities or if other variables explain this variation. To analyze this, we run a multiple regression with the dependent variable as MAE. As described more fully in Appendix A, the predictor or explanatory variables used in the analysis are percent Black population, percent Hispanic population, percent Asian population, median year built, median number of rooms, vacant units, and percent of homes sold. Note that percent of White population is not included as a predictor variable because it is used as a reference group in the analysis. For example, the parameter estimate on percent Asian population should be thought of as the impact of this variable compared to the White population on MAE.

- We find that the coefficients of percent Black population and percent Hispanic population are very small in magnitude and their p-values suggest that they do not significantly impact the size of median absolute errors.
- The coefficient of percent Asian is negative, but its p-value suggests that it is borderline insignificant at a 5% significance level. Increasing from 0% Asian to 20% Asian causes the median absolute error to decrease from 2.6% to only 2.3%.
- The coefficients of all housing stock variables are insignificant. The coefficients of median year built and median rooms are very small in magnitude; their p-values suggest that they do not significantly impact the size of MAE. The variable, vacant units, has a positive relationship with MAE; however, it is not a significant predictor of MAE.
- The results show that only one variable that we included in the analysis is significant in predicting the size of MAE, that is, percent of homes sold. It is found to have a negative relationship with MAE.

TABLE 2. ESTIMATION RESULTS OF MEDIAN ABSOLUTE ERRORS

PARAMETER	ESTIMATE	P-VALUE
Intercept	0.0068	0.93
Percent of Black Population	-0.0003	0.91
Percent of Hispanic Population	0.0035	0.27
Percent of Asian Population	-0.0132	0.09***
Median Year Built	0.0000	0.80
Median Rooms	0.0007	0.39
Vacant Units	0.0065	0.57
Percent of Homes Sold	-0.0539	0.01**
Adjusted R Squared	0.44	

**Significant at 5%, ***significant at 10%

Our model can explain only 44% of the variability in MAE. The remaining 56% is left to be explained by variables not included in our model. Our aim was to determine if racial factors are responsible for the variability in MAE, and we find that racial compositions are weak influencers of MAE. Likewise, finding any variable that correlates to differences in MAE is difficult to do – racial or otherwise.

Conclusions

The VeroVALUE AVM is blind to racial, gender, or related demographic data – both as it relates to parties involved in a specific transaction and the hundreds or thousands of properties and related data sets analyzed as part of the AVM determination of value. This report has examined whether, despite the fact that VeroVALUE has no visibility or knowledge into race, gender and other demographics, the VeroVALUE AVM produces biased results, potentially as a result of bias that is inherent in the underlying data it analyzes. We conclude that P15L, the proportion of properties that are undervalued by 15% or more, is not significantly correlated (at a 95% confidence level) with the proportion of Black, Hispanic, Asian, and White populations in a ZIP code. Related, there is no evidence of systemic overvaluation from the VeroVALUE AVM as the percentage of White population increases. We also conclude that the variation in MAE is not significantly explained by the racial compositions of communities and the significant predictor of its variation is the percentage of housing stock sold in a ZIP code. In summary, we found no evidence of racial bias in the VeroVALUE AVM.

Recommendations

This report is focused on the performance of the VeroVALUE AVM. While the results of this report are based on one metropolitan area, we deliberately picked a very racially diverse community for our analyses. While we recognize the need to conduct similar analyses in other areas of the country to strengthen our conclusions, we do not anticipate that our results will change significantly in other geographical areas. However, all AVMs are not created equally and, therefore, performance may vary greatly between leading professional-grade and consumer-grade AVMs. Based on the results of our analyses and performance of Veros' AVM metrics, we recommend that other AVM providers conduct similar research to help demonstrate that their AVMs likewise do not have any algorithmic bias.

AVMs with high confidence scores that are shown to be free of bias and whose accuracy has been tested, can be used as a check to determine whether appraised or other sources of value are at risk for significant under- or overvaluation. Because AVMs are low cost and easy to use, this analysis could be easily accomplished by running a professional-grade AVM against each appraised or alternative property valuation as a verification of value and potential indication of bias. Appraised values in agreement with a professional-grade AVM at high confidence intervals would be deemed low risk for bias, while those appraisals in significant disagreement with a professional-grade AVM could be escalated for a more detailed review.

Other Considerations: Research on Appraisal Bias and Future Study

While the purpose of this report is to analyze the performance of Veros' VeroVALUE AVM in ZIP codes with different racial compositions, an understanding of racial bias in the current appraisal industry is also important. Due to a lack of broader availability of appraisal data, there have been only a limited number of quantitative research studies on appraisal bias. It is vital that researchers have access to appraisal information to conduct their own analyses.

The limited research that does exist does not present a consensus on the presence of appraisal bias. While some of the studies conclude that minority-owned homes are undervalued by appraisers, others do not find evidence of systemic racial bias. It is imperative that further research be carried out in this sphere utilizing variables that have not been previously considered to determine the causes for the differences in home prices. For example, researchers may include a larger set of variables that fully incorporate buyer demand for housing in different neighborhoods in addition to a full spectrum of variables that include information on the quality of housing stock and neighborhood characteristics.

With respect to the AVM analyses, while we believe this study is representative of VeroVALUE's performance across racially diverse communities in the United States, we plan to conduct future studies including other major cities and regions to get a more comprehensive and granular idea of performance as it relates to bias. Additionally, this report uses data from December 2021, when the market was a sellers' market, characterized by steep gains in home prices. We intend to continue our analysis under varying market conditions and in other regions.

About Reena Agrawal and Eric Fox

Reena Agrawal, Research Economist

Reena Agrawal received her PhD in Economics from Vanderbilt University and MA in Economics from The Ohio State University and has several years of industrial experience in economic research and analysis.

Eric Fox, Chief Economist

Eric Fox, Chief Economist and Sr. Vice President of Data Modeling, provides expert leadership in predictive technologies, economic modeling methodologies, and collateral valuation forecasting. He brings more than 30 years of experience to his role, including statistical and econometric modeling, probabilistic life methodology development, statistical training, probabilistic design software development, and probabilistic financial analysis.

Fox has published more than 20 technical papers on probabilistic and statistical methods. He received his master's degree in statistics and a bachelor's degree in mathematics and economics from Purdue University.

About Veros Real Estate Solutions

Veros Real Estate Solutions, an innovator in mortgage technology since 2001, is a proven leader in predictive technology for the housing finance industries and a top-ranking provider of real estate valuations and analytics for the entire mortgage lending value chain, from origination to the capital markets.

Veros delivers enterprise risk management solutions used by many of the country's leading lenders, servicers and investors. Our systems automate the ordering, tracking, review, acceptance, quality control, scoring and delivery of appraisals, broker price opinions (BPOs) and automated valuation models (AVMs). In addition, we offer sophisticated risk assessment products, analytics and real estate data to enhance the power of valuations, as well as automate the criteria, assignment and management of these products.

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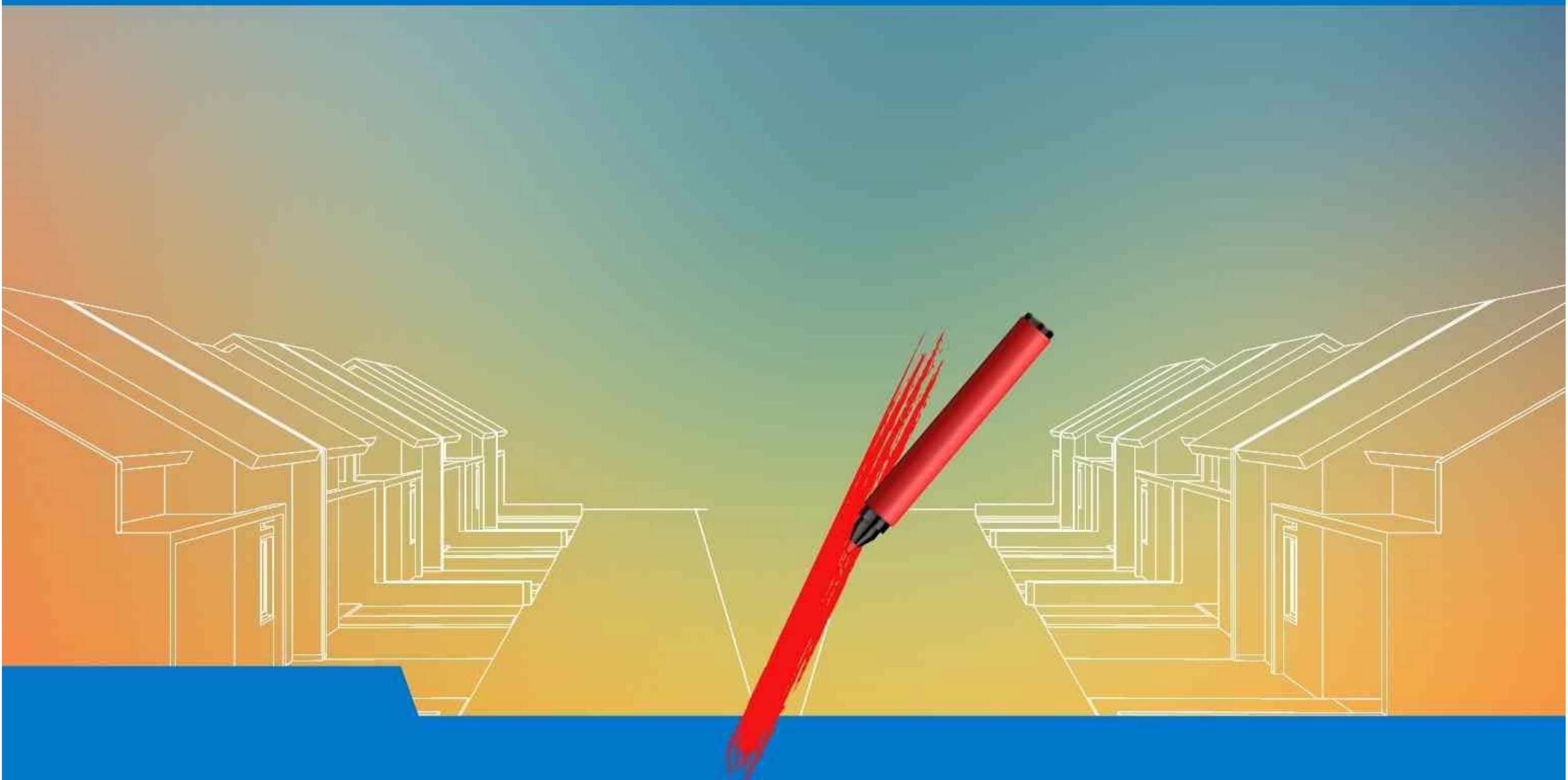
Appendix A: Variable Definitions and Sources

VARIABLE	DEFINITION	MEAN	SE	MIN	MAX
Percent of White Population	People who identified as non-Hispanic White (source: ACS)	35.83%	27.54%	1.00%	81.80%
Percent of Black Population	People that identified as non-Hispanic Black (source: ACS)	31.44%	34.16%	0.90%	95.40%
Percent of Hispanic population	People that identified as Hispanic (source: ACS)	23.06%	22.32%	1.30%	83.00%
Percent of Asian Population	People that identified as non-Hispanic Asian (source: ACS)	7.38%	8.60%	0.00%	39.40%
Percent of Other Population	People who were not White, Black, Hispanic or Asian (source: ACS)	2.30%	1.28%	0.30%	5.70%
Median Year Built	Median Year Structure Built (source: ACS).	1953	17	1939	2001
Median Rooms	Median number of rooms in all housing structures in the ZIP code (source: ACS)	4.74	0.85	2.70	6.30
Vacant Units	A housing unit is vacant if no one is living in it at the time of interview. Units occupied by persons who are staying two months or less and who have a more permanent residence elsewhere are classified as "vacant." New units not yet occupied are classified as vacant housing units if construction has reached a point where all exterior windows and doors are installed, and final usable floors are in place. Vacant units are excluded from the housing inventory if they are open to the elements or condemned or they are to be demolished. (Source: ACS)	12.24%	5.90%	4.70%	33.10%
Percent of Homes Sold	Number of homes sold in 2021 as a percentage of property count in the ZIP code (source: Veros).	7.81%	4.27%	1.17%	18.29%

www.veros.com

communications@veros.com

866.458.3767



Does historical redlining influence today's AVM estimates?

This study investigates the potential for bias in home valuations generated by an AVM when analyzed across the boundaries delineated in historical redlining maps, despite the absence of data on demographics or redlining boundaries.

Reena Agrawal, Ph.D., Research Economist
Eric Fox, Chief Economist

June 2023

www.veros.com communications@veros.com

Veros Real Estate Solutions

Contents

Does historical redlining influence today's AVM estimates?

Executive Summary

Investigation into the repercussions of racial discrimination in the housing market has prompted numerous stakeholders to question whether any such prejudice may be grounded in the historical practice of redlining. This paper is designed to consider whether all valuation methodologies are by definition biased as a result of historical redlining. Automated Valuation Models (AVMs) provide a distinct benefit on property valuations because they do not rely on any data related to historical redlining maps or leverage any demographic information.

This study investigates the potential impact of historical redlining by examining AVM predictions generated by VeroVALUE℠ for single-family properties in historically redlined versus non-redlined neighborhoods in Los Angeles County, California.

