How Automated Valuation Models Can Disproportionately Affect Majority-Black Neighborhoods

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Automated valuation models, or AVMs, hold great promise for reducing the costs of and increasing the accuracy of home valuations. They allow financial institutions to estimate a home's value with a reduced role for human opinion. By limiting the human element, estimating a home's value should become less expensive and more accurate. In the COVID-19 pandemic, automation and technology like AVMs have allowed home purchases and refinances to continue by eliminating the need for a certified appraiser or any human access to the property being assessed.

But AVMs in majority-Black neighborhoods produce larger errors, relative to the underlying sales price, than AVMs in majority-white neighborhoods, potentially contributing to the wide housing wealth gap between Black and white homeowners. By refining the current AVM, this valuation disparity could be eliminated, and the benefits of homeownership could be more equitably available to all homeowners.

Recent Events Raise the Profile of AVM Technology

After the Great Recession, in-person home appraisals received scrutiny. Many housing experts believed that widespread appraisal bias contributed to the housing crisis.[1] In-person appraisals are susceptible to charges of racial discrimination and human bias. Appraisers could use a neighborhood's racial composition as a proxy for other measures used to determine a home's value, perpetuating racial disparities in housing (Howell and Korver-Glenn 2018).

These concerns about appraisal accuracy boosted the appeal of AVMs as both a supplement to and a substitute for in-person appraisals. AVMs apply mathematical algorithms to a database of housing activity, including sales transactions, to calculate a specific home's value. After the Great Recession, the government-sponsored enterprises approved the use of AVMs to confirm the accuracy of in-person appraisals. Amid the pandemic, the use of AVMs in lieu of in-person appraisals has increased to limit person-to-person interactions during the homebuying process.[2] By eliminating human involvement, AVMs could also correct for racial bias from appraisers evaluating homes and the conditions in majority-Black neighborhoods.

But AVMs have drawbacks. Historically, AVMs have not been able to take a property's condition into account when determining a home's value.[3] Like in-person appraisals, the accuracy of AVMs depends on having a large-enough number of comparable sales in the area to ensure greater accuracy (Dornfest et al. 2018). And the use of comparable sales in the area may reinforce past racial bias.

If these drawbacks create less accurate home value estimates, they can have important implications for households and policymakers. A home's value determines a homeowner's housing equity and the mortgage's loan-to-value ratio, which is one metric used to assess credit risk (Dornfest et al. 2018, 2). Less accurate home valuations undermine estimates of housing equity and can exaggerate the amount of risk a homeowner represents. One inaccurate valuation can then infect an entire neighborhood when it is used as a comparable sale for other estimates. Nationwide, reduced accuracy in home valuations impairs policymakers' understanding of the health and risks presented by the household sector and the financial system overall (Goodman et al. 2019).

Nevertheless, we believe AVMs can be a useful tool in determining home valuations and that a greater understanding of the differences in how AVMs are used with purchase and refinance mortgages will help industry stakeholders use this tool more effectively.

Data and Methodology

To examine whether AVM accuracy differs by race, this study compares AVM values with sales prices associated with arm's-length transactions at the property level between majority-Black and majority-white neighborhoods. As computer models, AVMs do not know the race of the homeowner or the predominant race of the neighborhood in which the home is located (Avenancio-León and Howard 2020). As a result, although we find that the AVM we analyzed produced less accurate results in the majority-Black neighborhoods selected, we avoid the term "discrimination," which implies motive. But this does not preclude the possibility that AVMs may reinforce instances of past discrimination.

We analyzed Atlanta, Georgia; Memphis, Tennessee; and Washington, DC. Each city had a significant Black population share and produced solid property-level pairings between AVM estimates and sales prices to analyze. We first show results for Atlanta and Memphis and then compare them with those for Washington, DC, as an initial check on how pervasive these findings are geographically. In each city, instead of using the entire core-based statistical area (CBSA), we used the counties with strong historical deeds data that we could match with the AVM data. These counties are a small proportion of the total number of counties in each CBSA but account for the majority of the CBSA population. The Atlanta, Memphis, and Washington, DC, counties account for 17 percent, 22 percent, and 33 percent of the total counties in their CBSAs, respectively, and 63 percent, 74 percent, and 56 percent of their respective populations.

We employed property records data from a major data provider to combine information on AVM values, sales prices, and transaction dates for each traded property from 2000 to 2018 for those selected counties within each city. We then used five-year (2014–18) American Community Survey data to extract the share of Black and white homeowners at the census tract level and merge the racial composition information with the property records data.

To characterize the difference between AVM values and sales prices, we constructed three measurements. First, we calculated direction of inaccuracy, or the average difference between the sales prices and AVM values, to capture the direction of AVM error. Averaging across sales and AVM price differences implies that positive differences are offset by negative differences. For example, if one home was overvalued in its appraisal by $20,000, and another was undervalued by $20,000, the average of those two sales price and AVM differences would be zero. Consequently, averaging across sales and AVM price differences provides a sense of the direction of the inaccuracy—that is, whether homes are being generally overvalued or undervalued by AVMs.

