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Uneven development and the anti-politics machine: Algorithmic violence and market-based neighborhood rankings

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ABSTRACT

This paper investigates the role of supposedly objective algorithms in producing uneven urban spaces through market-based neighborhood rankings. Focusing on the Market Value Analysis (MVA), we argue that municipal governments' failure to explicitly account for the racialized and class-based production of urban space in ranking algorithms hinders their capacity to foster equitable and vibrant neighborhoods. Instead, these algorithms deepen existing inequalities and reinforce market-based approaches to neighborhood typologies and spatial organization, effectively serving as tools for capital accumulation. Through a comparative analysis of the Market Value Analysis (MVA) and historical Home Owners' Loan Corporation (HOLC) maps across 10 cities, we illustrate how the MVA preserves wealth while simultaneously producing poverty in certain areas to benefit affluent landowners. We argue that the MVA typology, presented under the guise of technological objectivity, functions as part of an anti-politics machine that depoliticizes and institutionalizes race- and class-based housing segregation. By positioning city residents as "customers" and aligning government spending with market-driven priorities, the MVA algorithm places profit motives above the immediate needs of vulnerable communities. Consequently, it perpetuates and amplifies existing disparities in urban geographies, reinforcing racial capitalism through ostensibly "objective" market-based approaches to public policy. Toward realizing a more equitable and just future, our findings challenge claims of the objectivity of technical planning products and instead elucidate the role algorithms can play in the differential valuation of urban territory.

1. Introduction

> "Here's the analysis that will help guide Dallas' housing policy: The new Market Value Analysis is a *technical* tool that will inform some of the most important decisions the city needs to make" (emphasis added, excerpt from a Dallas-based lifestyle magazine, Macon, 2018).

An abundance of urban data has helped popularize a discourse valorizing "technical" and "objective" data-driven municipal policy tools. These tools, including various forms of neighborhood housing market typologies, are used by urban planners to evaluate neighborhood housing markets and direct municipal investment based on their perceived health. Rather than targeting investment toward areas with the greatest need, municipalities employ these typologies following a strategy of "build[ing] from strengths" (Pritchett et al., 2021: 7) which aligns with the broader logics of neoliberalism and austerity governance. Residents in neighborhoods most in need of municipal investment and services, but classified as being in "distressed" housing markets, are not only denied equitable treatment but are further marginalized as the lack of investment perpetuates their status, deepening cycles of poverty. We argue that the depoliticization and institutionalization of market-based neighborhood ranking algorithms are integral to a larger anti-politics machine, one that obscures the social processes behind algorithmic design and interpretation, and reinforces a market-driven approach to urban development that perpetuates inequality and marginalization.

The algorithms employed to make these determinations are considered secretive intellectual property; firms commodified the algorithmic analysis, charging municipalities to create and update maps of neighborhood housing market typologies. The appeal of these algorithms partly lies in the claim that they are data-driven and, thus, infallible to bias in the dispensation of municipal resources. The focus on the data itself directs attention away from both how the algorithm makes determinations (the work of the algorithm or the "drive" in data-driven) and how municipalities might (re)interpret potential insights.

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Consequently, the formulation of market-oriented algorithmic neighborhood rankings disregards the intricate patterns imprinted on the topography of the city by persistent class-based and racially discriminatory policies throughout history. Algorithms that approach the city's geography as if it were an unmarked canvas, neglecting its intricate historical sedimenting under the processes of racial capitalism, are likely to reinforce and solidify prevailing spatial disparities.

This paper aims to critically examine the use of market-based algorithmic neighborhood typologies and their role in perpetuating urban inequality. Specifically, we focus on the Market Value Analysis (MVA), a neighborhood classification analysis first introduced in 2001 and sold to over 40 municipalities. The MVA claims to provide an objective assessment of neighborhood housing markets to guide economic development and investment, but it fails to explicitly consider the historical and contemporary processes that have produced and perpetuated spatial disparities. As the epigraph of this section demonstrates, the technical framing of the MVA contributes to its depoliticized role in determining funding and value. By highlighting the inherent limitations and biases of these rankings, we unravel the illusion of objectivity surrounding them and shed light on their implications for urban governance and social justice.

This article contributes to the literature on the use of algorithms, and their framing as "objective," for spatial ordering in urban and political geography in two significant ways. Firstly, we argue for the necessity of adopting a relational analysis that considers the production of poverty and wealth simultaneously. While much of the discussion surrounding residential security maps focuses on the conditions of poverty and the disadvantages faced by redlined areas, understanding the enduring legacy of Home Owners' Loan Corporation's (HOLC) Residential Security maps (redlining maps hereafter) classification requires recognizing the persistence of wealthy, predominantly white enclaves. By broadening the analysis to encompass both ends of the socio-economic spectrum, we uncover how seemingly objective neighborhood typologies actively sustain wealth accumulation for those in power, perpetuating socio-economic inequalities through spatial and racial hierarchies.

Secondly, our research contributes to the discourse on algorithmic violence by revealing the ways in which supposedly objective neighborhood typology algorithms perpetuate existing inequalities and reinforce market-based approaches to spatial ordering. These algorithms serve as tools for capital accumulation, reproducing hierarchies of territorial difference. By presenting algorithms as apolitical and unbiased, they effectively conceal the entrenchment of capitalist practices that categorize neighborhoods hierarchically to generate value. Neighborhood ranking algorithms work as an anti-politics machine through a dual process of depoliticization and institutionalization, deepening existing algorithmic biases and entrenching spatial segregation. The inherent bias and market-driven nature of algorithmic neighborhood rankings demands further scrutiny and critique.

This paper begins with a review of the literature on algorithms, redlining, and urban geography, highlighting how algorithms, though often seen as neutral, are deeply tied to historical racial and class-based discrimination. We then trace the origins of biased neighborhood rankings to the 1930s HOLC Residential Security Maps, drawing parallels with modern tools like the MVAs. After explaining our methods and results, we argue that algorithms like the MVA act as anti-politics tools, masking racialized power dynamics and reinforcing disinvestment in Black areas while preserving wealth in predominantly white ones. We conclude by urging a critical reassessment of algorithmic tools like the MVA, which actively uphold racial and economic hierarchies, and advocate for more equitable urban policy solutions.

2. The work of algorithms

Algorithms bring to mind images of computers whirring away to read large amounts of input data and expeditiously solve whatever complex problem is at hand. For urban scholars and policymakers, this imagery is reinforced by exposure to large tech firms seeking to capitalize on the technocratic ideal of a placeless smart city. Urban ills are framed as problems requiring massive amounts of data, a few keystrokes to prioritize issues such as economic growth or "the environment," and large computers to crunch out an objective "answer"(Barns, 2020; Mattern, 2017; Rose, 2020).[1]

The term "algorithm" traces its origins back to the 9th century Persian scholar Muhammad Abu-Abdullah Abu-Jafar ibn Musa Al-Khwarizmi Al-Majusi Al-Qutrubbulli (Muhammad ibn Musa al-Khwarizmi), who is considered the progenitor of concepts of traditional algebra. In his book "Computing with Indian Numbers," Al-Khwarizmi provided detailed procedures on how to utilize an abacus—a device used to aid in computations—to solve mathematical problems. Therefore, algorithms are not inherently a form of computation in themselves, nor do they require complexity or silicon processors. Rather, they are sets of instructions for performing computational tasks or problem-solving operations. In the case of Al-Khwarizmi, the algorithm outlined the steps to follow when utilizing an abacus for mathematical calculations. In modern contexts, algorithms guide the operation of computer processors and switches to solve complex computational problems.