The study identified four boundaries (redlined vs non-redlined) in Los Angeles that were suitable to test AVM property value estimates. The use of multiple regression analysis was employed to investigate which variables, specifically physical home attributes, are responsible for the differences observed in VeroVALUE estimates. Of particular interest in this analysis was the role of location as a determinant of home prices. The study compared the VeroVALUE estimates of homes located in redlined versus non-redlined neighborhoods after controlling for physical attributes.

This study concludes that home valuations provided by the VeroVALUE AVM for Los Angeles are not impacted by historical redlining. This research also finds that historical redlining has resulted in homes located within redlined neighborhoods typically having less square-footage, smaller lot sizes, and higher variations in quality and condition compared to homes in non-redlined areas, leading to lower median property values. However, after controlling for these physical attributes, the VeroVALUE AVM returns comparable estimates for properties on either side of the redline. In an environment where housing finance stakeholders consider both accuracy and fairness across the entire valuation spectrum, the AVM is demonstrating that it can be an invaluable tool to achieve both goals.

Introduction

Racial disparities in access to credit and homeownership have put minority communities at a disadvantage in their ability to build equity and accumulate wealth. Discussions on the wealth gap in the housing sector started in the context of appraisals because of allegations of racial bias. The inquiry into the implications of racial discrimination within the housing market has led many stakeholders to scrutinize whether such biases are rooted in the historical practice of redlining. Automated valuation models (AVMs) offer a distinct advantage as they do not depend on any data pertaining to historical redlining maps or demographic information concerning the involved parties in real estate transactions. However, there are some that believe that any property valuation solution may be unwittingly influenced or biased through the infusion of historically biased data that stems from decades-old discriminatory practices. There is also the possibility that an AVM might be utilizing proxy variables in their models that might lead to biased estimates. This might happen if a model uses a variable that appears to be neutral but may be highly correlated to race, such as the level of homeownership (Burt, 2020). A modeler may include such a variable unintentionally, which may lead to unintentional discrimination or disparate impact. The VeroVALUE AVM does not employ homeownership rates in its models and to our knowledge, most other AVMs do not use it either.

In a previous study, we found that VeroVALUE does not exhibit racial bias and is no less accurate in minority communities (Agrawal & Fox, 2022). The current study analyzes if an AVM, a technological home valuation methodology, produces biased home valuations across boundaries drawn in redlining maps despite not utilizing any demographic or race data and having no access to the redlining maps. While there is considerable research on the impact of redlining on access to credit, housing, food access, health, education, and income outcomes, there is sparse quantitative research on the impact of redlining on contemporary automated home valuation estimates.

We do not dispute the existence of historical discrimination and biases and their likely impact on home values. We aim to test if Veros' AVM, VeroVALUE, produces different results for properties (after controlling for some key physical attributes) based on historical redlining maps.

A History of Redlining

In 1933, in the aftermath of the Great Depression, the newly elected Roosevelt administration launched the New Deal – a set of plans to alleviate the impact of the depression. These programs were meant to help in economic recovery through job creation, investments in public works, and creating stability in the banking system. The depression had led to a large decrease in national income and more than a million homeowners faced foreclosure. To address the dire situation in the housing market, the Home Owners' Loan Corporation (HOLC) was created in 1933 with a directive to purchase underwater mortgages and refinance them at easier terms to borrowers. This program was designed to be short-lived, and in a span of three years (1933 to 1936) the HOLC managed to refinance "nearly one in five mortgaged homeowners" (Fishback et. al., 2022, p. 6).

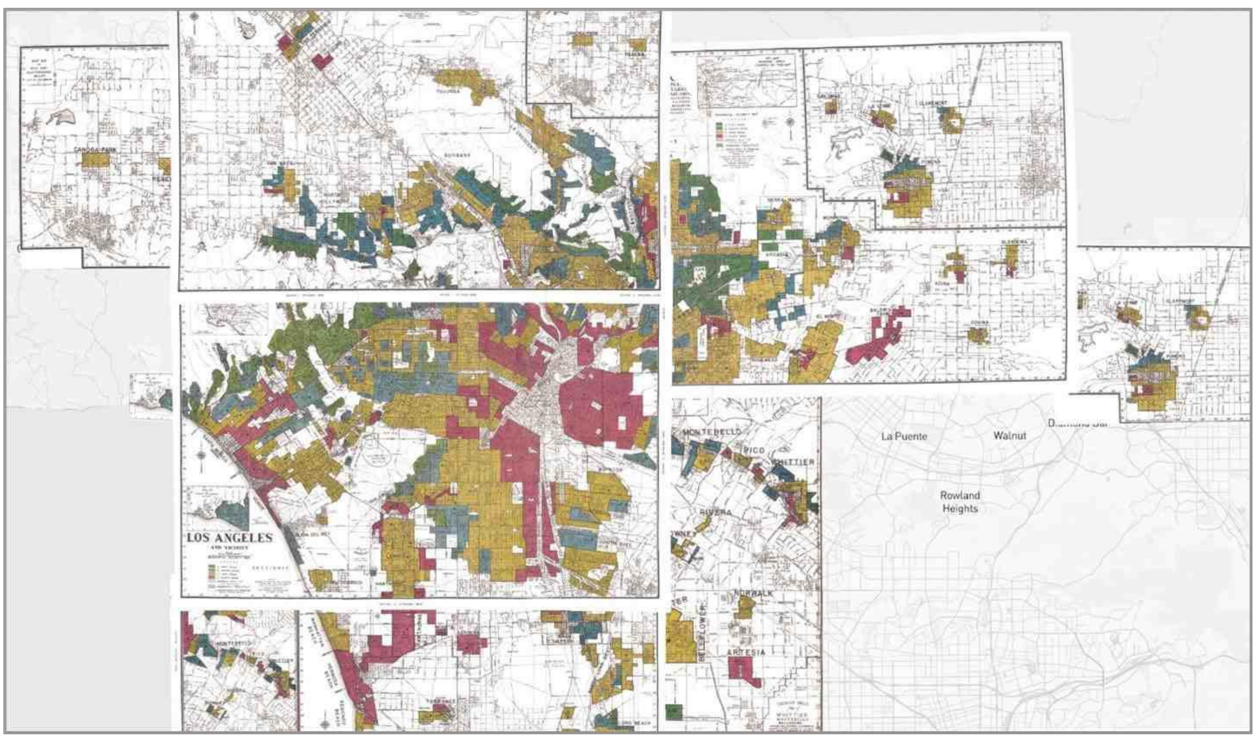
The HOLC started assessing mortgage risk by gathering information on housing markets across the U.S. to develop a sound housing finance program. They determined risk based not only on the attributes of the property for which the loan was being sought but also on the characteristics and racial composition of the neighborhood in which the property was located. According to Woods (2012), entire neighborhoods were deemed "dangerous bank investments whenever undesirable residents inhabited them" (p. 1038). Undesirable residents were defined as "racial or ethnic minorities, or low-income inhabitants" (Woods, 2012, p. 1038). The usage of these risk assessment standards in national lending policy led to "disadvantaging entire communities it deemed a hazardous bank investment" (Woods, 2012, p. 1038).

The HOLC generated color-coded maps that provided a visual assessment of risk in the various mortgage markets (see the map of Los Angeles County below). These maps, also known as Residential Security Maps, documented the perceived risk evaluations and assessments of local loan officers, city officials, appraisers, and real estate professionals. HOLC's Mortgage Rehabilitation Division produced maps of over 200 cities with populations over 40,000, based on the assessments of these real estate professionals, thereby assigning grades to neighborhoods as follows:

1. Grade A or green for "Best" – these were ethnically homogenous and had room to be further developed,
2. Grade B or blue for "Still Desirable" – they were already completely developed but were still considered desirable,
3. Grade C or yellow for "Definitely Declining" – these were not only declining but showed "infiltration of a lower grade population," and
4. Grade D or red for "Hazardous" – these neighborhoods had low homeownership rates, old housing structures, and an "undesirable population" (Hillier, 2003; Mitchell & Franco, 2018).

MAP 1: REDLINING MAPS OF LOS ANGELES COUNTY, CALIFORNIA

Nelson, et. al., Mapping Inequality, Retrieved February 15, 2023,
https://dsl.richmond.edu/panorama/redlining/#loc=10/34.005/-118.544&city=los-angeles-ca



The racially biased assessments of the HOLC agents in creating these maps is evident from the textual descriptions that accompany these maps (Fishback et. al., 2022). Here are some examples of racially biased assessments based solely on race from texts accompanying these maps from the redlined areas in Los Angeles (Nelson, et. al.,2021):

"This area is favorably located but is detrimentally affected by 10 owner occupant [Black] families" - D7.

“Population is heterogeneous and many are of the lower income group. The subversive racial elements are comparatively few in number and are largely in the canyon bottom. While this area is not entirely blighted, it is thought that the trend of desirability will contitute [sic] downward” - D31.

“Population is heterogeneous and borders the subversive” - D41.

A large proportion of the neighborhoods that were graded hazardous or color-coded red were largely populated by Black residents. Rothstein (2017) claims that one of the biggest consequences of housing segregation has been suppressed incomes and wealth for these families. Since Black families were prevented from buying homes in White suburbs, they continued to stay in economically depressed neighborhoods, primarily as renters. As a result, these families were unable to build home equity in the White neighborhoods, which have registered substantial gains in prices over the decades.

Other research has also found a similar impact of the HOLC redlining maps. Aaronson, Faber, Hartley, Mazumder, & Sharkey (2021) find that lower-graded regions experienced a decline in homeownership, house values, and credit scores, thus highlighting the important function that credit has in propelling growth and development of communities. They also conclude that the HOLC maps had a significant causal effect on a wide variety of outcomes such as the level of household income, the probability of living in a high poverty neighborhood, the probability of transitioning to the top of the income distribution, and credit scores. Appel & Nickerson (2016) conclude that discriminatory credit rationing led to a decrease in house prices for minority homeowners in 1990. A researcher found these residential security maps at the National Archives, after which a team at the University of Richmond digitized them and made them available to the public (https://dsl.richmond.edu/panorama/redlining/#loc=5/39.1/-94.58).

The VeroVALUE AVM

The VeroVALUE AVM has been developed and is maintained by Veros’ in-house team of modelers, statisticians, economists, data operators, and industry experts. With a track record spanning over two decades, it has consistently demonstrated exceptional performance in delivering home valuations. VeroVALUE utilizes data from multiple data sources, including public records (county assessors and recorders), multiple listing services (MLS), and related property databases, which are refreshed daily on over 100 million properties. VeroVALUE is one of several professional-grade AVMs in the market today. VeroVALUE is the source of the AVM findings within this report; this report does not provide results with respect to other professional-grade or consumer-grade AVMs in the market.

The VeroVALUE AVM is based on a “blended” approach that uses multiple and intentionally different methods in each of the following modeling categories:

(1) **Comparative assessment models:** These models are based on hundreds of recent sales so that the impact of a few incorrectly valued properties is significantly reduced or eliminated. The vast set of data used in the generation of VeroVALUE does not include any data on demographics such as race or socioeconomic status of any party involved in the real estate transaction or any protected class data – race, color, national origin, religion, sex (including gender identity and sexual orientation), familial status, disability – as identified by the Fair Housing Act. VeroVALUE also does not use any historic HOLC map boundaries.

(2) **Index models:** Index models incorporate time trends of thousands of home prices in geographical areas such as ZIP codes, counties, and metropolitan areas. These models take a previous sales price of a subject property and update that value to current pricing by utilizing measured changes in prices in that area between the previous known sale date and the current time-period.

(3) **Hedonic models**: These are valuation models based on the physical attributes (such as square footage, number of bedrooms, number of bathrooms, year built, lot size, and many other features) of thousands of properties. These models estimate the influence that various physical attributes of a property can have on its price. However, this data does not include the physical condition of the individual properties currently.

Each valuation method is backed by many predictive technologies, including linear and non-linear regression models, econometric and statistical time trend models, probabilistic analyses, and optimization approaches.

Further, as a "blended" AVM, VeroVALUE only returns property valuations when there is strong agreement among the multiple valuation models using the many different modeling approaches. Estimates from the various models are reconciled through a separate process or model that weighs each model and how likely it is to produce an accurate valuation. When all models are in high agreement, the AVM produces very accurate property valuations at high confidence levels. When all models exhibit large disagreement, the AVM is unable to produce an accurate valuation. In the latter scenario, a "no hit" is declared, and the AVM does not return an estimated value (or the value is returned with a low confidence score).

Unlike any other property valuation product or service, an AVM confidence score provides excellent insight into the quality of an AVM's determination of value. The Veros Confidence Score (VCS) is specifically designed to be a predictive measurement of the accuracy of the subject property's estimated market value. The Veros AVM provides a correlation between confidence scores and the accuracy of the value estimate. High values of the VCS, such as those between 90 and 99, correlate to high levels of P10. P10 is the percent of total observations in which an AVM rendered a value within +/-10% of the known benchmark value. As levels of VCS go down, the value of P10 also declines.