Second, we calculated the magnitude of inaccuracy, or the absolute difference between the sales prices and AVM values. If one home is overvalued by $20,000 and another is undervalued by $20,000, each sales price–AVM differential has an absolute value of $20,000. Thus, the average difference in this case would be $20,000, which captures the magnitude of inaccuracy, regardless of whether it is positive or negative.

Third, we calculated the percentage magnitude of inaccuracy, or the magnitude of inaccuracy divided by the sales price. To use our two homes, an appraisal may be different from the sales price by $20,000. But if one of those homes is worth $100,000 and the other is worth $200,000, the $20,000 difference is more significant for the $100,000 home.

Finally, we conducted a regression analysis, using the 2018 data alone, to examine the key drivers affecting the percentage magnitude of inaccuracy.

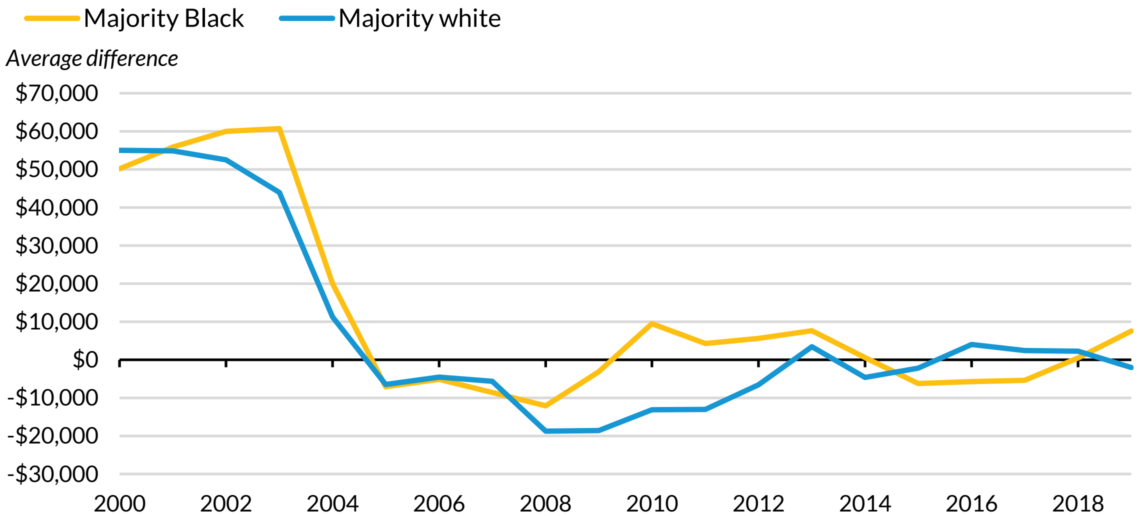
How Does AVM Inaccuracy Disproportionately Affect Majority-Black Neighborhoods?

Our results indicate that directional inaccuracy does not systematically differ according to neighborhood racial composition in Atlanta or Memphis and has not been significant since 2005. Figure 1 demonstrates that across the Atlanta CBSA, the average inaccuracy across majority-Black neighborhoods has fluctuated around zero since 2005. In the Memphis CBSA, the average error across majority-Black neighborhoods has been systematically below zero over time but only to a modest degree. This suggests that for single-family properties in the Memphis area, AVMs typically overestimate the actual sales price of those properties but only slightly. Figure 1 also shows that in both Atlanta and Memphis, the average difference across majority-Black neighborhoods is neither consistently above nor consistently below that of majority-white neighborhoods.

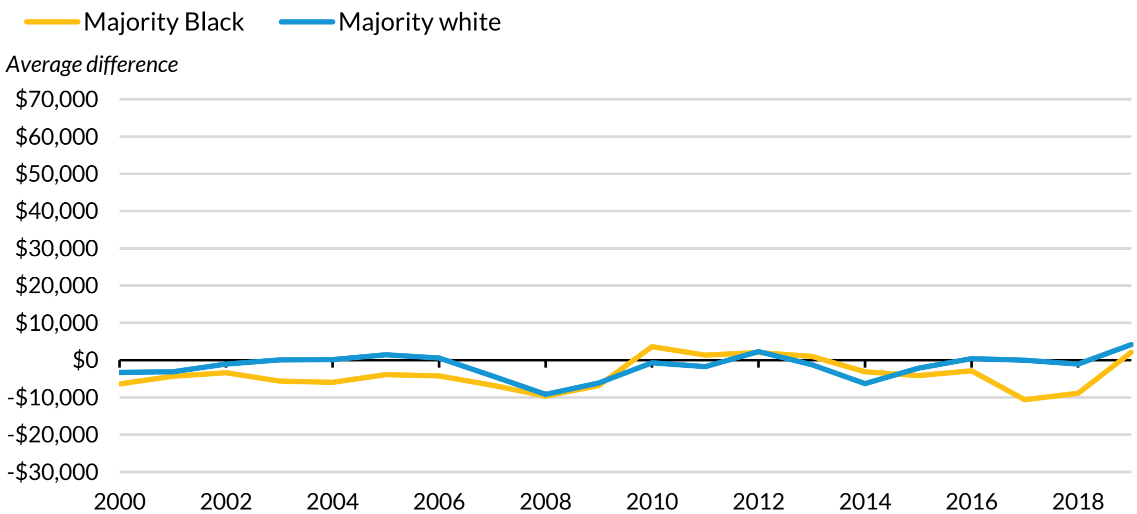
FIGURE 1

Directional Inaccuracy, by Majority Race in Neighborhood

Atlanta-Sandy Springs-Roswell, GA



Memphis, TN-MS-AR



URBAN INSTITUTE

Source: Urban Institute calculations of property records data and American Community Survey data.