Understanding algorithms as "instructions to solve a problem" brings agency and accountability to the algorithm creator(s) and, importantly, how they frame the problem that the algorithm addresses. Ọnụọha (2018) coins the term "algorithmic violence" to capture "the violence that an algorithm or automated decision-making system inflicts by preventing people from meeting their basic needs." While often presented by states, private companies, and non-profit organizations as necessary tools for solving complex social problems, algorithms can reinforce systemic—or historic—biases and widen social disparities. Ọnụọha uses the term to highlight how automated decision-making systems deny, exclude, or obscure marginalized communities. Algorithmic violence then stems from the appearance of algorithmic neutrality and objectivity and the tendency to reproduce societal inequalities by either overlooking or misusing data related to marginalized populations (Ọnụọha 2018). Safransky (2020) builds on this notion by demonstrating how, in housing markets and urban planning, algorithms reinforce historical patterns of spatial inequality, further formalizing these biases and masking the political and racial dimensions of urban development.

There are numerous examples of how algorithmic bias and prejudice lead to harmful outcomes. In the realm of technology, for instance, Google job ads were shown to display high-income jobs to men more frequently than to women (Datta et al., 2015). Similarly, facial recognition algorithms identified the gender of white men with 99% accuracy but could only do so for non-white women with 35% accuracy (Raji & Buolamwini, 2019). Another case involved an algorithm used in judicial sentencing, which inaccurately predicted higher recidivism rates for Black defendants than the actual statistics support (Mattu, & Angwin-KirchnerSurya, 2016). Scholars have also highlighted the role of data-driven governance in reinforcing socio-spatial inequalities and power dynamics in urban environments (Datta, 2018; Leszczynski, 2016). Noterman (2022) argues that algorithms designed to predict urban vacancy without considering how "race is spatialized" (McClintock, 2018, p. 3) reinforce racialized property relations and perpetuate inequality. By focusing solely on identifying vacancy, these algorithms ignore long-standing processes and policies that disenfranchise Black residents and people in poverty. As a result, these algorithms label racialized communities as vacant, erasing the presence of Black

[1] One of the most prolific examples of smart city algorithms are those to solve the ubiquitous urban ill of traffic congestion. Outcomes describe how to reduce congestion through things like pricing and built-form interventions. A quick Google Scholar search reveals that there are even algorithms to better *simulate* traffic in smart city traffic models.

residents and reinforcing stereotypes that link Blackness with poverty and underdevelopment (McKittrick, 2011, 2013; Noterman, 2022). This approach ultimately justifies speculative reinvestment in these areas, positioning them for resettlement by wealthier, predominantly white populations deemed more "appropriate" users of the land (Noterman, 2022). Safransky (2020) shows that data-driven maps of market value in Detroit, assumed to be objective, closely resemble the discriminatory redlining maps of the 20th century, which denied loans to African Americans and other marginalized groups. These maps have played a crucial role in sustaining the urban racial segregation that persists in many U.S. cities today. Safransky warns that this could lead to a new form of racist risk assessment, where race continues to be a determinant of market value and investment potential. Similarly, Datta (2018) critiques smart city initiatives like the RC100 program in India, which excluded those without digital access, reinforcing historical social inequalities by privileging citizens with property rights and access to digital infrastructure. These digital tools, far from democratizing urban planning, have deepened the divide between the propertied and the dispossessed, extending historical inequalities into the digital realm.

In her work, Benjamin (2019) brings attention to the deceptive nature of algorithms designed to address racism, coining the term "New Jim Code" to describe this phenomenon. These intricate algorithms, promoted as "AI for good," aim to transfer decision-making from potentially biased humans to seemingly impartial machines. However, Benjamin argues that these algorithms often reflect and perpetuate existing inequities while masquerading as progressive solutions. The concept of the New Jim Code highlights how these algorithms reinforce discrimination, presenting a need for critical scrutiny of their underlying biases and power dynamics. For example, different counties and states have proposed using machine learning algorithms to eliminate racial biases of judges in the bail system.

As Benjamin (2019) demonstrates, equity-focused digital technologies and algorithms perpetuate inequity since they are agnostic of the power relations embedded within them. Even when power relations are confronted, the myth of algorithmic techniques being beyond bias appears hard to resist (Safransky, 2020). As algorithms become more complex (for example, with AI and machine-learning), the difficulty in understanding how algorithms operate—and disentangling potential bias—also increases. The "training" of AI algorithms, or simply their inputs, reflect existing social hierarchies. Racist and sexist social structures become embedded within their logic, reflecting the sorting of humans according to their differentiated "value" under global racial capitalism (Robinson, 2021). In sum, power relations and inequality become embedded in the lack of transparency in how algorithms are designed, what is chosen as inputs (or training data), how they operate, and how they come to decisions. The facade of objectivity and the lack of transparency enables the deployment and diffusion of digital technologies by politicians, planners, and technologists. Thus, attempts to ameliorate inequalities in fact enshrine algorithmic biases while simultaneously averting critique due to the very perception of their objectivity.

In each example, the algorithm reflects and reinforces existing hierarchies of power. Since algorithms are built from the world as-is, they run the risk of embedding wider societal biases and reinforcing inequalities—unless they seek to directly dismantle structures which produce inequality. Even bias on the small scale may in sum reproduce society-wide hierarchies and inequalities. By exploring the transformative power of algorithms in shaping urban spaces, we underscore the importance of understanding their implications within the broader context of social and spatial justice.

The framing of policies as objective and apolitical is not limited to technology. Ferguson argued that international development organizations presented their interventions and aid as technical and apolitical in what he described as an "anti-politics machine" (Ferguson, 1994). The anti-politics machine serves as a framework to describe the way a series of interlinked processes "depoliticizes everything it touches, everywhere whisking political realities out of sight, all the while performing, almost unnoticed, its own pre-eminently political operation of expanding bureaucratic state power" (Ferguson, 1994: xv). Watson (2009) critiques techno-managerial approaches to urban planning that are presented as rational and objective but are actually based on notions of urban land use developed in European cities. In this way, state and private interests are able to (re)shape the city in more subvert ways that seek to "sweep" away poor residents (Watson, 2009). The anti-politics machine has been especially relevant as new data are produced through surveillance and community initiatives. Ferguson's framework has been applied to critique supposedly technical approaches to urban planning. In the case of Johannesburg, South Africa, for example, urban planners embraced Geographic Information Science (GIS) as a technical tool to address segregation (Lupton & Mather, 1997). GIS is employed in ways that predetermined the basis on which land use claims were made. With parallels to the MVA, Johannesburg City Planners mapped vacant land in the city, coding it as high, medium and low priority development (Lupton & Mather, 1997). In the context of smart-cities, Sadowski and Levenda (2020) deploy the anti-politics machine to suggest that smart energy technologies are framed as a way to limit agency in the implementation of policy.