Objective and Research Methodology

HOLC created maps for over 200 cities in every geographical region of the US, depicting the perceived risk assessments of local real estate professionals (local loan officers, city officials, appraisers, and bankers), which were largely based on racial compositions of neighborhoods. But even before these maps were created, restrictive covenants were used to segregate neighborhoods. These were clauses in property deeds that restricted the sale of the property to people of certain races or ethnicities. Many segregated neighborhoods existed because home deeds and "pacts among neighbors" prevented resales to Black people (Rothstein, 2017, p. 77). In Los Angeles alone, between 1937 to 1948, there were over a hundred lawsuits that demanded the eviction of Black residents from their homes based on such clauses (Rothstein, 2017). Tijerina (2019) contends that in Los Angeles, "[t]he crises of high rents, displacement, homelessness, budget shortages, and other failures and injustices … can be attributed in part to the legacy of redlining" (p.1). Also, the detrimental effects of redlining can be seen today, with communities in the northeast and eastside of Los Angeles having some of the lowest homeownership rates in Los Angeles County (Tijerina, 2019). Therefore, with its large and diverse population, Los Angeles is a good candidate in the U.S. to study the impact of redlining on the automated valuation tools of today.

Our approach to testing the performance of VeroVALUE involved the assumption that if HOLC map boundaries have an impact on AVM predictions, the disparities would be most apparent between neighborhoods that were rated as the worst (red) and best (green). This was based on the findings of researchers who have highlighted the financial disinvestment and decline in homeownership rates, home values, and credit scores in low-graded, predominantly minority neighborhoods compared to higher-graded, predominantly White neighborhoods (Rothstein, 2017; Appel & Nickerson, 2016). To ensure that our testing was adequate, we wanted to focus on areas where red neighborhoods (worst) had contiguous boundaries with green (best) neighborhoods, selecting properties that were geographically close to one another. By doing so, we were able to employ a hedonic modeling approach that considers only the physical attributes of homes and ignores location-related variables that might influence an AVM's assessment of properties (Aaronson, Hartley, & Mazumder, 2021; Appel & Nickerson, 2016).

Examples of location variables that might influence the valuation of a property include access to places of work, transportation amenities, presence or absence of multi-family properties, or other attributes of local areas such as proximity to parks or retail establishments. The only location variable we use is whether the property lies in a HOLC designated red or non-redlined neighborhood. The other reason for testing the AVM in a small geographic region is because the VeroVALUE AVM selects comparable properties in a small radius around the subject property; so, if a property lies on the border of two different neighborhoods (for example, a red and blue block), the VeroVALUE AVM will seek comparable properties on both sides of the boundary.

We did not find any redlined neighborhoods (D-graded areas) with contiguous boundaries with the best or green-graded neighborhoods (A-graded areas) in the HOLC map of Los Angeles. Therefore, we identified red or worst (D-graded areas) – and blue or second-best (B-graded areas) boundaries that were in close proximity to one another.[1] Although we use B versus D boundaries instead of A versus D, the former comparison is a valid choice because mortgage funds were ample for the B areas as they were for the A areas, while mortgage funds were very limited or nonexistent for the D areas. We therefore conducted our analysis in areas where red-graded neighborhoods shared boundaries with blue-graded (second best) neighborhoods. Our study also tests whether our assumption of analyzing spatially close neighborhoods is appropriate. We do this by testing if AVM estimates differ between spatially distant neighborhoods within a red-graded block. Estimates may differ for homes in spatially distant neighborhoods within a redlined area due to external factors other than HOLC grades or other physical attributes not included in our analysis. Further, all results presented here are attributable to the VeroVALUE AVM alone.

We identified four such boundaries in Los Angeles, that is, areas where single-family homes were present on both sides of the boundary to enable the testing of the AVM predictions generated by VeroVALUE. Other areas had red-blue boundaries, but they had retail establishments and multi-family structures on both sides of the boundary, rendering them unsuitable for analysis. Map 2 shows the following four areas that are analyzed in our study:

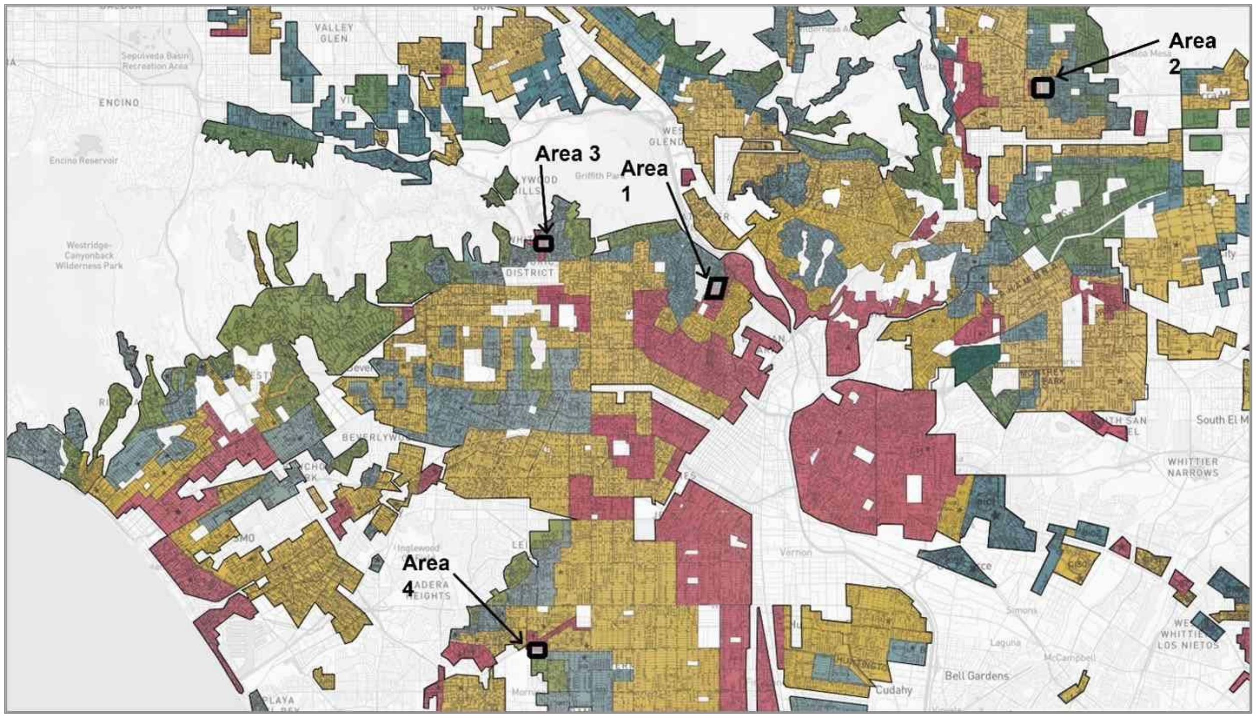
- Area 1 – the boundary between B75 and D31
- Area 2 – the boundary between B30 and D7
- Area 3 – the boundary between B69 and D28
- Area 4 – the boundary between B83 and D41

Further, to test if the AVM produces different estimates for spatially distant neighborhoods, we analyzed two neighborhoods within a red-graded block of Area 1 (D31). We analyzed home prices in two selected blocks within D31 – one bounded by highways and the other bounded by a lake on one side.

MAP 2: HOLC MAP OF LOS ANGELES COUNTY SHOWING THE FOUR AREAS OF STUDY.

Nelson, et. al., Mapping Inequality, Retrieved February 15, 2023, https://dsl.richmond.edu/panorama/redlining/#loc=10/34.005/-118.544&city=los-angeles-ca

[1] Throughout our analysis we use B/blue/second-best and D/red/worst interchangeably.



For our analyses, we looked at the house price estimates (from September 2022) provided by the VeroVALUE AVM for all single-family homes on either side of the HOLC boundaries mentioned above, within a very tightly defined geographic band, typically 2-3 city blocks. The physical attributes of these homes used in the analyses were derived from Veros' data, which includes nationwide public record and MLS listing data. We utilize multiple regression analysis to examine which variables determine the variation in VeroVALUE estimates.[2] The response variable in our analyses is VeroVALUE estimates (log-transformed values are used in the regression), and the predictor variables used are the following physical attributes of residential properties: lot size in square feet (log-transformed value), living area in square feet (log-transformed value), number of bedrooms, number of bathrooms, pool, fireplace, and

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[2] Multiple linear regression is a statistical technique that uses several explanatory variables to predict the outcome of a response variable. It is used to determine the relationship between a response variable and a predictor variable while simultaneously considering the effects of other predictor variables. By accounting for the effects of these other variables, we can isolate and measure the relationship between the response variable and predictor variable of interest. We also need some measure to show how strongly the independent variable is associated with the dependent variable. To determine this, p-values are used. P-value measures how likely it is that any observed difference is due to chance. Values close to 0 indicate that the observed difference is unlikely due to chance, while values closer to 1 suggest no difference other than due to chance. To quantify the strength of evidence, a standard level of 5% is used, so that if $p<0.05$, we say that the variable is significant in explaining the variation in the dependent variable. Further, how well a linear regression model "fits" a dataset is determined by R-squared. Also commonly called the coefficient of determination, R-squared is the proportion of the variance in the response variable that can be explained by the predictor variables – it is the fraction of the variation in the dependent variable, Y, that is accounted for by or predicted by the independent variables. Any multiple regression analysis should ensure the following: (1) residuals are normally distributed (use Shapiro-Wilk test to test for normality), and (2) multicollinearity is absent, that is, the predictor variables should not be linearly related (use variance inflation factors to determine presence of multicollinearity). All regressions were run using PROC GLM in SAS.

a location variable (whether the home is located in a blue or red neighborhood). We use the same methodology and variables to test the performance of AVM estimates in two spatially distant neighborhoods within a red-graded area – D31.

Data and Results

All HOLC maps shown here have been retrieved from the “Mapping Inequality” website.[3] Further, for all geospatial analyses with respect to the HOLC maps, we utilized the GeoJSON files provided by the “Mapping Inequality” website; these files were also used to generate maps that show our specific areas of interest and analyses.[4] All data for physical attributes and VeroVALUE estimates were retrieved from Veros’ databases.

The regression results for the four selected red-blue boundaries in the Los Angeles region are provided below.

Area 1. The B75 – D31 Boundary

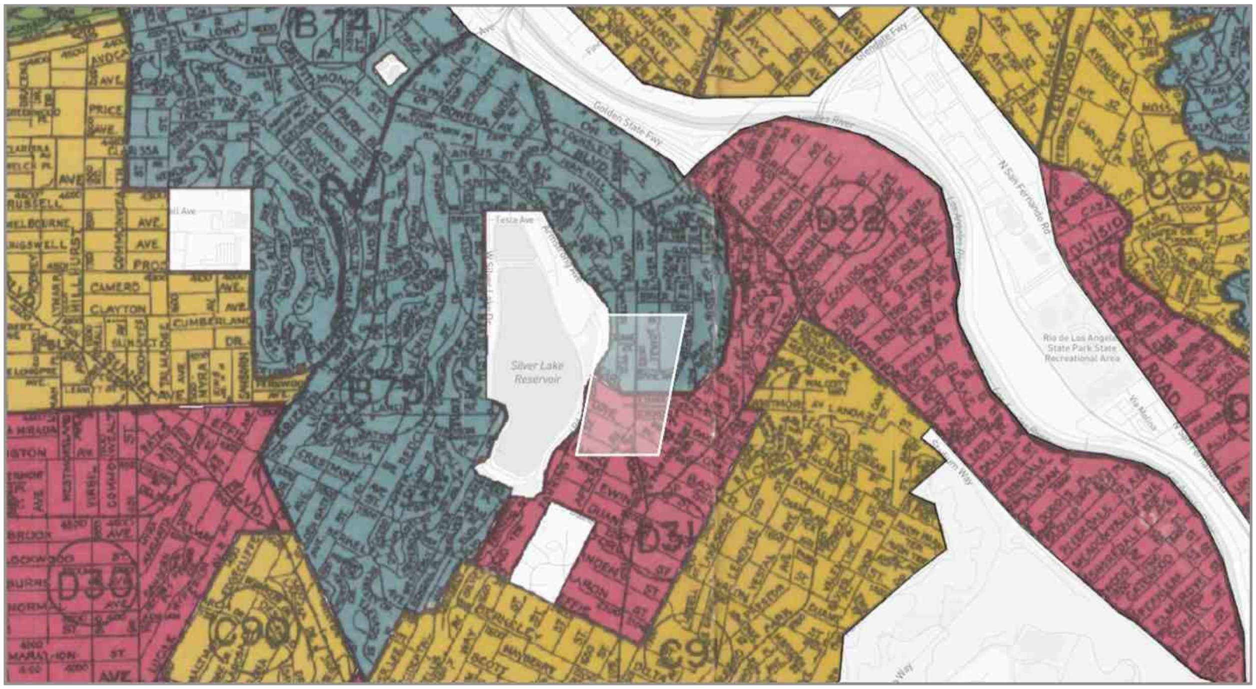
Maps 3a and 3b show the blue (B75) and red-graded (D31) neighborhoods, the test area denoted by the white polygon, and the homes that lie within this polygon that are used in the regression analysis. All single-family homes used in the analysis are shown as black dots, as determined by their respective geo-coordinates. B75 was assigned a blue-grade and not a green-grade because of a lack of proper direction in development as well as because “[t]he topography of the area protects it form [sic] the subversive elements of adjacent lower grade area” (Nelson, et. al., 2021). On the other hand, HOLC assigned D31 a red grade based on the slow development of the area and “substandard to standard” construction, as well as due to the population being heterogeneous and of the lower income group. In 1939, residents in B75 were mainly white-collar workers versus mostly skilled and unskilled artisans and laborers in D31. Mortgage funding was ample for B75 but very limited for D31. House prices and rents in 1939 were much higher for B75 ($5,000-$9000 and $50-$90, respectively) compared to those in D31 ($2,500-$3,500 and $25-$40, respectively). Further, 100 new homes were constructed in B75 in 1938 versus just two in D31 (Table A1).

