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ABSTRACT
iBuyers are firms that use automated valuation models (AVMs), streamline home buying processes, and provide all-cash offers to purchase homes. Although the previous literature has explored the roles and limitations of iBuyers in the housing market, empirical research on the racial implications of these algorithmic home buying processes remains understudied. Using a spatial lag model, this study shows the spatial clustering of iBuyer profit margins, that iBuyers gain more profits when they resell to individuals than institutions, and that some iBuyers have a statistically significant correlation between their profit margins and the proportion of marginalized racial groups within a census tract, while controlling for individual housing characteristics, neighborhood housing quality and demand, and neighborhood amenities and socioeconomic factors. These findings suggest that the more adeptly iBuyers can forecast housing values, the greater the potential to maximize profits from homeowners in communities of color. Consequently, this research contributes to the understanding of how technological mechanisms operate within a purportedly race-neutral framework and advocates for the development and deployment of algorithmic systems guided by the principles of antisubordination, rather than relying solely on notions of "fairness" and anticlassification.

KEYWORDS
Automated valuation models; iBuyer; racial capitalism; appraisal bias

Introduction

Housing has long been a target of financialization due to its ability to be highly standardized and provide a stable fixed income. This has led to the development of various methods for assessing the value of a house, both for public and private needs such as taxation and sales. With recent advances in data science and machine learning, as well as the expansion of available real estate data, new players in the market known as iBuyers have emerged. These companies, such as Opendoor, Offerpad, Zillow Offers (which ended its iBuyer service in November 2021), Redfin Now (which ended its service in 2022), and others, rely on proprietary machine learning models to predict housing prices and facilitate the buying and selling of homes through streamlined processes, such as cash offers.

Previous literature has examined the burgeoning roles of iBuyers in the housing market (Anderson et al., 2024; Harrison et al., 2024; Seiler & Yang, 2022), as well as the limitation of the iBuyer business model (Buchak et al., 2020). However, there remains a gap in empirical research regarding the racial implications of algorithmic home-buying processes, although there are some exceptions on home valuation algorithms (Lu, 2019; Yu, 2020). This is particularly relevant given the history of racial discrimination and segregation in the U.S. housing market (Jackson, 1980; Massey & Denton, 1993; Rugh et al., 2015), which has shaped the current environment and can impact the effects of these practices, even if race is not explicitly considered in the development of valuation algorithms and iBuyer business models. In this context, it is difficult to consider iBuying business practices outside of the long

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history of residential segregation, as automated valuation could serve to naturalize "the decay and death of a very complex Black sense of place" (McKittrick, 2011, p. 951). From this perspective, iBuyers can be one of the examples that "incorporates race, or proxies for race into hedonic models, naturalizing the withholding of finance to space coded as non-white" (Fields & Raymond, 2021, p. 1633).

This study examines how iBuyers, as seemingly neutral and objective actors, engage their algorithmic business model in relation to neighborhoods, particularly along racial lines. I focus on neighborhood-level associations to highlight how algorithmic models operating under colorblind assumptions impact profit margins. By understanding the mechanisms of how iBuyers operates in the long history of neighborhood inequality, this research contributes to a more nuanced understanding of the factors driving iBuyers' profit mechanisms and the potential vulnerabilities faced by homeowners in communities of color.

This research attends to the literature on housing financialization and racial capitalism, examining how the racial logic of financialization drives the exploitation of the current racial structure in the U.S. housing market. This research also situates itself in a broader literature on neighborhood inequality and segregation to understand the contemporary real estate algorithms. By linking this work with existing literature on the topic of exploitation in housing sectors (Desmond & Wilmers, 2019), this research aims to provide a deeper understanding of the ways in which seemingly neutral practices and policies could disadvantage people of color in the contemporary housing market.

Background

iBuyers: Automated valuation, cash offer, and repair exemption

The emergence of the iBuying industry is closely linked to a technocratic intervention facilitated by Silicon Valley. Particularly, the focus of this intervention lies in the home-buying process, perceived as old-fashioned by tech sectors. The core value proposition of iBuying industry revolves around streamlining the home-buying experience through the integration of automation at every stage. Also, iBuyers add value to the market by serving as liquidity providers, mostly cash offers, which could facilitate other social benefits, such as increased labor mobility. The iBuying process entails several key steps. Initially, a seller submits property information to an iBuyer. Subsequently, the iBuyer employs a machine learning model to estimate the buying price and present an initial offer. Following this, a final cash offer is made, along with an in-person inspection and their pricing algorithms. The iBuyer then performs home repairs with minimal capital investment, aiming to resell the property within a span of 3 to 4 months. They charge a flat service fee (5–6%), but they also charge repair, title, or escrow fees based on the inspection they perform.

Opendoor is the first known iBuying company. Opendoor started operating in Phoenix in 2014 because the city's homogeneous house listings (i.e., cookie-cutter houses) are easier to be trained in their machine learning model. Other follow-up companies, such as Offerpad, Zillow Offers, and Redfin Now, started to emerge as well starting from 2015. All these concentrate on single-family homes and, as Figure 1 shows, their geographies are mostly aligned with the Sun Belt region. Figure 2 shows that their volume of home purchases increased rapidly during the pandemic period, which is in line with the increase in home purchases by institutional investors (Malone, 2023).

A key aspect of the iBuyer business model is the development of their automated valuation models (AVMs). The process of assessing home value by iBuyers is generally similar across companies. Table 1 provides an example of the information required by Opendoor for its initial inspection. The sellers provide basic information and, if possible, interior photos. Opendoor then returns with an initial quote based on its assessment algorithm within a few days. If the house is deemed suitable for purchase, an inspector is sent to the property to confirm the accuracy of the information and conduct a more thorough inspection. Based on this inspection, a final price is offered, considering any necessary repairs. In a podcast, Opendoor's CTO emphasized the advanced nature of the company's valuation algorithm, which allows for both accurate appraisals and efficient operations at scale. To

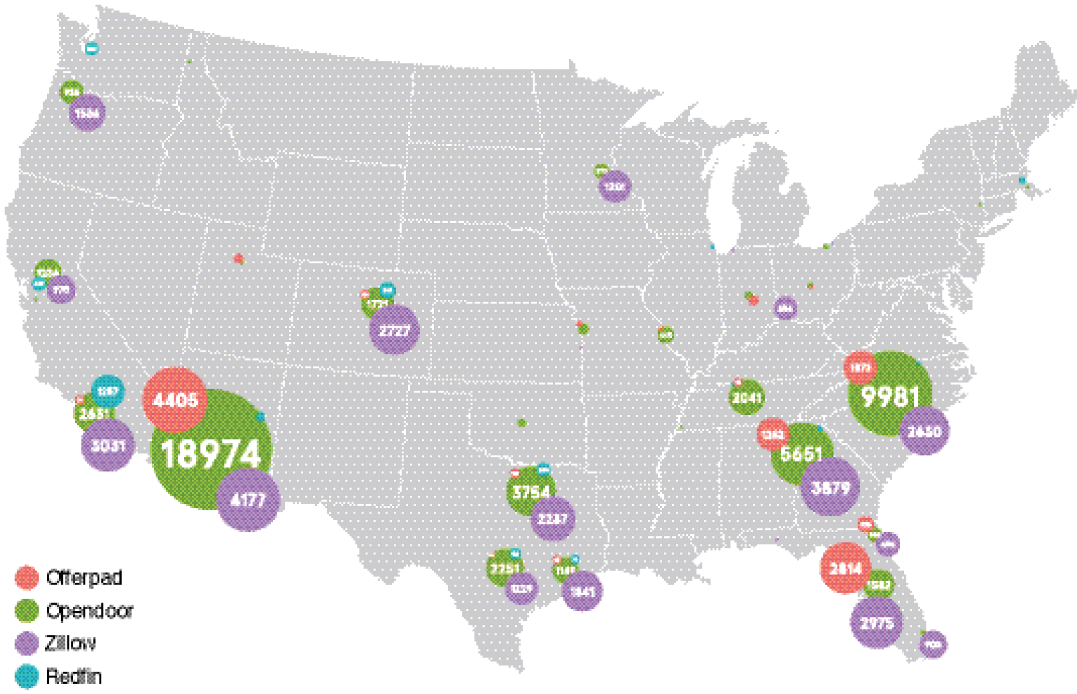

Figure 1. Spatial distribution of iBuyer transactions. Source: Zillow ZTRAX.