We argue that algorithms work as an anti-politics machine through a dual process of depoliticization and institutionalization. The process of depoliticization builds from decades long narratives of technological objectivity, but embeds the power and bias of its creators to sidestep the continual political process of deliberation. Algorithms are presented as objective instructions, and in our case, naturalize the processes of ranking neighborhoods. The process of institutionalization establishes depoliticized algorithms in the operations at various levels of government and in corporations. This naturalizes their function and outputs, ensuring their social, political, and economic obduracy. As Ettlinger (2022: 51–52) puts it, bigoted and unequal technical outcomes do not primarily stem from the technology itself; rather, they are derived from the value systems ingrained within technological and technical design frameworks, which in turn steer the practices facilitated by these technologies.

Thinking about algorithms as "instructions to solve a problem," again, necessitates transparency to understand the agency and accountability of algorithms' creator(s), intended uses, and, importantly, how they frame the problem that the algorithm addresses. Thus, merely advocating for transparency in algorithm construction and operation may not be sufficient. Transparency often focuses primarily on the technological aspects, neglecting to attribute accountability to both the algorithmic systems and the individuals behind them (Safransky, 2020, p. 6). Approaching algorithms as problem-solving instructions underscores the need for transparency to comprehend the agency and accountability of the algorithm's creators, intended applications, and, crucially, how they define and frame the problem being tackled. Noble sees this as the imprint of the technology (in this case algorithm) creators: "In short, technology bears the social 'imprint' of its authors. It follows that 'social impacts' issue not so much from the technology of production as from the social choices that technology embodies" (Noble, 1979, p. 104). We contend that embracing this perspective of algorithms and their role in the anti-politics machine, is a necessary step to more comprehensively understand algorithms and their societal implication.

3. Redlining as algorithm

Understanding algorithms as a reflection of social agency in creating instructions can help us reconsider the historic 1930s Residential Security Maps. This perspective sheds light on the agency of the map creators, their biases, how those biases were codified into a set of instructions, and how they manifested in the hierarchical categorization of neighborhoods.

"Redlining" maps were a product of the HOLC, a New Deal corporation created with government backing from the Federal Home Loan

Bank Board. The stated purpose of HOLC was to prevent foreclosure by refinancing loans currently in, or close to, default. The HOLC made one million low-interest loans to homeowners during their active mortgage offering period of 1933–1936. It was not until the end of 1935 that the HOLC implemented an initiative to appraise real estate risk levels across US cities (Hillier, 2003a). Staffed with existing HOLC employees, and in consultation with local informants such as real estate agents, appraisers, and lenders, HOLC created 239 Residential Security Maps across US cities, counties, and regions (Hoagland & Stone, 1961; Jackson, 1980; Hillier, 2003a). "The purpose of these maps was to study the factors which govern the desirability of the security underlying long term residential mortgages" (United States Federal Home Loan Bank Board, 1940, 7). The maps, however, confer the "desirability of the security" not on the home itself, but on the neighborhood, rendering "security" as an explicitly spatial issue. Loans, and their perceived risk, were lumped together by spatial proximity regardless of the individual applicant or home.

To classify neighborhoods, HOLC staff and local informants used various built environment inputs, such as housing type and housing age, as well as egregious descriptions of inhabitants based on occupation/class, national heritage, and "threat of infiltration of foreign-born, negro, or lower grade population(s)"—a farrago of prejudices that in turn, assigns value to homogenous, Protestant, "native white" neighborhoods (Nelson et al., 2020). HOLC aggregated these characteristics to yield a classification as A, B, C, or D. Neighborhoods in the "A" category were described as "Best," were nearly all white Protestant, and cartographically depicted with blue. Loans in the "D" category were considered the least safe, primarily because of a concentration of Black inhabitants, immigrants, and low-income populations, and consequently cartographically depicted in red for "hazardous" (Markley, 2023).

Data for the HOLC were collected via forms that codified inputs in both the content and the structure of the form (what questions were asked). The data on these forms were then used by HOLC to determine neighborhood ranking—the redlining algorithm. More data was collected in poorer neighborhoods. For example, in a "desirable" suburban area of Baltimore, such as Linthicum Heights, little is needed to classify this neighborhood as the second tier "B" category. Linthicum Heights is a neighborhood of "good character", distant from the city center, and has no recording of out-of-place deviants (see Baltimore's B23 district in Nelson et al., 2020). Conversely, inclusive of West Baltimore, the extensive data collected for a typical bottom-tier "D" neighborhood includes rents, occupation of residents, estimated income, and remarks regarding vandalism (see Baltimore's D4 district in Nelson et al., 2020). Survey takers expressed concern about the containment of the "negro concentration" to prevent further "infiltration." The disparity between the data collected on top-tier versus bottom-tier neighborhoods is endemic of the surveillance and control of Black bodies and Black spaces and impulse to document "vice" (Browne, 2012; Hartman, 2019; Robertson et al., 2012). The pattern of detailing perceived threat and perceived immorality is consistently used to characterize majority-Black and immigrant neighborhoods in HOLC classifications from every city (Nelson et al., 2020). Yet, the data collected on neighborhoods are considered objective data and part of the form used to rank the neighborhood; thus the gradings become depoliticized and the outcomes are naturalized through an anti-politics machine. Further, the Residential Security Map categories, as well as their recent research on them, place undue emphasis on "redlined" areas over other neighborhood categories (Markley, 2023, 2024) and on the historical maps over more recent racist housing practices (Gioielli, 2022). This preference is reflected in a greater focus on the maps themselves at the cost of their accompanying field notes. Additionally, the map grades have been consistently treated as fixed rankings, ranging from "most favorable" to "least favorable," which leads to the oversight of the "considerable internal variability" within the HOLC categories (Markley, 2023, p. 3).

Recent work on HOLC and the Residential Security Maps "recasts the maps and their accompanying field notes as windows into the governing racial–spatial ideology of 20th-century US real estate capital" (Markley, 2023, p. 196; see also Hillier, 2003a). Although the HOLC did not use their security maps in the determination of federal loans, there was significant personnel crossover between the HOLC and the FHA. The FHA's first *Underwriters Manual,* published in 1935, had similar language to HOLC's in regards to what constituted quality in a neighborhood (Rothstein, 2018). The FHA later created their own maps which contained "striking similarities" between the FHA maps and the HOLC maps—including the survey instrument, the ranking scheme, and the colors used for each area—which should not be a surprise due to the directive to share information between the agencies (Hillier, 2003b, pp. 402–404). In later initiatives, in 1938 and again between 1937 and 1942, the FHA referenced the HOLC maps and personnel to create additional "Housing Market Analyses" (Hillier, 2003b, p. 403; Hoagland & Stone, 1961). Importantly, while the FHA *Underwriter's Manual* sought to help underwriters assess individual properties, it was the HOLC maps which captured the instructions to categorize entire neighborhoods across the US, institutionalizing and codifying the basis of a racially segregating algorithm.