MAP 3A

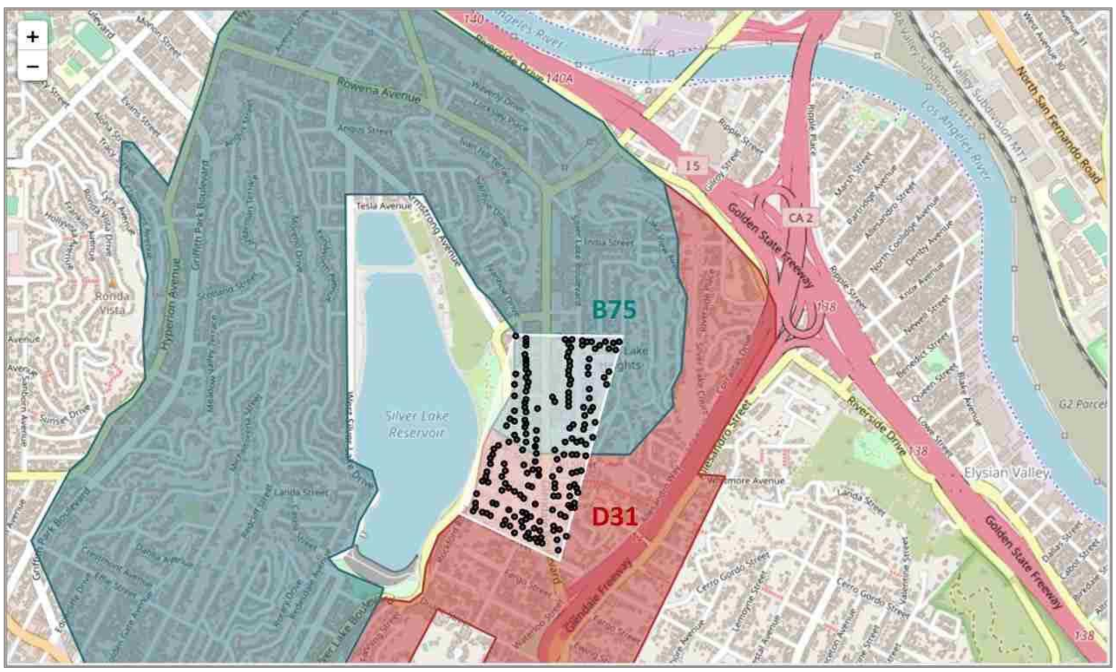
Nelson, et. al., Mapping Inequality, Retrieved February 15, 2023, https://dsl.richmond.edu/panorama/redlining/#loc=10/34.005/-118.544&city=los-angeles-ca

[3] Nelson, et. al., Mapping Inequality, Retrieved February 15, 2023, https://dsl.richmond.edu/panorama/redlining/#loc=10/34.005/-118.544&city=los-angeles-ca

[4] All geospatial analyses in this study were conducted using the GeoPandas module in Python.



MAP 3B[5]



[5] Shapefiles for D31 and B75 were accessed from the Mapping Inequality website (Nelson, et. al., 2021).

Table 1 provides a summary of the current physical attributes of all single-family homes mapped in the white polygon in Map 3b which are also located in B75 and D31. The typical living area of a home in B75 is slightly smaller than that of a home in D31. Further, the mean and median values of homes in D31 are slightly higher than homes in B75. VCS (Veros Confidence Score) values are also similar in both neighborhoods, suggesting that the AVMs accuracy is comparable for the two areas. VCS is not used as a predictor variable in the regression analyses; we provide its value only to show the AVM's relative accuracy in the red versus blue areas.

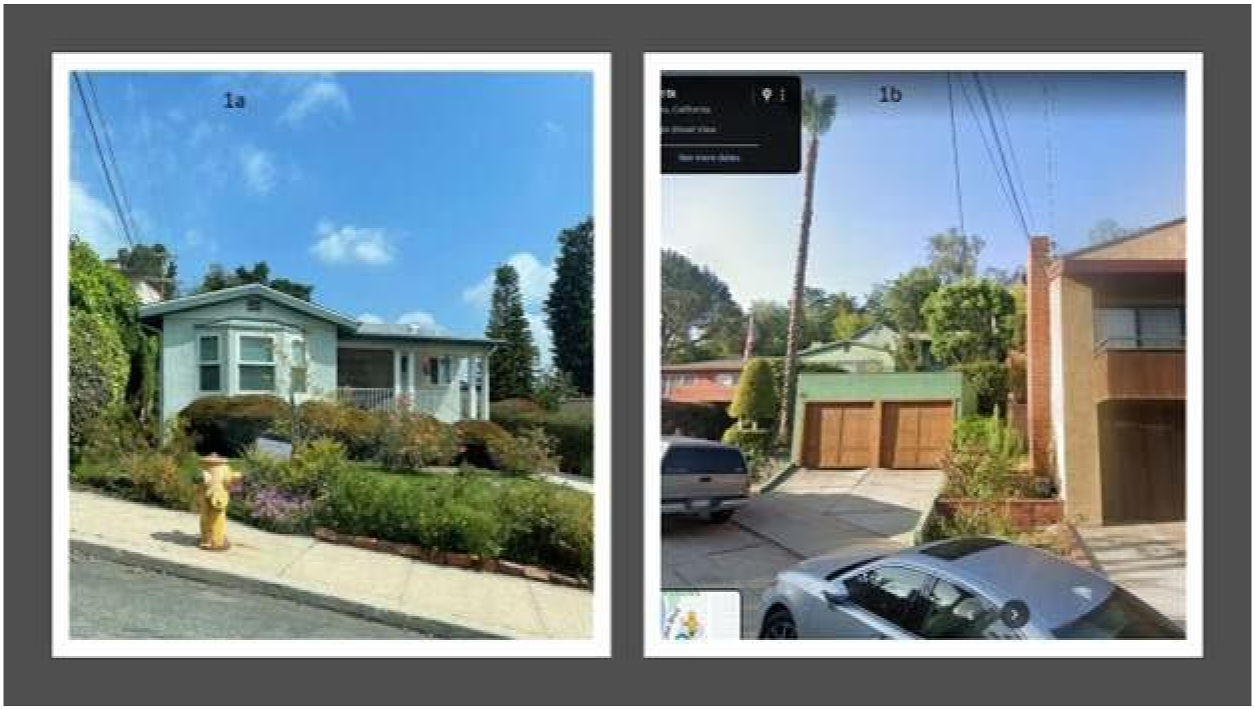
TABLE 1. PHYSICAL ATTRIBUTES OF HOMES IN B75 AND D31

HOLC ID	**B75 (n=97)**		**D31 (n=97)**	
	Mean	Median	Mean	Median
VeroVALUE	1,708,505	1,708,000	1,742,124	1,721,000
Lot size square feet	7,039	6,722	6,277	7,024
Living area square feet	1,604	1,498	1,767	1,844
Number of bedrooms	2.6	2.0	2.8	3.0
Number of bathrooms	2.0	2.0	2.3	2.0
Pool	0.1	0.0	0.1	0.0
Fireplace	0.5	1.0	0.3	0.0
VCS	87	88	86	87

While driving through the neighborhoods that were in the HOLC assigned D31 area, we came across an older hillside community with homes of differing quality and views. The accompanying image (Picture 1) depicts a street view of homes in the area. In addition to single-family homes, there were multi-family homes and apartments in the neighborhood, some of which appeared to need some maintenance.[6]

[6] Neighborhood descriptions for D31, B75, Blocks X & Y, D41 and B83 were provided by Jeffrey Hogan, SRA, AI-RRS, VP Valuations, Veros Real Estate Solutions.

PICTURE 1. HOMES IN D31[7]



The B75 area also consisted of hillside neighborhoods with older homes, but in contrast to the D31 area, there was a greater proportion of homes with higher quality construction, more attractive designs, and better upkeep of homes. The streets in this area were generally wider and quieter, and there were fewer multi-family homes in the neighborhoods.

Descriptive statistics pertaining to the sample of residences employed in our investigation (Table 1) indicate that the mean living area of properties located in D31 is larger compared to those located in B75. Upon closer scrutiny, we discovered that 12 residences in D31 were constructed post 2000, while none were built in B75 after 2000. The mean living area of these 12 properties is 2,645 square feet. For the remaining homes, the average living area was comparable to that of homes in B75. This evidence suggests that the historical impact of redlining is not permanent in all communities and that the physical characteristics of residences are undergoing change over time within this community (D31).

[7] 1b: Google (n.d.). [Google map of Earl Street, Los Angeles, CA]. Retrieved May 9, 2023, from https://tinyurl.com/AreaD31

PICTURE 2. HOMES IN B75

The results of the regression are provided in Table 2, which shows that the location variable is small and insignificant; that is, the location of a home, whether it is in B75 or D31, does not impact its VeroVALUE estimate. Land area is insignificant, while the size of the living area has a positive and significant coefficient, suggesting that a home with a larger living area has a higher valuation. The number of bedrooms and bathrooms are insignificant predictors of VeroVALUE for this sample of properties. However, homes without a fireplace (negative and significant coefficient) or a pool (negative and marginally significant coefficient) are valued lower. The value of R-squared for this regression is 49%, suggesting that the model explains 49% of the variation in house prices, whereas the remainder is explained by variables outside the model. It is possible that other physical attributes or external factors, such as lake view or proximity to the lake/park, are influencing house prices.

TABLE 2. REGRESSION RESULTS FOR B75-D31

Dependent variable - VeroVALUE (Log-transformed)		
Variable	Estimate	p-value
Intercept	10.6011	<.0001*
Lot size sq ft (Log-transformed)	0.0346	0.3346
Living area sq ft (Log-transformed)	0.4910	<.0001*
Number of bedrooms	0.0233	0.2520
Number of bathrooms	-0.0407	0.1431
Pool (absent)	-0.1058	0.0739***
Fireplaces (absent)	-0.1271	0.0002*
Location (B75)	0.0017	0.9583
R-squared	49%	

*Significant at 1%, ***significant at 10%

The regression results for area 1 show that the variation in AVM values between a historically redlined area (D31) and a historically good area (B75) that are geographically close to one another is explained primarily by the living square footage, and presence of a pool and fireplace, but not by the geographical location (a historical redlined area or not) of the property. Hence, the VeroVALUE did not undervalue properties in the redlined area or overvalue properties in blue-graded area. The AVM does not see whether a property is in a redlined or a blue area; however, we do not make any predictions about the possibility of such considerations being included or excluded in a human appraisal.

D31 – Blocks X and Y

The redlined area D31 provides a fortuitous opportunity to test if spatially distant homes within a single redlined neighborhood can be valued differently, even after accounting for physical attributes. The northeast corner of D31 is bounded by two noisy highways (Block Y), while a section towards the west is away from the highways but is bounded by a lake (Block X). We specifically selected these two blocks because their respective locations have visible distinctions: the two highways that bound Block Y on the northeast corner and a lake that bounds Block X on its western boundary.

MAP 3C[8]

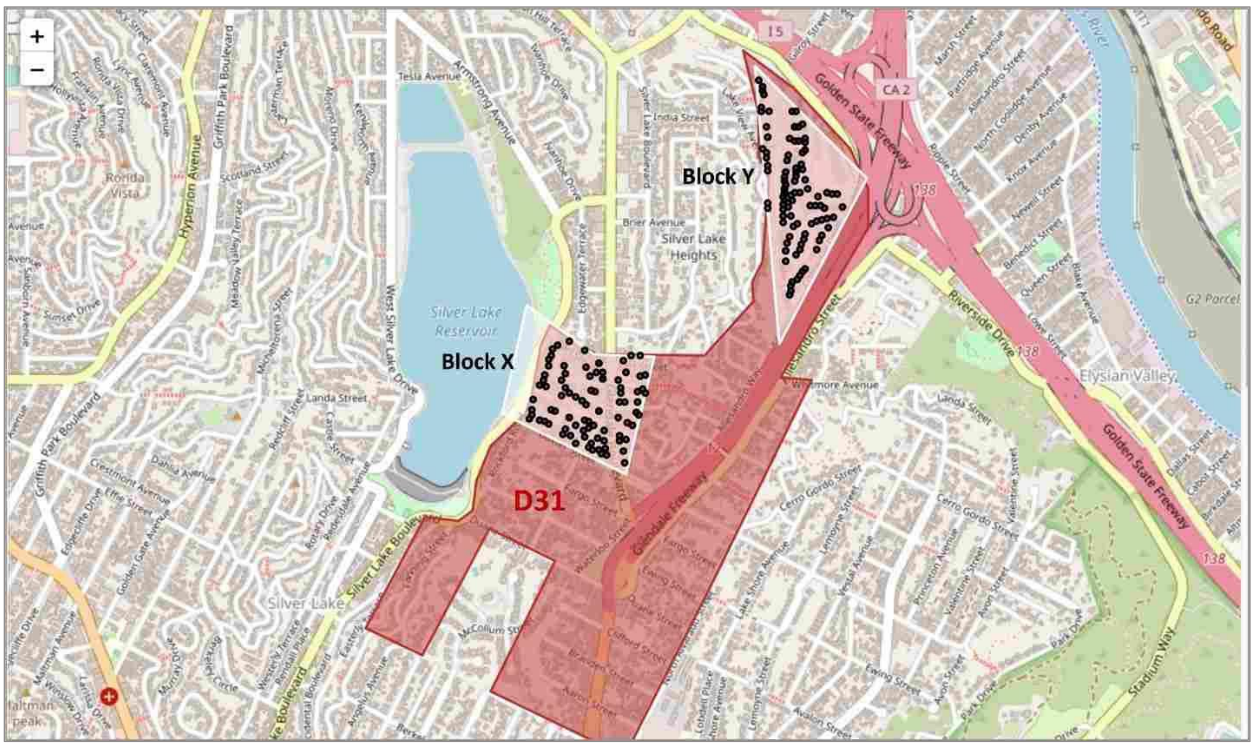


Table 3 summarizes the physical attributes of homes in Blocks X and Y. The lot sizes and living areas of homes in Block X are larger than in Block Y. Additionally, more homes in Block X have pools and fireplaces than in Block Y. The mean and median VeroVALUE estimates are higher for properties in Block X, while the median VCS scores are in the 87-89 range for both blocks.