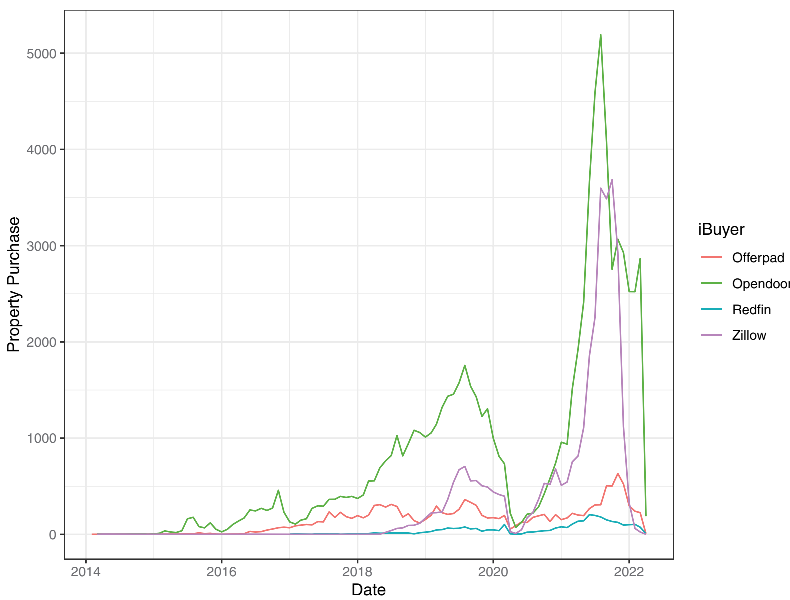

Figure 2. Temporal distribution of iBuyer purchases. Source: Zillow ZTRAX.

generate competitive offers, Opendoor considers the history of transactions for homes that are still on the market, the characteristics of the surrounding area, and recent trends in the housing market (ThoughtSpot, 2022). Zillow Offers, another iBuyer company, similarly considers comparable homes in the area and Zestimate, its own algorithm for assessing home value (Zillow, 2021).

Table 1. Opendoor's data fields for the initial quote.

Fields Type	Fields
Basic Information	Bedrooms, Full Bathrooms, Partial Bathrooms, House Size, Floors, Year Built, Pool, Covered Parking, Garage Space, Kitchen Countertops, Homeowner's Association Join, Entry Type
Basement	Finished Size, Unfinished Size
Kitchen Countertop Types	Laminate, Corian, Solid Stone Slab, Granite Tile, Other Tile
Other Characteristics	Solar Panels, Foundation Issues, Fire Damage, Well Water, Septic System, Asbestos Siding, Horse Property, Mobile Home, Cesspool on Property

Similar to Opendoor, other companies required questionnaires from sellers for the initial quote.

However, Opendoor also uses "adaptive" machine learning systems that allow it to incorporate changes in conditions in local and regional areas as well as a variety of data types, including photos and sensory signals, in its evaluations of home values. These systems enable Opendoor to rapidly test the impact of new data on the accuracy of its estimates, and to determine whether incorporating seemingly unrelated data can improve the performance of its algorithms. For example, the company may use photos, such as "photos for defects like ugly power lines," or incorporate information about the proximity of a home to a park, to refine its estimates of competitive pricing (Ponsford, 2022).

These adaptive data systems are backed by "human-in-the-loop" structure. Human-in-the-loop refers to the use of human labor to annotate and evaluate machine learning models. Opendoor emphasizes that they work with people who annotate visual data and labels (Ponsford, 2022). In particular, Opendoor places a strong emphasis on incorporating local knowledge into its model by working with local appraisers and real estate brokers, who serve as a final check on the accuracy of the company's data model (Opendoor, 2022a). This could potentially mean the annotation and evaluation of the heterogeneous data are guided by local real estate people.

One of the main advantages of using an iBuyer to sell a home is the streamlined process they offer, which includes the handling of repair processes and the provision of credit to buyers. In traditional home sales, negotiations over repairs can be a time-consuming and uncertain aspect of the process, requiring sellers to complete significant repairs or renovations before placing their property on the market. In contrast, thanks also to the algorithms, iBuyers assess the repair needs of a property and deduct the cost from the final offer, allowing sellers to move out without having to complete any repairs themselves. This can be particularly beneficial for sellers, as it simplifies the home selling process and removes the need for costly repairs or renovations (Opendoor, 2022a).

The optimization of repair processes, thanks to the reuse of local contractors and bulk discounts, may be a source of profits for these companies. However, some sellers have raised concerns that iBuyers may inflate repair costs and charge for repairs that are not actually completed. For example, a Reddit user claimed that Opendoor requested $20,000 for repairs, including $7,000 for foundation issues, but then placed the property on the market without completing these repairs.[1] However, it is possible that Opendoor relisted the property with a low margin and disclosed the fact that the foundation repairs were not completed to potential buyers. Opendoor's FAQ states that they can "give the next buyer of the home the opportunity to negotiate repairs," indicating that buyers have the option to purchase a home at a lower price and make certain repairs themselves in the future (Opendoor, 2022b). Overall, this suggests that iBuyers may have discretion in extracting value from the streamlined processes they offer, as they have the resources to bring in inspectors, optimize repair costs, and negotiate higher selling prices with future buyers.

Vulnerable homeowners may be more likely to view iBuying as an attractive option to sell their homes. Previous studies have shown that these groups are disproportionately represented among iBuyer customers (Seiler & Yang, 2022). An NPR article highlights the experience of Black homeowners who inherit homes from their grandparents or parents, which can come with taxes and debts and may require significant repairs or renovations (Wamsley, 2021). These financial burdens can make it difficult for these homeowners to invest in their properties or to afford the cost of repairs or renovations when selling their homes. The racial wealth gap and racial homeownership gap in the U.S. highlight the importance of preserving home equity wealth (Darity et al., 2018; Derenoncourt et al., 2024), but many vulnerable homeowners may not have the capital to invest in their homes. In such cases, iBuyers may present an attractive option, as they can do cash offers and allow sellers to move out without having to complete any repairs or renovations. However, there is a cost for such attraction; given that iBuyers offer typically 2% less than the open market value (Seiler & Yang, 2022) and considering the fees (~5%) that iBuyers charge for their services and repairs, the sellers would have sold their homes at significantly low price.