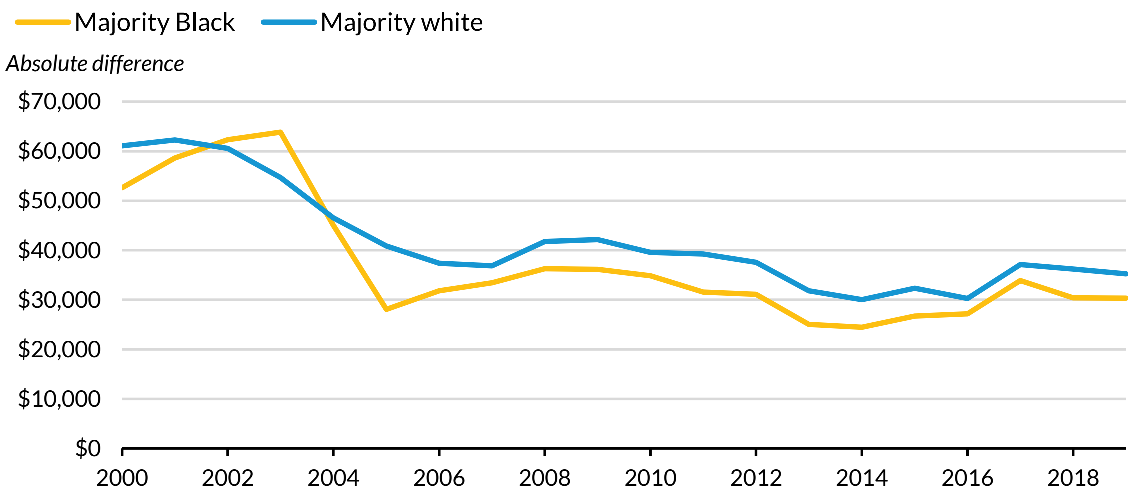
In contrast, the magnitude of inaccuracy in majority-Black neighborhoods is consistently below the inaccuracy amount in majority-white neighborhoods in the two cities we analyzed. Figure 2 shows that except in 2002 to 2004, AVM inaccuracy in majority-Black neighborhoods in the Atlanta CBSA was smaller than in majority-white neighborhoods. Data from Memphis also reveal that the magnitude of inaccuracy in majority-Black neighborhoods was smaller than in majority-white neighborhoods. The results from both areas may in part reflect the greater turnover of homes in majority-Black neighborhoods. Turnover—measured as sales in each neighborhood as a share of the housing stock—

was somewhat higher in majority-Black neighborhoods than in majority-white neighborhoods, and higher turnover rates allow for more comparable home sales that can be used by an AVM when determining a home's value.

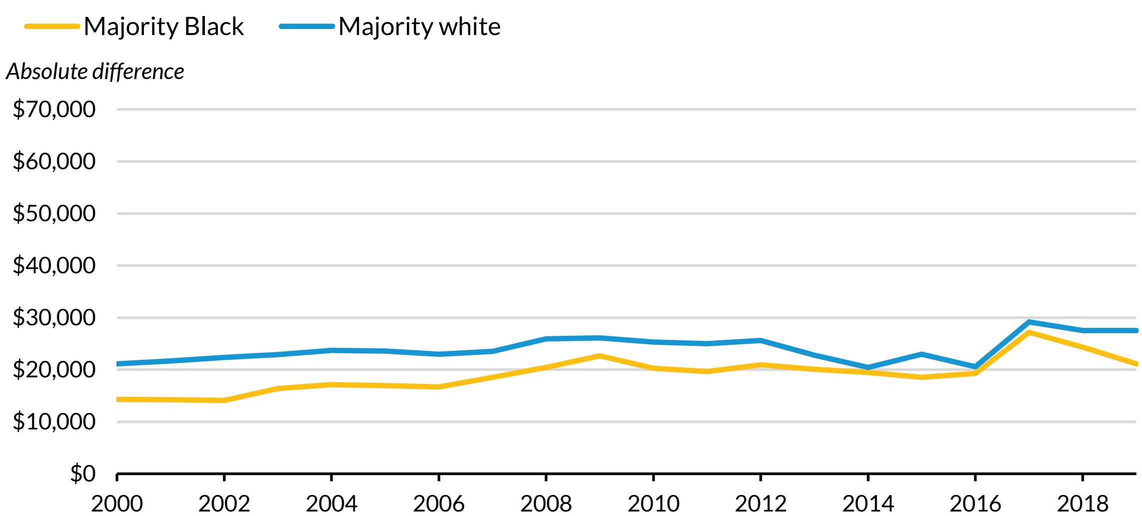
FIGURE 2

Magnitude of Inaccuracy, by Majority Race in Neighborhood

Atlanta-Sandy Springs-Roswell, GA



Memphis, TN-MS-AR



URBAN INSTITUTE

Source: Urban Institute calculations of property records data and American Community Survey data.