4. Algorithmic neighborhood rankings and value

Despite its development over seven decades after the HOLC maps, the MVA directly continues the practice of algorithmically assigning value to different neighborhoods based on attempts to understand, and profit from, the housing market. The Reinvestment Fund (RF) was established as a non-profit community development financial institution (CDFI) in Philadelphia and receives money from the local, state, and federal government, philanthropic institutions, private companies, and individual investors (Goldstein, 2014). The RF develops and deploys the MVA to "guide key decisions about allocations of programs and resources" (Goldstein, 2014, p. 82) such as local schooling, housing, and food geographies through the production of technical products like MVA geographies as well as the creation of other data and policy solutions. As a CDFI, TRF was ostensibly established to help underserved markets, and CDFIs as a group of institutions were established to rectify redlining practices (Goldstein, 2014). However, as Ruha Benjamin notes, oftentimes organizations and algorithms which are intended to rectify systemic inequality can instead reify and expand these social orderings. The inputs used for "objective" algorithms to classify neighborhoods begin with a spatiality of the city that was predicated on decades of racist spatial ordering and classification. Tools such as the MVA parallel other trends in neoliberal urban planning in which the state and private organizations partner to use state resources to maintain white property values. The products of these neoliberal planning technologies become naturalized, depoliticized, and embedded within private organizations and municipal institutions through the anti-politics machine.

Since 1985, the Reinvestment Fund (RF) has been classifying neighborhoods and local markets to direct investment strategies for governments at the city, county and state level. The Market Value Analysis (MVA) is the RF's self-described "most effective tool" for informing public and private investment strategies (The Reinvestment Fund, 2022a). Over 40 states, cities and municipalities around the United States have paid TRF to grade and map their neighborhoods using the MVA since 2001 (The Reinvestment Fund, 2022a). The MVA is unique for each city and time period, but the different grading scales translate to a schema that categorizes neighborhoods overall from strong to distressed. More recently MVAs have used grading scales from A to H, or I, with A being the most desirable grade. The cartographic color choice for the grading scale and the grading scale itself varies, but the purple, blue, and green representation of "stronger" markets and the yellow, orange and red representation of more "distressed" markets parallels the HOLC maps of 1930s and 40s. The visual and categorical parallels between the MVA and the HOLC maps are not merely aesthetic or historical echoes; they carry significant implications for urban investment and disinvestment patterns.

According to a publication by the RF CEO and published by the Federal Reserve Bank of Boston, Federal Reserve Bank of Cleveland, and the Federal Reserve Board, the resulting MVA housing market typology and maps are advertised and advocated as the basis for spatial distribution of billions of dollars of public and private investment (Goldstein, 2010) and subsequent disinvestment. Planners and policymakers funnel more government resources into areas which were determined to already have a strong market and thus maintain the market in that area, as well as areas identified as transitional with the supposed aim of improving the market in that location.

Cities around the country use the MVA provided by the Reinvestment Fund to allocate significant portions of their annual budgets—ranging from hundreds of millions to billions of dollars per fiscal year. For instance, Baltimore has purchased five iterations of the MVA from TRF since 2005 to guide public and private investment. The city relies on MVA data to “match strategic interventions with appropriate market conditions” and to “guide day-to-day decisions by assessing market capacity and development potential” (Baltimore City Planning Department, 2014). The MVA has also been instrumental in reducing code enforcement programs in weak-market neighborhoods, while targeting demolition and acquisition activities—primarily for land banking (Goldstein, 2014). Baltimore’s Department of Housing uses the MVA for programs such as Vacants to Value, which budgeted $3.4 million for municipal property acquisition and sale (The Reinvestment Fund, 2023b).

Similar trends are evident in other cities as well. In Dallas, public officials and private stakeholders utilize the MVA to craft intervention strategies for weaker markets, though often without clearly stating the goals for those neighborhoods, while promoting "sustainable growth" in stronger markets (City of Dallas, 2023). Likewise, in Detroit, the MVA has been used to justify cutting off essential services like water and sewage in weak-market areas—neighborhoods that are predominantly Black and poor (Le, 2021). Kansas City follows a similar pattern, using the MVA to allocate funding toward steady housing markets, with its influence extending across city plans and policies, including land banking and economic development initiatives (City of Kansas City, 2021). In New Orleans, the MVA has helped guide limited development funds since 2012, restoring properties to commerce by identifying areas suitable for market-rate residential development (The Reinvestment Fund, 2023c). Meanwhile, in Philadelphia, the MVA directed $275 million in bond proceeds, focusing on maintaining housing markets in middle neighborhoods (The Reinvestment Fund, 2023c). Pittsburgh also uses the MVA to target intervention strategies in weak markets while supporting growth in stronger ones (Urban Redevelopment Authority of Pittsburgh, 2021). In St. Louis, the MVA informed a community development investment system aimed at distressed neighborhoods, although most of the funding targeted middle-market areas through grants and special loan products (Strengthening St. Louis Neighborhoods Task Force & Guenther, 2014). Despite the Reinvestment Fund’s claims that the MVA is a “powerful and proven guide to both daily operations and long-term planning,” it becomes clear that these strategies often fail to prioritize funding for the neighborhoods most in need (The Reinvestment Fund, 2023a). The need to purchase these typologies demonstrates an increased reliance on so-called experts, in what Li (2011) describes as “rendering technical” of societal problems.

The data driving these investment decisions are collected from both public and private sources, are generally consistent, yet still vary by city. The MVA utilizes various underlying datasets from public and private sources to produce the final market typology. The underlying datasets can include data related to foreclosure filings, vacant homes, median home sales price, percent public housing and vouchers, residential water shutoffs, owner occupied housing, and new construction (Goldstein, 2012). These datasets parallel the method of classification of neighborhoods done by the HOLC for the Residential Security maps, which used density, vacancy, foreclosures and industrial activity to grade areas and assess investment risk (Nelson et al., 2020). Analyzing data at the block group level, the MVA uses cluster analysis to group similar markets and produce maps that rank areas from “best” to “transitional” to “distressed” (Goldstein, 2012). Much like the HOLC maps, these rankings are ground-truthed based on people’s perceptions of housing conditions, resulting in classifications that further entrench existing hierarchies of neighborhood stability.

The RF and its partners frequently describe the MVA classification system as “data-based”, “objective”, and “transparent” (Goldstein, 2012; Market Value Analysis (MVA) for Allegheny County & the City of Urban Redevelopment Authority of Pittsburgh, 2021). Ira Goldstein, President of Policy Solutions for the RF, said, “it [MVA] is really designed to be apolitical. It is an objective, rigorously done, evidence-based portrayal of a community’s real estate market” (Market Value Analysis - An Overview, 2016). The RF does not only claim the market classification itself is objective, but the decisions made using the MVA are objective as well. “The RF created the MVA to give public officials the basis for making informed, objective decisions about how to prioritize resources and services” (Goldstein, 2011). Fitting with broader trends to obscure the management and distribution of resources within institutions toward the “supposedly depoliticized, instrumental rationalities of engineering cultures” (Graham & Marvin, 2001, p. 20), it is not surprising that objectivity is assigned to the proprietary MVA maps and the algorithms which the RF developed to produce the maps. However, ranking neighborhoods in tiers naturalizes the notion that developers’ investments are required to strengthen transitional neighborhoods, without questioning what caused these neighborhoods to become distressed in the first place.