Racial capitalism and financialization in housing

Urban scholarship on racial capitalism provides valuable perspectives on understanding the urbanization process beyond the concept of spatial fix, which addresses how the overaccumulation of capital leads to urbanization as a means to absorb surplus value (Harvey, 2001). Within spatial fix, racial inequality is often viewed as a byproduct of uneven development. To challenge this colorblind perspective, following Robinson (2000)'s argument that European civilization through capitalism have rendered cultural and regional differences into racial ones in the production process, Dantzler (2021) contends that the urbanization process must recognize the interplay between race *and* class, because "[t]he ability for certain groups to create surplus value for themselves requires an engagement with questions surrounding inherent rights to land and property" (Dantzler, 2021, p. 118) and such rights are predominantly granted to privileged races. Additionally, Dorries et al. (2022) explores how racial capitalism can extend contemporary work on settler colonial urbanism, emphasizing the role of property relations as a technique of racial domination in cities. Such literature acknowledges that the historical processes producing racial-economic stratification in cities and that the processes persist into present.

Using racial capitalism as a framework of analysis, Fields and Raymond (2021) argue that housing financialization is a racialized process, since the production of racial differences is necessary to create value in real estate. For example, the values of assets and land related to a dominant group are considered as most valuable, which leads to spatial sorting and segregation that separates and steers subordinated groups of people into certain areas, devaluing their space. This spatial sorting contributes to the "predatory inclusion" theorized by Taylor (2019), in which the Federal Housing Administration (FHA) expanded credit to Black people, but mostly in segregated urban centers in the 1970s. The process of abstraction, through automated valuation, is one of the keys to understanding housing financialization and racialization. Abstraction is one of the crucial processes of financialization because financialization needs to measure the value of assets. Through the technology of abstraction, financialization sweeps away historical consideration and lived experience, therefore "reproduc[ing] and remain[ing] embedded in enduring racialized regimes of accumulation" (Fields & Raymond, 2021, p. 1626). Relatedly, as Benjamin (2019) suggests, these technologies can obscure the racist nature of domination while still perpetuating existing inequalities through processes such as imposing higher security deposits on housing voucher holders or higher insurance fees on low-income or wealth individuals (Hatch, 2017; So, 2023). Such practices convert the history of injustices into risks associated with marginalized individuals, imposing additional financial burdens on them.

The iBuying industry illustrates how exchange value is extremely prioritized over use value in housing. This prioritization, which emphasizes the treatment of homes as financial assets by businesses and investors, marginalizes the value of homes as a place of shelter. As a result, this emphasis on financial gain over the fundamental need for housing can perpetuate economic and social inequality, exacerbating existing disparities (Aalbers, 2017). Furthermore, the participation of institutional and corporate buyers, enabled by globalized finance and digital technologies, in the purchase and management of housing represents a further prioritization of exchange value over use value. This trend, supported by Silicon Valley ventures, has resulted in an unprecedented level of housing being bought and managed, a phenomenon theorized by Fields (2022) as "Automated Landlord."

The presence of corporate landlords can have negative effects and potential racial implications for vulnerable communities of color. For example, a "buying spree" by corporate landlords concentrated in Black neighborhoods in Charlotte, North Carolina, and Milwaukee, Wisconsin, highlights the significant impact on local housing markets (McMillan & Jackson, 2022). These corporate landlords often target homes in communities of color and hoard them, reducing opportunities for people of color to purchase homes and forcing them to rent instead. This hoarding allows corporate landlords to become powerful players by controlling the housing supply and markets. Additionally, corporate buyers such as iBuyers have the power to set and negotiate prices through economies of scale and optimization, which can be difficult for potential homebuyers of color to compete with due to their ability to offer all cash without strings attached.

iBuyers, while distinct from corporate single-family rental (SFR) landlords, share many techniques and dynamics with this market. Although iBuyers focus on purchasing homes to resell, rather than to rent long-term, there is a growing intersection and reliance between these two sectors. When Zillow and other iBuyers began selling properties during market downturns, many of their homes were sold to institutional SFR landlords, bypassing individual buyers altogether. These transactions illustrate the interconnectedness of iBuyers and corporate SFR landlords, where both models rely on economies of scale, digital platforms, and financialization to accumulate housing, often at the expense of first-time buyers, particularly in communities of color (Buhayar et al., 2022). By facilitating bulk sales to institutional investors, iBuyers contribute to a cycle that removes affordable homes from the market and exacerbates the housing crisis, reinforcing racial and economic inequality.

Neighborhood effects, segregation, and racialized property appraisal

Neighborhoods in the U.S. exhibit significant disparities along racial and class lines due to a longstanding history of residential segregation (Massey & Denton, 1993). Segregation poses a fundamental social problem in the U.S., particularly by contributing to the sorting and hoarding of opportunities and resources in white affluent neighborhoods (Garboden, 2023). Although declining from the 80s, segregation metrics like the dissimilarity index remain persistently high (Ellen, 2024). Urban sociologists have studied neighborhood effects and segregation broadly in two branches (Steil et al., 2021). One line of scholarship on neighborhood effects examines the constrained set of "choice" of households and the factors that contribute to the persistence of segregation (Bayer et al., 2007). For instance, Rosen (2020) shows how housing providers designate properties for housing voucher holders in lower-opportunity neighborhoods, contributing to the concentration of racialized poverty. The other line of scholarship examines how these constructed patterns of segregation impact various outcomes, including education (Chetty et al., 2016), financial services (Faber, 2013), and housing.

One concerning impact of neighborhood inequality and real estate transactions is discrimination in appraisal. To purchase or refinance the property with a mortgage loan, the property needs to be appraised by a licensed appraiser. This appraisal process has been criticized that it is racially biased in that the appraisal system is partially based on past credit rationing practices within neighborhoods. Consequently, disparities in appraisal outcomes along racial lines could potentially exert a lasting influence on the overall property values within an entire neighborhood (Korver-Glenn, 2018). Although it is unlawful to justify the value of a home by the racial composition of the neighborhood, nevertheless, appraisers can still use proxies that are correlated with the racial composition of the neighborhood, including educational attainment, household income, and amenities, among others (Appraisal Institute, 2013). Through such a process, the appraisal process can pick up the neighborhood inequality and how difficult it was to get credit in the past (Howell & Korver-Glenn, 2018). In other words, appraisal reflects past unequal conditions of neighborhoods, thereby perpetuating neighborhood-level inequality.

Previous studies have shown that homes in communities of color are often appraised at lower values than comparable homes in white neighborhoods, even when controlling for socioeconomic factors. Recently, using unprecedented appraisal data released by the Federal Housing Finance Agency (FHFA), Howell and Korver-Glenn's (2022) study found that, when controlling for socioeconomic characteristics and amenities, appraisers valued homes in white neighborhoods around $371,000 more than homes in communities of color. In addition, the racial appraisal gap in the neighborhood in 2021 has increased by 75% compared to 2013. This is in line with the findings of racial disparities at the tract level using historical census data (Howell & Korver-Glenn, 2021). In particular, the authors show that there is more home value inequality between white neighborhoods and neighborhoods of color even when the majority of a metropolitan area is nonwhite people, and prior appraised value does not explain all the inequality. This suggests that neighborhood racial composition, which was structured because of historical segregation and disinvestment, as well as segregation-induced socioeconomic inequality, is one of the biggest determinants of such disparities.