[8] Shapefile for D31 was accessed from the Mapping Inequality website (Nelson, et. al., 2021).

TABLE 3. PHYSICAL ATTRIBUTES OF HOMES IN D31 – BLOCKS X AND Y

HOLC ID	Block X (n=90)		Block Y (n=94)	
	Mean	Median	Mean	Median
VeroVALUE	1,748,189	1,701,500	1,443,404	1,417,000
Lot size square feet	6,164	6,936	5,490	5,400
Living area square feet	1,761	1,758	1,455	1,330
Number of bedrooms	2.7	3.0	2.8	3.0
Number of bathrooms	2.3	2.0	2.0	2.0
Pool	0.1	0.0	0.0	0.0
Fireplace	0.4	0.0	0.1	0.0
VCS	86	87	88	89

The following pictures, which were captured by the authors, show the street views of homes in Blocks X and Y. Neighborhood Y is situated close to two highways, while Neighborhood X is close to Silver Lake. Block Y consists of older hillside properties with differing degrees of quality and views. Certain residences lacked garage access, and the area had narrow streets. Despite some homes having views of the freeways, their elevated position offered pleasing vistas, making them appealing to potential home buyers. It is worth noting that there was some traffic noise present.

PICTURE 3. HOMES IN BLOCK Y[9]

The residences situated in Block X seemed to possess more substantial dimensions, particularly those situated towards Silver Lake. These properties presented superior aesthetic appeal and larger plots of land.

[9] 3a - Google (n.d.). [Google street view of Riverside Place, Los Angeles, CA]. Retrieved May 9, 2023, from https://tinyurl.com/D31BlockY

PICTURE 4. HOMES IN BLOCK X

The results of the regression (Table 4) show that lot size and living areas are significantly and positively correlated with the VeroVALUE. The number of bedrooms and bathrooms are insignificant predictors of VeroVALUE, while the presence of a fireplace or pool positively influences the valuation of properties. Most importantly, the location variable is positive and significant. This implies that properties in Block X are valued around 5.6% more than properties in block Y after accounting for physical attributes. The significance of the location variable (Block X or Y) could be due to the omission of other physical attributes or external variables not included in the regression analysis. Perhaps the proximity of highways to Block Y renders lower values for properties in this area compared to properties that are in Block X that are closer to a lake, which possibly provides better views and activities that are not measured in the regression. The R-squared value for this regression is 70%, an improvement over the value for the B75-D31 regression, indicating that a large proportion of the price variation can be explained by proximity to a highway or a lake.

TABLE 4. REGRESSION RESULTS FOR D31 – BLOCKS X AND Y

Dependent variable - VeroVALUE (Log-transformed)		
Variable	Estimate	p-value
Intercept	10.6238	<.0001*
Lot size sq ft (Log-transformed)	0.1246	0.0002*
Living area sq ft (Log-transformed)	0.3607	<.0001*
Number of bedrooms	0.0106	0.5035
Number of bathrooms	0.0253	0.2229
Pool (absent)	-0.0580	0.0581***
Fireplaces (absent)	-0.1598	0.0015*
Location (Block X)	0.0559	0.0395**
R-squared	70%	

*Significant at 1%, **significant at 5%, ***significant at 10%

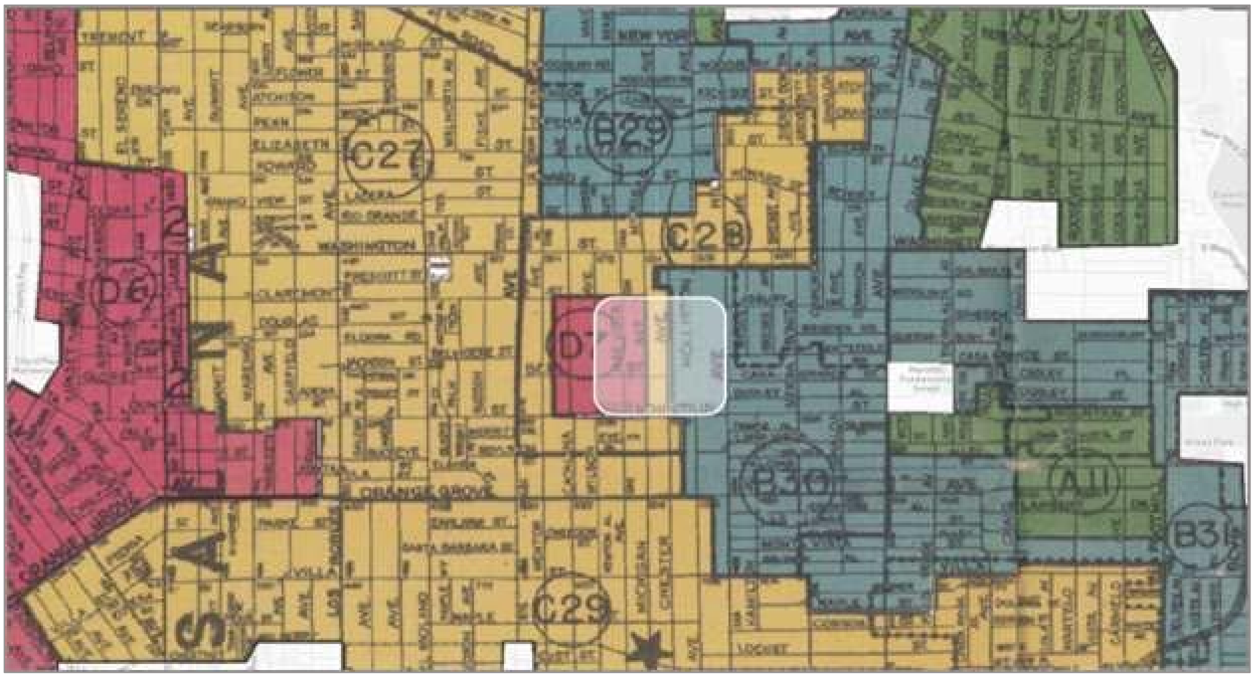
This analysis shows that estimates may differ for homes in spatially distant neighborhoods within a redlined area due to some external factors.

Area 2. The B30 – D7 Boundary

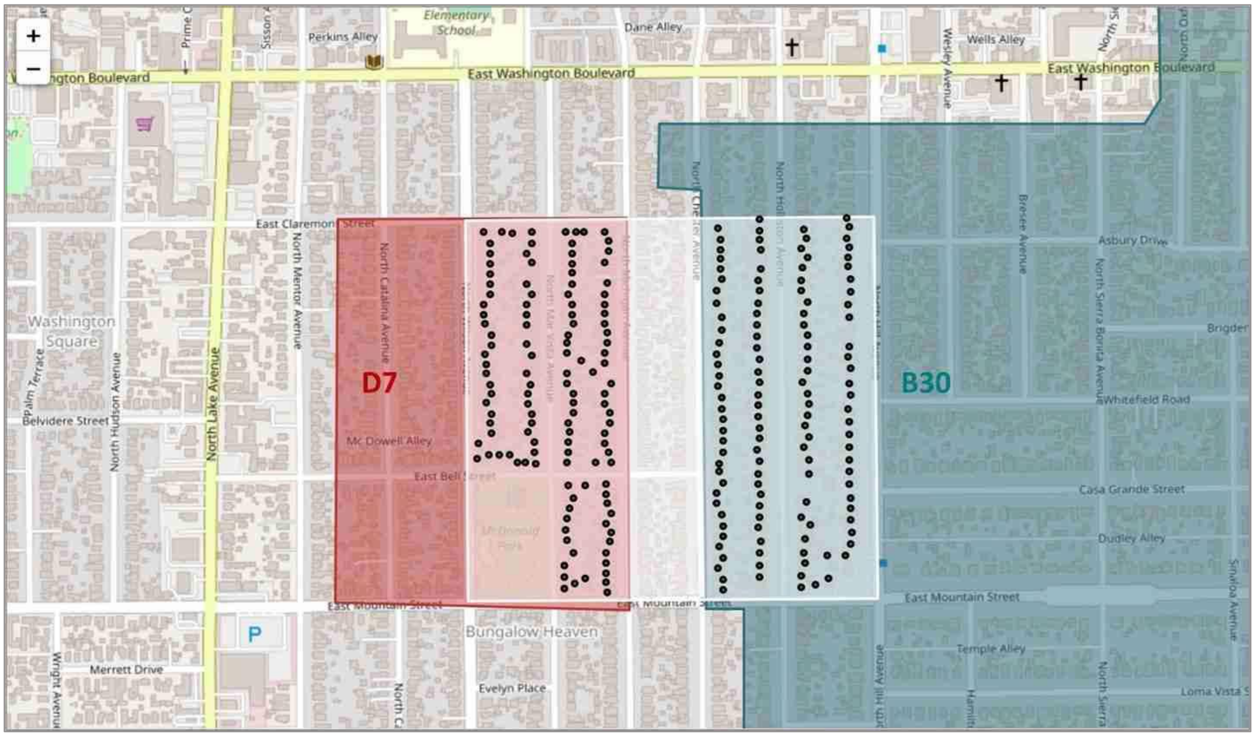
The first map (4a) shows the location of the B30 and D7 neighborhoods in the Los Angeles area. Map 4b shows D7 in red and B30 in blue, along with a white rectangle – our area of interest.

MAP 4A

Nelson, et. al., Mapping Inequality, Retrieved February 15, 2023, https://dsl.richmond.edu/panorama/redlining/#loc=10/34.005/-118.544&city=los-angeles-ca



MAP 4B[10]



We selected the D7-B30 boundary despite there being a yellow or C-graded block between the two. The yellow-graded block (C28) is narrow and spans just two rows of houses.

Based on texts accompanying the HOLC maps, the D7 neighborhood was assigned a red grade based "solely on account of racial hazards" (Nelson, et. al., 2021). On the other hand, B30 was assigned a blue grade because "[p]opulation [was] highly respectable and homogeneous." Table A2 (appendix) shows the housing and population characteristics of the two blocks that existed in 1939. The occupation of the residents of B30 was mostly business and professional individuals as opposed to artisans and laborers in D7; correspondingly, the income levels in B30 were twice that of incomes in D7. It can be inferred that homes in D7 were smaller than those in B30 in the late 1930s because the former had fewer rooms and lower prices and rental costs than the latter. Further, mortgage funds in B30 are listed as ample versus limited in D7. Also interesting is that no new homes were built in D7 in 1938, while 25 new homes were constructed in B30 that year.

Table 5 summarizes the current physical attributes of all single-family homes mapped in the white rectangle in map 4b, for which a VeroVALUE was returned. Additionally, all these properties had data on lot size, living area, number of bedrooms, bathrooms, presence or absence of a pool, and fireplace. The table also provides the mean and median value of VCS, which shows that the accuracy of the AVM is similar across both areas.

[10] Shapefiles for D7 and B30 were accessed from the Mapping Inequality website (Nelson, R.K., et. al.).