Insights from other locations reveal how technological rationalities are obscured by discursive depoliticization, ultimately becoming entrenched within bureaucratic processes and institutions. Ferguson (1994), for example, demonstrated how international development organizations functioned as anti-politics machines, framing their interventions as purely technical and apolitical. When these projects failed to meet their goals, instead of addressing the underlying issues, new projects were introduced, further entrenching bureaucratic power. In much the same way, the MVA mirrors existing racial and income divisions, directing investment and policy accordingly. By presenting these actions as neutral and data-driven, the MVA perpetuates inequality, masking the deeply political nature of its decisions.

5. Data and methods

Our analysis was designed to examine whether the “objective” Market Value Analysis typology reflects and reproduces the neighborhood typology produced by the HOLC Residential Security Maps. Since the HOLC maps reflected the racist practices of real estate agents, lawyers, and urban planners, our analysis sought to understand the area of overlap of the HOLC maps and their relative counterparts in the MVA analysis, by city. The RF has not created the MVA for all US cities, but has focused on deindustrializing cities and growth cities in the sunbelt. Thus, our analysis examines only the ten large cities that have both MVA and HOLC Residential Security Maps and are the primary cities of their metropolitan area. These cities include: Baltimore, MD; Dallas, TX; Houston, TX; Indianapolis, IN; Jacksonville, FL; Kansas City, MO; Milwaukee, WI; New Orleans, LA; Philadelphia, PA; and Pittsburgh, PA.

Where possible we used the most recent MVA.[2] For all cities, MVA’s have 8 or 9 categories of rankings between A through H or I. The categories are ordinal where A represents the “premium” housing market and H and I represent “distressed” housing markets. We combined areas in the top 2 and bottom 2 MVA categories. Everything else we combined into a single middle category. This allowed us to compare HOLC’s A

[2] Baltimore is the only exception where we used 2014 typology because the more recent version includes typologies that do not correspond to the housing market.

(coded as "best") and D (coded as "hazardous") categories to their corresponding top 2 and bottom 2 categories. We downloaded shapefiles of HOLC categorizations from the Mapping Inequality archival website (Nelson et al., 2020) and trimmed them to municipal city boundaries. We purchased the MVA categorizations from the RF and matched their block group IDs to shapefiles from the Census Bureau (U.S. Census Bureau, 2019; Walker & Herman, 2022). The MVA typology also includes a non-residential category reserved for industrial districts where there are not enough residences, resibdential sales, or other data to categorize. We include this designation in Table 1. We clipped waterways from both sets of shapefiles for consistency.

Our analysis was completed in two parts. First, we performed an overlay analysis. We intersected the HOLC and MVA shapefiles to understand how areas categorized by the HOLC in the 1930s were categorized in the 2010s by the MVA. For each of our 10 cities, we computed the percentage of area of overlap between each HOLC grade and the three groupings for MVA typology (top 2, middle, bottom 2). This work is presented in Figs. 1 and 2, and Table 1. We contend that a large area of overlap not only shows the staying power of the classification by HOLC, but the potential for the RF to reinscribe and institutionalize the typology. Second, we performed a demographic analysis. We asked who lives in each MVA category, again grouping into top 2, middle, and bottom 2. For each city, we matched the MVA against the same 5-year American Community Survey data at the block group level.

Our assertion is that if the upper and lower segments of the MVA exhibit similar spatial patterns and similar areas to those in the upper and lower segments of the HOLC evaluations, then algorithms designed to categorize neighborhoods must address the manner in which algorithmic inputs—particularly those related to the preexisting racist and classist spatial ordering of the city—or risk reproducing those same racist and classist patterns. We then situate and contextualize the results of this quantitative analysis within the city of Baltimore, using two neighborhoods classified in the top and bottom of both the Residential Security Maps and the MVA. While this study represents only 10 cities, future work could include additional cities if the MVA product is expanded to other municipalities that also have a corresponding Residential Security Map. Further, we are only examining the area of overlap between two sets of spatial products, yet, future work could examine the socio-demographics of each neighborhood.

6. Results

In our overlay analysis for our 10 cities, we found that on average almost 50% of the area that was D-rated by the HOLC in the 1930s were rated in the bottom 2 categories of the MVA in the 2010s or repurposed into industrial or commercial spaces (see Table 1 and the D-rated column of Fig. 1). This finding affirms existing research on the performance of D-rated neighborhoods over time: they are more likely to have higher poverty rates, and in this case, have a distressed housing market. Yet, there was a considerable range among cities. Jacksonville, for example, had over 80% of its D-rated areas in the bottom 2 MVA typology. Dallas and Houston had 63% and 58%, respectively. The two lowest were Baltimore and New Orleans, 20% and 13% respectively, but both cities underwent large-scale redevelopment. Notably, Baltimore's redevelopment happened in the 1970s and 1980s as part of a broader trend of revitalization that took the form of "Disney-fication" (Harvey, 1989).

One other important trend can be gleaned from the D-rated neighborhoods. Several cities saw large parts of their D-rated neighborhoods turned into non-residential or industrial centers. Kansas City saw 35% of its D-rated area turned into non-residential, notably followed by Pittsburgh at 24%, Milwaukee at 13%, Baltimore at 12%, and New Orleans at 10%. The variation in HOLC D-rated areas, while predominantly persistent in being rated as distressed, is also to be expected since all 10 of the cities we examined had larger percent of their area categorized as D than A.

A significant insight gleaned from the overlay analysis is the

Table 1
Cross-reference of each HOLC category and the MVA's top 2 categories, the middle categories, the bottom 2 categories, and non-residential. Each row adds to 100%.

City	HOLC Rating	MVA Rating			
		Top 2, %	Middle, %	Bottom 2, %	Non-Residential, %
Baltimore 2014	A	62.7	36.5	0.4	0.4
Dallas 2019	A	86.0	14.2	0.0	0.0
Houston 2014	A	60.5	36.4	0.1	3.0
Indianapolis 2018	A	66.2	32.2	1.6	0.0
Jacksonville 2015	A	97.3	2.7	0.0	0.0
Kansas City 2016	A	70.8	6.7	0.0	22.5
Milwaukee 2013	A	36.4	63.5	0.0	0.1
New Orleans 2018	A	85.6	12.7	0.4	1.3
Philadelphia 2015	A	62.0	22.4	1.1	14.4
Pittsburgh 2016	A	88.1	9.3	0.0	2.6
HOLC A Average		**71.6**	**23.7**	**0.4**	**4.4**
Baltimore 2014	B	16.3	77.1	4.3	2.3
Dallas 2019	B	20.4	66.2	14.0	0.0
Houston 2014	B	30.6	56.7	11.0	1.8
Indianapolis 2018	B	12.4	78.7	8.8	0.0
Jacksonville 2015	B	37.3	42.2	20.4	0.0
Kansas City 2016	B	47.7	47.7	3.1	1.4
Milwaukee 2013	B	40.3	47.6	2.5	9.7
New Orleans 2018	B	80.0	15.9	2.4	1.6
Philadelphia 2015	B	34.8	61.4	2.1	1.7
Pittsburgh 2016	B	21.1	63.0	11.7	4.2
HOLC B Average		**34.1**	**55.6**	**8**	**2.3**
Baltimore 2014	C	10.8	42.8	43.3	3.0
Dallas 2019	C	1.4	55.3	43.6	0.0
Houston 2014	C	9.9	43.1	45.3	1.6
Indianapolis 2018	C	11.2	72.6	13.4	2.9
Jacksonville 2015	C	4.4	59.1	35.9	0.6
Kansas City 2016	C	8.6	61.9	19.9	9.6
Milwaukee 2013	C	20.4	54.5	18.9	6.2
New Orleans 2018	C	52.4	36.3	9.9	1.5
Philadelphia 2015	C	14.9	55.1	26.8	3.2
Pittsburgh 2016	C	4.8	55.9	29.9	9.4
HOLC C Average		**13.9**	**53.7**	**28.7**	**3.8**
Baltimore 2014	D	37.5	30.1	19.9	12.4
Dallas 2019	D	0.2	35.5	63.2	1.3