The iBuyer business model is heavily based on AVMs but given that previous research has identified racial disparities due to the history of segregation and resulting socioeconomic inequality, it is uncertain whether their machine learning models can avoid racial bias caused by historical segregation. Without taking into account the historical context of how the input data was generated, machine learning models may "learn" and reinforce disparities that were created by seemingly race-neutral markers as objective truths, justifying different treatment. There are many other examples—racial disparities in acceptance of prime mortgage loans, as shown in the Home Mortgage Disclosure Act (HMDA) data, reflect the history of housing discrimination that has limited the accumulation of wealth through practices such as redlining, racially restrictive covenants, and predatory lending. These historical inequalities are then perpetuated through algorithms used in the FinTech industry that impose higher interest rates on prime loans for certain racial groups (Bartlett et al., 2022; Haupert, 2022). To address this lack of historical perspective, researchers have suggested that the development of truly fair algorithms should consider an anti-subordination principle, which asserts that legal guarantees of equal citizenship cannot be fully realized as long as there is widespread social stratification and calls for reforming institutions and practices that reinforce the subordinate position of historically oppressed groups (Keswani & Celis, 2024). Practically, the Fair Housing Act's disparate impact standard, which focuses on the shared effects of an action rather than intent, can address the broader discriminatory effects of these algorithms and address the ongoing systemic disadvantages faced by marginalized groups (Steil, 2022). To this end, further research is needed to understand how iBuyers' models generate more profits and how historical segregation, disinvestment, and socio-economic inequality impact their business practices.

Research design

This study relies upon quantitative analyses using property transaction and assessment data, mainly in the neighborhood-level variances. I am particularly interested in examining which neighborhoods iBuyers received higher profit margins, especially along racial lines. The hypothesis of this research is that *iBuyers gain relatively higher profits in neighborhoods predominantly occupied by marginalized racial groups compared to those with a majority of white residents*. This hypothesis is informed by previous literature on algorithmic bias and residential segregation; if algorithms "learn" the current segregated neighborhoods as just "fair" conditions, iBuyers' automated valuation models and business logic would reproduce and/or exacerbate racial inequality by gaining profits from minoritized neighborhoods (Taylor, 2019) and exploiting the struggles of vulnerable homeowners.

This research aims to better understand how the components of the iBuying industry (i.e., cash offers, repair fees, and automated valuation models) are situated in racialized neighborhood conditions. To that end, the quantitative analysis focuses on their final-stage operations, potentially revealing higher profits from historically marginalized areas, thereby suggesting a disparate impact. This study is not about reverse-engineering iBuyer proprietary algorithms to identify specific sources or causal relationships of racial bias, which is almost impossible without internal auditing. Rather, with the antisubordination principle, this study focuses on the impact of iBuying practices in the context of the long history of segregation and neighborhood-level disinvestment, by focusing on the neighborhood-level differences.

While I acknowledge that individual-level racial characteristics could be important, this paper aims to emphasize how neighborhood-level effects play a crucial role in shaping iBuying practices. The persistent racial and class segregation in U.S. neighborhoods, a legacy of historical discrimination, continues to influence property values, access to financial services, and housing stability. This study is centered on the broader structural forces of neighborhood inequality in which iBuyers' operations are contextualized on. Understanding neighborhood-level consequences are important for understanding the systemic disparities impacting historically marginalized communities.

Methods and data

I collected housing transactions made by four public iBuyers (Opendoor, Zillow Offers, Redfin Now, and Offerpad) from Zillow ZTRAX (Zillow, 2020) ranging from January 2014 to February 2022. ZTRAX is a national-level property transaction and assessment database that has been available to academic researchers or nonprofits. Four iBuyers are all public companies, thus it is possible and necessary to check their subsidiaries through the Securities and Exchange Commission (SEC) because some subsidiaries' names are not necessarily matched with the name of the parent company:

- Offerpad: "OFFERPAD" or "OP SPE" or "BAIR GROUP"
- Opendoor: "OPENDOOR" or "OD"
- Redfin Now: "REDFINNOW" or "RDFN VENTURES"
- Zillow Offers: "ZILLOW" or "SPH"

The profit margin, the outcome variable of this study, is calculated based on two consecutive transactions involving the same property and an iBuyer as both the buyer and seller. To collect the data for this analysis, I identified transactions in which an iBuyer was involved in both the first and second transactions on a single property. The profit margin was then calculated by dividing the selling price by the buying price.

While exact acquisition costs may vary by property, iBuyers consistently deduct repair costs from the initial offer, which means these costs are reflected in the resale price. Opendoor notes that they "deduct the repairs charge from your proceeds and manage the repairs after closing" (Opendoor, 2024), while Offerpad states that they ask sellers to "sign an addendum to your sales contract for the credit … and adjust our sales price accordingly" (Offerpad, n.d.). If a seller receives an offer of $100,000 from an iBuyer, this amount likely incorporates, for instance, a $10,000 repair credit, meaning the actual property value assessed is $110,000 before the repair deduction. By offering $100,000 after accounting for repairs, the iBuyer ensures that these repair costs are embedded in the price structure upfront. This approach allows the profit margin calculations, based on resale prices, to more accurately reflect iBuyers' profits, as repair costs are likely already factored in. Although other holding or acquisition costs may vary slightly, iBuyers' rapid flipping practices (days between two transactions averaging around 98 days) suggest these costs are minimized compared to the repair deductions which are typically a significant part of the cost structure.

Figure 3 shows the distribution of profit margins by iBuyers. I included only single-family housing transactions and excluded transactions with an amount greater than $10 million and transactions with a profit margin greater than 2. Additionally, I excluded Zillow's records when the buy or sell date was after November 2, 2021, as this was when Zillow announced the end of their iBuying industry, and transactions after this date would be considered abnormal. Lastly, I excluded property transactions without a selling amount, as this information is crucial for calculating profit margins. This exclusion

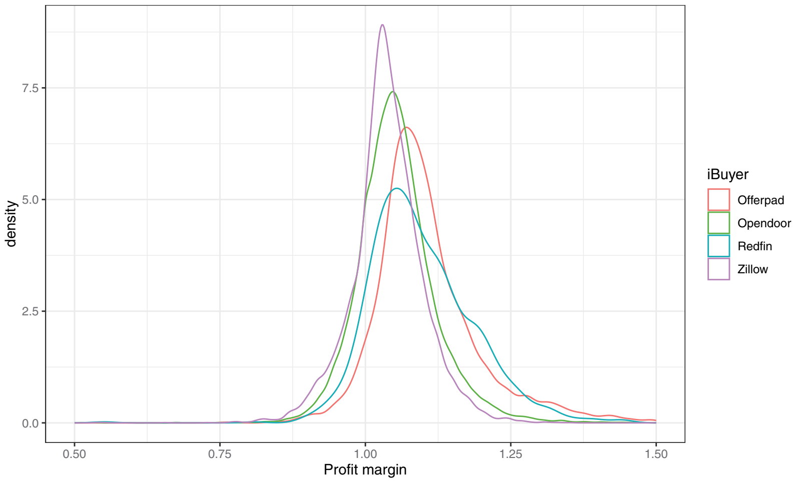

Figure 3. Distribution of profit margin by iBuyers. Note: A profit margin of 1 means an iBuyer buys a property and sells it at the same price.

removed almost all properties in Nevada and Texas, as these states do not require the disclosure of transaction values.

Table 2 presents the descriptive statistics of the main data: the dependent variable (profit margin), property-level and neighborhood-level independent variables.