TABLE 5. PHYSICAL ATTRIBUTES OF HOMES IN B30 AND D7

HOLC ID	B30 (n=128)		D7 (n=126)	
	Mean	Median	Mean	Median
VeroVALUE	1,562,359	1,567,000	1,300,706	1,314,000
Lot size square feet	10,701	10,385	7,927	8,241
Living area square feet	1,965	1,843	1,468	1,412
Number of bedrooms	3.2	3.0	2.9	3.0
Number of bathrooms	2.1	2.0	1.7	2.0
Pool	0.2	0.0	0.1	0.0
Fireplace	0.9	1.0	0.8	1.0
VCS	89	90	89	90

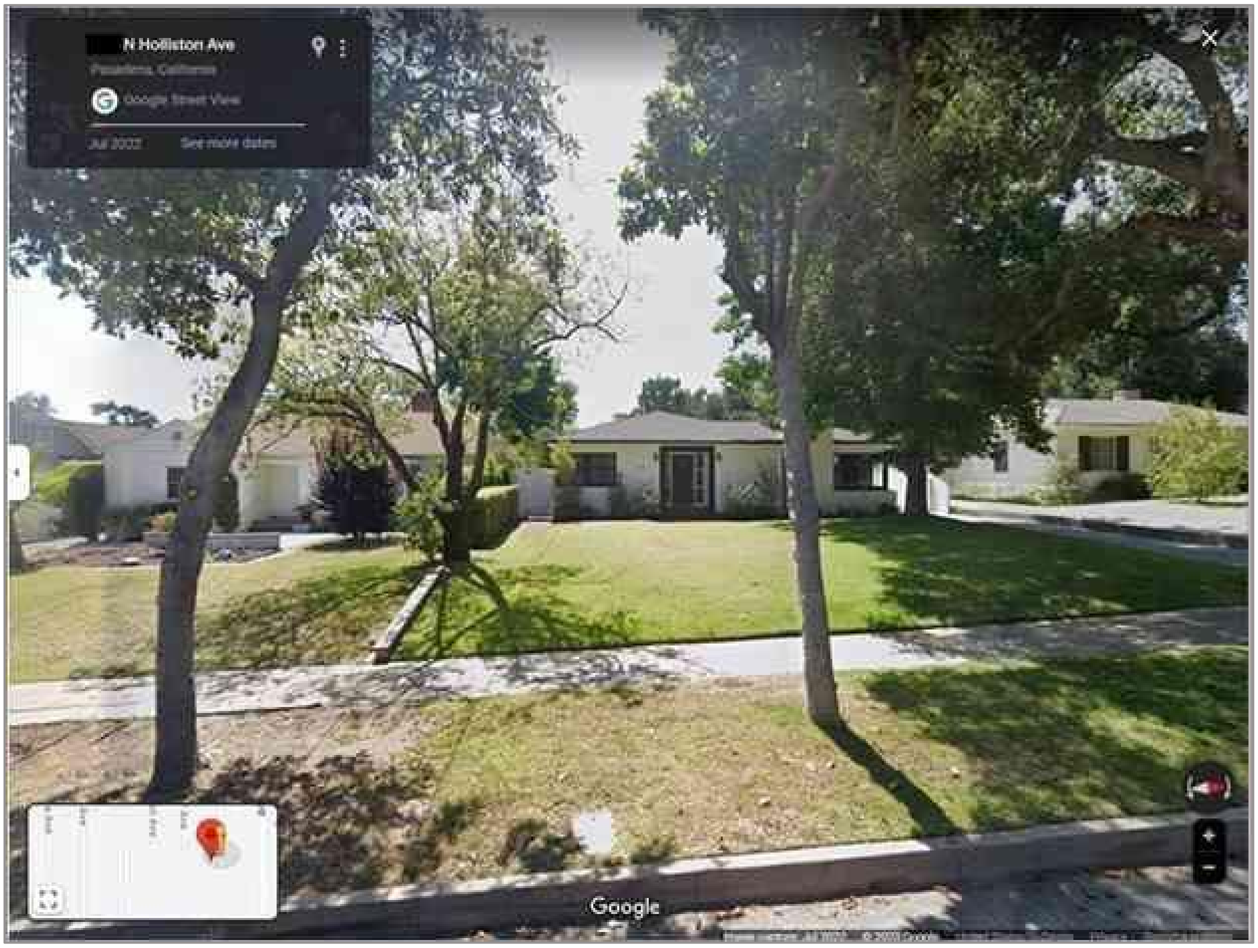
Homes located within the B30 boundary have larger lots and living areas compared to homes in D7. Further, the mean values of the number of bedrooms and bathrooms are slightly higher in B30 than in D7. Also, the median VeroVALUE of homes in B30 is much higher than that of homes in D7. Our analysis tests whether the differences in VeroVALUE can be explained by the physical attributes of the properties on either side of the boundary or if the difference in valuation is attributable to the property's geographical location (B30 versus D7).

The pictures below (5 and 6) show the street views of homes from the two areas (D7 and B30) obtained from Google Maps. Homes in B30 appear to have better maintenance, larger lots and living areas compared to properties in D7.

PICTURE 5. HOMES IN D711

[11] Google (n.d.). [Google street view of Mar Vista Ave., Los Angeles, CA]. Retrieved May 9, 2023, from https://tinyurl.com/AreaD7

PICTURE 6. HOMES IN B30[12]



The results of the regression are provided in Table 6, which shows that the coefficient of the location variable is small and insignificant; that is, the location of a home, whether it is in B30 or D7, does not impact its VeroVALUE estimate. Land area is insignificant, while the size of the living area has a positive and significant coefficient, suggesting that a home with a larger living area has a higher valuation. The number of bedrooms has a negative and significant coefficient, suggesting that for a given living area, fewer bedrooms result in a higher valuation for a property. Also, the number of bathrooms has a positive association with the AVM estimates. The presence or absence of a pool or fireplace does not significantly influence the dependent variable. R-squared for this regression is high, suggesting that the model explains 79% of the variability in house prices.

[12] Google (n.d.). [Google street view of N Holliston Ave., Los Angeles, CA]. Retrieved May 9, 2023, from https://tinyurl.com/AreaB30

TABLE 6. REGRESSION RESULTS FOR B30-D7

Dependent variable - VeroVALUE (Log-transformed)		
Variable	Estimate	p-value
Intercept	9.7035	<.0001*
Lot size sq ft (Log-transformed)	0.0520	0.1121
Living area sq ft (Log-transformed)	0.5402	<.0001*
Number of bedrooms	-0.0307	0.0052*
Number of bathrooms	0.0379	0.0008*
Pool (absent)	0.0027	0.8920
Fireplaces (absent)	-0.0053	0.8002
Location (B30)	0.0025	0.8785
R-squared	79%	

*Significant at 1%

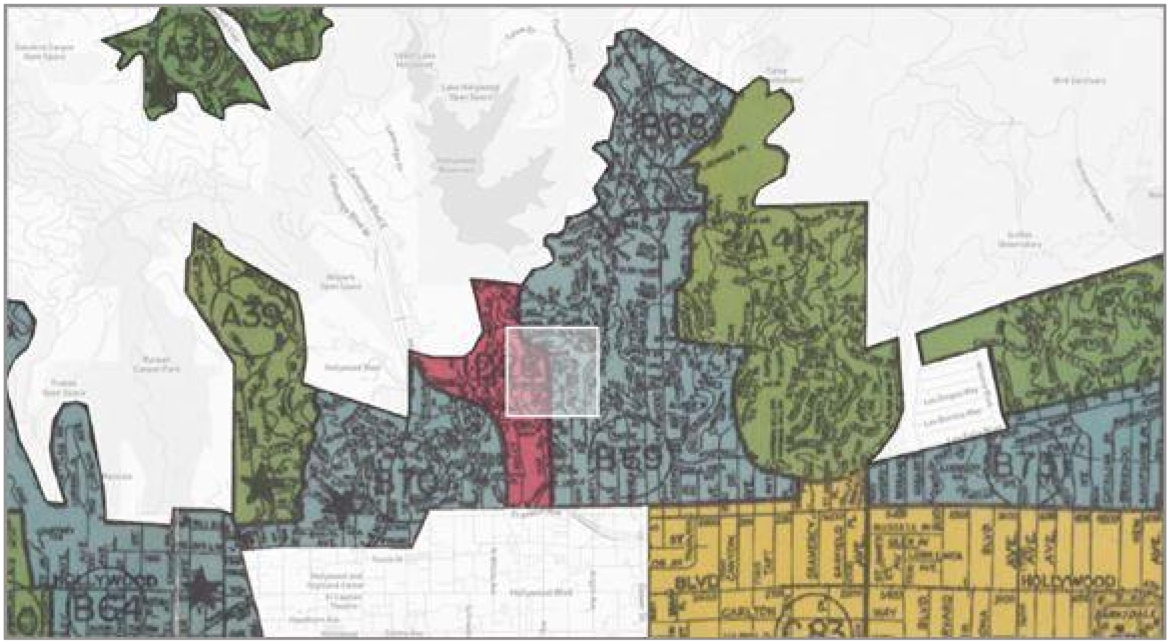
The regression results show that the variation in AVM values in today's market between a historically redlined area (D7) and a historically higher-graded area (B30) that are adjacent to one another is explained primarily by the living square footage, and the number of bedrooms and bathrooms, while the location of a property (a historical redlined area or not) is not a significant predictor of VeroVALUE estimates. Whether appraised values could have potential bias by a human appraiser based on the location of a house in a historically redlined area is beyond the scope of this paper.

Area 3. The B69 – D28 Boundary

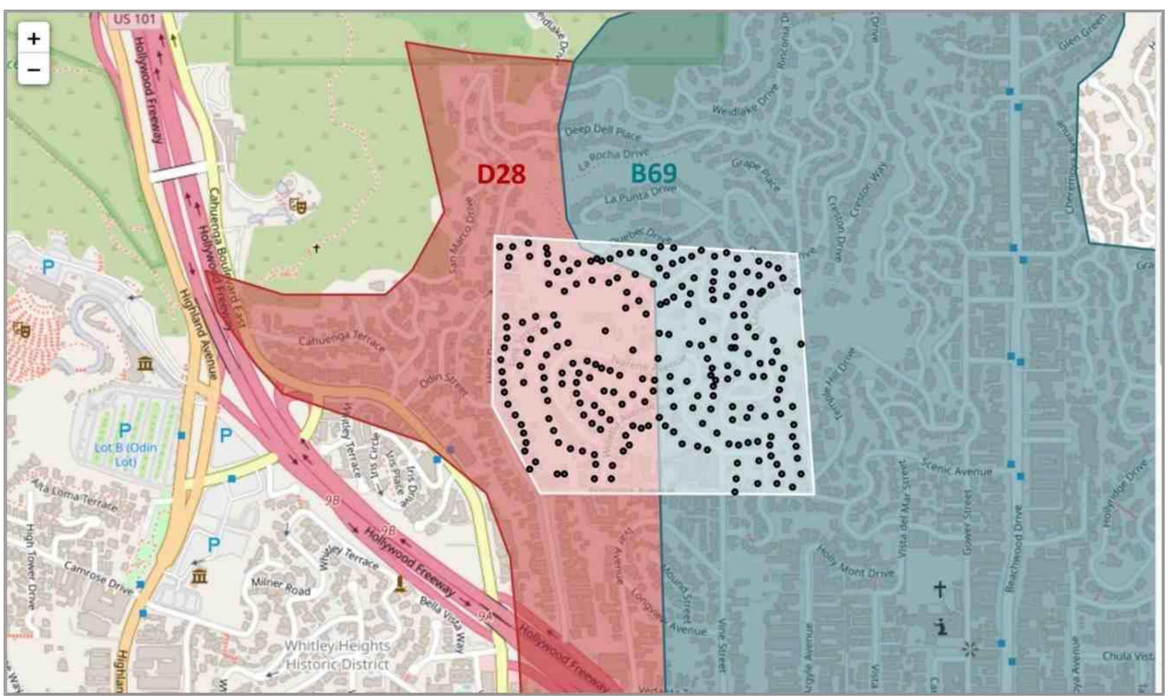
Maps 5a and 5b show the blue (B69) and red graded (D28) blocks, along with the homes used in the regression analysis. This boundary provides an interesting case since here, the red block – D28 – was assigned a red grade only due to "the psychological hazard of the Mullholland Dam," despite its homogeneous population (Nelson, et. al., 2021). No Black families lived in D28 when the HOLC maps were generated. This block was perhaps an exception to the redlining rule, where it was deemed "hazardous" based solely on the presence of a dam rather than the demographic characteristics of its population. B69 was assigned only a blue grade rather than green because of the area's age and obsolescence. The 1939 price and rental values of homes in B69 and D28 were almost identical, and so were the occupations of the inhabitants. The key difference was the availability of mortgage funds – ample for B69 but very limited for D28. Table A3 (appendix) shows the housing and population characteristics of the two blocks that existed in 1939.

MAP 5A

Nelson, et. al., Mapping Inequality, Retrieved February 15, 2023,
https://dsl.richmond.edu/panorama/redlining/#loc=10/34.005/-118.544&city=los-angeles-ca



MAP 5B[13]



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[13] Shapefiles for D28 and B69 were accessed from the Mapping Inequality website (Nelson, et. al., 2021).

Homes located within the B69 boundary have larger living areas compared to homes in D28 and correspondingly higher VeroVALUE estimates (Table 7). Average lot sizes are similar in both areas, while the average number of bathrooms and bedrooms is higher in B69 compared to D28. The accuracy of the VeroVALUE estimates as measured by the VCS scores is also similar.

TABLE 7. PHYSICAL ATTRIBUTES OF HOMES IN B69 AND D28

HOLC ID	B69 (n=121)		D28 (n=107)	
	Mean	Median	Mean	Median
VeroVALUE	2,043,636	1,950,000	1,951,579	1,871,000
Lot size square feet	6,440	5,140	6,487	5,805
Living area square feet	2,060	1,931	1,885	1,708
Number of bedrooms	2.9	3.0	2.8	3.0
Number of bathrooms	2.5	2.0	2.2	2.0
Pool	0.2	0.0	0.2	0.0
Fireplace	0.7	1.0	0.7	1.0
VCS	89	89	88	88

The following pictures showing the street views of homes in D28 and B69 were obtained from Google Maps (maps.google.com). Neighborhoods in D28 and B69 seem similar in terms of property quality.

PICTURE 7. HOMES IN D28[14]

[14] Google (n.d.). [Google street view of Ivarene Ave., Los Angeles, CA]. Retrieved May 9, 2023, from https://tinyurl.com/AreaD28

PICTURE 8. HOMES IN B69[15]

The regression results (Table 8) show that the location variable is small and insignificant; that is, the location of a home, whether it is in B69 or D28, does not impact its VeroVALUE estimate. Land and living areas have positive and significant coefficients, suggesting that a home with a larger living area or a larger lot size has a higher valuation. The number of bedrooms is an insignificant predictor of home values, whereas the number of bathrooms is a positive and significant predictor of VeroVALUE. Homes without a fireplace or a pool are valued lower as both coefficients are significant and negative. The high value of R-squared (72%) indicates that a large proportion of the variance in home values in this area can be explained by their physical attributes.