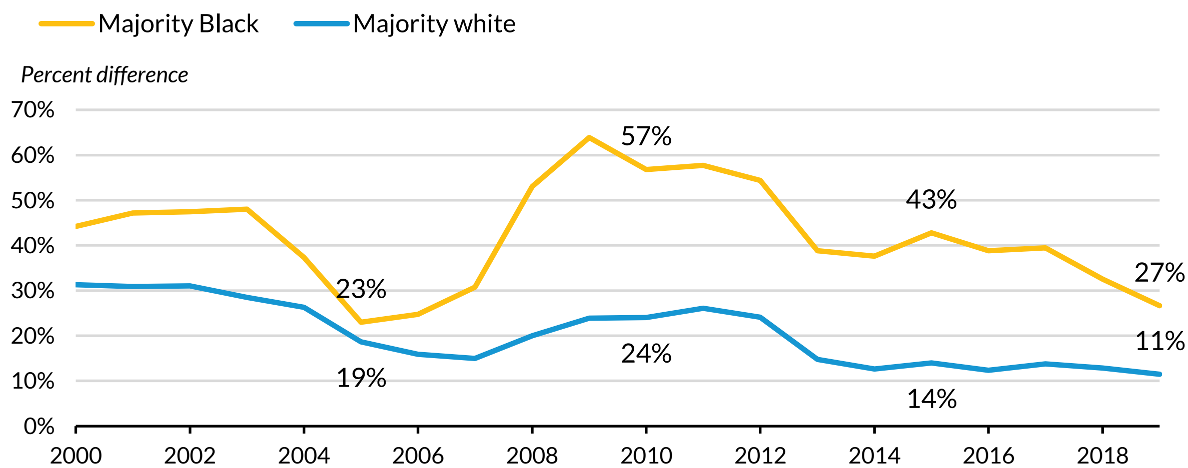
Finally, we calculated the percentage magnitude of inaccuracy (figure 3) and find that the magnitude of inaccuracy is much higher in majority-Black neighborhoods in Atlanta and Memphis. The higher percentage magnitude of inaccuracy in majority-Black neighborhoods is attributable to average home values in majority-Black neighborhoods being lower than in majority-white neighborhoods.

The percentage magnitude of inaccuracy is roughly twice as large in majority-Black neighborhoods as in majority-white neighborhoods and is notably more volatile. For example, in 2009, the percentage magnitude of inaccuracy in majority-Black areas in Atlanta was 64 percent, compared with 24 percent in majority-white neighborhoods. Although it has steadily improved since then, as of 2019, it was still more than twice the size in majority-Black neighborhoods than in majority-white neighborhoods. These results are consistent over time in both the Atlanta and Memphis CBSAs.