(*continued on next page*)

Table 1 (*continued*)

City	HOLC Rating	MVA Rating			
		Top 2, %	Middle, %	Bottom 2, %	Non-Residential, %
Houston 2014	D	12.5	25.8	57.6	4.0
Indianapolis 2018	D	5.7	48.1	43.2	3.0
Jacksonville 2015	D	1.6	16.1	79.7	2.6
Kansas City 2016	D	0.5	28.5	35.9	35.0
Milwaukee 2013	D	10.7	47	29.8	12.5
New Orleans 2018	D	25.4	51.9	12.7	10.1
Philadelphia 2015	D	20.3	43.3	27.8	8.6
Pittsburgh 2016	D	10.0	39.9	26.1	23.9
HOLC D Average		**12.4**	**36.6**	**39.6**	**11.3**

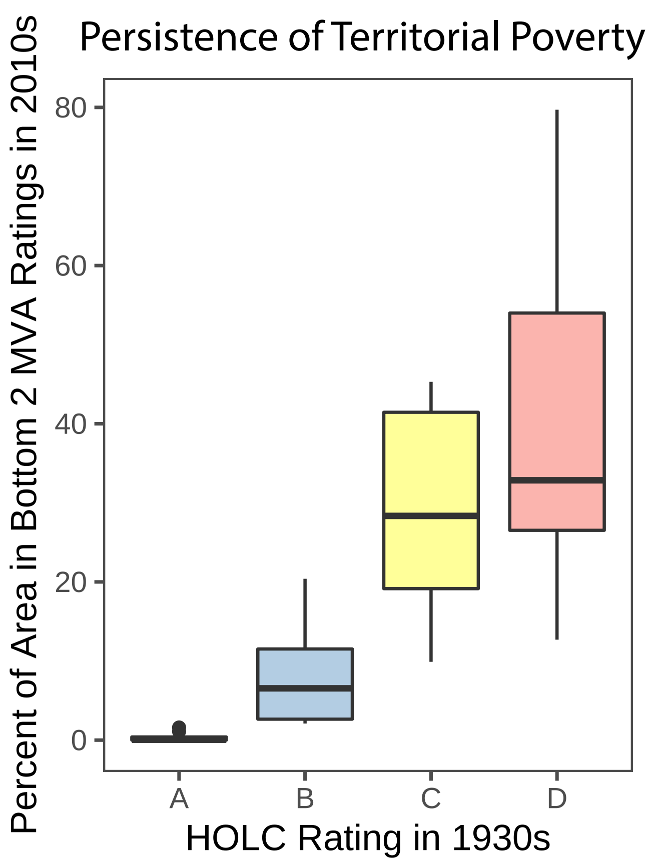

Fig. 1. The territorial preservation of poverty, showing the percentage of area by HOLC rating that were then rated in the MVA's bottom 2 categories.

persistence of wealth in areas that were A-rated in the 1930s. On average, almost 72% of the area that was A-rated by the HOLC in the 1930s was rated in the top 2 categories of the MVA in the 2010s (see Table 1 and the A-rated column in Fig. 2). For Jacksonville, 97% of the area that was categorized as A by the HOLC was listed in the top 2 categories of the MVA. Dallas, New Orleans, and Pittsburgh were in the 85–90% range and all the remaining cities except Milwaukee were in the 60%–70% range. Milwaukee had only 35% of its A-rated area in the top 2 categories. Another almost 50% of Milwaukee's HOLC A-rated area is

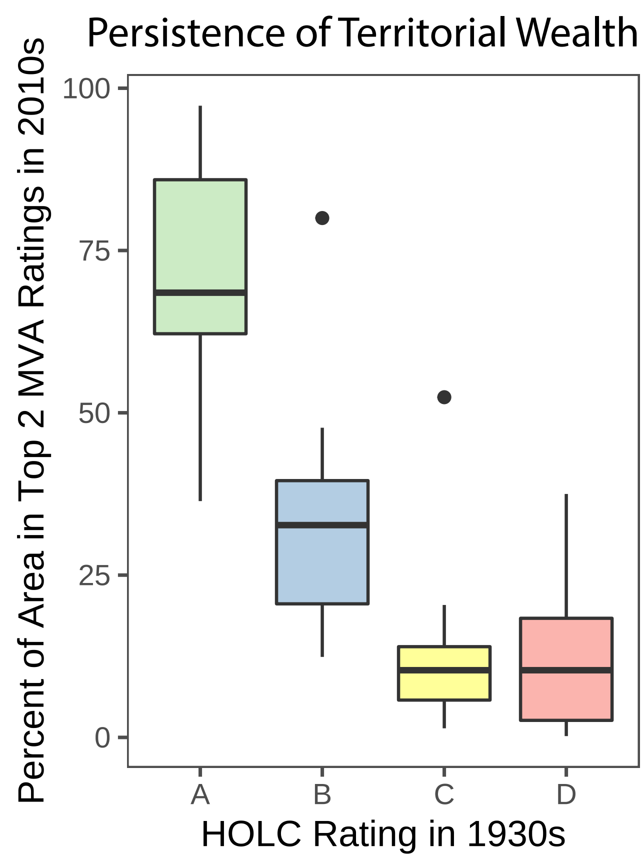

Fig. 2. The territorial preservation of wealth, showing the percentage of area by HOLC rating that were then rated in the MVA's top 2 categories.

now rated by the MVA in their middle categories, signaling a move down-market, but not to the highest ranking of the MVA. Further, for Milwaukee, 40% of the HOLC B-rated area was rated in the top 2 categories of the MVA. That is, Milwaukee neighborhoods with HOLC's B-rating fared better overall in preserving wealth than their A-rated counterparts. Yet, among all cities, the overall trend is toward territorial wealth preservation.

The strong pattern of territorial wealth preservation is evident if we look at how much area "flipped" from HOLC's A-rating to MVA's bottom 2 categories. In none of our 10 cities did more than 2% of the A-rated area become rated in the bottom 2 MVA categories. The average across cities was 0.4% (see the A-rated column in Fig. 1). In fact, in half of the cities there was no overlap at all (see the D-rated section of Table 1). This pattern was stronger than the territorial persistence of poverty, or asking how much of HOLC's D-rated areas "flipped" to MVA's top 2 categories. On average, 12% of HOLC's D-rated area was categorized in MVA's top 2 categories (see the HOLC D-rated column in Fig. 2). Yet, values ranged from between Dallas' near 0% to Baltimore's 37.5%, reflecting local real estate conditions. Baltimore, New Orleans, and Philadelphia all converted over 20% of their HOLC D-rated areas to MVA's top 2 categories primarily in downtown areas and in areas that were predominantly immigrant neighborhoods in the 1930s.