TABLE 8. REGRESSION RESULTS FOR B69-D28

Dependent variable - VeroVALUE (Log-transformed)		
Variable	Estimate	p-value
Intercept	10.5848	<.0001*
Lot size sq ft (Log-transformed)	0.1209	<.0001*
Living area sq ft (Log-transformed)	0.3778	<.0001*
Number of bedrooms	0.0139	0.2943
Number of bathrooms	0.0301	0.0350**
Pool (absent)	-0.1106	<.0001*
Fireplaces (absent)	-0.0664	0.0015*
Location (B69)	0.0074	0.6858
R-squared	72%	

*Significant at 1%, **significant at 5%

[15] Google (n.d.). [Google street view of Alcyona Dr., Los Angeles, CA]. Retrieved May 9, 2023, from https://tinyurl.com/AreaB69

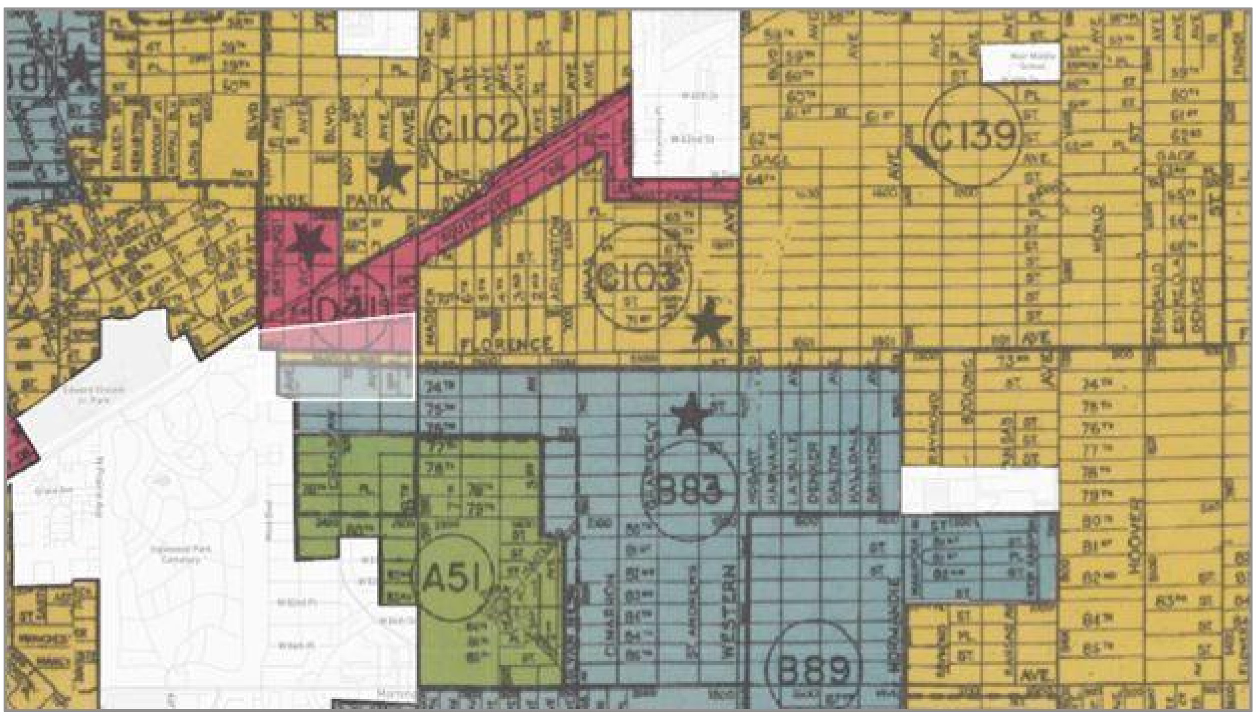
In summary, the AVM model does not know about historical redlined areas, whether they were assigned the red grade based on their racial composition or due to the presence of a dam. The physical attributes of homes explain the variations in home values in Area 3, and not the location of a property (a historical redlined area or not).

Area 4. The B83 – D41 boundary

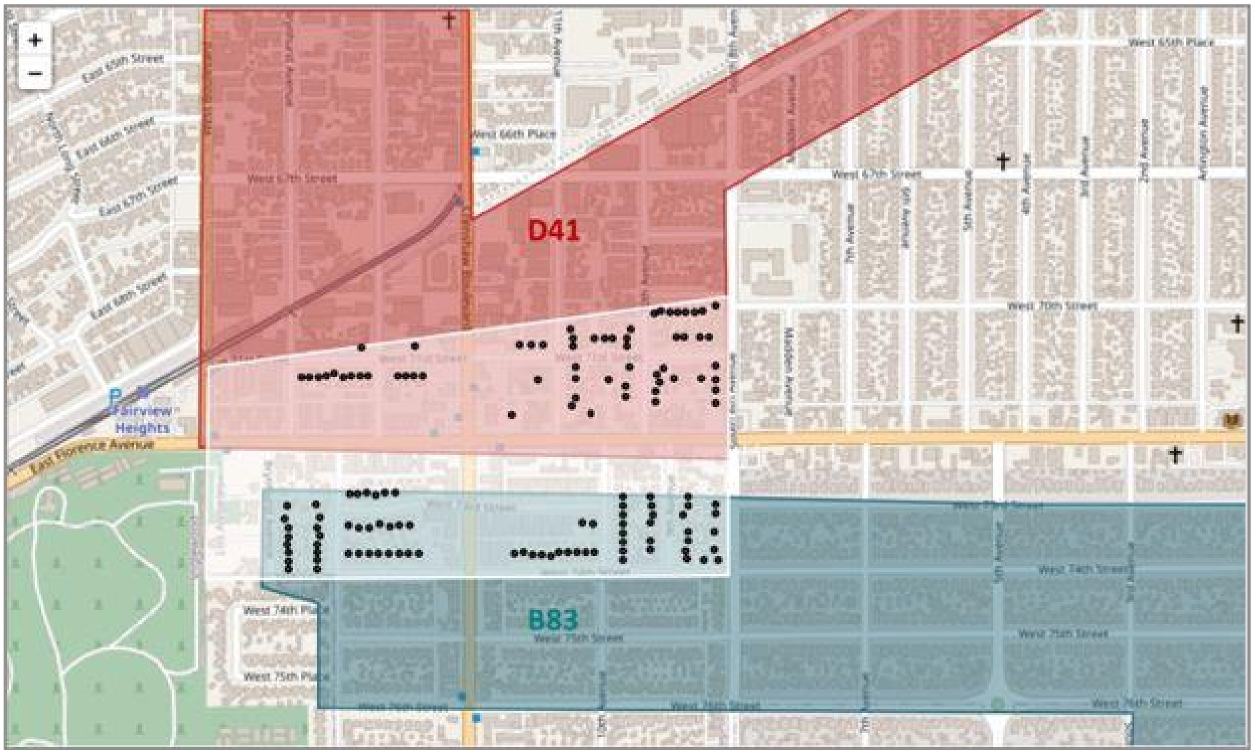
Areas B83 and D41 are shown in maps 6a and 6b, with map 6b also depicting the homes used in the regression analysis. B83 was assigned only a blue grade instead of a green grade because of the presence of many multiple-family structures and the high percentage of development in the area (Nelson, et. al., 2021). Its population is listed as “homogeneous,” primarily consisting of professionals and businessmen, white-collar workers, and skilled artisans, earning wages in the $1,800-$3,600 range. D41 was assigned a red grade not only due to the “heterogeneous” population, but also because of shoddy construction, a railway line intersecting the area, and residences being interspersed with light industry. Inhabitants of D41 were mostly factory workers, artisans, or laborers with wages in the range of $700-$1,000. Additionally, homes were smaller and older in D41 compared to those in B83, with the average price of homes in D41 at $1,500-$2,000 compared to $4,000-$5,500 in B83. Finally, mortgage funds were ample in B83, while none were available for D41 (see Table A4).

MAP 6A

Nelson, et. al., Mapping Inequality, Retrieved February 15, 2023,
https://dsl.richmond.edu/panorama/redlining/#loc=10/34.005/-118.544&city=los-angeles-ca



MAP 6B[16]



Currently, homes in B83 have larger lot sizes and living areas, and more bathrooms (Table 9). Additionally, more homes have a fireplace in B83 than in D41. VeroVALUE estimates are also higher for properties in B83 compared to those in D41. The accuracy of the VeroVALUE estimates (VCS) is similar for the two areas.

TABLE 9. PHYSICAL ATTRIBUTES OF HOMES IN B83 AND D41

HOLC ID	B83 (n=76)		D41 (n=61)	
	Mean	Median	Mean	Median
VeroVALUE	803,474	794,500	756,066	747,000
Lot Size square feet	6,346	6,083	5,122	5,005
Living area square feet	1,488	1,412	1,368	1,295
Number of bedrooms	2.9	3.0	3.1	3.0
Number of bathrooms	1.8	2.0	1.6	1.0
Pool	0.0	0.0	0.0	0.0
Fireplace	0.6	1.0	0.2	0.0
VCS	89	90	89	90

[16] Shapefiles for D41 and B83 were accessed from the Mapping Inequality website (Nelson, et. al., 2021).

While driving through the D41-B83 neighborhoods we found that the D41 region's properties were characterized by smaller lots and homes, which varied in quality. Moreover, the streets were poorly maintained, and several multi-family homes and apartments were scattered amidst the single-family homes.

PICTURE 9. HOMES IN D41

In contrast, residences in B83 were situated on larger plots of land and had a greater proportion of high-quality homes and wider, well-maintained, quieter streets, making them more desirable.

PICTURE 10. HOMES IN B83

The regression results (Table 10) indicate that the location variable is small and insignificant; that is, the location of a home, whether it is in B83 or D41, does not impact its VeroVALUE estimate. Land area is insignificant, while living area is a positive and significant predictor of VeroVALUE, implying that a home with a larger living area has a higher valuation. The number of bedrooms and bathrooms are insignificant predictors of VeroVALUE for this sample of homes. Homes without a fireplace or a pool are valued lower, as both coefficients are significant and negative. The R-squared value is high (62%), demonstrating the strength of the relationship between prices and the explanatory variables.

TABLE 10. REGRESSION RESULTS FOR B83-D41

Dependent variable - VeroVALUE (Log-transformed)		
Variable	Estimate	p-value
Intercept	10.7910	<.0001*
Lot size sq ft (Log-transformed)	0.0555	0.2099
Living area sq ft (Log-transformed)	0.3369	<.0001*
Number of bedrooms	-0.0117	0.3001
Number of bathrooms	0.0176	0.2482
Pool (absent)	-0.0393	0.0267**
Fireplaces (absent)	-0.1157	0.0743***
Location (B83)	-0.0040	0.8416
R-squared	64%	

*Significant at 1%, **significant at 5%, ***significant at 10%

The differences in AVM values in area 4 are explained by the physical characteristics of the homes and not by their location whether in a historically redlined area or a historically good area. The location of a property (a historically redlined area or not) is not a significant predictor of VeroVALUE estimates. Hence, VeroVALUE does not assign lower values to properties in redlined areas or higher values to properties in blue-graded areas of the HOLC maps.

Conclusions

We find that when we compare the physical attributes of homes in 1939 redlined areas versus blue-graded areas based on texts accompanying the HOLC maps, homes in the blue areas were typically larger, of better quality, and priced higher. The most important distinction was the availability of ample mortgage funds in the blue neighborhoods versus very limited or no mortgage funds in the redlined areas. Further, in 1939, residents in redlined areas had lower incomes and, in combination with the lack of mortgage funds, could not build homes or afford larger homes (tables A1, A2, A3, and A4). The impact of redlining exists even today, after nearly nine decades – homes located in historically redlined neighborhoods are characterized by smaller lot sizes and living areas compared to homes that are in historically blue-graded neighborhoods. We also found that residences in historically redlined neighborhoods had more variations in the quality of construction and upkeep. In addition to the physical distinctions, there are likewise differences in home values (tables 5, 7, and 9), which points to the impact of historical redlining.

We tested if the VeroVALUE AVM generates different outcomes for homes located on either side of a red boundary (as drawn in the HOLC maps) within a narrow geographic band after controlling for physical attributes. This narrow geographic band would be consistent with "comparable sales" that an AVM would use in its analyses. The comparative assessment models utilized in estimating VeroVALUE consider all recent sales within a given radius around the target property. Hence the valuation of a property on or near the boundary of a HOLC map could include "comparable sales" on both sides of the redline. We analyzed VeroVALUE estimates across four boundaries in Los Angeles. The regression results show that after controlling for physical attributes such as the size of spatially proximate residential properties, the location of a property (a historically redlined area or not) is not a significant predictor of VeroVALUE estimates. Therefore, based on the results of this study for Los Angeles, estimates provided by VeroVALUE show no indication of undervaluing properties in redlined areas or overvaluing properties in blue-graded areas of the HOLC maps. Also, HOLC boundaries did not correspond with administrative borders such as census tracts or wards (Hillier, 2003). Hence the demarcation made by these boundaries does not exist directly or through proxies in our AVM. We find in this study that the VeroVALUE AVM has no indications of algorithmic bias due to historic redlining practices, just as our previous study showed that it had no algorithmic bias due to the racial composition of neighborhoods (Agrawal & Fox, 2022). This report also concludes that estimates may differ for homes in spatially distant neighborhoods within a redlined area. This is due to some external factors other than HOLC grades (e.g., lake view or proximity to a highway) or other physical attributes that are not included in our analysis.