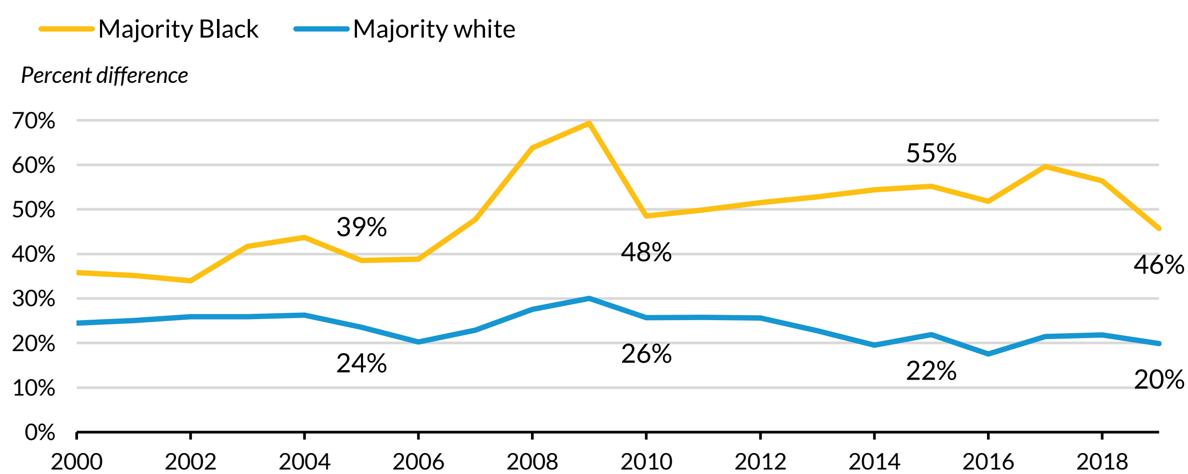
FIGURE 3

Percentage Magnitude of Inaccuracy, by Majority Race in Neighborhood

Atlanta-Sandy Springs-Roswell, GA



Memphis, TN-MS-AR



URBAN INSTITUTE

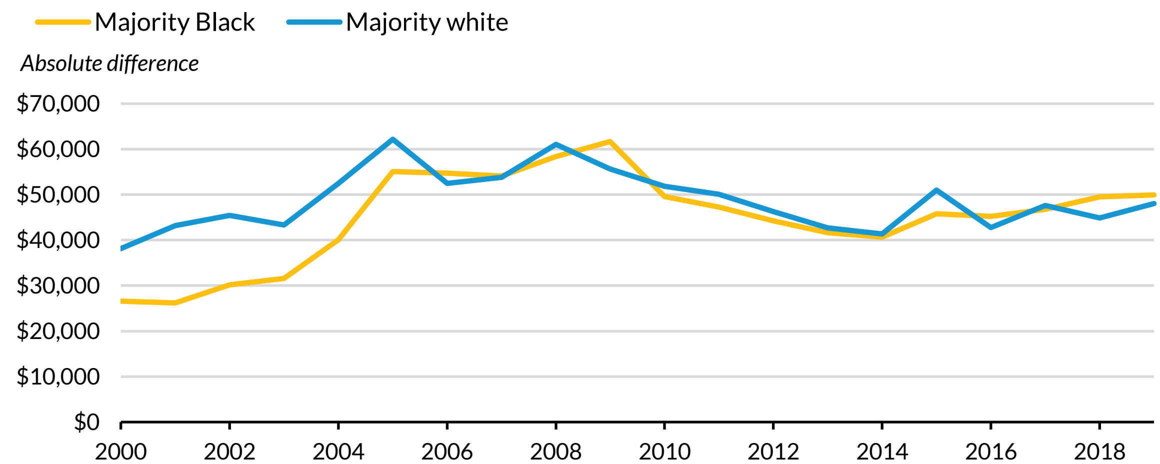
Source: Urban Institute calculations of property records data and American Community Survey data.

In the Washington, DC, CBSA, which includes parts of Maryland, Virginia, and West Virginia, the magnitude of inaccuracy has been generally similar for both majority-Black and majority-white neighborhoods since 2005 (figure 4). But the percentage magnitude of inaccuracy in majority-Black neighborhoods has consistently been larger than in majority-white neighborhoods. The bottom line is that the magnitude of inaccuracy may be similar in majority-Black and majority-white neighborhoods, but the lower sales prices in majority-Black neighborhoods increase the percentage magnitude of inaccuracy significantly in all three cities we examined.

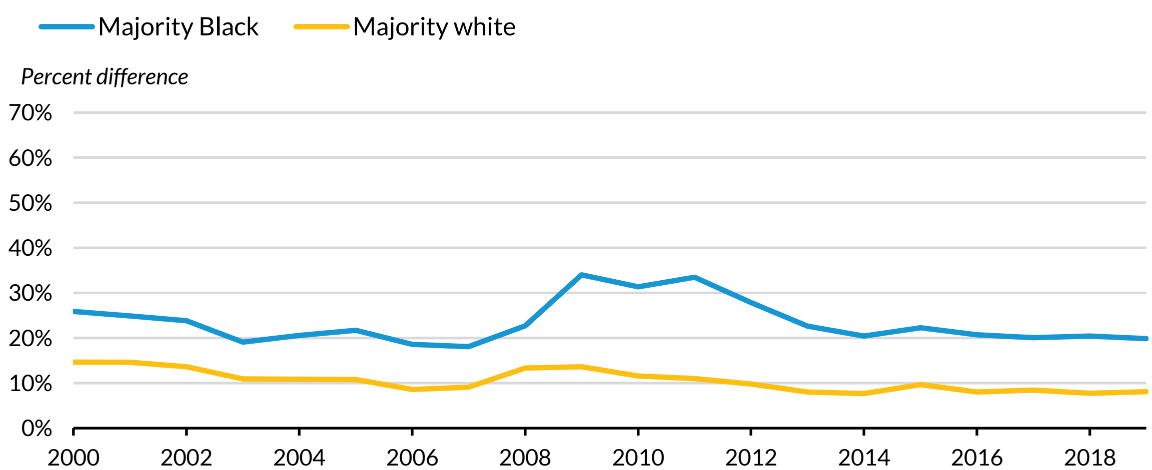
FIGURE 4

Magnitude of Inaccuracy in Washington-Arlington-Alexandria, DC-VA-MD-WV

Absolute difference



Percentage difference



URBAN INSTITUTE

Source: Urban Institute calculations of property records data and American Community Survey data.

What Are the Key Drivers of the Percentage Magnitude of Inaccuracy, and How Do They Differ between Neighborhoods?

Although the magnitude of inaccuracy in majority-Black and majority-white neighborhoods may be similar, the lower sales prices in majority-Black neighborhoods increase the percentage magnitude of inaccuracy significantly in all three cities we examined, possibly causing greater damage to the overall home values in these neighborhoods.