Individual housing characteristics, including house size, lot size, and the presence of amenities (e.g., patio, pool, fireplace), were obtained from ZTRAX. I included the days between two transactions as an approximation for Days-on-the-Market (DOM). Given the iBuying business model, where properties are promptly sold, the days between transactions can reasonably serve as a proxy for DOM. For conventional homeowners, the days between transactions would typically be significantly longer than DOM; however, iBuyers' transactions are consistently prompt, averaging around 98 days (Mean: 98.8 days, SD: 59.2 days).

For the neighborhood-level analysis, variables that represent neighborhood racial composition, housing quality and demand, and amenities and socioeconomic characteristics were included. For neighborhood racial composition, I included the percentage of Black, Latino and other nonwhite people. Consequently, this allows to interpret the coefficients of the percentage of nonwhite people with regards to the percentage of white people; put differently, the reference group is the percentage of white people in a tract.

For neighborhood housing quality and demand, I included housing vacancy rates, median number of rooms, detached single-family housing rate, and median housing-built year in a tract from the ACS data. I included the percentage of listings that reduced their price on the market, as measured annually by Zillow at the tract level. This metric indicates housing demand, with a high percentage suggesting a declining housing market. I averaged these percentages over the period from 2014 to 2021 because this study is interested in within year-quarter variations. Since tract-level data had 2,352 missing entries, I filled these gaps using the county-level percentage of listings with price reductions.

Lastly, I included neighborhood-level amenities and socioeconomic characteristics, such as unemployment rate, poverty rate, homeownership rate, mean commute time, median home value, median income, and the proportion of bachelor's degree holders from the ACS data. I collected data on the number of amenities per capita and park coverage rate in a census tract, using the National Establishment Time Series data (2014–2017) and the Trust for Public Land Park Serve Database, respectively, as described in the study by Howell and Korver-Glenn (2022).

To measure the impact of racial composition on iBuyers' profit margin, I conducted a spatial autoregressive regression (SAR) model. Given the empirical evidence supporting the existence of

Table 2. Summary statistics ($N = 43{,}659$).

Variable	N	Mean	*SD*	Median	Min	Max
Dependent variable						
Profit margin, standardized	43,659	0	1	−0.06	−13	11
Independent variables						
Individual housing characteristics						
iBuyer type						
Offerpad	3,723	9%				
Opendoor	30,554	70%				
Redfin	964	2%				
Zillow	8,418	19%				
iBuyer buys from						
Individual	41,879	96%				
Company	1,780	4%				
iBuyer sells to						
Individual	37,032	85%				
Company	6,627	15%				
Days between transactions		99	59	85	6	1,180
House price, logged		13	0.41	13	11	15
House size, logged		7.5	0.36	7.5	3.9	9.6
Lot size, logged		8.9	0.67	8.9	5.4	12
Fireplace						
Yes	12,325	28%				
No	31,334	72%				
Garage						
No	27,311	63%				
Yes	16,348	37%				
Pool						
No	39,137	90%				
Yes	4,522	10%				
Patio or deck						
No	41,866	96%				
Yes	1,793	4%				
Built year/10	43,659	200	1.5	200	189	202
Neighborhood-level characteristics						
Neighborhood Racial Composition						
% of Black people in Tract		14	19	6.7	0.00	100
% of Latino people in Tract		22	18	17	0.01	99
% of white people in Tract		55	23	59	0	100
% of other Non-white people in Tract		9.4	7.9	7.5	0	80
Neighborhood Housing Quality and Demand						
Tract median rooms		6.1	1.1	6.1	1.4	10
Tract detached single family housing rate		0.77	0.21	0.83	0	1
Tract vacancy rate		0.071	0.063	0.057	0.00	0.9
Tract median year built/10		199	1.3	200	194	201
Tract % of listings with price reductions		16	3.8	16	2.9	25
Neighborhood Amenities and Socioeconomic Characteristics						
Tract homeownership rate		0.72	0.17	0.75	0.018	1
Tract unemployed rate		0.05	0.033	0.043	0.00027	0.38
Tract poverty rate		0.086	0.063	0.072	0.00041	0.64
Tract mean commute time		29	5.7	29	12	78
Tract amenity per capita, logged		−5.5	1	−5.4	−30	−0.75
Tract park coverage rate		0.038	0.079	0.0088	0	0.89
Tract median home value, logged		12	0.42	12	9.2	15
Tract median income, logged		11	0.34	11	9.5	12
Tract bachelor's degree holder rate		0.35	0.16	0.33	0.01	0.92

spillover effects and the theoretical basis that neighboring sales influence property valuation (Hui & Liang, 2016; Lin et al., 2009), the adoption of an SAR model was deemed appropriate. This model aligns with the inherent dynamics of real estate markets, particularly in the context of iBuyer AVMs (ThoughtSpot, 2022), which typically consider nearby sales in their valuation processes.

To determine the SAR model, I created an Ordinary Least Square (OLS) model using the dependent variable and independent variables in Table 2 with year-quarter fixed effects. Then I checked the values of the Lagrange Multiplier (LM) test (Anselin, 1988) to see if there is a spillover effect of the dependent variables in the OLS model (Appendix Table A1). Spatial weights are constructed using K-Nearest Neighbors (KNN). Following Kubara and Kopczewska (2023), I chose to use k = 40 because it yields the minimum Akaike Information Criterion (AIC), which is an estimation of the best fit for the data (Appendix Figure A1). All of the test results suggest that there is a spillover effect. Among potential listed spatial regression models including spatial lag, error, and spatial autoregressive moving average (SARMA) model, spatial dependence tests, such as Moran's I and the Anselin-Kelejian (AK) test, show that only a spatial lag model can effectively remove spatial dependence. Spatial two-stage least squares (2SLS) regression is used to estimate the endogenous dependent variable using the instruments of covariates from explanatory variables. The final spatial lag model to be analyzed is given by the following equation:

$$y = \rho W y + X\beta + \theta + \varepsilon$$

Where y is a vector of profit margins between two transactions of a property made by an iBuyer, ρ and β are the parameter vectors of interest, Wy is the spatially lagged dependent vector y with W as the spatial weights matrix, X is a matrix of explanatory variables, including neighborhood racial composition, individual housing characteristics, neighborhood housing quality and demand, neighborhood amenities, and socioeconomic characteristics, as well as dummy variables for iBuyers and interaction terms for iBuyers and neighborhood racial composition. θ represents the vector of year-quarter fixed effects, and ε is the vector of error terms.

Results

Table 3 presents the results of the spatial lag model with year-quarter fixed effects. This model examines the relationship between iBuyers' profit margins and neighborhood racial composition, accounting for the multifaceted process through which profits are generated. The analysis includes covariates such as individual housing characteristics, neighborhood housing quality and demand, neighborhood amenities, and socioeconomic factors. In essence, the interpretation of the model addresses how iBuyer profits are shaped across various scales and contexts, including the financialization and institutionalization of housing, racial segregation, and related dynamics such as information and resource asymmetry, disinvestment, and opportunity hoarding.