While the current study has analyzed redlined neighborhoods in Los Angeles, we believe it is important to continue studying other historically redlined neighborhoods in metros across the United States to validate that similar conclusions are obtained. This is because VeroVALUE is modeled to incorporate comparable properties in a radius around the target property and does not include any protected class variables or geographic boundaries related to HOLC maps. We intend to undertake a future study that will include other major cities and regions to get a more comprehensive idea of VeroVALUE's performance with respect to historical redlining.

Recommendations

This report is focused on the home valuation estimates provided by VeroVALUE. The results of this report are based on four redlined areas in Los Angeles that had contiguous borders with blue-graded areas in the HOLC maps. The results show that the VeroVALUE AVM does not value homes differently based on their location in the HOLC maps. However, all AVMs are not created equally and, therefore, performance may vary for other AVMs. Based on the results of our analyses, we recommend that other AVM providers conduct similar research to help demonstrate whether their AVMs likewise do not have any algorithmic bias with respect to redlined areas or with respect to racial compositions of neighborhoods. AVMs with high confidence scores that are shown to be free of historical redlining bias and whose accuracy has been tested, can be used as a check to determine whether appraisals or other sources of value are at risk for significant under- or overvaluation depending on a property's location inside or outside of a historically redlined area. Because AVMs are low-cost and easy to use, this analysis could be accomplished by running a professional-grade AVM against each appraised or alternative property valuation to verify value and a potential indication of bias. Appraised values in agreement with a professional-grade AVM with a high confidence score would be deemed low risk for bias. In contrast, those appraisals in significant disagreement with a professional-grade AVM could be escalated for a more detailed review. In a context where housing finance stakeholders look at both accuracy and fairness across the valuation spectrum, the AVM is proving itself to be an invaluable instrument in attaining these objectives.

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Appendix

The following tables show information for the red and blue blocks analyzed in this study from the texts accompanying the HOLC maps.

TABLE A1: 1939 POPULATION & HOUSING CHARACTERISTICS OF B75 & D31 RESIDENTIAL AREAS.

Adapted from “Mapping Inequality,” by Nelson, et. al., 2021, American Panorama

	B75	**D31**
Population characteristics		
Class and occupation	Professional people, minor executives, small businesspeople, white-collar workers, etc.	Small businesspeople, white-collar workers, skilled and unskilled artisans, laborers, etc.
Income	$1,800-$5,000	$1,000-$2,400
Foreign families	0%	10%
Black families	0%	1%
Building attributes		
	Predominating: 75%	Predominating: 90%
Type and size	6-8 rooms	4-6 rooms
Construction	Frame and stucco	Frame and shack
Average age	5 years	15 years
Repair	Good	Poor
Owner occupied	80%	35%
1939 Price bracket	$5,000-$9,000	$2,500-$3,500
1939 Rent bracket	$50-$90	$25-$40
New construction in the past year	Number: 100; Type: 5 to 8 rooms. Price: $5,500-$9,000	Number: 2; Type: 5 rooms. Price: $4,000
Mortgage funds	Ample	Very limited
Area description		
	The terrain is exceptionally rugged with many precipitous building sites which present construction problems and hazards. Land improved 50% of a possible 80%. Deed restricted to single-family dwellings with provision for multiple-family structures in stipulated parts. Zoning conforms to deed restrictions. Conveniences are all readily available. The major portion of this area was subdivided some 14 years ago, and the district has experienced a steady growth with activity pronounced since the advent of the FHA financing. Construction and maintenance are of good quality. The population consists largely of families in moderate circumstances. The district directly west of and overlooking Silver Lake is a particularly sightly location and has been the scene of great activity during the past several years. The topography of the area protects it from the subversive elements	The terrain is a canyon bottom and hillside with rugged contours and many construction hazards. Land improved by 40%. Zoned for single-family but multi-family is permitted in parts. Conveniences are all readily available. This area was subdivided some 25 years ago but has developed very slowly and has never shown any great amount of activity. Construction varies from substandard to standard, with some shacks in the canyon bottom along the Pacific Electric Railway. Maintenance is spotted but generally of poor quality. The population is heterogeneous, and many are of the lower income group. The subversive racial elements are comparatively few in number and are largely in the canyon bottom. While this area is not entirely blighted, it is thought that the trend of desirability will continue downward. The area is accorded a "high red" grade.

	of the adjacent lower-grade area. The immediate future of the district appears to be favorable, but past development has been somewhat ragged, indicating a lack of proper direction and well-planned promotion. While certain scattered parts might be accorded a higher rating, the area, as a whole, does not warrant better than a “medial blue” grade.	

TABLE A2: 1939 POPULATION & HOUSING CHARACTERISTICS OF B30 & D7 RESIDENTIAL AREAS.

Adapted from “Mapping Inequality,” by Nelson, et. al., 2021, American Panorama

	B30	D7
Population characteristics		
Class and occupation	Business and professional people, retired people, city employees, white-collar workers, etc.	Skilled artisans, letter carriers, laborers, and WPA workers
Income	\$1,800-\$3,600	\$700-\$1,800
Foreign families	Few	Few
Black families	0%	5%
Building attributes		
	Predominating: 75%	Predominating: 90%
Type and size	5, 6, and 7 rooms	5 and 6 rooms
Construction	Frame, stucco, and masonry	Frame and stucco
Average age	15 years	18 years
Repair	Fair to good	Fair
Owner occupied	60%	80%
1939 Price bracket	\$3,500-\$5,000	\$2,750-\$3,750
1939 Rent bracket	\$30-\$50	\$25-\$35
New construction in the past year	Number: 25; Type: 6 & 7 rooms. Price: \$6,000-\$8,000	Number: 0
Mortgage funds	Ample	Limited
Area description		
Description	No construction hazards. Land improved by 85%. Homesites are average large. Deed restrictions have expired. Zoning is largely single-family residential. Conveniences are all readily available. This area began some 35 years ago as a suburban district of small orchard homes. Many of the original owners were retired people with a moderate income. This stabilizing influence is still apparent. Construction is uniform of sound character. Maintenance, while somewhat spotted, is generally of good quality. The population is highly respectable and homogeneous. Improvements are of many periods and are heterogeneous from the	No construction hazards or flood threats. Land improved by 85%. Zoned single-family residential. All conveniences. This area is favorably located but is detrimentally affected by ten owner-occupant Black families located in the center of the area north and south of Bell St. between Mar Vista and Catalina Aves. Although the Black families are said to be of the better class, their presence has caused a wave of selling in the area, and it seems inevitable that ownership and property values will drift to lower levels. Construction, maintenance, and architectural designs, while not of the highest type, are generally of good

	standpoint of architectural designs. The price brackets shown above are nominal as sizes of homesites vary greatly, and front foot values are not well-established owing to sales being made upon a building site basis. It is a close question as to the grade of this area; in many respects, it is "definitely declining." However, the type, quality, and amount of recent new construction coupled with its proximity to a rapidly growing area, seems to warrant the assignment of a "low blue" grade.	quality. The area is accorded a "high red" solely on account of racial hazards. Otherwise, a medial yellow grade would have been assigned.

TABLE A3: 1939 POPULATION & HOUSING CHARACTERISTICS OF B30 & D7 RESIDENTIAL AREAS.

Adapted from "Mapping Inequality," by Nelson, et. al., 2021, American Panorama

	B69	D28
Population characteristics		
Class and occupation	Business and professional people, motion picture artists and technicians, white-collar workers, etc.	Business and professional people, white-collar workers, skilled artisans, etc.
Income	$1,800-$5,000	$1,800-$3,600
Foreign families	0%	0%
Black families	0%	0%
Building attributes		
	Predominating: 85%	Predominating: 90%
Type and size	5, 6 and 7 rooms	5 - 7 rooms
Construction	Frame and stucco	Frame and stucco
Average age	17 years	20 years
Repair	Fair to good	Fair to good
Owner occupied	75%	50%
1939 Price bracket	$5,500-$7,500	$5,000-$7,500
1939 Rent bracket	$45-$65	$45-$70
New construction in the past year	Number: 125, Type: 5 to 7 rooms, Price: $5,500-$8,000	Number: 0
Mortgage funds	Ample	Very limited
Area description		
	Level to hillside slopes in the southern portion, with the northern part much more rugged and with many construction hazards. Land improved by 75%. Zoning is largely single-family residential with multi-family structures permitted in stated blocks in the southern part. Conveniences are all from readily to reasonably available. This area was subdivided about 25 years ago and developed rapidly under the stimulus of promotional efforts. While still a good area, it has lost much of its earlier popularity. Construction is of good	No construction hazards. Land improved by 65% out of a possible 90%. Conveniences are all reasonably available, including proximity to downtown Hollywood. Street improvements are adequate in the southern part of the area, but in the northern section, many of the thoroughfares are dirt roads. This area was subdivided about 25 years ago, and its greatest development was prior to 1925. Since that time, Mulholland Dam at the northern boundary of the area has proved a definite hazard to desirability,

	quality, and maintenance indicates pride of ownership. Although widely differing in income range, the population is of the better class. Improvements are characterized by a wide range of age and architectural designs. The area has experienced quite a little building activity in the past 2 or 3 years, largely due to FHA Title II financing. Rental demand is excellent, and the trend, particularly in the southern part, is toward income properties. The area is protected from the adverse influence of area D-28 to the west by rugged terrain. Owing to the area's age, obsolescence, and somewhat mixed character, it is assigned a “low blue” grade.	for a while engineers pronounce the dam safe, there is a widespread popular feeling to the contrary. Construction is generally of high grade, and maintenance shows pride in occupancy. The population is fairly homogeneous, and many original owners still occupy their homes. Improvements are characterized by age and obsolescence. There is a wide divergence of opinion among authorities regarding the grade of this area. However, the psychological hazard of the Mullholland Dam is thought to be a prime factor, and in order to "flag" this influence, the area is accorded a "high red". If however, as some contend, the reservoir is discarded with the establishment of water supply from the Boulder Dam, there will be a sharp upturn in the grade of the area.

TABLE A4: 1939 POPULATION & HOUSING CHARACTERISTICS OF B83 & D41 RESIDENTIAL AREAS.

Adapted from “Mapping Inequality,” by Nelson, et. al., 2021, American Panorama

	B83	D41
Population characteristics		
Class and occupation	Professional and businesspeople, white-collar workers, skilled artisans, etc.	Factory workers, artisans, laborers and WPA workers.
Income	$1,800-$3,600	$700-$1,000
Foreign families	0%	10%
Black families	0%	0%
Building attributes		
	Predominating: 90%	Predominating: 80%
Type and size	5-6 rooms	3-4 room bungalows
Construction	Stucco	Stucco and frame
Average age	8 years	15 years
Repair	Fair to good	Poor
Owner occupied	85%	20%
1939 Price bracket	$4,000-$5,500	$1,500-$2,000
1939 Rent bracket	$35-$45	$15-$20
New construction in the past year	Number: 35, Type: 5-6 room bungalows, Price: $4,500-$6,000	Number:10, Type: 4 room stucco, Price: $2,250-$2,500
Mortgage funds	Ample	None
Area description		
Description	No construction hazards. Land improved by 90%. Deed restrictions govern	No construction hazards. Land improved by 90%. Zoning is mixed, but the area is

	improvements, provide for uniform “setbacks,” and protect against subversive racial elements. Conveniences are all readily available. This well-planned district has good streets, subdivided some 15 or more years ago, and is now nearing complete development. Construction is of high standard quality, and maintenance is of good character. Harmonious architectural designs and uniform “setbacks” add greatly to the appearance of the district. The population is of the medial income level and is homogeneous. A number of multiple-family structures are scattered throughout the area, and these, coupled with a high percentage of development, preclude higher than a “medial blue” grade.	predominantly single-family dwellings. Conveniences are all readily available. This area is 20 years or more old and has never been a popular residential district. Construction is nondescript, ranging from "shack" to substandard construction. The population is heterogeneous and borders the subversive. An interurban and railway line bisects the area, and along Redondo Blvd., residences are interspersed with light industry. The whole area has the aspect of being shoddy and cramped. Adjacence to Inglewood Park Cemetery is a detrimental factor. Proximity to industrial employment is a favorable influence and helps rentals. The area is blighted and accorded a "medial red" grade.

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A mortgage technology innovator since 2001, Veros Real Estate Solutions (Veros) is a proven leader in enterprise risk management and collateral valuation services. The firm combines the power of predictive technology, data analytics, and industry expertise to deliver advanced automated solutions that control risk and increase profits throughout the mortgage industry, from loan origination to servicing and securitization. Veros’ services include automated valuation, fraud and risk detection, portfolio analysis, forecasting, and next-generation collateral risk management platforms. Veros is the primary architect and technology provider of the GSEs’ Uniform Collateral Data Portal® (UCDP®). Veros also works closely with the FHA to support its Electronic Appraisal Delivery (EAD) portal. The company is also making the home buying process more efficient for our nation’s Veterans through its appraisal management work with the Department of Veterans Affairs. For more information, visit www.veros.com or call 866-458-3767.