What causes the AVM accuracy gap between majority-Black and majority-white neighborhoods in these three cities? We answer this question by assessing neighborhood characteristics that may contribute to a greater percentage magnitude of inaccuracy and show how these characteristics differ between majority-Black and majority-white neighborhoods. These neighborhood characteristics are grouped along four dimensions: home values, differences in properties within a neighborhood, neighborhood conditions, and turnover rates. Table 1 presents summary statistics.

Majority-Black neighborhoods have lower home values. The average property value of single-family homes sold in majority-Black neighborhoods in the United States was $169,855 in 2018, significantly less than the average in majority-white neighborhoods ($424,810).

Majority-Black neighborhoods have older homes and a greater variety of homes, by age and value. To capture property differences within neighborhoods, we constructed two variables: the standard deviation of neighborhood property ages and the percentage deviation of neighborhood home values. Standard and percentage deviation measure the dispersion of properties by age and home value, respectively. Table 1 indicates that homes in majority-Black neighborhoods have greater dispersion in both home prices and property age. In addition, properties in majority-Black neighborhoods were, on average, older than those in majority-white neighborhoods.

Majority-Black neighborhood conditions differ from those of white neighborhoods. To capture neighborhood conditions, we included measures of gentrification, distressed sales, and household income.

Majority-Black neighborhoods are more likely to experience gentrification, which generally causes permanent and rapid home price increases as land values increase.[4] AVMs cannot quickly pick up these house price shocks, contributing to greater AVM errors in gentrifying neighborhoods.

We consider a neighborhood to be gentrified if it meets two criteria (Ellen and O'Regan 2008): the tract-level income is less than 70 percent of the income in the metropolitan statistical area (MSA) and the neighborhood (identified at the census tract level) experienced at least a 10 percentage-point increase in the ratio of tract-level income to MSA-level income over the year. Under this definition, 7.3 percent of majority-Black neighborhoods in the US were gentrified in 2018, which is almost five times the share of majority-white neighborhoods that were gentrified.

In addition, majority-Black neighborhoods experienced significantly more distressed sales. Forced home sales, such as foreclosures, more often occur among low-price homes than among high-price homes (Campbell, Giglio, and Pathak 2011). If a distressed sale results in a lower price than similar homes in the neighborhood, AVM accuracy is likely to be compromised. Among all home sales nationally in majority-Black neighborhoods in 2018, 16.0 percent were distressed home sales, almost four times the rate in majority-white neighborhoods (4.4 percent).

Average household income in majority-Black neighborhoods is nearly half that in majority-white neighborhoods. Lower incomes in majority-Black neighborhoods partly explain lower sales prices in these neighborhoods, which can increase the percentage magnitude of inaccuracy (Neal, Choi, and Walsh 2020).

Majority-Black neighborhoods experience high turnover rates. In this analysis, we define turnover rate as the number of home sales per year divided by the number of homes. As AVM algorithms are based on comparable sales, greater turnover rates would provide a larger sample of comparable sales for AVM algorithms to provide more accurate estimates. The turnover rates in majority-Black neighborhoods are slightly higher than those of majority-white neighborhoods.

TABLE 1

Summary Statistics in 2018

	Black Neighborhood		White Neighborhood	
Variable	**Mean**	**SD**	**Mean**	**SD**
Home value	$169,855	$128,275	$424,810	$279,438
Property age (years)	47.5	24.4	41.3	23.1
Standard deviation of neighborhood property ages (years)	14.3	7.0	12.9	7.3
Percentage deviation of neighborhood property values	40.1%	15.4%	31.2%	12.0%
Gentrified neighborhood	7.3%	26.1%	1.5%	12.2%
Share of neighborhood distressed home sales	16.0%	22.5%	4.4%	13.3%
Neighborhood median household income	$55,647	$27,525	$108,177	$43,647
Number of households in neighborhood	2,160	1,249	2,343	1,155
Neighborhood-level turnover rate	8.7%	4.6%	6.9%	3.7%

Sources: Property records data and American Community Survey data.

Note: SD = standard deviation.

Using the variables in table 1, we conducted a regression analysis using ordinary least squares regressions to examine the impact of those factors on the percentage magnitude of inaccuracy in Atlanta, Memphis, and Washington, DC, with 2018 as our analysis period.[5] Table 2 presents the results of all regressions. In all the regressions, we include county fixed effects to control for local factors. The dependent variable is the percentage magnitude of inaccuracy. A positive sign in the coefficient means that the independent variable is associated with a higher percentage magnitude of inaccuracy. For example, the coefficient of share_distressed_sales (0.016**) shows that a 1 percentage-point increase in the share of distressed sales leads to a 1.6 basis-point increase in the percentage magnitude of inaccuracy. In this example, the two asterisks indicate that the coefficient is statistically significant at the 95 percent confidence level. Significance at the 99 percent confidence level, three asterisks, is a stronger reading, while significance at the 90 percent confidence level, one asterisk, is weaker.