This model shows some notable patterns between neighborhood racial composition and iBuyer profit margins, controlling for spatial dependence, individual housing and transaction characteristics, neighborhood housing quality, demand, amenities, and socioeconomic factors. Specifically, Opendoor (the reference iBuyer in the model) exhibits a profit margin increase of 0.0031 standard deviations (SD) for every 1% increase in the Black population within a tract, and 0.0028 SD for every 1% increase in the population of other nonwhite groups, both with a significance level of $p < .001$. However, no statistically significant relationship is observed between Opendoor's profit margin and the percentage of Latino residents in a tract. Zillow does not show a statistically significant relationship between its profit margin and the percentage of Black residents in a tract. However, there is a statistically significant and positive relationship between Zillow's profit margin and the percentage of Latino residents in a tract, with a 0.0025 SD increase per 1% increase in the Latino population ($p < .001$). Offerpad demonstrates a slightly negative relationship between profit margin and the percentage of Black residents in a tract (−0.0010 SD, $p < .001$), while Redfin exhibits a positive and statistically significant relationship between profit margin and the percentage of other nonwhite residents (0.006 SD, $p < .05$).

For clarity and ease of interpretation, I use the model's predicted values to estimate profits while holding all control variables at their mean values, varying only the racial composition of the neighborhoods. The interpretation focuses exclusively on statistically significant relationships. This result suggests that when Opendoor buys and sells a $300,000 home, it would gain $5,406 more when the

Table 3. Spatial lag model result for the impact of neighborhood level characteristics on iBuyer profit margin.

Dependent Variable Profit Margin, Standardized	Coeff. (Std. Err)	Spatial Lag Model Impacts		
		Direct	Indirect	Total
Spatial Lag				
W × Profit Margin	0.2614*** (0.0274)			
Independent Variables				
Neighborhood Racial Composition				
% of Black People in Tract	0.0031*** (0.0004)	0.0031	0.0011	0.0042
% of Latino People in Tract	0.0004 (0.0004)	0.0004	0.0001	0.0005
% of Other nonwhite People in Tract	0.0028*** (0.0007)	0.0028	0.001	0.0039
iBuyer				
Offerpad	0.6655*** (0.0548)	0.6655	0.2355	0.901
Redfin	0.5218*** (0.0739)	0.5218	0.1846	0.7065
Zillow	−0.1406*** (0.0217)	−0.1406	−0.0497	−0.1903
iBuyer × Neighborhood Racial Composition				
Offerpad × % of Black People in Tract	−0.0041*** (0.0012)	−0.0041	−0.0015	−0.0056
Redfin × % of Black People in Tract	−0.0019 (0.0057)	−0.0019	−0.0007	−0.0026
Zillow × % of Black People in Tract	−0.0031*** (0.0006)	−0.0031	−0.0011	−0.0042
Offerpad × % of Latino People in Tract	0.0005 (0.0013)	0.0005	0.0002	0.0007
Redfin × % of Latino People in Tract	0.0014 (0.0017)	0.0014	0.0005	0.0019
Zillow × % of Latino People in Tract	0.0025*** (0.0005)	0.0025	0.0009	0.0033
Offerpad × % of Other non-white People in Tract	−0.0041 (0.0035)	−0.0041	−0.0014	−0.0055
Redfin × % of Other non-white People in Tract	0.006* (0.0026)	0.006	0.0021	0.0081
Zillow × % of Other non-white People in Tract	−0.0001 (0.0011)	−0.0001	0.0000	−0.0001
Individual Housing and Transaction Characteristics				
Mean House Price, logged	−0.5744*** (0.0664)	−0.5744	−0.2032	−0.7776
iBuyer Sells to Company	−0.3587*** (0.0141)	−0.3587	−0.1269	−0.4857
iBuyer Buys from Company	−0.0037 (0.0285)	−0.0037	−0.0013	−0.005
Lot size, logged	0.0394*** (0.0089)	0.0394	0.0139	0.0533
House size, logged	−0.0213 (0.0279)	−0.0213	−0.0075	−0.0288
Fireplace	0.0132 (0.0111)	0.0132	0.0047	0.0179
Garage	−0.0352** (0.0129)	−0.0352	−0.0125	−0.0477
Pool	0.0535** (0.0172)	0.0535	0.0189	0.0724
Patio or Porch	−0.0899*** (0.0256)	−0.0899	−0.0318	−0.1216
Year Built/10	−0.0275*** (0.0054)	−0.0275	−0.0097	−0.0372
Days Between Transactions	−0.0029*** (0.0001)	−0.0029	−0.001	−0.004
Neighborhood Housing Quality and Demand				
Tract Vacancy Rate	−0.1783* (0.0773)	−0.1783	−0.0631	−0.2413
Tract Median Number of Rooms	−0.0049 (0.0083)	−0.0049	−0.0017	−0.0066
Tract Detached Single Family Housing Rate	0.0049 (0.0385)	0.0049	0.0017	0.0067
Tract % of Listings with Housing Price Reductions	−0.0085*** (0.0015)	−0.0085	−0.003	−0.0115
Tract Median Housing Year Built/10	−0.0015 (0.0067)	−0.0015	−0.0005	−0.0021
Neighborhood Amenities and Socioeconomic Characteristics				
Tract Unemployment Rate	−0.09 (0.145)	−0.09	−0.0318	−0.1218
Tract Poverty Rate	−0.0668 (0.1013)	−0.0668	−0.0236	−0.0904

(*Continued*)

Table 3. (Continued).

Dependent Variable Profit Margin, Standardized	Coeff. (Std. Err)	Spatial Lag Model Impacts Direct	Indirect	Total
Tract Homeownership Rate	0.0526 (0.0481)	0.0526	0.0186	0.0712
Tract Mean Commute Time	0.0024** (0.0009)	0.0024	0.0009	0.0033
Tract Amenity per Capita, logged	0.0004 (0.0035)	0.0004	0.0001	0.0005
Tract Park Coverage Rate	0.1192* (0.0508)	0.1192	0.0422	0.1613
Tract Median Home Value, logged	0.0829* (0.0397)	0.0829	0.0293	0.1122
Tract Median Income, logged	0.0427 (0.0315)	0.0427	0.0151	0.0579
Tract Bachelor Degree Holder Rate	−0.3403*** (0.0315)	−0.3403	−0.1204	−0.4607
Fixed-effect				
Year-quarter		Yes		
Fit Statistics				
Observations		43,659		
AK Test		1.7168		
Pseudo R-squared		0.2381		

White robust standard-errors in parentheses. Spatial weights are constructed through K-Nearest Neighbors (k = 40). The reference categories are the following: Transaction made by Opendoor; iBuyer buys from an individual; iBuyer sells to an individual. The Anselin-Kelejian (AK) test shows the residuals are not correlated with the spatial lag of residuals.
Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, .: 0.1.

home is in a neighborhood of 70% of Black people and it would gain $4,883 more when the home is in a neighborhood of 70% of other nonwhite people. When Zillow buys and sells a $300,000 home, it would gain $4,360 more when the home is in a neighborhood of 70% Latino people. When Offerpad buys and sells a $300,000 home, it would gain $1,744 less when the home is in a neighborhood of 70% Black people. When Redfin buys and sells a $300,000 home, it would gain $10,464 more when the home is in a neighborhood of 70% other nonwhite people.

Regarding individual housing and transaction characteristics, lower profits are statistically significantly associated with more expensive homes and with sales to corporate buyers. Previous investigative journalism has addressed the impact of iBuyers selling properties to corporate single-family rental landlords on the housing stock (Buhayar et al., 2022). This result add context by suggesting that iBuyers tend to realize relatively lower profits when selling properties to companies compared to individual buyers. A potential mechanism for this trend could be the greater resources, information, and volume purchasing power available to institutional buyers.