Matching the MVA year with the corresponding 5-year ACS release, we examined the percentage of residents that were non-Hispanic white and non-Hispanic Black (see Table 2). We selected only these two race/ethnicity categories because of their correspondence to HOLC categories. Across all areas that were in the MVA's bottom 2 categories, only 10% of residents were white and almost 57% of residents were Black. This dichotomy was most evident in New Orleans and Baltimore. In New Orleans, residents in the MVA's bottom 2 categories were 85% Black and

Table 2
The percent of non-Hispanic white and non-Hispanic Black in the top 2 and bottom 2 categories of the MVA typology.

	MVA Rating Top 2		MVA Rating Bottom 2	
	% non-Hispanic white	% non-Hispanic Black	% non-Hispanic white	% non-Hispanic Black
Baltimore 2014	63.1	21.1	6.4	87.0
Dallas 2019	82.6	2.6	7.1	32.6
Houston 2014	59.0	7.9	4.1	44.7
Indianapolis 2018	74.6	14.6	36.8	44.4
Jacksonville 2015	73.5	8.6	16.7	76.2
Kansas City 2016	86.5	4.2	14.8	62.0
Milwaukee 2013	74.6	9.9	7.4	70.3
New Orleans 2018	70.1	17.1	8.5	85.4
Philadelphia 2016	68.4	12.7	5.1	66.7
Pittsburgh 2016	75.7	5.5	38.1	51.7
Total	**69.7**	**11.2**	**10.7**	**56.5**

almost 9% white. In Baltimore, residents in the MVA's bottom 2 categories were 87% Black and almost 7% white. Pittsburgh had the highest percentage of white residents in the MVA's bottom 2 categories, at 38%, and was 52% Black. The relative low percentages in Dallas and Houston can be explained by the cities' Hispanic population.

Similar to our overlay analysis, the most interesting results were in the territorial preservation of wealth which revealed stronger racial dynamics in the "top" of the housing market. We found that areas classified in the top 2 categories of the MVA were majority white, similar to the A-rated HOLC areas. The starkest contrast was in Kansas City, where the areas in the top 2 categories of the MVA were 87% white and only 4% Black. Conversely, the top 2 MVA categories for Baltimore were 21% Black—the highest of any city—and 63% white, which is partially explained by the complete redevelopment of Baltimore's core. For all cities combined, the top 2 MVA categories were 70% white and only 11% Black.

7. Anti-politics and relational preservation of wealth

Our analysis demonstrates the bifurcating and on-going effects not only of the property practices associated with redlining, but also of the techno-political ways of categorizing and ranking neighborhoods according to a market logic. By doing so, city bureaucrats and powerful elites reify abstract rankings into reality, cementing the futures of wealthy neighborhoods to stay wealthy and the plight of economically-distressed neighborhoods as in need of investment. By honing in on two neighborhoods in Baltimore that were developed at about the same time, we can situate how our findings play out on-the-ground, illustrate broader points regarding the anti-politics machine and relational wealth preservation, and how the MVA reinscribes market-based approaches to spatial ordering.

The Oliver neighborhood is located within the "Black Butterfly," a metaphor coined by scholar Lawrence Brown (2021) to describe the spatial pattern of racial segregation and uneven investment in Baltimore. In the 1930s, the HOLC characterized the neighborhood as having high proximity to industry and commercial sectors, listing heavy concentrations of foreigners and Black people. The entire neighborhood received the lowest "D" rating on HOLC Residential Security Maps because of these "nuisances." During the 1960s and 1970s, Oliver was also home to the Baltimore chapter of the Black Panther Party (Royster-Hemby, 2006). More recently, the neighborhood served as a filming location for the Baltimore-based HBO drama, *The Wire*, as an emblematic neighborhood riddled with disinvestment, crime, and drugs. Oliver is 96.3% of non-Hispanic Black (U.S. Census Bureau, 2020). The median income is $34,199—about 20,000 lower than the median in the city—and a majority of residents rent their homes. According to the 2008–2012 American Community Survey, Oliver had 953 vacant properties, but by the 2015–2019 survey, vacant properties were reduced by 89% (U.S. Census Bureau, 2020). This reduction in vacancy is often attributed to various revitalization and land acquisition projects led by the not-for-profit organization ReBuild Metro in collaboration with the RF, the organization that conducted the MVA of the area. While recommending that public investment be spent in other neighborhoods, the RF has directly purchased 51 properties in the Oliver neighborhood as of 2019. Many of the RF partners and subsidiaries create new entities for ownership, creating new names, which makes it difficult to determine exactly how many RF partially- or fully-owned properties there are in the neighborhood. By examining the publicly available property records for 2021 (Maryland Department of Assessments and Taxation, 2021), we believe the number could be as high as 250.

In contrast, the Roland Park neighborhood is located within the "White L"—Brown's (2021) counterpart to the "Black Butterfly." The Black Butterfly is marked by disinvestment and in stark contrast, the White L is marked by investment in neighborhoods that are mostly white. The Roland Park neighborhood was built by The Roland Park Company with backing from hundreds of British investors (Glotzer, 2020). The most prominent investors and their families were able to invest because of the capital directly tied to slavery or other forms of segregation (Glotzer, 2020). Thus it is no surprise that the company sought to develop the neighborhood and secure higher long-term return through racial exclusion and spurring the use of racially restrictive covenants in Baltimore and the United States (Glotzer, 2020; Pietila, 2010). Entire neighborhoods could legally restrict certain land-uses and certain residents, considered "nuisances," and in the case of Roland Park, this meant that Black people, factories and other industrial, and livestock were prohibited (Fogelson, 2005; Glotzer, 2017). When the Roland Park Company sought to develop nearby Guilford, their marketing campaign centered around an exhaustive 23-page set of restrictions (Fogelson, 2005). All of Guilford and most of Roland Park were rated as "A" in 1930's HOLC Residential Security Maps, while some parts of Roland Park were rated "B" because the homes were expensive. The 2015–2019 American Community Survey shows the tract that encompasses the majority of Roland Park as being 85% non-Hispanic white, with the next largest race/ethnicity being non-Hispanic Asian at 6% (U.S. Census Bureau, 2020). The median household income is $234,531—nearly $180,000 more than the median in the city and $200, 332 more than the Oliver neighborhood (U.S. Census Bureau, 2020). Guilford has a median household income of $180,441 and is 82% non-Hispanic white (U.S. Census Bureau, 2020). The RF ranked both neighborhoods in the top categories in the MVA (The Reinvestment Fund, 2022a).

Despite the continued interventions by public, private and non-profit organizations guided by the MVA, Oliver continues to be classified as a "distressed" neighborhood. Oliver is not an outlier in the lack of change in market grade. In Baltimore, even with population loss, market fluctuations and the utilization of MVAs to direct large amounts of funding since 2005, a majority of the block groups have not seen significant changes in their MVA typology. Because of the RF's high rankings for Guilford and Roland Park in the MVA, the RF recommends prioritizing residential services to secure high property values.