The key findings from table 2 are as follows:

1. **Majority-Black neighborhood.** The black neighborhood coefficient in column 1 shows that compared with majority-white neighborhoods, AVM inaccuracy in majority-Black neighborhoods is 20 percentage points greater. In this case, the magnitude of the coefficient in column 1 means that for a home with a median sales price of $140,000 in a majority-Black neighborhood, the percentage AVM error will be $28,000 greater than for a property with the same sales price in a majority-white neighborhood, after controlling only for county fixed effects. But the magnitude of this Black neighborhood coefficient is significantly reduced to 5 percentage points after controlling for home values in column 2 and is further reduced to 3.1 percentage points after controlling for neighborhood conditions and turnover rates in column 4. This means that for the same $140,000 property in a majority-Black neighborhood, the percentage AVM error will drop from $28,000 in column 1 to $4,340 in column 4. The Black neighborhood coefficient remains statistically significant, its magnitude smaller when we include other variables. Instead, sales price explains most of the gap. As noted, majority-white neighborhoods tend to have higher sales prices than majority-Black neighborhoods in our sample.
2. **Neighborhood heterogeneity.** The standard deviation of neighborhood property ages loses significance after controlling for neighborhood quality, moving from significance at the 99 percent confidence level to significance at the 90 percent confidence level. Nevertheless, with a coefficient of 0.039, dispersion in property age has a mild impact on the magnitude of percentage AVM inaccuracy. The dispersion of home values has a stronger impact. Not only is home value dispersion statistically significant at the 99 percent level, but the positive coefficient of 0.411 indicates that greater home value dispersion causes a larger magnitude of percentage AVM error.
3. **Neighborhood conditions.** The coefficients on the share of distressed home sales and gentrification are positive, indicating that having a larger share of distressed home sales and gentrified neighborhoods tends to increase the percentage magnitude of inaccuracy. The negative coefficient in neighborhood household income indicates that low-income neighborhoods are more likely to have a greater percentage magnitude of inaccuracy.
4. **Turnover rate.** The negative sign in the turnover rate coefficient shows how having greater comparable sales reduces AVM inaccuracy. Higher turnover rates generate more comparable sales, which help AVMs produce more accurate estimates under central tendency.

Majority-Black neighborhoods tend to have lower home values, more heterogeneous properties, higher shares of distressed home sales and gentrified neighborhoods, and lower household incomes. All these factors are associated with a greater magnitude of percentage error in AVM estimations. Neighborhood heterogeneity, neighborhood quality, and turnover reflect racial disparities, which may be rooted in racial bias and may inform the percentage AVM inaccuracy gap between majority-Black and majority-white neighborhoods. Even after controlling for these characteristics, the predominant race of the neighborhood still plays a statistically significant role in the determination of the percentage AVM inaccuracy gap. Because the AVM does not know the majority race of the neighborhood, the statistical significance of the neighborhood variable suggests that additional or more precise explanatory variables may be needed to address its statistical significance.

TABLE 2

Regression Results

	Dependent Variable: AVM Accuracy (%)			
	(1)	**(2)**	**(3)**	**(4)**
Black neighborhood	20.091*** (0.334)	5.043*** (0.409)	3.480*** (0.407)	3.066*** (0.431)
Log (Home value)		-15.637*** (0.256)	-13.188*** (0.262)	-11.105*** (0.324)
Standard deviation of neighborhood property ages			0.088*** (0.020)	0.039* (0.020)
Percentage deviation of neighborhood property values (%)			0.441*** (0.012)	0.411*** (0.012)
Share of neighborhood distressed home sales (%)				0.016** (0.007)
Gentrified neighborhood				1.728*** (0.670)
Log (Neighborhood median household income)				-3.366*** (0.482)
Log (Number of households in neighborhood)				-4.731*** (0.298)
Neighborhood-level turnover rate (%)				-0.136*** (0.035)
Constant	6.502*** (1.400)	217.398*** (3.714)	171.790*** (3.840)	222.735*** (5.369)
County fixed effects	Yes	Yes	Yes	Yes
Observations	87,148	87,148	87,120	87,120
R^2	0.100	0.137	0.154	0.157
Adjusted R^2	0.100	0.137	0.153	0.157
Residual standard error	37.570 (df=87,132)	36.790 (df=87,131)	36.438 (df=87,101)	36.365 (df=87,096)
F-statistics	644,504*** (df=15; 87132)	863,508*** (df=16; 87,131)	877,915*** (df=18; 87,101)	705,377*** (df=23; 87,096)

Note: AVM = automated valuation model.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Boosting Investment and Expanding Valuation Inputs Can Reduce Racial Differences in AVM Inaccuracy

These results highlight some determinants of the percentage AVM inaccuracy and explain why this measure of error may be greater in majority-Black neighborhoods relative to majority-white ones.

Factors related to majority-Black neighborhoods contribute to the racial gap in percentage AVM inaccuracy. But even after controlling for these measurable characteristics, some lost accuracy is associated with the majority race of the neighborhood.

One way to improve conditions in majority-Black neighborhoods is to encourage direct investment to these communities (Tatian et al. 2012). Small businesses tend to reinvest in their local communities in support of job creation (Baily, Dyanan, and Elliott 2010), and Black-owned businesses in particular help stabilize underserved communities (Valley Economic Development Center 2015). Expanded capital access in support of small businesses in majority-Black neighborhoods will lead to increased hiring, which should reduce the likelihood of distressed sales and increase household incomes.