With respect to neighborhood housing quality and demand, higher vacancy rates and a higher percentage of listings with price reductions are statistically significantly associated with lower profits. This suggests that iBuyers are responsive to prevailing housing market conditions. Regarding neighborhood amenities and socioeconomic characteristics, the model shows that iBuyers tend to realize higher profits in neighborhoods with higher average home values and longer commute times, while profits are lower in tracts with higher levels of educational attainment. Simultaneously, the analysis reveals that iBuyers gain less profit when selling more expensive individual homes (−0.57 SD, $p < .001$).

These findings on individual and neighborhood-level property values highlight two contrasting dynamics that could influence iBuyer profit margins. On the one hand, the higher profits in neighborhoods with higher average home values may suggest that iBuyers are capitalizing on the overall demand and desirability of these areas, which could allow for more favorable pricing conditions. However, the fact that iBuyers gain less profit when selling more expensive individual homes indicates that the margins shrink when the properties themselves are higher in value. This may be because wealthier sellers are more price-sensitive or better informed, limiting the markup that iBuyers can charge, or because competition in higher-end housing markets reduces their ability to realize large profits.

These results suggest that while iBuyers benefit from operating in neighborhoods with higher home values, they face diminishing returns on more expensive individual properties. They may reflect iBuyers' difficulties in extracting large margins from wealthier individual buyers. This underscores the complexity of how iBuyers navigate different housing markets, as neighborhood-level characteristics interact with property-level factors to shape profit opportunities. Moreover, understanding these dynamics requires attention to the racialized and systemic histories that have shaped neighborhood desirability and property values in the first place, including the long-standing effects of housing discrimination, disinvestment, and wealth inequality.

Lastly, it warrants to interpret the spatial dependence and the spatial lag impact of the independent variables. All coefficients for the spatial lag of the dependent variable (ρ) are positive and statistically significant, indicating that iBuyers' profit margins are spatially clustered. It suggests that iBuyers' profitability is not isolated to individual transactions but rather diffuses across neighboring areas, influenced by both direct and indirect factors.

In terms of the spatial lag model's impact, the indirect impacts of the independent variables capture the spillover effects that one neighborhood's characteristics can have on surrounding areas. This calculation uses an impact measure that accounts for the feedback effects caused by spatial dependence (how changes in one property affect others and back again). For instance, the percentage of Black and other nonwhite residents in a tract has a small but positive indirect effect on iBuyer profit margins, meaning that an increase in the nonwhite population in one tract not only contribute to relatively more profits directly but also has a positive spillover effect on neighboring properties. The indirect impact for the percentage of Black residents, while modest (0.0011), reinforces the notion that the racial composition of one neighborhood can influence the economic outcomes of nearby areas.

Discussion and conclusion

On competitive pricing and neighborhood inequality

The analysis warrants a critical reflection on the proprietary valuation models of iBuyers. The process of proposing competitive pricing for homes involves all sorts of characteristics of individual housing, as well as the data of neighborhood conditions with the annotation of heterogeneous data by human workers guided by local real estate people, which may perpetuate existing inequalities. It is important to note that this does not imply that the individuals performing this task are racists. Rather, the aim of optimizing the model for profit may not explicitly intend to discriminate against communities of color, but as the analysis suggests that the profit margins of iBuyers are spatially clustered and some iBuyers on average gains more profits on communities of color, the impact of such optimization may disproportionately affect homeowners in the communities of color. This suggests that the seemingly neutral operation of technology-driven business models can still take advantage of neighborhood structures, particularly those historically characterized by residential segregation and neighborhood-level disinvestment.

The challenges of offering competitive pricing, and the incorporation of "local" real estate knowledge as a result, suggest the need for further critical reflection. For example, Zillow Offers and Redfin Now both ceased operations due to difficulties in accurately forecasting home prices. Some news articles suggest that Zillow's model was unable to capture the idiosyncratic characteristics that deterred potential buyers (Etzioni, 2022). Using deep learning techniques and human-in-the-loop systems with "local" knowledge using unstructured data, as Opendoor currently does, iBuyers may be able to optimize their algorithms and increase profits. However, the analysis indicates that the iBuyer business model with competitive pricing may have implications, given the historical context of neighborhood inequality. While this research was unable to investigate the iBuyers' ML models, and therefore further research is needed to confirm these findings, this suggests that the more accurately iBuyers can predict housing values for profit, the more they may extract value from vulnerable homeowners in neighborhoods of color.

Vulnerabilities of selling homes

The underlying business logic of iBuyers in the real estate industry, which involves purchasing properties for the purpose of resale after making necessary repairs, while also managing negotiations regarding repair costs/credits with prospective buyers, is not necessarily unique. Colloquially known as "flippers," they specialize in finding discounted, often distressed properties for cash buyer investors who are looking to either rent or flip them for profit. By leveraging their contractual rights, they assign the contract to the buyer for a fee (Preis et al., 2023). However, what sets iBuyers apart is their operation of large-scale property flipping, a capability made possible through the implementation of automation through algorithms. This operational approach holds notable implications for neighborhood disparities and the historical context of housing discrimination within the U.S., as the analysis shows that higher profit margins are spatially clustered, and iBuyers gain fewer profits in higher home value tracts and gain more profits in communities of color.

A potential mechanism for understanding the iBuying business model in communities of color could be associated with the vulnerabilities encountered by sellers. iBuyers extend offers that are marginally lower than prevailing open market rates, yet these offers provide immediate cash and exempt sellers from repairs. Considering that iBuyers' service fees, typically in the range of 5–6% are similar to conventional real estate commissions, Sellers might be so attracted by these cash offers and/or repair exemptions that they accept lower-than-market-value offers. It could be attributed to the limited financial means of the sellers or insufficient savings, hindering their ability to prepare their homes for the open market. In this context, such sellers might view iBuyer offers as reasonable. Put differently, this implies that sellers who possess adequate funds to undertake repairs and list their properties on the open market might not opt for iBuyer services. This underscores the critical role of financial considerations in influencing sellers' choices between iBuyers and traditional selling methods.

A more alarming case would be the cases of homeowners who may have retained their homes (and home equity), had there been safety nets, such as home repair programs. For example, low-income homeowners who inherit homes from their relatives but with taxes and debts and require renovations, like in the cases covered by NPR (Wamsley, 2021), would be attracted by iBuyers and willing to sell their home at a lower rate than the open market because of the cash offer and repair exemption. This is closely related to the persistent racial wealth gap as they would lose the opportunity to accumulate wealth through home equity. This opportunity is closely related to build intergenerational wealth through home equity, as properly maintained properties is often seen as "the chance to start building her own wealth" (Wamsley, 2021). In addition, rising property taxes, particularly in rapidly gentrifying neighborhoods, disproportionately affect low-income and often Black or Latino homeowners, making it even more difficult to retain ownership.