The patchwork of markets produced by the MVA's typology are used by planners to produce or reinforce territorial differences. In this case, the RF's purchase of properties in "distressed" neighborhoods reveal that perhaps the MVA typology is functioning as it should: as a tool to keep property values low in some areas and relationally keeping property values high in others—similar to the relational way in which the Roland Park Company sought to secure long-term profits. However, we anticipate the RF as one to secure low-pricing in "distressed" areas, providing opportunities for real estate capitalists to purchase properties at market-bottom prices in speculative hopes of future investment. The RF recommends deprioritizing city services like nuisance abatement, dead tree removal, and quality of life enforcement in the lowest ranked neighborhoods (Goldstein, 2014; Mourning, 2015), reinforcing low property values. As the RF and its partners purchase properties and homeowners and tenants move out, the inputs to the MVA algorithm change. For example, while we do not know the full array of inputs to the MVA algorithm nor how they are computed to create the typology, we know that inputs include, or have included, percentage of property sales that are as a result of foreclosure, percentage of subsidized housing units, percentage of housing units with over $10,000 in permits, and variation in sale prices. With larger numbers of units owned by the RF, their own typology would rank a neighborhood in a "higher" or "healthier" market typology which would signal city officials and urban planners to direct public money in that neighborhood, raising the property value and allowing the RF to profit from its investment. While this change hasn't happened (yet) in Oliver, it appears primed to do that.

A change in ranking in the market typology is not just a signal for municipal investment. City officials and urban planners celebrate the release of the MVA typology and are open about their use of it. For example in the release of Baltimore's 2014 release, the city's newsletter stated that "Baltimore's Housing Market Typology has been used to help guide public policy, market studies, community plans, grant funding applications and capital improvement programming" (Baltimore City Planning Department, 2014). Private businesses use these maps and may decide to invest or not invest in business based on their perceived risk. Shockingly similar to the HOLC maps D-rated neighborhoods, the MVA uses red to denote "distressed" housing markets.

While we found that 40% of HOLC's D-rated areas, like Oliver, were ranked in the bottom 2 MVA categories as "distressed" housing markets, we again argue that perhaps the more important finding was in relation to the territorial preservation of wealth. Nearly 72% of HOLC's A-rated areas ranked in the top 2 MVA categories, almost double the rate of preservation of poverty. Another way to put that is that the MVA directs investment to preserve the territorial integrity of "healthy" housing markets to protect the wealth of primarily white home owners (see Table 2). This preservation *simultaneously and relationally* reinforces decline in BIPOC and majority Black neighborhoods to later extract profit. The real estate practices encapsulated in redlining were intended to manipulate the housing market to spatially produce suburban white wealth through the relational production of "organized abandonment" (Harvey, 2007, p. 397) and "ungeographic space" (McKittrick, 2006) that mapped onto Black communities across US cities. The MVA typology operates similarly to the complex web of actors captured in the HOLC maps, and our analysis reveals how "redlining" wasn't just a set of practices in the 1930s that shaped the city in racialized and classed ways—new maps and algorithms like the MVA contribute to a broader, more contemporary understanding of redlining in modern urban governance.

8. Conclusion

In this paper, we empirically demonstrate how purportedly objective algorithms, such as the Market Value Analysis (MVA), contribute to the production of uneven urban spaces by categorizing neighborhoods in ways that perpetuate existing race and class-based inequalities. These algorithms, which fail to account for the historical and ongoing processes of segregation, not only reflect but also reinscribe market-based approaches that prioritize capital accumulation over equitable urban development—producing profits through the reproduction of hierarchies of territorial difference. The "problem" of cities continues to be framed as one of effective resource allocation, which can then be solved by purchasing data from so-called experts. Decontextualized algorithms thus serve to justify dispossession and protect white wealth under the guise of maximizing the efficiency of government resource allocation, further entrenching practices that relationally extract profit from economically disadvantaged neighborhoods.

We contribute to the literature on algorithmic violence and the anti-politics machine by showing how market-based algorithms like the MVA serve as a critical tool within the anti-politics machine, depoliticizing urban planning decisions and embedding race- and class-based segregation within public policy and development practices. Algorithms such as the MVA are problematic not simply because they are not objective but rather because they further institutionalize inequality. We extend the concept of algorithmic violence by revealing how these algorithms, presented as neutral, shield the political nature of their outcomes while perpetuating and reinforcing historical patterns of racialized geographies of wealth and poverty. Through an analysis of 10 cities with both MVA and HOLC maps, we demonstrate how the MVA mirrors the racialized practices of redlining by protecting wealth in predominantly white areas while reproducing poverty in marginalized communities. We recast redlining not as a historical legacy but as an ongoing practice embedded in modern real estate and investment algorithms like the MVA, which determine the worthiness of neighborhoods for public and private investment (see also Gioielli, 2022; Markley, 2023). Ahistorical market-oriented algorithmic neighborhood typologies serve as a form of technopolitics that influences the allocation of resources through the categorization of neighborhoods. The lasting impacts of these planning, development, and real estate practices are evident not only in the persistence of segregation in the geography of cities (Aaronson et al., 2017; Taylor, 2019) but also by the persistence of "technopolitical regimes" consisting of "linked sets of individuals, engineering and industrial practices [abstracting/surveying neighborhoods], technological artifacts [GIS and spatial tools specific to neighborhood classification], political programs, and institutional ideologies acting together to govern technological development and pursue technopolitics" (Hecht, 2001, pp. 253–293, p. 256). The introduction of the MVA allows for the facade of objectivity afforded by technological complexity to become a powerful tool in the institutionalization and entrenchment of race- and class-based housing segregation practices.

Over 40 states, cities, and municipalities have now purchased MVAs over the last two decades. We expect this to expand to and entrench a policy of using algorithms to justify initiatives of disinvestment and resource allocation. Billions of dollars of federal, state, and local funds are allocated using the MVA as part of their underlying reasoning. Beyond government spending, nonprofits, corporations and private businesses also use the MVAs to guide their decision making. Ironically, the RF bemoans the difficulty in getting home loans in "distressed" housing markets, but they contribute to this by reproducing maps that determine the worthiness of housing investment.

By framing city residents as "customers" and government spending as a technocratic exercise oriented toward market factors, the MVA effectively compels governments to deprioritize the immediate material needs of vulnerable constituents and to approach communities as entities which must respond to the profit motive. When an algorithm is driven by the a priori conditions of segregated cities and the imperatives of market strength, that algorithm is bound to reproduce and magnify existing uneven geographies (see Markley, 2024; Noterman, 2022). Yet our claim is that the MVA algorithm consequently insulates (white) wealth and justifies *further* dispossession, while claiming to be an objective tool for maximizing the efficiency of government spending. As a result, the machinations of racial capitalism are further embedded in the geography of the city and the utilization of market-based approaches to city planning and spatial ordering are further embedded in public policy. Dozens of city governments continue to adopt algorithm-driven policy solutions for ostensibly "objective" and "apolitical" decision-making; our findings signal the need for a thorough dismantling of investment-oriented algorithmic neighborhood typologies and the anything-but-objective algorithms that (re)produce relational difference through perceived territorial value.

CRediT authorship contribution statement

Dillon Mahmoudi: Conceptualization, Data curation, Formal analysis, Supervision, Writing – original draft, Writing – review & editing. **Dena Aufseeser:** Investigation, Supervision, Writing – original draft, Writing – review & editing. **Alicia Sabatino:** Data curation, Formal analysis, Investigation, Methodology, Software, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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