Another way to improve neighborhood conditions is by supporting mission-related purchases of distressed sales. Amid the financial crisis and Great Recession, Congress authorized funding to purchase foreclosed properties. The Neighborhood Stabilization Program, which built on the Community Development Block Grant Program, was part of a package of US Department of Housing and Urban Development programs adopted to deal with the consequences of the housing market collapse (Spader et al. 2015). Program grantees, which included local governments, nonprofits, and multiple partner collaborations (i.e., a consortium) under the second round of the Neighborhood Stabilization Program (HUD, n.d.), undertook activities to help stave off the negative effects of foreclosures.

The eligible activities included establishing financial assistance for the purchasers of foreclosed homes, purchasing and rehabilitating homes and residential properties that have been abandoned or foreclosed upon, establishing and operating land banks, demolishing blighted structures, and redeveloping demolished or vacant properties as housing. The program also encouraged grantees to target areas with the greatest need, identified by the areas with the highest share of foreclosed properties and home purchases financed through subprime loans, and the greatest likelihood of a future rise in foreclosures. Qualitative analysis of the second round of this program, obtained through interviews with grantees, suggests that it may have helped stabilize home prices (HUD, n.d.). These homes were ultimately made available to low-income households looking to purchase a primary residence.[6]

The statistical results also indicate that even though the discrepancy in home values between majority-Black and majority-white neighborhoods has been shown to be connected to in-person appraisals,[7] simply expanding AVM use may not eliminate racial disparities (Bartlett et al. 2019). Encouraging modelers to expand the variables included in their AVMs could reduce the magnitude of error in majority-Black neighborhoods.

Conclusion

Amid growing demand for financial technology solutions in response to documented evidence of race-based discrimination and the COVID-19 pandemic, the use of AVMs in the housing process is poised to increase. To this end, Fannie Mae and Freddie Mac continue to improve and use these tools.[8] The AVMs Fannie Mae and Freddie Mac use may differ from the ones we used in our analysis, but our findings suggest that the expanded use of AVMs could disproportionately affect majority-Black neighborhoods and reinforce the impacts of past racial discrimination that often resulted in the undervaluation of Black-owned homes (Howell and Korver-Glenn 2020).

A significantly lower appraised value, even from an AVM estimate, could lead to a cancelled sales contract, which can contribute to the Black-white homeownership rate gap and the Black-white wealth gap.[9] Even if a too-low AVM estimate does not cancel a home sale, it could still reduce wealth accumulation, further compounding the Black-white wealth gap.

Conversely, a home value estimate that is too high could artificially boost home values, making a homeowner's balance sheet appear healthier or less risky than it really is. In addition, when used as a "comparable sale," a home with too high of an assessed value would increase the probability of default, raising the risk of neighborhood economic malaise.

When aggregated across society, these risks also have implications for policymakers responsible for macroeconomic and financial market supervision. More research is needed to identify the full scope of policy implications stemming from AVM inaccuracy. Nevertheless, the policy suggestions we present are meant to ensure that as the use of AVMs increases, its costs are better understood and more progress is made to ensure that all households experience the benefits of homeownership.

Notes

1 Laurie Goodman and Jun Zhu, "A Significantly Improved Appraisal Process Has Reduced the Riskiness of Refinance Mortgages," *Urban Wire* (blog), Urban Institute, March 7, 2019, https://www.urban.org/urban-wire/significantly-improved-appraisal-process-has-reduced-riskiness-refinance-mortgages.

2 Michael Neal and Laurie Goodman, "Appraisal Waivers Have Helped Homeowners Find Payment Flexibility amid Pandemic-Induced Economic Struggles," *Urban Wire* (blog), Urban Institute, October 16, 2020, https://www.urban.org/urban-wire/appraisal-waivers-have-helped-homeowners-find-payment-flexibility-amid-pandemic-induced-economic-struggles.

3 "Where's the Real Value in Automated Valuation Models (AVMs)?" Realtors Property Resource blog, accessed December 21, 2020, http://blog.narrpr.com/news/wheres-real-value-automated-valuation-models-avms/.

4 The measure of gentrification used in Guerrieri, Hartley, and Hurst (2013) differs slightly from (but is still consistent with) the calculation we employ.

5 We use the log form of house values, neighborhood median household income, and number of households in the neighborhood for this regression analysis.

6 "Neighborhood Stabilization Program (NSP)," Alameda County Community Development Agency, accessed December 21, 2020, https://www.acgov.org/cda/hcd/homeownership/nsp/forsale.htm.

7 "Neighborhood Stabilization Program (NSP)," Alameda County Community Development Agency.

8 Veros, "AVMs Make a Comeback," *HousingWire*, April 6, 2017, https://www.housingwire.com/articles/39787-avms-make-a-comeback/.

9 Ingrid Case, "4 Ways to Challenge a Home Appraisal," Interest.com. June 25, 2019, https://www.interest.com/mortgage/4-smart-moves-to-challenge-a-home-appraisal/.

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