One way to provide opportunities for homeowners of color to maintain homeownership and contribute to reducing the racial wealth gap would be to offer a range of options for home repairs. Previous research has shown that about a third of the 100 largest cities offer home repair grants, and about half offer home repair loans, thanks mostly to the Community Development Block Grant (CDBG) programs. Programs vary by city; for example, many cities offer zero- or low-interest loans for repairs like sewer line replacements or energy efficiency upgrades, such as those supported by the U.S. Department of Energy's Weatherization Assistance Program. Cities like Los Angeles, Dallas, and San Jose offer extensive repair programs with budgets exceeding $1 million, whereas smaller cities like Buffalo and North Las Vegas allocate less than $500,000. Most loans are forgivable if the property owner maintains occupancy for 10 to 15 years, offering a critical safety net to lower-income homeowners facing urgent repair needs (Mayes & Martin, 2022). Additionally, HUD recently updated the FHA 203(k) program, increasing the maximum allowable rehabilitation cost for the limited option from $35,000 to $75,000 and extending rehabilitation periods. These changes, aimed at making the program more accessible, allow more homeowners, particularly those in historically disinvested neighborhoods, to secure financing for critical repairs (Goodman & Zinn, 2024).

In this context, the majority of municipal home repair programs are strategically formulated to preserve home retention. By giving vulnerable homeowners the “choice” between selling their homes to iBuyers and maintaining them, they would be able to make decisions based on what they believe is best for their circumstances. For those who own only one home for their living, these repair options may be particularly appealing, as they would allow homeowners to retain their land and housing and potentially accumulate wealth through home equity.

“Race for profit” in colorblind racism

The case of iBuying exemplifies the simultaneous processes of devaluation and extraction, illustrating what Markley (2024, p. 11) theorizes as “planned spatial obsolescence” in the U.S. housing market. This concept suggests that value production in one location requires the creation of “anti-value” elsewhere, manifesting as economic loss in segregated or devalued areas. In this context, residential segregation serves as a mechanism that delineates where value accumulates and where economic loss is concentrated. In this context, iBuying serves as a unique example; within the framework of residential segregation and devaluation, these practices extract value by further devaluing segregated neighborhoods, contributing to exacerbating the inequality embedded in unequal property relations.

To this end, the iBuying business model, while representing a race-neutral, algorithmic approach to property flipping practices, inadvertently perpetuates systemic racism. This model operates within a market structured by racial segregation and devaluation, reinforcing the economic logic underlying them. In doing so, their practices reproduce racialized inequalities, effectively enables capital to extract value from those areas while offloading the economic loss, providing a double benefit to capital (Markley, 2024) at the expense of racially and economically disadvantaged communities.

This practice has implications for the role of contemporary technologies and algorithms in a society where deeply racialized practices and policies continue to disadvantage people of color. For example, current regulations related to racial discrimination prohibit the use of identity markers such as race or gender in the development of policies or practices. While these prohibitions are often justified as a means of creating “fair” algorithms or attitudes, the problem is that these race-neutral markers, such as credit score, are often strongly correlated with other socioeconomic characteristics, and machine learning algorithms can pick up on these correlations and use them to increase the accuracy of their predictions. As a result, while iBuyers’ algorithms or business logic may not be harmful in and of themselves, by actively not engaging with a housing market that has been deeply discriminatory, they end up participating in the extraction of value from vulnerable homeowners.

Following Bonilla-Silva (2018), I argue that to advocate for race neutrality in law and technologies is to create “New Racism” (Bonilla-Silva, 2018, p. 38); in order not to unthinkingly discriminate, practices and policies should intentionally recognize and examine the impact of race in which their business or public policies operates. The key is to explicitly bring the conversation of race to the table in every step of designing, developing, testing, and auditing technologies. Incorporating a *race-conscious* approach is not for discriminating against people of color. Rather, it entails recognizing the necessity of acknowledging and addressing historical injustices faced by people of color. This perspective on race-consciousness serves as a crucial tool to both identify potential discriminatory practices and establish avenues for rectification, ultimately playing a pivotal role in advancing racial justice.

Note

1. https://perma.cc/T9VS-SK6W.

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Appendix

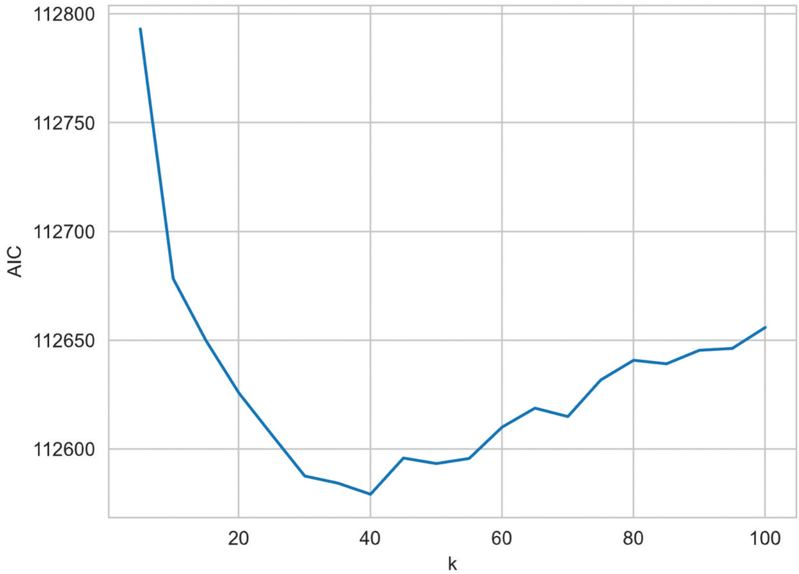

Figure A1. Models with incremental KNN (5-100) for finding the minimum of AIC. It suggests k = 40 would yield the lowest AIC.

Table A1. Lagrange multiplier diagnostics for spatial dependence.

Test	MI/DF	Value	Prob.
Moran's I (error)	0.0214	21.611	0.0000
Lagrange Multiplier (lag)	1	372.740	0.0000
Robust LM (lag)	1	19.151	0.0000
Lagrange Multiplier (error)	1	444.430	0.0000
Robust LM (error)	1	90.841	0.0000
Lagrange Multiplier (SARMA)	2	463.581	0.0000

This specification of the OLS model is the same as the model in Table 3.

Weighting estimator

I created a weighting estimator to estimate the causal effect of neighborhood composition on iBuyers' profit margins, to compare to the main SAR model. Specifically, I estimated the continuous treatment effect of neighborhood racial composition. In this analysis, I assume that the covariates largely satisfy the unconfoundedness assumption, one of the key identification assumptions for weighting: $D_i \perp\!\!\!\perp (Y_i(1), Y_i(0)) | X_i$. I derived weights from Bayesian Additive Regression Trees (BART)-based propensity scores for each neighborhood racial composition variable (continuous), using the same covariates as in the main SAR model. Most covariate balances (as measured by standardized mean differences) were ≤ .1. Following Nguyen et al. (2017), I applied double adjustment in the weighted regression for any covariate with a standardized mean difference greater than 0.1. The estimation was then performed using g-computation, where predicted values were computed from the weighted regression with treatment status, and the causal effect was estimated based on these predicted values. Table A2 shows that the results are largely consistent with those from the SAR model, showing similar statistical significance across the two iBuyers (In the SAR model, Opendoor demonstrates a positive and statistically significant relationship with the percentage of Black residents in a tract, while Zillow shows a similar relationship with the percentage of Latino residents). However, Opendoor exhibited a statistically significant relationship between the proportion of nonwhite residents (other than Black) and profit margin, but when aggregated across all iBuyers, this effect became diluted and lost statistical significance.

Table A2. Weighting estimator results.

Outcome Profit margin, standardized	(1)
Treatment	
% of Black People	0.00836***
	(0.000796)
% of Latino People	0.00149**
	(0.00055)
% of Other non-white People	−0.00117
	(0.00153)
Observations	43,659

Delta standard-errors in parentheses.
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05..*